Labor Adjustment Cost: Implications from Asset Prices *

Dongwei Xu †

Click Here for Latest Version: Paper

Abstract: This paper explores the relation between a firm's labor input and its equity return, and studies its implications on macroeconomics and asset pricing. At the firm-level, a 1 percent increase in hours is associated with a 0.6 percent decrease in future equity return. A production-based asset pricing model rationalizes this empirical fact with labor adjustment cost on hours and adjustment cost shock that lowers adjustment cost. A positive adjustment cost shock encourages adjustment in the economy and hence redistributes consumption to investment. Firms adjusting hours more and taking advantage of lower adjustment cost are able to pay out more when marginal utility is high. Therefore, these firms are less risky and earn lower equilibrium return. Estimation of the model matches firm-level moments, pooled distributions, and equity return predictability of hours and employment growth. Adjustment cost shock recovered from the model captures a countercyclical component in business cycle fluctuation, and affects firm-level real quantities favorably and asset prices negatively.

JEL classifications: G12, E23, J23, E13

Keywords: Hours; Labor Adjustment; Adjustment Cost; Equity Return; Real Business Cycles

---

*I would like to express my deepest gratitude to Marianne Baxter for her continuous support, patient guidance and thoughtful advice. I would like to thank Andrea Vedolin and Stephen Terry for their insights, suggestions, and encouragement.

†Address: Department of Economics, Boston University; 270 Bay State Road, Boston, MA 02215, USA; email: xud@bu.edu; phone: +1 (314) 552-1366; website: https://dongweix.github.io/

1 Introduction

Labor input is an essential and integral component in a firm's optimization. At the micro-level, firms' decisions of labor input take place along two dimensions. Concerning employment (extensive margin), firms determine what and how many workers to hire/fire. With regard to hours (intensive margin), firms make choices and adjustments regarding working shifts/lengths. Like many other ones at the firm-level, these decisions by nature are forward-looking and time-varying. Therefore, a firm's labor input contains information about its equity returns and cash flows in the future. Moreover, patterns in labor input across firms can reveal conditions of and changes in the aggregate economy.

In this paper, I study empirically and quantitatively whether the firm's labor input choices of hours and employment represent a source of macroeconomic risk that is priced in the cross-section of equity return in the presence of labor adjustment cost. I show empirically that firms with high hours growth are associated with low equity returns, supported by both firm- and portfolio-level evidence. To elucidate the underlying economic mechanism and to quantify the impacts of hours and employment on equity return, I develop a production-based asset pricing model with dynamic labor input that is explicit about hours and employment. The model reveals and recovers a macroeconomic shock that reduces firms' adjustment cost and affects representative households' marginal utility. Using SMM procedure for structural estimation of the model, I quantitatively reproduce dynamics between hours and employment, relative magnitudes of adjustment cost, and equity return predictability of labor input. To further understand the economic forces in the model, I perform empirical investigations of and find supportive evidence for the model's implications about aggregate business cycle fluctuations and firm-level real quantities and asset prices.

The model rationalizes the negative relation between hours growth and equity return with an economic mechanism similar to investment-specific shock. The model's two key ingredients are (1) the labor adjustment cost that is explicit about hours and employment, and (2) the adjustment cost shock that lowers adjustment cost at the micro-level and affects representative households' marginal utility at the macro-level. In the economy, a positive adjustment cost shock lowers the adjustment cost for all firms and hence promotes adjustment along all dimensions of production input. Therefore, the positive adjustment cost shock encourages aggregate investment, redistributed from and contractionary to aggregate consumption. At the firm-level, firms who adjust hours and/or employment in face of the positive adjustment cost shock benefit from lowed adjustment cost. As a result, these firms pay out more relatively in the cross-section when the aggregate consumption is lower. Combining these two forces, firms with higher hours growth are less risky and hence associated with lower equilibrium equity return.

I start my analyses by demonstrating the robust empirical fact that firms with high hours growth are associated with lower equity returns. Towards this end, an intermediate task is to construct a measure of hours at the firm level. This task poses an empirical challenge shared by many studies on macroeconomics and asset pricing, because there is no readily available data of hours measured for public firms through standardized financial reporting system (e.g., 10-Q and 10-K). To overcome the obstacle, I implement a novel crosswalk among three micro-level datasets, namely the CRSP/Compustat Merged, the BLS/Current Population Survey, and the BLS/Occupational Employment Statistics. In particular, I construct a measure of hours composed of industry-specific occupational hours, which is further aggregated from individual-level data. In a series of validation exercises, my measure of hours shows significant robustness and empirical plausibility. First, the crosswalk successfully identifies about 71% of the observations in the dataset of public firms listed in three major U.S. Exchanges from 1997 to 2017; examining these identified firm-year observations, I find they are not skewed towards specific industries nor concentrated at particular periods, suggesting the general applicability of my results to follow. Next, my firm-level measure implied aggregate series of hours, compared to the national average series of hours from BLS/Current Employment Statistics (CES), exhibits remarkable similarities in the pattern, especially around the episode of the

2007-09 financial crisis. Last but not least, my measure of hours is robust to different weighting schemes applied across individuals or occupations; it is also robust to alternative occupation compositions that are intuitively industry-specific and time-varying.

The main empirical findings in this paper are twofold. First, I document a negative relation between a firm's hours growth and its future equity return; that is, a high current hours growth predicts a low future equity return. To establish this intertemporal linkage, I implement a set of equity return predictability regressions at the firm level; a 1% increase in the firm's current hours is associated with a 0.6% drop of the firm's future equity return. The negative relation is furthermore evinced at the portfolio level. I find that portfolios of firms sorted by cross-sectional hours growth manifest monotonically decreasing patterns in both excess equity returns and Sharpe ratios; more concretely, the univariate low- and high-hours growth quintile portfolios yield an equity return spread of -6% per annum. My second main empirical finding is that the negative relation is not derived from nor subsumed by employment and capital, nor leading pricing factors measured at the firm-level that are known to predict equity return. Most strikingly, I investigate the marginal predictability of hours growth, relative to that of employment growth, on equity return, and show that the impact of hours growth on equity return is statistically unchanged, irrespective of the impact of employment growth.

These two main empirical findings guide the theoretical assumptions and quantitative analyses to follow. The rest of the paper firstly proposes a production-based asset pricing model where labor input choices and labor adjustment costs are explicit about hours and employment. The novel departure of the model is the existence of labor adjustment cost on hours, analogous and additional to that on employment. Comparing to previous studies, the labor adjustment cost on hours serves two vital purposes in my model. First, the labor market friction associated with adjusting hours signals the equity return predictability originated from adjusting hours; i.e., the model delivers a negative association between current hours growth and future equity return, consistent with my main empirical findings. Second, the labor adjustment cost on hours itself is at the very core of discussing labor adjustment cost. I follow the strand of literature on dynamic factor demand with adjustment cost to model this novel friction, consisting of non-convex, linear, and convex components; the model hence can disentangle hours and employment and further shed light on the root structure and driving force of labor adjustment cost.

I use the simulated method of moments (SMM) to solve the model numerically. The model successfully matches a variety of targeted and non-targeted firm-level empirical regularities indicative of the underlying economic mechanism of the model: (1) the means, variances, skewnesses, and kurtoses of hours and employment growth, (2) the first-order persistence (coefficients) of hours and employment growth, and (3) the same-period and cross-period correlation (coefficients) between hours and employment growth. In addition to firm-level moments, the model also delivers pooled distributions (across all firms and years) of hours and employment growth that are notably close to data. As is argued and implemented by studies on dynamic factor demand, pooled distribution is informative about the adjustment cost. Therefore, the model also delivers the relative magnitudes of labor adjustment cost on hours and employment across three forms of cost components.

I assess my model in two aspects. First, I inspect the equity return predictability by probing the empirical fact in the model. Applying the same set of equity return predictability regressions to the model simulated data, I find the negative relation between a firm's current hours and its future equity return is qualitatively and quantitatively reproduced. A 1% increase in current hours is associated with a decrease in future equity return of 0.61% in the data and 0.47% in the model; for employment, the two numbers in the data and the model are both 0.15%. Second, I examine the relative magnitudes of labor adjustment cost along two margins of hours and employment, and across three forms of non-convex, linear, and quadratic components. Consistent with the pooled distributions of hours and employment growth, I find that the non-convex component, in the form of disruption to production, accounts for over 90% of the labor adjustment cost, suggesting the disruption to production the driving force of labor adjustment cost. Furthermore, the labor adjustment cost on hours is about 20% of the labor adjustment cost, suggesting the importance of explicit modeling of hours and employment.

Finally, I explore the model's implications for aggregate business cycle fluctuations and for firm-level real quantities and asset prices. I perform my investigations in languages of both macroeconomics and asset pricing by firstly constructing an empirical proxy of adjustment cost shock using factor-mimicking portfolio procedure. Next, I test four implications from the model using the adjustment cost shock proxy. First, I show the adjustment cost shock captures a countercyclical component in business cycle fluctuations as is assumed in the model. A one-standard deviation increase of adjustment cost shock increases aggregate investment by 1.6% per annum over a two-year horizon, and decreases aggregate consumption by 0.5% per annum over a four-year horizon, controlling for the productivity shock (CAPM factor). Second, I estimate the risk price of the adjustment cost shock using Fama-French 25 size-value and 17 industry portfolios. Consistent with the model, the adjustment cost shock has a negative risk price, and hence loading of the adjustment cost shock decreases equity returns. Third, I show firms with higher hours growth respond more to a positive adjustment cost shock and pay out more. Fourth, in a similar fashion, I show firms with higher hours growth respond more to a positive adjustment cost shock and earn lower equity return, as a result of such firms being able to pay out more during times when aggregate consumption is scarce. Taking these together, I find supportive results for implications from the economic mechanism of the model.

In summary, this paper illustrates how and why my main empirical findings regarding the labor input and equity return matter for both macroeconomics and asset pricing. In particular, my main empirical findings additionally shed light on the dynamics between hours and employment, on the structure of labor adjustment cost, and on the properties of a recovered shock that affects aggregate business cycle fluctuations and firm-level outcomes.

Literature Review This paper relates to four strands of literature. First, the paper contributes to the literature on dynamic factor demand with adjustment cost by introducing a new channel through which the labor market friction impacts the firms' labor input choices. The majority of studies in this strand treats the employment margin as the firm's labor input (e.g., Yashiv [2000], Hall [2004], and Merz & Yashiv [2007]) or assumes a frictionless hours margin (e.g., Bloom [2009], Cooper & Willis [2009], and Cooper et al. [2015]). This paper shows that the labor market friction associated with adjustment along the hours margin, in addition to that along the employment margin, unfolds an essential and integral component of the labor adjustment cost. Similar to that on employment, the labor adjustment cost on hours plays a central role in determining the firm's cash flow. Thus, this paper complements the existing discussions on labor adjustment cost and broadens our understanding of the connections between labor input and real quantities at the firm-level.

A rapid growing strand of literature relates labor market frictions to the cross-section of equity returns (see, among others, Gourio [2007], Chen et al. [2011], Kuehn et al. [2017], and Liu [2019]). Eisfeldt & Papanikolaou [2013] proposes the concept of organization capital, represented by the labor force of the firm (key talent), and shows that the firms with more organization capital earn higher equity return due to the risks associated with key talent's options from outside of the firm. Donangelo [2014] measures the flexibility of workers to walk away from industries and accordingly constructs the labor mobility index; the paper finds the firms in industries with higher labor mobility are riskier and earn higher equity returns. Belo et al. [2014a] and Belo et al. [2017] finds that the firms with higher hiring rates earn lower equity returns because of labor adjustment cost, a similar relation documented by my paper, and such negative association is steeper in industries requiring on average more high-skilled workers, adjusting whom imposes higher labor adjustment cost to firms. Zhang [2019] studies a firm's opportunities to replace routine-tasked workers with automation, i.e., labor-technology substitution, and shows that the firms with higher shares of routine-tasked workers earn lower equity returns, because such firms are less risky with the real option of "wait and see". Bretscher [2019] explores the firm's ability to offshore the employed labor force in production, i.e., labor offshorability, and finds that firms with higher offshorability scores earn lower equity returns. My work differs from these studies by exploring the dynamics of labor input fundamentals, which provides a novel framework studying the hours and employment in context of the cross-section of equity returns.

My results also contribute to studies on the production-based asset pricing models relating asset prices to firms' production decisions (Cochrane [1991], Cochrane [1996], and Jermann [1998]), among which, Belo [2010] creatively adopts a habit-formation specification (Campbell & Cochrane [1999]) for the firm's production technology that can be shifted across states, and finds that the state-dependent marginal rate of transformation from a representative producer also possesses the cross-sectional explanatory power. An influential work by Zhang [2005] proposes an investment-based asset pricing model based on the first principle of investment, and I use a similar neoclassical framework in my model. Papanikolaou [2011] studies investment shock in a general equilibrium framework where the investment-specific shock benefits firms producing investment goods relative to those producing consumption goods, and hence encourages savings and discourages consumption from households. My addition to this strand of literature is the empirical identification and analytical discussion of hours, a key yet often-simplified aspect of the production primitive decisions.

Last but not least, my paper accords with and contributes to a strand of the international economics literature that uses data on economic quantities across countries and emphasizes the empirical fact that a considerable fraction of the labor adjustment takes place along the hours margin (Ohanian et al. [2008], Ohanian & Raffo [2012], and Llosa et al. [2014]). I show that the labor market friction associated with adjustment along the hours margin also has important implications for asset price, in addition to economic quantities. Furthermore, different from these studies, the analyses in my paper use the firm-level data and hence put forward a structure that can be utilized to discuss both the macro and the micro impacts of policy implementations (e.g., fiscal stimulus such as the German Kurzarbeit system).

Layout The rest of this paper is organized as follows. Section 2 details my procedure for measuring firms' hours. Section 3 presents my main empirical findings. Section 4 develops a simple production-based asset pricing model, which is assessed in Section 5. Section 6 tests implications at aggregate- and firm-level. Section 7 concludes.

2 Measuring the Hours

Understanding the impacts of a firm's labor inputs on real quantities and asset prices requires firm-level data on hours, employment, and equity return. This section describes the data and methodology that I use to construct my measure of hours. I relegate additional details in measurement construction and robustness investigations to Appendix A.1.

2.1 Data

First, I obtain the industry-specific occupational data from the BLS/Occupational Employment Statistics (OES) program. The OES program dataset is based on an establishment-level survey that provides employment and wage information for about 800 six-digit Standard Occupational Classification (SOC) occupations in all three-digit Standard Industrial Classification (SIC) System or four-digit North American Industry Classification System (NAICS) industries at annual frequency. The survey features about 0.2 million establishments semiannually and finishes one survey cycle triennially, resulting a sample of 1.2 million establishments. The survey covers all full-time and part-time, wage-and-salary workers in non-farm industries, and represents approximately 62% of non-farm employment in the U.S.

Of the OES program dataset, the parts of my interest are, for each industry, (1) all the possible occupations within the industry, (2) each occupation's employment counts, and (3) each occupation's hourly wages. The program starts from 1988 and I use data starting 1997, the earliest year from which these three parts of industry-specific occupational data is available[1]. As a result, each observation of the OES program dataset is uniquely identified by year, industry, and occupation, and contains the corresponding information on employment and wage. The resulting OES program dataset spans years from 1997 to 2017; the average number of industries each year is 292, covering about 95% of all three-digit SIC or four-digit NAICS industries; the average number of occupations each year is 807, covering about 99% of all six-digit SOC occupations[2].

My measure of hours is composed by industry-specific occupational hours that is aggregated from individual-level data. Therefore, I obtain the individual-level data on hours from the BLS/Current Population Survey (CPS) March Annual Social and Economic Supplement (ASEC) program. The handling of CPS individual-level data reflects two cautionary objectives. First, to facilitate better resemblance to employees in the public firms, I retain individuals that are in the labor force and are employed, and exclude individuals who either work for the government or work as unpaid family workers. Second, to enhance the representativeness of industry-specific occupational hours, I require the number of individuals in one industry-occupation pair of each year to be no less than 20[3]. The final CPS program dataset spans years from 1997 to 2017, with the average number of surveyed individuals being $46'839$ each year.

[1]The entire span of the OES program is from 1988 to 1995 and from 1997 to 2017 (the program did not conduct surveys in 1996). Extending the dataset coverage to earlier years is possible and is on my agenda. For now I do not use data prior to 1996 for two reasons. First, during 1988-1995, the program did not collect information with regard to wages; however, the hourly wage is a crucial component for my measure of hours in aggregating industrial-specific occupational hours. Second each industry is surveyed once in every survey cycle (three years); as a result, the industry-specific occupational data is only available for some industries at a given year from 1988 to 1995. For example, the manufacturing industries (SIC: 2011-3999) were surveyed in 1989, 1992, and 1995; on the other hand, in 1992, the survey industries are agricultural services (SIC: 0711-0783), manufacturing industries (SIC: 2011-3999) and hospitals (SIC: 8062-8069). Some empirical works (notably for example, Donangelo [2014]) extend the coverage to 1991 by forward filling, repeatedly using the same industry-specific occupational data for the following years until the industry next surveyed.

[2]Across years, the OES has experienced several major updates in industry and occupation classifications. Specifically, the occupation classification system is OES proprietary occupational classification system from 1997 to 1999, SOC-2000 from 1999 to 2009, and SOC-2010 from 2010 to 2017; the industry classification system is SIC-1987 from 1997 to 2002, NAICS-2002 from 2002 to 2007, NAICS-2007 from 2008 to 2011, and NAICS-2012 from 2012 to 2017. See Appendix A.1.1.c for details on crosswalks among these classification systems

[3]The implementation of these two objectives are detailed in Appendix A.1.1.b, where I elaborates on effects of different choices on the resulting sizes of individual-level data.

The third is the CRSP/Compustat Merged (CCM) dataset. I follow the literature to obtain the financial and accounting data for my analyses. From the Center for Research in Security Prices (CRSP) dataset, I require the securities to be ordinary common shares (shrcd = 10 or 11) and to be listed on New York Stock Exchange, American Stock Exchange, or Nasdaq Stock Market (exchcd = 1, 2, or 3); I also correct the delisting bias using the CRSP Delisting Stock Events dataset. From the Compustat Fundamentals Annual (FUNDA) dataset, I require the firms to be not within the regulated electric, gas, and sanitary services industries (SIC major group 49), to be not within the leveraged finance, insurance and real estate industries (SIC major groups 60 to 69), and to have a fiscal year-end month of December; I match the equity return data from July of year $t+1$ to June of year $t+2$ to the accounting data from January of year t to December of year t.

The equity return R is the stock returns given by CRSP data item RET (returns). The employment N is the number of employees given by FUNDA data item EMP (employees). The capital stock is K from FUNDA data item PPENT (total net property, plant and equipment), lagged following real business cycle literature[4], and the capital investment is I from FUNDA data items CAPX (capital expenditures) less SPPE (sales of property, plant, and equipment), where missing values of SPPE are supplemented using zeros. Once the employment and capital levels are constructed, their empirical growth G^N and G^K are defined using DHS method (Davis et al. [1996a])[5] as $G^N_{jt} = (N_{jt} - N_{j,t-1})/[0.5 \times (N_{jt} + N_{j,t-1})]$ and $G^K_{jt} = I_{jt}/[0.5 \times (K_{jt} + K_{j,t+1})]$, respectively.

[4]The lagging means, for example, the capital at the end of period $t-1$ from the accounting data $\tilde{K}_{j,t-1}$ is treated as the capital at the beginning of period t, K_{jt}, for arbitrary firm j. One can well skip such manually lagging and define the capital aligned exactly to the accounting data. In principle, there is not material difference between these two choices except notation conversions; however, in practice, the difference between these two choices becomes confusing. Therefore, I delegate a part in the Appendix A.1.1.a to discuss the detailed process of defining the capital and its growth in the data with and without manually lagging the capital from the accounting data.

[5]I also vary the definitions of empirical employment and capital growth in Appendix A.1.1.a. I defined two types of growth rate, the simple growth rate and the DHS growth rate; for capital, I also distinguish between investment-ratio (the investment to capital) and capital growth rate (the capital differential to capital level). While the statistical features of all these definitions are surely different, the equity return predictability of all these definitions are not in any quantitatively crucial way. Most importantly, in Appendix A.1.1.a, I show in an exhausted fashion that my main empirical findings are very robust to different definitions of growth rates for employment and capital.

2.2 Methodology

I define the measure of hours in three steps. Let t denote year, i industry, o occupation, p person, and j firm. The first step operates as follows,

$$H_t^{(i,o)} = \sum_{p \in \mathrm{CPS}_t(i,o)} \Omega_t^{(i,o,p)} \times H_t^{(i,o,p)}. \tag{1}$$

On the right-hand side, $\mathrm{CPS}_t(i,o)$ represents the set of individuals in the CPS program dataset at year t that work at occupation o in industry i. Of each person p, $\Omega_t^{(i,o,p)}$ and $H_t^{(i,o,p)}$ are respectively the weight and hours from individual-level data. Therefore, the left-hand side aggregates individual-level data and gives the industry-specific occupational hours[6].

The second step utilizes the industry-specific occupational employment counts and hourly wages to form industrial hours; in particular, it takes the industry-specific occupational hours $H_t^{(i,o)}$ from Eq. (1) and weighs each occupation according to the expense associated with changing hours of this occupation:

$$H_t^{(i)} = \sum_{o \in \mathrm{OES}_t(i)} \left(\frac{N_t^{(i,o)} \times W_t^{(i,o)}}{\Sigma_{o \in \mathrm{OES}_t(i)} N_t^{(i,o)} \times W_t^{(i,o)}} \times H_t^{(i,o)} \right). \tag{2}$$

In this step, for industry i in year t, (1) $\mathrm{OES}_t(i)$ is the set of all the possible occupations, (2) $N_t^{(i,o)}$ is each occupation's employment counts, and (3) $W_t^{(i,o)}$ is each occupation's hourly wages. Therefore, the second step reveals two advantages associated with my measure of hours. First, it places more weights on occupations with greater expense impacts to the

[6]In CPS, there are two measures of individual hours: the hours usually worked per week at all jobs (the data item `uhrsworkt`) and the hours usually worked per week at main job (the data item `uhrswork1`), both of which are associated with the sample weight (the data item `asecwt`). In Appendix A.1.1.b, I vary the empirical definitions of the individual-level weight and hours to provide robustness checks. Both measures of hours would give my main empirical findings on the equity return predictability of hours growth. However, the part-time workers represents a sizable fraction of total employment (BLS: 5%), and the part-time workers are substantial in industries of retail trade and services (Nardone [1986]). Therefore, in the main contexts, I use the measure of hours that includes possible secondary part-time jobs.

cash flows, by implementing the marginal cost-based weighting scheme of $N \times W$. Second, it takes into the consideration the influences from evolution of industry-specific occupation compositions across time $\text{OES}_t(i)$[7].

In the third step, I set the firm j's hours using its industrial hours,

$$H_{jt} = H_t^{(i)} \mid j \in i. \tag{3}$$

That is, the firm's annual hours is approximated by the industrial average of the year[8]. Given the frequency of the data, I regard the approximation admissible. As is to be shown in Section 3, this approximation, which can be viewed as a source of measurement errors, would bias my coefficient estimates in regression downwards and hence the proposed impact of changing hours on equity return is likely to provide a conservative lower bound. Finally, the hours growth is then $G^H_{jt} = (H_{jt} - H_{j,t-1})/[0.5 \times (H_{jt} + H_{j,t-1})]$.

3 Empirical Evidence

In this section, I investigate the empirical impact of labor input on equity return. First, I demonstrate the negative association: firms with current higher hours growth are expected to have lower equity returns in the future, controlling for employment and capital. Second, I explore the patterns in impacts of hours and employment on equity return, which helps me to understand the dynamics between hours and employment. My main empirical findings from this section regulate the modeling choices and guide the quantitative exercises. Therefore, I show my main empirical findings via two complementary econometric methodologies: a regression approach and a portfolio approach, combining which together crosschecks the

[7]In Appendix A.1.2.b, I convey the implications from these two advantages in Eq. (2), and define my measure of hours using alternative weighting schemes and different occupation compositions. I show that my measure of hours significantly reduces measurement errors and that my empirical findings are extremely robust to various approaches aggregating industry-specific occupational hours.

[8]I discuss and disalarm the approximation in Appendix A.1.2.b from the lenses of asset pricing investigations. Specifically, I construct industrial representative firms and demonstrate that the approximation does not change my main empirical findings in meaningful way.

results and establishes the robustness.

3.1 Firm-Level Evidence

To understand the marginal predictability, I deploy a set of firm-level equity return predictability regressions; specifically, I run the panel ordinary least square regressions in the form of

$$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G_{jt}^H + b_N \times G_{jt}^N + b_K \times G_{jt}^K + \boldsymbol{b} \times \boldsymbol{F}_{jt} + e_{j,t+1}. \qquad (4)$$

In this specification, on the left-hand side, $R_{j,t+1}$ is the firm j's future annual equity return, calculated from July of year $t+1$ to June of year $t+2$. On the right-hand side, a_0, a_j, a_{t+1} are respectively the constant, the firm fixed effect, and the year fixed effect. The key variables on the right-hand side are the firm j's current annual hours growth G_{jt}^H and employment growth G_{jt}^N, measured from January of year t to December of year t. Additionally on the right-hand side, G_{jt}^K is firm j's current investment ratio; $\boldsymbol{F}_{jt}$ is a vector of five pricing factors measured at the firm-level, namely, the market capitalization (size) and book-to-market ratio (Fama & French [1992, 1993]), the investment-to-assets and return-on-equity (Hou et al. [2015]), and the profitability (Novy-Marx [2013])[9].

In Table 1, columns [1] to [3] report the equity return predictability regression results using the firm's current hours growth G_{jt}^H and/or employment growth G_{jt}^N in Eq. (4). The results in these three columns are straightforward. First focusing on columns [1] and [2], the high current hours growth is associated with low equity return in the future; the coefficient estimate of hours growth is $b_H = -62.86(14.74)$. Similarly, the negative association also holds for employment growth, as is documented by Belo et al. [2014a] and reproduced here; the coefficient estimate of employment growth is $b_N = -13.93(1.43)$. From coefficient estimates b_H and b_N, the negative predictability of hours and employment on equity return is my

[9]See Appendix A.1.1.a for details of defining the pricing factors and other control variables at the firm-level.

Table 1. Firm-Level Equity Return Predictability Regressions Results. NOTE: This table tabulates the baseline results of firm-level equity return predictability regressions in the form of Eq. (4). On the left-hand side, $R_{j,t+1}$ is the firm j's future annual equity return. On the right-hand side, a_0, a_j, a_{t+1} are respectively the constant, the firm fixed effects, and the year fixed effects. The key variables on the right-hand side are the firm j's current annual hours growth G_{jt}^H and employment growth G_{jt}^N. Additionally on the right-hand side, G_{jt}^K is firm j's current investment ratio; $\boldsymbol{F}_{jt}$ is a vector of five pricing factors measured at the firm-level, namely, the market capitalization (size) and book-to-market ratio, the investment-to-assets and return-on-equity, and the profitability. Each column runs one firm-level equity return predictability regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using panel OLS with firm standard error clusters; the sample spans years from 1998 to 2017 annually.

	[1]	[2]	[3]	[4]	[5]	[6]
Regression Method	OLS	OLS	OLS	OLS	OLS	OLS
Dependent Variable	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$
b_H: Hours Growth G_{jt}^H	-62.86^{***}		-61.11^{***}	-60.23^{***}	-54.00^{***}	-54.03^{***}
	(14.74)		(14.71)	(14.67)	(13.35)	(12.57)
b_N: Employment Growth G_{jt}^N		-13.93^{***}	-14.96^{***}	-11.23^{***}	1.52	-10.28^{***}
		(1.43)	(2.15)	(2.24)	(2.13)	(1.48)
Investment Ratio	No	No	No	Yes	No	No
Pricing Factors	No	No	No	No	Yes	No
Fixed Effects	Firm,Year	Firm,Year	Firm,Year	Firm,Year	Firm,Year	Year
Observations	23,030	42,063	23,030	23,030	23,029	23,030
Firms	4,473	5,824	4,473	4,473	4,473	4,473
Years	1998 – 2017	1998 – 2017	1998 – 2017	1998 – 2017	1998 – 2017	1998 – 2017

first main empirical finding and rests at the very core of my argument in this paper: it not only inspires the model in which the equity return predictability of hours and employment is mapped to the labor adjustment cost on hours and employment, but also the negative predictability serves as one implications from which the economic mechanism implied by the model is tested against the data.

Next, comparing column [1] to [3] and columns [2] to [3], the estimated negative slopes for hours growth and those for employment growth are statistically indifferent: the coefficient estimate of hours growth is $b_H = -61.11(14.71)$ with employment and the coefficient estimate of employment growth is $b_N = -14.96(2.15)$ with hours. This speaks to my second main empirical finding, that the correlation between impacts of hours and employment on future equity return at the firm-level is low. Intuitively, the hours and employment are two substitutable margins of labor inputs and the firm optimizes by strategically complements one with the other. When the labor adjustment cost occurs explicitly along both margins of labor inputs, the correlation between the firm's choices of hours and employment are thus naturally reduced to reflect the firm's explicit optimization along both margins; moreover, because of the labor adjustment cost, the firm's current choices of hours and employment additionally reveals information about the firm's future choices of hours and employment, indicative of the firm's future cash flow and equity return.

Moving to the columns [4], I additionally include the investment ratio G^K_{jt}, and my two main empirical findings are consistent with results from columns [1] to [3]. To interpret the economic magnitude of the coefficient estimate of $b_H = -60.23(14.67)$, a 1% increase in the firm's current hours is associated with a 0.6% decrease in the firm's future equity return, controlling for employment and capital, and this negative association is statistically significant, more than four-standard deviations away from zero. To further inspect the marginal equity return predictability, I calculate the standard deviations of hours, employment, and capital growth in the data. A one standard deviation increase in the firm's current hours is associated with a 2.40% decrease in the firm's future equity return, whereas such one standard deviation negative association is 2.36% for employment and 2.51% for capital, all of which are of similar magnitudes. It suggests that, the firm's labor input of hours has an impact on the firm's real quantities and asset prices that is economically comparable to those from employment and capital.

To make my results more comparable to previous studies and the cross-sectional equity return literature, I also include columns [5] and [6]: in column [5], I augment equity return predictability with firm-level measures of pricing factors; in column [6], I remove the firm fixed effect a_j from the equity return predictability. Both columns are coherent to my main empirical findings, so I omit the detailed discussion of results. Additionally in Appendix A.2.1, I also implement the Fama-MacBeth procedure (Fama & MacBeth [1973]), vary the independent variables specification, change the fixed effects augmentation, and modify the outliers definition to crosscheck results from here.

3.2 Portfolio-Level Results

In portfolio approach, I reiterate my main empirical finding that firms with high hours growth are associated with low equity return. To begin with, I form the univariate quintile portfolios sorted by the cross-sectional hours growth and use the quintile portfolios to build around my portfolio-level analyses; in Appendix A.2.2, I also construct and investigate and repeat analyses for the bivariate portfolios independently and sequentially sorted by additionally the cross-sectional employment growth or investment ratio.

Specifically, I construct the univariate quintile portfolios as follows. At the end of year t, each firm's annual hours growth is measured from January of year t to December of year t; then the cross-section of firms are sorted into five portfolios based on respective annual hours growth, where the breakpoints for the portfolios are essentially the quintiles from the cross-sectional distribution of the hours growth; postformation, the portfolio future annual equity returns are defined and measured from July of year $t+1$ to June of year $t+2$; such procedure is repeated at the end of year $t+1$. In reporting portfolio-level results, I use three commonly used measures, (1) the value-weighted, (2) the equal-weighted, and (3) the microcaps-excluded, equal-weighted (Fama & French [2008, 2012]) portfolio equity returns, where the microcaps are the firms with market capitalization that is below the NYSE 20-percentile threshold in each cross-section (Hou et al. [2018]). By constructing and presenting results with all the three measures of portfolio equity returns, I avoid possible conceptual misinterpretation[10] and my portfolio-level results thus provide a more comprehensive view of not only the publicly listed firms but also generally the private firms in the economy.

Consistent with the firm-level evidence, across all the three measures, firms with high

[10]The value-weighting realistically reflects the wealth effects (Fama [1998]) but is usually dominated by a small group of individual firms that accounts for a majority of total market capitalization (for example, the FAANG stocks); the equal-weighting corrects the biasing dominance by assigning the equal weights to such firms but on the other hand is heavily influenced by the left-tail microcaps firms which accounts for over half of all the public listed firms in counts but only about 3-percent of market capitalization in size (Fama & French [2008, 2012]); the equal-weighting excluding microcaps fixes issues in value- and equal-weighting but by completely erasing microcaps loses implications for private firms which are generally smaller than microcaps but accounts for about two-thirds of total employment in the economy (Belo et al. [2014a]).

Table 2. Portfolio-Level Main Results. Note: This table tabulates the main results of the portfolio-level analyses using the univariate quintile portfolios sorted by the cross-sectional hours growth. Reading horizontally, the columns [1] to [6] use value-weighted, the columns [7] to [12] use equal-weighted, and the columns [13] to [18] use equal-weighted, microcaps excluded portfolio equity returns, where the microcaps are the firms with a market capitalization that is below the NYSE 20-percentile threshold in each cross-section (Hou et al. [2018]). Of each weighting scheme, from left to right, the first five columns are quintile portfolios respectively, and the last column is the quintile portfolio spread, defined as low-minus-high (L-H). Reading vertically, panel A provides portfolio equity excess return summary statistics, including the mean of portfolio equity excess returns $\mu(r^e_{t+1}) = \mu(r_{t+1}) - \mu(r_{f,t+1})$, the standard deviation of portfolio equity excess returns $\sigma(r^e_{t+1})$, and portfolio Sharpe ratio. Next, panels B to D present portfolio excess equity return anomalies implied by asset pricing models. Specifically, panel B employs the capital asset pricing model (Sharpe [1964]; Lintner [1965]; Black [1972]), panel C the Fama-French 3-factor model (Fama & French [1992, 1993]), and panel D the Fama-French 5-factor model (Fama & French [2015]). Of each the three panels, the row-block (1) reports the model implied anomaly, defined as the intercept a, and its t-statistic; the row-block (2) shows regression summary statistics, including the mean absolute errors (m.a.e.), the ratio of RMSE (root of mean squared errors) and RMSR (root of mean squared returns) from Lettau et al. [2019], the adjusted R^2, and the p value from regression F-test. The sample spans years from 1997 to 2017 annually.

		Value-Weighted						Equal-Weighted						Microcaps-Excl. Equal-Weighted					
		L	2	3	4	H	L-H	L	2	3	4	H	L-H	L	2	3	4	H	L-H
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]
	Panel A	Portfolio Excess Return Summary Statistics																	
	Mean $\mu(r^e_{t+1})$	0.10	0.07	0.06	0.05	0.03	0.07	0.14	0.14	0.12	0.06	0.07	0.07	0.12	0.11	0.09	0.04	0.05	0.07
	Std Dev $\sigma(r^e_{t+1})$	0.17	0.19	0.20	0.18	0.22	0.14	0.22	0.26	0.29	0.31	0.25	0.15	0.17	0.18	0.24	0.26	0.25	0.19
	Sharpe ratio	0.53	0.34	0.27	0.24	0.13	0.44	0.62	0.52	0.42	0.18	0.28	0.39	0.69	0.61	0.36	0.14	0.21	0.32
	Panel B	Excess Equity Return Anomaly from Capital Asset Pricing Model																	
(1)	Intercept a	0.11	0.11	0.08	0.07	0.04	0.06	0.17	0.20	0.17	0.10	0.11	0.04	0.14	0.15	0.12	0.07	0.08	0.04
	[t]	3.13	2.83	2.11	1.83	1.07	2.91	4.07	5.88	4.71	2.05	2.15	2.32	5.49	5.09	3.84	1.82	1.84	1.71
(2)	MAE	0.15	0.14	0.15	0.14	0.17	0.11	0.17	0.18	0.21	0.22	0.16	0.10	0.13	0.14	0.19	0.20	0.17	0.13
	RMSE/RMSR	0.82	0.86	0.93	0.94	0.97	0.90	0.79	0.68	0.85	0.93	0.91	0.87	0.76	0.72	0.89	0.96	0.95	0.91
	Adjusted R^2	−0.05	0.04	−0.06	−0.06	−0.05	−0.04	−0.04	0.33	0.04	0.02	0.00	0.06	−0.06	0.14	−0.02	−0.02	−0.05	0.03
	F-test: p-value	0.52	0.12	0.83	0.93	0.27	0.20	0.32	0.00	0.08	0.10	0.06	0.05	1.00	0.01	0.41	0.16	0.23	0.08
	Panel C	Excess Equity Return Anomaly from Fama-French 3 Factor Model																	
(1)	Intercept a	0.12	0.09	0.07	0.04	0.02	0.08	0.15	0.19	0.17	0.07	0.07	0.06	0.14	0.14	0.13	0.04	0.05	0.07
	[t]	3.47	2.45	2.45	1.07	0.45	3.91	3.04	4.84	2.95	1.34	1.19	3.03	4.24	4.48	3.25	1.03	0.81	2.10
(2)	MAE	0.14	0.12	0.14	0.14	0.16	0.09	0.16	0.17	0.22	0.21	0.16	0.09	0.12	0.13	0.19	0.19	0.16	0.11
	RMSE/RMSR	0.81	0.82	0.93	0.87	0.94	0.80	0.78	0.67	0.85	0.83	0.83	0.79	0.75	0.71	0.89	0.87	0.89	0.83
	Adjusted R^2	−0.17	0.02	−0.19	−0.02	−0.11	0.08	−0.12	0.26	−0.08	0.11	0.06	0.13	−0.17	0.06	−0.15	0.04	−0.03	0.09
	F-test: p-value	0.73	0.08	0.97	0.16	0.35	0.24	0.01	0.00	0.13	0.00	0.00	0.16	0.37	0.05	0.41	0.01	0.30	0.25
	Panel D	Excess Equity Return Anomaly from Fama-French 5 Factor Model																	
(1)	Intercept a	0.11	0.11	0.13	0.03	0.05	0.04	0.14	0.15	0.24	0.03	0.08	0.04	0.14	0.14	0.22	0.03	0.06	0.05
	[t]	2.39	2.91	4.05	0.70	1.07	2.10	2.22	4.50	4.96	0.42	1.38	1.52	2.60	4.42	7.04	0.43	1.05	2.11
(2)	MAE	0.14	0.13	0.15	0.13	0.16	0.09	0.16	0.17	0.20	0.22	0.16	0.09	0.12	0.12	0.17	0.20	0.17	0.11
	RMSE/RMSR	0.80	0.82	0.89	0.86	0.93	0.72	0.76	0.64	0.79	0.79	0.82	0.79	0.74	0.68	0.82	0.86	0.89	0.83
	Adjusted R^2	−0.32	−0.13	−0.26	−0.17	−0.25	0.13	−0.25	0.23	−0.10	0.07	−0.06	0.00	−0.32	−0.00	−0.11	−0.08	−0.19	−0.07
	F-test: p-value	0.68	0.00	0.04	0.05	0.18	0.00	0.01	0.00	0.00	0.00	0.02	0.23	0.31	0.00	0.00	0.01	0.31	0.12

hours growth are associated with low equity return in equilibrium. In panel A of Table 2, I calculate the summary statistics of quintile portfolio equity returns. The equilibrium equity excess return monotonically decreases moving from low (portfolios L: columns [1], [7], and [13]) to high (portfolios H: columns [5], [11], and [17]) quintile portfolios; furthermore, the Sharpe ratio also decreases moving from low to high quintile portfolios across three measures, suggesting that compensation per unit of risk associated decreases as hours growth increases.

I additionally emphasize two observations that stand out. First, the difference in the portfolio equity excess returns is economically large. The average portfolio equity return spread (portfolios L-H, Low-minus-High: columns [6], [12], and [18]) is -7% per annum for all the three measures. This -7% portfolio equity return spread is in the same order of magnitudes as those for risk factors commonly used in the asset pricing literature: for example, the size, value, profitability, and investment factors from the Fama-French 5-factor model (Fama & French [2015]) have average annual returns ranging from 3.82% to 0.64% (Mkt-RF: 6.22%; SMB: 3.07%; HML: 0.64%; RMW: 3.82%; CMA: 2.76%) during the same span of years. Second, the fact that all the three measures yield the same -7% portfolio equity return spread is interesting by itself. By comparing the value- (column [6]) and equal- (column [12]) weighted portfolio equity return spreads, the negative relation between hours growth and equity return is likely to be meaningfully latent for both the large and the small firms. Comparing the equal-weighted (column [12]) and the microcaps-excluded, equal- (column [18]) weighted portfolio equity return spreads, I can further infer that, this negative relation is also likely to be as strong among private firms in the economy, which are usually even more micro than microcaps but altogether account for about two-thirds of the total labor employment in the U.S.

I also investigate the extent to which the variation in the portfolio equity excess returns can be explained by the exposure to common risk factors in the well-established asset pricing factor models. The analyses are indicative about the dimensions of risks that are implicitly represented by the hours growth in a reduced-form approach, and is informative about the ingredients necessary to model the labor adjustment cost in a structural approach. The asset pricing factor models deployed are (1) the capital asset pricing model (CAPM: Sharpe [1964]; Lintner [1965]; Black [1972]), (2) the Fama-French 3-factor model (Fama & French [1992, 1993]), and (3) the Fama-French 5-factor model (Fama & French [2015]); specifically, the time-series regressions take the following general form

$$r^e_{q,t+1} = a_q + \boldsymbol{b}_q \times \boldsymbol{F}^{\text{Model}}_t + e_{q,t+1}. \tag{5}$$

On the left-hand side, $r^e_{q,t+1}$ is the portfolio q's equity excess return, and the right-hand side has a vector the pricing factors $\boldsymbol{F}^{\text{Model}}_t$ in respective model. In Table 2, panel B has market excess return $(r^{MKT} - r^F)_t$ on the right-hand side, panel C additionally the size r^{SMB}_t and value r^{HML}_t factors, and panel D furthermore the profitability r^{RMV}_t and investment r^{CMA}_t factors. In all specifications, I interpret the intercept a_q as the pricing error resulted from the respective asset pricing factor model, and hence the intercept a_q manifests how large and significant the model-implied anomaly is.

It is clear that the firm's hours choice represents a source of macroeconomic risk that is well priced in the cross-section of equity returns but not explained by the leading risk factors. From row-block (1) in panels B to D, across all three measures of portfolio equity excess returns in all three asset pricing factor models, the estimated intercepts a_q remain economically large and statistical significant. Especially for the portfolio equity return spreads in columns [6], [12], and [18], the estimated intercepts a_q are mostly in the same order of magnitudes as the portfolio equity return spreads themselves, the left-hand side variables. This clearly demonstrates the failures of existing risk factors in capturing the underlying macroeconomic risk and explaining the negative relation between hours growth and equity return. Such failures are further evidenced by row-block (2) in panels B to D, where the mean absolute errors (m.a.e.) are large, and the ratios of root of mean squared errors to the root of mean squared returns (RMSE/RMSR: Lettau et al. [2019]) are high.

Overall, the portfolio-level results confirm the negative relation between hours growth and equity return coherent to the firm-level evidence. Such negative relation motivates the modeling choice of mapping equity return predictability of hours and employment to labor adjustment cost on hours and employment in Section 4. Furthermore, the predictability of hours growth on equity return is not derived from common firm-level variables nor subsumed by leading risk factors, proposing and rationalizing the modeling assumption on non-TFP macroeconomic risk as additional business cycle fluctuation driver.

4 A Model with Dynamic Labor Input

To rationalize my main empirical findings, I consider a production-based asset pricing model from the neoclassical business cycle theory. As suggested by the discussions in Section 3, the equity return predictability of hours and employment is conceptually captured by labor adjustment cost on hours and employment. The model builds on existing works on incorporating labor inputs dynamics (Cooper et al. [2015]) and labor market frictions (Belo et al. [2014a]) into firms' explicit decisions of hours and employment.

4.1 Economic Environment

Formally, the economy is populated with a large number of firms that uses homogeneous factor inputs to produce a homogeneous good. Each firm is indexed by $j \in J$ and produces according to the Cobb-Douglas technology with the explicit labor input choices along both margins of hours and employment

$$Y_{jt} = A_t Z_{jt} (H_{jt} N_{jt})^{\alpha}, \tag{6}$$

where parameter α is the labor share. In this production function, A_t is the aggregate and Z_{jt} is the idiosyncratic productivity processes. In the model, the aggregate productivity affects the firm-level equity return via the marginal utility of representative agent in equilibrium, and the idiosyncratic productivity creates the cross-sectional heterogeneity at the firm-level.

The compensation function follows Bils [1987] in the form of

$$W_{jt} = N_{jt}(\omega_0 + \omega \cdot H_{jt}^{\xi}), \tag{7}$$

where parameter ξ controls the elasticity of compensation function with respect to hours, and ω_0 and ω represent the fixed and variant wage rates, respectively. The compensation function in this form has the ability to uniform hours across firms in a frictionless equilibrium, despite the scale of production, and ensures all firms to choose a uniform level of hours in absence of labor market friction.

The interesting parameter in the compensation function is the elasticity ξ. By different parameterization, the compensation function nests different cases often seen in the literature. When $\xi = 0$ the compensation function ignores the hours margin of labor input completely; in this case, $(\omega_0 + \omega)$ is an invariant per-worker wage rate. When $\xi = 1$, the compensation function is defined over the total hours (the product of hours and employment), but assumes a constant per-hour salary irrespective of the level of hours; in this case, ω is an invariant per-worker-hour wage rate. When $\xi \in (0, 1)$, the compensation is not economically plausible, for that the compensation function in this case implies a negative second-order derivative with respect to hours and hence suggests the overtime hours is decreasingly compensated as the overtime hours increases. Therefore, $\xi > 1$ is the most appropriate and relevant case for discussing the two margins of labor inputs explicitly. Formally,

Condition 1. *The elasticity of marginal compensation function with respect to hours is positive; that is, the curvature parameter xi of hours H in compensation function (Eq.* (7)*) satisfies $\xi > 1$.*

Economically, Condition 1 ensures that the compensation function has non-negative first- and second-order derivatives with respect to hours; or equivalently, the condition ensures that the elasticity of marginal compensation with respect to hours is positive, i.e., $\xi - 1 > 0$; that is, as hours increases, the marginal compensation is positive and cannot be decreasing. In Cooper & Willis [2009], estimation of the elasticity parameter implies $\xi > 2$ except in the restricted quadratic adjustment cost case where $\xi = 1.78$. Bloom [2009] has $\xi = 3.42$ in estimating the specification with only the labor adjusting friction, and $\xi = 2.09$ in estimating the specification with both the capital and the labor adjusting frictions. In Cooper et al. [2015], which has the most relevant economic environment to this paper, the estimation across all four labor adjustment cost restricted cases implies $\xi > 1$ and the most-preferred specification gives $\xi = 1.013$.

Finally, the law of motion for employment N_{jt} is given by $N_{jt} = (1-\delta)N_{j,t-1} + D^N_{jt}$, where D^H_{jt} is the employment net flow and $\delta \in (0,1)$ is the employment destruction rate, the rate at which the employment depreciates for any exogenous (relative to the decision-maker of the firm) reasons, such as retirement, quitting, and illness. I follow the neoclassical business cycle literature to let the employment net flow D^N_{jt} attach to the employment N_{jt} in the same period, as opposed to in the next period as in the capital case[11]. Therefore, the employment growth is given by $G^N_{jt} = D^N_{jt}/N_{j,t-1}$[12]. There is no exogenous destruction to hours, and thus the law of motion for hours H_{jt} is simply $H_{jt} = H_{j,t-1} + D^H_{jt}$, where D^H_{jt} is the change of hours, and the hours growth is $G^H_{jt} = D^H_{jt}/H_{j,t-1}$[13].

[11]See, among other, King & Thomas [2006] for discussion of this convention. In the data and in my model, I let labor input decisions take place at the frequency of t = one year; therefore, the same-period attachment assumption is realistic given the model.

[12]Among others, Hall [2004] models adjustment cost on net growth rate of employment. As is mentioned by Cooper & Willis [2009] and Cooper et al. [2015], due to data limitations, the gross hiring and firing are usually not observable; therefore, the gross growth rate of employment involves calibration of the separation rate δ. Empirically, equivalently to per annum, Merz & Yashiv [2007] uses $\delta = 0.344$, Bloom [2009] $\delta = 0.1$, and Belo et al. [2014a] $\delta = 0.12$; Belo et al. [2017] further calibrate the monthly destruction rate to be $\delta = 0.03$ for the high-skilled workers and $\delta = 0.04$ for the low-skilled workers; Bloom et al. [2018] let quarterly destruction rate $\delta = 0.088$ to match a annual separation of 35% in Shimer [2005]. More strictly, Nickell [1986] uses the law of the motion $N = (\mathrm{h}_t - \mathrm{f}_t - \delta)N_{-1}$, where h_t and f_t proportional hiring and firing rates. A model incorporating the gross hiring and the gross firing explicitly and matching the micro-level evidence from this paper is a interesting research topic (for example, see Abowd & Kramarz [2003] for an effort towards this end using the French micro-level data and Cooper et al. [2007] for a treatment using the search model) and is on my research agenda.

[13]The empirical hours growth G^H_{jt} and employment growth G^N_{jt} defined in Section 2 and used in Section 3 are different from the theoretical growth here. To be consistent with the literature and convention, in model

Following dynamic factor demand literature (e.g., Cooper & Haltiwanger [2006]; Cooper & Willis [2009]; Cooper et al. [2015]), I allow the firms to make explicit labor input choices of hours and employment, and hence the labor adjustment cost occurs explicitly along both margins of hours and employment. Therefore, I assume a labor adjustment cost function that is fairly rich in structure and broadly representative of the literature, incorporating non-convex, linear, and convex components. Based on the empirical evidence demonstrated by Section 3, the equity return predictability of hours and employment is mapped to labor adjustment cost on hours and employment. In Section 5, I investigate the theoretical and quantitative role of labor adjustment cost in detailed exercises, from which I show the plausibility of my assumption on labor adjustment cost in matching the empirical regularities.

The labor adjustment cost on the hours and employment are respectively C^H_{jt} and C^N_{jt} specified by the following symmetric function form,

$$\begin{aligned} C^H_{jt} &= c^H_d Y_{jt} \times \mathbf{1}_{G^H_{jt} \neq 0} + c^H_i W_{jt} \times |G^H_{jt}| + c^H_q H_{t-1} \times (G^H_{jt})^2 \\ C^N_{jt} &= c^N_d Y_{jt} \times \mathbf{1}_{G^N_{jt} \neq 0} + c^N_i W_{jt} \times |G^N_{jt}| + c^N_q N_{t-1} \times (G^N_{jt})^2 \end{aligned} \tag{8}$$

where $c^{H,N}_{d,i,q}$ are non-negative parameters, and $\mathbf{1}_{\sim}$ is the nonzero indicator. The labor adjustment cost function reflects the possible non-convexity, linearity, and convexity that might exist during the costly process of adjusting labor inputs. The first component is a disruption cost. The parameter c_d represents a non-convex fraction of disruption to the production process; hence $1 - c_d$ is the remaining share of output after the disruption, should the adjustment take place. The usage of non-convex adjustment cost has been empirically successful in literature and hence widely emphasized. For example, in discussing labor adjustment cost, Cooper & Willis [2009] and Cooper et al. [2015] use a set of micro-level evidence and show that, the non-convex disruption cost is necessary and critical for simultaneously matching

specification I use theoretical growth (e.g., labor adjustment cost function) and in empirical exercises I use empirical growth (e.g., equity return predictability regressions). Later during comparing data- and model-implied firm-level moments in Section 5, I also compute empirical growth from the simulated data and compare empirical growth from model and from data in a consistent way.

aggregate moments and explaining plant-level observations. The next component is a piecewise linear component. The piecewise linearity suggests a type of cost occurred during the adjustment depending not on the sign of but rather the size of adjustment. As a result, the parameter c_i controls the size of per-capita labor adjustment cost denominated as a fraction of compensation. Bloom [2009] argues such linear cost can take the form of labor partial irreversibility and captures the per-capita cost occurred during the process of hiring, training, negotiating, and firing. The partial irreversibility in dynamic factor demand literature is initially advocated in the context of capital; the difference between buying and selling prices of the capital reflects the transaction cost, which may originate from the capital specificity and lemons problem (Cooper & Haltiwanger [2006]). The argument is analogous in the context of labor; the labor partial irreversibility cost arises from labor specificity (training workers along the extensive margin) and lemons problems (negotiating shifts along the intensive margin). The last component is a convex quadratic cost. Since the marginal cost is linear in adjustment, the parameter c_q determines the sensitivity of the quadratic cost component in response to the relatively rapid versus sluggish labor adjustment; as a result, the convex quadratic cost combined with persistent firm-specific productivity prevent a firm from instantaneously adjusting labor input (Belo et al. [2014a] and Belo et al. [2017]). In Appendix A.3, I further consider an adjustment cost function nesting more components[14]

I allow the labor adjustment costs to be stochastic following Belo et al. [2014a],

$$C_{jt} = \frac{C_{jt}^N + C_{jt}^H}{X_t}, \tag{9}$$

in which X_t represents an aggregate stochastic process that captures the economy-wide condition for labor adjustment. Therefore, the aggregate stochastic process of X_t is an adjustment cost wedge that affects the effective costs occurred by the adjusting firms and

[14]The analyses there build on Cooper & Willis [2009] and Cooper et al. [2015]. The adjustment cost function takes into consideration the implication drawn from the labor adjusting friction discussions from Merz & Yashiv [2007], Bloom [2009], Belo et al. [2013], Belo et al. [2014a], Belo et al. [2017], and Bloom et al. [2018].

a shock to X_t is an adjustment cost shock that describes the change in aggregate labor adjustment opportunities.

The adjustment cost shock is important for generating my main empirical finding that firms with high hours growth are associated with low equity return. In the economy, a positive adjustment cost shock leads to larger adjustment cost wedge and hence lowers the adjustment cost occurred by firms who adjust hours and/or employment. Therefore, the positive adjustment cost shock benefits such adjusting firms and enables them to pay out relative more in the cross-section. On the other hand, since the positive adjustment cost lowers the adjustment cost in the economy and encourages more investment (capital adjustment) at the aggregate-level, the aggregate investment (capital adjustment) has a temporary contractionary effect on aggregate consumption, which leads to high marginal utility states[15]. Combining these two forces, firms with high hours growth are able to pay out more during states where the marginal utility is high; as a result, these firms are less risky in equilibrium and earn low equilibrium equity return.

Economically, the adjustment cost shock can be conceptually mapped as several economic forces that have been empirically documented by previous studies. For example, a positive adjustment cost shock that lowers the adjustment cost is equivalent to an increase in the per-hour or per-worker labor efficiency in the economy[16], because the improvement in labor efficiency allows the firms to achieve the same level of payout with smaller increases of hours and/or employment. Also, a positive adjustment cost shock works similar to some labor-market specific aggregate fluctuations. For example, a positive adjustment cost shock is mechanically equivalent to a decrease in the vacancy postings (Liu [2019]) or a decrease of

[15]The model here does not discuss capital dynamics but captures the crowding-out effects in a reduced-form fashion by specifying the stochastic discount factor as a function of aggregate shocks. Another way of thinking about the effect of adjustment cost shock on marginal utility is via the marginal product of capital. With positive adjustment cost shock, the marginal product of capital in the economy is higher and therefore, households are encouraged to reduce consumption and save more, to facilitate the investment equilibrium. As a result, a positive adjustment cost shock leads to high marginal utility states.

[16]The improvement of labor efficiency is analogous to the more efficient capital introduced by investment in Greenwood et al. [1997, 2000], and equivalent to the more skilled labor introduced by hiring in Belo et al. [2017].

the aggregate labor market tightness in general (Kuehn et al. [2017]), because the overall enlargement of the outside options from the labor market makes it easier and cheaper for firms to hire/fire (along the labor input margin of employment) and to negotiate shifts/hours (along the labor input margin of hours)[17].

There are three stochastic primitives in the economy, all of which are assumed to follow logarithm first-order Markov processes. Specifically, the aggregate productivity is $\log(A_{t+1}) = \rho_A \cdot \log(A_t) + \sigma_A \cdot \epsilon^A_{t+1}$, the idiosyncratic productivity $\log(Z_{j,t+1}) = \rho_Z \cdot \log(Z_{jt}) + \sigma_Z \cdot \epsilon^Z_{j,t+1}$, and the adjustment cost wedge $\log(X_{t+1}) = \rho_X \cdot \log(X_t) + \sigma_X \cdot \epsilon^X_{t+1}$. In these standard specifications, the $\rho_{A,Z,X}$ are the first-order autocorrelation coefficients and the $\sigma_{A,Z,X}$ are the conditional volatility coefficients. The i.i.d. standard normal innovation terms $\epsilon^{A,X}_{t+1}, \epsilon^Z_{j,t+1}$ are uncorrelated with leads and lags, and nor in the cross-section.

Given the stochastic primitives, the future payout is discounted at a stochastic discount rate. Without a explicit households side in the model, I write the intertemporal stochastic discount factor as a function of aggregate productivity shock and aggregate adjustment cost shock

$$M_{t+1} = (R^f_{t+1})^{-1} \frac{\exp\{\gamma_A \Delta \log(A_{t+1}) + \gamma_X \Delta \log(X_{t+1})\}}{\mathbb{E}[\exp\{\gamma_A \Delta \log(A_{t+1}) + \gamma_X \Delta \log(X_{t+1})\}]}. \tag{10}$$

where Δ denotes first-order difference operator and $\mathbb{E}[\cdot]$ is the expectation operator. In this specification, the parameters $\gamma_{A,X}$ are the loadings of stochastic discount factor on the aggregate shocks. The sign of $\gamma_A < 0$ captures the general equilibrium mechanism that the low-aggregate-productivity states are associated with low outputs and consumption, and hence high marginal utility growth and large stochastic discount factor. On the other hand, the parameter $\gamma_X > 0$ indicates that a positive adjustment cost shock, by lowering the adjustment cost, redistributes outputs from consumption to investments, and hence produces high marginal utility growth and large stochastic discount factor. Therefore, without ex-

[17]Note that, such outside options include the development/advancement of the labor-substitutable technology (Zhang [2019]) such as the automation (Acemoglu & Restrepo [2020]).

plicit capital dynamics in the model, the sign of $\gamma_X > 0$ captures the general equilibrium consumption crowding-out effect from investment surging.

Finally, the firm faces an optimization problem described by the following Bellman equation

$$V(A_t, X_t, Z_{jt}, H_{j,t-1}, N_{j,t-1}) := V_{jt} = \max_{H_{jt}, N_{jt}} \{(Y_{jt} - W_{jt} - C_{jt}) + \mathbb{E}[M_{t+1} \cdot V_{j,t+1}]\}. \tag{11}$$

That is, given the inherited labor input choices of hours and employment, the firm chooses hours and employment in the current period according to the law of motions, to maximize its current period payout and expected discounted future equity value. As desired, the optimization problem endogenously relates the labor input choices of hours and employment to the equity return in the intertemporal. Moreover, the optimization problem defines the equity return as $R_{j,t+1} = V_{j,t+1}/[V_{j,t} - (Y_{jt} - W_{jt} - C_{jt})]$ and gives the Euler pricing formula as $1 = \mathbb{E}[M_{t+1}R_{j,t+1}]$.

4.2 Estimation

My main empirical findings suggest negative equity return predictability of both hours and employment growth and my model implies an economic mechanism through which the labor adjustment cost on hours and employment affects the future value of the firm. Therefore, in the baseline model, I focus on estimating the labor adjustment cost that is explicit on hours and employment, and define the vector of estimated parameters

$$\theta = (c_d^N, c_i^N, c_q^N, c_d^H, c_i^H, c_q^H) \tag{12}$$

to understand the empirical findings in a structural way and to test the model's economic mechanism quantitatively. More importantly, the estimation of θ also suffices discussions on the root structure and the leading components of labor adjustment cost at the firm-level.

Table 3. Calibration. NOTE: This table reports the calibration of the baseline model operating at the frequency of one annum. I set the labor share with decreasing return of scale $\alpha = 0.73$. This value is implied by the labor share of 2/3 from a constant return to scale production function, and an isoelastic demand curve with the price elasticity of demand of 5. The parameter ξ controls the curvature of compensation function with respect to the hours. A value of $\xi > 1$ ensures a positive elasticity of the marginal compensation function with respect to the hours; I let $\xi = 1.013$ from Cooper et al. [2015], which has the most relevant economic environment. In specifying the stochastic processes in model, I follow Khan & Thomas [2008] closely; I use the same persistent coefficient value for all the three stochastic processes $\rho_A = \rho_X = \rho_Z = 0.859$; I assign the conditional volatility value $\sigma_X = \sigma_A = 0.014$ for the aggregate processes and $\sigma_Z = 0.022$ for the idiosyncratic process. Two parameters in stochastic discount factor from are the loadings on the two aggregate shocks. From Belo et al. [2014a], I let the loading on the aggregate productivity shock $\gamma_A = -6.75$ and that on the aggregate adjustment cost shock $\gamma_X = +14.5$.

Definition	Symbol	Value	Source
Production function labor share	α	0.73	Cooper et al. [2015]
Compensation function hours curvature	ξ	1.013	Cooper et al. [2015]
Annual employment destruction rate	δ	0.12	Bloom [2009]
Persistence coefficient of aggregate productivity	ρ_A	0.859	Khan & Thomas [2008]
Conditional volatility of aggregate productivity	σ_A	0.014	Khan & Thomas [2008]
Persistence coefficient of adjustment cost wedge	ρ_X	0.859	Khan & Thomas [2008]
Conditional volatility of adjustment cost wedge	σ_X	0.014	Khan & Thomas [2008]
Persistence coefficient of idiosyncratic productivity	ρ_Z	0.859	Khan & Thomas [2008]
Conditional volatility of idiosyncratic productivity	σ_Z	0.022	Khan & Thomas [2008]
Risk-free rate	R^f	0.015	Belo et al. [2014a]
Loading of SDF on aggregate productivity shock	γ_A	-6.75	Belo et al. [2014a]
Loading of SDF on aggregate adjustment cost shock	γ_X	$+14.5$	Belo et al. [2014a]

Turning to the calibrated parameters of the baseline model, I use the values reported in previous studies whenever possible. Noting that the data on employment, hours, and equity return are all measured at annual frequency, I fix the length of one period in model to correspond to one year in data and calibrate accordingly. Doing so allows me to directly draw comparison between the data- and the model-implied moments. Table 3 reports the calibration of the baseline model. I set the labor share in Eq. (6) with decreasing return of scale $\alpha = 0.73$ (Cooper et al. [2015]). This value is implied by the labor share of 2/3 from a constant return to scale production function, and an isoelastic demand curve with the price elasticity of demand of 5. The parameter ξ from Eq. (7) controls the curvature of compensation function with respect to the hours. As is stated by Condition 1, a value of $\xi > 1$ ensures a positive elasticity of the marginal compensation function with respect to the hours. By the discussion directly following Condition 1, I let $\xi = 1.013$ from Cooper et al. [2015], which has the most relevant economic environment to this paper. In calibrating the stochastic primitives in model, I follow Khan & Thomas [2008] closely; I use the same persistent coefficient value for all the three stochastic processes $\rho_A = \rho_X = \rho_Z = 0.859$, and I assign the conditional volatility value $\sigma_X = \sigma_A = 0.014$ for the aggregate processes and $\sigma_Z = 0.022$ for the idiosyncratic process[18]. Two interesting parameters in stochastic discount factor from Eq. (10) are the loadings on the two aggregate shocks. From Belo et al. [2014a], I let the loading on the aggregate productivity shock $\gamma_A = -6.75$ and that on the aggregate adjustment cost shock $\gamma_X = +14.5$.

To numerically solve the model, I use the simulated method of moments (SMM) with value function iteration. It is clear that the state variables $(A_t, X_t, Z_{jt}, H_{j,t-1}, N_{j,t-1})$ in value function Bellman equation from Eq. (11) determines equilibrium of the model as well as the endogenous behavior of real quantities and asset prices in the model. To construct the discretized state space spanned by the state variables vector, for exogenous stochastic state variables, I use the method described in Terry & Knotek II [2011] to determine the transition matrix; for endogenous choice/state variables, I use the grid search method combined with cubic Hermite interpolation to enhance precision. To evaluate the model fit, I include 2675 firms in one simulation of the economy in the model to match the average number of firms per year in the data (2675.48); for every firm, I simulate 300 periods, of which, the first half is dropped to mitigate the influence from the arbitrary initial conditions and the remaining 150 periods are treated as from stationary equilibrium. See Appendix A.4 for more details on the choices and algorithms in numerical implementation.

The SMM approach requires informative vector of moments. I additionally take two cautionary steps in choosing the vector of moments. First, given that the model is abstract

[18]In Khan & Thomas [2008], the persistent coefficients of aggregate and idiosyncratic productivity process are directly equaled at $\rho_A = \rho_Z = 0.859$; the conditional volatility of aggregate and idiosyncratic productivity shocks are $\sigma_A = 0.014$ and $\sigma_Z = 0.022$. From Belo et al. [2014a], in pinning down the specification of the aggregate adjustment cost wedge process, one strategy is to use the conditional volatility of the equity market index to compute the conditional volatility σ_X, and to use the time series of aggregate payout ratio (from the National Income and Product Accounts) to estimate the persistent coefficient ρ_X; however, this strategy would depend the capital dynamic and does not seem to be plausible for my model. Given this, I simply allow the two aggregate stochastic processes to share the same parameterization by setting $\rho_X = \rho_A = 0.859$ and $\sigma_X = \sigma_A = 0.014$.

Table 4. Firm-Level Moments and Pooled Distributions of Hours and Employment Growth. Note: This table summarizes the moments matching in data, baseline model, and counterfactual analysis. In presenting the moments, I report firstly the firm-level moments in panel A and secondly the pooled distribution moments in panel B. In panel A, the subpanel A.1 lists the six targeted and the subpanel A.2 the seven non-targeted; in panel B, the subpanel B.1 tabulates pooled distribution statistics for the hours growth and the subpanel B.2 those for the employment gorwths. Across columns, the moments are described in columns [1] and [2]. The values of the moments are tabulated in columns [3] to [4]. Specifically, the column [3] lists the value from the data, and the column [4] from the baseline model. In calculating the data values in column [3], I compute using bootstrapping. For the model values in column [4], I compute using simulated 2675 firms across 300 years. In defining the inaction, the maintenance, and the spike rates of the pooled distributions, I use the cutoff values from Cooper & Haltiwanger [2006] and Cooper et al. [2007] with updates to match the frequency of my data.

	Moments		Values	
	Description	Definition	Data	Baseline
	[1]	[2]	[3]	[4]
Panel A	Firm-Level			
Panel A.1	Targeted			
	Kurtosis of hours growth	$kurt(G^H)^{1/4}$	1.927	1.818
	Kurtosis of emp't growth	$kurt(G^N)^{1/4}$	1.668	1.495
	Persistence of hours growth	$rho(G^H)$	−0.376	−0.227
	Persistence of emp't growth	$rho(G^N)$	−0.005	−0.110
	Same-period correlation coeff.	$corr(G^H, G^N)$	0.029	0.000
	Cross-period correlation coeff.	$corr(G^H, G^N_{-1})$	−0.024	−0.026
Panel A.2	Non-Targeted			
	Cross-period correlation coeff.	$corr(G^H_{-1}, G^N)$	0.012	0.032
	Mean of hours growth	$mean(G^H)$	0.001	0.001
	Mean of emp't growth	$mean(G^N)$	0.051	0.003
	Variance of hours growth	$var(G^H)^{1/2}$	0.032	0.032
	Variance of emp't growth	$var(G^N)^{1/2}$	0.210	0.095
	Skewness of hours growth	$skew(G^H)^{1/3}$	0.538	0.556
	Skewness of emp't growth	$skew(G^N)^{1/3}$	0.719	0.702
Panel B	Pooled Distributions (Non-Targeted)			
Panel B.1	Hours Growth			
	Negative spike rate (%)	$G^H \in (-\infty, -0.2]$	0.00	0.00
	Negative maintenance rate (%)	$G^H \in (-0.2, -0.1]$	1.40	3.07
	Inaction rate (%)	$G^H \in (-0.1, +0.1)$	96.81	93.61
	Positive maintenance rate (%)	$G^H \in [+0.1, +0.2)$	1.79	3.32
	Positive spike rate (%)	$G^H \in [+0.2, +\infty)$	0.00	0.00
Panel B.2	Employment Growth			
	Negative spike rate (%)	$G^N \in (-\infty, -0.2]$	9.04	2.03
	Negative maintenance rate (%)	$G^N \in (-0.2, -0.1]$	12.09	13.52
	Inaction rate (%)	$G^N \in (-0.1, +0.1)$	58.60	69.03
	Positive maintenance rate (%)	$G^N \in [+0.1, +0.2)$	10.13	13.16
	Positive spike rate (%)	$G^N \in [+0.2, +\infty)$	10.14	2.26

away from capital, the moments conceptually shall involve no capital-related variables, such as sales; therefore, I regulate the targeted moments to be insensitive to inclusion/exclusion of capital. Second, I do not explicitly target any asset pricing-related moments from my empirical exercises; rather, I follow Cooper et al. [2015] to restrict the targeted moments to be only about real quantities. Table 4 lists a variety of 23 moments, six of which are targeted. In presenting the moments, I report firstly the firm-level moments in panel A and secondly the pooled distribution moments in panel B. In panel A, the subpanel A.1 lists the six targeted and the subpanel A.2 the seven non-targeted; in panel B, the subpanel B.1 tabulates pooled distribution statistics for the hours growth and the subpanel B.2 tabulates those for the employment gorwth. Given the nonlinearity, especially the discontinuity, structurally embedded in the model, I can not in general expect exact matches between data- and model-implied moments. However, Table 4 demonstrates that my estimation leads to a broadly successful fit of the targeted moments and matches the non-targeted moments very closely as well.

5 Assess the Model

I use this section to assess the model along two dimensions. First, my main empirical findings establish a negative equity return predictability of hours growth on equity return (in Table 1), and this negative predictability goes untargeted deliberately in my estimation. Therefore, my first assessment builds on the empirical negative equity return predictability and test it in the model. Second, the untargeted pooled distributions of hours and employment growth (in Table 4) put forward empirical regularities on the magnitudes of labor adjustment cost, which is an important channel in my model. Thus, I use my second assessment to discuss the patterns in pooled distributions computed from the data and understand the driving force of labor adjustment cost implied by my model.

Table 5. Assess the Equity Return Predictability in the Model. NOTE: This table compares the firm-level equity return predictability regressions in the data and in the model. On the left-hand side, $R_{j,t+1}$ is the firm j's future annual equity return. On the right-hand side, a_0, a_j, a_{t+1} are respectively the constant, the firm fixed effects, and the year fixed effects. The key variables on the right-hand side are the firm j's current annual hours growth G^H_{jt} and employment growth G^N_{jt}. Each column runs one firm-level equity return predictability regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using panel OLS with firm standard error clusters. In examining the equity return predictability of hours growth in the data, I use the sample spanning years from 1998 to 2017 annually. In calculating model-implied predictability of hours growth on equity return , I use simulated data with 2675 firms, to match the average number of firms within one year in data (2675.48), across 300 years, where the first half is dropped to mitigate the influence from initial conditions.

	[1]	[2]	[3]	[4]	[5]	[6]
	Data			Model		
Regression Method	OLS	OLS	OLS	OLS	OLS	OLS
Dependent Variable	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$
b_H: Hours Growth G^H_{jt}	-62.86^{***}		-61.11^{***}	-47.45^{***}		-47.46^{***}
	(14.74)		(14.71)	(0.95)		(0.95)
b_N: Employment Growth G^N_{jt}		-13.93^{***}	-14.96^{***}		-14.82^{***}	-14.83^{***}
		(1.43)	(2.15)		(0.38)	(0.38)
Fixed Effects	Firm,Year	Firm,Year	Firm,Year	Firm,Year	Firm,Year	Firm,Year
Observations	23,030	42,063	23,030	371,825	371,825	371,825
Firms	4,473	5,824	4,473	2,675	2,675	2,675
Years	$1998-2017$	$1998-2017$	$1998-2017$	$t: 151-300$	$t: 151-300$	$t: 151-300$

5.1 Equity Return Predictability of Hours Growth

To establish the negative predictability of hours growth on equity return in the model, I use the same set of firm-level equity return predictability regressions from Eq. (4)[19], reproduced in the following form

$$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + e_{j,t+1}. \tag{13}$$

In Table 5, the columns [1] to [3] uses the empirical data and the columns [4] to [6] uses the model simulated data. The baseline model does a relatively good job in matching my main empirical findings at the firm-level qualitatively and quantitatively. First, from the column [3], the data suggests that a 1% increase in the firm's current hours is associated with a decrease in future equity return of 0.61%, and a 1% in the firm's current employment is

[19]Since the model is abstract away from capital, I suppress the investment ratio and other capital-related pricing factors as control regressors.

associated with a decrease in future equity return of 0.15%. Reading horizontally, the column [6] demonstrates that those 1% increases in firm's current hours and employment in the model are associated with the future equity value decreases of 0.47% and 0.15%, respectively. Second, the columns [1] to [3] indicates that the correlation between impacts of hours and employment on future equity return at the firm-level is low. This is intuitively captured by the model in which firms make explicit hours and employment decisions. In the model, the labor adjustment cost occurs explicitly along both margins of labor inputs, the coefficient estimates of b_H and b_N across columns [4] to [6] are statistically stable. Taken together, the results Table 5 show that the baseline model is consistent with my main empirical findings.

It worth emphasizing the results in this section in a bigger-picture point of view. The dynamic labor demand literature requires micro-level data on hours and employment. As a result, studies along this line has a natural focus on discussing the real quantities at the micro-level while the impacts of hours and employment on asset prices are unclear in a data-consistent way. On the other hand, in production-based asset pricing empirical works attempting to understand micro-level equity return in a structural way, the micro-level data on hours and employment is rather limited. As a result, the interactions between hours and employment and their individual impacts on equity return are still to be unfolded. From my paper, I view my work at the intersection of these two strands of literature and my results providing coherent discussions of dynamics between hours and employment and their impacts on both real quantities and asset prices. More importantly, the equity return predictability recovered from this section does not require explicit targets of asset pricing-related moments. Therefore, my paper should be viewed as strong evidence supporting our understandings from both strands of literature.

5.2 Driving Force of Labor Adjustment Cost

The general specification of the labor adjustment cost in Eq. (8) helps the model to shed light on the root structure and the leading component of the labor adjusting friction. In this

Table 6. Implied Magnitudes of Labor Adjustment Cost. NOTE: This table reports the magnitudes of labor adjustment cost implied by estimation of the baseline model. Reading across columns, the labor adjustment cost occurs along both margins of hours and employment; reading across rows, there are three adjustment cost components considered, namely, the non-convex disruption, the linear irreversibility, and the convex quadratic. To compare the magnitudes, I calculate the relative size of labor adjustment cost in form of each component along either margin as a faction of total labor adjustment cost.

	Employment	Hours	
Non-convex disruption	70.71	19.47	90.18
Linear irreversibility	7.42	1.61	9.03
Convex quadratic	0.28	0.50	0.79
	78.42	21.58	100.00

section, I utilize the pooled distributions of hours and employment growth from panel B of Table 4, and use patterns from the data in column [3] and estimation from the model in column [4] to discus the performance of model in matching the relative magnitudes of labor adjustment cost.

Drawing implications from Cooper & Haltiwanger [2006] and Cooper et al. [2007], I summarize the pooled distributions by bin statistics. I categorize growth into three types, namely, the inaction (growth rate less than 10% in absolute value), the spike (growth rate exceeding 20% in absolute value), and the maintenance (growth rate in-between 10% and 20% in absolute value). First, from column [3] in panel B of Table 4, both hours and employment display frequent inactivity at the firm-level: more than 95% of the hours adjustments are inactivity, and the inactivity accounts for about 60% of employment adjustments. This observation from the pooled distributions suggest that the firms at micro-level are likely to face a sizable disruption cost, since the non-convexity prevents the firms from frequently adjusting. In addition to inaction, the comparisons between maintenance and spikes of hours and employment reveal the relative magnitudes of the linear and the convex components of labor adjustment cost. Conditional on non-inactivity, the hours growth is more likely to be maintenance as opposed to spikes, whereas, the employment growth is more likely to spikes than to be maintenance. Therefore, I expect the labor adjustment cost to impose a larger quadratic component on hours and larger irreversibility component on employment.

Table 6 calculates the magnitudes of labor adjustment cost on hours and employment across three components. Consistent with pooled distributions of hours and employment growth, the non-convex disruption cost is large on both hours and employment, and the non-convex disruption cost combined accounts for about 90% of labor adjustment cost. Additionally, the labor adjustment cost on hours is non-negligible; the labor adjustment cost on hours represents about 20% of labor adjustment cost. To sum up, the model correctly identifies the non-convex disruption to production as the driving force of labor adjustment cost, and further highlights the importance of allowing labor adjustment cost to occur on hours and employment explicitly.

6 Discuss Model Implications

In this section, I discuss model implications for aggregate business cycle fluctuations and firm-level real quantities and asset prices.

The economic mechanism of the model operates via two ingredients, the adjustment cost shock at the aggregate level and the labor adjustment cost at the micro-level. In the economy, a positive adjustment cost shock lowers adjustment cost and hence encourages aggregate investment (capital adjustment) which has a temporary contractionary effect on aggregate consumption. Therefore, the model provides two aggregate implications. In language of macroeconomics, the adjustment cost shock captures a countercyclical component of business cycle; in language of asset pricing, the adjustment cost shock has a negative price of risk.

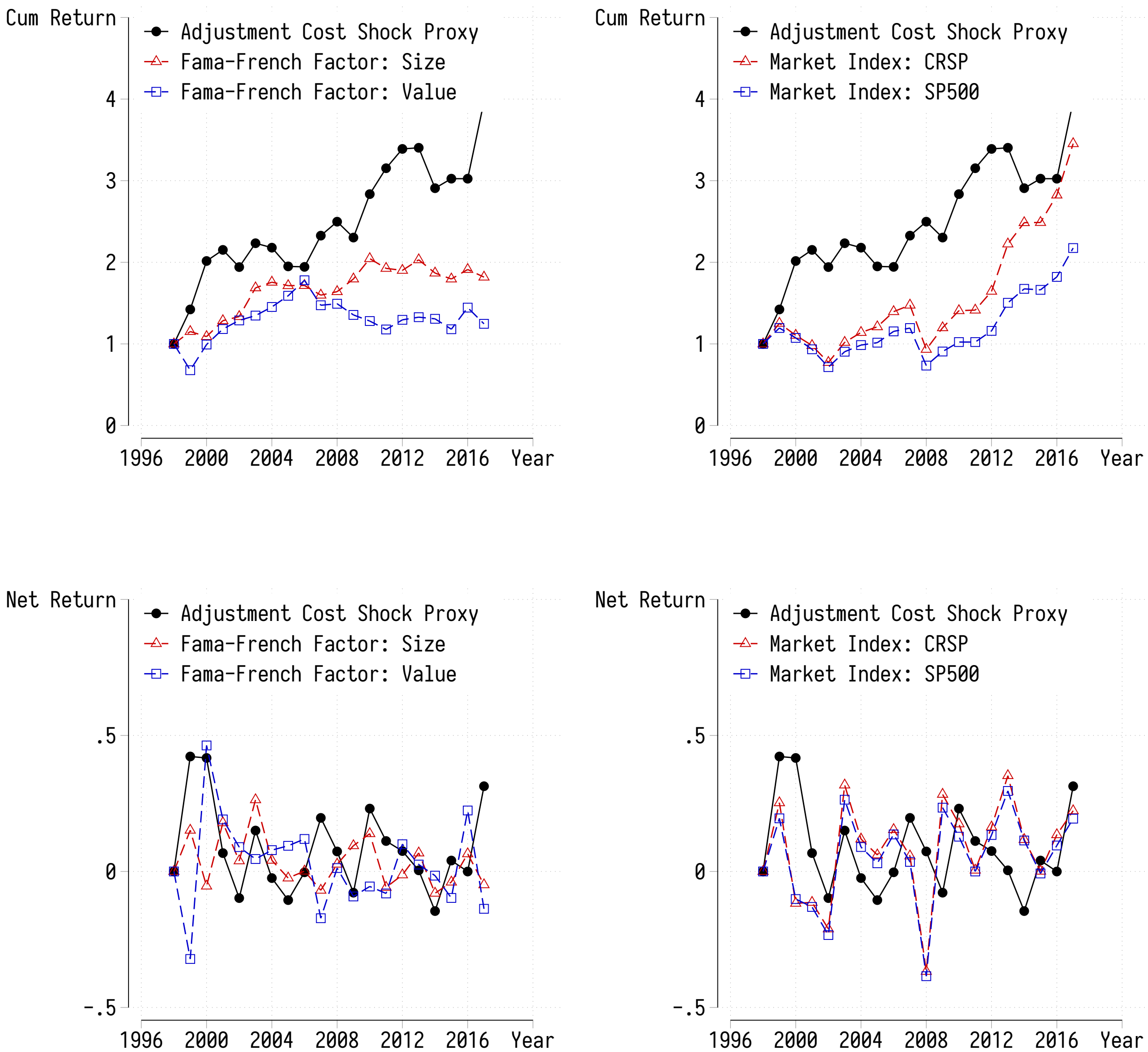
Turning to firm-level implications, firms who adjust hours and/or employment in face of a positive adjustment cost shock are benefited by the lowered adjustment cost. As a result, such firms are able to pay out relative more in the cross-section when aggregate consumption is low and the marginal utility is high, and hence earn lower equity return in equilibrium for lower riskiness. Therefore, the model provides two firm-level implications on real quantities and asset prices. Firms who adjusting hours more are more responsive to adjustment cost shock; with more responsiveness, the model predicts that firms, first, pay out more and, second, earn lower equity return.

I begin by constructing a model-implied empirical proxy of the adjustment cost shock. The construction follows the factor-mimicking portfolio procedure (e..g, Fama & French [1992, 1993]) and generates a return-based proxy for adjustment cost shock[20]. Specifically, I construct the univariate tertile portfolios defined by 30− and 70-percentiles of the cross-sectional hours growth and calculate the tertile portfolio equity return spread between low- and high-hours growth portfolios. In Appendix A.3.1, I show the equity return difference between firms with low- and high-hours growth as a covariant of the adjustment cost shock. Intuitively, larger adjustment cost shock lowers the adjustment cost even more and hence the negative relation between hours growth and equity return is even steeper.

In Fig. 1, I compare the adjustment cost shock proxy to Fama-French factors as well as market indices. In the upper panels, I normalize all series to start with one and compare the cumulative returns. It is clear from the upper-right panel that the constructed adjustment cost proxy has magnitudes in the same order with market indices. In the lower panels, I compare the net return across all series. From the lower-right panel comparing the adjustment cost shock proxy to market indices, the adjustment cost shock proxy exhibits noisy countercyclicality with market indices on the background, which suggests using market indices in the following empirical exercises as controls, which is known to predict business cycle fluctuations.

[20]Generally speaking, three ways are usually implemented for constructing a macroeconomic shock. First, the return-based proxy (e.g., Fama & French [1992, 1993]) makes use of the different exposures of equity return to the macroeconomic shock in the cross-section and use portfolio equity return difference as the proxy. Second, the statistic-based proxy (e.g., Bloom et al. [2018]) makes indirect inference of pooled distribution of certain real variable which demonstrates timely and consistent response to the macroeconomic shock. Third, the price-based proxy (e.g., Greenwood et al. [1997, 2000]) captures the price effect from certain real variable responding to the macroeconomic shock and compute the proxy from the transitory changes in price series. As is mentioned by Papanikolaou [2011], the return-based proxy utilizes the financial data and hence is available at relative high frequencies. In my paper, the statistic- and price-based proxies will introduce additional measurement errors. On the one hand, the statistic-based proxy depends on the cross-sectional distribution of hours growth (as is used in Belo et al. [2017]) and is subject to controls I implement in handling CPS dataset which enhance the representativeness of individual-level data but dampen the matching between firm-level and individual-level data. On the other hand, a price-based proxy, which in my paper is wage-based proxy, is unavailable directly. Therefore, the return-based proxy in my paper is relative advantageous to the other two and hence is preferred.

Figure 1. Compare Adjustment Cost Shock Proxy to Fama-French Factors and Market Indices. NOTE: This figure compares adjustment cost shock proxy to Fama-French factors and market indices. To facilitate better comparisons, in the upper panels, I normalize the starting points for all series to be one and compare the cumulative returns; in the lower panels, I compare the net returns.



6.1 Implications for Aggregate Business Cycle Fluctuations

The model implies a two-factor structure of empirical stochastic discount factor,

$$M_t = a_M + \gamma^{\text{MKT}} F_t^{\text{MKT}} + \gamma^{\text{ACS}} F_t^{\text{ACS}}, \tag{14}$$

where F_t^{MKT} is market factor and F_t^{ACS} is adjustment cost shock factor, and hence γ^{MKT} and γ^{ACS} are respective loadings. By the model, the stochastic discount factor loads positively on the adjustment cost shock, i.e., $\gamma^{\text{ACS}} > 0$.

The positive loading can be translated into two testable aggregate implications. First, a positive adjustment cost shock F_t^{ACS} increases the stochastic discount factor M_t and hence leads to high marginal utility states. To test this mechanism, I estimate the dynamic responses of aggregate output, consumption, and investment to the adjustment cost shock and compare the estimated responses to those implied by the model. Specifically, the estimation regressions take the form of

$$\frac{1}{s+1}[\log(\Gamma_{t+s}) - \log(\Gamma_{t-1})] = a_s + \beta^{ACS} F_t^{\text{ACS}} + \beta^{\text{MKT}} F_t^{\text{MKT}} + e_{ts}; s = 0, \cdots, S. \tag{15}$$

On the left-hand side, Γ_t denotes the aggregate output, consumption, or investment. Thus the left-hand side measures the annualized S-year horizon growth rate. To better interpret the coefficient $\beta^{ACS,MKT}$, I normalize the factors $F_t^{\text{ACS,MKT}}$ to zero mean and unit standard deviation. Therefore, the interpretation of coefficient estimate is the impact on S-year horizon average growth rate of the aggregate output, consumption, or investment from a one-standard deviation increase of factors $F_t^{\text{ACS,MKT}}$.

In Table 7, I tabulate the dynamics responses from aggregate output in the top panel, those from aggregate consumption in the middle panel, and those from aggregate investment in the bottom panel[21]. The results support the use of F_t^{ACS} as a proxy for adjustment

[21]In Appendix A.5.1, I present the full results of aggregate dynamic response regression, with and without

Table 7. Aggregate Dynamic Response Regressions Results. NOTE: This table tabulates the results of aggregate dynamic response regressions in the form of Eq. (15). On the left-hand side, Γ_t denotes the aggregate output, consumption, or investment. Thus the left-hand side measures the annualized S-year horizon growth rate. To better interpret the coefficient $\beta^{ACS,MKT}$, I normalize the factors $F_t^{\mathrm{ACS,MKT}}$ to zero mean and unit standard deviation. Each column runs one aggregate dynamic response regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using OLS with standard errors corrected for heteroscedasticity and serial correlation (Newey & West [1987]). Following Papanikolaou [2011], I define the aggregate output as the real gross domestic product excluding real government consumption expenditures and gross investment, the aggregate consumption as real personal consumption expenditures on nondurable goods and services, and the aggregate investment as real private nonresidential fixed investment. The sample spans years from 1998 to 2017 annually.

Dependent Variable	Output	Output	Output	Output	Output
Future S-Year Horizon	s=0	s=1	s=2	s=3	s=4
β^{ACS}: Adj Cost Shock F_t^{ACS}	0.57	0.07	−0.24	−0.14	0.11
	(0.45)	(0.37)	(0.33)	(0.24)	(0.26)
Observations	19	18	17	16	15
Years	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017
Dependent Variable	Consumption	Consumption	Consumption	Consumption	Consumption
Future S-Year Horizon	s=0	s=1	s=2	s=3	s=4
β^{ACS}: Adj Cost Shock F_t^{ACS}	−0.60**	−0.77***	−0.76***	−0.50***	−0.19
	(0.26)	(0.20)	(0.15)	(0.13)	(0.21)
Observations	19	18	17	16	15
Years	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017
Dependent Variable	Investment	Investment	Investment	Investment	Investment
Future S-Year Horizon	s=0	s=1	s=2	s=3	s=4
β^{ACS}: Adj Cost Shock F_t^{ACS}	2.66*	1.57*	0.06	−0.42	−0.06
	(1.32)	(0.78)	(0.66)	(0.48)	(0.46)
Observations	19	18	17	16	15
Years	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017

cost shock implied by the model. First, a positive adjustment cost shock lead to declines in aggregate consumption and hence high marginal utility states. In terms of magnitudes, a one-standard deviation increase of adjustment cost shock introduces a inverse hump-shaped responses from aggregate consumption, with a decrease in annualized growth rate of 0.5% over four years. Next, the aggregate investment increases sharply in response to a positive adjustment cost shock in the short horizon. The aggregate investment grows by 2.7% in response to a one-standard deviation increase of adjustment cost shock in one-year horizon and by 1.6% per annum in two-year horizon. The responses of aggregate investment is fairly drastic and short-lived. Third, the aggregate output has insignificant responses to adjustment cost shock, which is consistent with the model's point of view that what the adjustment cost shock triggers is a redistribution effects of consumption to investment.

After showing that the adjustment cost shock represents a countercyclical component in business cycle fluctuations, I verify the next aggregate testable implication in a set of asset pricing tests. The asset pricing tests build on the relation between the positive loading of adjustment cost shock in stochastic discount factor and the negative risk price of adjustment cost shock in equity return[22]. Following Cochrane [2009], the empirical stochastic discount factor in Eq. (14) implies a beta pricing formula in the following form

$$\mathbb{E}[R_{\iota,t+1} - R_{f,t+1}] = \lambda^{\text{MKT}} \beta_{\iota}^{\text{MKT}} + \lambda^{\text{ACS}} \beta_{\iota}^{\text{ACS}}; \iota = 1, \cdots, \mathcal{I}. \tag{16}$$

where the left-hand side is a portfolio ι's expected risk premium in the set of testing portfolios $\mathcal{I}$. On the right-hand side, $\beta_{\iota}^{\text{MKT,ACS}}$ are the portfolio ι's risk loadings of market and adjustment cost shock factors, respectively; the $\lambda^{\text{MKT,ACS}}$ are the estimated risk prices for market and adjustment cost shock factors implied by the testing portfolio set $\mathcal{I}$. Therefore, I use two sets of testing portfolios to crosscheck the sign and magnitudes of estimated risk price for adjustment cost shock. The two testing portfolios sets are the Fama-French 25 portfolios sorted by size (ME) and book-to-market (BM) and Fama-French 17 industry portfolios. I use the Fama-MacBeth method (Fama & MacBeth [1973]) to perform my estimation of risk price[23][24].

market factor as control. Generally speaking, the aggregate responses presented here are barely affected by exclusion of market factor as control. I also show in there the impulse response functions of aggregate output, consumption, and investment to adjustment cost shock; the results there are consistent with the conclusion here that the adjustment cost has a contractionary impact on aggregate consumption and hence captures the countercyclical component of business cycle fluctuations.

[22]With some algebra, it can be readily show that, given the empirical stochastic discount factor in the form of Eq. (14), in Eq. (16) the risk loading is $\beta_{\iota}^{\text{ACS}} = \mathbb{V}[R_{\iota,t+1} - R_{f,t+1}]/\mathbb{V}[F_t^{\text{ACS}}]$ and the risk price is $\lambda^{\text{ACS}} = -\gamma^{\text{ACS}}\mathbb{V}[F_t^{\text{ACS}}]$. Therefore, a positive loading of adjustment cost shock in stochastic discount factor implies a negative risk price of adjustment cost shock in equity return.

[23]The Fama-MacBeth method makes use a slight different beta pricing formula from Eq. (16); see Appendix A.5.2 for a detailed formulation.

[24]As is pointed out by Cochrane [2009], the Fama-MacBeth method is equivalent to one-step generalized method of moments (GMM), in which the weighting matrix is an identity matrix. As is argued by many (e.g., Ferson & Foerster [1994]), two-step GMM in scenarios where the sample size is small results in biased standard errors of coefficient estimation. Intuitively, when the time-series size is small relative to cross-sectional size, as is the case of my estimation here, the weighting matrix from two-step or continuous-updating GMM is poorly

Table 8. Asset Pricing Tests of Adjustment Cost Shock Risk Price.. Note: This table reports the asset pricing test results of adjustment cost shock risk price. To calculate risk prices, I use two sets of testing portfolios, the Fama-French 25 portfolios size (ME) and book-to-market (BM) sorted and Fama-French 17 industry portfolios. Each column runs one asset pricing test regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using Fama-Macbeth method (Fama & MacBeth [1973]) with standard errors corrected for heteroscedasticity and serial correlation (Newey & West [1987]). The sample spans years from 1998 to 2017 annually.

	[1]	[2]	[3]	[4]
Regression Method	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth
Testing Portfolios	ME-BM Sorted	ME-BM Sorted	Industry	Industry
Risk Price λ^{MKT} of Market Factor F_t^{MKT}	0.85***	0.39**	1.38**	0.44***
	(0.21)	(0.15)	(0.53)	(0.13)
Risk Price λ^{ACS} of Adj Cost Shock Factor F_t^{ACS}		−0.31***		−0.28***
		(0.10)		(0.09)
Standard Errors	Newey-West	Newey-West	Newey-West	Newey-West
Observations	500	500	340	340
Portfolios	25	25	17	17
Years	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017

Table 8 reports estimated risk prices for the CAPM model (columns [1] and [3]) and the linear two-factor asset pricing model (columns [2] and [4]) implied my model. The negative coefficient estimates of λ^{ACS} in columns [2] and [4] show a negative risk price associated with the adjustment cost shock and hence a positive loading of adjustment cost shock in stochastic discount factor in my model: a positive adjustment cost shock leads to increases of stochastic discount factor and high marginal utility states.

This asset pricing result from the second aggregate testable implication is consistent with investment-specific shock literature (e.g., Papanikolaou [2011]; Kogan & Papanikolaou [2013, 2014]; Belo et al. [2017]; Kogan et al. [2017]) where a non-productivity shock encourages investment which causes a contractionary effect on consumption[25]. The asset pricing result together with the business cycle results from previous section are two interpretation of the economic force associated with the adjustment cost shock. By the two aggregate implications, my model-implied proxy of adjustment cost shock is consistent with the data.

estimated for insufficient time-series size. See, for example, Lettau & Ludvigson [2001] for a discussion.

[25]In this case, one might view that the Barro-King curse (Barro & King [1984]) is desirably achieved as opposed to the New Keynesian discussions.

6.2 Implications for Firm-Level Real Quantities and Asset Prices

In the final section, I show that the adjustment cost shock has impacts on firms' payout[26] and equity return in ways that are consistent with the model. The model's mechanism suggests that in periods with a positve adjustment cost shock, firms adjusting hours more are more responsive to adjustment cost shock, and hence are able to payout more and earn lower equity return. I first examines firms' responses of payout to the adjustment cost shock using the following specification,

$$\Pi_{j,t} = b^{(1)} \times F_t^{\text{ACS}} + \sum_{p=2}^{P=3} b^{(p)} \times D_{jt}^{(p)} \times F_t^{\text{ACS}} + c^{(1)} + \sum_{p=2}^{P=3} c^{(p)} \times D_{jt}^{(p)} + d \times \Pi_{j,t-1} + e_{j,t}. \quad (17)$$

On the left-hand side, $\Pi_{j,t}$ is firm j's payout at end of year t. I measure the payout in three empirical ways. First, I define the payout intensity as the ratio of cash flow (data item `EBIT`: Earnings Before Interest and Taxes) to total assets (data item `AT`: Assets); second, I also measure the payout log-level as the logarithm of cash flow, and third I measure the payout growth as the first-order logarithm difference of cash flow. The right-hand side of Eq. (17) takes several components. F_t^{ACS} is the adjustment cost shock. $D_{jt}^{(p)}$ is tertile dummy for firm j at the end of year t; it takes value one if firm j is in the p-th portfolio at the end of year t in the tertile portfolio set.

By Eq. (17) specification, the coefficients of interest are $b^{(p=1,2,3)}$. In particular, $b^{(p)}$ measures the different responses from payout to a positive adjustment cost shock via adjusting hours. Moving from $p = 1$ to $p = 3$, the coefficient $b^{(p)}$ captures how much more firms respond to a positive adjustment cost shock by adjusting hours more. Therefore, the interpretation of $b^{(p=1,2,3)}$ is related to model's mechanism that firms with high hours growth are associated with low equity returns because such firms take advantage of positive adjustment cost shocks and are able to payout more.

[26]In this analysis, I assume the empirical cash flow measures, EBIT and EBITDA (COMPUSTAT data item `ebit` and `ebitda`), are covariants with firms' payout.

Table 9. Firm-Level Payout Response Regressions. NOTE: This table tabulates the results of firm-level payout response regressions in the form of Eq. (17). On the left-hand side, $\Pi_{j,t}$ is firm j's annual payout measured from January of year t to December of year t. On the right hand side, F_t^{ACS} is the aggregate adjustment cost shock, measured as the portfolio equity return spread from July of year t to June of year $t+1$. $D_{jt}^{(p)}$ is firm j's portfolio assignment at the end of year t; for example, $D_{jt}^2 == 1$ indicates firms in the second portfolio univariate sorted by cross-sectional hours growth. Additionally on the right-hand site, $\Pi_{j,t}$ is firm j's annual payout measured from January of year $t-1$ to December of year $t-1$. Each column runs one firm-level payout response regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I measure payout as the payout intensity (ratio of cash flow to total assets) on columns [1] and [2], as the payout log-level in columns [3] and [4], and payout growth in columns [5] and [6]. For each measurement, I estimate the responses with and without the payout control. I implement all regressions using OLS. The sample spans years from 1998 to 2017 annually.

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable at t	Payout Intensity		Payout Log-Level		Payout Growth	
Control Variable at $t-1$	No	Yes	No	Yes	No	Yes
$b^{(1)}$: F_t^{ACS}	-0.10^{***}	-0.07^{***}	-0.23^{***}	-0.24^{***}	-0.54^{***}	-0.26^{***}
	(0.01)	(0.01)	(0.07)	(0.06)	(0.09)	(0.07)
$b^{(2)}$: $F_t^{\text{ACS}} \times D_{jt}^{(2)}$	0.10^{***}	0.06^{***}	0.20^{**}	0.26^{***}	0.42^{***}	0.18^{**}
	(0.02)	(0.02)	(0.09)	(0.08)	(0.12)	(0.09)
$b^{(3)}$: $F_t^{\text{ACS}} \times D_{jt}^{(3)}$	0.15^{***}	0.09^{***}	0.63^{***}	0.60^{***}	0.83^{***}	0.66^{***}
	(0.02)	(0.02)	(0.13)	(0.12)	(0.16)	(0.12)
Observations	24,640	24,592	18,601	17,293	17,293	15,198
Firms	4,508	4,493	3,573	3,343	3,343	3,032
Years	1998 – 2017	1998 – 2017	1998 – 2017	1998 – 2017	1998 – 2017	1998 – 2017

Table 9 tabulates the coefficient estimates of $b^{(p=1,2,3)}$ for three measures of payout with and without payout controls from previous period. Across all three measures, moving from the first to the third portfolio of cross-sectional hours growth, firms with higher hours growth demonstrates larger responses to the adjustment cost shock. All coefficient estimates are statistically significant, suggesting the responses from firms' payout are profound in the data. In addition, moving from the first to the third portfolio, the coefficient estimates of $b^{(p=1,2,3)}$ increase from negative to positive. This means the more responsiveness of payout put firms with higher hours growth in positions to take advantage of the adjustment cost shock and hence to payout more. In Appendix A.5.3, I show additional results on two aspects. First, the responses of firms' payout go beyond one period; that is, I vary the left-hand side variable to be $\Pi_{j,t+1}$ and find similar relation between higher hours growth and more payout responses. This is intuitive; once the firms adjust hours to a more desired level, they continue to payout more during the following periods with higher output and lower adjustment cost.

Table 10. Firm-Level Equity Return Response Regressions Results. NOTE: This table tabulates the results of firm-level equity return response regressions in the form of Eq. (18). On the left-hand side, $R_{j,t+1}$ is firm j's annual equity return from July of year $t+1$ to June of year $t+2$. On the right hand side, F_t^{ACS} is the aggregate adjustment cost shock, measured as the portfolio equity return spread from July of year t to June of year $t+1$. $D_{jt}^{(p)}$ is firm j's portfolio assignment at the end of year t; for example, $D_{jt}^{2} == 1$ indicates firms in the second portfolio univariate sorted by cross-sectional hours growth. Additionally on the right-hand site, $\Phi_{j,t}$ is some control variable for firm j measured by end of year t. Each column runs one firm-level equity return response regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using OLS. The sample spans years from 1998 to 2017 annually.

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable at $t+1$	Euqity Return					
Control Variable at t	No	Equity Return	Payout Intensity	Payout Growth	Payout Log-Level	Output Log-Level
$b^{(1)}$: F_t^{ACS}	0.01	−0.00	0.01	−0.07	−0.02	0.00
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$b^{(2)}$: $F_t^{\text{ACS}} \times D_{jt}^{(2)}$	−0.25***	−0.22***	−0.26***	−0.21***	−0.25***	−0.24***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$b^{(3)}$: $F_t^{\text{ACS}} \times D_{jt}^{(3)}$	−0.45***	−0.42***	−0.45***	−0.34***	−0.33***	−0.46***
	(0.11)	(0.11)	(0.11)	(0.09)	(0.09)	(0.11)
Observations	24,824	24,824	24,602	16,400	18,936	24,824
Firms	4,567	4,567	4,496	3,255	3,635	4,567
Years	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017

Second, the use of tertile portfolios of cross-sectional hours growth is not material; I replace the tertile portfolios with quintile portfolios and the relation between higher hours growth and more payout responses repeats. Taking together, the coefficient estimates show firms' with higher hours growth have larger payout response to a positive adjustment cost shock and such more responsiveness enables these firms to payout more.

Finally, I test the implication for firm-level equity returns in a similar specification to Eq. (17), with the difference lies on the dependent variable. In particular,

$$R_{j,t+1} = b^{(1)} \times F_t^{\text{ACS}} + \sum_{p=2}^{P=3} b^{(p)} \times D_{jt}^{(p)} \times F_t^{\text{ACS}} + c^{(1)} + \sum_{p=2}^{P=3} c^{(p)} \times D_{jt}^{(p)} + d \times \Phi_{j,t} + e_{j,t+1}. \tag{18}$$

On the left-hand side, $R_{j,t+1}$ is the firm j's annual equity return measured from July of year $t+1$ to June of year $t+2$; on the right-hand side, $\Phi_{j,t}$ is one of the five control variables for firm j: equity return, payout intensity, payout growth, payout log-level, and output log-level.

Table 10 tabulates the coefficient estimates of $b^{(p=1,2,3)}$ for equity return responses. The interpretation of $b^{(p=1,2,3)}$ are similar to before except for the sign difference. Moving from the first to the third portfolio, the coefficient estimates of $b^{(p=1,2,3)}$ decrease from insignificant positive to significant negative. This means that the more responsiveness of equity return from firms with higher hours growth decreases firms' equilibrium equity return. Therefore, the investigation here shows equilibrium equity returns of firms with higher hours growth have higher loading of adjustment cost shock, and such higher loading reduces the riskiness of firms and hence their equilibrium equity returns.

To summarize, my exercises from this section show that firms with higher hours growth respond more to a positive adjustment cost shock. Such responsiveness put these firms in a position where they can pay out more. Because these firms' payout are higher when the marginal utility is high (from the positive adjustment cost shock), these firms are less risky compared to firms with lower hours growth and hence earn lower equilibrium equity returns. In general, the payout and equity return responses discovered in this section provide evidence on the impacts of adjustment cost shock on firm-level real quantities and asset prices.

7 Conclusion

Hours has an intrinsic and impregnable impact on real quantities and asset prices. For U.S. public firms listed in the three major Exchanges, a 1-percent increase in the firm's current hours is associated with a 0.6-percent drop of the firm's future equity return. Meanwhile, the low- and high-hours growth quintile portfolios yield an equity return spread of 6 percents per annum. The robust empirical fact that firms with higher hours growth are associated with lower equity return pilots my theoretical and quantitative analyses.

A production-based asset pricing model rationalizes the empirical fact with labor adjustment cost in hours via which the equity return predictability is captured by labor market friction associated with adjusting hours. To reproduce the empirical fact qualitatively and quantitatively, the model also makes use of an adjustment cost shock that lowers adjustment cost at the firm-level and redistributes consumption to investment at the aggregate level. Therefore, firms with higher hours growth are positioned to pay out more when consumption is scarce. Such firms are thus less risky in equilibrium and associated with lower equilibrium equity return.

I make two main points in this paper. First, the labor adjustment cost on hours creates the intertemporal relation between hours and equity return observed in the data. In my model, the labor market friction associated with adjustment nests explicit components along the hours margin of labor input. As a result, a firm's current hours is not a derived choice from current employment but reveals information about the firm in the future. Empirical evidence supports the model's assumption. Estimation of the model suggests that about 20 percent of labor adjustment cost attributes to adjustment along the hours margin of labor input. In this sense, this paper advocates, along with previous studies, that adjustment cost manifests an important channel influencing firms' choices and outcomes. Additionally, this paper proposes novel perspectives on the relation between labor adjustment cost and equity return.

Second, the adjustment cost shock suppresses consumption at the aggregate level and enables firms adjusting hours more to pay out more. My model utilizes a macroeconomic shock that loads positively in the stochastic discount factor and has a heterogeneous effect on real quantities and asset prices in the cross-section. In bringing the model's implications to the data, a series of empirical inspections find favorable results for the model's mechanism. Given the nature of the adjustment cost shock, the results presented in this paper has broader implications for business cycles and cross-sectional asset pricing studies with investment shocks. Particularly, this paper emphasizes the redistribution effect of investment on consumption by providing additional supporting empirical and theoretical evidence in the context of labor, and by discussing this effect's implications for labor input and equity return at the firm-level.

References

Abowd, J. M. & Kramarz, F. (2003). The costs of hiring and separations. *Labour Economics*, 10(5), 499–530.

Acemoglu, D. & Restrepo, P. (2020). Robots and jobs: Evidence from us labor markets. *Journal of Political Economy*, 128(6), 000–000.

Barro, R. J. & King, R. G. (1984). Time-separable preferences and intertemporal-substitution models of business cycles. *The Quarterly Journal of Economics*, 99(4), 817–839.

Belo, F. (2010). Production-based measures of risk for asset pricing. *Journal of Monetary Economics*, 57(2), 146–163.

Belo, F., Li, J., Lin, X., & Zhao, X. (2017). Labor-force heterogeneity and asset prices: The importance of skilled labor. *The Review of Financial Studies*, 30(10), 3669–3709.

Belo, F., Lin, X., & Bazdresch, S. (2014a). Labor hiring, investment, and stock return predictability in the cross section. *Journal of Political Economy*, 122(1), 129–177.

Belo, F., Lin, X., & Vitorino, M. A. (2014b). Brand capital and firm value. *Review of Economic Dynamics*, 17(1), 150–169.

Belo, F., Xue, C., & Zhang, L. (2013). A supply approach to valuation. *The Review of Financial Studies*, 26(12), 3029–3067.

Bils, M. (1987). The cyclical behavior of marginal cost and price. *The American Economic Review*, (pp. 838–855).

Black, F. (1972). Capital market equilibrium with restricted borrowing. *The Journal of Business*, 45(3), 444–455.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3), 623–685.

Bloom, N., Floetotto, M., Jaimovich, N., Saporta-Eksten, I., & Terry, S. J. (2018). Really uncertain business cycles. *Econometrica*, 86(3), 1031–1065.

Bretscher, L. (2019). From local to global: Offshoring and asset prices. *London Business School Working Paper*.

Campbell, J. Y. & Cochrane, J. H. (1999). By force of habit: A consumption-based explanation of aggregate stock market behavior. *Journal of Political Economy*, 107(2), 205–251.

Chan, L. K., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance*, 56(6), 2431–2456.

Chen, H. J., Kacperczyk, M., & Ortiz-Molina, H. (2011). Labor unions, operating flexibility, and the cost of equity. *Journal of Financial and Quantitative Analysis*, 46(1), 25–58.

Cochrane, J. H. (1991). Production-based asset pricing and the link between stock returns and economic fluctuations. *The Journal of Finance*, 46(1), 209–237.

Cochrane, J. H. (1996). A cross-sectional test of an investment-based asset pricing model. *Journal of Political Economy*, 104(3), 572–621.

Cochrane, J. H. (2009). *Asset pricing: Revised edition*. Princeton University Press.

Cooper, R. & Haltiwanger, J. (2006). On the nature of capital adjustment costs. *The Review of Economic Studies*, 73(3), 611–633.

Cooper, R., Haltiwanger, J., & Willis, J. (2007). Search frictions: Matching aggregate and establishment observations. *Journal of Monetary Economics*, 54, 56–78.

Cooper, R., Haltiwanger, J., & Willis, J. (2015). Dynamics of labor demand: Evidence from plant-level observations and aggregate implications. *Research In Economics*, 69(1), 37–50.

Cooper, R. & Willis, J. (2009). The cost of labor adjustment: Inferences from the gap. *Review of Economic Dynamics*, 12(4), 632–647.

Davis, S. J. & Haltiwanger, J. (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics*, 107(3), 819–863.

Davis, S. J., Haltiwanger, J., & Schuh, S. (1996a). Job creation and destruction. *Cambridge, MA: Mit Press*.

Davis, S. J., Haltiwanger, J., & Schuh, S. (1996b). Small business and job creation: Dissecting the myth and reassessing the facts. *Small Business Economics*, 8(4), 297–315.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The role of entrepreneurship in us job creation and economic dynamism. *Journal of Economic Perspectives*, 28(3), 3–24.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2016). Where has all the skewness gone? the decline in high-growth (young) firms in the us. *European Economic Review*, 86, 4–23.

Doidge, C., Karolyi, G. a., & Stulz, R. M. (2017). The us listing gap. *Journal of Financial Economics*, 123(3), 464–487.

Donangelo, A. (2014). Labor mobility: Implications for asset pricing. *The Journal of Finance*, 69(3), 1321–1346.

Eisfeldt, A. L. & Papanikolaou, D. (2013). Organization capital and the cross-section of expected returns. *The Journal of Finance*, 68(4), 1365–1406.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49(3), 283–306.

Fama, E. F. & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, 47(2), 427–465.

Fama, E. F. & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3–56.

Fama, E. F. & French, K. R. (2008). Dissecting anomalies. *The Journal of Finance*, 63(4), 1653–1678.

Fama, E. F. & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, 105(3), 457–472.

Fama, E. F. & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1–22.

Fama, E. F. & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3), 607–636.

Ferson, W. E. & Foerster, S. R. (1994). Finite sample properties of the generalized method of moments in tests of conditional asset pricing models. *Journal of Financial Economics*, 36(1), 29–55.

Flood, S., King, M., Rodgers, R., Ruggles, S., & Warren, J. R. (2020). Integrated public use microdata series, current population survey: Version 7.0 [dataset]. *IPUMS-CPS, University of Minnesota*.

Gourio, F. (2007). Labor leverage, firms' heterogeneous sensitivities to the business cycle, and the cross-section of expected returns. *Working paper, Federal Reserve Bank*.

Greenwood, J., Hercowitz, Z., & Krusell, P. (1997). Long-run implications of investment-specific technological change. *The American Economic Review*, (pp. 342–362).

Greenwood, J., Hercowitz, Z., & Krusell, P. (2000). The role of investment-specific technological change in the business cycle. *European Economic Review*, 44(1), 91–115.

Grullon, G., Larkin, Y., & Michaely, R. (2015). The disappearance of public firms and the changing nature of us industries. *Available At Dx. Doi. Org/10.2139/ssrn*, 2612047.

Hall, R. E. (2004). Measuring factor adjustment costs. *The Quarterly Journal of Economics*, 119(3), 899–927.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3), 650–705.

Hou, K., Xue, C., & Zhang, L. (2018). Replicating anomalies. *The Review of Financial Studies*, 0(0).

İmrohoroğlu, A. & Tüzel, Ş. (2014). Firm-level productivity, risk, and return. *Management Science*, 60(8), 2073–2090.

Jermann, U. (1998). Asset pricing in production economies. *Journal of Monetary Economics*, 41(2), 257–275.

Khan, A. & Thomas, J. K. (2008). Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics. *Econometrica*, 76(2), 395–436.

King, R. G. & Thomas, J. K. (2006). Partial adjustment without apology. *International Economic Review*, 47(3), 779–809.

Kogan, L. & Papanikolaou, D. (2013). Firm characteristics and stock returns: The role of investment-specific shocks. *The Review of Financial Studies*, 26(11), 2718–2759.

Kogan, L. & Papanikolaou, D. (2014). Growth opportunities, technology shocks, and asset prices. *The Journal of Finance*, 69(2), 675–718.

Kogan, L., Papanikolaou, D., Seru, A., & Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2), 665–712.

Kuehn, L.-A., Simutin, M., & Wang, J. J. (2017). A labor capital asset pricing model. *The Journal of Finance*, 72(5), 2131–2178.

Lettau, M. & Ludvigson, S. (2001). Resurrecting the (c) capm: A cross-sectional test when risk premia are time-varying. *Journal of political economy*, 109(6), 1238–1287.

Lettau, M., Ludvigson, S. C., & Ma, S. (2019). Capital share risk in u.s. asset pricing. *The Journal of Finance*.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*, 47(1), 13.

Liu, Y. (2019). Labor-based asset pricing. *Working paper, University of Rochester - Simon Business School*.

Llosa, G., Ohanian, L., Raffo, A., & Rogerson, R. (2014). Firing costs and labor market fluctuations: A cross-country analysis. *Working paper, Society for Economic Dynamics*.

Merz, M. & Yashiv, E. (2007). Labor and the market value of the firm. *American Economic Review*, 97(4), 1419–1431.

Nardone, T. J. (1986). Part-time workers: who are they. *Monthly Lab. Rev.*, 109, 13.

Newey, W. K. & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica: Journal of The Econometric Society*, (pp. 703–708).

Nickell, S. J. (1986). Dynamic models of labour demand. *Handbook of Labor Economics*, 1, 473–522.

Novy-Marx, R. (2011). Operating leverage. *Review of Finance*, 15(1), 103–134.

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, 108(1), 1–28.

Ohanian, L., Raffo, A., & Rogerson, R. (2008). Long-term changes in labor supply and taxes: Evidence from oecd countries, 1956–2004. *Journal of Monetary Economics*, 55(8), 1353–1362.

Ohanian, L. E. & Raffo, A. (2012). Aggregate hours worked in oecd countries: New measurement and implications for business cycles. *Journal of Monetary Economics*, 59(1), 40–56.

Papanikolaou, D. (2011). Investment shocks and asset prices. *Journal of Political Economy*, 119(4), 639–685.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., & Sobek, M. (2020). Integrated public use microdata series, usa: Version 10.0 [dataset]. *IPUMS-USA, University of Minnesota*.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425–442.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, 95(1), 25–49.

Terry, S. J. & Knotek II, E. S. (2011). Markov-chain approximations of vector autoregressions: Application of general multivariate-normal integration techniques. *Economics Letters*, 110(1), 4–6.

Yashiv, E. (2000). Hiring as investment behavior. *Review of Economic Dynamics*, 3(3), 486–522.

Zhang, L. (2005). The value premium. *The Journal of Finance*, 60(1), 67–103.

Zhang, M. B. (2019). Labor-technology substitution: Implications for asset pricing. *The Journal of Finance*, 74(4), 1793–1839.

A Appendix

Labor Adjustment Cost: Implications from Asset Prices

Dongwei Xu

Latest Versions of Paper and Slides

Abstract: This paper explores the relation between a firm's labor input and its equity return, and studies its implications on macroeconomics and asset pricing. At the firm-level, a 1 percent increase in hours is associated with a 0.6 percent decrease in future equity return. A production-based asset pricing model rationalizes this empirical fact with labor adjustment cost on hours and adjustment cost shock that lowers adjustment cost. A positive adjustment cost shock encourages adjustment in the economy and hence redistributes consumption to investment. Firms adjusting hours more and taking advantage of lower adjustment cost are able to pay out more when marginal utility is high. Therefore, these firms are less risky and earn lower equilibrium return. Estimation of the model matches firm-level moments, pooled distributions, and equity return predictability of hours and employment growth. Adjustment cost shock recovered from the model captures a countercyclical component in business cycle fluctuation, and affects firm-level real quantities favorably and asset prices negatively.

JEL classifications: G12, E23, J23, E13

Keywords: Hours; Labor Adjustment; Adjustment Cost; Equity Return; Real Business Cycles

A.1 Measuring the Hours

A.1.1 Data

To construct the measure of hours margin for a publicly listed firm's labor input, I utilizes three micro-level datasets, namely the CRSP/Compustat Merged (CCM), the BLS/Current Population Survey (CPS) March Annual Social and Economic Supplement (ASEC), and the BLS/Occupational Employment Statistics (OES).

A.1.1.a CRSP/Compustat Merged (CCM) I obtain the CCM from Wharton Research Data Services (WRDS), University of Pennsylvania via Python access module `wrds`. The accounting data is from the library `comp` table `funda`[A.1]; in library `crsp`, I extract equity price and return data from table `msf`, equity trading data from table `msenames`, and equity delisting data from table `msedelist`.

Sample Selection In exporting accounting data from COMPUSTAT, I regulate the observations to (1) be stadardized presented (`datafmt` = STD), (2) be reported in a industrial format (`indfmt` = INDL), (3) be prepared with consolidated information (`consol` = C), (4) be included by domestic universe of firms (`popsrc` = D), (5) be collected in USD currency (`curcd` = USD), and (6) have a fiscal year-end of December (`fyr` = 12). Additionally, I exclude observations that (a) are within the regulated electric, gas, and sanitary services industries (SIC major group 49), (b) are within the leveraged finance, insurance and real estate industries (SIC major groups 60 to 69), and (c) have non-positive records of assets, employment, capital, or sales. In exporting equity data from CRSP, I require the observations to (1) be ordinary common shares (`shrcd` = 10 or 11), and (2) be publicly listed on New York Stock Exchange, American Stock Exchange, or Nasdaq Stock Market (`exchcd` = 1, 2, or 3). Additionally, I delete the observations with incorrect/inconsistent first trading date (`namedt`) or last trading date (`nameendt`) according to equity trading data; furthermore, I correct the delisting bias with the return post security delisting (`dlret`) using equity delisting data.

Variable Definition I define the capital K as the lagged data item `PPENT` (total net property, plant and equipment) and the investment I as the data items `CAPX` (capital expenditures) minus `SPPE` (sales of property, plant, and equipment), where the missing values of `SPPE` are supplemented as zeros. The employment N is the data item `EMP` (employees) and the net

[A.1] I follow the instructions from WRDS support page (Access WRDS data from Python on your computer) to query the data using SQL which has the advantage of providing more powerful and granular controls over the empirical processing.

hiring is then calculated as the first-order difference of the employment N as in Belo et al. [2014a].

I also construct other relevant firm characteristic variables following as closely as possible the respective studies. In particular, the market capitalization (size) and book-to-market ratio are constructed following Fama & French [1992, 1993]. The investment-to-assets and return-on-equity are constructed following Hou et al. [2015]. The operating leverage is the operating costs, defined as the data items `COGS` (cost of goods sold) plus `XSGA` (selling, general, and administrative expenses), scaled by assets (the data item `AT`) following Novy-Marx [2011]. The profitability is the gross profits from the data item `GP` (or, revenues minus cost of goods sold, the data items `REVT` minus `COGS`) scaled by assets (the data item `AT`) following Novy-Marx [2013]. The organization capital (intensity) is the organization capital (implied by selling, general, and administrative expenses, the data item `XSGA`, using the perpetual inventory method) scaled by asset (the data item `AT`) following Eisfeldt & Papanikolaou [2013]. The brand capital (intensity) is the brand capital (implied by advertising expenses, the data item `XAD`, using the perpetual inventory method) scaled by asset (the data item `AT`) following Belo et al. [2014b]. The R&D intensity is R&D expenditure from the data item `XRD` (research and development expenses) scaled by sales (the data item `SALE`) following Chan et al. [2001]. The staffing intensity is staff expenditure from the data item `XLR` (staff expense - total) scaled by sales (the data item `SALE`).

Turning to equity data, I define the equity return as the security return (the data item `RET`) plus the delisting return (the data item `DLRET`). The equity price is the closing price or bid/ask average (the data item `PRC`) and the equity share number is the number of publicly held shares (the data item `SHROUT`); the product of equity price and share number gives the equity market value.

Employment Growth Given the firm j's employment N_{jt} at the end of period t, the net hiring/firing (net addition/subtraction to the employment) measured from the beginning to the end of period t is then the first difference

$$D_{jt}^{N} = N_{jt} - N_{j,t-1}, \tag{A.1}$$

where the employment $N_{j,t-1}$ at the beginning of period t is inherited from the end of period $t-1$. Given the employment and the net hiring/firing, I use two complementary definitions to capture the net employment growth[A.2]. The first definition is from Belo et al. [2014a]

$$G_{jt}^{N,1} = \frac{D_{jt}^{N}}{0.5 \times (N_{jt} + N_{j,t-1})} = \frac{N_{jt} - N_{j,t-1}}{0.5 \times (N_{jt} + N_{j,t-1})}. \tag{A.2}$$

In this definition, the denominator is the average employment during the period, measured by the arithmetic mean of employment $0.5 \times (N_{jt} + N_{j,t-1})$ at the beginning and the end of period t. As a result, the employment growth from this definition is bounded within $[-2, 2]$ by construction. In literature, the definition in the format of Eq. (A.2) is widely used and commonly termed as the DHS growth rate following Davis et al. [1996b]. As is discussed by at early as Davis & Haltiwanger [1992], the DHS growth rate incorporates and indicates the deaths (births) by the left (right) endpoint. The second definition of employment growth measures the net hiring/firing relative to the employment before the hiring/firing. That is,

$$G_{jt}^{N,2} = \frac{D_{jt}^{N}}{N_{j,t-1}} = \frac{N_{jt} - N_{j,t-1}}{N_{j,t-1}}, \tag{A.3}$$

in which the denominator is the employment $N_{j,t-1}$ at the beginning of period t and the numerator is the employment change $N_{jt} - N_{j,t-1}$ from the beginning to the end of period t. Of the two definitions, I use the first one (Eq. (A.2)) as the benchmark definition and the second one (Eq. (A.3)) as a crosscheck.

[A.2] As is mentioned by Cooper & Willis [2009] and Cooper et al. [2015], an empirical challenge in discussing the employment growth is that, the gross hiring and firing are usually not observable. Therefore, the gross employment growth $g_{jt} = [N_{jt} - (1-\delta)N_{j,t-1}]/N_{j,t-1}$ additionally requires calibration of the separation rate δ. More precisely, Nickell [1986] proposes the law of the motion $N_{jt} = [h_{jt} - f_{jt} + (1-\delta)]N_{j,t-1}$, where h_t and f_t are the proportional hiring and firing rates, and hence the growth employment growth is then the difference between the two $g_{jt} = h_{jt} - f_{jt}$.

Investment Ratio and Capital Growth For capital, the definitions are analogous to those for employment. However, there are two sidenotes worthy mentioning and discussing. First, both definitions of employment growth measure the net hiring/firing (Eq. (A.1)) relative to the denominators (Eqs. (A.2) and (A.3)), which is due to the empirical limitation that no assumption-free measure of gross hiring/firing available. On the other hand, in defining the capital growth, both the net and the gross investment/divestment measures are empirically available and hence I consider and construct the definitions separately for the net and the gross capital growth. Second, aligning capital with non-lagged and lagged empirical accounting capital records are both used in the literature; depending on the choices of aligning capital, the time subscripts in defining capital growth are different. Perhaps more importantly, aligning capital with non-lagged empirical accounting records provides a clear and straightforward definition of the capital growth, whereas aligning capital with lagged empirical accounting records gives a better mapping between empirical capital growth and capital growth in the model. To be clear, I explicitly consider and construct the definitions of capital growth separately for aligning capital with non-lagged and lagged empirical accounting capital records.

First, consider the case of aligning capital with non-lagged empirical accounting records. In this case, the capital stock K at the end of fiscal period $t-1$ from empirical accounting record is $K_{j,t-1}$. By this notation, the firm j's capital stock at the beginning of period t is inherited as $K_{j,t-1}$ and that at the end of period t is K_{jt}. Therefore, the first definition of capital growth (investment ratio) is

$$G_{jt}^{K,1} = \frac{I_{jt}}{0.5 \times (K_{jt} + K_{j,t-1})}. \tag{A.4}$$

This is the definition used in Belo et al. [2014a, 2017]. In this definition, the numerator is the investment/divestment made from the beginning to the end of period t; the denominator is the average capital stock during the period t, measured by the arithmetic mean of capital $0.5 \times (K_{jt} + K_{j,t-1})$ at the beginning and the end of period t. This first definition, commonly termed as the DHS (Davis et al. [1996b]) investment ratio, measures the investment/divestment a firm made during the period t relative to the average capital stock during the same period t. Similarly, the second definition of capital growth measures the investment ratio by

$$G_{jt}^{K,2} = \frac{I_{jt}}{K_{j,t-1}}. \tag{A.5}$$

That is, it measures the investment/divestment during the period t relative to the capital stock at the beginning of period t. This definition is used by, for example, Belo et al. [2014b]. Given the investment ratios defined in Eqs. (A.4) and (A.5) as the gross capital growth, the net capital growth is firstly defined by the following DHS (Davis et al. [1996b]) equation

$$G_{jt}^{K,3} = \frac{K_{jt} - K_{j,t-1}}{0.5 \times (K_{jt} + K_{j,t-1})}. \tag{A.6}$$

Again, this third definition measures the net capital addition/subtraction during the period t by the average capital stock of the same period t; hence this third definition is bounded within $[-2, 2]$ by construction. Finally, the fourth definition follows naturally and takes the form of

$$G_{jt}^{K,4} = \frac{K_{jt} - K_{j,t-1}}{K_{j,t-1}}. \tag{A.7}$$

Both the third (Eq. (A.6)) and the fourth (Eq. (A.7)) definitions measures the net investment/divestment and take the exactly forms of employment growth in Eq. (A.2) and Eq. (A.3) respectively. Therefore, in addition to investment ratio, or equivalently, the gross capital growth, measured in the first (Eq. (A.4)) and the second (Eq. (A.5)) definitions, these two measures of net capital growth preserve more resemblance to the employment growth and hence suffice robustness examinations of the capital growth definition empirically.

Second, turn to the case of aligning capital with lagged empirical accounting records. To start with, as mentioned, by using lagged empirical accounting capital records, the empirical capital growth is better mapped to capital growth in a neoclassical framework[A.3]. To see this, consider the law of motion for capital at the period t for firm j

$$K_{j,t+1} = (1 - \delta_K)K_{jt} + I_{jt}, \tag{A.8}$$

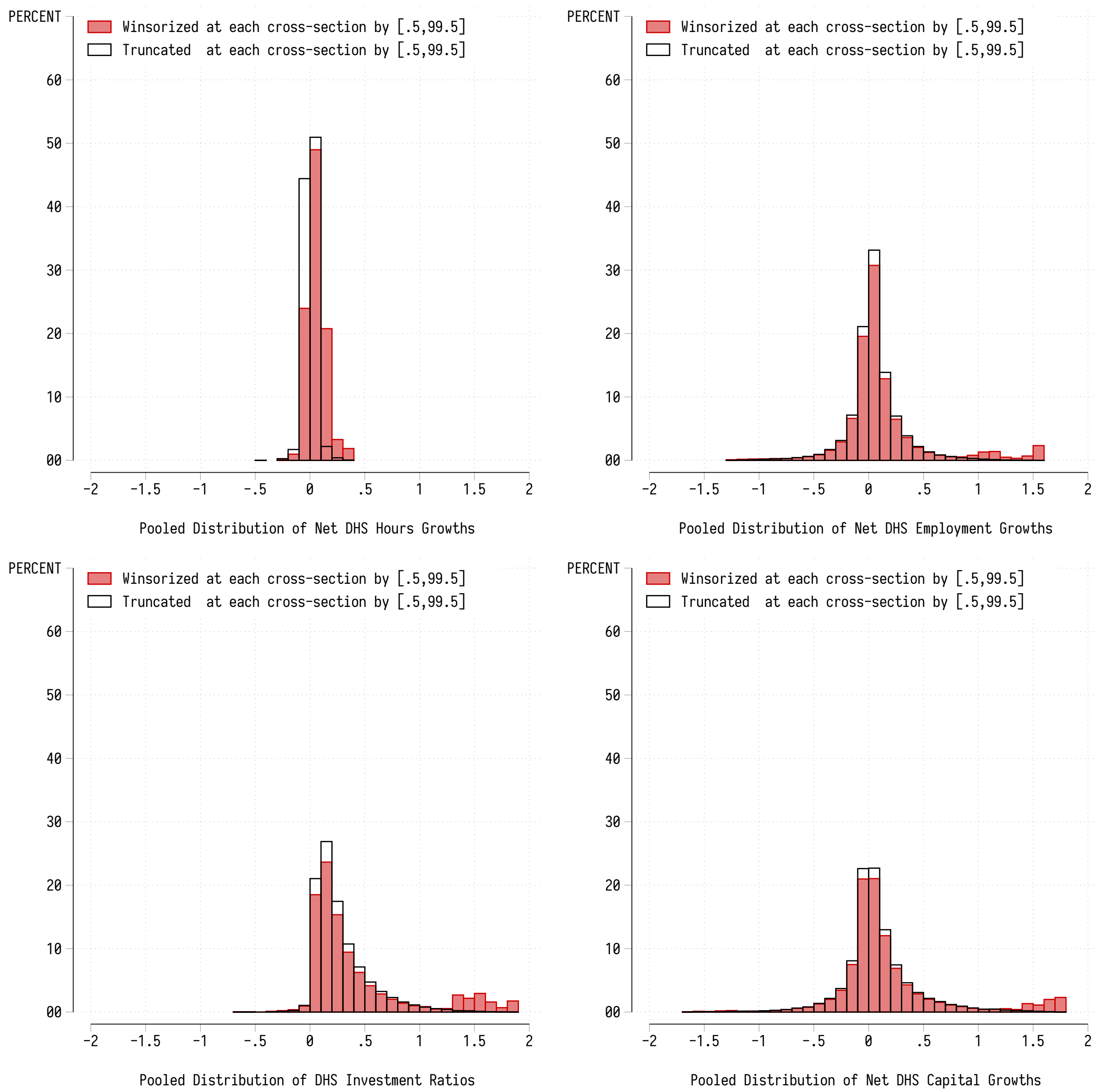
where K_{jt} is the capital stock at the beginning of period t, or equivalently, the capital stock at the end of period $t-1$. Therefore, the capital stock at the beginning of period t, K_{jt} is measured by the empirical accounting capital record at the end of period $t-1$, ${}_{j,t-1}$; that is, the capital stock at period t, K_{jt} is empirically mapped to the lagged accounting capital record at period $t-1$, ${}_{j,t-1}$. More concretely, for example, the capital stock at the beginning of 2010, $K_{j,2010}$, is taken from the empirical accounting capital record from balance sheet report ended in 2009, and hence mapped to the capital stock at the end of 2009 $\tilde{K}_{j,2009}$. Therefore, the four definitions of capital growth are similarly constructed using

$$\begin{aligned}
Eq.\ (\text{A.4})\quad \text{equivalency} &: G_{jt}^{K,1} = \frac{I_{jt}}{0.5 \times (K_{j,t+1} + K_{jt})} \\
Eq.\ (\text{A.5})\quad \text{equivalency} &: G_{jt}^{K,2} = \frac{I_{jt}}{K_{jt}} \\
Eq.\ (\text{A.6})\quad \text{equivalency} &: G_{jt}^{K,3} = \frac{K_{j,t+1} - K_{jt}}{0.5 \times (K_{j,t+1} + K_{jt})} \\
Eq.\ (\text{A.7})\quad \text{equivalency} &: G_{jt}^{K,4} = \frac{K_{j,t+1} - K_{jt}}{K_{jt}}
\end{aligned}$$

Compare Capital and Employment Growth Definitions In Table A.1, I examine the two definitions of employment growth (Eqs. (A.2) and (A.3)) and four definitions of capital growth (Eqs. (A.4) to (A.7)). In particular, I run the equity return predictability regressions in the identical form of Eq. (4) and compare the point estimates of coefficients b_N and b_K.

[A.3] See Belo et al. [2013] for a justification of applying this neoclassical convention in defining capital growth.

Figure A.1. Pooled Distributions of Empirical Definitions of Hours, Employment, and Capital Growth. NOTE: This figure plots the pooled distributions of a variety of empirical definitions measuring hours, employment, and capital growth. To be specific, the upper-left panel depicts the pooled distribution of $G^{H,1}_{jt}$, the DHS hours growth from Eq. (A.12); the upper-right panel depicts the pooled distribution of $G^{N,1}_{jt}$, the net DHS employment growth from Eq. (A.2); the lower-left panel depicts the pooled distribution of $G^{K,1}_{jt}$, the DHS investment ratio from Eq. (A.4); the lower-right panel depicts the pooled distribution of $G^{K,3}_{jt}$, the net DHS capital growth from Eq. (A.6). Of each panel, I plot firstly the Winsorized series in shades (red) and secondly the truncated series in clear outlines, where the outliers are defined as those within the top or bottom half-percent percentiles of each cross-section, consistent with Belo et al. [2014a]. I include not the simple versions of the hours growth (Eq. (A.13)), the employment growth (Eq. (A.3)), the investment ratio (Eq. (A.5)), nor the net capital growth (Eq. (A.7)) simply because those series are dramatically skewed by values outside of $[-2, 2]$ intervals.



In reference to Table 1, the two definitions of employment growth are very robust to each other, significant across all columns [2] to [11] and [13] to [22], with the point estimates from the first definition, the net DHS employment growth on average about 10 bps higher than those from the second definition. Of the four definitions of capital growth, three definitions, the first the DHS investment ratio, the third the net DHS capital growth, and the fourth the net simple capital growth are robust whereas the second the simple investment ratio is not. Nevertheless, the signs and magnitudes across all definitions of employment and capital growth are of similar magnitudes to those in Table 1; to be consistent with Belo et al. [2014a, 2017], I use the first definition of employment growth from Eq. (A.2) and the first definition of capital growth from Eq. (A.4) to present my baseline results.

A.1.1.b BLS/Current Population Survey (CPS) From Integrated Public Use Microdata Series (IPUMS), University of Minnesota (Flood et al. [2020]), I obtain the CPS microdata, including the Basic Monthly and the Annual Social and Economic (ASEC) supplement. Furthermore, also from Integrated Public Use Microdata Series (IPUMS), University of Minnesota (Ruggles et al. [2020]), I obtain the U.S. census (USA) microdata, consist of the American Community Surveys (ACS)[A.4].

Sample Selection The CPS and the USA are preserved and presented in a harmonized way, meaning the following outlined sample selection procedure applies to the Basic Monthly, the ASEC, and the ACS.

Of each period, I exclude the observations where the individuals are not in the labor force indicated by the labor force status (the data item `labforce` = 0 or 1). Then, I require the individuals to have the employment status of either "at work" or "has job but not at work last week" (the data item `empstat` = 10 or 12); this requirement excludes individuals who

[A.4] The decennial censuses microdata is available from 1790 to 2010; that is, the censuses microdata is only available in years of 2000 and 2010 during the sample spans from 1997 to 2017. On the other hand, the ACS microdata is available annually starting from 2000. Therefore, I obtain and use the annual ACS instead of the decennial censuses microdata.

Table A.1. Asset Pricing Investigation on Empirical Definitions of Hours, Employment, and Capital Growth. NOTE: This table tabulates the equity return predictability regressions results using a variety of empirical definitions to measure hours, employment, and capital growth. To be specific, $G_{jt}^{H,1}$ is the DHS hours growth from Eq. (A.12) and $G_{jt}^{H,2}$ is the simple hours growth from Eq. (A.13); $G_{jt}^{N,1}$ is the net DHS employment growth from Eq. (A.2) and $G_{jt}^{N,2}$ is the net simple employment growth from Eq. (A.3); $G_{jt}^{K,1}$ is the DHS investment ratio from Eq. (A.4), $G_{jt}^{K,2}$ is the simple investment ratio from Eq. (A.5), $G_{jt}^{K,3}$ is the net DHS capital growth from Eq. (A.6), and $G_{jt}^{K,4}$ is the net simple capital growth from Eq. (A.7). The regression specification follows Eq. (4), which includes constant, firm fixed effects, year fixed effects, and firm standard error clusters. Each column represents one regression, the right-hand side independent variables in which are indicated by RHS block. All regressions feature 24'824 observations and 4567 firms, with a sample spans from 1997 to 2017 annually.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
LHS	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$
RHS	$G_{jt}^{H,1}$	$G_{jt}^{H,1}$ $G_{jt}^{N,1}$	$G_{jt}^{H,1}$ $G_{jt}^{N,1}$ $G_{jt}^{K,1}$	$G_{jt}^{H,1}$ $G_{jt}^{N,1}$ $G_{jt}^{K,2}$	$G_{jt}^{H,1}$ $G_{jt}^{N,1}$ $G_{jt}^{K,3}$	$G_{jt}^{H,1}$ $G_{jt}^{N,1}$ $G_{jt}^{K,4}$	$G_{jt}^{H,1}$ $G_{jt}^{N,2}$	$G_{jt}^{H,1}$ $G_{jt}^{N,2}$ $G_{jt}^{K,1}$	$G_{jt}^{H,1}$ $G_{jt}^{N,2}$ $G_{jt}^{K,2}$	$G_{jt}^{H,1}$ $G_{jt}^{N,2}$ $G_{jt}^{K,3}$	$G_{jt}^{H,1}$ $G_{jt}^{N,2}$ $G_{jt}^{K,4}$
b_H	-0.69^{***}	-0.67^{***}	-0.66^{***}	-0.68^{***}	-0.66^{***}	-0.66^{***}	-0.68^{***}	-0.66^{***}	-0.68^{***}	-0.66^{***}	-0.67^{***}
(se)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
b_N		-0.21^{***}	-0.20^{***}	-0.22^{***}	-0.13^{***}	-0.16^{***}	-0.10^{***}	-0.10^{***}	-0.10^{***}	-0.05^{**}	-0.06^{***}
(se)		(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
b_K			-0.05^{***}	0.01^{*}	-0.13^{***}	-0.04^{***}		-0.06^{***}	0.01	-0.15^{***}	-0.05^{***}
(se)			(0.01)	(0.00)	(0.02)	(0.01)		(0.01)	(0.00)	(0.02)	(0.01)
$\bar{R}^2$	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]
LHS	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$	$R_{j,t+1}$
RHS	$G_{jt}^{H,2}$	$G_{jt}^{H,2}$ $G_{jt}^{N,1}$	$G_{jt}^{H,2}$ $G_{jt}^{N,1}$ $G_{jt}^{K,1}$	$G_{jt}^{H,2}$ $G_{jt}^{N,1}$ $G_{jt}^{K,2}$	$G_{jt}^{H,2}$ $G_{jt}^{N,1}$ $G_{jt}^{K,3}$	$G_{jt}^{H,2}$ $G_{jt}^{N,1}$ $G_{jt}^{K,4}$	$G_{jt}^{H,2}$ $G_{jt}^{N,2}$	$G_{jt}^{H,2}$ $G_{jt}^{N,2}$ $G_{jt}^{K,1}$	$G_{jt}^{H,2}$ $G_{jt}^{N,2}$ $G_{jt}^{K,2}$	$G_{jt}^{H,2}$ $G_{jt}^{N,2}$ $G_{jt}^{K,3}$	$G_{jt}^{H,2}$ $G_{jt}^{N,2}$ $G_{jt}^{K,4}$
b_H	-0.68^{***}	-0.66^{***}	-0.65^{***}	-0.67^{***}	-0.65^{***}	-0.65^{***}	-0.67^{***}	-0.65^{***}	-0.67^{***}	-0.65^{***}	-0.66^{***}
(se)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
b_N		-0.21^{***}	-0.20^{***}	-0.22^{***}	-0.13^{***}	-0.16^{***}	-0.10^{***}	-0.10^{***}	-0.10^{***}	-0.05^{**}	-0.06^{***}
(se)		(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
b_K			-0.05^{***}	0.01^{*}	-0.13^{***}	-0.04^{***}		-0.06^{***}	0.01	-0.15^{***}	-0.05^{***}
(se)			(0.01)	(0.00)	(0.02)	(0.01)		(0.01)	(0.00)	(0.02)	(0.01)
$\bar{R}^2$	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

are (1) in the armed forces, (2) unemployed, or (3) not in the labor force. Next, I regulate the individuals to be within the classes of works (the data item `classwrk` = 20, 21, or 22) who work for wage or salary, excluding those who (1) are self-employed, (2) are unpaid family worker, (3) work for wage or salary but for nonprofit, (4) work at federal, state, or local government, and (5) are in the armed forces. Finally, I allow the individuals to be either full- or part-time workers (the data item `wkstat`).

Variable Definition In CPS, there are two measures of individual hours. The hours usually worked per week at all jobs (the data item `uhrsworkt`) and the hours usually worked per week at main job (the data item `uhrswork1`), both of which are associated with the sample weight (the data item `asecwt`). A third related variable is the hours worked last week (the data item `ahrsworkt`), which is unsuitable for analyses in this paper. In USA, there is one measure of individual hours, namely the usual hours worked per week (the data item `uhrswork`), which is associated with the sample weight (the data item `perwt`). I use both the two measures in CPS and the one measure in USA to define the individual hours. To more accurately measure the firm side labor input choice of hours, I present the baseline results using the measure of hours at all jobs in CPS. After defining the individual hours, a final step is to retain observations with non-missing records of individual hours.

The impacts of (1) performing sample selection procedure and (2) retaining non-missing values post defining individual hours are demonstrated in Table A.2.

Representativeness of Individual Hours To construct the firm-level labor input of the hours margin, I crosswalk three micro-level dataset, as outlined in Section 2.2. The very core of such crosswalk among the individual hours and the industry-specific occupational information requires the representativeness of individual hours within one industry-occupation pair. That is, for one occupation within one industry in an arbitrary year, the set of individuals and their hours shall provide a representative picture for the hours margin labor input of firms. Therefore, some control over the representativeness of individual hours within one industry-occupation pair shall be implemented. Towards this end, the control I choose and implement is that I require the number of observations in one industry-occupation pair of each year to be no less than 20, which corresponds to deleting about 37% of observations.

Obviously, there is a tradeoff between representativeness of individual hours and representative of industrial hours. To see this, by increasing the number-of-observation requirement for one (industry, occupation) pair, the industry-specific occupational hours is more likely to give a good grasp of the true value; on the other hand, the overly tighten this requirement, a direct and more severe result is that, the number of occupations within the industry in this (industry, occupation) pair is more likely to plunge. That is, the occupations in this industry are less likely to be mapped with the aggregated individual hours and hence aggregating their industry-specific occupational hours result in a insufficient representation of the industrial hours.

I use Table A.2 to demonstrate such tradeoff. Reading from left to right, the column [1] gives the numbers of observations in the original raw sample. After applying the sample selection procedure, the selected sample sizes are listed in column [2]. The column [3] further defines individual hours and shows the numbers of observations with non-missing records. Next, the columns [4] to [8] tabulate the percentiles for the number of observations within one industry-occupation pair; clearly, as the percentiles moving from 25 to 50, the numbers of observations within one industry-occupation pair increase. Note here that the control I implement corresponds to about 37-percentile. Finally, the columns [9] to [13] show the resulting numbers of observations in sample, after requiring that the the number of observations within one industry-occupation pair be no less than n, where n varies from 10 to 30. As the requirement becomes stricter, n increase and the resulting number of observations in sample decreases.

I use four ways to aggregate individual hours for one industry-occupation pair, essentially forming the industry-specific occupational hours. In particular, the four ways correspond to

Table A.2. Summary Statistics of BLS/Current Population Survey (CPS). NOTE: This table tabulates the summary statistics of BLS/CPS AECS. In columns [1] to [3], the number of observations are listed, where the column [1] represents the original sample, the column [2] the sample after selection procedure, and the column [3] the sample with non-missing individual hours measures. In columns [4] to [9], the percentiles of number of observations in one industry-occupation pair are calculated. From these columns, it can be inferred that the control of 20 observations in one industry-occupation pair of each year corresponds to about 37% of observations. Finally, the columns [10] to [15] present the number of observations when controlling the requirement for number of observations within one industry-occupation pair of each year.

	Sample # Obs			Percentiles of # Obs in One (Industry, Occupation)					# Obs in One (Industry, Occupation) No Less Than n				
	Original	Selected	Nomiss	p25	p30	p35	p40	p45	n=10	n=15	n=20	n=25	n=30
Year	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
1997	131,854	52,905	47,873	7	9	13	17	23	29,427	26,716	24,689	22,941	21,793
1998	131,617	53,640	25,280	4	5	7	9	12	14,738	13,261	12,093	11,234	10,571
1999	132,324	54,124	49,090	7	10	13	18	24	30,922	27,797	25,550	23,999	22,694
2000	133,710	55,408	50,521	7	10	14	19	25	32,046	29,220	26,971	25,269	23,847
2001	218,269	88,476	80,817	11	16	22	31	40	56,054	51,918	48,806	46,421	44,243
2002	217,219	85,994	78,095	11	16	23	31	42	53,935	49,946	47,322	45,038	43,018
2003	216,424	84,756	76,515	9	13	18	23	32	51,280	47,039	44,059	41,495	39,138
2004	213,241	84,013	75,840	9	13	18	25	33	50,124	46,229	43,133	40,503	38,836
2005	210,648	83,101	74,694	9	12	17	25	34	49,205	45,114	42,250	39,746	38,137
2006	208,562	83,621	75,480	9	13	18	25	35	49,830	45,907	42,773	40,701	38,676
2007	206,639	83,273	76,091	9	13	19	27	36	50,305	46,501	43,697	41,609	39,636
2008	206,404	82,530	75,365	9	13	18	25	36	50,040	45,984	43,054	40,413	38,654
2009	207,921	79,359	72,299	9	13	18	26	34	48,015	44,233	41,271	39,199	37,444
2010	209,802	78,399	71,680	9	12	18	24	33	47,688	43,761	41,229	38,923	37,092
2011	204,983	76,991	70,524	8	12	17	23	33	46,744	43,009	39,930	37,958	36,340
2012	201,398	76,746	70,262	9	12	17	23	32	46,722	42,988	40,345	37,845	36,140
2013	202,634	77,334	71,043	8	12	17	24	34	46,980	43,452	40,736	38,330	36,494
2014	199,556	77,043	69,061	9	12	17	24	33	45,866	42,178	39,526	37,287	35,852
2015	199,024	77,116	71,212	9	13	18	26	36	47,606	43,958	41,130	39,174	37,244
2016	185,487	72,220	67,018	9	12	18	25	35	44,387	40,964	38,473	36,446	34,817
2017	185,914	73,235	68,171	9	13	18	25	35	45,358	41,854	39,254	37,100	35,401

the aggregation method described in Eq. (1) and are defined as follows.

$$
\begin{array}{llcllcl}
[1] & \text{Hour}_t^{(i,o)} & = & \sum_{p \in \text{CPS}_t(i,o)} & \text{Equal-Wght}_t^{(i,o,p)} & \times & \text{Hour-Main-Job}_t^{(i,o,p)} \\
[2] & \text{Hour}_t^{(i,o)} & = & \sum_{p \in \text{CPS}_t(i,o)} & \text{Person-Wght}_t^{(i,o,p)} & \times & \text{Hour-Main-Job}_t^{(i,o,p)} \\
[3] & \text{Hour}_t^{(i,o)} & = & \sum_{p \in \text{CPS}_t(i,o)} & \text{Equal-Wght}_t^{(i,o,p)} & \times & \text{Hour-All-Jobs}_t^{(i,o,p)} \\
[4] & \text{Hour}_t^{(i,o)} & = & \sum_{p \in \text{CPS}_t(i,o)} & \text{Person-Wght}_t^{(i,o,p)} & \times & \text{Hour-All-Jobs}_t^{(i,o,p)}
\end{array}
\tag{A.9}
$$

In particular, the left-hand side of Eq. (A.9) is the industry-specific occupational hours. The first aggregation method captures the hours worked at main job from CPS and aggregates each individual equally within one industry-occupation pair; the second aggregation method also captures the hours worked at main job but aggregates individuals using their

CPS personal weights. Similarly, the third and fourth methods operates on the hours worked at all jobs instead of hours worked at main job.

To uncover impacts from the various aggregation methods, I construct the hours growth from these four aggregation methods and detect the impacts from the perspective of equity return predictability regressions. In Table A.3, the hours growth implied by the four methods described in Eq. (A.9) are tabulated in columns from [1] to [4], while the specification of regressions are varied across panels. In referencing to Tables 1 and A.1, the negative slopes are of similar magnitudes. Specifically, the point estimates of coefficient B_H are generally larger when the aggregation operates on the hours worked at all jobs and/or assigns CPS personal weighs. In panel D, column [3], the negative slope is about 60-bps using hours worked at all jobs aggregated with CPS personal weights, controlling for employment and capital growth.

A.1.1.c BLS/Occupational Employment Statistics (OES) I obtain the OES dataset from the BLS website directly. The OES program produces employment and wage estimates annually for about 800 occupations. These estimates are available for the nation as a whole, for individual states, and for metropolitan and nonmetropolitan areas. Under the scope of my analyses, the estimates regarding national occupational estimates for specific industries are of my interest.

Coverage and Scope The OES program surveys approximately 0.18 to 0.2 million establishments semiannually (May and November of each year) and finish one survey cycle in three years, resulting a 1.1 million sample triennially. Of each establishment, the survey covers all full-time and part-time, wage-and-salary workers in non-farm business from payroll records. The survey does not cover the self-employed workers, owners or partners in unincorporated business, household workers, or unpaid family workers. This motivates the exclusion of certain classes of workers in CPS (the data item `classwrk` = 20, 21, or 22).

Of the OES dataset, the part of my interest is the industry-specific occupational data.

Table A.3. Asset Pricing Investigation on Individual Hours Measures in BLS/Current Population Survey (CPS). Note: This table tabulates the equity return predictability regressions results using a variety of measures of individual hours in BLS/Current Population Survey (CPS). Reading across columns from [1] to [4], the measure of individual hours varies, corresponding to Eq. (A.9). Across panels, the RHS regressors differ. In particular, panel A includes $G_{jt}^{H,1}$, the DHS hours growth from Eq. (A.12). Panel B additionally has $G_{jt}^{N,1}$, the net DHS employment growth from Eq. (A.2), and panel C additionally has $G_{jt}^{K,1}$, the DHS investment ratio from Eq. (A.4). Panel D has $G_{jt}^{H,1}, G_{jt}^{N,1}, G_{jt}^{K,1}$ and finally panel E has $G_{jt}^{H,1}, G_{jt}^{N,1}, G_{jt}^{K,3}$, where $G_{jt}^{K,3}$ is the net DHS capital growth from Eq. (A.6), crosschecking the definition of capital growth. The regressions follow Eq. (4) and are repeated as the panel headings for clearer presentation. The regressions always include constants, firm fixed effects, year fixed effects, and firm standard error clusters, and feature 24'824 observations and 4567 firms, with a sample spans from 1997 to 2017 annually.

		Marginal Cost-Based				Employment Number-Weighted			
		Hours Worked at Main Job		Hours Worked at All Jobs		Hours Worked at Main Job		Hours Worked at All Jobs	
		Equal Weighted	Person Weighted	Equal Weighted	Person Weighted	Equal Weighted	Person Weighted	Equal Weighted	Person Weighted
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A	b_H	−0.48***	−0.60***	−0.54***	−0.69***	−0.57***	−0.68***	−0.63***	−0.76***
	(se)	(0.12)	(0.12)	(0.12)	(0.13)	(0.11)	(0.11)	(0.11)	(0.12)
	$\bar{R}^2$	0.07	0.07	0.07	0.07	0.08	0.08	0.08	0.08
	p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B	b_H	−0.46***	−0.59***	−0.52***	−0.67***	−0.55***	−0.66***	−0.60***	−0.73***
	(se)	(0.11)	(0.12)	(0.12)	(0.13)	(0.11)	(0.11)	(0.11)	(0.12)
	b_N	−0.21***	−0.21***	−0.21***	−0.21***	−0.22***	−0.22***	−0.22***	−0.22***
	(se)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	$\bar{R}^2$	0.07	0.07	0.07	0.07	0.09	0.09	0.09	0.09
	p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel C	b_H	−0.45***	−0.53***	−0.50***	−0.60***	−0.55***	−0.62***	−0.61***	−0.69***
	(se)	(0.12)	(0.12)	(0.12)	(0.13)	(0.11)	(0.11)	(0.11)	(0.12)
	b_K	−0.27***	−0.27***	−0.27***	−0.27***	−0.23***	−0.23***	−0.23***	−0.23***
	(se)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	$\bar{R}^2$	0.07	0.07	0.07	0.07	0.09	0.09	0.09	0.09
	p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel D	b_H	−0.44***	−0.53***	−0.49***	−0.59***	−0.53***	−0.61***	−0.59***	−0.67***
	(se)	(0.12)	(0.12)	(0.12)	(0.13)	(0.11)	(0.11)	(0.11)	(0.12)
	b_N	−0.16***	−0.16***	−0.16***	−0.16***	−0.18***	−0.18***	−0.18***	−0.18***
	(se)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	b_K	−0.22***	−0.22***	−0.22***	−0.22***	−0.18***	−0.18***	−0.18***	−0.18***
	(se)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	$\bar{R}^2$	0.08	0.08	0.08	0.08	0.09	0.09	0.09	0.09
	p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel E	b_H	−0.45***	−0.57***	−0.51***	−0.66***	−0.53***	−0.65***	−0.59***	−0.72***
	(se)	(0.11)	(0.12)	(0.12)	(0.13)	(0.11)	(0.11)	(0.11)	(0.12)
	b_N	−0.13***	−0.13***	−0.13***	−0.13***	−0.13***	−0.13***	−0.13***	−0.13***
	(se)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
	b_K	−0.13***	−0.13***	−0.13***	−0.13***	−0.13***	−0.12***	−0.13***	−0.12***
	(se)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
	$\bar{R}^2$	0.07	0.07	0.07	0.07	0.09	0.09	0.09	0.09
	p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

The program starts from 1988, and did not conduct surveys in 1996. From 1988 to 1995, the program did not collect the interested industry-specific occupational data in a comprehensive manner. Specifically, during these period of time, each industry is surveyed only once in every survey cycle (three years). Therefore, a certain industry is only surveyed twice (e.g., Services) or thrice (e.g., Manufacturing). As a result, the industry-specific occupational data is only available for certain industries at a given year from 1988 to 1995. In Table A.4, I list the industries together with their available years on the left panel, and the years together with the corresponding surveyed industries on the right panel. Due to this survey structure from 1988 to 1995, I use OES dataset starting 1997, the earliest year from which the industry-specific occupational data is comprehensively measured and available[A.5].

Sample Selection and Variable Definition Of each year's OES data, I obtain four set of variables. The first is industry information, from either three-digit Standard Industrial Classification (SIC) system or four-digit North American Industry Classification System (NAICS); the second is by-industry occupation information, from either five-digit OES proprietary occupational classification system or six-digit Standard Occupational Classification (SOC) system. Across years, the dataset has experienced several major updates in industry and occupation classifications. Specifically, the occupation classification system is OES proprietary occupational classification system from 1997 to 1999, SOC-2000 from 1999 to 2009, and SOC-2010 from 2010 to 2017[A.6]; the industry classification system is SIC-1987 from 1997 to 2002, NAICS-2002 from 2002 to 2007, NAICS-2007 from 2008 to 2011, and NAICS-2012 from 2012 to 2017[A.7].

The third and fourth are industry-specific occupational data; the third is estimated total

[A.5]Empirical works such as Donangelo [2014] extend the coverage into 1990-1996 by forward filling, repeatedly using the same industry-specific occupational data for the following years until the same industry is next surveyed. For example, in Table A.4, the same Manufacturing and Hospital data in 1989 is forwarded to fill 1990, 1991, and 1992, for 1993 is the next year when Manufacturing and Hospital is surveyed. By this forward filling technique, the earliest year when all industries are covered is then 1990.

[A.6]The crosswalk tables are provided by the U.S. U.S. Department of Labor's Employment and Training Administration (jointly with states) and obtained from its website.

[A.7]The concordance tables are provided by the U.S. Census Bureau and obtained from its website.

Table A.4. Industries Surveyed From 1988 To 1995 by BLS/Occupational Employment Statistics (OES) program. NOTE: This table lists the industries together with their available years on the left panel, and the years together with the corresponding surveyed industries on the right panel. During 1988-1995 each industry is surveyed only once in every three-year survey cycle; No survey is conducted in 1996. Therefore, I start my sample from 1997.

By-Industry Available Years			By-Year Available Industries	
Industry	1987 SIC Code	Years Available	Years	Industries Available
Agricultural services	07	1992, 1995	1988	Transportation and public utilities; Wholesale trade; Retail trade; Educational services
Mining	10-14	1990, 1993	1989	Manufacturing; Hospitals
Construction	15-17	1990, 1993	1990	Mining; Construction; Finance, insurance, and real estate; Services
Manufacturing	20-39	1989, 1992, 1995	1991	Transportation and public utilities; Wholesale trade; Retail trade; Educational services
Transportation and public utilities	40-49	1988, 1991, 1994	1992	Agricultural services; Manufacturing; Hospitals
Wholesale trade	50-51	1988, 1991, 1994	1993	Mining; Construction; Finance, insurance, and real estate; Services
Retail trade	52-59	1988, 1991, 1994	1994	Transportation and public utilities; Wholesale trade; Retail trade; Educational services
Finance, insurance, and real estate	60-67	1990, 1993	1995	Agricultural services; Manufacturing; Hospitals
Services	70-87, 89	1990, 1993		
Hospitals	806	1989, 1992, 1995		
Educational services	82	1988, 1991, 1994		

employment and the fourth is mean and median of annual/hourly wages[A.8][A.9]. Finally I exclude occupations with missing wage or employment estimates.

A.1.2 Methodology

I explain in detail the definition and the robustness investigations of my measure of hours.

A.1.2.a Three-Step Definition My measure of hours replies on the three equations defined in Section 2.2, reproduced as follows. Denote t year, i industry, o occupation, p person, and

[A.8] The OES survey calculates the annual or hourly wages with full-time equivalence. Specifically, the annual wages are calculated by multiplying the hourly mean wages by $2,080$ hours, which is assumed to be the number of hours for full time per annum. For occupations without available the hourly mean wages published, the annual wages are directly calculated from the reported survey data.

[A.9] Starting from 1999, large values of annual/hourly wages are top-coded. For example, in 1999, indicators apply when the wages exceed \$70.00 per hour or \$$145,600$ per year; in 2017, indicators apply when the wages exceed \$100.00 per hour or \$$208,000$ per year. I use the top-coded value as the annual/hourly wages. Given that the occupation within a industry is weighted by marginal cost, I expect the influences from the top-coding very minimal. Also, the interdeciles and the interquartiles of annual/hourly wages are available starting from 2001.

j firm.

$$
\begin{aligned}
\text{Hour}_t^{(i,o)} &= \sum_{p \in \text{CPS}_t(i,o)} \text{Wght}_t^{(i,o,p)} \times \text{Hour}_t^{(i,o,p)} \\
\text{Hour}_t^{(i)} &= \sum_{o \in \text{OES}_t(i)} \left(\frac{\text{Empt}_t^{(i,o)} \times \text{Wage}_t^{(i,o)}}{\sum_{o \in \text{OES}_t(i)} \text{Empt}_t^{(i,o)} \times \text{Wage}_t^{(i,o)}} \times \text{Hour}_t^{(i,o)} \right) \\
H_{jt} &= \text{Hour}_t^{(i)} \mid j \in i
\end{aligned}
\tag{A.10}
$$

In these steps, (1) $\text{CPS}_t(i,o)$ is the set of individuals in CPS at year t that work at occupation o in industry i; (2) $\text{Wght}_t^{(i,o,p)}$ and $\text{Hour}_t^{(i,o,p)}$ are respectively the individual weight and hours; (3) $\text{OES}_t(i)$ is the set of occupations in OES at year t within industry i; (4) $\text{Empt}_t^{(i,o)}$ and $\text{Wage}_t^{(i,o)}$ are respectively industry-specific occupational employment and wages.

Hours Growth The intermediate contribution from my measure of hours is defining the labor input choice of hours at the firm-level. Given the firm j's hours H_{jt} at the end of period t, the change[A.10] in hours is then

$$
D_{jt}^H = H_{jt} - H_{j,t-1}. \tag{A.11}
$$

Similarly to employment growth, two definitions of hours growth are calculated. The first DHS hours growth is

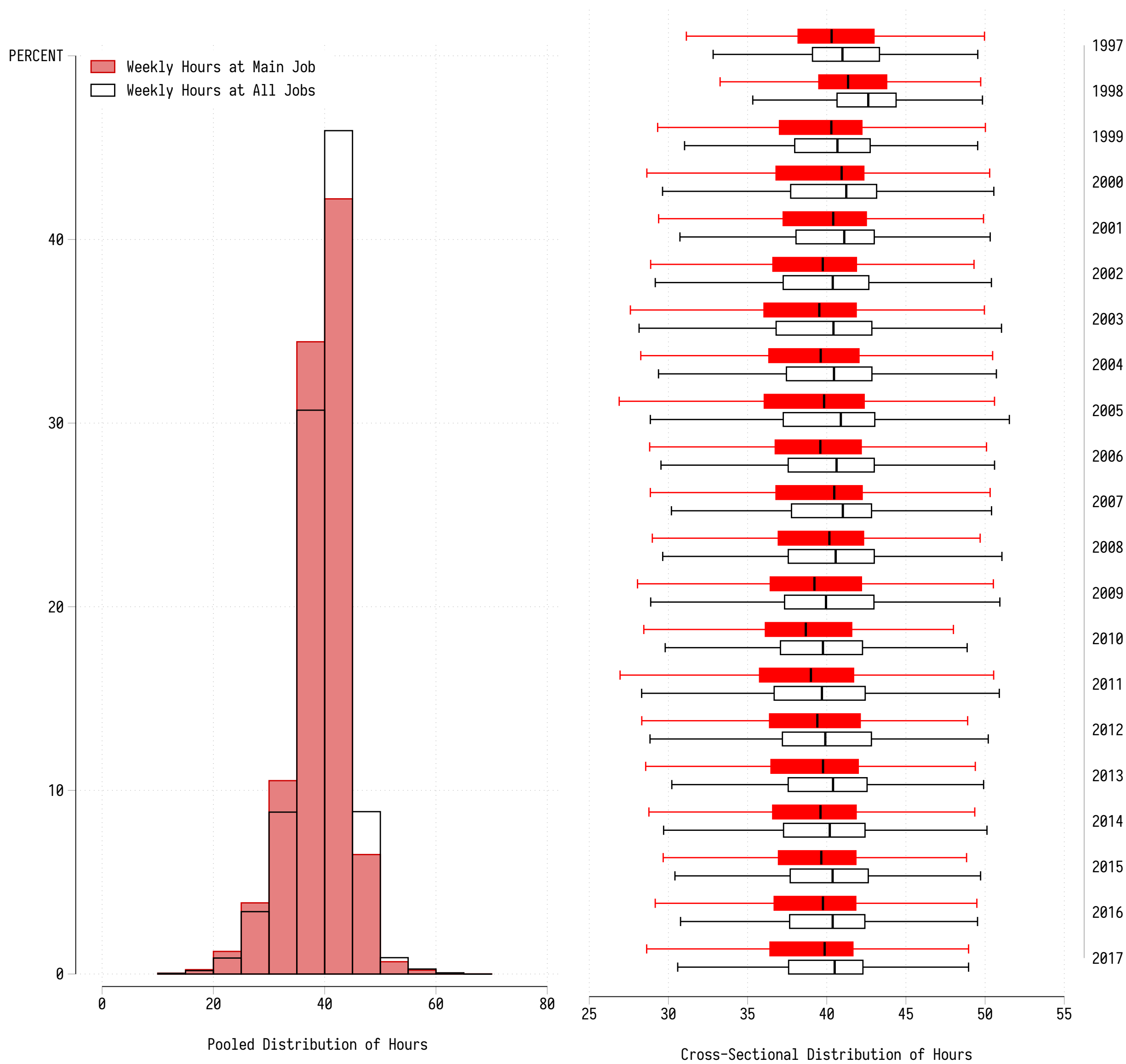
$$
G_{jt}^{H,1} = \frac{D_{jt}^H}{0.5 \times (H_{jt} + H_{j,t-1})} = \frac{H_{jt} - H_{j,t-1}}{0.5 \times (H_{jt} + H_{j,t-1})}, \tag{A.12}
$$

and the second simple hours growth is

$$
G_{jt}^{H,2} = \frac{D_{jt}^H}{H_{j,t-1}} = \frac{H_{jt} - H_{j,t-1}}{H_{j,t-1}}. \tag{A.13}
$$

[A.10] The change in hours is assumed to be free of exogenous destruction; hence the gross and net changes, distinguished explicitly in measuring employment and capital growth, are identical for hours.

Figure A.2. Pooled and and Cross-Sectional Distributions of Hours From BLS/Occupational Employment Statistics (OES). NOTE: This figure plots the pooled distribution of hours on the left panel, and the cross-sectional distributional statistics on the right panel. The hours are industry-specific occupational hours across years, from aggregating the individual hours from BLS/Current Population Survey (CPS) for each industry-occupation pair in BLS/Occupational Employment Statistics (OES) of each year from 1997 to 2017.



Compare Hours Growth Definitions In Table A.1, the panel A reports equity return predictability regression results using the first DHS hours growth, and the panel B reports using the second simple hours growth. Comparing the negative slopes across specifications, it is straightforward to see that the negative association between the firm's current hours growth and its future equity return is qualitatively and quantitatively identical.

A.1.2.b Indirect Validation It is crucially important that my measure of hours is insensitive to methodological choices empirically, and the negative association between the firm's current hours growth and its future equity return are robust to alternative methodological choice. Therefore, I use this section to validate my measure of hours indirectly, and the next section provides direct validation. It is useful to keep in mind that, the goal of the indirect validation exercises is to ensure the predictability from current hours growth robustly persists despite of various changes made to the measure of hours, and hence comes indeed from the hours growth.

Alternative Individual Weight Variables As mentioned in Eqs. (1) and (A.10), the first step aggregates individual hours using the individual weight assigned by CPS. To inspect whether the empirical findings are driven by this choice, I use the alternative equal weighting scheme and construct my measure of hours otherwise identically.

Alternative Individual Hours Variables Furthermore, the individual hours is mapped to the usual hours worked at all jobs instead of at main job only. Though the hours at all jobs gives a better approximation of the firms' labor input choices of hours, measuring individual hours by hours at main job shall give a similar negative association between the firm's current hours growth and its future equity return, simply because the two series share similar cross-sectional distribution patterns across time (Fig. A.2). To test this intuition, I use the alternative hours at main job for individual hours and construct my measure of hours otherwise identically.

That is, in the first step, the industry-specific occupational hours is

$$
\begin{array}{llll}
[1] & \text{Hour}_t^{(i,o)} & = \sum_{p \in \text{CPS}_t(i,o)} \text{Equal-Wght}_t^{(i,o,p)} \times \text{Hour-Main-Job}_t^{(i,o,p)} \\
[2] & \text{Hour}_t^{(i,o)} & = \sum_{p \in \text{CPS}_t(i,o)} \text{Person-Wght}_t^{(i,o,p)} \times \text{Hour-Main-Job}_t^{(i,o,p)} \\
[3] & \text{Hour}_t^{(i,o)} & = \sum_{p \in \text{CPS}_t(i,o)} \text{Equal-Wght}_t^{(i,o,p)} \times \text{Hour-All-Jobs}_t^{(i,o,p)} \\
[4] & \text{Hour}_t^{(i,o)} & = \sum_{p \in \text{CPS}_t(i,o)} \text{Person-Wght}_t^{(i,o,p)} \times \text{Hour-All-Jobs}_t^{(i,o,p)}
\end{array}, \tag{A.14}
$$

where the individual hours are either from hours at all jobs or from hours at main job, and are either weighted equally or by the CPS personal weight. The results are discussed by Eq. (A.9) and Table A.3 (see above).

Alternative Occupation Weighting Schemes In the second step (Eqs. (2) and (A.10)), I implement a marginal cost-based weighting scheme. One advantage of this weighting scheme is its accurate capturing of the practical expenses associated with adjusting hours; as a result, it places more weights on occupations with greater impacts to the cash flows.

One might be, however, concerned about that, the marginal cost-based weighting scheme chosen is subject to changes of employment $\text{Empt}_t^{(i,o)}$ or wages $\text{Wage}_t^{(i,o)}$ in certain occupation o within the given industry i, in a way that the predictability of hours growth on equity return is substantially driven by the other margin of labor input (employment) or factor price of labor input (wages). To address concerns along this line, I further test three alternative weighting schemes as follows.

$$
\begin{array}{llll}
(1) & \text{Hour}_t^{(i)} & = & \sum\limits_{o \in \text{OES}_t(i)} \left(\dfrac{\text{Empt}_t^{(i,o)} \times \text{Wage}_t^{(i,o)}}{\sum_{o \in \text{OES}_t(i)} \text{Empt}_t^{(i,o)} \times \text{Wage}_t^{(i,o)}} \times \text{Hour}_t^{(i,o)} \right) \\
(2) & \text{Hour}_t^{(i)} & = & \sum\limits_{o \in \text{OES}_t(i)} \left(\dfrac{\text{Empt}_t^{(i,o)}}{\sum_{o \in \text{OES}_t(i)} \text{Empt}_t^{(i,o)}} \times \text{Hour}_t^{(i,o)} \right) \\
(3) & \text{Hour}_t^{(i)} & = & \sum\limits_{o \in \text{OES}_t(i)} \left(\dfrac{\text{Wage}_t^{(i,o)}}{\sum_{o \in \text{OES}_t(i)} \text{Wage}_t^{(i,o)}} \times \text{Hour}_t^{(i,o)} \right) \\
(4) & \text{Hour}_t^{(i)} & = & \sum\limits_{o \in \text{OES}_t(i)} \left(\dfrac{1}{||\text{OES}(t, ind)||} \times \text{Hour}_t^{(i,o)} \right)
\end{array} \tag{A.15}
$$

In Eq. (A.15), the first weighting scheme in (1) is the marginal cost-based, aggregating each industry-specific occupational hours by the marginal cost associated with adjusting this occupation's hours. The second weighting scheme in (2) is the employment-based; it weights each industry-specific occupational hours by the number of workers in this occupation. The third weighting scheme in (3) is the wages-based and aggregates each industry-specific occupational hours by the mean annual wages of a typical worker in this occupation. The last weighting scheme in (4) equally weights all occupations within a industry.

I indirectly validate my measure of hours using the marginal cost-based weighting scheme by constructing all alternative occupation weighting schemes implied measures of hours and implementing the same firm-level equity return predictability regressions in Eq. (4). In Table A.5, I place results from the marginal cost-based weighting scheme (the original results in Table 1) in columns [1] to [3], and those from the three alternative occupation weighting schemes in columns [4] to [12][A.11]. Comparing the point estimates of coefficient b_H, the negative slopes are all significant, suggesting the negative association between the firm's current hours growth and its future equity return is robust to alternative weighting schemes used to aggregate industry-specific occupational hours. One observation stands out when comparing the results. When the impacts from factor price of labor input are manually muted (the employment-based), the negative slopes are estimated to be steeper; when the impacts from the other margin of labor input are muted (the wages-based), the negative slopes become smaller; when both channels are shut down, the estimated negative slopes are very similar to those when both channels are in place. This is an interesting research question by itself; my speculation is that, the factor price marks an important channel through which the firm's labor input choices are made. (some lit discussion TBA)

[A.11]Note that, results from equity return predictability regressions without the hours growth as a regressor are not changed and hence not repeated in Table A.5. Note also that, due to the availability of employment and wages information in OSE, the numbers of observations and firms are different.

Alternative Industry Occupation Compositions The industry-specific occupation compositions, denoted by $o \in \mathrm{OES}_t(i)$ in the second step (Eqs. (2) and (A.10)) is time-varying. Therefore, my measure of hours takes into account the exiting and entering occupations in a certain industry, and aggregates each occupation's hours by its contemporaneous weight in this industry.

One particular concern regrading the industry-specific occupation compositions might be that, the time-varying occupation compositions capturing the exiters and entrants might, on the other hand, be influenced by structural changes to occupation composition in an industry, in a way that the predictability of hours growth on equity return is substantially driven by the marginal occupations rather than the incumbent occupations. To address concerns along this line, I further test three alternative specifications of occupation compositions as follows.

$$
\begin{aligned}
&(1)\quad \mathrm{Hour}_t^{(i)} &&= \sum_{o\in \mathrm{OES}_t(i)} \left(\frac{\mathrm{Empt}_t^{(i,o)} \times \mathrm{Wage}_t^{(i,o)}}{\sum_{o\in \mathrm{OES}_t(i)} \mathrm{Empt}_t^{(i,o)} \times \mathrm{Wage}_t^{(i,o)}} \times \mathrm{Hour}_t^{(i,o)} \right) \\
&(2)\quad \mathrm{Hour}_t^{(i)} &&= \sum_{o\in \mathrm{OES}_{t_0}(i)} \left(\frac{\mathrm{Empt}_{t_0}^{(i,o)} \times \mathrm{Wage}_{t_0}^{(i,o)}}{\sum_{o\in \mathrm{OES}_{t_0}(i)} \mathrm{Empt}_{t_0}^{(i,o)} \times \mathrm{Wage}_{t_0}^{(i,o)}} \times \mathrm{Hour}_t^{(i,o)} \right) \\
&(3)\quad \mathrm{Hour}_t^{(i)} &&= \sum_{o\in \mathrm{OES}_T(i)} \left(\frac{\mathrm{Empt}_T^{(i,o)} \times \mathrm{Wage}_T^{(i,o)}}{\sum_{o\in \mathrm{OES}_T(i)} \mathrm{Empt}_T^{(i,o)} \times \mathrm{Wage}_T^{(i,o)}} \times \mathrm{Hour}_t^{(i,o)} \right) \\
&(4)\quad \mathrm{Hour}_t^{(i)} &&= \sum_{o\in \mathrm{OES}_{t-1}(i)} \left(\frac{\mathrm{Empt}_{t-1}^{(i,o)} \times \mathrm{Wage}_{t-1}^{(i,o)}}{\sum_{o\in \mathrm{OES}_{t-1}(i)} \mathrm{Empt}_{t-1}^{(i,o)} \times \mathrm{Wage}_{t-1}^{(i,o)}} \times \mathrm{Hour}_t^{(i,o)} \right) \quad t > t_0 \\
& && \sum_{o\in \mathrm{OES}_t(i)} \left(\frac{\mathrm{Empt}_t^{(i,o)} \times \mathrm{Wage}_t^{(i,o)}}{\sum_{o\in \mathrm{OES}_t(i)} \mathrm{Empt}_t^{(i,o)} \times \mathrm{Wage}_t^{(i,o)}} \times \mathrm{Hour}_t^{(i,o)} \right) \quad t = t_0
\end{aligned}
\tag{A.16}
$$

In Eq. (A.16), the first occupation composition in (1) specifies the set of occupations using contemporaneous information from OES, aggregating each industry-specific occupational hours by the associated marginal cost from the same period of time. The second occupation composition in (2) specifies the set of occupations and corresponding marginal cost weights using the information from the initial period in sample ($t_0 = 1997$); as a result, the second specification assumes a constant occupation composition across all years identical to that in

Table A.5. Indirect Validation Exercises on Alternative Occupation Weighting Schemes. NOTE: This table tabulates robust additional results for firm-level equity return predictability regressions. Specifically, I use alternative weighting schemes defined in Eq. (A.15) to construct my measure of hours and perform firm-level regressions using the corresponding measures of hours from alternative weighting schemes. Specifications of regressions here are identical to those in Eq. (4); the sample spans years from 1998 to 2017 annually.

		Marginal Cost-Based			Employment-Based			Wages-Based			Equal		
		(1) in Eq. (A.15)			(2) in Eq. (A.15)			(3) in Eq. (A.15)			(4) in Eq. (A.15)		
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Panel A	Without Pricing Factors $\boldsymbol{F}_{jt}$: $R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + b_K \times G^K_{jt}$											
(1)	b_H	−62.86	−61.11	−60.23	−71.68	−69.15	−68.27	−53.86	−51.37	−50.47	−66.00	−62.91	−62.13
	(se)	14.74	14.71	14.67	12.90	12.87	12.85	14.11	14.08	14.06	12.88	12.86	12.85
	[t]	−4.26	−4.15	−4.10	−5.56	−5.37	−5.31	−3.82	−3.65	−3.59	−5.13	−4.89	−4.84
(2)	b_N		−14.96	−11.23		−14.97	−11.74		−14.94	−11.20		−14.96	−11.73
	(se)		2.15	2.24		1.71	1.77		2.15	2.24		1.71	1.78
	[t]		−6.95	−5.02		−8.78	−6.62		−6.93	−5.00		−8.76	−6.60
(3)	b_K			−8.73			−7.90			−8.75			−7.93
	(se)			1.67			1.34			1.68			1.34
	[t]			−5.21			−5.91			−5.22			−5.92
(4)	# Obs.	23030	23030	23030	34686	34686	34686	23030	23030	23030	34686	34686	34686
	# Firms	4473	4473	4473	4978	4978	4978	4473	4473	4473	4978	4978	4978
	Within R^2	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01
	F-test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Panel B	With Pricing Factors $\boldsymbol{F}_{jt}$: $R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + b_K \times G^K_{jt} + \boldsymbol{b} \times \boldsymbol{F}_{jt}$											
(1)	b_H	−53.86	−54.00	−53.83	−44.45	−44.67	−44.52	−63.25	−63.25	−63.12	−56.46	−56.46	−56.35
	(se)	13.35	13.35	13.36	12.51	12.51	12.51	11.76	11.76	11.77	11.61	11.60	11.61
	[t]	−4.04	−4.05	−4.03	−3.55	−3.57	−3.56	−5.38	−5.38	−5.36	−4.86	−4.87	−4.85
(2)	b_N		1.52	2.69		1.54	2.72		−0.02	1.02		−0.01	1.03
	(se)		2.13	2.19		2.13	2.19		1.70	1.75		1.70	1.75
	[t]		0.71	1.23		0.72	1.24		−0.01	0.58		−0.01	0.59
(3)	b_K			−3.06			−3.08			−2.85			−2.86
	(se)			1.76			1.76			1.46			1.46
	[t]			−1.74			−1.76			−1.96			−1.97
(4)	# Obs.	23029	23029	23029	23029	23029	23029	34685	34685	34685	34685	34685	34685
	# Firms	4473	4473	4473	4473	4473	4473	4978	4978	4978	4978	4978	4978
	Within R^2	0.13	0.13	0.13	0.13	0.13	0.13	0.11	0.11	0.11	0.11	0.11	0.11
	F-test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

the first year. On the contrary, the third specification in (3) uses the occupation composition from the last period ($T = 2017$) across all year. The last occupation composition in (4) aggregates the industry-specific occupational hours using the previous period information, except for the initial period.

The indirect validation of my measure of hours first construct the three alternative occupation compositions implied measures of hours and implement the same firm-level equity return predictability regressions in Eq. (4). In Table A.6, I place results using the contemporaneous (current-year) occupation compositions (the original results in Table 1) in columns [1] to [3], and those from the three alternative occupation composition specifications in columns [4] to [12]. Comparing the point estimates of coefficient b_H, the negative slopes are all significant, suggesting the negative association between the firm's current hours growth and its future equity return is robust to alternative occupation compositions used to aggregate industry-specific occupational hours. Furthermore, the estimated negative slopes are extremely stable across all occupation composition specifications, suggesting the occupations exhibit rigidity within a given industry. (some lit discussion TBA)

Representative Firms in Industries In the final part of indirect validation, I focus on the third step in Eqs. (2) and (A.10). The third step approximates the a firm's labor input choice of hour margin using its industrial average. This approximation is likely to bias the estimated impact from hours growth downwards and hence the negative slope provides a conservative lower bound. I further test this approximation and perform indirect validation exercise. To do this, I aggregate all firms within one industry, at which level the hours are calculated, and form industrial representative firms, the hours, employment, and capital growth of which are computed in the same way as before.

The indirect validation uses the same equity return predictability regressions in Eq. (4)

at the industry level; in particular, for industry i, the regressions take the following form

$$R_{i,t+1} = a_0 + a_i + a_{t+1} + b_H \times G_{it}^H + b_N \times G_{it}^N + b_K \times G_{it}^K + \boldsymbol{b} \times \boldsymbol{F}_{it}. \tag{A.17}$$

Results from these industry-level equity return predictability regressions are presented in Table A.7, from which the negative association between the current hours growth and future equity return is not changed.

A.1.2.c Direct Validation

Micro Coverage The first way of direct validation is to show that the measure of hours correctly identifies a large portion of firm-year observations in the entire sample.

I interpret "correct identification" in three folds. First, my measure of hours produces a reasonable comprehensive coverage of all observations; second, the matched observations are not skewed towards certain periods in time (for example, recessions) nor towards certain industries[A.12] (e.g., Bretscher [2019] finds industries with low potential to offshore production earn higher equity returns and such risk premium is concentrated in manufacturing industries.). The skewness in time/industry domains will not alter the conclusions reached but rather limit the scope of applicability of the conclusions.

Fig. A.3 visualizes the aforementioned three goals. The left panel (A) shows the micro coverage by year and the right panel shows by SIC 500-bins. Of both panels, to understand the magnitudes of sample size, I tabulate the number of sample observations (by year/SIC) as vertical bars on the left vertical axis. On the right vertical axis, I scatter the corresponding fraction of matched sample observations (by year/SIC) as circles. In both panels the dashed horizontal line indicates the matched fraction of the entire sample is as high as 71 percents.

Given that about three fourths of the sample observations are matched, my measure of

[A.12] An emerging strand of literature seeks to understand the declining number of U.S. (public) firms (e.g., Doidge et al. [2017]; Grullon et al. [2015]; Decker et al. [2014, 2016]) by looking at industry cross-sections.

Table A.6. Indirect Validation Exercises on Alternative Occupation Composition Specifications. Note: This table tabulates robust additional results for firm-level equity return predictability regressions. Specifically, I use alternative occupation composition defined in Eq. (A.16) to construct my measure of hours and perform firm-level regressions using the corresponding measures of hours from alternative occupation compositions. Specifications of regressions here are identical to those in Eq. (4); the sample spans years from 1998 to 2017 annually.

		Current-Year Composition			Starting-Year Composition			End-Year Composition			Previous-Year Composition		
		(1) in Eq. (A.16)			(2) in Eq. (A.16)			(3) in Eq. (A.16)			(4) in Eq. (A.16)		
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Panel A	Without Pricing Factors $\boldsymbol{F}_{jt}$: $R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + b_K \times G^K_{jt}$											
(1)	b_H	−62.86	−61.11	−60.23	−62.18	−60.12	−59.39	−67.85	−66.01	−65.57	−64.87	−62.60	−61.69
	(se)	14.74	14.71	14.67	13.69	13.66	13.64	14.45	14.42	14.38	14.46	14.43	14.39
	[t]	−4.26	−4.15	−4.10	−4.54	−4.40	−4.36	−4.69	−4.58	−4.56	−4.49	−4.34	−4.29
(2)	b_N		−14.96	−11.23		−15.09	−11.66		−15.85	−12.00		−15.32	−11.37
	(se)		2.15	2.24		1.97	2.07		2.24	2.31		2.18	2.27
	[t]		−6.95	−5.02		−7.65	−5.65		−7.09	−5.19		−7.03	−5.02
(3)	b_K			−8.73			−8.18			−8.88			−9.17
	(se)			1.67			1.59			1.73			1.82
	[t]			−5.21			−5.16			−5.14			−5.04
(4)	# Obs.	23030	23030	23030	27275	27275	27275	23296	23296	23296	23934	23934	23934
	# Firms	4473	4473	4473	4578	4578	4578	4493	4493	4493	4462	4462	4462
	Within R^2	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01
	F-test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Panel B	With Pricing Factors $\boldsymbol{F}_{jt}$: $R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + b_K \times G^K_{jt} + \boldsymbol{b} \times \boldsymbol{F}_{jt}$											
(1)	b_H	−53.86	−54.00	−53.83	−55.59	−55.67	−55.61	−56.86	−56.85	−56.85	−58.38	−58.50	−58.35
	(se)	13.35	13.35	13.36	12.47	12.47	12.47	13.14	13.15	13.15	13.16	13.16	13.17
	[t]	−4.04	−4.05	−4.03	−4.46	−4.47	−4.46	−4.33	−4.32	−4.32	−4.44	−4.44	−4.43
(2)	b_N		1.52	2.69		0.69	1.80		−0.15	1.29		0.93	2.43
	(se)		2.13	2.19		1.93	2.00		2.16	2.22		2.12	2.20
	[t]		0.71	1.23		0.36	0.90		−0.07	0.58		0.44	1.10
(3)	b_K			−3.06			−2.97			−3.65			−3.88
	(se)			1.76			1.70			1.78			1.98
	[t]			−1.74			−1.74			−2.05			−1.95
(4)	# Obs.	23029	23029	23029	27274	27274	27274	23295	23295	23295	23933	23933	23933
	# Firms	4473	4473	4473	4578	4578	4578	4493	4493	4493	4462	4462	4462
	Within R^2	0.13	0.13	0.13	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12	0.12
	F-test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

hours produces a fairly good micro coverage of U.S. publicly listed firms. Moreover, the matched fractions of observations (by year/SIC) are roughly uniformly distributed over the corresponding time and industry domains, indicating that my main empirical findings are not specific to certain episodes or industries.

Macro Magnitude I find my measure of hours varies intuitively across sectors and over time. To concretize this observation, in the second way of validation, I aggregate my measure of hours at the firm-level and calculate the implied aggregate measure of hours at each cross-section. The resulting time-series of aggregated firm-level hours correctly identifies the recent financial crisis episode in both its peak and its trough. Furthermore, I compare the aggregated firm-level hours to the national average hours published by BLS/Current Employment Statistics (CES) program dataset, and find the two series exhibiting remarkable similarities in the pattern, especially around the recent episode of the 2007-09 financial crisis. Fig. A.4 visualizes the comparison.

The BLS/CES program conducts monthly surveys based on establishment-level payroll records, and hence the BLS/CES dataset is by construction orthogonal to the three micro-level datasets used in my measure of hours. In Fig. A.4, I plot the aggregated firm-level weekly hours on the left vertical axis, and the national average weekly hours from BLS/CES dataset on the right vertical axis. The aggregated firm-level weekly hours is annual whereas the BLS/CES national average weekly hours is monthly. To facilitate a better comparison, I intensify the aggregated firm-level weekly hours to monthly frequency by assigning the same values to months within the same year (backward-filling). The resulting monthly aggregated firm-level weekly hours thus has horizontal bars for a given year. The aggregated firm-level hours captures reasonably well both the timing and the magnitude, of both the fall before and the rise after the financial crisis in 2009. I regard the similarity of time-series pattern, especially around the recent recession periods, supportive of the empirical plausibility in

Table A.7. Indirect Validation Exercises With Industry Representative Firms. NOTE: This table tabulates industry-level equity return predictability regressions in the form of Eq. (A.17). Results here are obtained by aggregating firms to form industry representative firms, where the industries are defined by SIC three-digit codes. Each column in each panel runs one industry-level equity return predictability regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using panel OLS with industry standard error clusters; the sample spans years from 1998 to 2017 annually.

		Hours & Employment Growth Only			Add DHS Investment Ratio			Add Simple Investment Ratio		
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Panel A	Without Pricing Factors $\boldsymbol{F}_{it}$									
(1)	b_H	-0.34^{**}		-0.35^{**}	-0.34^{**}		-0.33^{**}	-0.33^{**}		-0.34^{**}
	(se)	(0.14)		(0.14)	(0.14)		(0.14)	(0.15)		(0.15)
	[t]	[−2.45]		[−2.42]	[−2.43]		[−2.37]	[−2.25]		[−2.32]
(2)	b_N		−0.03	−0.00		−0.03	0.00		−0.03	−0.02
	(se)		(0.02)	(0.03)		(0.02)	(0.03)		(0.02)	(0.04)
	[t]		[−1.57]	[−0.12]		[−1.27]	[0.07]		[−1.17]	[−0.55]
(3)	b_K				−0.05	-0.02^{*}	−0.05	0.04^{**}	0.01	0.05^{**}
	(se)				(0.03)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
	[t]				[−1.57]	[−1.68]	[−1.58]	[2.32]	[0.95]	[2.37]
(4)	# Observation	2306	4380	2291	2281	4368	2281	2290	4135	2290
	# Industry	224	257	223	223	257	223	223	255	223
	$\bar{R}^2$	0.18	0.21	0.19	0.19	0.21	0.19	0.19	0.22	0.19
	p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B	With Pricing Factors $\boldsymbol{F}_{it}$									
(1)	b_H	-0.32^{**}		-0.31^{**}	-0.31^{**}		-0.30^{**}	-0.29^{**}		-0.30^{**}
	(se)	(0.13)		(0.14)	(0.13)		(0.14)	(0.14)		(0.14)
	[t]	[−2.37]		[−2.24]	[−2.34]		[−2.22]	[−2.09]		[−2.11]
(2)	b_N		−0.02	0.01		−0.02	0.01		−0.02	−0.01
	(se)		(0.02)	(0.03)		(0.02)	(0.03)		(0.02)	(0.03)
	[t]		[−1.21]	[0.32]		[−1.08]	[0.39]		[−0.88]	[−0.20]
(3)	b_K				−0.02	−0.01	−0.02	0.06^{***}	0.02	0.06^{***}
	(se)				(0.03)	(0.01)	(0.03)	(0.02)	(0.02)	(0.02)
	[t]				[−0.60]	[−0.77]	[−0.68]	[3.17]	[1.33]	[3.13]
(4)	# Observation	2295	4367	2280	2280	4367	2280	2279	4124	2279
	# Industry	224	257	223	223	257	223	223	255	223
	$\bar{R}^2$	0.21	0.23	0.21	0.21	0.23	0.21	0.22	0.23	0.22
	p-val	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

my measure of hours[A.13].

A.2 Empirical Evidence

In this section, I show the robustness of my main empirical findings that (1) firms with higher hours growth are associated with lower equity return in the equilibrium, and (2) such association is not derived nor subsumed by employment, capital, and other firm-level variables known to predict equity return. The robustness is shown via two general approaches, the regression approach and the portfolio approach, as in 3.1 and 3.2, respectively.

A.2.1 Firm-Level Equity Return Predictability Regressions

The firm-level results are represented by firm-level equity return predictability regressions. What the firm-level equity return predictability demonstrate are (1) firms with higher hours growth are associated with lower equity return in the equilibrium, and (2) such association is not derived nor subsumed by employment, capital, and other firm-level variables known to predict equity return.. At the firm-level, I use the equity return predictability regressions to evidence such negative association, in the format of Eq. (4), reproduced as follows.

$$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + b_K \times G^K_{jt} + \boldsymbol{b} \times \boldsymbol{F}_{jt} + e_{j,t+1}. \qquad \text{(A.18)}$$

In this specification, on the left-hand side, $R_{j,t+1}$ is the firm j's future annual equity return, calculated from July of year $t+1$ to June of year $t+2$. On the right-hand side, a_0, a_j, a_{t+1} are respectively the constant, the firm fixed effect, and the year fixed effect. The key variables are the firm j's current annual growth rates (G) of three production input choices, hours (H), employment (N), and capital (K), measured from January of year t to December of

[A.13]It is interesting that the different in levels is about exactly six hours. I view the difference in levels of the two series originating from the sources of the datasets. More specifically, the raw dataset of hours, BLS/CPS, conducts person-level surveys and measures both the weekly straighttime and the weekly overtime, whereas the BLS/CES conducts plant-level surveys and measures the weekly straighttime in all industries but the weekly overtime only in manufacturing industry. Therefore, my proposed explanation of the difference in levels are that (1) the supply-demand survey biases and (2) the lack of overtime measurement in BLS/CES series. The investigation of the difference provides an interesting topic to explore.

Figure A.3. Observations Matched By Year (1997-2017) and SIC (500-Bins). Note: The left vertical axis scales the number of observations by year (left panel) or by SIC (right panel); the right vertical axis measures the fraction of matched observations in percentages. Overall, my measure of hours landed 71% of observations in the dataset of public firms from 1997 to 2017.

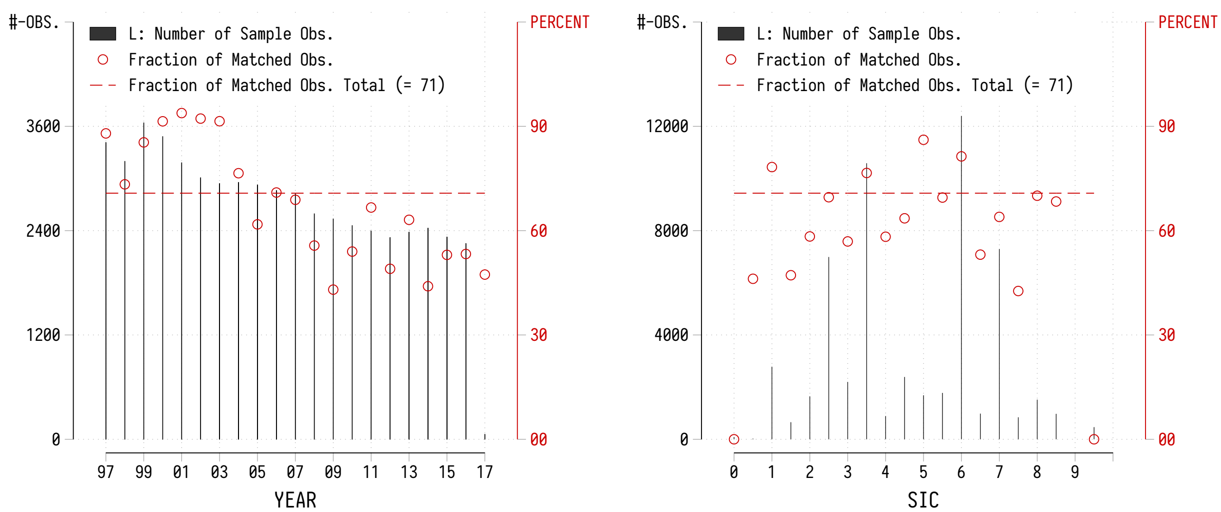


Figure A.4. Compare Aggregated Firm-Level Hours to National Average Hours. Note: The firm-level measure of hours is annual. To facilitate a better comparison, I intensify the aggregated firm-level weekly hours to monthly by assigning the end-of-year annual value to all months within the year (backward-filling). This explains the horizontal bars in the aggregated firm-level weekly hours.

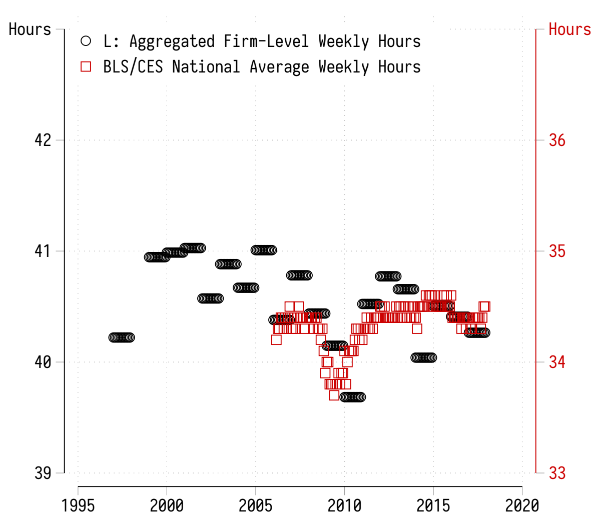
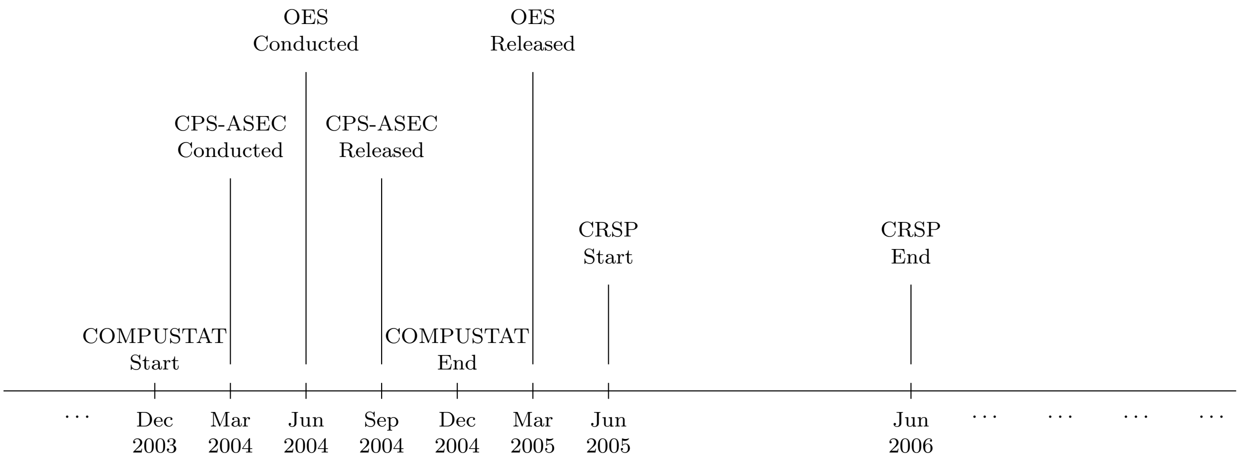


Figure A.5. Information Formation in Firm-Level Equity Return Predictability Regressions. NOTE: This figure shows that the information set formation in equity return predictability regression. I use actual year to illustrate. The financial report data (10K) contained in COMPUStat are measured from January of year t (=2004) to December of year t (=2004). The hours construction starts from CPS-ASEC, which is conducted from March of year t (=2004) to September of year t (=2004). The involved OES is conducted from June of year t (=2004) to March of year $t+1$ (=2005). The resulting measure of hours is then merged to financial report data and together are matched to equity return data contained in CRSP from July of year $t+1$ (=2005) to June of year $t+2$ (=2006).



year t. Additionally on the right-hand side, $\boldsymbol{F}$ is a vector of five pricing factors.

It is important to show that the equity return predictability regressions show indeed predictability; that is, the information formation to construct the right-hand side variables is before in calendar time the information formation to construct the right-hand side variable. In Fig. A.5, I show the information formation sequence in equity return predictability regressions. The right-hand side variables are constructed three-month before the right-hand side equity return in the future.

I use this section to show the robustness of equity return predictability in four dimensions. In particular, I vary the right-hand side independent variables in two ways: I change the definition of key variables regrading the hours, employment, and capital growth, and include additional leading pricing factors know to predict asset prices at the firm-level. Second, I alter the regressions with different fixed effects and standard error clusters specifications; the purpose of this variation is to make contact with existing studies, which may have different different fixed effects and standard error clusters specifications. Third, I define differently the outliers with regards to hours, employment, and capital growth in the cross-section, and change the way to mitigate unwanted influence from such outliers. Fourth, I also implement the firm-level equity return predictability regressions with Fama-MacBeth procedure.

A.2.1.a Independent Variables On one hand, as is outlined in Eqs. (A.12) and (A.13), Eqs. (A.2) and (A.3), and Eqs. (A.4) to (A.7), there are a total of two hours growth, two employment growth, four capital growth (two net and two gross). I show in Table A.1 that the negative equity return predictability of hours growth is robust. The coefficient estimates of b_H in Eq. (A.18) across all specifications Table A.1 are statistically significant, uniformly at least four-standard deviation away from zero, and stable at around 60 to 70, indicating that a 1% increase in hours is associated with about 0.6% to 0.7% decrease in future equity return. Equally important, this coefficient estimates also show little evidence that the negative association between current hours and equity return is derived from current employment nor capital.

On the other, I also include a vector of five firm-level variables in the form of pricing factors which are known to predict equity return by literature; the five pricing factors measured at the firm-level are the market capitalization (size) and book-to-market ratio (Fama & French [1992, 1993]), the investment-to-assets and return-on-equity (Hou et al. [2015]), and the profitability (Novy-Marx [2013]). Including these factors in regressions provides investigations whether the equity return predictability of hours growth is subsumed by leading firm-level variables. The results here are thus indicative of whether the hours is a primitive decision at the firm-level and, if not, informative about what other choices are.

Table A.8 tabulates results of firm-level equity return predictability regressions with pricing factors. Reading horizontally, the columns [1] to [5] sequentially adds the pricing factors, and the column [6] run regressions with all pricing factors together. Across panels, the right-hand side specifications of hours, employment, and/or capital growth are different. Panel A includes hours growth, panel B additionally employment growth, and panel C additionally capital growth (investment ratio).

It is straightforward to see that the negative association between current hours and equity return is not subsumed by pricing factors. The coefficient estimates of b_H across all specifications in Table A.8 are statistically significant, uniformly at least four-standard deviation away from zero, and stable at around 50 to 60, indicating that a 1% increase in hours is associated with about 0.5% to 0.6% decrease in future equity return. It is also intuitive that, the other two significant independent variables are the size factor and the profitability factor. The size factor introduces information about the scale of production on which the firm operates; since hours, employment, and capital growth does not vary substantially across firms of different sizes, the introduction of size factor provides additionally key information and hence is informative about equity return in the intertemporal. The profitability factor is also significant controlling valuation ratios (column [6]). Profitable firms generate significantly higher equity returns than unprofitable ones. As is argued by İmrohoroğlu & Tüzel [2014], the profitability is tightly and positively correlated with the firm-level productivity; therefore, the profitability factor also provides additionally information information that is not captured by the hours, employment, and/or capital growth.

A.2.1.b Fixed Effects and Standard Error Clusters In firm-level equity return predictability regressions of Eq. (A.18), I include the firm- and year-fixed effects, and firm standard error clusters. In this section, I test whether the fixed effects or the standard error clusters specification play any key role in equity return predictability of hours growth.

Specifically, of Table A.9, in panel A, the year fixed effects are removed; panel B removes the firm fixed effects; panel C removes the firm-level standard error clusters. Without year fixed effects, the coefficient estimates of b_H is around 20 to 30, indicating that a 1% increase in hours is associated with about 0.2% to 0.3% decrease in future equity return. Note that, without year fixed effects, such negative equity return predictability revealed is not only a cross-sectional pattern across firm conditional on aggregate economy conditions but also a

Table A.8. Firm-Level Equity Return Predictability Regressions With Pricing Factors. NOTE: This table tabulates detailed results on asset pricing factor in firm-level equity return predictability regressions in the form of Eq. (A.18). Specifically, $\boldsymbol{F}_{jt}$ is a vector of five pricing factors measured at the firm-level, namely, the market capitalization (size) and book-to-market ratio, the investment-to-assets and return-on-equity, and the profitability. Reading vertically, panels differ only in specifications of hours, emplpoyment and capital growth on the right-hand side. Each column in each panel runs one firm-level equity return predictability regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using panel OLS with firm standard error clusters; the sample spans years from 1998 to 2017 annually.

		[1]	[2]	[3]	[4]	[5]	[6]
Panel A:	LHS = Future Equity Return; RHS = Hours Growth + Pricing Factors						
	Hours Growth	−57.68***	−64.90***	−62.35***	−68.74***	−68.61***	−52.89***
		(11.82)	(12.59)	(13.16)	(13.04)	(13.00)	(11.88)
	Log Market Capitalization	−39.39***					−41.09***
		(1.53)					(1.91)
	Log Book-to-Market Ratio		22.59***				−0.48
			(1.36)				(1.52)
	Investment-to-Asset Ratio			−37.95**			−15.25
				(14.73)			(13.94)
	Return on Equity				−0.00***		−0.00***
					(0.00)		(0.00)
	Gross Profitability					2.87	15.34***
						(5.41)	(5.51)
Panel B:	LHS = Future Equity Return; RHS = Hours & Employment Growth + Pricing Factors						
	Hours Growth	−57.78***	−63.77***	−60.78***	−67.17***	−67.01***	−53.08***
		(11.83)	(12.58)	(13.14)	(13.01)	(12.98)	(11.89)
	Employment Growth	2.17	−16.52***	−20.66***	−21.22***	−21.26***	3.32
		(2.40)	(2.42)	(2.59)	(2.43)	(2.42)	(2.56)
	Log Market Capitalization	−39.57***					−41.42***
		(1.56)					(1.96)
	Log Book-to-Market Ratio		22.05***				−0.59
			(1.36)				(1.53)
	Investment-to-Asset Ratio			−29.46**			−16.47
				(14.66)			(14.05)
	Return on Equity				−0.00***		−0.00***
					(0.00)		(0.00)
	Gross Profitability					3.40	15.31***
						(5.46)	(5.50)
Panel C:	LHS = Future Equity Return; RHS = Hours & Employment & Capital Growth + Pricing Factors						
	Hours Growth	−53.11***	−56.64***	−59.21***	−59.16***	−59.00***	−52.51***
		(11.95)	(12.67)	(13.12)	(13.12)	(13.08)	(11.90)
	Employment Growth	4.92*	−12.04***	−16.00***	−16.27***	−16.31***	4.99*
		(2.62)	(2.65)	(2.67)	(2.68)	(2.67)	(2.61)
	Capital Growth (Investment Ratio)	−9.46***	−20.80***	−24.59***	−21.73***	−21.71***	−9.79***
		(2.92)	(3.05)	(3.51)	(3.05)	(3.04)	(3.32)
	Log Market Capitalization	−40.58***					−41.04***
		(1.63)					(1.97)
	Log Book-to-Market Ratio		22.44***				−0.38
			(1.41)				(1.53)
	Investment-to-Asset Ratio			23.64			4.61
				(16.61)			(16.13)
	Return on Equity				−0.00***		−0.00***
					(0.00)		(0.00)
	Gross Profitability					3.49	15.21***
						(5.45)	(5.49)
Observations		22644	22644	22645	22645	22645	22644
Firms		4393	4393	4394	4394	4394	4393

stronger time-series pattern independent of aggregate economy conditions. Without firm-fixed effects, the coefficient estimates of b_H is around 50, indicating that a 1% increase in hours is associated with about 0.5% decrease in future equity return. This is a stronger impact of hours growth on equity return, because it shows that, irrespective of firm-level idiosyncracy, the hours remains a primitive firm-level decisions in the intertemporal. Removing firm standard error clusters also does not change the coefficient estimates of b_H. Overall the fixed effects and standard error clusters specifications have little impact on the negative association between current hours and equity return.

A.2.1.c Outliers Due to measurement errors, outliers can have a unwanted but substantial impacts on firm-level regression estimates. Additionally, previous studies have implemented different definitions of outliers as well as different approaches to deal with unwanted effects from outliers[A.14]. In Table A.10, panel A defines outliers as observations with employment and capital growth outside of cross-sectional $[0.5, 99.5]$ percentiles, the same as in the baseline results in Table 1, but instead of winsorizing, and uses truncation to handle outliers; panel B winsorizes outliers but defines outliers more aggressively from $[0.5, 99.5]$ to $[1, 99]$ at each cross-section.; finally, panel C winsorizes outliers defined only by the DHS investment ratio, same as Belo et al. [2014a]. Results show that definitions of and approaches to deal with outliers have little impact on the negative association between current hours and equity return at the firm-level.

A.2.1.d Regression Method Table A.11 uses Fama-MacBeth method (Fama & MacBeth [1973]), instead of OLS, to perform estimation slopes $b_{H,N,K}$ in Eq. (A.18). Results show, with control of firm scale, the (logarithm of) market capitalization, the coefficient estimates of b_H is around 80 to 90, indicating that a 1% increase in hours is associated with about 0.8% to 0.9% decrease in future equity return.

[A.14]For example, Novy-Marx [2013] defines outliers as observations outside of the cross-sectional 1- and 99-percentiles; Belo et al. [2014a] defines outliers as observations outside of the cross-sectional 0.5- and 99.5-percentiles.

Table A.9. Firm-Level Equity Return Predictability Regressions With Different Fixed Effect and Standard Error Cluster Specifications. Note: This table tabulates additional results of firm-level equity return predictability regressions in the form of Eq. (A.18). Results here differs from those in Table 1 in specification of fixed effects and standard error clusters. Specifically, regressions in Table 1 have year fixed effects, firm fixed effects, and firm standard error clusters. On the other hand, in panel A, regressions has no year fixed effects; there are no firm fixed effects in regressions in panel B; in panel C, I do not include firm standard error clusters. Each column in each panel runs one firm-level equity return predictability regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using panel OLS; the sample spans years from 1998 to 2017 annually.

		Without Pricing Factors						Including Pricing Factors					
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Panel A	No Year Fixed Effects											
(1)	b_H	−30.82		−26.87	−26.47		−24.73	−32.76		−32.27	−31.70		−31.74
	(se)	11.10		11.10	11.04		11.05	10.19		10.19	10.19		10.18
	[t]	−2.78		−2.42	−2.40		−2.24	−3.21		−3.17	−3.11		−3.12
(2)	b_N		−16.36	−16.48		−12.72	−11.82		−4.94	−2.23		−2.85	0.25
	(se)		1.36	1.91		1.40	2.00		1.33	1.85		1.38	1.93
	[t]		−12.08	−8.62		−9.07	−5.92		−3.70	−1.20		−2.07	0.13
(3)	b_K				−13.41	−8.11	−10.05				−5.94	−5.28	−6.02
	(se)				1.45	1.15	1.54				1.59	1.24	1.64
	[t]				−9.22	−7.07	−6.52				−3.73	−4.27	−3.68
(4)	# Obs.	23030	42063	23030	23030	42063	23030	23029	42062	23029	23029	42062	23029
	# Firms	4473	5824	4473	4473	5824	4473	4473	5824	4473	4473	5824	4473
	Within R^2	0.01	0.00	0.01	0.01	0.01	0.01	0.13	0.10	0.13	0.13	0.11	0.13
	F-Test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Panel B	No Firm Fixed Effects											
(1)	b_H	−55.36		−54.03	−54.03		−53.45	−54.32		−53.43	−53.39		−53.01
	(se)	12.60		12.57	12.57		12.56	12.49		12.47	12.47		12.46
	[t]	−4.39		−4.30	−4.30		−4.26	−4.35		−4.29	−4.28		−4.26
(2)	b_N		−10.55	−10.28		−8.78	−7.54		−8.98	−8.15		−7.14	−5.21
	(se)		1.08	1.48		1.17	1.59		1.08	1.51		1.16	1.60
	[t]		−9.78	−6.93		−7.51	−4.75		−8.32	−5.40		−6.13	−3.26
(3)	b_K				−7.20	−3.36	−5.07				−7.26	−3.76	−5.79
	(se)				0.99	0.82	1.07				1.05	0.85	1.11
	[t]				−7.26	−4.10	−4.74				−6.92	−4.40	−5.19
(4)	# Obs.	23030	42063	23030	23030	42063	23030	23029	42062	23029	23029	42062	23029
	# Firms	4473	5824	4473	4473	5824	4473	4473	5824	4473	4473	5824	4473
	Within R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.01
	F-Test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Panel C	No Firm Standard Error Clusters											
(1)	b_H	−62.86		−61.11	−61.09		−60.23	−53.86		−54.00	−53.65		−53.83
	(se)	13.05		13.04	13.03		13.03	12.15		12.15	12.15		12.15
	[t]	−4.82		−4.69	−4.69		−4.62	−4.43		−4.44	−4.41		−4.43
(2)	b_N		−13.93	−14.96		−11.06	−11.23		−0.34	1.52		0.70	2.69
	(se)		1.38	2.04		1.40	2.08		1.31	1.93		1.34	1.98
	[t]		−10.08	−7.35		−7.91	−5.39		−0.26	0.79		0.53	1.36
(3)	b_K				−11.68	−6.92	−8.73				−2.33	−2.81	−3.06
	(se)				1.56	1.18	1.61				1.62	1.25	1.66
	[t]				−7.47	−5.88	−5.41				−1.43	−2.24	−1.85
(4)	# Obs.	23030	42063	23030	23030	42063	23030	23029	42062	23029	23029	42062	23029
	# Firms	4473	5824	4473	4473	5824	4473	4473	5824	4473	4473	5824	4473
	Within R^2	0.00	0.00	0.01	0.01	0.01	0.01	0.13	0.10	0.13	0.13	0.10	0.13
	F-Test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

A.2.2 Portfolio Approach

This section deploys the portfolio approach to crosscheck my main empirical findings. In summary, firms with high hours growth are associated with low equilibrium equity return. There are two points made in this empirical evidence argument. First, I show that current high hours growth predict low equity return in the future. Second, such negative equity return predictability of hours growth is not derived from employment growth nor subsumed by leading pricing factors known to predict equity return.

With portfolio approach, I show my main empirical findings via two parts. First, I show portfolios sorted by cross-sectional hours growth yield monotonically equity returns, which is demonstrated in Table 2. Second, I show such negative association between current hours growth and future equity return is not derived by employment growth. To do so, I form portfolios sorted firstly by cross-sectional employment growth and secondly by cross-sectional hours growth; such bivariate portfolios demonstrate again sizable equity return spreads along the dimension of hours growth. Third, I show the negative associate cannot be subsumed by leading factors.

A.2.2.a Bivariate Portfolios The bivariate portfolios are constructed as follow. For independent sorting algorithm, firms are sorted by cross-sectional hours growth and cross-sectional employment growth; then the bivariate portfolio assignments are simply the quintile portfolio assignments of each dimension.

To show that the negative association between current hours growth and future equity return is not derived by current employment growth. I further implement a sequential sorting algorithm. Specifically, at the end of year t, each firm's annual hours and employment growth are both measured from January of year t to December of year t. Next, the cross-section of firms are sorted firstly into five portfolios based on respective annual employment growth, where the breakpoints for the portfolios are essentially the quintiles from the cross-sectional distribution of the employment growth. Then within each portfolio sorted by

Table A.10. Firm-Level Equity Return Predictability Regressions With Different Outlier Definitions and Winsorization/Truncation Choices. NOTE: This table tabulates additional results of firm-level equity return predictability regressions in the form of Eq. (A.18). Results here differs from those in Table 1 in how the outliers are defined and handled. Specifically, outliers in Table 1 are observations with G^N or G^K outside of $[0.5, 99.5]$ and are winsorized in regressions. On the other hand, in panel A, outliers are observations with G^N or G^K outside of $[0.5, 99.5]$ but are truncated in regressions; in panel B, outliers are more aggressively defined as observations with G^N or G^K outside of $[1, 99]$ and are winsorized in regressions; in panel C, outliers are just observations with G^K outside of $[0.5, 99.5]$, same as Belo et al. [2014a], and are winsorized in regressions. Each column in each panel runs one firm-level equity return predictability regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using panel OLS with firm standard error clusters; the sample spans years from 1998 to 2017 annually.

		Without Pricing Factors						Including Pricing Factors					
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Panel A	Outliers: Truncation of Both G^N and G^K outside of $[0.5, 99.5]$											
(1)	b_H	−64.79		−62.54	−61.67		−60.81	−55.67		−55.80	−55.03		−55.26
	(se)	15.02		14.98	14.97		14.95	13.62		13.62	13.64		13.63
	[t]	−4.31		−4.18	−4.12		−4.07	−4.09		−4.10	−4.04		−4.05
(2)	b_N		−18.14	−19.23		−14.46	−13.50		−0.88	1.43		0.59	4.05
	(se)		1.84	2.76		1.94	2.95		1.81	2.66		1.88	2.82
	[t]		−9.83	−6.96		−7.47	−4.57		−0.48	0.54		0.32	1.43
(3)	b_K				−16.41	−8.56	−12.64				−5.32	−3.87	−6.50
	(se)				2.12	1.52	2.28				2.23	1.60	2.36
	[t]				−7.76	−5.63	−5.55				−2.39	−2.42	−2.76
(4)	# Obs.	22605	41290	22605	22605	41290	22605	22604	41289	22604	22604	41289	22604
	# Firms	4436	5782	4436	4436	5782	4436	4436	5782	4436	4436	5782	4436
	Within R^2	0.00	0.00	0.01	0.01	0.01	0.01	0.13	0.10	0.13	0.13	0.10	0.13
	F-Test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Panel B	Outliers: Winsorization of Both G^N and G^K outside of $[1, 99]$											
(1)	b_H	−65.83		−66.70	−60.64		−60.16	−49.77		−53.95	−53.61		−53.78
	(se)	13.74		14.32	14.52		14.51	12.72		13.22	13.21		13.22
	[t]	−4.79		−4.66	−4.18		−4.15	−3.91		−4.08	−4.06		−4.07
(2)	b_N		−9.58	−9.95		−7.95	−6.72		−0.10	1.66		0.20	2.61
	(se)		1.13	1.74		1.24	1.98		1.11	1.65		1.15	1.75
	[t]		−8.44	−5.73		−6.40	−3.40		−0.09	1.01		0.17	1.49
(3)	b_K				−8.63	−3.76	−6.72				−1.55	−0.76	−2.31
	(se)				1.39	1.03	1.51				1.32	1.00	1.40
	[t]				−6.20	−3.67	−4.45				−1.17	−0.76	−1.65
(4)	# Obs.	27729	45308	25741	23464	42848	23464	24914	42847	23463	23463	42847	23463
	# Firms	5074	6050	4685	4508	5865	4508	4847	5865	4508	4508	5865	4508
	Within R^2	0.00	0.00	0.01	0.01	0.00	0.01	0.13	0.10	0.13	0.13	0.10	0.13
	F-Test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Panel C	Outliers: Winsorization of Only G^K outside of $[0.5, 99.5]$											
(1)	b_H	−63.47		−62.99	−61.67		−61.42	−54.31		−54.46	−54.14		−54.30
	(se)	14.71		14.69	14.65		14.64	13.34		13.35	13.35		13.36
	[t]	−4.31		−4.29	−4.21		−4.19	−4.07		−4.08	−4.06		−4.06
(2)	b_N		−1.27	−1.13		−0.91	−0.68		−0.05	0.37		0.03	0.44
	(se)		0.39	0.59		0.31	0.45		0.24	0.34		0.23	0.33
	[t]		−3.26	−1.89		−2.96	−1.51		−0.19	1.10		0.14	1.32
(3)	b_K				−11.08	−9.00	−10.82				−1.57	−2.18	−1.75
	(se)				1.61	1.17	1.61				1.78	1.28	1.77
	[t]				−6.89	−7.72	−6.72				−0.88	−1.71	−0.99
(4)	# Obs.	23241	42431	23241	23241	42431	23241	23240	42430	23240	23240	42430	23240
	# Firms	4493	5847	4493	4493	5847	4493	4493	5847	4493	4493	5847	4493
	Within R^2	0.00	0.00	0.00	0.01	0.00	0.01	0.13	0.10	0.13	0.13	0.10	0.13
	F-Test p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A.11. Firm-Level Equity Return Predictability Regressions Using Fama-MacBeth Method. NOTE: This table tabulates additional results of firm-level equity return predictability regressions in the form of Eq. (A.18). Results here differs from those in Table 1 in that the regressions here are implemented by Fama-MacBeth method (Fama & MacBeth [1973]), whereas regressions in Table 1 are implemented using panel OLS with firm standard error clusters. Each column in each panel runs one firm-level equity return predictability regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis; the sample spans years from 1998 to 2017 annually.

		[1]	[2]	[3]	[4]	[5]	[6]
Panel A:	LHS = Future Equity Return; RHS = Hours Growth + Pricing Factors						
	Hours Growth	−68.58*	−89.63*	−46.47	−70.51*	−64.47	−91.25**
		(37.09)	(43.82)	(34.66)	(37.48)	(37.76)	(39.46)
	Log Market Capitalization	−2.37**					−2.27
		(1.06)					(1.31)
	Log Book-to-Market Ratio		7.12				1.14
			(4.18)				(2.61)
	Investment-to-Asset Ratio			−0.36			20.31
				(16.51)			(24.78)
	Return on Equity				−7.08		−7.78
					(8.57)		(8.30)
	Gross Profitability					−8.19	−13.98
						(16.32)	(24.87)
	Observations	24823	24823	22645	24824	24824	22644
	Firms	4566	4566	4394	4567	4567	4393
Panel B:	LHS = Future Equity Return; RHS = Hours & Employment Growth + Pricing Factors						
	Hours Growth	−62.57	−83.88*	−34.21	−64.78*	−59.99	−77.49**
		(36.44)	(41.86)	(40.91)	(37.02)	(37.56)	(35.33)
	Employment Growth	−13.03*	−9.90*	−17.66*	−19.76	−11.60**	−15.68
		(7.37)	(4.72)	(10.06)	(11.96)	(4.71)	(10.54)
	Log Market Capitalization	−2.25**					−2.17
		(1.04)					(1.29)
	Log Book-to-Market Ratio		6.78				0.67
			(4.02)				(2.89)
	Investment-to-Asset Ratio			14.65			32.24
				(22.46)			(32.93)
	Return on Equity				−8.53		−8.81
					(9.95)		(9.27)
	Gross Profitability					−7.99	−14.47
						(16.03)	(25.10)
	Observations	24823	24823	22645	24824	24824	22644
	Firms	4566	4566	4394	4567	4567	4393
Panel C:	LHS = Future Equity Return; RHS = Hours & Employment & Capital Growth + Pricing Factors						
	Hours Growth	−61.14	−83.92*	−33.09	−63.23	−62.98	−75.77**
		(38.01)	(43.16)	(43.08)	(38.45)	(38.52)	(34.85)
	Employment Growth	−10.05	−8.22	−15.66	−17.50	−9.04*	−14.07
		(7.38)	(4.79)	(10.33)	(12.05)	(4.69)	(11.06)
	Capital Growth (Investment Ratio)	−8.55**	−4.44	−9.00***	−9.77**	−6.29*	−8.64***
		(3.47)	(2.85)	(3.08)	(4.24)	(3.52)	(2.59)
	Log Market Capitalization	−2.39**					−2.28*
		(1.12)					(1.29)
	Log Book-to-Market Ratio		6.52				0.16
			(4.02)				(2.90)
	Investment-to-Asset Ratio			26.71			43.01
				(24.70)			(34.56)
	Return on Equity				−9.37		−9.10
					(10.61)		(9.56)
	Gross Profitability					−6.48	−14.25
						(16.39)	(25.01)
	Observations	22644	22644	22645	22645	22645	22644
	Firms	4393	4393	4394	4394	4394	4393

cross-sectional employment growth, the firms are secondly sorted by respective annual hours growth, where the breakpoints are quintiles of firms' hours growth within this portfolio. As a result, the cross-section of firms are firstly sorted into five portfolios based on cross-sectional employment growth and secondly sorted into five-by-five portfolios based on within-portfolio hours growth. Postformation, the portfolio future annual equity returns are defined and measured from July of year $t+1$ to June of year $t+2$; such procedure is repeated at the end of year $t+1$.

Table A.12 tabulates portfolio equity return for bivariate portfolios. In calculating the portfolio equity returns, I use two measures, the value-weighted measure in columns [1] to [6] and the equal-weighted measure in columns [7] to [12]. In panel A, the bivariate portfolios are sorted independently and in panel B, the bivariate portfolios are sorted sequentially, first on employment growth and second on hours growth. The results in this table, especially the columns [6] and [12], which show the portfolio equity return spreads (Low-Minus-High: L-H) along hours growth dimension, demonstrate that the negative association between current hours growth and future equity return is not derived from employment growth.

A.2.2.b Asset Pricing Factor Regressions Table A.13 tabulates the full results for panels B, C, and D in Section 3.2, Table 2. The interpretation of the results are identical. The portfolio-level results confirm the negative relation between hours growth and equity return coherent to the firm-level evidence. In particular, the predictability of hours growth on equity return is not derived from employment growth nor subsumed by leading risk factors, proposing and rationalizing the modeling assumption on non-TFP macroeconomic risk as additional business cycle fluctuation driver.

A.3 Theoretical Derivations

This section serves three purposes. First, I provide the solution of the baseline model. There are two versions of adjustment cost function considered in the baseline model: one is as

Table A.12. Bivariate Five-by-Five Portfolios Sorted by Employment and Hours Growth. Note: This table shows the future annual returns of two sets of bivariate portfolios. Panel (A) reports next-year annual returns for portfolios cross-sectional, two-way sequentially sorted firstly by current-year employment growth rate and secondly by current-year hours growth rate; panel (B) reports next-year annual returns for portfolios cross-sectional, two-way independently sorted by current-year employment growth rate and current-year hours growth rate. Of each panel, the future annual returns are value-weighted in columns [1]-[6], and are equal-weighted in columns [7]-[12]. Under either weighting method, the columns tabulates the quintiles based on cross-sectional distribution of hours growth rates and the rows tabulates the quintiles based on cross-sectional distribution of employment growth rates. The column L-H indicates the spread calculated across hours quintile portfolios and the row L-H indicates the spread calculated across employment quintile portfolios. The sample spans from 1997 to 2017.

		Value-Weighted						Equal-Weighted					
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Panel A:	Bivariate Five-by-Five Portfolios Sequentially Sorted by Employment and Hours Growth												
	G^N	G^H						G^H					
		L	2	3	4	H	L-H	L	2	3	4	H	L-H
	L	10.01	11.59	3.59	2.36	9.43	0.58	19.94	19.04	14.43	8.56	14.34	5.59
	2	17.74	11.85	8.73	9.76	10.93	6.81	17.65	22.25	14.52	13.58	15.63	2.03
	3	11.10	10.87	6.93	7.78	7.51	3.59	17.45	15.68	13.53	17.32	13.01	4.43
	4	9.79	14.80	3.76	2.75	4.84	4.96	16.88	16.32	10.03	8.03	8.74	8.14
	H	3.65	7.71	7.57	3.48	-1.69	5.34	9.13	9.67	10.62	1.33	0.40	8.72
	L-H	6.36	3.88	-3.98	-1.12	11.12		10.81	9.37	3.81	7.23	13.94	
Panel B:	Bivariate Five-by-Five Portfolios Independently Sorted by Employment and Hours Growth												
	G^N	G^H						G^H					
		L	2	3	4	H	L-H	L	2	3	4	H	L-H
	L	10.48	10.58	4.74	5.67	6.71	3.78	19.23	21.63	15.01	14.68	12.66	6.58
	2	17.06	11.69	10.18	17.75	9.01	8.05	17.25	23.43	15.54	14.81	13.47	3.77
	3	11.56	6.06	8.09	11.50	7.20	4.36	17.38	15.66	15.43	15.74	11.83	5.55
	4	10.36	14.11	4.02	7.27	2.01	8.35	16.60	15.87	9.85	9.49	7.89	8.71
	H	6.60	1.40	10.50	-2.55	-3.16	9.76	9.96	6.43	12.30	0.01	-0.78	10.74
	L-H	3.89	9.19	-5.76	8.22	9.87		9.27	15.20	2.71	14.66	13.43	

Table A.13. Results for Factor Regressions of Univariate Quintile Portfolios. Note: This table tabulates detailed resulst at the portfolio-level using the univariate quintile portfolios sorted by the cross-sectional hours growth. Reading horizontally, the columns [1] to [6] use value-weighted, the columns [7] to [12] use equal-weighted, and the columns [13] to [18] use equal-weighted, microcaps excluded portfolio equity returns, where the microcaps are the firms with a market capitalization that is below the NYSE 20-percentile threshold in each cross-section (Hou et al. [2018]). Of each weighting scheme, from left to right, the first five columns are quintile portfolios respectively, and the last column is the quintile portfolio spread, defined as low-minus-high (L-H). Reading vertically, panels A to C present factor regressions results for portfolio excess equity return anomalies implied by asset pricing models. Of each the three panels, for row-block (2), I include the MAE (mean absolute errors), the ratio of RMSE (root of mean squared errors) and RMSR (root of mean squared returns) from Lettau et al. [2019] who argues that higher ratio implies less regression power, the adjusted R^2, and the p value from regression F-test. The sample spans years from 1997 to 2017 annually.

	Value-Weighted Univariate Quintile Portfolios						Equal-Weighted Univariate Quintile Portfolios						Microcaps-Excl., Equal-Weighted Univariate Quintile Portfolios					
	L	2	3	4	H	L-H	L	2	3	4	H	L-H	L	2	3	4	H	L-H
Panel A CAPM: $r_{q,t+1} - r_{f,t+1} = a_q + b_q^{\mathrm{MKT}} F_t^{\mathrm{MKT}} + e_{q,t+1}$																		
α	0.09	0.09	0.06	0.05	0.02	0.06	0.09	0.09	0.06	0.05	0.02	0.06	0.12	0.13	0.10	0.05	0.06	0.04
[t]	2.21	2.03	1.39	1.12	0.51	2.91	2.21	2.03	1.39	1.12	0.51	2.91	4.11	3.89	2.90	1.20	1.28	1.71
b^{MKT}	0.09	−0.27	−0.02	0.02	0.14	0.09	0.09	−0.27	−0.02	0.02	0.14	0.09	0.03	−0.37	−0.21	−0.24	−0.11	0.28
[t]	0.91	−1.36	−0.08	0.14	1.34	1.35	0.91	−1.36	−0.08	0.14	1.34	1.35	0.30	−2.56	−0.71	−1.26	−0.97	1.87
MAE	0.16	0.15	0.15	0.15	0.17	0.11	0.16	0.15	0.15	0.15	0.17	0.11	0.13	0.14	0.20	0.21	0.18	0.13
RMSE/RMSR	0.88	0.91	0.96	0.97	0.98	0.90	0.88	0.91	0.96	0.97	0.98	0.90	0.82	0.78	0.93	0.98	0.97	0.91
Adj-R2	−0.05	0.01	−0.06	−0.06	−0.04	−0.04	−0.05	0.01	−0.06	−0.06	−0.04	−0.04	−0.06	0.10	−0.03	−0.03	−0.05	0.03
p-Val	0.37	0.19	0.94	0.89	0.20	0.20	0.37	0.19	0.94	0.89	0.20	0.20	0.77	0.02	0.49	0.22	0.34	0.08
Panel B 3-Factor Model: $r_{q,t+1} - r_{f,t+1} = a_q + b_q^{\mathrm{MKT}} F_t^{\mathrm{MKT}} + b_q^{\mathrm{SMB}} F_t^{\mathrm{SMB}} + b_q^{\mathrm{HML}} F_t^{\mathrm{HML}} + e_{q,t+1}$																		
α	0.10	0.07	0.05	0.02	0.00	0.08	0.10	0.07	0.05	0.02	0.00	0.08	0.12	0.12	0.11	0.02	0.03	0.07
[t]	2.48	1.70	1.59	0.50	0.04	3.91	2.48	1.70	1.59	0.50	0.04	3.91	3.21	3.41	2.68	0.50	0.44	2.10
b^{MKT}	0.10	−0.31	0.00	0.14	0.23	0.03	0.10	−0.31	0.00	0.14	0.23	0.03	0.08	−0.37	−0.24	−0.06	0.01	0.22
[t]	1.05	−1.77	0.01	0.91	1.86	0.35	1.05	−1.77	0.01	0.91	1.86	0.35	0.59	−2.52	−1.14	−0.28	0.09	1.35
b^{SMB}	−0.25	0.61	0.01	0.14	0.18	−0.45	−0.25	0.61	0.01	0.14	0.18	−0.45	−0.13	0.32	−0.12	−0.04	0.45	−0.62
[t]	−0.84	1.83	0.02	0.38	0.48	−1.93	−0.84	1.83	0.02	0.38	0.48	−1.93	−0.51	1.03	−0.25	−0.07	0.97	−2.10
b^{HML}	0.02	−0.13	0.09	0.50	0.37	−0.29	0.02	−0.13	0.09	0.50	0.37	−0.29	0.19	0.01	−0.13	0.80	0.51	−0.26
[t]	0.10	−0.43	0.24	2.00	0.99	−1.17	0.10	−0.43	0.24	2.00	0.99	−1.17	0.98	0.08	−0.31	2.65	1.43	−0.92
MAE	0.15	0.13	0.15	0.15	0.17	0.09	0.15	0.13	0.15	0.15	0.17	0.09	0.13	0.13	0.19	0.20	0.17	0.11
RMSE/RMSR	0.87	0.87	0.96	0.91	0.96	0.80	0.87	0.87	0.96	0.91	0.96	0.80	0.81	0.77	0.92	0.90	0.92	0.83
Adj-R2	−0.17	−0.01	−0.20	−0.05	−0.11	0.08	−0.17	−0.01	−0.20	−0.05	−0.11	0.08	−0.17	0.02	−0.16	0.01	−0.05	0.09
p-Val	0.72	0.12	0.99	0.21	0.30	0.24	0.72	0.12	0.99	0.21	0.30	0.24	0.61	0.10	0.53	0.03	0.39	0.25
Panel C 5-Factor Model: $r_{q,t+1} - r_{f,t+1} = a_q + b_q^{\mathrm{MKT}} F_t^{\mathrm{MKT}} + b_q^{\mathrm{SMB}} F_t^{\mathrm{SMB}} + b_q^{\mathrm{HML}} F_t^{\mathrm{HML}} + b_q^{\mathrm{RMV}} F_t^{\mathrm{RMV}} + b_q^{\mathrm{CMA}} F_t^{\mathrm{CMA}} + e_{q,t+1}$																		
α	0.09	0.09	0.11	0.01	0.02	0.04	0.09	0.09	0.11	0.01	0.02	0.04	0.11	0.11	0.20	0.00	0.03	0.05
[t]	1.58	1.96	2.86	0.15	0.43	2.10	1.58	1.96	2.86	0.15	0.43	2.10	1.86	3.17	5.61	0.03	0.51	2.11
b^{MKT}	0.20	−0.40	−0.38	0.28	0.09	0.37	0.20	−0.40	−0.38	0.28	0.09	0.37	0.12	−0.33	−0.87	0.10	−0.00	0.34
[t]	0.82	−1.62	−1.39	1.22	0.42	2.13	0.82	−1.62	−1.39	1.22	0.42	2.13	0.41	−1.74	−4.44	0.29	−0.01	1.24
b^{SMB}	−0.23	0.41	−0.33	0.17	−0.09	−0.12	−0.23	0.41	−0.33	0.17	−0.09	−0.12	−0.23	0.11	−0.67	−0.20	0.23	−0.48
[t]	−0.95	1.34	−0.86	0.49	−0.23	−0.54	−0.95	1.34	−0.86	0.49	−0.23	−0.54	−0.82	0.32	−1.35	−0.39	0.51	−2.05
b^{HML}	0.11	−0.24	0.37	0.50	0.35	−0.28	0.11	−0.24	0.37	0.50	0.35	−0.28	0.07	−0.37	0.22	0.50	0.34	−0.26
[t]	0.31	−0.62	0.75	1.40	0.58	−0.81	0.31	−0.62	0.75	1.40	0.58	−0.81	0.27	−1.25	0.41	1.01	0.63	−0.63
b^{RMV}	0.27	−0.29	−0.87	0.34	−0.37	0.88	0.27	−0.29	−0.87	0.34	−0.37	0.88	0.07	−0.05	−1.46	0.26	−0.12	0.31
[t]	0.57	−0.84	−2.61	0.81	−0.81	2.25	0.57	−0.84	−2.61	0.81	−0.81	2.25	0.15	−0.21	−4.36	0.43	−0.23	0.65
b^{CMA}	−0.22	0.25	0.13	−0.23	0.31	−0.49	−0.22	0.25	0.13	−0.23	0.31	−0.49	0.24	0.70	0.45	0.47	0.34	−0.04
[t]	−0.45	0.78	0.29	−0.68	0.59	−2.05	−0.45	0.78	0.29	−0.68	0.59	−2.05	0.62	2.09	0.94	0.89	0.83	−0.21
MAE	0.15	0.13	0.16	0.14	0.17	0.09	0.15	0.13	0.16	0.14	0.17	0.09	0.13	0.13	0.18	0.21	0.18	0.11
RMSE/RMSR	0.86	0.87	0.93	0.90	0.95	0.72	0.86	0.87	0.93	0.90	0.95	0.72	0.80	0.75	0.86	0.89	0.92	0.83
Adj-R2	−0.31	−0.19	−0.30	−0.20	−0.27	0.13	−0.31	−0.19	−0.30	−0.20	−0.27	0.13	−0.33	−0.07	−0.16	−0.12	−0.22	−0.07
p-Val	0.78	0.00	0.11	0.08	0.22	0.00	0.78	0.00	0.11	0.08	0.22	0.00	0.53	0.01	0.00	0.02	0.53	0.12

shown in Eq. (8) while the other one builds on Cooper & Willis [2009] and Cooper et al. [2015], and draws implications from discussions in Merz & Yashiv [2007], Bloom [2009], Belo et al. [2013], Belo et al. [2014a], Belo et al. [2017], and Bloom et al. [2018].

Second, I present a modified model without adjustment cost on hours and third, I present a modified model without adjustment cost shock. The goals are to show that both the modified models produce counterfactual moments compared to those from empirical data. The intuition is straightforward. Without adjustment cost on hours, the labor input choice of hours is completely characterized by an intratemporal first-order condition with respect to hours; therefore, the current hours growth is derived by employment growth, given realization of three exogenous processes. On the other hand, without adjustment cost shock, equity return in the economy is discounted at the stochastic discount factor with one macroeconomic shock, the productivity shock. In language of asset pricing, current hours increases in response to a positive productivity shock, which has a positive risk price; as a result, firms with high hours growth are associated with high equity return. In language of macroeconomics, firms with high hours growth are able to pay out more when aggregate consumption is abundant; these firms are riskier, because they comove with business cycles, and hence own higher equity return in equilibrium.

A.3.1 Solution to Baseline Model

The baseline model is outlined in Eqs. (6) to (11) and grouped and reproduced as follows.

$$
\begin{aligned}
& V_{jt} && = \max_{H_{jt},N_{jt}}\{(Y_{jt} - W_{jt} - C_{jt}) + \mathbb{E}[M_{t+1} \cdot V_{j,t+1}]\} \\
\text{s.t.} \quad & Y_{jt} && = A_t Z_{jt}(H_{jt}N_{jt})^{\alpha} \\
& W_{jt} && = N_{jt}(\omega_0 + \omega \cdot H_{jt}^{\xi}) \\
& C_{jt} && = (C_{jt}^{N} + C_{jt}^{H})/X_t \\
& M_{t+1} && = \{R_{t+1}^{f}\mathbb{E}[\exp(m_{t+1})]\}^{-1}\exp(m_{t+1}) \\
& m_{t+1} && = \gamma_A \Delta\log(A_{t+1}) + \gamma_X \Delta\log(X_{t+1})
\end{aligned}
\tag{A.19}
$$

where the adjustment cost on hours and employment are respectively

$$\begin{aligned} C_{jt}^{H} &= c_d^H Y_{jt} \times \mathbf{1}_{G_{jt}^H \neq 0} \quad + c_i^H W_{jt} \times |G_{jt}^H| \quad + c_q^H H_{t-1} \times (G_{jt}^H)^2 \\ C_{jt}^{N} &= c_d^N Y_{jt} \times \mathbf{1}_{G_{jt}^N \neq 0} \quad + c_i^N W_{jt} \times |G_{jt}^N| \quad + c_q^N N_{t-1} \times (G_{jt}^N)^2 \end{aligned} \tag{A.20}$$

The solution is characterized by the first-order condition with respect to hours

$$\begin{aligned} 0 = \quad & \alpha A_t Z_{jt} N_{jt}^{\alpha} H_{jt}^{\alpha-1} - \xi N_{jt} \omega H_{jt}^{\xi-1} - \{ \\ + \quad & c_d^H \alpha A_t Z_{jt} N_{jt}^{\alpha} H_{jt}^{\alpha-1} \mathbf{1}_{G_{jt}^H \neq 0} \\ + \quad & c_i^H \mathbf{A}_{G_{jt}^H} \xi N_{jt} \omega H_{jt}^{\xi-1} \\ + \quad & c_i^H \mathbf{S}_{G_{jt}^H} [N_{jt}(\omega_0 + \omega H_{jt}^{\xi})][(1+G_{jt}^H)/H_{jt}] \\ + \quad & c_q^H [2(G_{jt}^H)] \\ & \}/X_t - \{ \\ + \quad & c_d^N \alpha A_t Z_{jt} N_{jt}^{\alpha} H_{jt}^{\alpha-1} \mathbf{1}_{G_{jt}^N \neq 0} \\ + \quad & c_i^N \mathbf{A}_{G_{jt}^N} \xi N_{jt} \omega H_{jt}^{\xi-1} \\ & \}/X_t + \mathbb{E}[\{R_{t+1}^f \bar{M}_{t+1}\}^{-1} \exp\{\gamma_A \Delta \log(A_{t+1}) + \gamma_X \Delta \log(X_{t+1})\}\{ \\ + \quad & c_i^H [\mathbf{A}_{G_{j,t+1}^H} + \mathbf{S}_{G_{j,t+1}^H}][N_{j,t+1}(\omega_0 + \omega H_{j,t+1}^{\xi})][(1+G_{j,t+1}^H)/H_{j,t+1}] \\ + \quad & c_q^H [(G_{j,t+1}^H)^2 + 2(G_{j,t+1}^H)] \\ & \}/X_{t+1}] \end{aligned} \tag{A.21}$$

and the first-order condition with respect to employment

$$
\begin{aligned}
0 = \quad & \alpha A_t Z_{jt} N_{jt}^{\alpha-1} H_{jt}^{\alpha} - (\omega_0 + \omega H_{jt}^{\xi}) - \{ \\
+ \quad & c_d^N \alpha A_t Z_{jt} N_{jt}^{\alpha-1} H_{jt}^{\alpha} \mathbf{1}_{G_{jt}^N \neq 0} \\
+ \quad & c_i^N \mathbf{A}_{G_{jt}^N} (\omega_0 + \omega H_{jt}^{\xi}) \\
+ \quad & c_i^N \mathbf{S}_{G_{jt}^N} [N_{jt}(\omega_0 + \omega H_{jt}^{\xi})][((1 + G_{jt}^N) + (1 - \delta))/N_{jt}] \\
+ \quad & c_q^N [2(G_{jt}^N)] \\
& \}/X_t - \{ \\
+ \quad & c_d^H \alpha A_t Z_{jt} N_{jt}^{\alpha-1} H_{jt}^{\alpha} \mathbf{1}_{G_{jt}^H \neq 0} \\
+ \quad & c_i^H \mathbf{A}_{G_{jt}^H} (\omega_0 + \omega H_{jt}^{\xi}) \\
& \}/X_t + \mathbb{E}[\{R_{t+1}^f \bar{M}_{t+1}\}^{-1} \exp\{\gamma_A \Delta \log(A_{t+1}) + \gamma_X \Delta \log(X_{t+1})\}\{ \\
+ \quad & c_i^N [\mathbf{A}_{G_{j,t+1}^N} + \mathbf{S}_{G_{j,t+1}^N} (1 - \delta)][N_{j,t+1}(\omega_0 + \omega H_{j,t+1}^{\xi})][((1 = G_{j,t+1}^N) + (1 - \delta))/N_{j,t+1}] \\
+ \quad & c_q^N [(G_{j,t+1}^N)^2 + 2(G_{j,t+1}^N)(1 - \delta)] \\
& \}/X_{t+1}]
\end{aligned}
\tag{A.22}
$$

where $\mathbf{A}_{\{.\}}$ returns the absolute value, and $\mathbf{S}_{\{.\}}$ returns the sign of their arguments.

The adjustment cost discussions in dynamic factor demand literature have explored extensively in terms of components and yielded fruitful results. Speaking to this strand of literature, I next consider a broader function form of adjustment cost on hours and employment. In particular, I additional consider a non-convex component as a fixed reduction of payout and a linear component that is purely on the absolute size of adjustment.

$$
\begin{aligned}
C_{jt}^H &= c_f^H \times \mathbf{1}_{G_{jt}^H \neq 0} \quad + c_d^H Y_{jt} \times \mathbf{1}_{G_{jt}^H \neq 0} \quad + c_i^H W_{jt} \times |G_{jt}^H| \quad + c_l^H H_{t-1} \times |G_{jt}^H| \quad + c_q^H H_{t-1} \times (G_{jt}^H)^2 \\
C_{jt}^N &= c_f^N \times \mathbf{1}_{G_{jt}^N \neq 0} \quad + c_d^N Y_{jt} \times \mathbf{1}_{G_{jt}^N \neq 0} \quad + c_i^N W_{jt} \times |G_{jt}^N| \quad + c_l^N N_{t-1} \times |G_{jt}^N| \quad + c_q^N N_{t-1} \times (G_{jt}^N)^2
\end{aligned}
\tag{A.23}
$$

In this specification, $c_{f,d,l,i,q}$ are parameters. The adjustment cost functions reflects non-convexity, linearity, and convexity that might exist on the extensive margin of adjustment labor inputs. The first and second components are non-convex components. The first component is a fixed cost and c_f describes the level of reduction to firm's revenue in the form of cost of good sold. The second component is a disruption cost. c_d represents the disruption to firm's production process during adjustment. Hence $1 - c_d$ is the remaining production after the disruption, should the adjustment take place, $\mathbb{I}[G^N \neq 0] = 1$. Cooper & Willis [2009] and Cooper et al. [2015] use micro-level evidences and finds that, non-convex (disruption) cost is necessary and critical for matching aggregate moments and explaining plant-level observations. The next two components are linear components. Both linear components suggests that the size of the cost depends not on the sign of but the (scaled) size of adjustment. As a result, the linear components dampen partial adjustment (King & Thomas [2006]) and create inaction at the micro-level (Cooper & Willis [2009]; Cooper et al. [2015]). c_l in the third component is the constant marginal adjustment cost, scaled by inherited employment. c_i represents the per capita adjustment cost denominated as a fraction of compensation. Bloom [2009] argues such linear cost, a form of labor partial irreversibility, captures the per capita cost occurred during the process of hiring, training, negotiating, and firing[A.15]. The last component is a standard convex quadratic cost. c_q parameterizes the sensitivity of quadratic cost component in response to relatively rapid as opposed to relatively sluggish adjustment.

[A.15] Partial irreversibility is established in the context of capital; the difference between buying and selling prices of capital refects the transaction cost, which may origins from capital specificity and lemons problem (Cooper & Haltiwanger [2006]). The argument is analogous in the context of labor; the cost arises from labor specificity (training) and lemons problems (screening and/or negotiating).

The solution is characterized by the first-order condition with respect to hours

$$
\begin{aligned}
0 = \quad & \alpha A_t Z_{jt} N_{jt}^{\alpha} H_{jt}^{\alpha-1} - \xi N_{jt} \omega H_{jt}^{\xi-1} - \{ \\
+ \quad & c_d^H \alpha A_t Z_{jt} N_{jt}^{\alpha} H_{jt}^{\alpha-1} \mathbf{1}_{G_{jt}^H \neq 0} \\
+ \quad & c_i^H \mathbf{A}_{G_{jt}^H} \xi N_{jt} \omega H_{jt}^{\xi-1} \\
+ \quad & c_i^H \mathbf{S}_{G_{jt}^H} [N_{jt}(\omega_0 + \omega H_{jt}^{\xi})][(1 + G_{jt}^H)/H_{jt}] \\
+ \quad & c_q^H [2(G_{jt}^H)] \\
+ \quad & c_l^H \mathbf{S}_{G_{jt}^H} \\
& \}/X_t - \{ \\
+ \quad & c_d^N \alpha A_t Z_{jt} N_{jt}^{\alpha} H_{jt}^{\alpha-1} \mathbf{1}_{G_{jt}^N \neq 0} \\
+ \quad & c_i^N \mathbf{A}_{G_{jt}^N} \xi N_{jt} \omega H_{jt}^{\xi-1} \\
& \}/X_t + \mathbb{E}[\{R_{t+1}^f \bar{M}_{t+1}\}^{-1} \exp\{\gamma_A \Delta \log(A_{t+1}) + \gamma_X \Delta \log(X_{t+1})\}\{ \\
+ \quad & c_i^H [\mathbf{A}_{G_{j,t+1}^H} + \mathbf{S}_{G_{j,t+1}^H}][N_{j,t+1}(\omega_0 + \omega H_{j,t+1}^{\xi})][(1 + G_{j,t+1}^H)/H_{j,t+1}] \\
+ \quad & c_q^H [(G_{j,t+1}^H)^2 + 2(G_{j,t+1}^H)] \\
+ \quad & c_l^H \mathbf{S}_{G_{j,t+1}^H} \\
& \}/X_{t+1}]
\end{aligned}
\tag{A.24}
$$

and the first-order condition with respect to employment

$$
\begin{aligned}
0 = \quad & \alpha A_t Z_{jt} N_{jt}^{\alpha-1} H_{jt}^{\alpha} - (\omega_0 + \omega H_{jt}^{\xi}) - \{ \\
+ \quad & c_d^N \alpha A_t Z_{jt} N_{jt}^{\alpha-1} H_{jt}^{\alpha} \mathbf{1}_{G_{jt}^N \neq 0} \\
+ \quad & c_i^N \mathbf{A}_{G_{jt}^N} (\omega_0 + \omega H_{jt}^{\xi}) \\
+ \quad & c_i^N \mathbf{S}_{G_{jt}^N} [N_{jt}(\omega_0 + \omega H_{jt}^{\xi})][((1 + G_{jt}^N) + (1-\delta))/N_{jt}] \\
+ \quad & c_q^N [2(G_{jt}^N)] \\
+ \quad & c_l^N \mathbf{S}_{G_{jt}^N} \\
& \}/X_t - \{ \\
+ \quad & c_d^H \alpha A_t Z_{jt} N_{jt}^{\alpha-1} H_{jt}^{\alpha} \mathbf{1}_{G_{jt}^H \neq 0} \\
+ \quad & c_i^H \mathbf{A}_{G_{jt}^H} (\omega_0 + \omega H_{jt}^{\xi}) \\
& \}/X_t + \mathbb{E}[\{R_{t+1}^f \bar{M}_{t+1}\}^{-1} \exp\{\gamma_A \Delta \log(A_{t+1}) + \gamma_X \Delta \log(X_{t+1})\}\{ \\
+ \quad & c_i^N [\mathbf{A}_{G_{j,t+1}^N} + \mathbf{S}_{G_{j,t+1}^N}(1-\delta)][N_{j,t+1}(\omega_0 + \omega H_{j,t+1}^{\xi})][((1 + G_{jt}^N) + (1-\delta))/N_{j,t+1}] \\
+ \quad & c_q^N [(G_{j,t+1}^N)^2 + 2(G_{j,t+1}^N)(1-\delta)] \\
+ \quad & c_l^N \mathbf{S}_{G_{j,t+1}^N} (1-\delta) \\
& \}/X_{t+1}]
\end{aligned}
\tag{A.25}
$$

Comparing solutions described by Eqs. (A.21) and (A.22) and Eqs. (A.24) and (A.25), the optimal hours and employment are identical up to constant. Therefore, it is reasonable to expect that my results in this paper is robust to adjustment cost specifications in Eqs. (A.20) and (A.23). Furthermore, as to be shown momentarily, my illustration of importance of adjustment cost on hours and adjustment cost shock also preserves in a broader adjustment cost specification.

A.3.2 Role of Adjustment Cost on Hours

The key ingredient of the model is the existence of labor adjusting friction along the hours margin, analogous and additional to that along the employment margin. To quantify the importance of labor adjusting friction along the hours margin, I study an otherwise identical framework in absence of the labor adjustment cost on hours. The counterfactual analysis indicates that the firm in this model uses its choice of hours to accommodate its choice of employment. The results from such optimization, including (1) an inverse contemporaneous correlation between the firm's hours and employment growths, (2) a significant leading role of adjusting hours relative to adjusting employment in response to aggregate shocks, (3) a flatter pooled distribution of the hours growths, and (4) a more peaked pooled distribution of the employment growths, are inconsistent with the data.

More concretely, the equilibrium of this framework implies the following first-order condition with respect to hours

$$e^{\bar{c}} A_t Z_t N_{jt}^{\alpha-1} = H_{jt}^{\xi-\alpha} \tag{A.26}$$

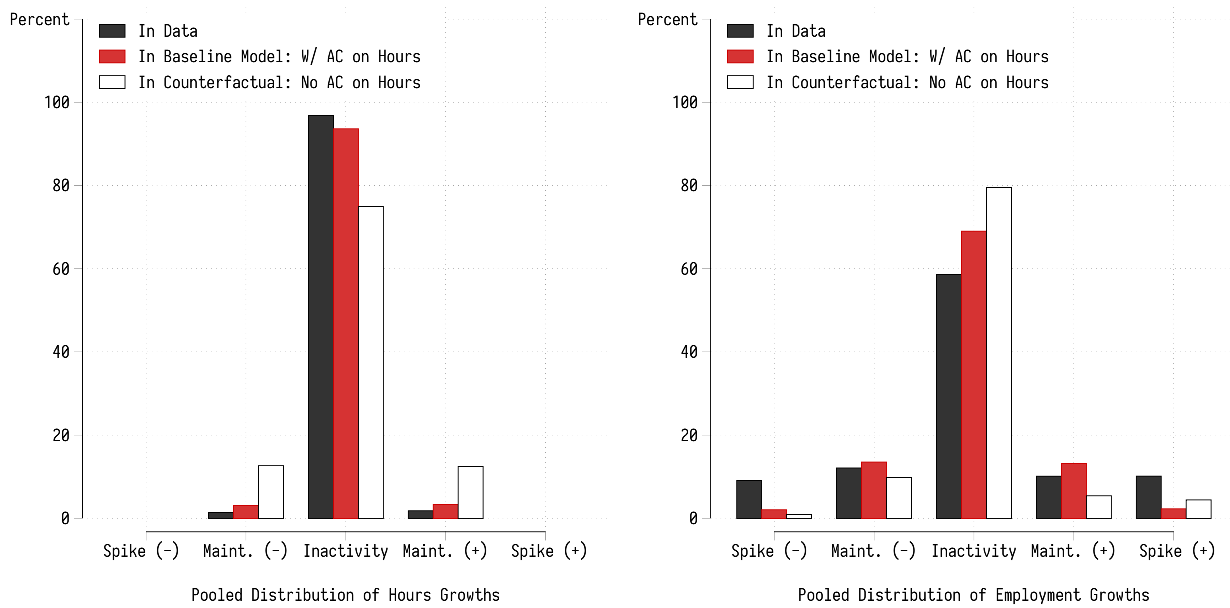
where $\bar{c} = \log\{[\alpha(1 - c_d^N \cdot \mathbf{1}_{G_{jt}^N \neq 0}/X_t)][\omega\xi(1 + c_i^N \cdot |G_{jt}^N|/X_t)]^{-1}\} \leq 0$. The intratemporal optimality condition in Eq. (A.26) demonstrates three key observations. First, after the realization of exogenous stochastic processes, the hours H_{jt} on the right-hand side is fully characterized by the employment N_{jt}. In terms of equity return predictability, conditional on the firm and year fixed effects, the impact of hours growth on cash flow shall be highly correlated with that of employment growth. Second, in reasonable parameteric space where $\xi > \alpha > 1$, the hours H_{jt} is likely to move in the opposite direction to the employment N_{jt}. This further means that the contemporaneous correlation between he hours and the employment growths is likely to be negative. Third, due to the labor adjusting friction along the employment margin, the hours H_{jt} reacts to the exogenous stochastic processes more rapidly and more radically, suggesting there would be more a substantial fraction of large changes (spikes) in hours. As a result, the pooled distribution of the hours growth would be flatter.

To fully understand the three observations, I estimate the counterfactual framework and calculate the corresponding moments. I present these results in the same format in the column [4] of Table A.14. In terms of the firm-level quantities in panel A, the counterfactual generates a kurtosis of the firm-level hours growths that is too low (4.009 versus 10.931 in the baseline model and 13.783 in the data). Also, the counterfactual fails to produce a larger kurtosis of the hours growths relatively to the employment growths that is observed in the data. From the second observation, the hours growths are likely to inversely related to the concurrent employment growths. The counterfactual thus produces a negative contemporaneous correlation between the hours and employment growths whereas in the baseline model and in the data, the contemporaneous correlation are both positive. Furthermore, the cross-period correlation between the hours and employment growths reveals a significant leading role of the hours adjustment relative to the employment adjustment. From the third observation, the hours H_{jt} responds to the exogenous stochastic processes more rapidly and the employment N_{jt} responds relatively sluggishly. Hence, say in response to a favorable aggregate shock, the hours initially increases ($corr(G^H_{-1}, G^N) = 0.183$) and subsequently decreases as the employment starts to act ($corr(G^H, G^N_{-1}) = -0.149$), both of which compared to the data are considerably large. Turning to the pooled distributions of the hours and the employment growths, the inaction rate of the hours growths is too low (74.93 versus 93.61 in the baseline model and 96.81 in the data) and that of the employment growths is too high (79.50 versus 69.03 in the baseline model and 58.60 in the data). This is anticipated from intratemporal optimality condition in Eq. (A.26). Because the labor adjusting friction is fully imposed onto the employment margin, the hours margin is more frequently adjusted and is more likely to incur large adjustments, resulting in a flatter pooled distribution of the hours growths and consequently a more peaked pooled distribution of the employment growths than those from the data.

Table A.14. Firm-Level Moments and Pooled Distributions of Hours and Employment Growth. NOTE: This table summarizes the moments matching in data and counterfactual analysis. In presenting the moments, I report firstly the firm-level moments in panel A and secondly the pooled distribution moments in panel B. In panel A, the subpanel A.1 lists the six targeted and the subpanel A.2 the seven non-targeted; in panel B, the subpanel B.1 tabulates pooled distribution statistics for the hours growth and the subpanel B.2 those for the employment gorwths. Across columns, the moments are described in columns [1] and [2]. The values of the moments are tabulated in columns [3] to [4]. Specifically, the column [3] lists the value from the data, and the column [4] from the counterfactual model. In calculating the data values in column [3], I compute using bootstrapping. For the model values in column [4], I compute using simulated 2675 firms across 300 years. In defining the inaction, the maintenance, and the spike rates of the pooled distributions, I use the cutoff values from Cooper & Haltiwanger [2006] and Cooper et al. [2007] with updates to match the frequency of my data.

	Moments		Values	
	Description	Definition	Data	Counterfactual
	[1]	[2]	[3]	[4]
Panel A	Firm-Level			
Panel A.1	Targeted			
	Kurtosis of hours growth	$kurt(G^H)^{1/4}$	1.927	1.415
	Kurtosis of emp't growth	$kurt(G^N)^{1/4}$	1.668	1.633
	Persistence of hours growth	$rho(G^H)$	−0.376	−0.296
	Persistence of emp't growth	$rho(G^N)$	−0.005	−0.045
	Same-period correlation coeff.	$corr(G^H, G^N)$	0.029	−0.066
	Cross-period correlation coeff.	$corr(G^H, G^N_{-1})$	−0.024	−0.149
Panel A.2	Non-Targeted			
	Cross-period correlation coeff.	$corr(G^H_{-1}, G^N)$	0.012	0.183
	Mean of hours growth	$mean(G^H)$	0.001	0.002
	Mean of emp't growth	$mean(G^N)$	0.051	0.002
	Variance of hours growth	$var(G^H)^{1/2}$	0.032	0.071
	Variance of emp't growth	$var(G^N)^{1/2}$	0.210	0.084
	Skewness of hours growth	$skew(G^H)^{1/3}$	0.538	0.669
	Skewness of emp't growth	$skew(G^N)^{1/3}$	0.719	0.851
Panel B	Pooled Distributions (Non-Targeted)			
Panel B.1	Hours Growth			
	Negative spike rate (%)	$G^H \in (-\infty, -0.2]$	0.00	0.00
	Negative maintenance rate (%)	$G^H \in (-0.2, -0.1]$	1.40	12.62
	Inaction rate (%)	$G^H \in (-0.1, +0.1)$	96.81	74.93
	Positive maintenance rate (%)	$G^H \in [+0.1, +0.2)$	1.79	12.45
	Positive spike rate (%)	$G^H \in [+0.2, +\infty)$	0.00	0.00
Panel B.2	Employment Growth			
	Negative spike rate (%)	$G^N \in (-\infty, -0.2]$	9.04	0.89
	Negative maintenance rate (%)	$G^N \in (-0.2, -0.1]$	12.09	9.81
	Inaction rate (%)	$G^N \in (-0.1, +0.1)$	58.60	79.50
	Positive maintenance rate (%)	$G^N \in [+0.1, +0.2)$	10.13	5.39
	Positive spike rate (%)	$G^N \in [+0.2, +\infty)$	10.14	4.41

Figure A.6. Pooled Distributions of the Hours and Employment Growths. NOTE: This figure plots the pooled distributions of hours growths (left panel) and the employment growths (right panel). In each panel, the horizontal axis specifies the types of growths, namely, the negative spike, the negative maintenance, the inactivity, the positive maintenance, and the positive spike. The vertical axis gives the corresponding fractions of each type. I calculate the pooled distribution using the data, the baseline model with adjustment cost on hours, and the counterfactual framework without adjustment cost on hours.



A.3.3 Role of Adjustment Cost Shock

My model utilizes a macroeconomic shock, the adjustment cost shock, to combine two forces. The force at the aggregate level redistributes aggregate consumption to aggregate investment to increase the marginal utility; the force at the firm level benefits firms who adjust hours more so such firms are able to pay out more during times when aggregate consumption is lower. This section illustrates the role of adjustment cost shock to justify the use of it.

I consider the following alternative specification of the model without adjustment cost shock.

$$
\begin{aligned}
& V_{jt} && = \max_{H_{jt},N_{jt}}\{(Y_{jt} - W_{jt} - C_{jt}) + \mathbb{E}[M_{t+1} \cdot V_{j,t+1}]\} \\
\text{s.t.} \quad & Y_{jt} && = A_t Z_{jt}(H_{jt}N_{jt})^{\alpha} \\
& W_{jt} && = N_{jt}(\omega_0 + \omega \cdot H_{jt}^{\xi}) \\
& C_{jt} && = C_{jt}^{N} + C_{jt}^{H} \\
& M_{t+1} && = \{R_{t+1}^{f}\mathbb{E}[\exp(m_{t+1})]\}^{-1}\exp(m_{t+1}) \\
& m_{t+1} && = \gamma_A \Delta\log(A_{t+1})
\end{aligned}
\tag{A.27}
$$

The optimal labor input choice of hours is characterized by first-order condition with respect to hours[A.16] (To get rid of the non-convexity, I set $G_{jt}^{H} > 0$.)

$$
1 = \mathbb{E}[M_{t+1}R_{j,t+1}^{H}] \tag{A.28}
$$

where the return is

$$
R_{j,t+1}^{H} = \frac{\left\{c_i^H(\mathbf{A}_{G_{j,t+1}^H} + \mathbf{S}_{G_{j,t+1}^H})\left[\frac{N_{j,t+1}(\omega_0 + \omega H_{j,t+1}^{\xi})}{H_{jt}}\right] + c_q^H\left[(G_{j,t+1}^H)^2 + 2(G_{j,t+1}^H)\right]\right\}}{-\left\{(1-c_d^H)\left[\alpha A_t Z_{jt} N_{jt}^{\alpha} H_{jt}^{\alpha-1}\right] - (1+c_i^H)\left[\xi N_{jt}\omega H_{jt}^{\xi-1}\right] - c_i^H\left[\frac{N_{jt}(\omega_0 + \omega H_{jt}^{\xi})}{H_{j,t-1}}\right] - c_q^H\left[2(G_{jt}^H)\right]\right\}} \tag{A.29}
$$

where the numerator is the marginal net adjustment cost in period $t+1$ and the denominator is the marginal net adjustment cost in period t. That is, the firm equates the current marginal net adjustment cost to the expected discounted future marginal net adjustment cost. Because of adjustment cost, the current labor input choice of hours strikes a balance between the adjustment cost occurring now and in the future.

In this model, a positive productivity shock $\Delta\log(A_{t+1})$ lowers the stochastic discount factor M_{t+1} and hence pushes up the future equity return $R_{j,t+1}^{H}$ in Eq. (A.28). Economically, when firms expect a productivity increase in the future, firms would like to allocate less adjustment cost to current period and more adjustment cost to future periods, because the

[A.16] For simplicity, I shut down the substitution effect of employment on hours; that is, I let the employment to not change.

more product from higher productivity would help cover the increased adjustment cost in the future. Therefore, in Eq. (A.29), the numerator increases and the denominator decreases, leading to a higher equity return in the future. Intuitively, this is pointed out by Barro & King [1984]; when the productivity shock is the only shock in my model, which is in core based business cycle theory, hours responds positive shock positively.

A.4 Numerical Solution

I numerically solve the model using the simulated method of moments (SMM) with value function iterations, where value function (Eqs. (A.19) and (A.20)) and the policy functions (Eqs. (A.21) and (A.22)) are solved on a discretized space spanned by state variable vector $(A_t, X_t, Z_{jt}, N_{j,t-1}, H_{j,t-1})$.

In terms of endogenous choice and state variables hours and employment. I specify 51 grid points along each dimension. In specifying these grid points, I first solve the frictionless model without labor adjustment cost to obtain the equilibrium levels of hours and employment in absence of adjustment cost. Next, I spread the grid points around the equilibrium levels using logarithm equal spaces; therefore, the grid points are more likely to appear at choices where the hours and employment are. In spreading the grid points, I also make sure the upper and lower bounds of the grid points are not binding, so solution of the model does not involve grid points on the left- or right-tail in stationary ergodic distributions of hours and employment. For exogeneous state variables aggregate productivity, adjustment cost shock, and idiosyncratic productivity, I follow Terry & Knotek II [2011]. In the model, all the three stochastic primitives follow first-order logarithm Markov processes. Using discretization, the three stochastic primitives are mapped into grid points with a three-dimensional transition matrix. I use three grid points for aggregate productivity, and five grid points for adjustment cost shock and idiosyncratic productivity. After setting up the algorithms, the endogenous and exogenous grid points defines the five dimensional discretized space where the numerical model inhabits. The numerical solution is obtained by iteration of value functions with cubic

Hermite interpolation to enhance the precision.

In simulating the model to get model-simulated data used in this paper, I include 2675 firms at the cross-section to match the average number of firms per year in my dataset (=2675.48). I also tried cases where the cross-section includes 1000, 3000, and 5000 firms. For each cross-section, the model is simulated from initial period for 300 periods (years), where the first half is dropped to mitigate the influence from initial conditions, and remaining 150 are treated as from stationary equilibrium. For the length of simulation, I also tried 200(=100+100), 500(=200+300), 700(=300+400), and 1000(=500+500) periods. In all cases, the results are robust to alternative sizes in the cross-section and lengths in the time-series.

A.5 Testing Mechanism and Implications

Recall the model's mechanism imply four testable implications, two at the aggregate-level and two at the firm-level. In particular, in language of macroeconomics, the first implication is that the adjustment cost shock captures a countercyclical component of business cycle. In language of asset pricing, that the adjustment cost shock has a negative price of risk is the second implication. At the firm-level, the model predicts that firms who adjusting hours more are more responsive to adjustment cost shock. Therefore, the third implication is that such firms pay out more due to decreased adjustment cost incurred, and the fourth implication is that such firms earn lower equity return for less riskiness associated.

A.5.1 Adjustment Cost Shock and High Marginal Utility

A positive adjustment cost shock F_t^{ACS} leads to high marginal utility states. To test this mechanism, I use the dynamic response regressions in Eq. (15) which is repeated as follows.

$$\frac{1}{s+1}[\log(\Gamma_{t+s}) - \log(\Gamma_{t-1})] = a_s + \beta^{ACS} F_t^{\text{ACS}} + \beta^{\text{MKT}} F_t^{\text{MKT}} + e_{ts}; s = 0, \cdots, S. \quad \text{(A.30)}$$

On the left-hand side, Γ_t denotes the aggregate output, consumption, or investment. Thus the left-hand side measures the annualized S-year horizon growth rate. To better interpret the coefficient $\beta^{ACS,MKT}$, I normalize the factors $F_t^{\text{ACS,MKT}}$ to zero mean and unit standard deviation. Therefore, the interpretation of coefficient estimate is the impact on S-year horizon average growth rate of the aggregate output, consumption, or investment from a one-standard deviation increase of factors $F_t^{\text{ACS,MKT}}$. In constructing the left-hand side variables, I follow Papanikolaou [2011]. In particular, I define the aggregate output as the real gross domestic product excluding real government consumption expenditures and gross investment, the aggregate consumption as real personal consumption expenditures on nondurable goods and services, and the aggregate investment as real private nonresidential fixed investment.

Table A.15 tabulate the full dynamics responses from aggregate output in the top panel, those from aggregate consumption in the middle panel, and those from aggregate investment in the bottom panel across one- to five-year horizons ($s = 0$ to $= 4$). As stated in the main context, the adjustment cost shock at the aggregate level originates a redistributional effect from aggregate consumption to aggregate investment. In the short-run from one- to two-year horizons, the adjustment cost shock has an immediate and radical favorable impact on aggregate investment, while in the long-run the productivity driving the aggregate investment dominates. For consumption, the dampening impact of adjustment cost shock is smoothed over one- to four-year horizons, displaying a hump-shaped responses.

A.5.2 Adjustment Cost Shock and Negative Risk Price

To show the negative risk price, I first establish the equivalence between positive SDF loading and negative risk price of adjustment cost shock in my model. The empirical stochastic discount factor of $M_t = a_M + \gamma^{\text{MKT}} F_t^{\text{MKT}} + \gamma^{\text{ACS}} F_t^{\text{ACS}}$ in Eq. (14) implies a Euler pricing formula

$$\mathbb{E}[M_{+1}(R_{\iota,t+1} - R_{f,t+1})] = 0 \tag{A.31}$$

for an arbitrary asset ι and risk free rate $R_{f,t+1}$. Replacing the empirical stochastic discount factor in Eq. (A.31) yields the beta pricing formula

$$\mathbb{E}[R_{\iota,t+1} - R_{f,t+1}] = \lambda^{\text{MKT}}\beta_\iota^{\text{MKT}} + \lambda^{\text{ACS}}\beta_\iota^{\text{ACS}} \tag{A.32}$$

where the risk prices of adjustment cost shock and productivity shock are respectively

$$\begin{aligned} \lambda^{\text{ACS}} &= -\gamma^{\text{ACS}}\mathbb{V}[F_t^{\text{ACS}}] \\ \lambda^{\text{MKT}} &= -\gamma^{\text{MKT}}\mathbb{V}[F_t^{\text{MKT}}] \end{aligned} \tag{A.33}$$

with the $\mathbb{V}[\cdot]$ denotes the empirical variance expectation operator, and the risk quantities for arbitrary asset ι of adjustment cost shock and productivity shock are respectively

$$\begin{aligned} \beta_\iota^{\text{ACS}} &= \mathbb{V}[R_{\iota,t+1} - R_{f,t+1}]/\mathbb{V}[F_t^{\text{ACS}}] \\ \beta_\iota^{\text{MKT}} &= \mathbb{V}[R_{\iota,t+1} - R_{f,t+1}]/\mathbb{V}[F_t^{\text{MKT}}] \end{aligned} \tag{A.34}$$

Therefore, a positive loading of adjustment cost shock in stochastic discount factor implies a negative risk price of adjustment cost shock in equity return.

To test the negative risk price of adjustment cost shock, I perform Fama-MacBeth tests (Fama & MacBeth [1973]) on two set of testing portfolios sets, the Fama-French 25 portfolios sorted by size (ME) and book-to-market (BM) and Fama-French 17 industry portfolios. The Fama-MacBeth procedure follows a slight different specification as is outlined in Eq. (16); in particular, it uses the following two-stage estimation, first done for each portfolio ι across

Table A.15. Results of Dynamic Response Regressions for Output, Consumption, and Investment. NOTE: This table tabulates the results of aggregate dynamic response regressions in the form of Eq. (A.30). On the left-hand side, Γ_t denotes the aggregate output, consumption, or investment. Thus the left-hand side measures the annualized S-year horizon growth rate. To better interpret the coefficient $\beta^{ACS,MKT}$, I normalize the factors $F_t^{\mathrm{ACS,MKT}}$ to zero mean and unit standard deviation. Each column runs one aggregate dynamic response regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using OLS with standard errors corrected for heteroscedasticity and serial correlation (Newey & West [1987]). The sample spans years from 1998 to 2017 annually.

Dependent Variable	Output	Output	Output	Output	Output
Future S-Year Horizon	s=0	s=1	s=2	s=3	s=4
β^{ACS}: Adj Cost Shock F_t^{ACS}	0.57	0.07	−0.24	−0.14	0.11
	(0.45)	(0.37)	(0.33)	(0.24)	(0.26)
β^{MKT}: Productivity Shock F_t^{MKT}	0.37	0.91*	0.60*	0.35	0.21
	(0.61)	(0.50)	(0.31)	(0.25)	(0.22)
Observations	19	18	17	16	15
R-Squared	0.09	0.28	0.24	0.12	0.07
p-Value	0.23	0.20	0.17	0.36	0.61
Years	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017
Dependent Variable	Consumption	Consumption	Consumption	Consumption	Consumption
Future S-Year Horizon	s=0	s=1	s=2	s=3	s=4
β^{ACS}: Adj Cost Shock F_t^{ACS}	−0.60**	−0.77***	−0.76***	−0.50***	−0.19
	(0.26)	(0.20)	(0.15)	(0.13)	(0.21)
β^{MKT}: Productivity Shock F_t^{MKT}	−0.14	0.22	0.28	0.29	0.31*
	(0.47)	(0.34)	(0.21)	(0.17)	(0.14)
Observations	19	18	17	16	15
R-Squared	0.16	0.41	0.57	0.47	0.33
p-Value	0.10	0.01	0.00	0.01	0.13
Years	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017
Dependent Variable	Investment	Investment	Investment	Investment	Investment
Future S-Year Horizon	s=0	s=1	s=2	s=3	s=4
β^{ACS}: Adj Cost Shock F_t^{ACS}	2.66*	1.57*	0.06	−0.42	−0.06
	(1.32)	(0.78)	(0.66)	(0.48)	(0.46)
β^{MKT}: Productivity Shock F_t^{MKT}	0.54	2.43**	2.16***	1.25***	0.81**
	(1.53)	(1.12)	(0.63)	(0.38)	(0.29)
Observations	19	18	17	16	15
R-Squared	0.17	0.33	0.36	0.27	0.20
p-Value	0.15	0.01	0.01	0.02	0.05
Years	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017	1998 − 2017

time and second done in the cross-sectional at each period t.

$$\begin{aligned}\forall\iota: R_{\iota,t} &= a_\iota + \beta_\iota^{\text{MKT}} F_t^{\text{MKT}} + \beta_\iota^{\text{ACS}} F_t^{\text{ACS}} + e_{\iota,t}^{\iota}, t = 1, \cdots, \mathcal{T} \\ \forall t: R_{\iota,t} &= a_t + \lambda_t^{\text{MKT}} \beta_\iota^{\text{MKT}} + \lambda_t^{\text{ACS}} \beta_\iota^{\text{ACS}} + e_{\iota,t}^{t}, \iota = 1, \cdots, \mathcal{I}\end{aligned} \tag{A.35}$$

Therefore, the risk prices of adjustment cost shock and productivity shock are respectively

$$\begin{aligned}\lambda^{\text{ACS}} &= \mathbb{E}[\lambda_t^{\text{ACS}}] \\ \lambda^{\text{MKT}} &= \mathbb{E}[\lambda_t^{\text{MKT}}]\end{aligned} \tag{A.36}$$

Table A.16 reports the risk prices of for the CAPM model (columns [1] and [3]) and the linear two-factor asset pricing model (columns [2], [3], [5] and [6]) implied my model. In addition to results in the paper, I show robustness of the risk price estimation by constructing the adjustment cost shock using tertile portfolio spread in columns [2] and [3], and quintile portfolio spread in columns [5] and [6]. Specifically, I construct the univariate tertile portfolios defined by 30$-$ and 70-percentiles of the cross-sectional hours growth and calculate the tertile portfolio equity return spread between low- and high-hours growth portfolios as the first adjustment cost shock proxy, $F_t^{\text{ACS-3}}$. Next, I construct the univariate quintile portfolios defined by 20$-$, 40$-$, 60$-$ and 80-percentiles of the cross-sectional hours growth and calculate the quintile portfolio equity return spread between low- and high-hours growth portfolios as the second adjustment cost shock proxy, $F_t^{\text{ACS-5}}$. Treating $F_t^{\text{ACS-3}}$ and $F_t^{\text{ACS-5}}$ as adjustment cost shock, λ^{ACS-3} and λ^{ACS-5} reports the estimated associated risk prices. The negative coefficient estimates of λ^{ACS} in columns [2], [3], [5] and [6] show a negative risk price associated with the adjustment cost shock; that is, a positive adjustment cost shock leads to increases of stochastic discount factor, or equivalently, high marginal utility states.

A.5.3 Adjustment Cost Shock and Firm-Level Payout

At the firm-level, my model's economic mechanism implies that, in periods with a positive adjustment cost shock, firms adjusting hours more are more responsive to adjustment cost

Table A.16. Negative Risk Price of Adjustment Cost Shock in Asset Pricing Tests. NOTE: This table reports the asset pricing test results of adjustment cost shock risk price. To calculate risk prices, I use two sets of testing portfolios, the Fama-French 25 portfolios size (ME) and book-to-market (BM) sorted and Fama-French 17 industry portfolios. To make the estimated risk price more robust, I construct two proxies for adjustment cost shock using factor mimicking procedure on univariate tertile and quintile portfolios, denoted as $F_t^{\text{ACS-3}}$ and $F_t^{\text{ACS-5}}$, and hence risk prices associated are denoted as λ^{ACS-3} and λ^{ACS-5}. Each column runs one asset pricing test regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using Fama-Macbeth method (Fama & MacBeth [1973]) with standard errors corrected for heteroscedasticity and serial correlation (Newey & West [1987]). The sample spans years from 1998 to 2017 annually.

	[1]	[2]	[3]	[4]	[5]	[6]
Method	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth	Fama-MacBeth
Portfolios	ME-BM Sorted	ME-BM Sorted	ME-BM Sorted	Industry	Industry	Industry
λ^{MKT}	0.85***	0.39**	0.27**	1.38**	0.44***	0.29***
	(0.21)	(0.15)	(0.12)	(0.53)	(0.13)	(0.09)
λ^{ACS-3}		−0.31***			−0.28***	
		(0.10)			(0.09)	
λ^{ACS-5}			−0.35***			−0.32***
			(0.09)			(0.10)
S.E.	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West	Newey-West
Observations	500	500	500	340	340	340
Portfolios	25	25	25	17	17	17

shock, and hence are able to payout more and to earn lower equity return in equilibrium. This section provides additional results on the testing the third implication.

As before, I use both $F_t^{\text{ACS-3}}$ and $F_t^{\text{ACS-5}}$ as adjustment cost shock to test the favorable impact on firms' payouts. In particular (similar to Eq. (17)),

$$\Pi_{j,t} = b^{(1)} \times F_t^{\text{ACS-}\mathcal{P}} + \sum_{p=2}^{\mathcal{P}} b^{(p)} \times D_{jt}^{(p)} \times F_t^{\text{ACS-}\mathcal{P}} + c^{(1)} + \sum_{p=2}^{\mathcal{P}} c^{(p)} \times D_{jt}^{(p)} + d \times \Pi_{j,t-1} + e_{j,t} \tag{A.37}$$

where $\mathcal{P} = 3$ for tertile portfolios and $F_t^{\text{ACS-3}}$, and $\mathcal{P} = 5$ for quintile portfolios and $F_t^{\text{ACS-5}}$.

Table A.17 tabulates coefficient estimation of $b^{(p)}$. For both $\mathcal{P} = 3$ and $= 5$, across all cases, moving from the low- to high-portfolio of cross-sectional hours growth, firms with higher hours growth demonstrates larger and significant responses to the adjustment cost shock. Moreover, the coefficient estimates of $b^{(p=1)}$ and $b^{(p=\mathcal{P})}$ increase from negative to positive, suggesting that more responsiveness to adjustment cost shock enables firms to pay out more.

Table A.17. Firm-Level Payout Response Regressions Results. NOTE: This table tabulates the results of firm-level payout response regressions in the form of Eq. (A.37). On the left-hand side, $\Pi_{j,t}$ is firm j's annual payout measured from January of year t to December of year t. On the right hand side, there are two proxies of adjustment cost shock. First, $F_t^{\text{ACS-3}}$ is the tertile portfolio equity return spread from July of year t to June of year $t+1$. Second, $F_t^{\text{ACS-5}}$ is the quintile portfolio equity return spread from July of year t to June of year $t+1$. $D_{jt}^{(p)}$ is firm j's portfolio assignment at the end of year t; for example, $D_{jt}^2 == 1$ indicates firms in the second portfolio univariate sorted by cross-sectional hours growth in either tertile or quintile portfolios. Additionally on the right-hand site, $\Pi_{j,t}$ is firm j's annual payout measured from January of year $t-1$ to December of year $t-1$. Each column runs one firm-level payout response regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I measure payout as the payout intensity (ratio of cash flow to total assets) on columns [1], [2], [9], and [10], as the payout growth in columns [3], [4], [11], and [12], as the payout log-level in columns [5], [6], [13], and [14], and output log-level in columns [7], [8], [15], and [16]. For each measurement, I estimate the responses with and without the payout control. I implement all regressions using OLS. The sample spans years from 1998 to 2017 annually.

Dependent Variable at t	Payout Intensity		Payout Growth		Payout Log-Level		Output log-Level	
Control Variable at $t-1$	No	Yes	No	Yes	No	Yes	No	Yes
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
$b^{(1)}$: $F_t^{\text{ACS-3}}$	−0.10***	−0.09***	−0.23***	−0.04	−0.54***	−0.40***	−0.26***	−0.03
	(0.01)	(0.01)	(0.07)	(0.07)	(0.09)	(0.07)	(0.05)	(0.04)
$b^{(2)}$: $F_t^{\text{ACS-3}} \times D_{jt}^{(2)}$	0.10***	0.07***	0.20**	0.01	0.42***	0.57***	0.15*	0.20***
	(0.02)	(0.02)	(0.09)	(0.12)	(0.12)	(0.10)	(0.08)	(0.06)
$b^{(3)}$: $F_t^{\text{ACS-3}} \times D_{jt}^{(3)}$	0.15***	0.14***	0.63***	0.68***	0.83***	0.79***	0.23**	0.29***
	(0.02)	(0.02)	(0.13)	(0.16)	(0.16)	(0.15)	(0.10)	(0.09)
R-Squared	0.00	0.37	0.00	0.01	0.00	0.85	0.01	0.93
p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
$b^{(1)}$: $F_t^{\text{ACS-5}}$	−0.11***	−0.10***	−0.22***	−0.10	−0.48***	−0.32***	−0.25***	0.04
	(0.01)	(0.01)	(0.08)	(0.08)	(0.09)	(0.08)	(0.05)	(0.04)
$b^{(2)}$: $F_t^{\text{ACS-5}} \times D_{jt}^{(2)}$	0.10***	0.08***	0.07	0.08	0.04	−0.02	0.12*	−0.17***
	(0.02)	(0.02)	(0.10)	(0.16)	(0.13)	(0.11)	(0.07)	(0.06)
$b^{(3)}$: $F_t^{\text{ACS-5}} \times D_{jt}^{(3)}$	0.12***	0.09***	0.03	−0.36**	0.40***	0.26**	0.22***	−0.06
	(0.02)	(0.02)	(0.11)	(0.15)	(0.13)	(0.12)	(0.08)	(0.07)
$b^{(4)}$: $F_t^{\text{ACS-5}} \times D_{jt}^{(4)}$	0.07***	0.04**	0.37***	0.26*	0.57***	0.84***	−0.07	0.18***
	(0.02)	(0.02)	(0.12)	(0.14)	(0.14)	(0.13)	(0.09)	(0.06)
$b^{(5)}$: $F_t^{\text{ACS-5}} \times D_{jt}^{(5)}$	0.14***	0.13***	0.49***	0.75***	0.84***	0.65***	0.33***	0.15*
	(0.02)	(0.02)	(0.13)	(0.17)	(0.15)	(0.16)	(0.09)	(0.09)
R-Squared	0.00	0.38	0.00	0.01	0.00	0.85	0.00	0.93
p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table A.18. Firm-Level Equity Return Response Regressions Results. NOTE: This table tabulates the results of firm-level equity return response regressions in the form of Eq. (A.38). On the left-hand side, $R_{j,t+1}$ is firm j's annual equity return from July of year $t+1$ to June of year $t+2$. On the right hand side, there are two proxies of adjustment cost shock. First, $F_t^{\text{ACS-3}}$ is the tertile portfolio equity return spread from July of year t to June of year $t+1$. Second, $F_t^{\text{ACS-5}}$ is the quintile portfolio equity return spread from July of year t to June of year $t+1$. $D_{jt}^{(p)}$ is firm j's portfolio assignment at the end of year t; for example, $D_{jt}^2 == 1$ indicates firms in the second portfolio univariate sorted by cross-sectional hours growth in either tertile or quintile portfolios. Additionally on the right-hand site, $\Phi_{j,t}$ is a control variable for firm j measured by end of year t: for example, equity return, payout intensity, payout growth, payout log-level, and output log-level. Each column runs one firm-level equity return response regression, with *, **, and *** denoting 10%, 5%, and 1% significance levels, and standard errors in parenthesis. I implement all regressions using OLS. The sample spans years from 1998 to 2017 annually.

Dependent Variable at $t+1$	Euqity Return				
Control Variable at t	No	Equity Return	Payout Intensity	Payout Growth	Payout Log-Level
	[1]	[2]	[3]	[4]	[5]
$b^{(1)}$: $F_t^{\text{ACS-3}}$	0.01	−0.00	0.01	−0.07	−0.02
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$b^{(2)}$: $F_t^{\text{ACS-3}} \times D_{jt}^{(2)}$	−0.25***	−0.22***	−0.26***	−0.21***	−0.25***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$b^{(3)}$: $F_t^{\text{ACS-3}} \times D_{jt}^{(3)}$	−0.45***	−0.42***	−0.45***	−0.34***	−0.33***
	(0.11)	(0.11)	(0.11)	(0.09)	(0.09)
R-Squared	0.00	0.00	0.01	0.01	0.01
p-Value	0.00	0.00	0.00	0.00	0.00
	[6]	[7]	[8]	[9]	[10]
$b^{(1)}$: $F_t^{\text{ACS-5}}$	−0.05	−0.07	−0.06	−0.06	−0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$b^{(2)}$: $F_t^{\text{ACS-5}} \times D_{jt}^{(2)}$	0.02	0.04	0.01	−0.03	−0.07
	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)
$b^{(3)}$: $F_t^{\text{ACS-5}} \times D_{jt}^{(3)}$	0.05	0.07	0.05	−0.04	0.02
	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)
$b^{(4)}$: $F_t^{\text{ACS-5}} \times D_{jt}^{(4)}$	−0.15*	−0.13*	−0.16**	−0.25***	−0.28***
	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)
$b^{(5)}$: $F_t^{\text{ACS-5}} \times D_{jt}^{(5)}$	−0.32***	−0.28***	−0.32***	−0.26***	−0.25***
	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
R-Squared	0.01	0.01	0.01	0.01	0.01
p-Value	0.00	0.00	0.00	0.00	0.00

A.5.4 Adjustment Cost Shock and Firm-Level Equity Return

Similarly, the fourth implication that firms adjusting hours more and paying out more earn lower equilibrium equity returns are tested in similar regressions to Eq. (18). Specifically, I run equity return response regressions again using both $F_t^{\text{ACS-3}}$ and $F_t^{\text{ACS-5}}$ as adjustment cost shock, in the following form

$$R_{j,t+1} = b^{(1)} \times F_t^{\text{ACS-}\mathcal{P}} + \sum_{p=2}^{\mathcal{P}} b^{(p)} \times D_{jt}^{(p)} \times F_t^{\text{ACS-}\mathcal{P}} + c^{(1)} + \sum_{p=2}^{\mathcal{P}} c^{(p)} \times D_{jt}^{(p)} + d \times \Phi_{j,t} + e_{j,t+1}. \tag{A.38}$$

On the left-hand side, $R_{j,t+1}$ is the firm j's annual equity return measured from July of year $t+1$ to June of year $t+2$; on the right-hand side, $\Phi_{j,t}$ is one of the five control variables for firm j: equity return, payout intensity, payout growth, payout log-level, and output log-level. Table A.18 shows equilibrium equity returns of firms with higher hours growth have higher loading of adjustment cost shock, and such higher loading reduces the riskiness of firms and hence their equilibrium equity returns.