Labor Hiring, Investment, and Stock Return Predictability in the Cross Section

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We study the impact of labor market frictions on asset prices. In the cross section of US firms, a 10 percentage point increase in the firm's hiring rate is associated with a 1.5 percentage point decrease in the firm's annual risk premium. We propose an investment-based model with stochastic labor adjustment costs to explain this finding. Firms with high hiring rates are expanding firms that incur high adjustment costs. If the economy experiences a shock that lowers adjustment costs, these firms benefit the most. The corresponding increase in firm value operates as a hedge against these shocks, explaining the lower risk premium of these firms in equilibrium.

I. Introduction

We study the impact of labor market frictions on asset prices in the cross section of US publicly traded firms. When firing and hiring workers are

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costly, the market value of a firm reflects the value of its installed labor force because the firm can extract rents as compensation for the costs associated with adjusting its labor force. In addition, these costs make hiring decisions forward looking and are thus potentially informative about the firm's future value. Consistent with this view, we show that in firm-level regressions, a 10 percentage point increase in the firm's current hiring rate is associated with a decrease of 1.5 percentage points in the firm's annual future stock return. In portfolio sorts, a long low-hiring/short high-hiring firms portfolio earns an average annual excess stock return of 5.6 percent (value weighted) to 10.4 percent (equal weighted). In this paper, we interpret this difference in average returns, which we refer to as the hiring return spread, as reflecting the relatively lower risk of the firms with higher hiring rates in the cross section, and relate this differential risk to the existence of frictions in the labor market.

To establish the link between labor hiring decisions and risk premiums, we propose an investment-based asset pricing model that treats a firm's labor hiring decision as analogous to an investment decision. The key feature of the model is the existence of labor, in addition to capital, adjustment costs. Firms make hiring and investment decisions to maximize firm value, taking as given a stochastic discount factor to value its cash flows. Cross-sectional heterogeneity is driven by idiosyncratic productivity shocks. Aggregate fluctuations and systematic risks are driven by a standard aggregate productivity shock and by an aggregate adjustment cost shock that affects the marginal cost of hiring and investing. Consistent with previous studies, the aggregate productivity shock carries a positive price of risk, and the adjustment cost shock carries a negative price of risk.

In the model, the negative relation between firms' hiring rates and risk premiums arises endogenously in the cross section as a result of differences in firms' productivity and the interaction between adjustment costs and the aggregate adjustment cost shock. The underlying economic mech-

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anism operates as follows. Firms with relatively high hiring rates are expanding because they have received good idiosyncratic productivity shocks in the recent past. Because idiosyncratic productivity is persistent and (convex) adjustment costs prevent firms from instantaneously adjusting their labor force and capital stock, these firms will want to continue to expand over the next few periods and thus incur high adjustment costs. If the economy experiences a shock that lowers adjustment costs, these firms will benefit the most from these lower costs, allowing them to expand faster and make profits more quickly. Therefore, the value of these firms increases relatively more during these times, thus providing a hedge against this shock given its negative price of risk. These firms therefore have relatively lower risk and hence lower expected returns in equilibrium.

The model is calibrated to match aggregate-level asset pricing and quantity moments, the value premium in the cross section, and key cross-sectional and time-series properties of the firm-level hiring and investment rates. The model then successfully replicates the observed levels of the hiring return spread with reasonable labor and capital adjustment cost parameters. Through several comparative statics exercises, we show that the existence of labor adjustment costs is important for the good quantitative fit of the model. When labor can be freely adjusted, the model generates a firm-level hiring rate that is too volatile (40 percent in the frictionless labor model vs. 24 percent in the baseline model with labor adjustment costs and 26 percent in the data) and a hiring return spread that is too small and even slightly negative, −0.4 percent per year. This result is intuitive. Without labor adjustment costs, the hiring rate inherits the high volatility of the aggregate and firm-specific shocks. Firms also take advantage of the costlessly adjustable labor input to further control the fluctuations of their payouts in response to the shocks, thus significantly reducing the dispersion in risk in the cross section. Taken together, the results of our analysis suggest that labor market frictions can have a significant impact on asset prices in financial markets.

The model is also consistent with other empirical regularities. First, as documented in previous studies, the investment rate is also negatively correlated with future stock returns. We show that the hiring rate contains information about future returns that is not fully contained in the investment rate. In firm-level regressions, when we control for the investment rate, a 10 percentage point increase in the firm's current hiring rate is associated with a decrease of 0.7–1.5 percentage points in the firm's annual future stock return. Similarly, when we control for the hiring rate, a 10 percentage point increase in the firm's current investment rate is associated with a decrease of 1.6–2.3 percentage points in the firm's annual future stock return. When the hiring and investment predictability is interpreted as reflecting the risk associated with labor and capital market frictions, respectively, the relative strength of the links suggests that the importance of labor market frictions for firms' risk is comparable with that of standard investment frictions, which have received the lion's share of attention in the investment literature. The model is consistent with the joint predictability of hiring and investment. The difference in the adjustment cost structure of labor and capital leads to different responses of firms' hiring and investment to the aggregate shocks. As a result, both variables are important in characterizing the overall risk of a firm.

Second, we show that the unconditional capital asset pricing model (CAPM) cannot explain the hiring return spread in the data. The sensitivity of the returns of firms with different hiring rates to the aggregate stock market factor (market risk) is negatively correlated with its average stock returns—the reverse of what the CAPM needs to explain the hiring return spread. As a result, the CAPM-implied pricing error of the hiring return spread is larger than the hiring return spread itself. The model replicates this finding, thus providing an economic explanation for the failure of the CAPM. According to the model, the aggregate stock market is mostly driven by the aggregate productivity shock, and thus it is weakly correlated with the aggregate adjustment cost shock, which is the main driver of the hiring return spread in the cross section. Finally, the Fama-French (1993) three-factor model captures reasonably well, at least in value-weighted portfolios, the size of the hiring return spread in both the data and the model, consistent with a risk-based interpretation of the hiring return spread.

Related literature.—Barring a few exceptions, labor market frictions are typically ignored in the investment-based asset pricing literature.[1] This approach is perhaps surprising given the central role of labor market frictions in modern theories of economic fluctuations (see, e.g., Hall 1999). We incorporate labor market frictions into a neoclassical dynamic investment-based asset pricing model (e.g., Zhang 2005). At the aggregate level, labor frictions are explicitly modeled in Danthine and Donaldson (2002; wage frictions) and in Merz and Yashiv (2007; hiring and firing frictions).[2] Our work differs because we perform the analysis at the firm level, which allows us to use both time-series and cross-sectional data. In addition, we examine the implications of labor adjustment costs for stock returns both in the data and in model simulations.

The search and matching models of Diamond (1982) and Mortensen and Pissarides (1994) emphasize the existence of search frictions in the

[1] Early contributions to the investment-based asset pricing literature include Cochrane (1991), Jermann (1998), Berk, Green, and Naik (1999), and Zhang (2005). Cochrane (2007) provides a review of this literature.

[2] See also Uhlig (2007), Bhamra and Lochstoer (2009), Favilukis and Lin (2013), and Petrosky-Nadeau, Zhang, and Kuhen (2013) for recent analysis of the link between labor market frictions and asset prices at the aggregate level.

labor market. In addition, training costs, disruption costs, and firing costs (e.g., severance pay) prevent firms from costlessly adjusting their labor stock. Our model captures these frictions in a reduced form, through a labor adjustment cost function. This approach is consistent with the large labor and investment demand literature that investigates the importance of capital and labor adjustment costs in explaining investment and hiring dynamics.[3] Bloom (2009) estimates labor and capital adjustment cost parameters at the plant level and finds adjustment costs to be sizable, but the work does not consider asset prices. We show that labor adjustment costs are also important for explaining the cross-sectional variation in asset prices. Thus, our work also contributes to the asset pricing literature linking firm characteristics to stock returns in the cross section. Fama and French (2008) provide a survey of this vast literature.

Our model features an aggregate adjustment cost shock. We show that this shock is analogous to an investment-specific shock, extended to affect the efficiency of both new labor and capital inputs, not just capital. Solow (1960), Greenwood, Hercowitz, and Krusell (1997), and many others study the macroeconomic implications of investment-specific shocks. Papanikolaou (2011) and Kogan, Papanikolaou, and Stoffman (2012) study the effect of investment-specific shocks on asset prices in a setup with frictionless labor and show that investment-specific shocks carry a negative price of risk in equilibrium. We incorporate this finding in our analysis and show that having both adjustment cost shocks and labor market frictions is important to endogenously generate a sizable hiring return spread and match key properties of firms' hiring rates.

The paper proceeds as follows. Section II shows the empirical links between hiring, investment, and stock returns in the cross section. Section III presents an investment-based asset pricing model with labor market frictions that we use to understand the empirical evidence. Section IV calibrates and solves the model numerically. Section V reports the fit of the model on the cross section of stock returns. Section VI provides a detailed analysis of the economic mechanisms driving the results. Finally, Section VII presents conclusions. A separate appendix with additional results and robustness checks is posted in the online data archive.

II. Empirical Evidence

In this section, we show the empirical links between hiring, investment, and stock returns in the cross section. We use the results reported here to motivate the investment-based asset pricing model with labor market frictions that we present in Section III.

[3] Hamermesh and Pfann (1996) and Bond and Van Reenen (2007) provide a survey of the literature. Hamermesh (1993) reviews a set of direct estimates of the costs of adjusting labor and shows that these costs can be substantial.

A. Data

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. The sample is from July 1965 to June 2010 and includes firms with common shares (shrcd = 10 and 11) and firms traded on the New York Stock Exchange, the American Stock Exchange, and NASDAQ (exchcd = 1, 2, and 3). We omit firms whose primary standard industrial classification is between 4900 and 4999 (regulated firms) or between 6000 and 6999 (financial firms). Following Cohen, Gompers, and Vuolteenaho (2002), we require a firm to have a December fiscal year end to align the accounting data across firms.[4] Finally, we correct for the delisting bias following the approach in Shumway (1997).

The key variables for the empirical work are the firm's labor hiring and investment rates.[5] The hiring rate is given by $HN_t = H_t/[0.5 \times (N_{t-1} + N_t)]$, in which the number of employees (N_t) is given by Compustat data item EMP, and net hiring (H_t) is given by the change in the number of employees from year $t - 1$ to year t ($H_t = N_t - N_{t-1}$). By construction, this measure of labor hiring is symmetric around zero and bounded between ±200 percent. The investment rate is given by $IK_t = I_t/[0.5 \times (K_{t-1} + K_t)]$, in which the physical capital stock (K_t) is given by data item PPENT (net property plant and equipment), and physical capital investment (I_t) is given by Compustat data item CAPX (capital expenditures) minus SPPE (sales of property, plant, and equipment). Missing values of SPPE are set to zero.

We note that the employment data in company accounts are often poorly measured because personnel information is subject to looser reporting and auditing requirements than financial statement variables. In particular, there is no distinction between full-time, part-time, and seasonal workers; there is no adjustment for hours worked; and the employee numbers are usually reported after rounding. Some firms report the average number of employees during the year whereas other firms report the number of employees at year end. In addition, by focusing only on the total number of employees, our hiring rate measure ignores heterogeneity among workers. Thus, because of these data limitations, our empirical analysis is likely to provide a conservative estimate of the link between hiring decisions and stock returns in the economy.

We also keep track of the following variables. Market equity (size) is price times shares outstanding at the end of December. The physical capital-to-market-equity ratio (KM) is the ratio of the firm's physical capital stock

[4] In the online appendix we report the main results obtained without the December fiscal year end restriction.

[5] Asness, Porter, and Stevens (2000) use firm-level changes in employees as an empirical proxy variable for distress in the cross section.

and market equity. Return on assets (ROA), a measure of profitability, is given by the ratio of Compustat data item NI (net income) to Compustat data item AT (book value of assets). Productivity (TFP) is firm-level total factor productivity from Tuzel and Imrohoroglu (2013). We exclude from the sample the firm-year observations with missing or negative capital stock data, missing number of employees and capital expenditures data, and missing investment and hiring rate data. The final sample includes a total of 75,381 firm-year observations. The data for the three Fama-French factors (small minus big [SMB], high minus low [HML], and market [MKT]) are from Kenneth French's web page.

B. *Hiring and Stock Returns*

To investigate the link between labor hiring decisions and future stock returns in the cross section, we construct 10 portfolios sorted on the firm's current hiring rate and report the portfolio's postformation average stock returns. We construct the hiring portfolios as follows. At the end of June of year t, we sort the universe of common stocks into 10 portfolios based on the firm's hiring rate at the end of year $t - 1$. To define the hiring rate breakpoints used to allocate firms into portfolios, we follow Fama and French (2008) and compute the deciles of the hiring rate cross-sectional distribution of all but micro cap firms in NYSE-AMEX-NASDAQ. The micro cap firms are defined as firms with a market capitalization that is lower than the bottom 20th percentile of the market capitalization cross-sectional distribution of NYSE firms. If we compute the portfolio breakpoints including micro cap firms, we often have too few medium-sized and large stocks on the extreme low- and high-hiring portfolios because the micro cap firms are plentiful (on average, micro caps are 60 percent of all sample stocks in NYSE-AMEX-NASDAQ) and have more volatile hiring rates. Once the portfolios are formed, their returns are tracked from July of year t to June of year $t + 1$. The procedure is repeated at the end of June of year $t + 1$.[6]

We report both average equal- and value-weighted portfolio returns across all firms, as well as average equal-weighted portfolio returns across a sample of firms that excludes the micro cap firms. Reporting these three sets of average returns allows us to provide a comprehensive picture of the link between hiring and stock returns in the overall economy. As discussed in Fama and French (2008), the properties of average equal-

[6] In the online appendix we also report the average returns of the hiring portfolios in which the portfolio breakpoints (deciles) are computed using the subsample of NYSE firms only, an alternative procedure often used in the empirical asset pricing literature (e.g., Fama and French 1993). As we explain in the online appendix, the updated Fama and French (2008) procedure that we use here allows us to incorporate the information about the very large firms traded in NASDAQ and AMEX (e.g., Apple and Microsoft) as well as avoid the use of micro cap firms (which are firms that tend to have accounting data of

weighted returns are dominated by the behavior of very small firms because, as noted, these firms are plentiful and also have more volatile returns. Similarly, the properties of average value-weighted returns are dominated by the behavior of a small number of very large (albeit important) firms because of the well-known heavy tails of the size distribution in the US stock market (Zipf 1949).[7] Thus, also reporting the properties of average equal-weighted returns of the hiring portfolios across a subsample of firms that excludes micro cap firms allows us to mitigate the extreme influence of the very small and very large firms in pure average equal- and value-weighted returns and thus characterize the empirical links for an average firm in the economy.[8]

The top rows in table 1 report the average excess stock returns (r^e, in excess of the risk-free rate) and Sharpe ratios of the 10 hiring portfolios. This table shows that, across the three sets of average returns, the firm's hiring rate forecasts stock returns. Firms with currently low hiring rates earn subsequently higher returns on average than firms with currently high hiring rates. The difference in returns is economically large and statistically significant. The average equal-weighted return spread (L−H, the hiring return spread) is 10.4 percent per year, and this value is more than 5.7 standard errors from zero. This hiring return spread remains large even when micro cap firms are excluded from the sample (6.9 percent per year), as well as across very large firms. The average value-weighted hiring return spread is 5.6 percent per year, and this value is more than 2.2 standard errors from zero. From the fact that the hiring return spread is smaller in value-weighted returns than in equal-weighted returns, we can infer that the hiring return spread is particularly strong among small firms, a common finding in the empirical asset pricing literature. This finding is interesting because private firms, which represent about two-thirds of total employment in the US economy, tend to be smaller than the publicly traded firms covered in the Compustat data. As such, the link between hiring and firm value documented here may represent a lower bound of the link for the majority of the firms in the US economy.

The Sharpe ratios of the hiring portfolios are also decreasing in firms' current hiring rate. Across the three sets of average returns, the Sharpe ratio of the portfolio of firms with low hiring rates is more than six times

inferior quality relative to the larger firms) traded in NYSE into the computation of the portfolio's breakpoints. In addition, in the online appendix, we also report the average returns of the hiring portfolios using a monthly (as opposed to annual) sorting procedure.

[7] See Malevergne, Santa-Clara, and Sornette (2011) for an analysis of the effect of the fat tails of the size distribution on portfolio diversification measures and standard asset pricing tests.

[8] In the online appendix, we characterize the link between hiring and stock returns across portfolios of firms with different sizes. In average equal-weighted returns, the links that we report here are strong across all size groups. In average value-weighted returns, the links that we report here are stronger among smaller firms and weaker among large firms.

TABLE 1
HIRING PORTFOLIOS

	Equal-Weighted												Value-Weighted					
	All Firms						All but Micro						All Firms					
	Low	2	5	9	High	L−H	Low	2	5	9	High	L−H	Low	2	5	9	High	L−H
	Excess Returns																	
r^e	12.32	12.34	9.87	6.69	1.88	10.44	8.64	9.20	8.33	5.81	1.74	6.89	7.03	5.96	4.15	4.90	1.42	5.61
[t]	2.90	3.51	3.03	1.70	.43	5.78	2.46	2.83	2.76	1.57	.41	3.48	2.47	2.26	1.76	1.52	.38	2.26
SR	.48	.58	.50	.28	.07	.92	.40	.45	.44	.25	.06	.53	.39	.34	.26	.24	.06	.34
	CAPM																	
	m.a.e. = 4.67						m.a.e. = 2.98						m.a.e. = 1.38					
α	6.57	7.06	4.72	.58	−4.75	11.32	2.89	3.80	3.14	−.42	−5.28	8.17	2.25	1.40	−.07	−.66	−4.78	7.03
[t]	2.57	3.96	3.22	.31	−2.11	6.45	1.86	2.66	2.84	−.28	−2.69	4.28	1.69	1.13	−.07	−.48	−2.73	2.90
b	1.22	1.12	1.09	1.29	1.40	−.19	1.21	1.14	1.10	1.32	1.49	−.27	1.01	.96	.89	1.18	1.31	−.30
[t]	22.83	27.78	31.74	31.90	29.66	−5.32	30.45	29.36	37.97	43.88	37.30	−6.13	31.99	32.67	37.82	41.01	31.98	−4.96
R^2	.57	.71	.77	.73	.69	.07	.78	.80	.85	.81	.77	.11	.78	.79	.82	.82	.77	.08
	Fama-French																	
	m.a.e. = 2.30						m.a.e. = 1.15						m.a.e. = 1.06					
α^F	2.27	3.03	1.61	−1.38	−6.32	8.59	−.53	.15	.68	−1.03	−5.06	4.53	.85	.14	.19	.71	−2.41	3.26
[t]	1.29	2.61	1.62	−1.12	−3.90	5.09	−.44	.15	.78	−.84	−3.35	3.00	.68	.11	.20	.58	−1.66	1.61
b	1.02	1.03	1.01	1.09	1.17	−.14	1.17	1.16	1.08	1.17	1.27	−.11	1.05	1.04	.95	1.06	1.15	−.10
s	1.16	.78	.65	.90	.98	.17	.56	.37	.36	.59	.69	−.13	.04	−.10	−.23	.22	.26	−.22
h	.28	.38	.28	−.02	−.12	.40	.36	.48	.28	−.13	−.31	.68	.22	.26	.05	−.32	−.51	.73
R^2	.80	.87	.90	.89	.84	.19	.87	.88	.90	.89	.87	.40	.79	.81	.84	.86	.84	.32

NOTE.—This table reports the average equal- and value-weighted excess stock returns and abnormal returns of 10 portfolios one-way sorted on hiring rate. We report portfolios 1 (low), 2, 5, 9, and 10 (high). The term r^e is the average annualized (× 1,200) portfolio excess stock return; [t] are heteroscedasticity and autocorrelation consistent t-statistics (Newey-West); SR is the portfolio Sharpe ratio; α and α^F are portfolio average abnormal returns, obtained as the intercept from monthly CAPM or Fama-French (1993) regressions, respectively, reported in annual percentages (× 1,200); m.a.e. is the mean absolute pricing errors (average of absolute values of α or α^F across portfolios); b, s, and h are the portfolio market, SMB, and HML betas, respectively. L−H stands for the low-minus-high hiring portfolio. The table reports the equal-weighted returns across a sample that includes all the firms with nonmissing data (all firms) and across a subsample of firms that excludes micro cap firms (all but micro), defined as the firms with size (market value) that is below the bottom 20th percentile of the cross-sectional size distribution of NYSE firms in June of each year. The sample is from July 1965 to June 2010.

larger than the Sharpe ratio of the portfolio of firms with high hiring rates.

To help interpret the hiring portfolios, panel A in table 2 (data) reports the time-series average of median portfolio-level characteristics of the hiring portfolios at the time of portfolio formation and 1 year after portfolio formation. The hiring rate is naturally related to other firm characteristics. The physical capital-to-market-equity ratio variable (which is closely correlated to the standard book-to-market-equity ratio) is negatively correlated with the portfolio-level hiring and physical capital investment rates. This fact is consistent with the neoclassical investment-based model because, in general (and as we show in the online appendix), the book-to-market ratio is a decreasing function of firms' investment rates. By linking hiring (and investment) to the book-to-market ratio, our analysis is thus also related to the well-known value premium, but our sorting is based on a macroeconomic-based variable, not a market-based variable. As we show below, however, the hiring return spread is distinct from the value premium in our model. In addition, in the online appendix, we show that the empirical link between hiring and future stock returns is weaker, but it still holds after controlling for the firm's book-to-market ratio. The average size characteristic across portfolios is not monotone (A-shaped), but firms with high hiring rates tend to be larger than firms with low hiring rates. Finally, firms with high hiring rates tend to be more productive and more profitable, as measured by TFP and return on assets.

C. *Hiring, Investment, and Stock Returns*

Previous studies document a negative relationship between the firm's investment rate and future stock returns in the cross section. As reported in table 2, the hiring and investment rates are positively correlated. Thus, part of the link between the firm's hiring rate and future stock returns reflects the negative correlation between investment and future stock returns. In this subsection, we extend the previous analysis by investigating the joint link between hiring, investment, and future stock returns in portfolios two-way sorted on hiring and investment and in firm-level multivariate regressions that include both the firm's hiring rate and the firm's investment rate as return predictors.

1. Hiring and Investment Portfolios

We form nine portfolios two-way sorted on hiring and investment as follows. At the end of June of year *t*, we first sort the universe of common stocks into three portfolios based on the firm's investment rate. Then, the firms in each one of these three investment portfolios are further

TABLE 2
Accounting Characteristics of the Hiring Portfolios

	A. Data						B. Model					
	Low	2	5	9	High	L−H	Low	2	5	9	High	L−H
Hiring rate:												
HN_t	−.19	−.06	.03	.21	.44	−.63	−.31	−.20	−.05	.22	.41	−.72
HN_{t+1}	−.01	−.01	.02	.07	.09	−.10	−.19	−.13	−.04	.12	.21	−.40
Investment rate:												
IK_t	.14	.16	.19	.31	.37	−.23	−.05	−.01	.06	.28	.46	−.51
IK_{t+1}	.15	.15	.19	.27	.29	−.14	−.04	.00	.07	.22	.32	−.36
Productivity and profitability:												
TFP_t	.46	.50	.55	.59	.60	−.14	.02	.02	.03	.05	.05	−.03
TFP_{t+1}	.48	.50	.54	.57	.58	−.10	.02	.02	.03	.05	.05	−.03
ROA_t	−.01	.03	.06	.06	.05	−.06	.12	.16	.28	.53	.72	−.60
ROA_{t+1}	.01	.04	.05	.05	.03	−.02	.13	.17	.28	.49	.62	−.49
Valuation:												
KM_t	.49	.55	.41	.28	.25	.24	.83	.72	.57	.44	.38	.46
KM_{t+1}	.46	.52	.43	.31	.31	.15	.79	.68	.55	.47	.44	.35
Size_t	3.61	4.68	5.20	4.71	4.46	−.85	4.65	4.60	4.70	5.03	5.01	−.36
Size_{t+1}	3.82	4.86	5.41	4.79	4.52	−.70	4.56	4.54	4.68	5.08	5.16	−.60

Note.—This table reports the time-series averages of the following portfolio-level characteristics of 10 portfolios one-way sorted on hiring rate. We report portfolios 1 (low), 2, 5, 9, and 10 (high). *HN* is the hiring rate; *IK* is the investment rate; TFP is total factor productivity; ROA is return on assets (in the model, ROA is measured as profits scaled by the stock of physical capital); size is the log market capitalization; *KM* is the physical-capital-to-market-equity ratio. L−H stands for the low-minus-high hiring portfolio. The subscripts t and $t + 1$ stand for portfolio-level characteristics measured at the time of portfolio formation (t) or 1 year after portfolio formation ($t + 1$). The portfolio-level characteristics are computed as the median value of each characteristic across all firms in the portfolio in July of any given year. Panel A reports the statistics in the data from July 1965 to June 2010. Panel B reports the statistics using data simulated from the model, obtained as averages from 500 samples of simulated data, each with 3,600 firms and 600 monthly observations.

sorted into three portfolios based on the firm's hiring rate. This sequential sorting guarantees a balanced number of firms in each portfolio (with an independent sorting, the off-diagonal portfolios have too few firms because the investment and hiring rates are positively correlated). The investment rate and hiring rate breakpoints for year t are the 30th and 70th percentiles of the cross-sectional distribution of the corresponding sorting variable at the end of year $t - 1$. To compute the breakpoints, we use the sample of all but micro cap firms in NYSE-AMEX-NASDAQ, consistent with the construction of the portfolios one-way sorted on hiring. Once the portfolios are formed, their returns are tracked from July of year t to June of year $t + 1$. The procedure is repeated at the end of June of year $t + 1$.

The top three panels in table 3 show that the two-way sorting procedure generates a reasonable spread in average excess returns across both the hiring (row L−H) and the investment (col. L−H) dimensions.

TABLE 3

Hiring and Investment Portfolios

	Equal-Weighted										Value-Weighted				
	All Firms *IK*					All but Micro *IK*					All Firms *IK*				
HN	L	M	H	L−H	[*t*]	L	M	H	L−H	[*t*]	L	M	H	L−H	[*t*]
	Excess Returns: r^e														
L	12.75	11.20	10.31	2.43	1.88	9.06	9.25	6.88	2.18	1.34	7.55	5.65	3.63	3.93	1.85
M	11.97	9.78	8.34	3.63	2.08	9.88	8.15	6.84	3.04	1.64	5.38	6.22	5.75	−.37	−.14
H	9.23	7.27	.87	8.35	4.01	8.51	6.25	1.10	7.40	2.97	7.46	4.44	−1.09	8.55	2.90
L−H	3.52	3.93	9.44			.55	2.99	5.77			.10	1.20	4.72		
[*t*]	2.74	3.49	5.50			.51	2.59	2.77			.06	.78	1.83		
	CAPM: α														
	m.a.e. = 4.79					m.a.e. = 3.00					m.a.e. = 2.31				
L	7.37	5.79	4.40	2.97	2.39	3.62	3.94	.88	2.74	1.73	3.11	1.28	−1.71	4.82	2.33
M	7.12	4.75	2.28	4.84	2.98	4.90	3.16	.69	4.21	2.41	1.55	1.94	.21	1.34	.57
H	3.81	1.56	−6.03	9.84	4.99	3.09	.56	−6.19	9.27	3.96	2.68	−.34	−8.00	10.68	3.81
L−H	3.56	4.23	10.43			.53	3.38	7.07			.43	1.62	6.29		
[*t*]	2.84	3.73	6.24			.48	2.95	3.51			.28	1.06	2.50		
	Fama-French: α^F														
	m.a.e. = 2.14					m.a.e. = 1.25					m.a.e. = 1.63				
L	2.59	1.95	1.62	.97	.83	−.71	.76	−.63	−.08	−.06	.95	.69	−1.17	2.12	1.06
M	2.70	1.89	.88	1.81	1.46	1.58	.88	.59	.99	.75	.21	2.50	3.00	−2.79	−1.37
H	−.04	−1.20	−6.36	6.32	3.96	.26	−1.10	−4.74	5.00	2.84	1.59	.35	−4.17	5.76	2.56
L−H	2.63	3.16	7.97			−.97	1.86	4.11			−.65	.34	3.00		
[*t*]	2.06	2.77	5.23			−.97	1.76	2.41			−.44	.23	1.43		

Note.—This table reports the average equal- and value-weighted excess stock returns and abnormal returns of nine portfolios two-way sorted on hiring rate (*HN*) and investment rate (*IK*). The sorting on the hiring rate is reported across rows L (low), M (mid), and H (high), and the sorting on the physical capital investment rate is reported across columns L, M, and H. L−H stands for the low-minus-high hiring portfolio (across rows) or the low-minus-high investment portfolio (across columns); r^e is the average annualized (× 1,200) portfolio excess stock return; [*t*] are heteroscedasticity and autocorrelation consistent *t*-statistics (Newey-West); α and α^F are the portfolio average abnormal returns, obtained as the intercept from monthly CAPM or Fama-French (1993) regressions, respectively, reported in annual percentages (× 1,200); m.a.e. is the mean absolute pricing errors (average of the absolute values of α or α^F). The table reports the equal-weighted returns across a sample that includes all the firms with nonmissing data (all firms) and across a subsample of firms that excludes micro cap firms (all but micro), defined as the firms with size (market value) that is below the bottom 20th percentile of the cross-sectional size distribution of NYSE firms in June of each year. The sample is from July 1965 to June 2010.

Within investment bins (within columns), firms with low hiring rates earn higher returns, on average, than firms with high hiring rates. Within hiring bins (within rows), firms with low investment rates earn higher returns, on average, than firms with high investment rates (we refer to this difference in returns as the investment return spread). Thus, the hiring rate contains some information about future stock returns that is not contained in the investment rate (and vice versa for the investment rate).

The magnitude of the hiring return spread is comparable, albeit smaller, with the magnitude of the investment return spread. In addition, the investment and, especially, the hiring return spreads are stronger in equal-weighted returns than in value-weighted returns. In equal-weighted returns (across all firms), within each investment bin, firms with low hiring rates outperform firms with high hiring rates by a value between 3.5 percent and 9.4 percent per year (the average hiring return spread across the three investment bins is 5.6 percent per year). Similarly, within each hiring bin, firms with low investment rates outperform firms with high investment rates by a value between 2.4 percent and 8.3 percent per year (the average investment return spread across the three hiring bins is 4.8 percent per year).

The equal-weighted hiring return spread remains large in the sample of firms that excludes micro cap firms. Here, the average hiring return spread across the three investment bins is 3.1 percent per year. The average investment return spread across the three hiring bins is 4.2 percent. Finally, the two-way sorted hiring and investment return spread is weaker in value-weighted returns. Here, firms with low hiring rates outperform firms with high hiring rates by a value between 0.1 percent and 4.7 percent per year (the average hiring return spread across the three investment bins is 2 percent per year). Similarly, firms with low investment rates outperform firms with high investment rates by a value between −0.3 percent (but not significant) and 8.5 percent per year (the average investment return spread across the three hiring bins is 4 percent per year). Taken together, the results show the coexistence of a hiring and investment return spread in the data, and this coexistence is stronger in average equal-weighted portfolio returns.

2. Firm-Level Return Predictability Regressions

We also investigate the marginal (relative to investment) predictability of hiring using stock return predictability regressions performed at the firm level. It is difficult to draw inferences about which sorting variables have unique information about future returns using a portfolio approach. The portfolio procedure requires the specification of breakpoints to sort the firms into portfolios, select the number of portfolios, and specify the order of the sorting procedure in multivariate sorts. All of these choices may influence the overall analysis. Thus, the firm-level regressions provide a cross-check.

We run standard firm-level cross-sectional regressions (Fama and MacBeth 1973) as well as pooled time-series ordinary least squares (OLS) regressions to predict stock returns using the lagged firms' hiring and investment rates as return predictors. The time-series regression allows for a clear economic interpretation of the regression slopes, and the two different econometric procedures allow us to further cross-check the results. In both regressions, the predictor variables are a constant and the lagged values of the firm's hiring and investment rates. To control for the strong influence of micro cap firms on the regression results, we also consider specifications with interaction terms in which the previous variables are interacted with a dummy variable (micro), which is equal to one if the firm is a micro cap firm in year $t - 1$ and zero otherwise.

Table 4, columns 1–4, reports the results from cross-sectional predictability regressions performed at a monthly frequency. The results are consistent with the portfolio-level results. Hiring and investment jointly predict stock returns with statistically significant negative slope coefficients. The estimated hiring rate slope coefficient ranges from −0.89 (specification 1) to −0.48 (in specification 4, controlling for the effect of micro cap firms and investment), and these values are all more than three standard errors from zero. The estimated investment rate slope coefficient ranges from −0.52 (specification 2) to −0.54 (in specification 4, controlling for the effect of micro cap firms and hiring), and these values are more than 1.9 standard errors from zero.

The results from pooled OLS predictability regressions reported in table 4, columns 5–8, are also consistent with the previous analysis. The estimation here is performed at an annual frequency and includes firm and year fixed effects. Both the hiring and investment rate slope coefficients are negative. The magnitude of the economic predictability is large. A 10 percentage point increase in the firm's hiring rate is associated with a 1.5 (or 0.7 for non–micro cap firms) percentage point decrease in the firm's annual future stock return, controlling for the investment rate. Similarly, a 10 percentage point increase in the firm's investment rate is associated with a 1.6 (or 2.3 for non–micro cap firms) percentage point decrease in the firm's annual future stock return, controlling for the hiring rate.

D. *Asset Pricing Tests*

We also investigate the extent to which the variation in the average returns of the hiring and investment portfolios can be explained by ex-

TABLE 4
FIRM-LEVEL STOCK RETURN PREDICTABILITY REGRESSIONS

	Cross-Sectional Regressions ($N = 1{,}569$)				Pooled OLS Regressions ($N = 65{,}805$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
HN_{t-1}	−.89	−.75	−.71	−.48	−.18	−.15	−.13	−.07
[t]	−5.93	−5.30	−3.38	−3.09	−5.87	−5.67	−3.36	−2.31
IK_{t-1}		−.52		−.54		−.16		−.23
[t]		−2.40		−1.90		−3.39		−3.63
Micro × HN_{t-1}			−.11	−.24			−.03	−.07
[t]			−.49	−1.20			−.88	−2.14
Micro × IK_{t-1}				.02				.13
[t]				.10				2.38

NOTE.—This table reports the estimation results from several variations of stock return predictability regressions of the form

$$r^s_{it} = a + b \times HN_{it-1} + c \times IK_{it-1} + d \times \text{Micro} + e \times \text{Micro} \times HN_{it-1} + f \times \text{Micro} \times IK_{it-1} + e_{it},$$

in which r^s_{it} is the firm i stock return, HN_{it-1} and IK_{it-1} are the lagged values of firm i's hiring and investment rates, and Micro is a dummy variable that is equal to one if firm i is a micro cap firm at time $t - 1$. Micro caps are defined as the firms with size (market value) that is below the bottom 20th percentile of the cross-sectional size distribution of NYSE firms in June of each year. Two alternative methodologies are used to estimate the regression. Columns 1–4 report the estimated average slope in the previous equation from Fama-MacBeth (1973) cross-sectional regressions estimated at the monthly frequency; [t] are heteroscedasticity and autocorrelation consistent t-statistics (Newey-West); N is the average number of firms in each cross section. Columns 5–8 report the estimated slope coefficients in the previous equation obtained by pooled OLS regressions in which r^s_{it} is firm i's compounded annual stock return from July of year t to June of year $t + 1$. The regression includes both year and firm fixed effects; [t] are t-statistics computed from standard errors clustered by firm and year; and N is the number of firm-year observations included in the estimation. The investment rate is winsorized at the top and bottom 0.5 percent in each cross section to decrease the influence of outliers. The estimates of the intercepts a and d are omitted. The sample is from July 1965 to June 2010.

posure to standard risk factors, as captured by the unconditional CAPM or the Fama-French (1993) three-factor model. This analysis is important because it provides information about the class of models that can potentially explain the data. In addition, this analysis provides a set of empirical moments that we can use to evaluate potential theoretical models of the hiring and investment return spreads.

To test the CAPM, we run monthly time-series regressions of the excess returns of each portfolio on a constant and the excess returns of the market portfolio (market). To test the Fama-French three-factor model, we augment the previous CAPM regressions with the size factor (SMB) and the value factor (HML). The intercepts from these regressions are the pricing errors (abnormal returns).

The middle and bottom panels of table 1 report the intercepts for both the CAPM (denoted as α) and the Fama-French three-factor model (denoted as α^F) regressions on the 10 hiring portfolios. Clearly, the CAPM cannot explain the pattern of average returns of these portfolios. The CAPM-implied pricing errors are large, with a mean absolute pricing error of 4.7 percent per year using equal-weighted returns across a sample that includes all firms (3 percent if we exclude micro cap firms) and 1.4 percent per year in value-weighted returns. The pricing error of the hiring spread portfolio is large, between 11.3 percent per year for equal-weighted returns (8.2 percent if we exclude micro cap firms) and 7 percent for value-weighted returns.

The previous analysis shows that the CAPM-implied pricing error of the hiring spread portfolio is larger than the hiring return spread itself. As such, the large CAPM pricing errors represent a higher hurdle for theoretical models than the hiring return spread itself. This result follows from the fact that the market betas (b) of the portfolios, the relevant measure of the quantity of risk of each portfolio according to the CAPM, goes in the wrong direction across the hiring portfolios. The portfolio of firms with currently low hiring rates has a lower market beta than the portfolio of firms with currently high hiring rates, which is inconsistent with the higher average returns (risk) of the low–hiring rate portfolio. In the separate online appendix, we show that a conditional version of the CAPM is also unable to explain the cross-sectional variation in the average returns of the hiring portfolios.

The Fama-French three-factor model is more successful here than the CAPM, especially when using value-weighted returns. For equal-weighted returns, the mean absolute pricing errors of the Fama-French model are less than half of the mean absolute pricing errors of the CAPM (2.3 percent here vs. 4.7 percent in the CAPM across all firms, and 1.2 percent here vs. 3.0 percent in the CAPM excluding micro cap firms). The Fama-French model still fails to capture the returns of the hiring spread portfolio in equal-weighted returns. For value-weighted returns, the mean absolute pricing errors are small, about 1.1 percent per year, and the abnormal return of the hiring return spread portfolio is 3.3 percent per year, and this value is only 1.6 standard errors from zero. Thus, the Fama-French three-factor model captures a large fraction of the cross-sectional variation in the average returns of the hiring portfolios, which suggests that the link between hiring and stock returns is, in principle, consistent with a risk-based interpretation. It also suggests that more than one aggregate risk factor is important to explain the hiring and investment return spreads.

The analysis of the results for the nine portfolios two-way sorted on hiring and investment reported in the middle and bottom panels of table 1 is qualitatively similar to the analysis of the 10 hiring portfolios, so we omit the detailed analysis of the results here (we use the results from this table in the evaluation of the theoretical model).

III. An Investment-Based Model with Labor Market Frictions

We consider a neoclassical investment-based asset pricing model augmented with labor market frictions and aggregate adjustment cost shocks to interpret the empirical evidence documented in the previous section.

A. *Economic Environment*

The economy is composed of a large number of firms that produce a homogeneous good. Firms make hiring and investment decisions to maximize market value.

1. Technology

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

$$Y_t = Z_t X_t^{1-\theta}[\alpha K_t^{1-1/\phi} + (1-\alpha)N_t^{1-1/\phi}]^{\theta/(1-1/\phi)}, \tag{1}$$

where $\alpha > 0$ controls the relative weight of the two inputs in the production process, $0 < \theta \leq 1$ is the degree of returns to scale, and the parameter $\phi > 0$ is the elasticity of substitution between physical capital and the labor stock. When $\phi \to 1$ the CES aggregator collapses to the Cobb-Douglas case, when $\phi \to +\infty$ the two inputs are perfect substitutes, and when $\phi \to 0$ the two inputs are perfect complements (Leontief). The term X_t is aggregate productivity, and Z_t is firm-specific productivity, the source of cross-sectional heterogeneity.

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

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

where δ_n is the 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). For tractability, the quit rate is specified to be constant as in Shapiro (1986).

Similarly, the law of motion of the firm's capital stock K_t is given by

$$K_{t+1} = (1-\delta_k)K_t + I_t, \quad 0 < \delta_k < 1, \tag{3}$$

where δ_k is the capital depreciation rate, and I_t is gross investment, which can be positive (investment) or negative (disinvestment).

Both labor hiring and capital investment are subject to nonconvex and convex adjustment costs. Labor adjustment costs are specified by the following function:

$$CN_t^{\text{adj}} = \begin{cases} b_n^+ Y_t + \dfrac{c_n^+}{2}\left(\dfrac{H_t}{N_t}\right)^2 N_t & \text{if } H_t > 0 \\ 0 & \text{if } H_t = 0 \\ b_n^- Y_t + \dfrac{c_n^-}{2}\left(\dfrac{H_t}{N_t}\right)^2 N_t & \text{if } H_t < 0, \end{cases} \tag{4}$$

in which c_n^+, c_n^-, b_n^+, and $b_n^- > 0$ are constants. The labor adjustment costs include training and screening of new workers, advertising of job positions, disruption costs (output that is lost through time taken to readjust the schedule and pattern of production), and separation costs (e.g., severance pay). The nonconvex cost component captures possible fixed disruption costs or fixed costs that are independent of the number of workers hired/fired. For example, the process of training new workers is likely to entail increasing returns to scale because the resources required to train one class are mostly independent of the class size. The convex cost component captures the fact that the adjustment costs may be related to the rate of adjustment because of higher costs for more rapid changes. We allow labor adjustment costs to be asymmetric to capture the fact that the cost of firing and hiring a worker may be different. We discuss the magnitude of the adjustment cost parameters in the calibration section below.

Capital adjustment costs are specified by the following function:

$$CK_t^{\text{adj}} \equiv I_t + \begin{cases} b_K^+ Y_t + \dfrac{c_k^+}{2}\left(\dfrac{I_t}{K_t}\right)^2 K_t & \text{if } I_t > 0 \\ 0 & \text{if } I_t = 0 \\ b_k^- Y_t + \dfrac{c_k^-}{2}\left(\dfrac{I_t}{K_t}\right)^2 K_t & \text{if } I_t < 0, \end{cases} \tag{5}$$

in which c_k^+, c_k^-, b_k^+, and $b_k^- > 0$ are constants. Note that we include investment expenditures (I_t) in this specification of capital adjustment costs. In addition to these expenditures, the capital adjustment costs include planning and installation costs, learning the use of new equipment, or the fact that production is temporarily interrupted. For example, a factory may need to close for a few days while a capital refit is occurring. Similar to labor, the nonconvex costs capture the costs of adjusting capital that are independent of the size of the investment, and the convex cost of investment captures the fact that the adjustment cost may be related to the rate of adjustment because of higher costs for more rapid changes. We allow the capital adjustment costs to be asymmetric to capture costly reversibility of capital. This costly reversibility can arise because of resale losses due to transaction costs or the market for lemons phenomenon.

Adjustment costs are stochastic. The total adjustment cost function of the firm is given by

$$\Psi_t = \frac{CN_t^{\mathrm{adj}} + CK_t^{\mathrm{adj}}}{S_t}, \tag{6}$$

in which S_t is a stochastic variable that captures changes in the aggregate cost of adjusting the inputs. We refer to S_t as an adjustment cost wedge and a shock to this wedge as an adjustment cost shock. This shock affects the marginal cost of hiring/firing workers and of investing/disinvesting in capital, thus affecting the ability of firms to grow or downsize. We can interpret the adjustment cost shock literally as a shock to the cost of adjusting the inputs. Alternatively, we can think of this cost as a shock to the efficiency of new labor and capital. For the same amount of total adjustment costs, firms can hire more workers and buy more capital if S_t increases. This is equivalent to hiring the same number of workers and buying the same units of capital, but these workers and capital are more productive. Under this interpretation, the adjustment cost shock that we consider here is analogous to a standard investment-specific shock, extended to affect the efficiency of both labor and capital.[9]

In general equilibrium an effect similar to an adjustment cost shock in our setup can arise for several reasons. For capital, a positive productivity shock in the investment good producers sector of the economy is equivalent to a positive capital adjustment cost shock because this investment-specific productivity shock can make new capital goods cheaper. For labor, an increase in the relative supply of new workers searching for a job is equivalent to a positive labor adjustment cost shock because this increase makes it easier and hence less costly for firms to find new workers in the presence of search frictions. Similarly, an improvement in the labor skills of the available labor force is equivalent to a positive labor adjustment cost shock because this improvement makes new workers more productive, thus allowing firms to hire relatively fewer workers to achieve the same desired increase in output. For simplicity and technical reasons (to avoid an increase in the number of state variables in the firm's problem), we consider only one adjustment cost shock that has the same proportional effect on the cost of adjusting labor and capital.

Finally, the firm also incurs fixed operating costs of production that are independent of firm size, which are captured by $F_t = fX_t$, with $f > 0$. We scale the fixed operating costs by aggregate productivity to allow for growth in the economy.

[9] Our specification of shocks to the adjustment cost technology nests the investment-specific shock in Greenwood et al. (1997). In our model, a positive aggregate adjustment shock improves the efficiency of both labor and capital by reducing their respective marginal cost (marginal q), whereas investment shocks in Greenwood et al.'s study affect only the efficiency of capital.

2. Stochastic Processes

Aggregate productivity follows a random walk process with a drift,

$$\Delta x_{t+1} = \mu_x + \sigma_x \varepsilon^x_{t+1}, \tag{7}$$

in which $x_{t+1} = \log(X_{t+1})$, Δ is the first-difference operator, ε^x_{t+1} is an independently and identically distributed (i.i.d.) standard normal shock, and μ_x and σ_x are the average growth rate and conditional volatility of aggregate productivity, respectively.

Firm-specific productivity follows the AR(1) process

$$z_{t+1} = \bar{z}(1 - \rho_z) + \rho_z z_t + \sigma_z \varepsilon^z_{t+1}, \tag{8}$$

in which $z_{t+1} = \log(Z_{t+1})$, ε^z_{t+1} is an i.i.d. standard normal shock that is uncorrelated across all firms in the economy and independent of ε^x_{t+1}, and $\bar{z}$, ρ_z, and σ_z are the mean, autocorrelation, and conditional volatility of firm-specific productivity, respectively.

The aggregate adjustment cost wedge follows the AR(1) process

$$s_{t+1} = \rho_s s_t + \sigma_s \varepsilon^s_{t+1}, \tag{9}$$

in which $s_{t+1} = \log(S_{t+1})$, ε^s_{t+1} is an i.i.d. standard normal shock that is independent of all the other shocks in the economy, and ρ_s and σ_s are the persistence and conditional volatility of the aggregate adjustment cost wedge, respectively.

Given the focus on the production side of the economy, we directly specify the stochastic discount factor $M_{t,t+1}$ (used to value the firm's cash flows arriving in period $t + 1$), as well as the equilibrium stochastic wage rate W_t, without explicitly modeling the consumer's problem. Firms are competitive and take these prices as given. The stochastic discount factor (marginal utility) is a function of the two aggregate shocks in the economy and is given by

$$M_{t,t+1} = \exp(-r_f)\frac{\exp(-\gamma_x \Delta x_{t+1} - \gamma_s \Delta s_{t+1})}{\mathbb{E}_t[\exp(-\gamma_x \Delta x_{t+1} - \gamma_s \Delta s_{t+1})]}, \tag{10}$$

where r_f is the (log) risk-free rate, $\gamma_x > 0$ and $\gamma_s < 0$ are the loadings of the stochastic discount factor on the two aggregate shocks, and the operator $\mathbb{E}_t[\cdot]$ represents the expectation over all states of nature at time t. The risk-free rate is constant. This allows us to focus on risk premia as the main driver of the results in the model as well as avoid parameter proliferation. The sign of the loadings of the stochastic discount factor on the two aggregate shocks follows from previous studies. The specification $\gamma_x > 0$ is consistent with most equilibrium models (see, e.g., Jermann 1998). Low-productivity states are associated with low output and thus low consumption and high marginal utility. The specification $\gamma_s < 0$

is consistent with the theoretical and empirical literature on the impact of investment-specific shocks on asset prices (Papanikolaou 2011; Kogan et al. 2012; Yang 2013; see also the online appendix for additional empirical analysis). A positive adjustment cost shock (positive investment shock) implies that it is easier for firms to hire and invest, which makes investment more desirable. In general equilibrium, if agents substitute resources away from consumption and into investment in those states of nature, the positive adjustment cost shock may be associated with high marginal utility states.

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

$$W_t = \tau_1 \exp(\tau_2 \Delta x_t), \tag{11}$$

with $\tau_1 > 0$ and $0 < \tau_2 < 1$. In this specification, τ_1 is a scaling factor, and the constraint $0 < \tau_2 < 1$ allows us to capture the empirical fact that the aggregate real wage rate is less volatile than aggregate output as well as some procyclicality of the real wage rate, as reported in Merz and Yashiv (2007) in US data.[10] In the online appendix, we consider a specification of the aggregate wage rate that is a function of both the aggregate productivity and adjustment cost shocks. Adding this additional effect in a reasonable calibration of the model has a very small impact on all the quantitative results reported here.

B. *Firm's Maximization Problem*

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

$$D_t = Y_t - W_t N_t - \Psi_t - F_t \tag{12}$$

to be the dividend distributed by the firm to the shareholders. The dividend consists of output Y_t, less the wage bill $W_t N_t$, total adjustment costs Ψ_t, which includes the purchase cost of investment, and fixed operating costs F_t. A negative dividend is considered as equity issuance.

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

$$V(\mathbb{S}_t) = \max_{\{I_{t+j}, K_{t+j+1}, H_{t+j}, N_{t+j+1}\}_{j=0}^{\infty}} \left\{ \mathbb{E}_t \left[\sum_{j=0}^{\infty} M_{t,t+j} D_{t+j} \right] \right\}, \tag{13}$$

[10] In the data, the number of workers N in the corporate sector is growing. To be consistent with this fact, we allow N to grow in the model. This specification requires the wage rate W to be stationary in the model to make the wage bill (WN) cointegrated with the rest of the growing variables so that the firm problem is well defined.

subject to the labor and capital accumulation equations (2) and (3) and the flow of funds constraint (12) for all dates *t*.

C. *Equilibrium Risk and Return*

In the model, risk and expected stock returns are determined endogenously along with the firm's optimal production decisions. To make the link explicit, we can evaluate the value function in equation (13) at the optimum and obtain

$$V(\mathbb{S}_t) = D_t + \mathbb{E}_t[M_{t,t+1} V(\mathbb{S}_{t+1})] \tag{14}$$

$$\Rightarrow 1 = \mathbb{E}_t[M_{t,t+1} R^s_{t+1}], \tag{15}$$

in which equation (14) is the Bellman equation for the value function, and the Euler equation (15) follows from the standard formula for stock return $R^s_{t+1} = V(\mathbb{S}_{t+1})/[V(\mathbb{S}_t) - D_t]$. Substituting the stochastic discount factor from equation (10) into equation (15) and some algebra yield the following equilibrium asset pricing equation:[11]

$$\mathbb{E}[r^e_{t+1}] = \lambda_x \times \beta^x + \lambda_s \times \beta^s, \tag{16}$$

where $r^e_{t+1} = R^s_{t+1} - R_f$ is the stock excess return, $R_f \equiv \exp(r_f) = \mathbb{E}_t[M_{t,t+1}]^{-1}$ is the gross risk-free rate, $\lambda_x = \gamma_x \mathrm{Var}(\Delta x_{t+1})$ and $\lambda_s = \gamma_s \mathrm{Var}(\Delta s_{t+1})$ are the price of risk of the aggregate productivity shock and aggregate adjustment cost shock, respectively, and $\beta^x = \mathrm{Cov}\,(r^e_{t+1}, \Delta x_{t+1})/\mathrm{Var}(\Delta x_{t+1})$ and $\beta^s = \mathrm{Cov}(r^e_{t+1}, \Delta s_{t+1})$ are the sensitivity (betas) of the firm's excess stock returns with respect to the two aggregate shocks in the economy.

According to equation (16), the equilibrium risk premiums in the model are determined by the endogenous covariances of the firm's excess stock returns with the two aggregate shocks (quantity of risk) and its corresponding prices of risk. The sign of the price of risk of the two aggregate shocks is determined by the two factor loading parameters (γ_x and γ_s) in the stochastic discount factor in equation (10). The prespecified signs of the loadings imply a positive price of risk of the aggregate productivity shock and a negative price of risk for the adjustment cost shock. Thus, all else equal, assets with returns that have a high positive covariance with the aggregate productivity shock are risky and offer high average returns in equilibrium. Similarly, all else equal, assets with returns that have a high positive covariance with the aggregate adjustment

[11] This derivation is standard. Equation (15) implies $\mathbb{E}_t[M_{t,t+1}(R^s_{t+1} - R_f)] = 0$ because $\mathbb{E}_t[M_{t,t+1}]R_f = 1$. Using a first-order log-linear approximation of the stochastic discount factor $M_{t,t+1}$ defined in eq. (10), the law of iterated expectations, and applying the formula for covariance $\mathrm{Cov}(X, Y) = \mathbb{E}[XY] - \mathbb{E}[X]\mathbb{E}[Y]$ to the previous equation, plus some algebra, yields eq. (16).

cost shock provide a hedge against this shock and thus offer low average returns in equilibrium.

IV. Model Solution

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. The Appendix provides a description of the solution algorithm (value function iteration) and the numerical implementation of the model.

A. *Calibration*

The model is solved at a monthly frequency, which is the frequency of the stock return data used in the empirical tests. Because all the firm-level accounting variables in the data are available only at an annual frequency, we time-aggregate the simulated accounting data to make the model-implied moments comparable with those in the data.

Table 5 reports the parameter values used in the baseline calibration of the model. The model is calibrated using parameter values reported in previous studies, whenever possible, or by matching the selected moments in the data reported in table 6.[12] To evaluate the model fit, the table reports the target moments in both the data and the model. To generate the model's implied moments, we simulate 3,600 firms for 1,000 monthly periods. We drop the first 400 months to neutralize the impact of the initial condition. The remaining 600 months of simulated data are treated as those from the economy's stationary distribution. We then simulate 500 artificial samples and report the cross-sample average results as model moments. Because we do not explicitly target the hiring and investment return spreads (and abnormal returns) in the baseline calibration, we use these moments to evaluate the model in Section V.

Firm's technology: general parameters.—We set the returns to scale in the production function (1) to be $\theta = 0.85$, close to the value used in Khan and Thomas (2008) and consistent with the estimates in Burnside, Eichenbaum, and Rebelo (1995). The share of capital in the production function is set to be $\alpha = 0.36$, following Gomes (2001). The elasticity of substitution between capital and labor stock is set to be $\phi = 0.5$, consistent with estimates in Antràs (2004) (see also Chirinko [2008] for a

[12] Because firms are all-equity financed in the model but use both debt and equity in the real data, we leverage up all returns generated in the model to make them comparable with the data. We compute the model-implied levered return as $r^e_{t+1} = (1 + \text{Debt/Equity}) \times (R^a_t - R_f)$, where R^a is the return of the all-equity firm in the model, R_f is the gross risk-free rate, and Debt/Equity is the average debt-to-equity ratio in the data, which is 0.67 during our sample period.

TABLE 5
Parameter Values of the Baseline Model

Parameter	Symbol	Value
Technology: general:		
Weight of physical capital in the production function	α	.36
Returns to scale	θ	.85
Elasticity of substitution between capital and labor	ϕ	.50
Rate of depreciation for capital	δ_k	.01
Quit rate of labor	δ_n	.01
Fixed operating cost	f	.0105
Technology: adjustment costs:		
Convex parameters in capital adjustment cost	c_k^+/c_k^-	3.1/34.1
Convex parameters in labor adjustment cost	c_n^+/c_n^-	1.2/1.2
Nonconvex parameters in capital adjustment cost	b_k^+/b_k^-	.04/.08
Nonconvex parameters in labor adjustment cost	b_n^+/b_n^-	.16/.20
Stochastic processes:		
Multiplicative coefficient on wage rate process	τ_1	.0095
Sensitivity of the wage rate to aggregate productivity	τ_2	.9
Average growth rate of aggregate productivity	μ_x	.013/12
Conditional volatility of aggregate productivity	σ_x	.055
Average level of firm-specific productivity	$\bar{z}$	−3.4
Persistence coefficient of firm-specific productivity	ρ_z	.97
Conditional volatility of firm-specific productivity	σ_z	.10
Persistence coefficient of adjustment cost wedge	ρ_s	.97
Conditional volatility of adjustment cost wedge	σ_s	.035
Real risk-free rate (%)	r_f	1.65/12
Loading of the stochastic discount factor on aggregate productivity shock	γ_x	6.75
Loading of the stochastic discount factor on the adjustment cost shock	γ_s	−14.5

survey of the relevant empirical literature on the estimation of this parameter). The capital depreciation rate δ_k and labor exit rate δ_n are set to be 1 percent per month, as in Bloom (2009). The fixed operating cost f is set to match the average aggregate physical-capital-to-market-equity ratio (KM) of 0.62 as closely as possible, subject to the requirement that the endogenous firm value in the model be positive. Thus, we set $f =$ 0.0105, which allows us to obtain an average aggregate KM of 0.57.

Firm's technology: adjustment costs.—We calibrate the labor and capital adjustment cost parameters to match several cross-sectional and time-series moments of firms' hiring as investment rates. We target 16 moments: the firm-level standard deviation, the second-order autocorrelation, skewness, and inter–fifth percentile ranges of hiring and investment rates, both in the cross section (average of cross-sectional moments) and in the time series (using pooled data across firms and years). To reduce the extreme influence of micro cap firms on the firm-level moments, we compute the previous moments excluding firms classified as micro cap firms in all of the firms' observations in our sample (we keep the firms that are classified as micro caps in only some observations, which allows us to maintain a large sample size).

TABLE 6
TARGET MOMENTS

Moment	Data	Model
Asset prices:		
Average stock market excess return (%)	4.85	4.84
Sharpe ratio of aggregate stock market	.31	.31
Average real risk-free rate (%)	1.65	1.65
Value premium (%)	6.73	5.46
Average aggregate capital-to-market-equity ratio	.62	.57
Real quantities and input prices:		
Standard deviation of aggregate profits	.14	.14
Standard deviation of wage rate	1.40	1.32
Average firm-level wage-bill-to-sales ratio	.46	.42
Correlation of aggregate payout and output	.38	.33
Firm-level hiring and investment rate: cross section:		
Standard deviation of *HN* (dispersion)	.23	.22
Standard deviation of *IK* (dispersion)	.21	.17
Correlation (HN_t, HN_{t-2})	.10	.10
Correlation (IK_t, IK_{t-2})	.37	.23
Skewness of *HN*	.74	.71
Skewness of *IK*	1.77	1.60
95th minus 5th percentile range of *HN*	.66	.73
95th minus 5th percentile range of *IK*	.61	.54
Firm-level hiring and investment rate: time series:		
Standard deviation of *HN*	.26	.24
Standard deviation of *IK*	.23	.22
Correlation (HN_t, HN_{t-2})	.10	.13
Correlation (IK_t, IK_{t-2})	.38	.20
Skewness of *HN*	.55	.92
Skewness of *IK*	2.05	1.64
95th minus 5th percentile range of *HN*	.72	.81
95th minus 5th percentile range of *IK*	.68	.68

NOTE.—This table presents the selected target moments used for the calibration of the baseline model. We compare the moments in the data with moments of simulated data. The model-implied moments are the mean values of the corresponding moments across simulations. The aggregate-level profits are defined as aggregate sales minus aggregate wage bill. Value premium is the average returns of the 10th decile minus the 1st decile book-to-market portfolio. The time series of the firm-level hiring rate moments are computed using pooled (across all firms and years) data. To compute the cross-sectional moments, we compute the relevant moment each year using the cross-sectional hiring and investment rate distribution and report the averages of the corresponding cross-sectional moments. The real data are from 1965 to 2010. The reported statistics for the model are obtained from 500 samples of simulated data, each with 3,600 firms and 600 monthly observations.

For simplicity, we specify convex labor adjustment costs to be symmetric and set $c_n^+ = c_k^- = 1.2$. We set the nonconvex labor adjustment cost parameters to be $b_n^+ = 0.16$ and $b_n^- = 0.20$.[13] The (small) asymmetry in nonconvex labor adjustment costs used here is consistent with the

[13] It is worth noting that nonconvex labor adjustment costs are important to generate nonlinearities, in particular, inactions in hiring rates. Unfortunately, data on inactions in the gross hiring rate are not available at the firm level, and hence we do not target this moment here.

analysis in the study by Bhamra and Lochstoer (2009), who show that, at the aggregate level, having larger firing costs than hiring costs is important to generate a sizable equity premium and return predictability from labor income variables in a general equilibrium model. The convex capital adjustment costs are set to be $c_k^+ = 3.1$ and $c_k^- = 34.1$, and the nonconvex capital adjustment costs are set to be $b_k^+ = 0.04$ and $b_k^- = 0.08$. The asymmetry in capital adjustment costs used here is consistent with that of Zhang (2005), who shows that costly reversibility of capital is important to generate a sizable value premium in a neoclassical investment-based model. Table 6 shows that this calibration of the model matches reasonably well several properties of the firm-level hiring and investment rates.

Stochastic processes.—In the model, the aggregate productivity shock is essentially a profitability shock. We set the conditional volatility of the aggregate productivity shock to be $\sigma_x = 0.055$ to match the volatility of aggregate profits (0.14 in both the data and the model). In the data, we measure aggregate profits using data from the National Income and Product Accounts and in the model as total output minus the wage bill. Given the volatility of the aggregate productivity shock, we set the conditional volatility of the aggregate adjustment cost shock to be $\sigma_s = 0.035$ to match aggregate stock market volatility as closely as possible, while keeping the hiring and investment rate volatilities at reasonable values, given the calibrated adjustment cost parameters. The persistence of the aggregate adjustment cost wedge ρ_s mostly affects the cyclicality of the adjustment costs and the aggregate payout. We set it to be $\rho_s = 0.97$ so that the correlation of aggregate payout and output is .33, close to .38 in the data (a smaller ρ_s leads to a less cyclical aggregate payout).

To calibrate the persistence and conditional volatility of the firm-specific productivity shock, we use the same values reported in Zhang (2005), $\rho_z = 0.97$ and $\sigma_z = 0.10$. The long-run average level of firm-specific productivity, $\bar{z}$, is a scaling variable. We set $\bar{z} = -3.4$, which implies that the average detrended long-run physical capital in the economy is 2. In the data, the wage rate per worker is smoother than aggregate output. We set the parameters $\tau_1 = .0095$ and $\tau_2 = .9$ in the wage rate specification to match the annual volatility of the Hodrick-Prescott-filtered aggregate wage rate per worker (1.40 in the data and 1.32 in the model) and the average firm-level wage-bill-to-sales ratio as closely as possible (0.46 in the data and 0.42 in the model). To calibrate the stochastic discount factor, we set the real risk-free rate to be $r_f = 1.65$ percent per year. We set the loading of the stochastic discount factor on the aggregate productivity shock to be $\gamma_x = 6.75$ and the loading of the stochastic discount factor aggregate adjustment cost shock to be $\gamma_s = -14.5$ by matching the average aggregate stock market excess return (and hence the aggregate Sharpe ratio, 0.31 in both the data and the model) and the value premium (the difference in the average value-weighted returns of the high minus low decile portfolio sorted on the firm's book-to-market ratio). We conduct comparative statics in Section VI to evaluate the impact of the stochastic discount factor loading parameters on the model's performance.

B. *Implied Adjustment Costs*

Table 6 shows that the baseline model does a reasonable job in matching a large set of target moments. How reasonable are the adjustment cost parameters used in the calibration? In particular, how do they compare with those previously estimated in the literature? To answer this question, table 7 reports five alternative measures of adjustment costs (rows 1–5) in the model. Row 1 reports the time-series average (across all firms and periods) of the monthly realized total (convex plus nonconvex excluding investment expenditures) adjustment costs, reported as a fraction of firms' annual sales, the metric used in Bloom (2009). We also report nonconvex and the marginal convex adjustment costs evaluated at the sample mean of the hiring rate, investment rate, wage rate, and adjustment cost wedge. Because of the asymmetry in the adjustment cost function, we compute conditional means of the previous variables using the subsample of firm-period observations with positive or negative hiring ($H > 0$ or $H < 0$) or with positive or negative investment ($I > 0$ or $I < 0$).[14] Row 2 reports the nonconvex labor and capital adjustment cost as a fraction of annual sales. Rows 3 and 4 report the marginal convex labor adjustment cost of hiring (firing) an additional worker as a fraction of the annual wage rate or as the number of months of work, respectively. Row 5 reports the marginal convex capital adjustment cost of investing (disinvesting), computed as the incremental cost that the firm incurs per each $100 of additional investment/disinvestment.

The implied magnitude of the alternative measures of adjustment costs in the model is reasonable. Row 1 in table 7 shows that, when we average across all firms and periods, the fraction of annual sales that is lost because of labor adjustment costs is around 1.6 percent and around 0.6 percent because of capital adjustment costs. These values are within the empirical estimates surveyed in Hamermesh and Pfann (1996), Merz and Yashiv (2007), and Bloom (2009).

In the analysis of the different components of adjustment costs, row 2 shows that the fraction of annual sales that is lost because of nonconvex

[14] Let $HN^{+,-}$, $IK^{+,-}$, $\exp(-s^{+,-})$ be the conditional mean of the gross hiring rate, gross investment rate, and adjustment cost wedge, computed using the firm-period observations with positive (+) or negative (−) hiring (or investment). With the adjustment cost function specified in eq. (6), the marginal convex hiring adjustment cost is $\exp(-s^{+,-})c_n^{+,-}|HN_t^{+,-}|$ and the marginal convex investment adjustment cost is given by $\exp(-s^{+,-})c_k^{+,-}|IK_t^{+,-}|$.

TABLE 7
Implied Adjustment Costs

	Labor			Capital		
Measure of Adjustment Costs	$H > 0$	$H < 0$	All	$I > 0$	$I < 0$	All
1. Average realized total (% annual sales)			1.63			.55
2. Nonconvex (% annual sales)	1.32	1.69		.32	.70	
3. Marginal convex (% annual wage)	21.47	14.16				
4. Marginal convex (months of work)	2.58	1.70				
5. Marginal convex (per $100 of investment)				$6.58	$8.70	

Note.—This table reports the magnitude of the adjustment costs implied by the baseline calibration of the model. Average realized total is the time-series average of realized total (nonconvex plus convex excluding investment expenditures) labor and capital adjustment costs across all periods and all firms (all), across the firm-period observations with positive or negative hiring ($H > 0$ or $H < 0$), or positive or negative investment ($I > 0$ or $I < 0$). The nonconvex adjustment cost of hiring/firing or investment/disinvestment is reported as a fraction of annual sales. The marginal convex adjustment cost moments are evaluated at the conditional mean (across firm-period observations with positive/negative hiring/investment) of the variable adjustment cost wedge, hiring rate, investment rate, and wage rate. For hiring, the marginal convex adjustment cost (hire or fire one additional worker) is reported as a fraction of the worker's average annual wage rate or as the number of working months that are lost because of the adjustment (row 3 × 12). For investment, the marginal convex adjustment cost is the incremental cost that the firm has to incur per each $100 of investment/disinvestment. The reported statistics for the model are obtained as averages from 500 samples of simulated data, each with 3,600 firms and 600 monthly observations.

labor adjustment costs is around 1.3 percent for hiring and 1.7 percent for firing. These values are close to the 1.1 percent of annual sales value estimated in Bloom (2009) (for both hiring and firing). For investment, the fraction of annual sales that is lost because of nonconvex adjustment costs of capital is 0.3 percent for positive investment and 0.7 percent for disinvestment. These values are both smaller than the estimate of 1.1 percent for nonconvex capital adjustment costs also estimated in Bloom (2009).

The marginal convex adjustment costs of both inputs are also reasonable. Evaluated at the conditional mean, the marginal adjustment cost of hiring a worker is 21.5 percent of the annual wage rate, which corresponds to 2.6 months of work, and the marginal adjustment cost of firing a worker is 14.2 percent of the annual wage rate, which corresponds to 1.7 months of work (these values are smaller for firing because the absolute value of the gross rate of hiring is smaller across observations in which firms are firing than when firms are hiring). These values compare well with the empirical estimates surveyed in the previous studies. For example, Merz and Yashiv (2007) estimate marginal hiring adjustment costs to be equal to two quarters of wage payments, and our calibrated values imply smaller values. For capital, our parameter values imply that, evaluated at the conditional mean, the firm has to incur an additional $6.70 for each additional $100 of investment and $8.70 for each additional $100 of disinvestment, which are also consistent with the empirical evidence reported in the previous studies.

V. Model Implications for the Cross Section of Stock Returns

We replicate the portfolio sorts and asset pricing tests performed in the empirical section using the artificial data obtained from the simulation of the model.

A. Hiring and Stock Returns

Panel A in table 8 (top rows) reports the average value-weighted excess returns of the 10 hiring portfolios in the model.[15] The calibration of the baseline model generates a pattern of average excess returns across the hiring portfolios that is similar to the pattern in the data. Firms with currently low hiring rates earn subsequently higher returns, on average, than firms with currently high hiring rates. The size of the hiring return spread is comparable with the data. In the model, the hiring return spread is 6 percent per year, which is close to the 5.6 percent per year value-weighted hiring return spread reported in table 1.

Panel A in table 8 also shows that the Sharpe ratios of the hiring portfolios are decreasing in firms' current hiring rate, consistent with the data. The Sharpe ratio of the portfolio of firms with low hiring rates is about four times larger (in the real data is six times larger) than the Sharpe ratio of the portfolio of firms with high hiring rates.

The model also replicates the pattern of the portfolio characteristics of the hiring portfolios in the data. Table 2 (panel B) shows that the model generates a negative relationship between the physical-capital-to-market-equity ratio and the hiring and investment rates, as well as a positive relationship of both productivity and profitability with the hiring rate. Also, smaller firms in the model tend to have relatively lower hiring rates, but this link is not monotonic.

B. Hiring, Investment, and Stock Returns

Panel B in table 8 (top rows) reports the average value-weighted excess returns of the nine portfolios two-way sorted on hiring and investment in the model. The pattern of average returns of the portfolios is in general consistent with the pattern observed in the data. In particular, the average excess returns are decreasing in both the investment and hiring rates.

[15] In the model, the average value- and equal-weighted returns are very similar. Thus, to facilitate the comparison between the model results and the data, we focus our comparison using average value-weighted returns only.

TABLE 8

Hiring and Investment Portfolios in Simulated Data

	A. One-Way Sorted							B. Two-Way Sorted *IK*				
	Low	2	5	9	High	L−H	*HN*	L	M	H	L−H	[*t*]
	Excess Returns							Excess Returns: r^e				
r^e	8.08	7.16	5.60	3.22	2.06	6.01	L	8.04	6.01	4.22	3.82	6.11
[*t*]	4.02	3.33	2.44	1.41	.91	8.00	M	7.19	5.25	3.28	3.91	6.33
SR	.57	.48	.35	.20	.13	1.16	H	6.54	4.61	2.11	4.43	7.21
							L−H	1.50	1.41	2.11		
							[*t*]	2.34	2.35	3.85		
	CAPM: m.a.e. = 1.66							CAPM: α, m.a.e. = 1.67				
α	3.79	2.55	.65	−1.74	−2.90	6.69	L	3.73	1.30	−.56	4.29	7.38
[*t*]	8.74	6.08	1.66	−4.55	−7.39	9.94	M	2.51	.28	−1.64	4.15	6.89
b	.88	.95	1.02	1.03	1.03	−.14	H	1.52	−.53	−2.85	4.37	7.16
[*t*]	91.50	105.93	133.51	130.08	118.85	−9.12	L−H	2.21	1.84	2.29		
R^2	.95	.96	.97	.97	.97	.19	[*t*]	4.02	3.29	4.24		
	Fama-French: m.a.e. = .38							Fama-French: α^F, m.a.e. = .35				
α^F	.63	.11	−.15	−.03	−.04	.67	L	.57	.01	−.06	.63	1.09
[*t*]	1.55	.26	−.34	−.07	−.10	1.23	M	.05	−.20	−.03	.07	.11
b	.96	1.01	1.02	.99	.97	−.01	H	−.06	−.10	−.06	.00	.01
s	.29	.21	.15	−.17	−.30	.58	L−H	.63	.11	.00		
h	.54	.43	.10	−.29	−.47	1.01	[*t*]	1.05	.17	.01		
R^2	.97	.97	.97	.98	.98	.59						

Note.—This table replicates the empirical analysis reported in tables 1 and 3, using simulated data from the model, obtained as averages from 500 samples of simulated data, each with 3,600 firms and 600 monthly observations. The table reports the average value-weighted excess returns and abnormal returns of 10 portfolios one-way sorted on hiring rate in panel A (we report portfolios 1 [low], 2, 5, 9, and 10 [high]) and nine portfolios two-way sorted on hiring rate (*HN*) and physical capital investment rate *IK* in panel B. In panel B, the sorting on the hiring rate is reported across rows L (low), M (mid), and H (high), and the sorting on the physical capital investment rate is reported across columns L, M, and H. L−H stands for the low-minus-high hiring portfolio (across rows) or the low-minus-high investment portfolio (across columns); r^e is the average annualized (× 1,200) portfolio excess stock return; [*t*] are heteroscedasticity and autocorrelation consistent *t*-statistics (Newey-West); SR is the portfolio Sharpe ratio; α and α^F are portfolio average abnormal returns, obtained as the intercept from monthly CAPM or Fama-French (1993) regressions, respectively, reported in annual percentage (× 1,200); m.a.e. is the mean absolute pricing errors (average of α or α^F); *b* are the portfolio market betas obtained as the slope coefficients associated with the market factor in the CAPM regression; *b*, *s*, and *h* are the portfolio market, SMB, and HML betas, respectively, obtained as the slope coefficients in the Fama-French regressions.

The model generates reasonable hiring and investment return spreads. When we control for the investment rate, the average (across investment bins) hiring return spread in the model is 1.7 percent per year, which is somewhat lower than the average hiring return spread of 2 percent per year in the data but is still more than 4.1 standard errors from zero (not reported). When we control for the hiring rate, the average (across hiring bins) investment return spread in the model is 4.1 percent per year, which almost exactly matches the average investment return spread of 4 percent in the data. The model also generates negative hiring and investment rate slope coefficients in firm-level cross-sectional predictability regressions. As we show in table 9 below (we examine this table as part of the comparative statics analysis), the hiring rate slope coefficient is −0.50 in the baseline model and −0.48 in the data (controlling for the effect of micro cap firms), and the investment rate slope coefficient is −0.30 in the baseline model, which is slightly smaller than the slope of −0.54 observed in the data (also controlling for the effect of micro cap firms).

Taken together, the results in this section show that the baseline model is consistent with the coexistence of the hiring and investment return spreads.

C. Asset Pricing Tests

Finally, we investigate whether the model can replicate the failure of the unconditional CAPM and the better performance of the Fama-French three-factor model in explaining the hiring and investment return spreads in the data. To perform the time-series asset pricing tests, we construct the market, the size (SMB), and the value (HML) factors in the model by replicating the approach in Fama and French (1993).

Panel A in table 8 shows that the baseline model matches well the failure of the unconditional CAPM in explaining the average returns of the hiring portfolios. The model generates large and statistically significant pricing errors, with a mean absolute pricing error that is very close to the data (1.7 percent per year in the model vs. 1.4 percent in the data). The pricing error of the hiring spread portfolio is large, 6.7 percent per year, which is more than 9.9 standard errors from zero and thus is larger than the hiring return spread itself (6 percent per year). As in the data, the CAPM fails in the model because the high–hiring rate firms have relatively higher market betas (b), and hence higher risk according to the CAPM, but relatively lower average returns.

Turning to the analysis of the Fama-French three-factor model, we first note that the model matches reasonably well the average returns of the market factor (4.9 percent in the data and 4.8 percent in the model, as reported in table 6), the size factor (SMB is 3.3 percent in the data and 3.4 percent in the model, not reported), and the value factor (HML is

4.8 percent in the data and 3.4 percent in the model, not reported). Thus, the baseline model is consistent with the well-documented coexistence of equity, size, and value premiums in the data.

The Fama-French three-factor model in the simulated data captures the cross-sectional variation in the returns of the hiring portfolios significantly better than the unconditional CAPM. Panel A in table 8 shows that the Fama-French pricing errors (α^F) are small and, in general, statistically insignificant. The hiring spread portfolio has a pricing error of only 0.7 percent per year (6.7 percent in the CAPM).

The analysis of the asset pricing test results across the portfolios two-way sorted on hiring and investment (reported in panel B of table 8) is qualitatively similar to the analysis across the 10 hiring portfolios, and so here we briefly state the main results. The unconditional CAPM is unable to fully explain the joint hiring and investment return spreads. The mean absolute pricing error is 1.7 percent per year (in the data it is 2.4 percent). The pricing error of the average (across the three investment bins) hiring spread portfolio is 2.1 percent per year, and the pricing error of the average (across the three hiring bins) investment spread portfolio is 4.3 percent per year. Although smaller than in the data, these pricing errors are economically large. The pricing errors of the Fama-French three-factor model across the average hiring and investment spread portfolios are both small and statistically indistinguishable from zero in the model, consistent with the results in the data across value-weighted portfolios.

The significant magnitude of the CAPM pricing errors in the model is an improvement over standard investment-based models in which aggregate productivity is the only source of aggregate risk (e.g., Zhang [2005], among others). In these models, the one aggregate risk factor structure implies that the conditional CAPM holds. As shown in Belo and Lin (2012), however, the unconditional CAPM also holds approximately (very low CAPM pricing errors) in these models because the endogenous cross-sectional variation in the portfolios' average returns is counterfactually explained by variation in the corresponding portfolios' unconditional market betas.[16]

VI. Inspecting the Mechanism

In this section we perform several analyses to show the economic forces driving the overall good fit of the model.

[16] We note that the failure of the unconditional CAPM in the data, at least for value portfolios, is potentially sample specific. Even though the CAPM is unable to explain the returns of value portfolios in the 1965–2010 period that we use here, Ang and Chen (2007) show that the CAPM explains reasonably well the returns of value portfolios in a long

A. The Driver of the Hiring Return Spread

The theoretical model proposed in Section III implies that risk premiums in the economy are determined by equation (16). To understand the hiring return spread, we must thus understand the endogenous sensitivity of the returns of the hiring portfolios to the two aggregate risk factors (quantity of risk), as well as the role of the corresponding prices of risk. To facilitate the exposition, the analysis in this section focuses on the 10 portfolios one-way sorted on hiring.

1. Quantity of Risk

The hiring return spread is driven by the differential exposure of the returns of the hiring portfolios to the aggregate adjustment cost shock, and not by differential exposure to the aggregate productivity shock. To show this result, we compute the sensitivity (betas) of the returns of the hiring portfolios with respect to the two aggregate shocks in the economy by running the following time-series regression in the simulated data:

$$r_{it}^{e} = a_i + \beta_i^x \times \Delta x_t + \beta_i^s \times \Delta s_t + e_{it}, \tag{17}$$

in which r_{it}^{e} is the monthly excess return of the ith hiring portfolio, Δx_t is the aggregate productivity shock, and Δs_t is the aggregate adjustment cost shock. Figure 1 plots the sensitivity of the returns of each portfolio to the two aggregate shocks. To highlight the cross-sectional dispersion in the exposure to the shocks, we report the portfolio sensitivity to each factor relative to the average (across portfolios) sensitivity.

Figure 1 documents two important features of the model. First, the average sensitivity of the returns of the hiring portfolios to the two risk factors is positive. This feature is intuitive: a realized positive aggregate productivity shock is good news for firms because it increases profitability, and hence the positive productivity shock is associated with an increase in market values and thus higher realized returns. At the same time, a positive realized aggregate adjustment cost shock is also generally good news for firms because it means that it is cheaper for firms to adjust their labor and capital inputs, allowing firms to increase their profits.

Second, the sensitivity of the returns of the hiring portfolios to the aggregate productivity shock is almost flat across the portfolios. In contrast, the dispersion in the sensitivity to the aggregate adjustment cost shock is large, and it is monotonically increasing across the hiring portfolios. In particular, the sensitivity of the high-hiring portfolio to the

sample from 1926 to 2001. Unfortunately, we do not have firm-level hiring and investment data for these earlier years, so we cannot examine the performance of the CAPM on hiring portfolios in this longer sample.

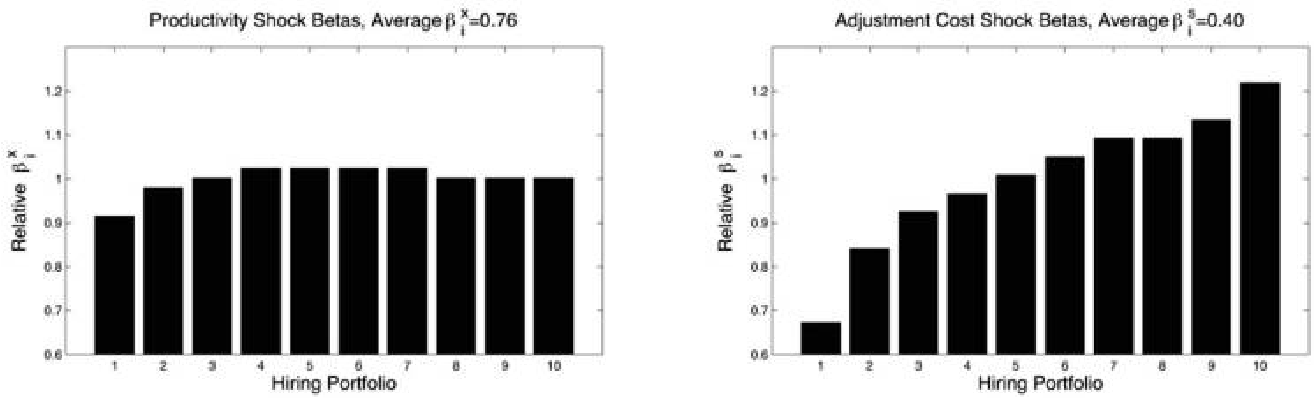

FIG. 1.—Risk exposures of the 10 hiring portfolios This figure reports the risk exposures of the 10 portfolios one-way sorted on hiring using data simulated from the model. It reports the slope coefficients from the following time-series regressions: $r_{it}^e = a_i + \beta_i^x \times \Delta x_t + \beta_i^s \times \Delta s_t + e_{it}$, in which r_{it}^e is the average excess return of portfolio $i = 1, \ldots, 10$, Δx_t is the aggregate productivity shock, and Δs_t is the aggregate adjustment cost shock. The slope coefficients β_i^x and β_i^s for each portfolio are expressed relative to the average of the corresponding slope coefficients across portfolios (i.e., $\beta_i^x/\bar{\beta}^x$, with $\bar{\beta}^x = (1/10) \times \sum_{i=1}^{10} \beta_i^x$ and similarly for β_i^s). The reported statistics for the model are obtained as averages from 500 samples of simulated data, each with 3,600 firms and 600 monthly observations.

adjustment cost shock is almost two times larger than the sensitivity of the low-hiring portfolio. This differential exposure is the fundamental difference in the quantity of risk of the hiring portfolios in the model and explains why the high-hiring firms have lower average returns in equilibrium.

The previous analysis also helps understand why the CAPM is unable to explain the cross-sectional variation in the average returns of the hiring (and investment) portfolios. In the baseline model, almost all of the variation of the aggregate stock market return is driven by shocks to aggregate productivity. Across panels, a multivariate time-series regression of the aggregate stock market return on the two risk factors has an average regression $R^2 \approx 98$ percent, a univariate regression on the aggregate productivity shock has an average regression $R^2 \approx 88$ percent, but a univariate regression on the aggregate adjustment cost shock has an average regression $R^2 \approx 10$ percent (results not tabulated). Thus, because the aggregate stock market return is mostly driven by the aggregate productivity shock, the market factor alone fails to capture the differential exposure of the hiring portfolios to the adjustment cost shock.

2. Price of Risk

According to equation (16), the impact of the differential firms' exposure to the aggregate shocks on equilibrium risk premiums depends on the price of risk of these shocks. To evaluate the importance of the price of risk of the two aggregate risk factors on the model's results, we perform comparative statics with respect to the loadings (γ_x and γ_s) of the stochastic discount factor on the two aggregate shocks.

Table 9 reports selected model-implied moments from several alternative specifications of the model, which we compare against the moments in the data (specification 0) and in the baseline calibration of the model (specification 1). In specifications 2 and 3, we specify the stochastic discount factor to have a low loading on the adjustment cost shock ($\gamma_s = -7$ vs. $\gamma_s = -14.5$ in the baseline model) and a low loading on the aggregate productivity shock ($\gamma_x = 1.5$ vs. $\gamma_x = 6.75$ in the baseline model), respectively. In these two specifications, we keep all the other model parameters equal to the baseline specification.

Specification 2 in table 9 shows that decreasing the size of the loading of the stochastic discount factor on the aggregate adjustment cost shock has a small effect on the properties of firms' hiring and investment rates. Except for some small differences, the quantity moments are similar to those in the baseline model. All of the interesting effects are reflected in the moments of asset prices. Here, both the hiring (one-way and two-way sorts) and investment return spreads are tiny (less than 1 percent per year). As a result, the corresponding CAPM-implied pricing errors of the

TABLE 9

Selected Data versus Model-Implied Moments across Alternative Calibrations

	Quantities				Asset Prices									
							HN Spread				*IK* Spread			
	SD		Skewness				One-Way		Two-Way		Two-Way		XS Slopes	
Specification	*HN*	*IK*	*HN*	*IK*	Market r^e	Value r^e	r^e	α	r^e	α	r^e	α	*HN*	*IK*
0. Data	.26	.23	.74	1.77	4.85	6.73	5.61	7.03	2.01	2.78	4.04	5.61	−.48	−.54
1. Baseline model	.24	.22	.71	1.60	4.84	5.46	6.01	6.69	1.67	2.11	4.05	4.27	−.50	−.30
2. Low price of risk of adjustment cost shock ($\gamma_s = -7$)	.24	.21	.69	1.56	5.70	.81	.58	2.15	.38	1.16	.12	.85	−.12	.20
3. Low price of risk of aggregate productivity shock ($\gamma_x = 1.5$)	.24	.21	.59	1.56	3.38	−2.97	5.08	4.86	1.20	1.21	3.55	3.34	−.26	−.49
4. No labor convex adjustment costs ($c_n^+ = c_n^- = 0, f = 0.015$)	.42	.25	.14	1.81	5.08	5.21	4.94	5.86	1.78	2.37	3.16	3.40	−.17	−.43
5. No labor nonconvex adjustment costs ($b_n^+ = b_n^- = 0, f = 0.031$)	.25	.21	.64	1.55	4.99	1.07	1.00	2.37	1.01	1.61	−.02	.68	−.62	.90
6. Frictionless labor ($c_n^+ = c_n^- = b_n^+ = b_n^- = 0, \delta_n = 0.01, f = 0.04$)	.40	.24	.19	1.78	4.83	−1.45	−.42	1.24	1.11	1.89	−1.57	−.77	−.11	.65
7. No fixed operating costs ($f = 0$)	.25	.22	.68	1.59	11.00	−.36	8.18	8.33	1.64	2.22	6.05	5.61	−.29	−.95

Note.—This table presents selected moments of the firm-level labor hiring rate (*HN*), the physical capital investment rate (*IK*), and asset prices both in the real data (specification 0) and implied by the simulation of the model under alternative calibrations (specifications 1–7). The table reports the following moments: the time-series standard deviation (SD) of firm-level *HN* and *IK*; the time-series average of the cross-sectional skewness of *HN* and *IK*; the average excess return on the value-weighted aggregate stock market (market); the average return of the high-minus-low book-to-market decile portfolio (value); *HN* spread is the labor hiring return spread across 10 portfolios one-way sorted on hiring (one-way) or the average hiring spread across investment portfolios in nine portfolios two-way double-sorted on hiring and investment portfolios (two-way); *IK* spread is the average investment return spread across hiring portfolios in nine portfolios two-way double-sorted on hiring and investment portfolios (two-way); XS slopes are the *HN* and *IK* slope coefficients in cross-sectional firm-level stock return predictability regressions (in the data, we report the slopes from the specification that controls for micro cap firms); r^e is the average annualized (× 1,200) excess portfolio return, and α is the corresponding annualized abnormal return implied by the CAPM. The reported statistics in the model are averages from 500 samples of simulated data, each with 3,600 firms and 600 monthly observations.

spread portfolios are too small. Similarly, the hiring and investment rate slope coefficients in the cross-sectional predictability regressions (XS slopes) are too small and even have the wrong sign for the investment rate (the hiring slope is −0.50 in the baseline model vs. −0.12 here, and the investment slope is −0.30 in the baseline model vs. 0.20 here). In addition, the risk premium on the aggregate stock market increases significantly (from 4.8 percent in the baseline model to 5.7 percent here), and the value premium is too small (5.5 percent in the baseline model to 0.8 percent here). This analysis shows that a sufficiently large and negative price of risk for the adjustment cost shock is crucial for the model to generate positive and sizable hiring and investment return spreads.

Specification 3 in table 9 shows that the properties of the firm's hiring and investment rates remain basically unchanged if we decrease the loading of the stochastic discount factor on the aggregate productivity shock. Thus, we can conclude that changes in the price of risk of the two aggregate shocks have a relatively small impact on real quantities, at least across the range of parameter values and set of moments considered here. The effect on asset prices is again substantial. The risk premium in the aggregate stock market is significantly reduced (from 4.8 percent in the baseline model to 3.4 percent here), and the value premium becomes negative (5.5 percent in the baseline model to −3 percent here). Importantly, the hiring return spread (in one-way and two-way sorts) and the investment return spread slightly decrease relative to the baseline model but remain large. This result thus confirms that the hiring and investment return spreads in the data are not driven by firms' exposure to the aggregate productivity shock. In addition, it shows that the hiring and investment return spreads are distinct from the value premium.

In the online appendix we provide empirical support for the sign of the price of risk of the two aggregate shocks required by our model. Here, we briefly summarize the findings. First, according to figure 1, the high-minus-low-hiring portfolio is a good proxy for the adjustment cost shock because the high- and low-hiring portfolios have roughly the same exposure to the aggregate productivity shock but have a significantly different exposure to the aggregate adjustment cost shock. We show that the returns of this portfolio are positively correlated with several proxies of investment-specific shocks (the correlation ranges from 10 percent to 64 percent), consistent with the analogy between the adjustment cost shock and investment-specific shock discussed in Section III.A.1. Because previous studies find a negative price of risk of the investment-specific shock (see Sec. III.A.2), our calibration is thus consistent with these studies. Second, using several alternative proxies of the adjustment cost and aggregate productivity shocks to measure the stochastic discount factor specified in equation (10), we estimate the price of risk of the two factors by the generalized method of moments and using the hiring portfolios as the test assets. We estimate the price of risk of the aggregate productivity factor to be positive and the price of risk of the aggregate adjustment cost shock to be negative across all the different proxies of the two aggregate shocks.

3. Intuition

Why do the returns of firms with currently high hiring rates have higher positive covariance with the aggregate adjustment cost shock in equilibrium? Given the negative price of risk of this shock, understanding this endogenous covariance is essential to understanding the positive hiring return spread.

The characteristics of the hiring portfolios reported in table 2 provide evidence that helps answer the previous question. Firms with currently high hiring rates are more productive (have received good productivity shocks in the past) than firms with low hiring rates. Going forward, and consistent with table 2, the high-hiring firms are expected to hire relatively more workers and invest more in the future because firm-specific productivity is persistent, and (convex) adjustment costs prevent firms from instantaneously adjusting their labor force and capital stock. Thus, these firms are expanding and incur high adjustment costs. If the economy experiences a positive adjustment cost shock, these firms will benefit the most from the lower adjustment costs, allowing them to expand faster and make more profits more quickly. The corresponding high increase in firm value explains the relatively higher positive covariance between the market value of these firms and the adjustment cost shock, consistent with the hiring portfolio's sensitivities to the aggregate shocks reported in figure 1. Given the negative price of risk of this shock, the returns of the high-hiring firms thus provide a hedge against this shock. They therefore have relatively lower risk and hence lower expected returns in equilibrium.

Contracting firms that are firing and disinvesting are also incurring adjustment costs. As such, these firms also benefit from a positive adjustment cost shock because this shock decreases the marginal convex and nonconvex adjustment costs of labor and capital. But these firms benefit much less from this positive adjustment cost shock than the expanding firms because of two effects. First, the adjustment costs are proportional to the shrinking (smaller) capital, labor, and output of the contracting firms. Second, the positive adjustment cost shock decreases the price of the investment good, which implies that the contracting firms get less from selling their unwanted capital. As such, the positive adjustment cost shock makes the capital stock of these firms more irreversible.

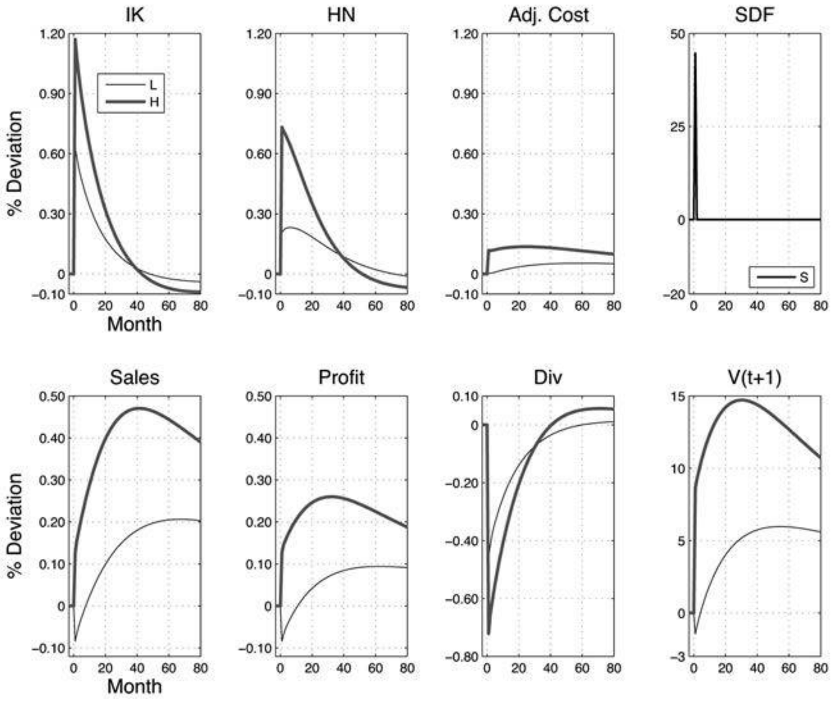

FIG. 2.—Impulse responses of selected endogenous variables in the baseline calibration of the model to a positive aggregate adjustment cost shock (reduction in marginal adjustment cost). The responses are measured in percentage point deviations relative to the long-run average values (time detrended, when applicable). To generate the response of a high-productivity (H) firm, we add a +3 percent firm-specific productivity shock. To generate the response of a low-productivity firm (L), we add a −3 percent firm-specific productivity shock. The frequency of the data is monthly. The term IK is firms' investment rate, HN is firms' hiring rate, Adj. Cost is firms' total (labor and capital) adjustment costs (net of investment expenditures), SDF is the stochastic discount factor (consumers' marginal utility), Sales is measured as output Y, Profit is sales minus wage bill, Div is firms' dividends, and V is the continuation value of the firm.

To illustrate the economic mechanism behind the previous analyses, figures 2 and 3 show impulse responses of selected endogenous variables in the baseline calibration of the model to a 3 percent positive aggregate adjustment cost shock (a reduction in the cost of adjusting the inputs) and to a 3 percent positive aggregate productivity shock, respectively. We report the responses of each variable relative to its (time-detrended) long-run average level. Because all firms in the economy are ex ante identical, we generate cross-sectional heterogeneity by examining the response of two firms in which their respective firm-specific productivity level is set 3 percent above and 3 percent below the long-run average level of firm productivity (we label these two firms as high- and low-productivity firms, respectively); furthermore, their productivity levels

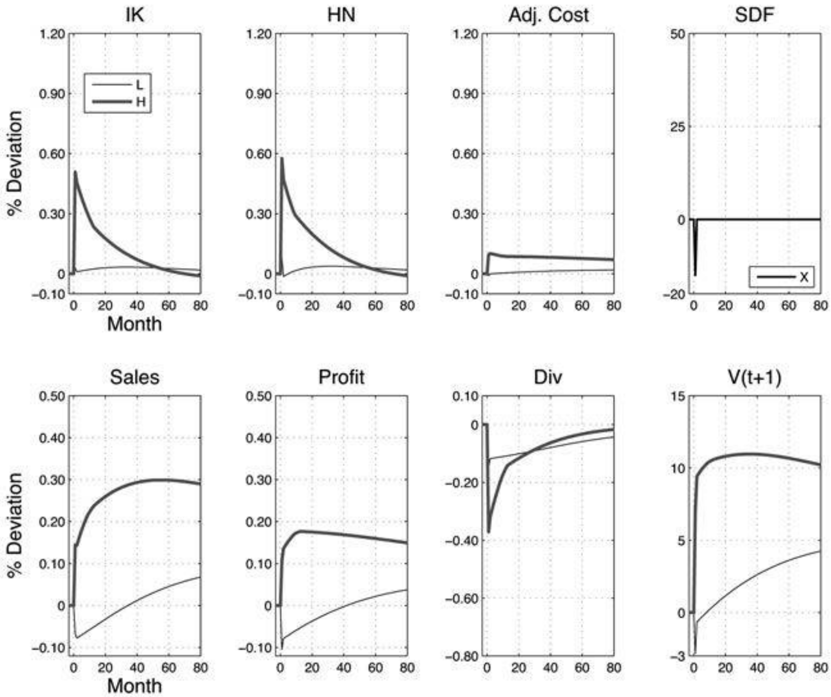

FIG. 3.—Impulse responses of selected endogenous variables in the baseline calibration of the model to a 3 percent positive aggregate productivity shock. The responses are measured in percentage point deviations relative to the long-run average values (time detrended, when applicable). To generate the response of a high-productivity (H) firm, we add a +3 percent firm-specific productivity shock. To generate the response of a low-productivity firm (L), we add a −3 percent firm-specific productivity shock. The frequency of the data is monthly. The term *IK* is firms' investment rate, *HN* is firms' hiring rate, Adj. Cost is firms' total (labor and capital) adjustment costs (net of investment expenditures), SDF is the stochastic discount factor (consumers' marginal utility), Sales is measured as output Y, Profit is sales minus wage bill, Div is firms' dividends, and V is the continuation value of the firm.

gradually mean-revert to the average level following equation (8).[17] The high- and low-productivity firms correspond roughly to the high– and low–hiring rate firms in the model. Even though the difference in productivity is not the only difference across these firms, it is clearly an important state variable.

Figure 2 shows that after a positive adjustment cost shock, both the high- and low-productivity firms increase their hiring and investment, but the increase for the high-productivity firm is larger. As a result, the total adjustment costs of both firms increase on impact, but this increase

[17] The long-run average level is determined by setting all shocks to the long-run average level, i.e., $z = -3.4$, $s = 0$, and $\Delta x = 0$.

is more pronounced for the high-productivity firm because the total adjustment cost function is increasing in the hiring and investment rates.[18] The increase in total adjustment costs leads to a sharp decrease in the dividend distributions of the high-productivity firm on impact. This is an optimal response because the firm wants to grow to take advantage of its persistent, yet temporary, higher productivity and lower marginal cost of adjusting the inputs. The dividends of the low-productivity firm also decrease on impact as a result of a combination of lower sales and higher adjustment costs, but this decrease is relatively smaller. After impact, the sales, profits, and dividends of the low-productivity firm and, especially, the high-productivity firm start increasing substantially after the shock. The high-productivity firm starts to distribute dividends that are larger than its long-run average value approximately 40 months after the shock.

As a result of the response of firms' profits and dividends over time, the continuation value (the present value of all future dividends at time $t + 1$) of the high-productivity firm increases substantially on impact, but the continuation value of the low-productivity firm slightly decreases (relative to its long-run average level) on impact. Because current dividends represent a small fraction of total firm value, the properties of firm-level stock returns are mostly determined by the change in the continuation value, the standard capital gains component of stock returns. As such, the returns of the high-productivity/high-hiring firms have a higher positive covariance with the adjustment cost shock than the returns of the low-productivity/low-hiring firms. Because the stochastic discount factor (marginal utility) is increasing in this shock because of its negative price of risk, the differential covariance implies that, all else equal, high-hiring firms have lower risk than low-hiring firms because the returns of the high-hiring firms are a hedge against the adjustment cost shock.

We now turn to the analysis of firms' responses to a positive aggregate productivity shock. Figure 3 shows that firms' responses to this shock go in the opposite direction for explaining the positive hiring return spread in the data. The magnitude of the responses to this shock is smaller than that for the adjustment cost shock (figs. 2 and 3 are in the same scale to facilitate the comparison). After a positive aggregate productivity shock, the high-productivity firm increases its hiring and investment, whereas the low-productivity firm leaves its hiring and investment almost un-

[18] Also note that the investment and hiring rate responses to the shock are not identical, which can be explained by the different capital and labor adjustment cost parameters. This in turn helps explain why both variables are informative about the firm's risk in portfolios two-way sorted on hiring and investment, because this differential response adds another layer of heterogeneity—a temporary difference in the capital-to-labor ratio across firms—on top of differences in firms' productivity.

changed on impact (relative to the average long-run level), and it slightly increases after the shock. As a result, the total adjustment costs of the more productive firm increase on impact relative to its long-run average value, but they remain almost unchanged for the less productive firm.

The increase in total adjustment costs of the high-productivity firm leads to a significant decrease in its dividends distribution on impact, despite its higher sales and profits. The dividends of the low-productivity firm also decrease on impact because of its lower output, but this decrease is substantially smaller. After impact, the dividends and sales of the high-productivity firm increase sharply. In turn, the continuation value of the high-productivity firm increases on impact, but the continuation value of the low-productivity firm decreases. Thus, the returns of the high-productivity/high-hiring firm have a higher positive covariance with the aggregate productivity shock than the returns of the low-productivity/low-hiring firm. Because marginal utility is decreasing in this shock because of its positive price of risk, this higher covariance implies that, all else equal, high-hiring firms have higher risk than low-hiring firms, which is not consistent with the empirical evidence.

B. *The Role of Labor Adjustment Costs*

The existence of labor adjustment costs is important for the overall good fit of the model. To show this importance, we compute the model-implied moments from three alternative calibrations of the labor adjustment cost function, which we report in table 9. In specifications 4 and 5, we shut down convex $(c_n^+ = c_n^- = 0)$ or nonconvex $(b_n^+ = b_n^- = 0)$ labor adjustment costs, respectively. In specification 6, we shut down both types of labor adjustment costs simultaneously. This last specification, the frictionless labor case, is the closest specification to a standard neoclassical model in which labor can be freely adjusted, and thus it constitutes a natural benchmark for evaluating the importance of labor frictions. Changing the parameters in the adjustment cost function changes the total risk in the economy. To make a meaningful comparison of the hiring and investment return spreads across the three specifications examined here with the baseline model, we adjust the fixed operating cost parameter so that the risk premium on the aggregate stock market is approximately the same and that the two aggregate shocks explain roughly the same amount of variations of the market returns across specifications. Thus, our analysis here is a comparative statics exercise holding aggregate risk constant.

In terms of quantities, specification 4 in table 9 shows that by removing convex labor adjustment costs, the model generates a firm-level hiring rate that is too volatile (0.42 here vs. 0.24 in the baseline model and 0.26 in the data). Also, this specification of the model fails to generate significant positive skewness for the hiring rate (0.14 here vs. 0.71 in the baseline model and 0.74 in the data). With only nonconvex labor adjustment costs, hiring is lumpy, with occasional but large spikes, which generates too much volatility in the hiring rate. Because the nonconvex labor adjustment costs are relatively small, labor adjustments are still too frequent (hiring and firing), which leads to a skewness of the hiring rate that is too small. Specification 5 shows that removing nonconvex labor adjustment costs has a small effect on real quantities. Specification 6 (the frictionless labor case) shows that the unreasonably large volatility of hiring and its low skewness remain the main problem in a specification of the model in which both convex and nonconvex adjustment costs are removed.

We now turn to the analysis of the effects of labor adjustment costs on asset prices. Removing either convex costs or, especially, nonconvex costs (or both) significantly reduces the hiring and investment return spreads relative to the baseline model. For example, the one-way hiring return spread is 4.9 percent without convex labor adjustment costs, only 1 percent without nonconvex labor adjustment costs, and even negative, −0.4 percent, in the frictionless labor case. These values are all considerably smaller than the 5.6 percent return spread observed in the data and 6 percent in the baseline model. Similarly, in the frictionless labor case, the hiring slope coefficient in the cross-sectional predictability regressions is too small (−0.11 here vs. −0.50 in the baseline model and −0.48 in the data), and the investment slope coefficient has the wrong sign (0.65 here vs. −0.30 in the baseline model and −0.54 in the data). In addition, without nonconvex labor adjustment costs, the model generates a tiny and sometimes negative value premium (the value premium is 1.1 percent without nonconvex labor adjustment costs in specification 5 and −1.5 percent with frictionless labor in specification 6 vs. 5.5 percent in the baseline model and 6.7 percent in the data).

C. *The Role of Fixed Operating Costs*

To examine the importance of fixed operating costs for the hiring and investment return spreads, in specification 7 we set the fixed operating cost to zero ($f = 0$). This comparative statics is interesting because fixed operating costs generate operating leverage. As shown in Zhang (2005), this operating leverage effect is a crucial ingredient for the ability of a neoclassical investment-based model with one capital good and one source of aggregate risk (productivity) to generate a sizable value premium. Because the fixed operating cost is set to zero, we cannot use this parameter to make the market risk premium similar to the baseline model, as in the previous specifications 4–6.

On the real quantity side, table 9 shows that shutting down fixed operating costs has a negligible impact on real quantities. This result is expected because fixed operating costs are essentially sunk costs and thus have a negligible impact on the hiring and investment policy functions.

Interestingly, the model-implied asset pricing moments reveal that fixed operating costs also do not decrease the size of the hiring and investment return spreads (in fact, these spreads increase because of the higher market risk premium). In contrast, shutting down the fixed operating cost has a strong negative effect on the ability of the model to match the value premium, which becomes negative in this specification (−0.4 percent here vs. 5.5 percent in the baseline model).

Because the hiring and investment return spreads remain sizable even without fixed operating costs, we can conclude that the investment and hiring return spreads are not driven by the operating leverage effect induced by fixed operating costs. This analysis is also consistent with the pattern of Sharpe ratios of the hiring portfolios. As shown in tables 1 and 8, the Sharpe ratios of the portfolios are strongly decreasing in firms' current hiring rate in both the data and the model. This pattern is not consistent with a pure operating leverage effect because both the average and standard deviation of returns scale linearly with leverage, which implies flat Sharpe ratios. Thus, the analysis and results reported here support the specification of a model in which the hiring return spread is not driven by operating leverage, but by exposure to a second (in addition to the standard aggregate productivity) aggregate shock.[19]

VII. Conclusion

Firms with relatively high hiring rates in the cross section of US publicly traded firms have lower future stock returns on average. In this paper, we provide an interpretation of this predictability as an equilibrium outcome reflecting the relatively lower macroeconomic risk of these firms and relate the empirical finding to frictions in the labor market. A neoclassical dynamic investment-based asset pricing model with stochastic adjustment costs in both labor and capital inputs matches

[19] Given the quasi-fixed nature of labor, there is an additional operating leverage effect due to a smooth wage bill. In the online appendix we show that this operating leverage does not drive our results. A calibration of the model with a constant wage (thus maximizing this additional operating leverage effect from wages) produces similar magnitudes of the hiring return spread and the value premium, when comparing with the baseline calibration of the model.

the observed levels of the hiring return spread, key properties of firm-level hiring and investment rates, and other empirical regularities.

Our results have implications for the asset pricing, labor economics, and macroeconomics literature. Our findings suggest that labor market frictions can have a significant impact on asset prices. Financial market variables, which are typically ignored in the labor economics literature, can thus be a useful source of information for quantifying frictions in labor markets. In addition, our analysis shows that risk premiums are an important determinant of hiring decisions. Given the importance of labor market fluctuations in business cycles, our results suggest that incorporating cross-sectional variation in risk premiums in current dynamic stochastic general equilibrium models can be important for an accurate understanding of employment dynamics over the business cycle and of how labor market frictions propagate and amplify the effect of shocks in the economy.

Interpreting a firm's hiring decision as analogous to an investment decision within a neoclassical model of investment provides a good start for understanding the link between labor market variables and asset prices. Naturally, there are several differences between capital and labor inputs, and within labor inputs across firms, that our simple model ignores here. For example, differences in the composition of labor (skilled and unskilled) across industries can lead to cross-sectional differences in firms' risk because the cost of hiring and firing skilled workers is higher than the cost of hiring and firing unskilled workers (Hamermesh 1993). Differences in employment protection legislation across countries are likely to affect the cost of hiring and firing workers and thus potentially generate cross-country differences in the level of country risk as well. Differences in workers' exit rates and workers' bargaining power across firms may lead to additional cross-sectional differences in firms' risk because these differences affects firms' ability to respond to shocks. Exploring the effect of these labor market characteristics on asset prices provides an interesting set of questions for future research.

Appendix

Numerical Algorithm and Calibration

It is easy to verify that all variables grow with X_t on the balanced growth path. Define

$$\{Y_t, I_t, H_t, K_{t+1}, N_{t+1}, \Psi_t, D_t, V_t, F_t\}$$
$$= \{y_t X_t, i_t X_t, h_t X_t, k_{t+1} X_t, n_{t+1} X_t, \psi_t X_t, d_t X_t, v_t X_t, f X_t\},$$

where $\{y_t,\ i_t,\ h_t,\ k_{t+1},\ n_{t+1},\ \psi_t,\ d_t,\ v_t,\ f\}$ are detrended stationary variables. In particular, the stationary adjustment cost is given as follows:

$$\psi_t = \exp(-s_t) i_t + \exp(-s_t) \begin{cases} b_k^+ y_t + \dfrac{c_k^+}{2} \left(\dfrac{i_t}{k_t}\right)^2 k_t \dfrac{X_t}{X_{t-1}} & \text{if } i_t > 0 \\ 0 & \text{if } i_t = 0 \\ b_k^- y_t + \dfrac{c_k^-}{2} \left(\dfrac{i_t}{k_t}\right)^2 k_t \dfrac{X_t}{X_{t-1}} & \text{if } i_t < 0 \end{cases}$$

$$+ \exp(-s_t) \begin{cases} b_n^+ y_t + \dfrac{c_n^+}{2} \left(\dfrac{h_t}{n_t}\right)^2 n_t \dfrac{X_t}{X_{t-1}} & \text{if } h_t > 0 \\ 0 & \text{if } h_t = 0 \\ b_n^- y_t + \dfrac{c_n^-}{2} \left(\dfrac{h_t}{n_t}\right)^2 n_t \dfrac{X_t}{X_{t-1}} & \text{if } h_t < 0. \end{cases}$$

The stationary optimization problem can be written as follows:

$$v_t(k_t, n_t, \varepsilon_t^x, z_t, s_t) = \max_{i_t, k_{t+1}, h_t, n_{t+1}} \left\{ d_t + \mathbb{E}_t \left[M_{t,t+1} \frac{X_{t+1}}{X_t} v_{t+1}(k_{t+1}, n_{t+1}, \varepsilon_{t+1}^x, z_{t+1}, s_{t+1}) \right] \right\}$$

subject to

$$d_t = y_t - w_t n_t \frac{X_{t-1}}{X_t} - \psi_t - f,$$

$$k_{t+1} = (1 - \delta_k) k_t \frac{X_{t-1}}{X_t} + i_t,$$

$$n_{t+1} = (1 - \delta_n) n_t \frac{X_{t-1}}{X_t} + h_t,$$

$$y_t = \exp(z_t) \left(\frac{X_t}{X_{t-1}}\right)^{-\theta} [\alpha k_t^{1-1/\phi} + (1-\alpha) n_t^{1-1/\phi}]^{\theta/(1-1/\phi)}.$$

Finally, the stock return is given as follows:

$$R_{t+1} = \frac{V_{t+1}}{V_t - D_t} = \frac{v_{t+1}(X_{t+1}/X_t)}{v_t - d_t}.$$

To solve the model numerically, we use the value function iteration procedure to solve the firm's maximization problem. The value function and the optimal decision rule are solved on a grid in a discrete state space. We specify a grid of 27 points for capital and labor, respectively, with upper bounds $\bar{k}$ and $\bar{n}$ that are large enough to be nonbinding. The grids for capital and labor stocks are constructed recursively, following McGrattan (1999), that is, $k_i = k_{i-1} + c_{k1} \exp(c_{k2}(i-2))$, where $i = 1, \ldots, 27$ is the index of grids points and c_{k1} and c_{k2} are two constants chosen to provide the desired number of grid points and two upper bounds $\bar{k}$ and $\bar{n}$, given two prespecified lower bounds $\underline{k}$ and $\underline{n}$. The advantage of this recursive construction is that more grid points are assigned around $\underline{k}$ and $\underline{n}$, where the value function has most of its curvature.

The aggregate productivity shock ε_t^x is an i.i.d. standard normal shock. We discretize ε_t^x into five grid points using Gauss-Hermite quadrature. The state variables s and z have continuous support in the theoretical model, but they have to be transformed into discrete state space for the numerical implementation. The popular method of Tauchen and Hussey (1991) does not work well when the persistence level is above 0.9. Because both the aggregate adjustment cost wedge and idiosyncratic productivity processes are highly persistent, we use the method described in Rouwenhorst (1995) for a quadrature of the Gaussian shocks. We use nine grid points for the s process and five grid points for the z process. In all cases, the results are robust to finer grids as well. Once the discrete state space is available, the conditional expectation can be carried out simply as a matrix multiplication. Cubic spline interpolation is used extensively to obtain optimal investment and hiring that do not lie directly on the grid points. Finally, we use a simple discrete global search routine in maximizing the firm's problem.

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