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Labor Adjustment Cost: Implications for Asset Prices*

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Abstract

This paper studies the asset pricing implications from the labor adjustment cost. I implement a novel crosswalk linking three micro-level datasets and measure the hours margin of a firm's labor input. At the firm-level, a 1 percent increase in hours is associated with a 0.6 percent decrease in future equity value. I rationalize this empirical fact in a production-based asset pricing model incorporating non-convex, linear, and convex labor adjustment cost components. Estimation of the model shows that (1) the disruption to production is the driving force of the labor adjusting friction, and that (2) the labor adjustment cost on hours is an essential component to produce the pooled distributions of the hours and the employment growths that are consistent with the data.

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1 Introduction

Dynamics in the labor input are an essential and integral component of a firm's optimization. At the micro-level, firms make decisions along both margins of hours (intensive margin) and employment (extensive margin) to maximize their values; in such microstructure, labor adjustment cost plays a crucial role in shaping interactions between employment and hours as well as determining the growths in outputs and values. Besides, Belo et al. [2014a] find that, in the contexts of asset pricing, the adjusting friction in the labor market persuades firms to be forward-looking; thus, the optimal employment possesses information about a firm's output and value in the intertemporal, affecting further the firm's equity return. Linking these findings on hours, employment, and equity return, it seems that the labor adjustment cost is an economically important channel, through which both margins of hours and employment affect not only economic quantities, such as outputs, but also asset prices, such as equity returns.

In this paper, I investigate empirically and quantitatively whether the firm's labor input choices of hours and employment are a source of macroeconomic risk that is priced in the cross-section of equity return in the presence of labor adjustment cost on both margins. I show empirically that the firms with current high hours growths are expected to have low equity returns in the future, supported by both the firm- and the portfolio-level results. To elucidate the underlying economic mechanism and to quantify the magnitude of labor adjusting friction, I develop a production-based asset pricing model with dynamic labor input that is explicit on a firm's choices of hours and employment. The model reveals that the labor adjusting friction prevents firms from changing hours frictionlessly and allows firms to weigh the options of changing hours now versus in the future; as a result, the firms with current high hours growths are expected to incur low adjustment costs, to generate high cash flows, and to earn low equity returns in the future. Using structural estimation of the model, I quantitatively reproduce a broad set of economic quantities and asset prices in the data and find that the disruption to production, in the form of non-convex labor adjustment cost on both margins of hours and employment, is the driving force of labor adjusting friction.

I start my analysis by identifying a robust empirical fact that relates a firm's current labor input choice of hours to its future equity value. 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, for there is no readily available data of hours measured for public firms through standardized financial reporting (e.g., 10-Q and 10-K) system. 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, and construct a measure of hours composed by industry-specific occupational hours which is further aggregated from individual-level data. In a series of validation exercises, my measure of hours demonstrates 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 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), an orthogonal dataset, exhibits remarkable similarities in the pattern, especially around the recent episode of the 2007-09 financial crisis. Last but not least, my measure of hours is robust to alternative weighting schemes applied to occupational hours and is also robust to occupation compositions that are both industry-specific and time-varying.

The main empirical findings in this paper are twofold. First, I find a strong negative relation between a firm's current hours and its future equity value; that is, the current high growth rate of hours predicts low future equity return. To establish this intertemporal linkage, I implement a set of equity return predictability regressions at the firm level; controlling for employment and capital, a 1% increase in the firm's current hours is associated with a 0.6% decrease in the firm's future equity value. The negative relation is furthermore evidenced at the portfolio level. I find that portfolios of firms sorted by the cross-sectional growth rates of hours manifest a monotonically decreasing pattern in both the excess equity returns and Sharpe ratios; more concretely, the univariate low- and high-hours growth quintile portfolios yield a negative equity return spread of -6% per year. My second main empirical finding is the low correlation between the impacts of changing hours and employment on equity return. I investigate the marginal predictability of hours growth, relative to that of employment growth, on equity return, and show that the impact of changing hours on equity return is statistically unchanged, irrespective of the impact of changing employment.

These two main empirical findings guide the theoretical assumptions and quantitative analyses to follow. In the rest of the paper, I firstly propose a production-based asset pricing model that allows firms to make explicit decisions on both hours and employment. The key ingredient of the model is the existence of labor adjusting friction along the margin of hours, analogous and additional to that along the margin of 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 changing hours; i.e., the model delivers a negative association between current hours growth and future equity return, consistent with empirical findings. The underlying economic mechanism operates intuitively. Firms who want to increase hours are expanding firms who receive positive idiosyncratic productivity shocks, the source of cross-sectional heterogeneity; by choosing desired higher levels of hours, these firms in the next period are thus expected to lower their labor adjustment costs; therefore, the expected dividends of these firms would be higher, and the expected equity returns would be lower. Second, the labor market friction associated with adjusting 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, consisted of non-convex, linear, and convex components; the model hence can disentangle hours and employment from an intratemporal Euler equation often derived from the economic environment with frictionless hours adjustment, and to further shed light on the root structure and the leading components of labor adjusting friction.

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 variances, skewnesses, and kurtoses of hours and employment growths, (2) the first-order persistence coefficients of hours and employment growths, and (3) the same-period and cross-period correlation coefficients between hours and employment growths. The model also delivers pooled (across all firms and years) distributions of hours and employment growths that are notably close to data. Cooper & Haltiwanger [2006] and Cooper et al. [2015], among others, show that the patterns in pooled distribution are informative about the structure of adjustment cost. I follow this receipt in discussing the labor adjusting friction and discover that the model-implied magnitudes of non-convex, linear, and convex adjustment cost components are consistent with the distributional observations calculated from empirical hours and employment growths. Specifically, I find that the non-convex component, described as any occurred disruption to the firm's production during the process of adjusting labor input, accounts for over 90% of the labor adjustment cost, suggesting the disruption to production the driving force of labor adjusting friction.

Turning to asset prices, I inspect the model's economic mechanism 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 value is qualitatively and quantitatively reproduced. A 1% increase in the firm's current hours is associated with a future equity value decrease 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%. To strengthen the connection between my model's economic mechanism and the movement in equity return, I also verify a corollary testable implication. In the model, firms with current high hours growths are expected to incur low labor adjustment costs and to earn low equity returns in the future; meanwhile, by increasing hours now, such firms in the current period incur high labor adjustment costs and earn high equity returns, i.e., a positive relation between a firm's current hours and its current equity value. Using a set of equity return concurrence regressions, I confirm such positive relation in both the data and the model.

Finally, I explore the theoretical and quantitative role of the labor adjusting friction along the margin of hours. To this end, I estimate and simulate an otherwise identical model without the labor adjustment cost on hours. Conceptually in this model, because adjusting hours is costless, the firm uses its choice of hours to fully accommodate its choice of employment; the results from such optimization include (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, all of which are in contrast to the data.

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 adjusting 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 adjusting friction along the hours margin, in addition to that along the employment margin, unfolds an important 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 output and value. Thus, my model complements the existing discussions on labor adjustment cost and improves our understanding of the link between labor input and firm value.

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, who impose higher labor adjustment cost. 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. 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. (Donangelo [2019]; Belo et al. [2020] TBA). My work differs from these studies by exploring the dynamics of labor input fundamentals, which provides a novel framework studying the hours and employment, and their impacts on the equity return.

My findings also contribute to studies on the production-based asset pricing models relating the asset prices to the 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. My addition to this strand of literature is the empirical identification and incorporation 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 adjusting frictions 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 (for example 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 the firms' hours. Section 3 presents my empirical findings. Section 4 develops a simple production-based asset pricing model, the economic mechanism of which is tested in Section 6. Section 7 concludes.

2 Measuring the Hours

Understanding the relation between a firm's labor input and its value requires the firm-level data on hours, employment, and equity return. In this section, I describe the data and methodology that I use to construct the measure of hours. I relegate additional details 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 count, and (3) each occupation's hourly wage. 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 four-digit NAICS industries; the average number of occupations each year is 807, covering about 99% of all six-digit SOC occupations.

My measure of hours is composed by industry-specific occupational hours that is aggre-

[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 wage information, which is crucial 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.

gated 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. 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. The final CPS program dataset spans years from 1997 to 2017, with the average number of surveyed individuals being $67'472$ each year.

The third is the CRSP/Compustat Merged (CCM) dataset. I follow the literature to provide 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[2], and the capital investment is I from FUNDA data items CAPX (capital expenditures) less SPPE (sales of property, plant,

[2]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 when the capital growth is calculated using the DHS method (Davis et al. [1996a]). Therefore, I delegate a part in the Appendix A.1.1 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.

and equipment), where missing values of SPPE are supplemented using zeros. Once the employment and capital levels are constructed, their empirical growths G^N and G^K are defined using DHS method (Davis et al. [1996a]).

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,

$$\text{Hour}_t^{(i,o)} = \sum_{p \in \text{CPS}_t(i,o)} \text{Wght}_t^{(i,o,p)} \times \text{Hour}_t^{(i,o,p)}. \tag{1}$$

On the right-hand side, $\text{CPS}_t(i,o)$ 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, $\text{Wght}_t^{(i,o,p)}$ and $\text{Hour}_t^{(i,o,p)}$ 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. In Appendix A.1, I vary the empirical definitions of the individual-level weight and hours to provide robustness checks.

The second step utilizes the industry-specific occupational employment and wage information to form industrial hours; in particular, it takes the industry-specific occupational hours $\text{Hour}_t^{(i,o)}$ from Eq. (1) and weights each occupation according to the wage expense associated:

$$\text{Hour}_t^{(i)} = \sum_{o \in \text{OES}_t(i)} \left(\frac{\text{Empt}_t^{(i,o)} \times \text{Wage}_t^{(i,o)}}{\Sigma_{o \in \text{OES}_t(i)} \text{Empt}_t^{(i,o)} \times \text{Wage}_t^{(i,o)}} \times \text{Hour}_t^{(i,o)} \right). \tag{2}$$

In this step, for industry i in year t, (1) $\text{OES}_t(i)$ is the set of all the possible occupations, (2) $\text{Empt}_t^{(i,o)}$ is each occupation's employment count, and (3) $\text{Wage}_t^{(i,o)}$ is each occupation's hourly wage. Therefore, there are two advantages of this definition. First, it places more weights on occupations with greater impacts to the cash flows, by implementing the marginal cost-based weighting scheme of Empt $\times$ Wage. Second, it takes into the consideration the influences from the evolution of industry-specific occupation compositions across time. In Appendix A.1, I convey the implications from these two advantages in Eq. (2), and demonstrate that the measure of hours is very robust to alternative weighting schemes and different occupation composition time-series assumptions.

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

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

That is, the firm's annual hours is approximated by the industrial average of the year. 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 downwards and hence the proposed impact of changing hours on equity return is likely to provide a conservative lower-bound. Furthermore, I discuss and disalarm the approximation in Appendix A.1 from the lenses of asset pricing investigations, and demonstrate that the approximation does not change the main empirical findings in any meaningful way.

3 Empirical Evidence

In this section, I show the empirical link between a firm's current labor input choice of hour and its future equity value. Two main empirical findings from this section arise and are of great importance in regulating the model and directing the quantitative exercises. First, I focus on the negative predictability. The firms with current high hours growths are expected to have low equity returns in the future, controlling for employment and capital. Second, I explore the correlation between the impacts of changing a firm's hours and employment on equity return. This helps me to understand the dynamics of a firm's choices of hours and employment form the perspective of asset prices. I show my main empirical findings via two complementary econometric methodologies: a regression approach and a portfolio approach, combining which together allows me to crosscheck the results and establish the robustness of my main empirical findings.

3.1 Firm-Level Evidence

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

$$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + b_K \times G^K_{jt} + \boldsymbol{b} \times \boldsymbol{F}_{jt}. \tag{4}$$

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 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 year t. Additionally on the right-hand side, $\boldsymbol{F}$ is a vector of five pricing factors, 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]). In Appendix A.2, I also implement the Fama-MacBeth procedure (Fama & MacBeth [1973]) to crosscheck the coefficients estimates.

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 indicated by table head. 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 growth rates $G_{jt}^{H,N,K}$, of three production input choices hours (H), employment (N), and capital (K), respectively. Additionally on the right-hand side, $\boldsymbol{F}_{jt}$ is a vector of five pricing factors, 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]). Panel A show regressions without $\boldsymbol{F}_{jt}$ and panel B with. Each column runs one firm-level equity return predictability regression. In particular, columns [1] to [3] and [7] to [9] show regressions with the growth rates of hours and employment $G_{jt}^{H,N}$, columns [4] to [6] and columns [10] to [12] show regressions with the growth rates of hours, employment, and capital $G_{jt}^{H,N,K}$. Rows summarize column regressions. Rows (1), (2), and (3) report regression coefficient estimation for growth rates of hours, employment, and capital $G_{jt}^{H,N,K}$ respectively; of any regression coefficient estimation, I report the point estimator $b_{H,N,K}$, as well as the standard errors in parentheses (se) and the t-statistic in brackets [t]. Row (4) shows the regression statistics, including the number of observations, the number of firms, the adjusted within R^2, and the p value from regression F-test. Row (5) specifies fixed effects in the regressions. I implement all regressions using panel OLS with firm standard error clusters; the sample spans from 1997 to 2017 annually.

		Hours & Employment			Adding Capital			Hours & Employment			Adding Capital		
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Panel A	Without Pricing Factors $\boldsymbol{F}_{jt}$:		$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G_{jt}^H + b_N \times G_{jt}^N + b_K \times G_{jt}^K$									
(1)	b_H	-62.86		-61.11	-61.09		-60.23	-55.36		-54.03	-54.03		-53.45
	(se)	14.74		14.71	14.69		14.67	12.60		12.57	12.57		12.56
	[t]	-4.26		-4.15	-4.16		-4.10	-4.39		-4.30	-4.30		-4.26
(2)	b_N		-13.93	-14.96		-11.06	-11.23		-10.55	-10.28		-8.78	-7.54
	(se)		1.43	2.15		1.48	2.24		1.08	1.48		1.17	1.59
	[t]		-9.71	-6.95		-7.46	-5.02		-9.78	-6.93		-7.51	-4.75
(3)	b_K				-11.68	-6.92	-8.73				-7.20	-3.36	-5.07
	(se)				1.59	1.21	1.67				0.99	0.82	1.07
	[t]				-7.35	-5.74	-5.21				-7.26	-4.10	-4.74
(4)	# Obs.	23030	42063	23030	23030	42063	23030	23030	42063	23030	23030	42063	23030
	# 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	0.00	0.00	0.00	0.00	0.00	0.00
	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
(5)	Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Firm FE	Y	Y	Y	Y	Y	Y	No	No	No	No	No	No
	Panel B	With Pricing Factors $\boldsymbol{F}_{jt}$:		$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G_{jt}^H + b_N \times G_{jt}^N + b_K \times G_{jt}^K + \boldsymbol{b} \times \boldsymbol{F}_{jt}$									
(1)	b_H	-53.86		-54.00	-53.65		-53.83	-54.32		-53.43	-53.39		-53.01
	(se)	13.35		13.35	13.36		13.36	12.49		12.47	12.47		12.46
	[t]	-4.04		-4.05	-4.02		-4.03	-4.35		-4.29	-4.28		-4.26
(2)	b_N		-0.34	1.52		0.70	2.69		-8.98	-8.15		-7.14	-5.21
	(se)		1.43	2.13		1.47	2.19		1.08	1.51		1.16	1.60
	[t]		-0.24	0.71		0.48	1.23		-8.32	-5.40		-6.13	-3.26
(3)	b_K				-2.33	-2.81	-3.06				-7.26	-3.76	-5.79
	(se)				1.74	1.30	1.76				1.05	0.85	1.11
	[t]				-1.34	-2.16	-1.74				-6.92	-4.40	-5.19
(4)	# Obs.	23029	42062	23029	23029	42062	23029	23029	42062	23029	23029	42062	23029
	# Firms	4473	5824	4473	4473	5824	4473	4473	5824	4473	4473	5824	4473
	Within R^2	0.13	0.10	0.13	0.13	0.10	0.13	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
(5)	Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	Firm FE	Y	Y	Y	Y	Y	Y	No	No	No	No	No	No

In panel A of Table 1, columns [1] to [3], report the equity return predictability regression results using the firm's current growth rates of hours G_{jt}^{H} and employment G_{jt}^{N} in Eq. (4). The results for these three columns are straightforward. First focusing on columns [1] and [2], the firm's high current growth of hours predicts the low future equity return of the firm; the coefficient estimate of hours growth is $b_H = -62.86(14.74)$. Additionally, the similar negative predictability also holds for the firm's choice of employment, documented by Belo et al. [2014a] and reproduced here; the coefficient estimate of employment growth is $b_N = -13.93(1.43)$. The negative predictability of a firm's current growth rates of hours and employment from b_H and b_N rests at the very core of my argument in this paper: it not only inspires the model with the labor adjusting friction along both margins of hours and employment but also serves as one of the 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 slope coefficients for hours growth and those for employment growth are statistically equivalent: 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 is my second main empirical finding, that the correlation between the impacts of firm's changing its current hours and employment on its future equity return is low. Intuitively, the hours and employment are two substitutable production inputs and the firm optimizes by strategically complements the one with the other. When there is labor adjusting friction along both margins of hours and employment, 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 adjusting friction, the firm's current labor input choices of hours and employment additionally reveals the information about the firm's future labor input choices of hours and employment, indicative of the firm's future cash flow and equity return.

Moving to the columns [4] to [6], I additionally include the firm's current growth rate of capital G_{jt}^{K}[3]. The two main empirical findings are consistent with results from columns [1] to [3]. To understand 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 value, controlling for employment and capital, and this negative association is statistically significant, more than 4-standard deviations away from zero. To further inspect the marginal equity return predictability, I calculate the standard deviations of hours, employment, and capital growths 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 value, 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, a firm's labor input choice of hours has an impact on a firm's cash flow and equity value that is economically comparable to those from employment and capital.

The columns [7] to [12] remove firm fixed effects from the regressions, making my results more comparable to previous studies (Belo et al. [2014a] and Belo et al. [2017]) and the cross-sectional equity return literature. I place the firm-level regression results with the pricing factor vector $\boldsymbol{F}_{jt}$ in the panel B. The analyses of the firm-level evidence with the pricing factor vector $\boldsymbol{F}_{jt}$ is qualitatively identical and quantitatively similar to the analyses of that without the pricing factor vector $\boldsymbol{F}_{jt}$, so I omit the detailed analysis of the results here. In addition, Appendix A.2 vary the specifications of (1) the fixed effects, (2) the standard error clusters, (3) the cross-sectional outliers, and (4) the winsorization and truncation to provide robust checks of the main empirical findings at the firm level. In the following, I show the negative association between a firm's current choice of hours and its future equity return using a portfolio approach as a crosscheck.

[3]In defining the growth rate of capital, I follow the empirical investment literature and calculate in three ways, namely, the investment ratio $G_{jt}^{K} = \frac{I_{jt}}{K_{jt}}$, the DHS growth rate $G_{jt}^{K} = \frac{K_{jt}-K_{j,t-1}}{0.5(K_{jt}+K_{j,t-1})}$ (Davis et al. [1996a]), and DD growth rate $G_{jt}^{K} = \frac{I_{jt}-0.12K_{j,t-1}}{0.5(K_{jt}+K_{j,t-1})}$ (Doms & Dunne [1998]). The results here use the DHS growth rate to be consistent with the hours and employment.

3.2 Portfolio-Level Results

I form the univariate quintile portfolios sorted by the cross-sectional hours growths and deploy the quintile portfolios in my portfolio-level analyses; in Appendix A.2, I also construct and investigate the bivariate and trivariate portfolios independently and sequentially sorted by additionally the cross-sectional employment and capital growths.

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 growths, 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[4] and my portfolio-level resutls thus provide a more comprehensive view about the relation between the current labor input of hours and its future cash flow for not only the publicly listed firms but also generally the private firms in the economy.

[4]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 growths. 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 return summary statistics, including the mean of portfolio equity returns $\mu(r_{t+1})$, 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. panel 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 (1) reports the model implied anomaly; the row (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 from 1997 to 2017 annually.

		Value-Weighted						Equal-Weighted						Equal-Weighted Excl. Microcaps					
		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	Equity Return Summary Statistics																	
	$\mu(r_{t+1})$	0.11	0.09	0.07	0.07	0.05	0.06	0.16	0.16	0.14	0.08	0.09	0.06	0.14	0.13	0.11	0.06	0.07	0.06
	$\mu(r^e_{t+1})$	0.10	0.07	0.06	0.05	0.03	0.06	0.14	0.14	0.12	0.06	0.07	0.06	0.12	0.11	0.09	0.04	0.05	0.06
	$\sigma(r^e_{t+1})$	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)	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)	m.a.e.	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	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)	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)	m.a.e.	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	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)	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)	m.a.e.	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	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

In panel A of Table 2, I calculate the summary statistics of quintile portfolio equity returns. Consistent with the firm-level evidence, across all the three measures, the current hours growth predicts the future equity return. Furthermore, the future equity (excess) returns monotonically decreases moving from low (L: columns [1], [7], and [13]) to high (H: columns [5], [11], and [17]) quintile portfolios; this means that, firms with current high hours growths are expected to have low equity returns in the future.

I additionally emphasize two observations that stand out. First, the difference in the portfolio equity (excess) returns is economically large. The average portfolio return spread (L-H, Low-minus-High: columns [6], [12], and [18]) is -6% per annum for all the three measures of portfolio equity returns. This -6% portfolio return spread is in the same order of magnitudes as those for risk factors commonly used in the finance 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 of portfolio equity returns yield the same -6% portfolio return spread is interesting by itself. By comparing the value- (column [6]) and equal- (column [12]) weighted portfolio return spreads, my proposed relation between a firm's current labor choice of hours and its future value is likely to be equally latent for both the large and the small firms. Comparing the equal-weighted (column [12]) and the microcaps-excluded, equal-weighted (column [18]) portfolio return spreads, I can further infer that, this negative relation is also 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 adjusting friction in a structural approach. The asset pricing factor models employed are the capital asset pricing model (CAPM: Sharpe [1964]; Lintner [1965]; Black [1972]), the Fama-French 3-factor model (Fama & French [1992, 1993]), and the Fama-French 5-factor model (Fama & French [2015]); specifically, the time-series regressions take the following general form

$$r_{t+1}^{e} = a + [b_{\mathrm{MKT}}, b_{\mathrm{SMB}}, b_{\mathrm{HML}}, b_{\mathrm{RMV}}, b_{\mathrm{CMA}}]'[(r_t^{\mathrm{MKT}} - r_t^{\mathrm{F}}), r_t^{\mathrm{SMB}}, r_t^{\mathrm{HML}}, r_t^{\mathrm{RMV}}, r_t^{\mathrm{CMA}}]. \quad (5)$$

On the left-hand side, r_{t+1}^{e} is the portfolio's equity excess return, and the right-hand side has the pricing factors. In Table 2, panel B has maket excess return $(r^{MKT} - r^{F})$ on the right-hand side, panel C additionally the size r^{SMB} and value r^{HML} factors, and panel D furthermore the profitability r^{RMV} and investment r^{CMA} factors. In all specifications, the intercept a is the pricing error resulted from the asset pricing factor model, and hence the intercept a manifests how large and significant the model-implied anomaly is.

It is clear that the firm's labor input choice of hours represents a source of macroeconomic risk that is well priced in the cross-section of equity return but not explained by the a single risk factor. From row (1) in panels B to D, across all three measures of portfolio equity excess returns in all three asset pricing factor models, the estimated anomalies a remain economically large and statistical significant. Especially for the portfolio return spreads in columns [6], [12], and [18], the estimated anomalies a are mostly in the same order of magnitudes as the portfolio return spreads themselves, the left-hand side variables. The failures of capturing the underlying macroeconomic risk and explaining the negative relation between a firm's current labor choice of hours and its future value are further evidenced by row (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.

4 A Model with Dynamic Labor Input

To rationalize the main empirical findings, I consider a production-based asset pricing model from the neoclassical business cycle theory; the key assumption of the model is the labor adjusting friction along both margins of hours and employment as suggested by the discussions in Section 3. The model builds on existing works on incorporating labor market friction (Belo et al. [2014a, 2017]) into investment-based asset pricing model (Zhang [2005]); the novel departure is the adjustment cost on hours. I use the model to explore the dynamics of labor input between both margins of hours and employment, and to understand the root structure and the leading components of the labor adjusting friction.

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 of 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], Caballero & Engel [1993], and Caballero et al. [1997] in the form of

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

where parameter ξ controls the elasticity of the 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 the firm, and ensures all firms to choose the identical level of hours in absence of the labor adjustment cost.

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 the constant per-worker, per-period invariant wage rate. When $\xi = 1$, the compensation function is defined over the total hours, the product of hours and employment, but assumes a constant average per-hour salary irrespective of the level of hours; in this case, ω is the constant per-worker, per-hour wage rate. When $\xi \in (0, 1)$, the compensation is not economically plausible, for that the compensation function then implies a negative second-order derivative with respect to hours, suggesting the overtime hours are decreasingly compensated as the overtime hours increase. Therefore, $\xi > 1$ is most the appropriate case for discussing dynamics between the two margins of labor input. Formally,

Condition 1. *The elasticity of marginal compensation function with respect to hours is positive; that is, the curvature parameter 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 $(\xi - 1)$ is positive; 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 in the capital case (see, among other, King & Thomas [2006] for discussion of this convention). Therefore, the employment growth is given by $G^N_{jt} = D^N_{jt}/N_{j,t-1}$[5]. 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 $G^H_{jt} = D^H_{jt}/H_{j,t-1}$.

Uncovering the driving force of the labor adjusting friction is my theoretical contribution from the paper. Therefore, I construct 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, I assume the labor adjusting friction along both margins of hours and employment; in Section 6, I investigate the theoretical and quantitative role of the labor adjusting friction along the margin of hours in a detailed exercise, from which I show the necessity of my assumption on labor adjusting friction in matching the empirical regularities.

[5] 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.

The adjustment cost on the hours and employment margins are respectively C_{jt}^H and C_{jt}^N specified by the following symmetric function form,

$$
\begin{aligned}
C_{jt}^H &= c_d^H Y_{jt} \cdot \mathbf{1}_{G_{jt}^H \neq 0} + c_i^H W_{jt} \cdot |G_{jt}^H| + c_q^H H_{t-1} \cdot (G_{jt}^H)^2 \\
C_{jt}^N &= c_d^N Y_{jt} \cdot \mathbf{1}_{G_{jt}^N \neq 0} + c_i^N W_{jt} \cdot |G_{jt}^N| + c_q^N N_{t-1} \cdot (G_{jt}^N)^2
\end{aligned}
\tag{8}
$$

where $c_{d,i,q}^{H,N}$ are non-negative parameters, and $\mathbf{1}$ is the nonzero indication function. The adjustment cost function reflects the possible non-convexity, linearity, and convexity that might exist during the costly process of adjusting labor input. 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 a empirical success in the literature and hence largely emphasized. For example, in discussing labor adjustment cost, Cooper & Willis [2009] and Cooper et al. [2015] use a set of micro-level evidence to show that, the non-convex disruption cost is necessary and critical for simultaneously matching 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 labor 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 firstly advocated in the context of capital; the difference between buying and selling prices of the capital refects the transaction cost, which may origin 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; thus such 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[6]

I allow the labor adjustment costs to be stochastic following Belo et al. [2014a] and Belo et al. [2017],

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

in which X_t represents an aggregate stochastic process that captures the economy-wide condition of labor adjusting friction. Therefore, the aggregate stochastic process of X is an adjustment cost wedge that affects the effective costs occurred by the adjusting firms and a shock to it is an adjustment cost shock that describes the change in aggregate labor adjusting opportunities.

The adjustment cost wedge is important for generating the negative relation between a firm's current hour and its future equity value in the cross-section. Mechanically, the adjustment cost shock affects the labor input choices of hours and employment in the intertemporal; in the economy, a positive adjustment cost shock elevates the adjustment cost wedge and hence lowers the adjustment cost. In the cross-section, firms who want to increase their hours are expending firms who received positive idiosyncratic productivity shocks relatively in the cross-section; if it is expected that the economy is to receive a positive adjustment cost shock, by choosing desired higher levels of hours in the current period, these firms in the next period are thus expected to take advantages of the higher adjustment cost wedge and

[6]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].

to lower their adjustment costs; therefore, relative to firms with smaller hours growths, the expected cash flows of these firms would be higher and the expected equity returns would be lower in the next period.

Economically, the adjustment cost shock can be conceptually thought of 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 (analogous to the more efficient capital introduced by investment in Greenwood et al. [1997, 2000], or to the more skilled labor introduced by hiring in Belo et al. [2017]), because the improvement in labor efficiency increase the unit production and allows the firms to achieve the same level of cash flow with smaller increases of hours and employment. Also, a positive adjustment cost shock works similar to a decrease in the vacancy postings (Liu [2019]) or a decrease of 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 margin of employment) and to negotiate shifts/hours (along the margin of hours). Additionally note that, such outside options include the development/advancement of the labor-substitable technology (Zhang [2019]) such as the automation (Acemoglu & Restrepo [2020]).

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, nor in the cross-section.

Given the stochastic processes, the future cash flow 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 explicit 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 the labor inputs along both margins in the current period according to the law of motions, to maximize its current period cash flow 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

$$R_{j,t+1} = \frac{V_{j,t+1} - (Y_{jt} - W_{jt} - C_{jt})}{V_{j,t}}, \tag{12}$$

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 the negative predictability from a firm's labor input choices of both margins and my model implies an economic mechanism through which the labor adjusting friction on both margins affects the firm's future value. Therefore, in the baseline model, I focus on estimating the labor adjustment cost and define the vector of estimated parameters

$$\theta = (c_d^N, c_i^N, c_q^N, c_d^H, c_i^H, c_q^H) \tag{13}$$

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 my discussion on the root structure and the leading components of the labor adjusting friction.

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 Eq. (7) controls the curvature of

Table 3. Calibration.

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]

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 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[7]. 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

[7] 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 $\sigma_X = \sigma_A = 0.014$.

value function Bellman equation from Eq. (11) determines equilibrium of the model as well as the endogenous behavior of the economic quantities and the asset prices in the model. To construct the discretized state space, 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 (years), 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 numerical implementation choices and algorithm.

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 away from the capital, the moments conceptually shall involve no capital-related variables, such as sales; therefore, I regulate the chosen moments to be insensitive to the inclusion or the exclusion of capital. Secondly, I do not explicitly target any asset pricing-related moments from empirical results; rather, I use these moments to test the model's economic mechanism and crosscheck the model fit in Section 6.

Table 4 lists a variety of 23 moments, 6 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 growths and the subpanel B.2 those for the employment gorwths. Given the nonlinearity, especially the discontinuity, structurally embedded in the model, I can not in general expect an exact match to data moments. However, Table 4 demonstrates that the estimation leads to a broadly successful fit of the targeted moments and matches the non-targeted moments very closely as well.

Table 4. Firm-Level Moments of and Pooled Distributions Statistics of Hours and Employment Growths. 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 growths 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 [5]. Specifically, the column [3] lists the value from the data, the column [4] from the baseline model, and the column [5] from the counterfactual framework. In calculating the data values in column [3], I compute using bootstrapping. For the model values in columns [4] and [5], 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	Counterfactual
	[1]	[2]	[3]	[4]	[5]
Panel A	Firm-Level				
Panel A.1	Targeted				
	Kurtosis of hours growth	$kurt(G^H)$	13.783	10.931	4.009
	Kurtosis of emp't growth	$kurt(G^N)$	7.750	4.995	7.119
	Persistence of hours growth	$rho(G^H)$	−0.376	−0.227	−0.296
	Persistence of emp't growth	$rho(G^N)$	−0.005	−0.110	−0.045
	Same-period correlation coeff.	$corr(G^H, G^N)$	0.029	0.000	−0.066
	Cross-period correlation coeff.	$corr(G^H, G^N_{-1})$	−0.024	−0.026	−0.149
Panel A.2	Non-Targeted				
	Cross-period correlation coeff.	$corr(G^H_{-1}, G^N)$	0.012	0.032	0.183
	Mean of hours growth	$mean(G^H)$	0.001	0.001	0.002
	Mean of emp't growth	$mean(G^N)$	0.051	0.003	0.002
	Variance of hours growth	$var(G^H)$	0.001	0.001	0.005
	Variance of emp't growth	$var(G^N)$	0.044	0.009	0.007
	Skewness of hours growth	$skew(G^H)$	0.156	0.172	0.299
	Skewness of emp't growth	$skew(G^N)$	0.371	0.346	0.616
Panel B	Pooled Distributions (Non-Targeted)				
Panel B.1	Hours Growths				
	Negative spike rate (%)	$G^H \in (-\infty, -0.2]$	0.00	0.00	0.00
	Negative maintenance rate (%)	$G^H \in (-0.2, -0.1]$	1.40	3.07	12.62
	Inaction rate (%)	$G^H \in (-0.1, +0.1)$	96.81	93.61	74.93
	Positive maintenance rate (%)	$G^H \in [+0.1, +0.2)$	1.79	3.32	12.45
	Positive spike rate (%)	$G^H \in [+0.2, +\infty)$	0.00	0.00	0.00
Panel B.2	Employment Growths				
	Negative spike rate (%)	$G^N \in (-\infty, -0.2]$	9.04	2.03	0.89
	Negative maintenance rate (%)	$G^N \in (-0.2, -0.1]$	12.09	13.52	9.81
	Inaction rate (%)	$G^N \in (-0.1, +0.1)$	58.60	69.03	79.50
	Positive maintenance rate (%)	$G^N \in [+0.1, +0.2)$	10.13	13.16	5.39
	Positive spike rate (%)	$G^N \in [+0.2, +\infty)$	10.14	2.26	4.41

5 Discuss Model Implication

5.1 Model Equity Return predictability

My main empirical findings suggest that the current high growth rate of hours predicts low future equity return. I first test this negative relation between a firm's current hours and its future equity value in the baseline model. In panel A of Table 5, I reproduce the firm-level equity return predictability regressions, *a la* Eq. (4). In particular, the columns [1] to [12] uses the empirical data and the columns [13] to [18] uses the model simulated data. From Section 4.2 and Table 4, I do not explicitly target the asset pricing moments in my estimation. Therefore, the baseline model does a relatively good job in matching my two 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 future equity value decrease of 0.61%, and a 1% in the firm's current employment is associated with a future equity value decrease of 0.15%. The column [15] 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 the impacts of firm's changing its current hours and employment on its future equity return is low. It is also verified in the model after examining the estimation of the coefficients of b_H and b_N across specifications in columns [13] to [15]. Taken together, the results in panel A show that the baseline model is consistent with my two main empirical findings.

Table 5. Firm-Level Equity Return Predictability and Concurrency Regressions Results. NOTE:

	Data												Model					
	Hours & Employment			Adding Capital			Hours & Employment			Adding Capital			Hours & Employment					
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]
Panel A	Predictability Regression: $R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G_{jt}^H + b_N \times G_{jt}^N + b_K \times G_{jt}^K$																	
(1) b_H	-62.86		-61.11	-61.09		-60.23	-55.36		-54.03	-54.03		-53.45	-47.45		-47.46	-47.43		-47.45
(se)	14.74		14.71	14.69		14.67	12.60		12.57	12.57		12.56	0.95		0.95	0.95		0.95
[t]	-4.26		-4.15	-4.16		-4.10	-4.39		-4.30	-4.30		-4.26	-49.92		-49.93	-49.91		-49.93
(2) b_N		-13.93	-14.96		-11.06	-11.23		-10.55	-10.28		-8.78	-7.54		-14.82	-14.83		-14.82	-14.83
(se)		1.43	2.15		1.48	2.24		1.08	1.48		1.17	1.59		0.38	0.38		0.38	0.38
[t]		-9.71	-6.95		-7.46	-5.02		-9.78	-6.93		-7.51	-4.75		-39.48	-39.50		-39.48	-39.50
(3) b_K				-11.68	-6.92	-8.73				-7.20	-3.36	-5.07						
(se)				1.59	1.21	1.67				0.99	0.82	1.07						
[t]				-7.35	-5.74	-5.21				-7.26	-4.10	-4.74						
(4) # Obs.	23030	42063	23030	23030	42063	23030	23030	42063	23030	23030	42063	23030	371825	371825	371825	371825	371825	371825
# Firms	4473	5824	4473	4473	5824	4473	4473	5824	4473	4473	5824	4473	2675	2675	2675	2675	2675	2675
Within R^2	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.01	0.00	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	0.00	0.00	0.00	0.00	0.00	0.00
(5) Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	No	No	No	No	No	No	Y	Y	Y	No	No	No
Panel B	Concurrency Regression: $R_{jt} = a_0 + a_j + a_t + c_H \times G_{jt}^H + c_N \times G_{jt}^N + c_K \times G_{jt}^K + \text{controls}_{t-1}$																	
(1) c_H	14.67		15.33	17.38		17.32	21.95		21.59	22.90		22.68	66.02		65.89	66.02		65.89
(se)	14.39		14.40	14.34		14.34	13.49		13.50	13.51		13.52	0.82		0.83	0.82		0.83
[t]	1.02		1.06	1.21		1.21	1.63		1.60	1.70		1.68	80.10		79.85	80.10		79.85
(2) c_N		-3.75	-4.52		0.88	0.55		5.43	5.15		8.40	8.48		38.97	38.92		38.97	38.92
(se)		2.42	2.62		2.44	2.67		2.01	2.20		2.11	2.31		0.41	0.41		0.41	0.41
[t]		-1.55	-1.73		0.36	0.21		2.70	2.34		3.99	3.67		95.72	95.68		95.72	95.68
(3) c_K				-14.80	-13.36	-14.94				-5.62	-6.79	-7.71						
(se)				2.19	1.94	2.24				1.47	1.33	1.52						
[t]				-6.76	-6.89	-6.66				-3.83	-5.10	-5.05						
(4) # Obs.	19307	23004	19307	19307	23004	19307	19307	23004	19307	19307	23004	19307	371825	371825	371825	371825	371825	371825
# Firms	4160	4485	4160	4160	4485	4160	4160	4485	4160	4160	4485	4160	2675	2675	2675	2675	2675	2675
Within R^2	0.00	0.00	0.00	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.03	0.05	0.03	0.03	0.05
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	0.00	0.00	0.00	0.00	0.00	0.00
(5) Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	No	No	No	No	No	No	Y	Y	Y	No	No	No

In the model, firms weighing the options of changing hours in the current period versus in the future period because of the labor adjusting friction along the hours margin. As a result, by adjusting hours now, the firms with current high hours growths incur high labor adjustment costs, generate low cash flows, and earn low equity returns. Therefore, in addition to the negative relation between a firm's current hours and its future equity value, the economic mechanism of my model also implies a positive relation between a firm's current hours and its current equity value. To further test the economic mechanism, I verify this corollary implication using the following firm-level equity return concurrency regressions

$$R_{jt} = a_0 + a_j + a_t + c_H \times G_{jt}^H + c_N \times G_{jt}^N + c_K \times G_{jt}^K + \text{controls}_{t-1}. \tag{14}$$

In this specification, R_{jt} on the left-hand side is the firm j's current annual equity return, and $G_{jt}^{H,N,K}$ are respectively the firm j's current annual growth rates G of hours (H), employment (N), and capital (K). I include the vector of previous annual growth rates in $\text{controls}_{t-1} = G_{j,t-1}^{H,N,K}$ and a_0, a_j, a_t are respectively the constant, the firm fixed effect, and the year fixed effect.

I focus on the coefficients on the current hours and employment growths c_H and c_N, which measure the impacts of a firm's current hours and employment growths on its current equity return and manifest the relation between a firm's current hours and its current equity value. I present the results in panel B of Table 5. The coefficient estimate of c_H ranges from 15.33 in column [3] to 22.68 in column [12]. Adding the capital and removing the firm fixed effect help increasing and identifying c_H statistically. Nevertheless, in the model the coefficient estimate of c_H is around 66 in columns [13] to [18]. Clearly, the model delivers a more substantial relation than the data does. This is likely due to the current cash flows is sensitive to more choice variables observed by the firm's decision maker. Qualitatively, the model implies a positive relation between a firm's current hours and its current equity value that is crosschecked with the empirical data.

5.2 Role of Labor Adjusting Friction Along the Hours Margin

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.

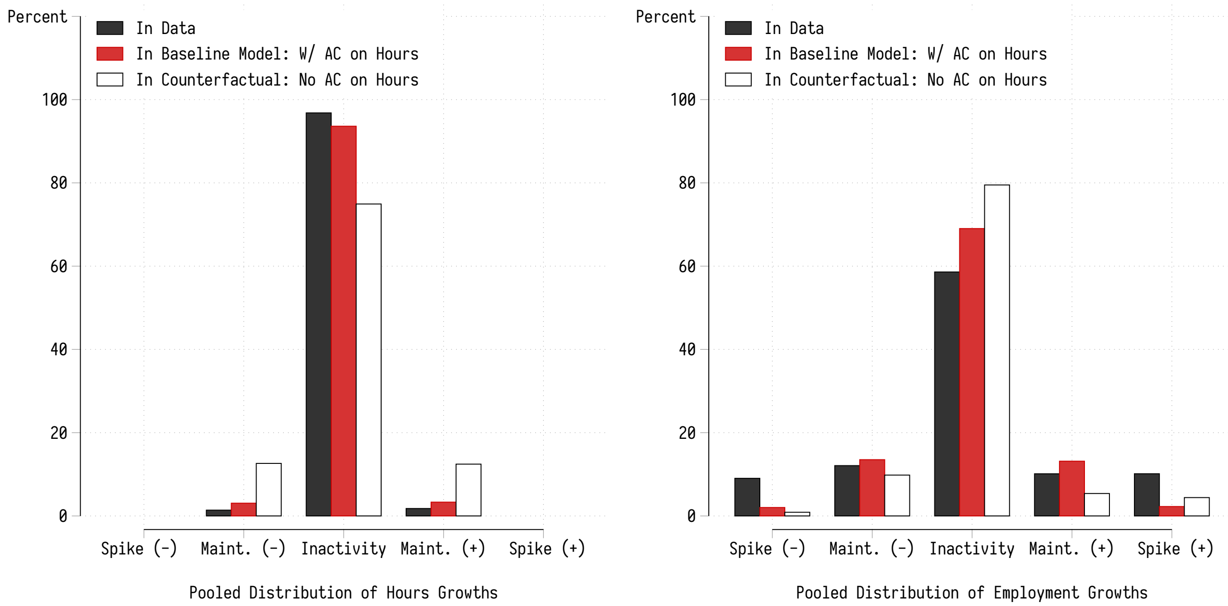
More concretely, the equilibrium of this framework implies the following first-order condition with respect to hours (see the full setup and first-order conditions in Appendix A.3)

$$e^{\bar{c}} A_t Z_t N_{jt}^{\alpha-1} = H_{jt}^{\xi-\alpha} \tag{15}$$

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. (15) 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 [5] of Table 4. 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. (15). 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.

Figure 1. 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.



5.3 Driving Force of the Labor Adjusting Friction

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 section, I focus on the pooled distributions of the hours and the employment growths from panel B of Table 4. I use the statistical observations from the empirical data in column [3] and the estimation of the baseline model in column [4] to discuss the relative magnitudes of the adjustment cost components. The baseline model suggests that the disruption to production is the driving force of the labor adjusting friction, which is consistent with the data.

Drawing implications from Cooper & Haltiwanger [2006] and Cooper et al. [2007], I summarize the pooled distributions by bin statistics. I categorize the hours and the employment growths 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

Table 6. Implied Adjustment Cost. NOTE: This table reports the magnitudes of the adjustment cost components implied by estimation of the baseline model. There are three adjustment cost components considered in the model (Eq. (8)), the non-convex disruption, the linear irreversibility, and the convex quadratic costs, respectively listed in rows (1) to (3). The panel A reports the measures of adjustment cost components in absolute magnitudes. Specifically, I report the non-convex disruption costs as percentages of the sales, the linear irreversibility costs as percentages of the wages, and the convex quadratic costs as percentages of the dividends. The panel B calculates the measures of adjustment cost components in relative magnitudes; each is computed as a fraction of total adjustment cost. Across columns, the adjustment cost components along either margin and both margins of hours or employment are presented.

	Adjustment Cost Component	Measure of Magnitude	Emp't	Hours	Both
Panel A	Magnitudes in Absolute Terms				
(1)	Non-convex disruption	as % of sales	0.0314	0.0078	0.0392
(2)	Linear irreversibility	as % of wages	0.0045	0.0009	0.0054
(3)	Convex quadratic	as % of dividends	0.0005	0.0008	0.0013
Panel B	Magnitudes in Relative Terms				
(1)	Non-convex disruption	as % of adjustment cost	70.7068	19.4732	90.1799
(2)	Linear irreversibility	as % of adjustment cost	7.4236	1.6084	9.0320
(3)	Convex quadratic	as % of adjustment cost	0.2845	0.5036	0.7881

in-between 10% and 20% in absolute value). First, from column [3] in panel B of Table 4, both margins of 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 the adjustment along the employment margin. This observation from the pooled distributions suggest that the firms are likely to face a sizable disruption cost, and the non-convexity prevents the firms from frequently adjusting the labor input along both margins of hours and employment. In addition to inaction, the comparisons between the maintenance and the spike rates across the hours and employment growths reveal the relative magnitudes of the linear and the convex components of the labor adjusting friction.

Conditional on non-inactivity, the hours growths are more likely to be the maintenance as opposed to the spikes, whereas, relative to hours growth, the employment growths are more likely to spikes than to be the maintenance. Therefore, I expect the labor adjusting friction to impose a higher quadratic cost on hours than on employment because the convexity encourages the small adjustments that are more likely to be the maintenance than the spikes. Similarly, the labor adjusting friction is likely to introduce higher irreversibility cost on employment than on hours for the linearity has a constant marginal cost for the adjustments, under which circumstance the spikes are more likely to take place.

To sum up, the column [1] from panel B of Table 4 shows that the model delivers a good fit of the pooled distributions of the hours and the employment growths. To further test the implications from the pooled distributions on the relative magnitudes of the adjustment cost components, Table 6 calculates the adjustment cost components on hours and employment. Consistent with the expectation, the non-convex disruption cost is large on either margin of hours or employment; furthermore, the non-convex disruption cost combining both margins accounts for over 90% of the labor adjustment cost, suggesting the disruption to production is the driving force of labor adjusting friction.

6 Inspect the Mechanism

The economic mechanism of my model is that, by weighing the options of changing hours now versus in the future, the firms with current high hours growths are expected to incur low adjustment costs, to generate high cash flows, and to earn low equity returns in the future. By adjusting the hours margin more, firms increase exposures of the equity return to the aggregate adjustment cost shock, which is assumed to be positive loaded in the stochastic discount factor and negative priced in equilibrium. In this section, I evaluate the economic mechanism via three sets of investigation exercises. First, I construct an empirical proxy for adjustment cost shock; using the empirical proxy, I demonstrate that the positive loading and negative price of the adjustment cost shock from the model are consistent with the data. Second, I show in both the data and the model, that the firms with current higher hours growths (1) are expected to earn lower equity returns in the future, but (2) earn higher equity returns in the current period due to the declines in cash flows. Finally, I test the theoretical and quantitative role of the labor adjusting friction along the hours margin in counterfactual analysis.

6.1 An Adjustment Cost Shock Proxy

In this section, I utilize my empirical and structural results to illustrate how the cross section of equity returns can identify the macroeconomic shock. To further extracts understanding of macroeconomic fluctuation, I start by constructing a proxy for the adjustment cost shock following factor asset pricing literature (e.g., Fama & French [1992, 1993]). That is, I use the time-series of the equity return spreads of the quintile portfolios univariate sorted by the hours growth in each cross-section as the time-series of the adjustment cost shocks[8].

6.2 Adjustment Cost Shock and Negative Risk Price

In the model, the adjustment cost shock is positively loaded in the stochastic discount factor (Eq. (10)); as a result, the adjustment cost shock has a negative price of risk. To test this assumption, I consider a two-factor structure asset pricing model following Cochrane [2009]. To be specific, the model implies a stochastic discount factor of

$$M_t = a_M + \gamma_{MKT} F_t^{MKT} + \gamma_{ACS} F_t^{ACS}, \tag{16}$$

where F_t^{MKT} is the market factor and F_t^{ACS} is the adjustment cost shock factor. To obtain the risk prices associated with the two factors, I implement the Fama-MacBeth procedure (Fama & MacBeth [1973]) following

$$\begin{array}{lcccccccl} \forall i: & R_{i,t} & = & \alpha_i & + & \beta_i^{MKT} F_t^{MKT} & + & \beta_i^{ACS} F_t^{ACS} & , t = 1, \cdots, T \\ \forall t: & R_{i,t} & = & a_i & + & \lambda_t^{MKT} \beta_i^{MKT} & + & \lambda_t^{ACS} \beta_i^{ACS} & , i = 1, \cdots, N \end{array} \tag{17}$$

The risk prices of the market factor F_t^{MKT} and the adjustment cost shock factor are then the time-series average of λ_t^{MKT} and λ_t^{ACS}, respectively.

In Table 7, I tabulates the results of risk price estimation for adjustment cost shock

[8] In literature, such identification strategy is commonly termed as the return-based measure of shocks (e.g., Papanikolaou [2011]; Kogan & Papanikolaou [2013, 2014]).

Table 7. Negative Risk Price of Adjustment Cost Shock Factor. NOTE:

Testing Portfolio	25 Fama-French Portfolios			17 Industry Portfolios		
RHS Factor F_t^{ACS}	No	3-Spread	5-Spread	No	3-Spread	5-Spread
	[1]	[2]	[3]	[4]	[5]	[6]
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)
	[4.02]	[2.59]	[2.27]	[2.61]	[3.47]	[3.17]
λ^{ACS}		−0.31***	−0.35***		−0.28***	−0.32***
		(0.10)	(0.09)		(0.09)	(0.10)
		[−3.16]	[−3.72]		[−3.22]	[−3.16]
Obs.	500	500	500	340	340	340
R2	0.00	0.00	0.00	0.00	0.00	0.00
p-Value	0.00	0.00	0.00	0.02	0.00	0.00

factor. I use two sets of testing portfolios, namely, the Fama-French 25 portfolios formed by size and book-to-market (from columns [1] and [2]) and 17 industry portfolios (from columns [3] and [4]). Of either set of testing portfolios, I implement both CAPM specification and 2-Factor specification. Consistent with the model, the estimated risk price of the market factor is positive (and significant), and that of the adjustment cost shock factor is negative (and significant). The sign of risk price also implies the sign of risk loading in the stochastic discount factor; therefore, the estimation results of risk prices from Table 7 cross-checks the model's specification of the stochastic discount factor in the model (Eq. (10)).

6.3 Adjustment Cost Shock and Cash Flow Movement

Table 8. Outcome Variables Movement. NOTE: This table

	Dependent Var	Cashflow Scaled $y_{j,t+1}$			Cashflow Growth $y_{j,t+1}$			Cashflow Logarithm $y_{j,t+1}$			Output Logarithm $y_{j,t+1}$		
	Control Var	No	$y_{j,t-1}$	$y_{j,t}$	No	$y_{j,t-1}$	$y_{j,t}$	No	$y_{j,t-1}$	$y_{j,t}$	No	$y_{j,t-1}$	$y_{j,t}$
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Panel A: 3-Spread	$y_{j,t+1} = a + b_j^{(1)} \times F_t^{ACS} + \sum_{p=2}^{P=3} b_j^{(p)} \times F_t^{ACS} \times D_{jt}^{(p)} + \sum_{p=2}^{P=5} c_j^{(p)} \times D_{jt}^{(p)} + d_j^{(-2)} \times y_{j,t-1} + d_j^{(-1)} \times y_{j,t} + e_{j,t+1}$											
(1)	F_t^{ACS}	−0.10***	−0.09***	−0.07***	−0.23***	−0.04	−0.24***	−0.54***	−0.40***	−0.26***	−0.26***	−0.03	−0.07**
		(0.01)	(0.01)	(0.01)	(0.07)	(0.07)	(0.06)	(0.09)	(0.07)	(0.07)	(0.05)	(0.04)	(0.03)
		[−8.41]	[−7.14]	[−6.33]	[−3.39]	[−0.57]	[−3.91]	[−5.79]	[−5.62]	[−3.98]	[−4.90]	[−0.67]	[−2.36]
(2)	$F_t^{ACS} \times D_{jt}^{(2)}$	0.10***	0.07***	0.06***	0.20**	0.01	0.26***	0.42***	0.57***	0.18**	0.15*	0.20***	0.08*
		(0.02)	(0.02)	(0.02)	(0.09)	(0.12)	(0.08)	(0.12)	(0.10)	(0.09)	(0.08)	(0.06)	(0.05)
		[5.80]	[4.25]	[3.78]	[2.16]	[0.06]	[3.09]	[3.44]	[5.46]	[1.99]	[1.95]	[3.38]	[1.83]
(3)	$F_t^{ACS} \times D_{jt}^{(3)}$	0.15***	0.14***	0.09***	0.63***	0.68***	0.60***	0.83***	0.79***	0.66***	0.23**	0.29***	0.33***
		(0.02)	(0.02)	(0.02)	(0.13)	(0.16)	(0.12)	(0.16)	(0.15)	(0.12)	(0.10)	(0.09)	(0.06)
		[6.75]	[6.35]	[4.24]	[5.02]	[4.13]	[4.95]	[5.17]	[5.11]	[5.46]	[2.38]	[3.33]	[5.14]
(4)	Obs.	13207	11724	13161	9443	6622	8022	10129	8250	9443	13087	11662	13087
	Firms	4144	3749	4126	3056	2309	2676	3262	2743	3056	4146	3752	4146
	Overall R2	0.00	0.37	0.47	0.00	0.01	0.02	0.00	0.85	0.89	0.01	0.93	0.96
	p-Value	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: 5-Spread	$y_{j,t+1} = a + b_j^{(1)} \times F_t^{ACS} + \sum_{p=2}^{P=5} b_j^{(p)} \times F_t^{ACS} \times D_{jt}^{(p)} + \sum_{p=2}^{P=5} c_j^{(p)} \times D_{jt}^{(p)} + d_j^{(-2)} \times y_{j,t-1} + d_j^{(-1)} \times y_{j,t} + e_{j,t+1}$											
(1)	F_t^{ACS}	−0.11***	−0.10***	−0.08***	−0.22***	−0.10	−0.21***	−0.48***	−0.32***	−0.25***	−0.25***	0.04	−0.07**
		(0.01)	(0.01)	(0.01)	(0.08)	(0.08)	(0.07)	(0.09)	(0.08)	(0.07)	(0.05)	(0.04)	(0.03)
		[−9.01]	[−7.56]	[−7.19]	[−2.92]	[−1.28]	[−2.97]	[−5.11]	[−4.03]	[−3.33]	[−4.82]	[1.01]	[−2.29]
(2)	$F_t^{ACS} \times D_{jt}^{(2)}$	0.10***	0.08***	0.08***	0.07	0.08	0.03	0.04	−0.02	0.04	0.12*	−0.17***	−0.02
		(0.02)	(0.02)	(0.02)	(0.10)	(0.16)	(0.09)	(0.13)	(0.11)	(0.10)	(0.07)	(0.06)	(0.04)
		[5.85]	[4.98]	[5.16]	[0.70]	[0.51]	[0.36]	[0.28]	[−0.16]	[0.41]	[1.68]	[−2.72]	[−0.55]
(3)	$F_t^{ACS} \times D_{jt}^{(3)}$	0.12***	0.09***	0.09***	0.03	−0.36**	0.09	0.40***	0.26**	0.03	0.22***	−0.06	−0.02
		(0.02)	(0.02)	(0.02)	(0.11)	(0.15)	(0.10)	(0.13)	(0.12)	(0.11)	(0.08)	(0.07)	(0.06)
		[5.87]	[4.12]	[4.73]	[0.28]	[−2.34]	[0.90]	[3.02]	[2.15]	[0.31]	[2.83]	[−0.86]	[−0.30]
(4)	$F_t^{ACS} \times D_{jt}^{(4)}$	0.07***	0.04**	0.03**	0.37***	0.26*	0.34***	0.57***	0.84***	0.38***	−0.07	0.18***	0.14***
		(0.02)	(0.02)	(0.02)	(0.12)	(0.14)	(0.11)	(0.14)	(0.13)	(0.12)	(0.09)	(0.06)	(0.05)
		[3.96]	[2.26]	[1.96]	[3.14]	[1.90]	[3.03]	[4.01]	[6.35]	[3.34]	[−0.82]	[2.88]	[2.71]
(5)	$F_t^{ACS} \times D_{jt}^{(5)}$	0.14***	0.13***	0.09***	0.49***	0.75***	0.49***	0.84***	0.65***	0.54***	0.33***	0.15*	0.37***
		(0.02)	(0.02)	(0.02)	(0.13)	(0.17)	(0.12)	(0.15)	(0.16)	(0.12)	(0.09)	(0.09)	(0.07)
		[6.45]	[5.90]	[4.48]	[3.88]	[4.30]	[4.07]	[5.52]	[4.16]	[4.49]	[3.57]	[1.78]	[5.60]
(6)	Obs.	13207	11724	13161	9443	6622	8022	10129	8250	9443	13087	11662	13087
	Firms	4144	3749	4126	3056	2309	2676	3262	2743	3056	4146	3752	4146
	Overall R2	0.00	0.38	0.47	0.00	0.01	0.02	0.00	0.85	0.89	0.00	0.93	0.96
	p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

6.4 Adjustment Cost Shock and Equity Return Movement

Table 9. Equity Return Movement. NOTE: This table

	Dependent Var	Current Equity Return $R_{j,t}$						Future Equity Return $R_{j,t+1}$					
	Control Var	No	Past(t-1) Equity Return	Past(t-1) Cashflow Scaled	Past(t-1) Cashflow Growth	Past(t-1) Cashflow Log	Past(t-1) Output Log	No	Current(t) Equity Return	Current(t) Cashflow Scaled	Current(t) Cashflow Growth	Current(t) Cashflow Log	Current(t) Output Log
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
	Panel A: 3-Spread	$R_{j,t+h} = a + b_j^{(1)} \times F_t^{ACS} + \sum_{p=2}^{P=3} b_j^{(p)} \times F_t^{ACS} \times D_{jt}^{(p)} + \sum_{p=2}^{P=5} c_j^{(p)} \times D_{jt}^{(p)} + d_j \times y_{j,t+h-1} + e_{j,t}$, where $h=0$ (col [1]-[6]) or $h=1$ (col [7]-[12])											
(1)	F_t^{ACS}	−0.83***	−0.85***	−0.87***	−0.29***	−0.60***	−0.85***	0.01	−0.00	0.01	−0.07	−0.02	0.00
		(0.10)	(0.10)	(0.10)	(0.04)	(0.09)	(0.10)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
		[−8.24]	[−8.38]	[−8.46]	[−7.38]	[−6.89]	[−8.33]	[0.25]	[−0.09]	[0.14]	[−1.47]	[−0.37]	[0.07]
(2)	$F_t^{ACS} \times D_{jt}^{(2)}$	1.05***	1.06***	1.02***	0.62***	0.94***	1.05***	−0.25***	−0.22***	−0.26***	−0.21***	−0.25***	−0.24***
		(0.11)	(0.11)	(0.11)	(0.07)	(0.10)	(0.11)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
		[9.70]	[9.61]	[9.27]	[8.37]	[9.84]	[9.61]	[−3.66]	[−3.34]	[−3.85]	[−3.02]	[−3.65]	[−3.62]
(3)	$F_t^{ACS} \times D_{jt}^{(3)}$	1.38***	1.35***	1.36***	1.05***	1.16***	1.35***	−0.45***	−0.42***	−0.45***	−0.34***	−0.33***	−0.46***
		(0.13)	(0.13)	(0.13)	(0.12)	(0.13)	(0.13)	(0.11)	(0.11)	(0.11)	(0.09)	(0.09)	(0.11)
		[10.43]	[10.06]	[10.25]	[8.43]	[9.24]	[10.11]	[−4.23]	[−3.95]	[−4.21]	[−3.77]	[−3.70]	[−4.28]
(4)	Obs.	15268	13591	13406	8450	10414	13591	13304	13304	13171	8600	10288	13304
	Firms	4833	4367	4285	2870	3366	4367	4194	4194	4128	2844	3296	4194
	Overall R2	0.02	0.03	0.03	0.01	0.02	0.03	0.00	0.00	0.01	0.01	0.01	0.01
	p-Value	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: 5-Spread	$y_{j,t+1} = a + b_j^{(1)} \times F_t^{ACS} + \sum_{p=2}^{P=5} b_j^{(p)} \times F_t^{ACS} \times D_{jt}^{(p)} + \sum_{p=2}^{P=5} c_j^{(p)} \times D_{jt}^{(p)} + d_j \times y_{j,t+h-1} + e_{j,t}$, where $h=0$ (col [1]-[6]) or $h=1$ (col [7]-[12])											
(1)	F_t^{ACS}	−0.88***	−0.89***	−0.90***	−0.36***	−0.66***	−0.89***	−0.05	−0.07	−0.06	−0.06	−0.03	−0.05
		(0.09)	(0.09)	(0.09)	(0.04)	(0.09)	(0.09)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
		[−9.46]	[−9.49]	[−9.58]	[−8.60]	[−7.22]	[−9.48]	[−1.01]	[−1.47]	[−1.18]	[−1.23]	[−0.63]	[−1.13]
(2)	$F_t^{ACS} \times D_{jt}^{(2)}$	0.73***	0.71***	0.70***	0.32***	0.67***	0.72***	0.02	0.04	0.01	−0.03	−0.07	0.02
		(0.15)	(0.15)	(0.15)	(0.09)	(0.12)	(0.15)	(0.07)	(0.07)	(0.07)	(0.08)	(0.07)	(0.07)
		[4.90]	[4.64]	[4.58]	[3.54]	[5.45]	[4.69]	[0.29]	[0.53]	[0.19]	[−0.45]	[−0.97]	[0.23]
(3)	$F_t^{ACS} \times D_{jt}^{(3)}$	0.77***	0.74***	0.72***	0.13	0.61***	0.73***	0.05	0.07	0.05	−0.04	0.02	0.05
		(0.11)	(0.11)	(0.11)	(0.08)	(0.11)	(0.11)	(0.07)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)
		[6.93]	[6.61]	[6.38]	[1.49]	[5.57]	[6.53]	[0.65]	[0.90]	[0.64]	[−0.46]	[0.28]	[0.75]
(4)	$F_t^{ACS} \times D_{jt}^{(4)}$	0.97***	0.98***	0.95***	0.74***	1.00***	0.97***	−0.15*	−0.13*	−0.16**	−0.25***	−0.28***	−0.15**
		(0.11)	(0.11)	(0.11)	(0.09)	(0.11)	(0.11)	(0.08)	(0.08)	(0.08)	(0.07)	(0.07)	(0.08)
		[8.94]	[9.00]	[8.71]	[8.46]	[9.10]	[8.95]	[−1.95]	[−1.65]	[−2.02]	[−3.47]	[−4.01]	[−1.98]
(5)	$F_t^{ACS} \times D_{jt}^{(5)}$	1.41***	1.40***	1.43***	1.18***	1.24***	1.41***	−0.32***	−0.28***	−0.32***	−0.26***	−0.25***	−0.33***
		(0.12)	(0.12)	(0.12)	(0.11)	(0.13)	(0.12)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)	(0.10)
		[11.43]	[11.35]	[11.56]	[10.44]	[9.73]	[11.44]	[−3.26]	[−2.92]	[−3.23]	[−2.98]	[−2.91]	[−3.34]
(6)	Obs.	15268	13591	13406	8450	10414	13591	13304	13304	13171	8600	10288	13304
	Firms	4833	4367	4285	2870	3366	4367	4194	4194	4128	2844	3296	4194
	Overall R2	0.03	0.04	0.04	0.02	0.03	0.04	0.01	0.01	0.01	0.01	0.01	0.01
	p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

7 Conclusion

The hours is an essential and integral margin of the labor input in firm-level production. When the labor adjusting friction is not asymmetrically imposed only to the employment margin, the labor adjustment cost on hours represents an important channel through which the firm's current hours preserves essential information on the firm's future cash flows, and hence affects the firm's future equity return. Indeed, as I show in the paper, the linkage between a firm's current labor input choice of hours and its future equity return provides a previously unexplored source of systematic risk that is related to the firm's production fundamental decisions and has important implications for the equity returns in the cross-section.

I present robust empirical evidence at both the firm- and the portfolio-level to establish the linkage in the data. Implementing a novel crosswalk that takes into consideration a firm's occupation compositions across time, I calculate the hours margin of the labor input for the publicly traded firms in the U.S. I find that the current high hours growth predicts low future equity return, and such negative relation between a firm's current hours and its future equity value is statistically significant and economically large. At the firm-level, a 1% increase in the firm's current hours is associated with a 0.6% decrease in the firm's future equity value, controlling for the employment and the capital, as well as the characteristics known by the literature to explain the cross-section of returns. For univariate quintile portfolios, the low-minus-high equity return spread is about 6% per annum across value-, equal-, and microcaps-excluded, equal-weighted equity return measures.

To understand the underlying economic mechanism, I develop a simple production-based asset pricing model with dynamic labor input and intuitively map the equity return predictability in the data to the labor adjusting friction in the model. The key insight of my model is that, when there is labor adjusting friction along the hours margin, the expanding firms weigh the options of adjusting hours now versus in the future. By optimizing to a more desired higher level of hours now, the firms are expected to incur low labor adjustment cost in the future. As a result, firms with current high hours growth are expected to generate high cash flows and earn low equity returns in the future.

I numerically solve the model using the simulated method of moments. Estimation of the model delivers a good fit to a variety of targeted and non-targeted moments at the firm-level as well as the pooled distribution of the hours and the employment growths in the data. The results from estimation demonstrate that labor adjusting friction along the hours margin is an essential component to match the economic quantities and generate my empirical findings. Examining the root structure and leading components of the labor adjustment cost, I find the non-convex disruption to production is the driving force to understand the labor adjusting friction.

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A Appendices

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`)

[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.

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 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 Growths 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

[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 $g_{jt} = h_{jt} - f_{jt}$.

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.

Capital Growths 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 growths. Second, aligning capital with non-lagged and lagged empirical accounting capital records are both used in the literature; depending on the choices 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 growths 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 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 $t-1$, $K_{j,t-1}$; that is, the capital stock at period t, K_{jt} is empirically mapped to the lagged accounting capital record at period $t-1$, $K_{j,t-1}$. 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

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

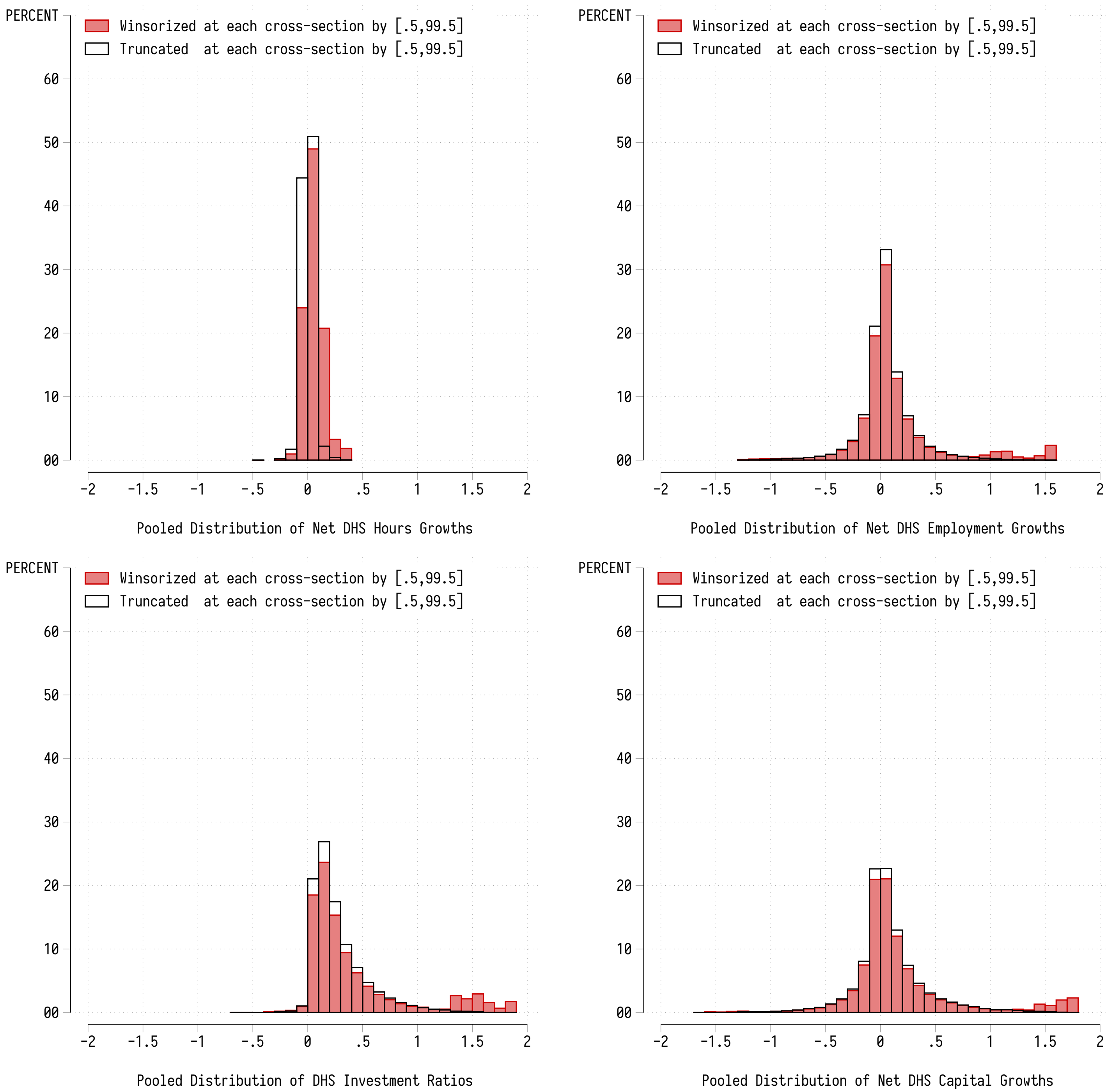
[A.3] See Belo et al. [2013] for a justification of applying this neoclassical convention in defining capital growth.

Table A.1. Asset Pricing Investigation on Empirical Definitions of Hours, Employment, and Capital Growths. NOTE: This table tabulates the equity return predictability regressions results using a variety of empirical definitions to measure hours, employment, and capital growths. 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)
[t]	[−5.27]	[−5.16]	[−5.07]	[−5.19]	[−5.07]	[−5.10]	[−5.19]	[−5.08]	[−5.22]	[−5.08]	[−5.12]
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)
[t]		[−8.75]	[−8.25]	[−8.87]	[−4.34]	[−5.80]	[−6.20]	[−5.85]	[−6.27]	[−2.54]	[−3.01]
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)
[t]			[−3.54]	[1.90]	[−5.77]	[−4.40]		[−4.20]	[1.62]	[−7.01]	[−4.88]
$\bar{R}^2$	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)
[t]	[−5.21]	[−5.11]	[−5.01]	[−5.13]	[−5.01]	[−5.05]	[−5.14]	[−5.03]	[−5.16]	[−5.02]	[−5.07]
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)
[t]		[−8.75]	[−8.25]	[−8.88]	[−4.34]	[−5.80]	[−6.21]	[−5.85]	[−6.28]	[−2.54]	[−3.02]
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)
[t]			[−3.54]	[1.90]	[−5.76]	[−4.39]		[−4.20]	[1.62]	[−7.01]	[−4.87]
$\bar{R}^2$	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

Figure A.1. Pooled Distributions of Empirical Definitions of Hours, Employment, and Capital Growths. NOTE: This figure plots the pooled distributions of a variety of empirical definitions measuring hours, employment, and capital growths. 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.



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. In reference to Table 1, the two definitions of employment growths 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 growths 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.

[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.

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 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 [9] 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 [10] 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

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	p50	n=10	n=15	n=20	n=25	n=30
Year	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[13]
1997	131,854	52,905	47,873	7	9	13	17	23	31	29,427	26,716	24,689	22,941	21,793
1998	131,617	53,640	25,280	4	5	7	9	12	16	14,738	13,261	12,093	11,234	10,571
1999	132,324	54,124	49,090	7	10	13	18	24	33	30,922	27,797	25,550	23,999	22,694
2000	133,710	55,408	50,521	7	10	14	19	25	37	32,046	29,220	26,971	25,269	23,847
2001	218,269	88,476	80,817	11	16	22	31	40	55	56,054	51,918	48,806	46,421	44,243
2002	217,219	85,994	78,095	11	16	23	31	42	56	53,935	49,946	47,322	45,038	43,018
2003	216,424	84,756	76,515	9	13	18	23	32	43	51,280	47,039	44,059	41,495	39,138
2004	213,241	84,013	75,840	9	13	18	25	33	47	50,124	46,229	43,133	40,503	38,836
2005	210,648	83,101	74,694	9	12	17	25	34	46	49,205	45,114	42,250	39,746	38,137
2006	208,562	83,621	75,480	9	13	18	25	35	48	49,830	45,907	42,773	40,701	38,676
2007	206,639	83,273	76,091	9	13	19	27	36	49	50,305	46,501	43,697	41,609	39,636
2008	206,404	82,530	75,365	9	13	18	25	36	47	50,040	45,984	43,054	40,413	38,654
2009	207,921	79,359	72,299	9	13	18	26	34	48	48,015	44,233	41,271	39,199	37,444
2010	209,802	78,399	71,680	9	12	18	24	33	45	47,688	43,761	41,229	38,923	37,092
2011	204,983	76,991	70,524	8	12	17	23	33	45	46,744	43,009	39,930	37,958	36,340
2012	201,398	76,746	70,262	9	12	17	23	32	43	46,722	42,988	40,345	37,845	36,140
2013	202,634	77,334	71,043	8	12	17	24	34	45	46,980	43,452	40,736	38,330	36,494
2014	199,556	77,043	69,061	9	12	17	24	33	45	45,866	42,178	39,526	37,287	35,852
2015	199,024	77,116	71,212	9	13	18	26	36	49	47,606	43,958	41,130	39,174	37,244
2016	185,487	72,220	67,018	9	12	18	25	35	51	44,387	40,964	38,473	36,446	34,817
2017	185,914	73,235	68,171	9	13	18	25	35	47	45,358	41,854	39,254	37,100	35,401

in sample decreases.

Aggregation of Individual Hours 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 the aggregation method described in Eq. (1) and are defined as follows.

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

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 $G^{H,1}_{jt}$, the DHS hours growth from Eq. (A.12). Panel B additionally has $G^{N,1}_{jt}$, the net DHS employment growth from Eq. (A.2), and panel C additionally has $G^{K,1}_{jt}$, the DHS investment ratio from Eq. (A.4). Panel D has $G^{H,1}_{jt}, G^{N,1}_{jt}, G^{K,1}_{jt}$ and finally panel E has $G^{H,1}_{jt}, G^{N,1}_{jt}, G^{K,3}_{jt}$, where $G^{K,3}_{jt}$ 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 include constants, firm fixed effects, year fixed effects, and firm standard error clusters, and feature 24'824 firm-year 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)
	[t]	[−4.15]	[−4.83]	[−4.49]	[−5.27]	[−5.33]	[−6.13]	[−5.60]	[−6.48]
	$\bar{R}^2$	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)
	[t]	[−3.99]	[−4.75]	[−4.32]	[−5.16]	[−5.10]	[−5.95]	[−5.35]	[−6.27]
	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)
	[t]	[−8.74]	[−8.78]	[−8.73]	[−8.75]	[−10.98]	[−10.99]	[−10.95]	[−10.96]
	$\bar{R}^2$	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)
	[t]	[−3.84]	[−4.29]	[−4.10]	[−4.56]	[−5.05]	[−5.53]	[−5.34]	[−5.84]
	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)
	[t]	[−9.26]	[−9.27]	[−9.23]	[−9.24]	[−10.14]	[−10.15]	[−10.12]	[−10.13]
	$\bar{R}^2$	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)
	[t]	[−3.75]	[−4.25]	[−3.99]	[−4.51]	[−4.88]	[−5.41]	[−5.16]	[−5.69]
	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)
	[t]	[−6.06]	[−6.09]	[−6.05]	[−6.08]	[−8.39]	[−8.41]	[−8.36]	[−8.38]
	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)
	[t]	[−7.15]	[−7.15]	[−7.12]	[−7.13]	[−7.65]	[−7.65]	[−7.64]	[−7.64]
	$\bar{R}^2$	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)
	[t]	[−3.91]	[−4.67]	[−4.24]	[−5.07]	[−5.00]	[−5.83]	[−5.27]	[−6.17]
	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)
	[t]	[−4.32]	[−4.35]	[−4.31]	[−4.34]	[−5.57]	[−5.59]	[−5.55]	[−5.56]
	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)
	[t]	[−5.81]	[−5.78]	[−5.80]	[−5.77]	[−6.85]	[−6.82]	[−6.86]	[−6.82]
	$\bar{R}^2$	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

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 growths 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 growths.

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. 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,

[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.

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		

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 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.

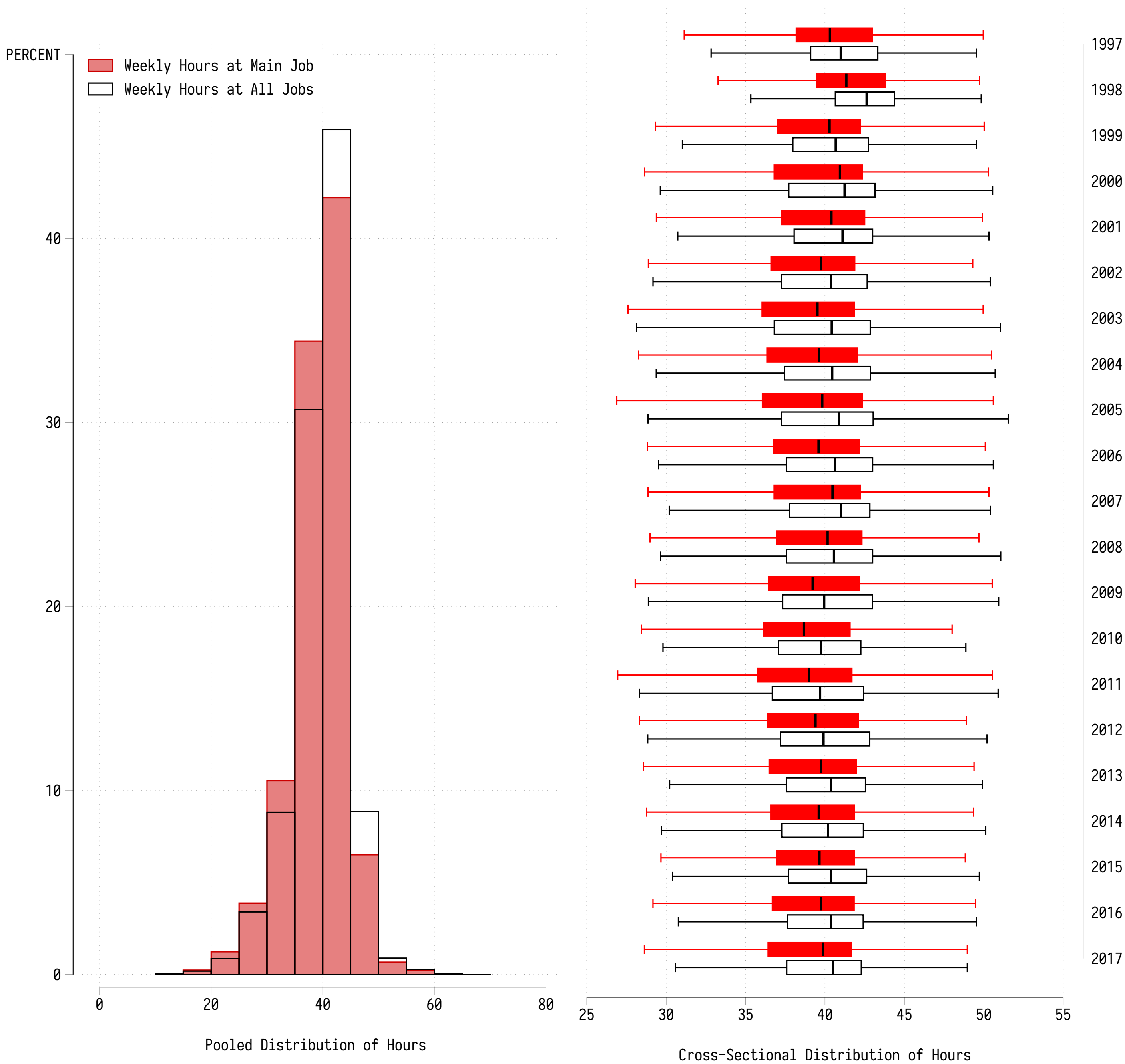
[A.6] The crosswalk tables are provided by the U.S. U.S. Department of Labor's Employment and Training Administration (jointly with states) and obtained from its website.

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

[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.

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.



A.1.2 Methodology

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 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 Growths 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

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

[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 growths, are identical for hours.

and the second simple hours growth is

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

Compare Hours Growths Definitions In Table A.1, the panel A reports equity return predictability regression results using the first DHS hours growths, and the panel B reports using the second simple hours growths. 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

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

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.

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

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.

Table A.5. Indirect Validation Exercises on Alternative Occupation Weighting Schemes. NOTE: .

		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

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)

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,

[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.

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.

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

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 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.

Table A.6. Indirect Validation Exercises on Alternative Occupation Composition Specifications. Note: .

		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

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 growths 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.

Table A.7. Indirect Validation Exercises With Industry Representative Firms. Note: .

		Hours & Employment Growth			Add DHS Investment Ratio			Add Simple Investment Ratio		
		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	Panel A	Without Pricing Factors $\boldsymbol{F}_{it}$:			$R_{i,t+1} = a_0 + a_i + a_{t+1} + b_H \times G^H_{it} + b_N \times G^N_{it} + b_K \times G^K_{it}$					
(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)	# Obs.	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 $\boldsymbol{F}_{it}$:			$R_{i,t+1} = a_0 + a_i + a_{t+1} + b_H \times G^H_{it} + b_N \times G^N_{it} + b_K \times G^K_{it} + \boldsymbol{b} \times \boldsymbol{F}_{it}$					
(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)	# Obs.	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

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 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.

[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.

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.

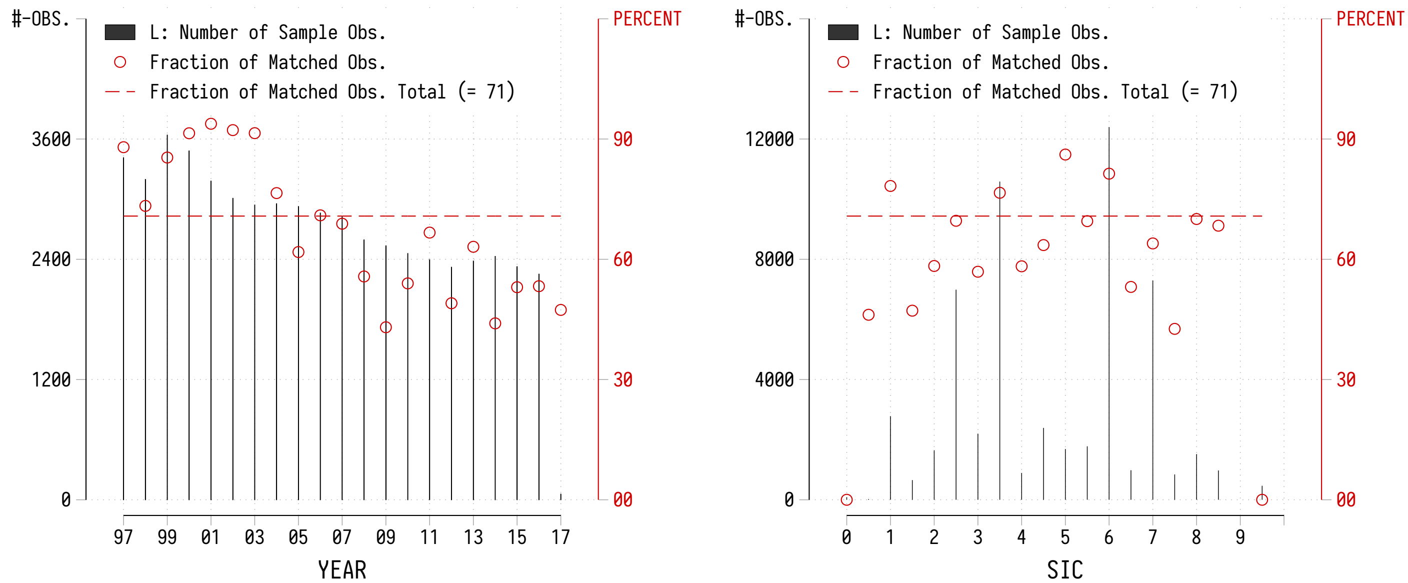
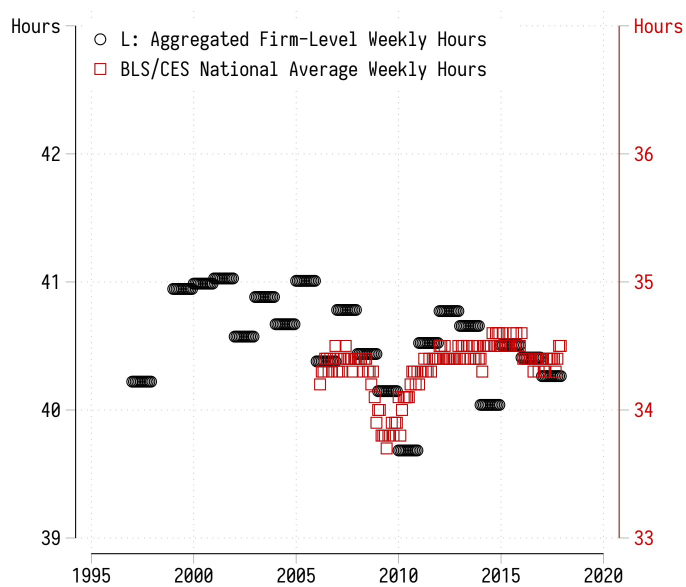


Figure A.4. Compare Aggregated Firm-Level Hours to National Average Hours. NOTE: The firm-level measure of hours is annual. To facilitate a better comparison, I intensify the aggregated firm-level weekly hours to monthly by assigning the end-of-year annual value to all months within the year (backward-filling).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



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 recession periods, supportive of the empirical plausibility in my measure of hours[A.13].

[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.

A.2 Empirical Evidence

A.2.1 Firm-Level Equity Return Predictability Regressions

My main empirical finding is that the firms with current high hours growths are expected to have low equity returns in the future, supported by both the firm- and the portfolio-level results. 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.

$$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G_{jt}^H + b_N \times G_{jt}^N + b_K \times G_{jt}^K + \boldsymbol{b} \times \boldsymbol{F}_{jt}. \tag{A.18}$$

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

I use this section to test the robustness of firm-level results. Specifically, I first vary the fixed effects and standard error clusters in Table A.8. 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. Next, I alter the definition of outliers in the cross-section and the method used to minimize unwanted influence from such outliers. In Table A.9, panel A defines outliers the same as is 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.

It is straightforward to see from results in Tables A.8 and A.9 that, the negative association between the firm's current hours growth and its future equity return is vastly robust to alternative equity return predictability regression specifications.

Table A.8. Firm-Level Equity Return Predictability Regressions With Different Fixed Effect and Standard Error Cluster Specifications. NOTE: .

$$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + b_K \times G^K_{jt} + \boldsymbol{b} \times \boldsymbol{F}_{jt}$$

		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
	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
	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
	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
	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
	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
	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.9. Firm-Level Equity Return Predictability Regressions With Different Outlier Definitions and Winsorization/Truncation Choices. NOTE: .

$$R_{j,t+1} = a_0 + a_j + a_{t+1} + b_H \times G^H_{jt} + b_N \times G^N_{jt} + b_K \times G^K_{jt} + \boldsymbol{b} \times \boldsymbol{F}_{jt}$$

		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
	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
	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
	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
	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
	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
	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

The portfolio formation follows the literature exactly, and is outlined in Section 3.2. The goal of implementing the portfolio approach are two folded. First, using the non-parametric univariate sorted portfolios manifest a monotonically decreasing pattern in both the excess equity returns and Sharpe ratios. Therefore, my main empirical findings on the negative association between current hours growths and future equity returns are additionally supported by the portfolio-level results.

Second, to see the risk associated with adjusting hours is not a derivative of existing, established risk factors, I employ three reduced-form factor pricing models, to disentangle the risks associated with adjusting hours from the risks that are explained by the risk factors. Furthermore, by examining the portfolio excess return against the multifactor models, the number of structural macroeconomical risks can also be checked and inferred.

The time-series regressions take the following form.

$$
\begin{array}{llcclll}
\text{CAPM:} & r^e_{i,t+1} & = & a_{CAPM} & +b_{i,\mathrm{MKT}}(r^{\mathrm{MKT}}_t - r^{\mathrm{F}}_t) & & \\
\text{3-Factor:} & r^e_{i,t+1} & = & a_{3f} & +b_{i,\mathrm{MKT}}(r^{\mathrm{MKT}}_t - r^{\mathrm{F}}_t) & +b_{i,\mathrm{SMB}} r^{\mathrm{SMB}}_t + b_{i,\mathrm{HML}} r^{\mathrm{HML}}_t & \\
\text{5-Factor:} & r^e_{i,t+1} & = & a_5 & +b_{i,\mathrm{MKT}}(r^{\mathrm{MKT}}_t - r^{\mathrm{F}}_t) & +b_{i,\mathrm{SMB}} r^{\mathrm{SMB}}_t + b_{i,\mathrm{HML}} r^{\mathrm{HML}}_t & \\
 & & & & & +b_{i,\mathrm{RMV}} r^{\mathrm{RMV}}_t + b_{i,\mathrm{CMA}} r^{\mathrm{CMA}}_t &
\end{array}
\tag{A.19}
$$

On the left-hand side, $r^e_{i,t+1}$ is the portfolio's equity excess return, and the right-hand side has the pricing factors. The CAPM has maket excess return $(r^{MKT} - r^F)$ on the right-hand side; the Fama-French 3-Factor model takes additionally the size r^{SMB} and value r^{HML} factors; the Fama-French 5-Factor model furthermore takes the profitability r^{RMV} and investment r^{CMA} factors. In all specifications across three different measures of portfolio returns (Tables A.10 to A.12), point estimates of intercept a manifest how large and significant the model-implied anomaly is.

Table A.10. Value-Weighted Univariate Quintile Portfolios: Summary Statistics and Implied Anomalies. NOTE: .

		Value-Weighted Univariate Quintile Portfolios					
		L	2	3	4	H	$L-H$
Panel A: Portfolio Excess Return	$\mu(r^{Exc})$	0.10	0.07	0.06	0.05	0.03	0.06
	$\sigma(r^{Exc})$	0.18	0.20	0.21	0.20	0.23	0.14
	Sharpe	0.53	0.34	0.27	0.24	0.13	0.44
Panel B: CAPM-Implied Anomaly	α Anomaly	0.09	0.09	0.06	0.05	0.02	0.06
	(se)	0.04	0.04	0.04	0.04	0.04	0.02
	[t]	2.21	2.03	1.39	1.12	0.51	2.91
	b_{MKT}	0.09	−0.27	−0.02	0.02	0.14	0.09
	(se)	0.10	0.20	0.25	0.15	0.10	0.07
	[t]	0.91	−1.36	−0.08	0.14	1.34	1.35
	M.A.E.	0.16	0.15	0.15	0.15	0.17	0.11
	RMSE/RMSR	0.88	0.91	0.96	0.97	0.98	0.90
	Adjusted R2	−0.05	0.01	−0.06	−0.06	−0.04	−0.04
	p - value	0.37	0.19	0.94	0.89	0.20	0.20
Panel C: 3-Factor Implied Anomaly	α Anomaly	0.10	0.07	0.05	0.02	0.00	0.08
	(se)	0.04	0.04	0.03	0.05	0.05	0.02
	[t]	2.48	1.70	1.59	0.50	0.04	3.91
	b_{MKT}	0.10	−0.31	0.00	0.14	0.23	0.03
	(se)	0.09	0.17	0.23	0.15	0.12	0.07
	[t]	1.05	−1.77	0.01	0.91	1.86	0.35
	b_{SMB}	−0.25	0.61	0.01	0.14	0.18	−0.45
	(se)	0.30	0.33	0.39	0.35	0.38	0.23
	[t]	−0.84	1.83	0.02	0.38	0.48	−1.93
	b_{HML}	0.02	−0.13	0.09	0.50	0.37	−0.29
	(se)	0.21	0.31	0.38	0.25	0.38	0.25
	[t]	0.10	−0.43	0.24	2.00	0.99	−1.17
	M.A.E.	0.15	0.13	0.15	0.15	0.17	0.09
	RMSE/RMSR	0.87	0.87	0.96	0.91	0.96	0.80
	Adjusted R2	−0.17	−0.01	−0.20	−0.05	−0.11	0.08
	p - value	0.72	0.12	0.99	0.21	0.30	0.24
Panel D: 5-Factor Implied Anomaly	α Anomaly	0.09	0.09	0.11	0.01	0.02	0.04
	(se)	0.06	0.04	0.04	0.06	0.05	0.02
	[t]	1.58	1.96	2.86	0.15	0.43	2.10
	b_{MKT}	0.20	−0.40	−0.38	0.28	0.09	0.37
	(se)	0.24	0.25	0.27	0.23	0.21	0.18
	[t]	0.82	−1.62	−1.39	1.22	0.42	2.13
	b_{SMB}	−0.23	0.41	−0.33	0.17	−0.09	−0.12
	(se)	0.25	0.31	0.38	0.35	0.39	0.22
	[t]	−0.95	1.34	−0.86	0.49	−0.23	−0.54
	b_{HML}	0.11	−0.24	0.37	0.50	0.35	−0.28
	(se)	0.35	0.39	0.50	0.36	0.61	0.35
	[t]	0.31	−0.62	0.75	1.40	0.58	−0.81
	b_{RMV}	0.27	−0.29	−0.87	0.34	−0.37	0.88
	(se)	0.48	0.34	0.33	0.41	0.46	0.39
	[t]	0.57	−0.84	−2.61	0.81	−0.81	2.25
	b_{CMA}	−0.22	0.25	0.13	−0.23	0.31	−0.49
	(se)	0.49	0.33	0.44	0.34	0.52	0.24
	[t]	−0.45	0.78	0.29	−0.68	0.59	−2.05
	M.A.E.	0.15	0.13	0.16	0.14	0.17	0.09
	RMSE/RMSR	0.86	0.87	0.93	0.90	0.95	0.72
	Adjusted R2	−0.31	−0.19	−0.30	−0.20	−0.27	0.13
	p - value	0.78	0.00	0.11	0.08	0.22	0.00

Table A.11. Equal-Weighted Univariate Quintile Portfolios: Summary Statistics and Implied Anomalies. NOTE: .

		Equal-Weighted Univariate Quintile Portfolios					
		L	2	3	4	H	$L-H$
Panel A: Portfolio Excess Return	$\mu(r^{Exc})$	0.14	0.14	0.12	0.06	0.07	0.06
	$\sigma(r^{Exc})$	0.22	0.26	0.30	0.31	0.25	0.15
	Sharpe	0.62	0.52	0.42	0.18	0.28	0.39
Panel B: CAPM-Implied Anomaly	α Anomaly	0.15	0.18	0.15	0.08	0.09	0.04
	(se)	0.04	0.04	0.04	0.05	0.05	0.02
	[t]	3.40	5.01	3.90	1.59	1.69	2.32
	b_{MKT}	−0.13	−0.79	−0.42	−0.41	−0.28	0.26
	(se)	0.16	0.15	0.26	0.26	0.15	0.12
	[t]	−0.85	−5.36	−1.63	−1.60	−1.84	2.10
	M.A.E.	0.17	0.19	0.22	0.22	0.17	0.10
	RMSE/RMSR	0.84	0.72	0.88	0.95	0.94	0.87
	Adjusted R2	−0.05	0.29	0.02	0.01	−0.01	0.06
	p - value	0.41	0.00	0.12	0.13	0.08	0.05
Panel C: 3-Factor Implied Anomaly	α Anomaly	0.13	0.17	0.15	0.05	0.05	0.06
	(se)	0.05	0.04	0.06	0.05	0.06	0.02
	[t]	2.49	4.10	2.56	0.87	0.81	3.03
	b_{MKT}	−0.05	−0.77	−0.39	−0.18	−0.12	0.20
	(se)	0.17	0.17	0.24	0.21	0.13	0.14
	[t]	−0.31	−4.62	−1.65	−0.85	−0.97	1.46
	b_{SMB}	−0.03	0.33	−0.20	−0.11	0.37	−0.46
	(se)	0.36	0.39	0.69	0.63	0.45	0.21
	[t]	−0.09	0.84	−0.28	−0.17	0.83	−2.21
	b_{HML}	0.34	0.11	0.14	0.99	0.64	−0.23
	(se)	0.24	0.17	0.37	0.33	0.31	0.17
	[t]	1.44	0.64	0.38	2.98	2.04	−1.37
	M.A.E.	0.17	0.18	0.22	0.22	0.17	0.09
	RMSE/RMSR	0.82	0.71	0.88	0.86	0.86	0.79
	Adjusted R2	−0.14	0.22	−0.10	0.08	0.03	0.13
	p - value	0.02	0.00	0.18	0.00	0.00	0.16
Panel D: 5-Factor Implied Anomaly	α Anomaly	0.12	0.12	0.21	0.00	0.06	0.04
	(se)	0.07	0.04	0.05	0.07	0.06	0.03
	[t]	1.66	3.48	4.12	0.02	0.86	1.52
	b_{MKT}	0.05	−0.48	−0.85	0.10	−0.17	0.37
	(se)	0.32	0.20	0.24	0.31	0.24	0.20
	[t]	0.14	−2.35	−3.52	0.31	−0.71	1.88
	b_{SMB}	−0.20	0.14	−0.77	−0.38	0.10	−0.35
	(se)	0.34	0.36	0.63	0.52	0.43	0.18
	[t]	−0.59	0.38	−1.21	−0.72	0.24	−1.90
	b_{HML}	0.03	−0.61	0.19	0.30	0.39	−0.34
	(se)	0.35	0.49	0.56	0.61	0.49	0.25
	[t]	0.07	−1.24	0.34	0.48	0.81	−1.36
	b_{RMV}	0.12	0.45	−1.16	0.41	−0.22	0.39
	(se)	0.50	0.31	0.37	0.65	0.46	0.30
	[t]	0.24	1.44	−3.11	0.63	−0.49	1.31
	b_{CMA}	0.57	0.99	0.84	1.14	0.56	0.06
	(se)	0.42	0.58	0.57	0.58	0.42	0.19
	[t]	1.34	1.72	1.47	1.98	1.35	0.31
	M.A.E.	0.16	0.17	0.21	0.22	0.17	0.09
	RMSE/RMSR	0.81	0.68	0.83	0.82	0.86	0.79
	Adjusted R2	−0.27	0.18	−0.14	0.03	−0.10	0.00
	p - value	0.02	0.00	0.00	0.00	0.04	0.23

Table A.12. Equal-Weighted, Microcaps-Excluded Univariate Quintile Portfolios: Summary Statistics and Implied Anomalies.
NOTE: .

		Equal-Weighted Univariate Quintile Portfolios Excluding Microcaps					
		L	2	3	4	H	$L-H$
Panel A: Portfolio Excess Return	$\mu(r^{Exc})$	0.12	0.11	0.09	0.04	0.05	0.06
	$\sigma(r^{Exc})$	0.18	0.18	0.25	0.27	0.26	0.19
	Sharpe	0.69	0.61	0.36	0.14	0.21	0.32
Panel B: CAPM-Implied Anomaly	α Anomaly	0.12	0.13	0.10	0.05	0.06	0.04
	(se)	0.03	0.03	0.04	0.04	0.05	0.03
	[t]	4.11	3.89	2.90	1.20	1.28	1.71
	b_{MKT}	0.03	−0.37	−0.21	−0.24	−0.11	0.28
	(se)	0.11	0.14	0.29	0.19	0.11	0.15
	[t]	0.30	−2.56	−0.71	−1.26	−0.97	1.87
	M.A.E.	0.13	0.14	0.20	0.21	0.18	0.13
	RMSE/RMSR	0.82	0.78	0.93	0.98	0.97	0.91
	Adjusted R2	−0.06	0.10	−0.03	−0.03	−0.05	0.03
	p - value	0.77	0.02	0.49	0.22	0.34	0.08
Panel C: 3-Factor Implied Anomaly	α Anomaly	0.12	0.12	0.11	0.02	0.03	0.07
	(se)	0.04	0.04	0.04	0.05	0.06	0.03
	[t]	3.21	3.41	2.68	0.50	0.44	2.10
	b_{MKT}	0.08	−0.37	−0.24	−0.06	0.01	0.22
	(se)	0.13	0.15	0.21	0.20	0.12	0.16
	[t]	0.59	−2.52	−1.14	−0.28	0.09	1.35
	b_{SMB}	−0.13	0.32	−0.12	−0.04	0.45	−0.62
	(se)	0.26	0.31	0.50	0.57	0.46	0.29
	[t]	−0.51	1.03	−0.25	−0.07	0.97	−2.10
	b_{HML}	0.19	0.01	−0.13	0.80	0.51	−0.26
	(se)	0.19	0.16	0.42	0.30	0.36	0.28
	[t]	0.98	0.08	−0.31	2.65	1.43	−0.92
	M.A.E.	0.13	0.13	0.19	0.20	0.17	0.11
	RMSE/RMSR	0.81	0.77	0.92	0.90	0.92	0.83
	Adjusted R2	−0.17	0.02	−0.16	0.01	−0.05	0.09
	p - value	0.61	0.10	0.53	0.03	0.39	0.25
Panel D: 5-Factor Implied Anomaly	α Anomaly	0.11	0.11	0.20	0.00	0.03	0.05
	(se)	0.06	0.04	0.04	0.07	0.06	0.02
	[t]	1.86	3.17	5.61	0.03	0.51	2.11
	b_{MKT}	0.12	−0.33	−0.87	0.10	−0.00	0.34
	(se)	0.30	0.19	0.19	0.33	0.25	0.27
	[t]	0.41	−1.74	−4.44	0.29	−0.01	1.24
	b_{SMB}	−0.23	0.11	−0.67	−0.20	0.23	−0.48
	(se)	0.28	0.34	0.49	0.53	0.46	0.24
	[t]	−0.82	0.32	−1.35	−0.39	0.51	−2.05
	b_{HML}	0.07	−0.37	0.22	0.50	0.34	−0.26
	(se)	0.28	0.30	0.52	0.50	0.53	0.41
	[t]	0.27	−1.25	0.41	1.01	0.63	−0.63
	b_{RMV}	0.07	−0.05	−1.46	0.26	−0.12	0.31
	(se)	0.46	0.24	0.33	0.60	0.51	0.48
	[t]	0.15	−0.21	−4.36	0.43	−0.23	0.65
	b_{CMA}	0.24	0.70	0.45	0.47	0.34	−0.04
	(se)	0.40	0.33	0.49	0.52	0.42	0.21
	[t]	0.62	2.09	0.94	0.89	0.83	−0.21
	M.A.E.	0.13	0.13	0.18	0.21	0.18	0.11
	RMSE/RMSR	0.80	0.75	0.86	0.89	0.92	0.83
	Adjusted R2	−0.33	−0.07	−0.16	−0.12	−0.22	−0.07
	p - value	0.53	0.01	0.00	0.02	0.53	0.12

A.3 Theoretical Derivations

A.4 Numerical Solution