

The Cross-Section of Labor Leverage and Equity Returns*

Andres Donangelo[†] François Gourio[‡] Matthias Kehrig[§] Miguel Palacios[¶]

ABSTRACT

The relative size and inflexibility of labor expenses lead to a form of operating leverage, which we call labor leverage. We derive a set of conditions for the existence of labor leverage even when labor markets are frictionless. Our model provides theoretical support for the use of firm-level labor share as a measure of labor leverage. Using Compustat/CRSP and confidential Census data, we provide evidence for the existence and for the economic significance of labor leverage: High labor-share firms have operating profits that are more sensitive to economic shocks and have higher expected returns.

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[†]Department of Finance, University of Texas at Austin. Address: 2110 Speedway; B6600, Austin TX 78712. E-mail: andres.donangelo@mcombs.utexas.edu. Phone: (510) 232-6841.

[‡]Economic Research, Federal Reserve Bank of Chicago. Address: 230 South LaSalle Street, Chicago IL 60604. E-mail: fgouriowork@gmail.com. Phone: (312) 322-5627.

[§]Department of Economics, Duke University. Address: 419 Chapel Drive, Durham, NC 27708-0097. E-mail: matthias.kehrig@gmail.com. Phone: (919) 660-1901.

[¶]Finance Department, University of Calgary. Address: 2500 University Dr NW, Calgary, AB T2N 1N4. E-mail: miguel.palacios@ucalgary.ca. Phone: (403) 220-2883.

Labor compensation is a major expense for firms: Despite its documented secular decline, the labor share still represents over 50% of the gross domestic product (GDP) in the United States.¹ Magnitude, however, is not the only distinguishing property of labor compensation. For asset pricing, an arguably equally important property of labor compensation is its smoothness relative to firms' cash inflows. This smoothness leads to a labor-induced form of operating leverage (henceforth *labor leverage*), which amplifies firm risk in a way analogous to financial leverage. While financial leverage has been extensively studied, there has been less work on labor leverage, likely because a theoretically supported empirical measure is lacking. This paper fills this gap and provides theoretical support and empirical validation for the firm-level labor share (i.e., the ratio between a firm's labor expenses and its value added) as a new measure of firm-level labor leverage. Moreover, this paper presents new evidence for the economic significance of labor leverage in explaining cross-sectional differences in the riskiness of cash flows, and in expected returns.

Our first contribution, which is presented in Section 1, is to provide a simple analytical discussion of the theoretical link between labor leverage, labor share, and the cross-section of stock returns in a frictionless setting. We show that the following are two sufficient conditions to create the labor leverage mechanism: (a) wages are smoother than shocks to a firm's output (e.g., productivity or demand shocks), and (b) labor and capital are strict complements in a firm's productive technology. The data support these two conditions. First, aggregate wages are less volatile than productivity, as is well known in the macroeconomics literature; we also show that labor costs are significantly less variable than other costs: For instance, in our sample, a 1.0% reduction in sales is associated, on average, with reductions of 1.08% in non-labor costs of but only 0.53% in labor costs. Second, as discussed by León-Ledesma, McAdam, and Willman (2010), Klump, McAdam,

¹Gollin (2002) finds that labor share is between 0.65 and 0.80 across most of the developed countries included in his sample. For a discussion of the global decline in labor share, see Piketty (2014), Karabarbounis and Neiman (2014), and Hartman-Glaser, Lustig, and Xiaolan (2017). Hartman-Glaser et al. (2017) show an increase in labor share for the median U.S. firm, despite the decline in aggregate labor share. Kehrig and Vincent (2017) find that, despite the aggregate labor share decline, labor expenses remain high for the vast majority of establishments.

and Willman (2012), and Oberfield and Raval (2014), among others, there is strong empirical evidence in the literature that the elasticity of substitution between capital and labor is less than one at the firm level. Finally, the model provides theoretical support for the use of labor share as a proxy for labor leverage.

Our second and main contribution, which is presented in Section 2, is to test the empirical predictions of this simple theory. Crucial to our work is the measurement of the labor share at the firm level. We consider three alternative measures of labor share. The first two measures are based on Compustat data and cover all non-financial industries. Our first measure, which we denote by *LS*, uses labor compensation to construct the labor share. One limitation of the Compustat data set is that only around 10% of firm-year observations have non-missing labor compensation information, which restricts the coverage of the *LS* measure. Our second measure, which we denote by *ELS*, is based on imputed labor costs, which allows us to greatly extend the sample covered by *LS*. We also consider a third measure, which is based on a sample of restricted-access firm-level Census data. This sample has higher quality labor compensation data but covers only manufacturing industries. We validate our three measures of labor share by showing that they are strongly correlated with each other, and that each of them is positively related to operating leverage, i.e. the sensitivity of operating profits to economic shocks. In particular, we show that the sensitivity of profits to real GDP, aggregate TFP, and market return is positive for the average firm, and is cross-sectionally increasing in labor share. This result, besides supporting our labor leverage mechanism, also validates our Compustat-based labor share measure and suggests that future researchers who are unable to access Census data can use the proxies we construct in Compustat.

We next proceed to study the implications of our proposed mechanism for expected returns. Our theory predicts a positive relation between labor share and expected returns, as long as a firm's productivity has a greater systematic risk loading than its wage rate. An equivalent sufficient condition is the greater volatility and procyclicality of productivity with respect to wages. To

address the challenge that expected returns are not directly observable in the data, we use two different types of proxies for expected returns: realized equity returns and systematic risk loadings (i.e., betas on risk factors). We find supporting evidence that expected returns are increasing in labor share: high labor share firms earn, on average, higher realized equity returns, and have higher betas.

Our final contribution, which is presented in Section 3, is to construct a production model (that nests the simple framework of Section 1), which can match qualitatively but also quantitatively what we observe in the data. We present such a model and estimate it using standard moments for risky-asset returns, as well as novel moments related to labor leverage. This calibration delivers a set of results that closely match relevant moments found in the data, giving credence to our proposed mechanism. The success of the calibration of the model also supports the hypothesis that labor leverage is a first-order driver of cross-sectional variation of firms' exposure to fundamental sources of risk and thus of cross-sectional variation in expected returns.

Our paper contributes to the literature that studies the relation between operating leverage and stock returns.² Within this literature, our paper is more closely related to the strand that discusses the relation between *labor-induced* forms of operating leverage and asset prices. Our proposed mechanism is based on the strict complementarity between labor and capital and the relative smoothness of wages, which are the simplest set of conditions that generates labor leverage. We focus on these two conditions because they can be easily tested in the data and because their existence does not rely on labor market frictions, which are intrinsically hard to measure and test. However, we note that frictions in labor markets are likely to be important additional drivers of labor leverage. Examples of documented frictions in labor markets that also generate labor leverage are labor contracts that insure workers against labor risk (e.g., Danthine and Donaldson (2002)),

²Some examples of this literature that focuses on the traditional (i.e., non labor-induced) form of operating leverage include: Lev (1974), Mandelker and Rhee (1984), Carlson, Fisher, and Giammarino (2004), Zhang (2005), and Novy-Marx (2011).

unionization of workers (e.g., Chen, Kacperczyk, and Ortiz-Molina (2012)), labor mobility and labor market segmentation (e.g., Donangelo (2014)), infrequent renegotiation of wages (e.g., Favilukis and Lin (2015)), and search and matching frictions in labor markets (e.g., Petrosky-Nadeau, Zhang, and Kuehn (2018)).³ The seminal labor leverage mechanism in Danthine and Donaldson (2002) is based on the existence of labor contracts that insure workers with limited market participation and that amplify cash flow risk to firm owners. Donangelo (2014) shows that labor mobility (i.e., the flexibility of workers to switch industries) represents a labor-induced form of operating leverage that also helps explain the cross-section of returns. Favilukis and Lin (2015) show that the infrequency of the renegotiation of wages represents a source of labor leverage that helps explain a number of asset pricing moments. Petrosky-Nadeau et al. (2018) show that search and matching frictions generate a labor-induced form of operating leverage in a general equilibrium model of unemployment. We view these alternative drivers of labor leverage as complementary to ours, since multiple channels are likely present in reality. Our theoretical contribution to this literature is to show that the strict complementarity of labor and capital and wage smoothness are sufficient condition for the existence of labor leverage. Our main empirical contributions to this literature are the validation of labor share as a new proxy for labor leverage and the additional empirical evidence for a positive cross-sectional relation between labor leverage and expected returns using this proxy.

1. Theoretical Motivation

In this section, we present and analyze the labor leverage mechanism, and demonstrate why the labor share is a valid proxy for labor leverage. In the interest of clarity, we use a two-period

³Other papers that relate labor to finance issues are Peterson (1994), Santos and Veronesi (2006), Merz and Yashiv (2007), Chen and Zhang (2011), Chen et al. (2012), Berk and Walden (2013), Eisfeldt and Papanikolaou (2013), Belo, Lin, and Bazdresch (2014), Xiaolan (2014), Schmidt (2014), and Favilukis, Lin, and Zhao (2015), Kuehn, Simutin, and Wang (2017).

model to develop the theoretical motivation for labor leverage. We extend the setting in Section 3, in which we present and estimate a dynamic model that embeds the proposed mechanism.

We start by considering a firm that generates value added Y according to

$$Y_t = X_t F[K_t, L_t], \quad (1)$$

where $t \in \{0, 1\}$ denotes the date, X denotes the firm's total factor productivity (TFP), L denotes labor, K denotes capital, and F is a homogeneous function of degree one so that the productive technology has the constant-returns-to-scale property. The firm takes as given the wage rate W , which is set in an implicit perfect labor market and is possibly correlated with the firm's TFP. Capital adjustment costs are sufficiently high as to make capital fixed in the instant considered (i.e., $K_t = K$). The firm's profit maximization problem at time t then defines optimized operating profits Π as:

$$\Pi_t = \max_{L_t} \{X_t F[K, L_t] - L_t W_t\}. \quad (2)$$

In what follows, we drop the time subscripts unless they are needed for clarity. We define labor leverage as the ratio of the elasticity of operating profit to TFP and the elasticity of value added to TFP, minus one, as given by:

$$\ell \equiv \frac{d \text{Log}[\Pi]/d \text{Log}[X]}{d \text{Log}[Y]/d \text{Log}[X]} - 1 \quad (3)$$

The intuition behind the definition in Equation 3 is that labor leverage captures the extent to which productivity or demand shocks are transformed into operating income shocks. We subtract one so that our measure is zero when there is no operating leverage. Note that the definition of labor leverage in this setting is analogous to the definition of general operating leverage (i.e., operating

leverage from both labor and non-labor costs). The reason is that, in our setting, only labor leads to operating leverage. In Appendix B.2, we briefly discuss the case in which the firm is also subject to fixed non-labor operating costs to illustrate how the definition of labor leverage is nested within the definition of general operating leverage discussed in Garcia-Feijoo and Jorgensen (2010). The following proposition relates labor leverage to labor share, as well as to other economic fundamentals:

Proposition 1 (Labor Leverage)

For a constant-returns-to-scale production function, labor leverage is given by

$$\ell = \frac{(1 - \gamma) \frac{S}{1-S} (1 - \theta)}{1 + \gamma \frac{S}{1-S} (1 - \theta)}, \quad (4)$$

where the subscripts K and L denote partial derivatives with respect to labor and capital, $\theta \equiv \frac{\partial \text{Log}[W]}{\partial \text{Log}[X]}$ is the elasticity of the wage to productivity, $\gamma \equiv \frac{F_K[K,L]F_L[K,L]}{F[K,L]F_{KL}[K,L]}$ is the elasticity of substitution between labor and capital, and $S \equiv \frac{LW}{Y}$ is the labor share. See Appendix B.1 for the derivation of Equation (4).

Proposition 1 shows that labor leverage is a function of the firm's labor share, the elasticity of substitution of capital and labor, and the response of wages to productivity changes. In particular, note that if wages respond one-for-one with productivity (i.e., $\theta = 1$), then the firm will have zero labor leverage. Hence, wage smoothness is a necessary condition for labor leverage to exist (i.e., $\ell > 0$). This condition is summarized in the assumption below:

Assumption 1 (Smoothness of Wages)

Wages are smooth relative to productivity: $\theta < 1$.

A common production function specification is the Cobb-Douglas: $F[K,L] = K^{1-\alpha}L^\alpha$, in which the elasticity of substitution between labor and capital is one (i.e., labor and capital are neither complements nor substitutes). In the knife-edged Cobb-Douglas case, labor leverage is

zero since labor share is constant, $S = \alpha$, and profits are a constant share of output, $\Pi = (1 - \alpha)Y$. In fact, an elasticity of substitution between labor and capital strictly below one is an additional necessary condition for the existence of labor leverage (i.e., $\ell > 0$). This condition is summarized in the assumption below:

Assumption 2 (Strict Complementarity of Labor and Capital)

The elasticity of substitution between labor and capital is less than one: $\gamma < 1$.

Note that Assumption 2 is a necessary and sufficient condition for the labor share to be increasing in productivity X and decreasing in the wage W . If the elasticity of substitution γ equals one, the labor share is constant. If the elasticity of substitution γ is greater than one, then the labor share is decreasing in productivity and increasing in the wage. As we show in the next section, Assumptions 1 and 2 are consistent with the data.

The proposition that follows shows that the two aforementioned assumptions jointly represent a necessary and sufficient set of conditions for the existence of labor leverage. Moreover, the proposition shows that the labor share is a valid proxy for labor leverage:

Proposition 2 (Labor Leverage and Labor Share)

Assumptions 1 and 2 imply:

- a. The existence of a strictly positive level of labor leverage: $\ell > 0$.*
- b. A strictly positive relation between labor leverage and labor share: $\frac{\partial \ell}{\partial S} > 0$.*

The corollary below shows how the capital-labor elasticity of substitution is related to the elasticities of value added growth and operating profit growth to shocks:

Corollary 1 (Useful Relation Involving Capital-Labor Elasticity of Substitution)

The elasticities of value added growth and operating profits growth to shocks are linearly related through the elasticity of substitution between labor and capital, as given by

$$\frac{\partial \text{Log}[Y]}{\partial \text{Log}[X]} - 1 = \gamma \left(\frac{\partial \text{Log}[\Pi]}{\partial \text{Log}[X]} - 1 \right). \quad (5)$$

See Appendix B.1 for details.

So far, the discussion shows that labor leverage makes operating profits relatively more sensitive to shocks. This higher cash flow risk will naturally affect expected returns, in a way that depends on the systematic risk exposure of TFP X and wages W . To demonstrate this in the simplest environment, we introduce a stochastic discount factor (SDF) M , and assume that the SDF M , the productivity X , and the wage W are jointly log-normally distributed.⁴ These assumptions imply that the firm's expected excess returns are given by

Proposition 3 (Expected excess asset returns)

$$\text{Log} \left[\frac{\mathbf{E}_0[R_1]}{r_F} \right] \simeq \beta_X + (\beta_X - \beta_W) \frac{S_0}{1 - S_0}, \quad (6)$$

where $R_1 \equiv \Pi_1/\mathbf{E}_0[M_1\Pi_1]$ denotes the firm's gross asset return, r_F is the gross risk free rate, and

$$\beta_X \equiv \text{Cov}_0(\text{Log}[M_1], \text{Log}[X_1]) \quad \text{and} \quad (7a)$$

$$\beta_W \equiv \text{Cov}_0(\text{Log}[M_1], \text{Log}[W_1]) \quad (7b)$$

denote the systematic risk exposures of the log TFP and the log wage, respectively.

See Appendix B.1 for details.

To obtain implications about the relation between labor share and expected returns, we need to make an extra assumption about the relative exposures of the TFP and of the wage to systematic risk:

Assumption 3 (Systematic risk loading of the TFP is strictly greater than the systematic risk loading of the wage)

$$\beta_X > \beta_W.$$

While assumption 1 ranks the relative smoothness of wages and productivity, Assumption 3 ranks the relative smoothness of the *projections* of wages and productivity on the stochastic dis-

⁴Section 3 extends this result to an infinite horizon continuous-time model.

count factor.⁵ The additional relative smoothness condition implied by Assumption 3 is also consistent with the data, as we show in the next section. Our final proposition shows that this assumption implies a positive relation between labor leverage and expected returns.

Proposition 4 (Expected returns and Labor Share)

Assumption 3 imply that $\text{Log} \left[\frac{\mathbf{E}_0[R_1]}{r_F} \right]$ is increasing in S .

See Appendix B.1 for details. This proposition provides another testable prediction of the labor leverage mechanism: A positive cross-sectional relation between labor share and expected returns.

2. Empirical Evidence

We first summarize the testable predictions of our model. We then discuss how we construct the labor share variables. We next present evidence in support of our key assumptions, and finally, we present evidence consistent with our testable implications.

2.1. Testable Predictions

The main empirical implications of the theoretical framework presented in the previous section are that (a) firms with high labor share exhibit higher sensitivity of cash flows to aggregate shocks (Proposition 2) and (b) firms with high labor shares have higher expected returns (Proposition 4).

2.2. Measurement of Labor Share and Summary Statistics

We construct three alternative measures of labor share. Each of our three measures is constructed as the ratio of a proxy of labor costs to a proxy of value added. We use these three measures in our empirical tests because each has unique strengths and weaknesses, as we discuss

⁵For instance, suppose that $\text{Log}[M] = -\eta \text{Log}[X]$ and $\text{Log}[W] = \theta \text{Log}[X]$. Then, the condition in Assumption 3 would be true if and only if $\theta < 1$.

below. The first two measures are based on publicly available Compustat data, while the third is based on confidential data from the U.S. Census.

Our first measure of labor share, which is denoted LS , is defined from Compustat items as follows:

$$LS_{it} \equiv \frac{\overbrace{\text{Labor Costs}_{it}}^{LS}}{\overbrace{\text{Value Added}_{it}}^{LS}} = \frac{XLR_{it}}{OIBDP_{it} + \Delta INVFG_{it} + XLR_{it}}, \quad (8)$$

where XLR is the Compustat variable *Staff Expense – Total*, used as a proxy for labor costs, $OIBDP$ is the Compustat variable *Operating Income Before Depreciation*, and $\Delta INVFG_{it} \equiv INVFG_{it} - INVFG_{i,t-1}$ is the change in the Compustat variable *Inventories – Finished Goods*. We set $\Delta INVFG_{it}$ to zero when either $INVFG_{it}$ or $INVFG_{i,t-1}$ are missing.

The denominator in Equation (8) approximates value added as follows. Value added is defined as total (gross) production less the cost of intermediate goods (e.g., materials). We approximate production as sales plus the change of inventories.⁶ We next approximate the cost of intermediates as total costs minus staff expenses. Overall, we obtain:

$$\overbrace{\text{Value Added}_{it}}^{LS} = \overbrace{(\text{Sales}_{it} + \Delta INVFG_{it})}^{\text{Value of Production}} - \overbrace{(\text{Sales}_{it} - OIBDP_{it} - XLR_{it})}^{\text{Cost of Intermediary Goods}}, \quad (9a)$$

$$= OIBDP_{it} + \Delta INVFG_{it} + XLR_{it}. \quad (9b)$$

Equations (9a) to (9b) reflect the standard decomposition of value added as the sum of payments to labor and to the firm’s owners. See Appendix A.1.2 for more details.

Our second empirical measure of labor share is denoted *extended labor share* (hereafter ELS),

⁶The results presented in the paper are qualitatively unaffected by excluding the change in inventories from our measures of labor share.

defined as follows:

$$ELS_{it} \equiv \frac{\widehat{\text{Labor Costs}}_{it}^{ELS}}{\widehat{\text{Value Added}}_{it}^{ELS}} = \frac{LABEX_{it}}{OIBDP_{it} + \Delta INVFG_{i,t} + LABEX_{it}}, \quad (10)$$

where $LABEX$ is an imputed measure of labor expenses constructed as:

$$LABEX_{it} \equiv \overline{WAGE}_t^I \left(\frac{EMP_{i,t-1} + EMP_{it}}{2} \right), \quad (11)$$

where EMP is Compustat variable *Number of Employees*, I denotes firm i 's industry, and \overline{WAGE}_t^I the average of

$$WAGE_{jt} \equiv \left(\frac{XLR_{jt}}{(EMP_{j,t-1} + EMP_{jt})/2} \right), \quad (12)$$

across firms $j \in I$ with non-missing values for these variables on year t . The ELS extends the coverage of the LS measure, which is limited by the fact that XLR is only available for around 10% of firm-year observations in our sample. We average the number of employees between years $t - 1$ and t because the number of employees is reported at year-end. We provide additional details about the merged CRSP–Compustat dataset used, about the sample construction procedure, and about the construction of the LS and ELS measures in Appendix A.1.

Our third empirical measure of labor share, which is constructed with data from the U.S. Census, is denoted *Census-based labor share* (hereafter CLS). The CLS measure is defined as

$$CLS_{it} \equiv \frac{\widehat{\text{Labor Costs}}_{it}^{CLS}}{\widehat{\text{Value Added}}_{it}^{CLS}} = \frac{SW_{it} + LC_{it}}{VA_{it}}, \quad (13)$$

where SW denotes salaries and wages, LC denotes ancillary labor costs such as employer-side social security contributions and contributions to retirement and health insurance plans, and VA denotes the value added which is computed as sales less inventory investment, resales, expenses

for intermediate inputs and services as well as energy and electricity inputs. One advantage of *CLS* relative to *LS* and *ELS* is that it is based on higher-quality labor compensation data. Another advantage is that it is not restricted to publicly-listed firms and it also covers privately-held firms. One limitation of the *CLS* measure is that it only covers firms in manufacturing industries. We provide in Appendix A.2 more details about the U.S. Census data used, about the procedure used to match Census data and Compustat data, and about the construction of the *CLS* measure. We set *LS*, *ELS*, and *CLS* as missing if these are negative or greater than one since these values have no clear interpretation in our theoretical framework.

Overall, we find that *LS* and *ELS* have correlations with *CLS* that are above 0.55 and that are highly statistically significant (see Appendix A.2 for details). Moreover, as we show in the remainder of this section, the empirical findings in this paper are consistent across our three measures. These facts are supporting evidence for the validity of the *LS* and *ELS* measures. We interpret this validating evidence for *LS* and *ELS* as a contribution that should encourage researchers with no access to confidential Census data but who wish to measure the labor share to use *LS* or *ELS*.

Table 1 reports summary statistics of the samples that underly each of our three measures. For each labor share measure, we first show the statistics for the entire sample of firms with non-missing values for the measure. Next, we show statistics for subsamples of firms grouped by *all-but-micro breakpoints*, which are defined by the labor share quintile breakpoints of the sample of firms with a market cap above the 20th percentile among all NYSE-listed stocks. Finally, we show statistics of firms grouped by *NYSE breakpoints*, which are defined by the labor share quintile breakpoints of the sample of NYSE-listed firms. Panels A, B, and C of Table 1 present statistics for the samples used in the tests involving *LS*, *ELS*, and *CLS* respectively. The statistics shown in Panels A and B represent the time-series average of the yearly median of each of the characteristics presented. The statistics shown in Panel C represent the time-series average of yearly *averages*.⁷

⁷We report averages but not medians in Panel C because of the U.S. Census confidentiality guidelines.

Panels A and B of Table 1 reports statistics for the samples of firms with non-missing *LS* and *ELS*, respectively. On both panels, the statistics shown by columns 1a and 1b suggest that the median of *ELS* conditional on missing *LS* is not significantly different from the median of *ELS* conditional on non-missing *LS*. This finding suggests that the *ELS* measure, which is based on imputed labor expenses, is consistent with the *LS*.

The general findings in columns 2 to 10 of Panels A and B are similar, so we discuss these two panels together in what follows. Column 2 reports that the logarithm of the ratio of the number of employees to the plant, property, and equipment (PPE), which represents an additional measure of labor intensity used in the literature, is, as expected, increasing in both *LS* and *ELS*. Columns 3 and 4 shows that B/M ratio is increasing and the logarithm of market size is decreasing in *LS* and *ELS*, which are findings consistent with the working hypothesis that high labor share firms are less productive and more exposed to systematic risk. Columns 5 and 6 shows that both the size and the level of tangibility of assets is decreasing in *LS* and *ELS*. These two trends are likely to be related: A possible explanation for the negative trend in asset values is a downward bias in asset value reporting, in particular since high labor share firms are both less capital intensive and have less tangible assets.⁸ Consistent with the lower asset tangibility of high labor share firms, Column 7 reports that organizational capital, which is not considered in a firm's financial reports, is increasing in labor share. Column 8 shows that financial leverage ratios are lower among higher labor share firms. Column 9 shows that high labor share firms are less profitable, as indicated by their lower return-on-equity (ROE) measures. This last finding is consistent with our theory in which a firm's labor share is inversely related to its productivity. Our theoretical motivation is silent on firms' investment decisions. However, all else equal, we should expect high labor share firms, which we expect to be less productive and to have higher discount rates, to invest less. Column 10 shows that, consistent with intuition, investment-to-asset ratios are decreasing, albeit mildly so,

⁸See Damodaran (2011) for a discussion of the relation between intangibles and a bias in asset value reporting.

across labor share quintiles.

Panel C of Table 1 reports time-series averages of *average* firm characteristics of portfolios of firms sorted on *CLS* in the matched Compustat–Census sample. Columns 1a–1c show that the three measures are monotonically increasing across the quintiles, which is consistent with Table A–1, which shows a positive and significant correlation between *CLS* and the Compustat-based measures. The general trends in the values of the statistics presented in columns 2–10 of Panel C are consistent with the trends in the corresponding columns of Panels A and B. One notable difference is that the average tangibility in Panel C is more homogeneous across quintiles than in Panels A and B, possibly due to the fact that matched Compustat–Census sample solely covers manufacturing industries. Another difference is that financial leverage is mildly increasing in the Census sample.

<< *Table 1 here* >>

2.3. *Evidence for the Sufficient Conditions Underlying Labor Leverage*

As discussed in the introduction, there is ample evidence in the literature for the strict capital-labor complementarity. The previous section shows that this is one of the sufficient conditions required for the existence of the labor leverage mechanism. In this section, we present empirical evidence consistent with the additional conditions that ensure the existence of the labor leverage mechanism and for its relevance for asset pricing: the smoothness of labor costs and the greater cyclicity of TFP relative to wages and labor costs.

Table 2 reports aggregate statistics that support the hypothesis that wages are smoother and less procyclical than output, profits, and TFP. The table shows that the volatility of the growth rate of before-tax profits (0.104) is 3.3 times the volatility of GDP growth (0.031), and the slope coefficient in a regression of profit growth on GDP growth, used as a proxy for procyclicality, is 1.950. On the other hand, the volatility of real wage growth (0.017) is around half of that of GDP

growth, thus materially smoother than profits. Moreover, the slope coefficient of real wage growth on GDP growth is only 0.142, which supports the assumption that wages are less procyclical than profits. TFP is slightly more volatile (volatility of 0.019) and significantly more procyclical (slope coefficient of TFP growth on GDP growth is 0.540) than real wage growth.

<< *Table 2 here* >>

Next, we investigate the firm level elasticity of total labor costs to sales. The existence of labor leverage implies that labor costs are less elastic to sales than non-labor costs. Table 3 shows cost elasticity estimates based on Compustat data (Panel A) and based on Census data (Panel B). Panel A shows that, for each dollar change in sales, staff expenses change 16¢ while all other operating costs (i.e., the sum of costs of goods sold and sales, general, and administrative expenses minus staff expenses) change 39¢. Panel A also shows that for each percentage point change in sales, staff expenses change by 0.53%, which is significantly less than the change in all operating expenses (0.82%) or non-labor operating expenses (1.08%). Table 3, Panel B, shows the results of a similar estimation procedure using U.S. Census data. The Census data used do not allow for the construction of variables that are fully aligned with those used in Panel A.⁹ Differences in variable definitions notwithstanding, the results in Panel B are qualitatively similar to the results in Panel A and confirm that labor expenses are less elastic than other operating expenses. A one dollar increase in sales leads to a 3¢ change in labor compensation, a 84¢ change in non-labor non-SG&A operating expenses, and a 86¢ change in the sum of operating expenses available in the sample. Panel B also shows that for each percentage point change in sales, labor compensation changes by 0.69%, which is lower than the percentage change in all operating expenses available in the sample (0.89%), and also less than non-labor non-SG&A operating expenses (0.99%). Overall, the findings in Table 3 support the hypothesis that labor costs are significantly less elastic than other operating costs, which is consistent with the existence of the proposed labor leverage mechanism.

⁹For instance, we do not have access to non-labor SG&A costs.

<< Table 3 here >>

2.4. Evidence for the Existence of the Labor Leverage Mechanism

Our theoretical motivation shows that relative smoothness of wages and the strict complementarity between labor and capital imply that labor share is countercyclical and that high labor share firms have operating profits that are more sensitive to shocks than low labor share firms. In this section, we present evidence for these two predictions. This evidence supports the existence of the proposed labor leverage mechanism and also the validity of our proposed labor share measures as proxies for labor leverage.

2.4.1. Countercyclicalities of Labor Shares

To establish the cyclicity of labor shares, we run the following panel data regressions with fixed effects:

$$S_{i,t}^g = \beta_{0,i} + \beta_1 x_t^g + \varepsilon_{i,t} \quad (14)$$

where S^g is the annual percentage growth in the measure of labor share under consideration (LS , ELS , and CLS) and x^g is the percentage growth in our business cycle proxy (GDP growth, TFP growth, or market returns). The subscript i in the intercept of the regression shown in Eq. (14) denotes firm-fixed effects.

Table 4 shows the estimates from regression (14) in our samples from Compustat and from the Census. The specifications based on Compustat data use the LS and ELS measures and are conducted at the firm level. The specifications based on Census data use CLS and are conducted at the firm level. The table shows that our three measures of labor share are time-varying and countercyclical. This result is consistent with the previous finding that wages are smooth and that

the capital-labor elasticity of substitution is less than one, since in that case the labor share is negatively related to productivity and output.

<< Table 4 here >>

2.4.2. Sensitivity of Profits to Aggregate Shocks

A telltale sign of a high level of operating leverage, labor induced or otherwise, is a high sensitivity of operating profits to exogenous shocks to a firm's sales or output. Hence, we investigate whether, as implied by Proposition (2), the labor share is positively related to the sensitivity of operating profits to shocks. To test this hypothesis, we run the following panel data regressions with interaction terms:

$$prof_{i,t}^g = \beta_{0,i} + \beta_1 x_t^g + \beta_2 x_t^g S_{i,t-1} + \beta_3 S_{i,t-1} + \varepsilon_{i,t} \quad (15)$$

where x is the proxy aggregate shock to output (GDP growth, TFP growth, or market returns), $prof^g$ is the percentage growth of operating profit before interest and depreciation, and S is the proxy of labor share under consideration, LS , ELS , or CLS . The proxy S is lagged one year to address the concern of simultaneity.¹⁰ The subscript i in the intercept of the regression shown in Eq. (15) denotes firm-fixed effects.

Table 5, Panel A, presents the results of tests based on Compustat data, which use firm-level LS and ELS measures of labor share. The first three specifications in Panel B show the results of tests based on the merged Compustat-Census sample, which use firm-level CLS as measure of labor share. The last three columns of the panel present results of tests based solely on Census data.

The results shown in Table 5 are broadly consistent across all specifications. Profit growth is positively exposed to aggregate shocks, and this sensitivity increases in labor share as given by the

¹⁰As presented in Table 4, labor share is negatively correlated with contemporaneous aggregate shocks.

positive signs of the coefficients of the interaction terms (i.e., β_2) from Eq. (15). The coefficients on the specifications that use market returns as proxy for aggregate shock to output is less statistically significant than in other specifications. A likely reason for this lower statistical significance is that market returns are driven not only by shocks to aggregate TFP but also to shocks to discount rates and to shocks to future expected cash flows.

Overall, Table 5 shows that operating profits of labor intensive firms are more sensitive to aggregate shocks, and support the economic significance of the labor-induced operating leverage mechanism. Moreover, these results show that the response to shocks of high labor share firms is consistent with the hypothesis that these have greater labor leverage. These results provide additional indirect validation for the three proxies for labor leverage proposed in this paper.

<< *Table 5 here* >>

2.5. *Expected Returns*

Our theoretical model predicts that, under relatively mild assumptions, firms with high labor share should earn higher expected returns than firms with low labor share. In this section, we investigate this prediction and explore the empirical relation between labor share and expected returns. To address the challenge that expected returns are not directly observable, we use two different types of proxies for them: realized stock returns and stock return loadings on risk factors (i.e., betas).

2.5.1. *Labor Shares and Realized Returns*

Table 6 presents the average monthly excess returns of equally-weighted and value-weighted quintile-portfolios of firms sorted on *LS*, *ELS*, and *CLS*, as well as the zero-investment portfolios that are long stocks in the highest labor share quintile and short stocks in the lowest labor share

quintile (i.e., the H-L portfolios).¹¹ The first set of results shown in Table 6 are based on tests that use equally-weighted returns. Across the different labor share measures, the average excess return of the equally-weighted H-L portfolio ranges from 0.35% per month (i.e., 4.3% per year) to 0.53% per month (i.e., 6.5% per year). The second and last set of results shown in Table 6 are based on tests that use value weighted-returns. Across the different labor share measures, the average excess return of the value-weighted H-L portfolio ranges from 0.29% per month (i.e., 3.5% per year) to 0.43% per month (i.e., 5.3% per year).

The portfolio sorts presented in Table 6 represent non-parametric tests of the model's prediction that high labor share firms are more exposed to risk and thus earn higher expected returns than low labor share firms. Relative to portfolio sort tests based on value-weighted returns, the tests based on equally-weighted returns provide more direct information about the differences in expected returns across firms with different levels of labor share, which is the focus of this paper. Portfolio tests based on value-weighted returns provide information about differences in expected returns *of the lowest labor-share firms within a given portfolio*, across portfolios of firms grouped by labor share. To see this, note that the most valuable firms are likely to have low labor share levels, since low labor share firms have higher productivity and lower exposure to systematic risk.¹² The finding that the returns of the H-L portfolios are positive is consistent with the existence of the labor leverage mechanism proposed in the paper and with its relevance for asset pricing.

<< *Table 6 here* >>

¹¹Appendix A.4 presents the details of the methodology used in the portfolio construction and the details of the sorting procedure.

¹²Portfolio sort tests based on value-weighted returns may be more appropriate to test pricing anomalies because these tests can be interpreted as the performance of trading strategies feasible to large investors (e.g., representative agents which are unable to purchase large quantities of micro-cap stocks) and are less subject to unrealistic excessive trading implied by equally-weighted returns. The research question studied in this paper is not, however, whether certain trading strategies earn returns that are anomalous (i.e., not explained by risk factors) or that are explained by a new proposed risk factor. This motivates our focus on equally-weighted returns. Another possible concern is that value-weighted returns are, by construction, less subject to the influence of micro caps than equally-weighted returns, as discussed by Harvey, Liu, and Zhu (2016) and Hou, Xue, and Zhang (2017). To address this concern, we ignore microcaps as defined in Fama and French (2008) when calculating the portfolio thresholds of our equally-weighted returns.

2.5.2. Conditional Factor Betas

The results of Tables 5, 4, and 6, which are discussed in the previous sections, show evidence consistent with the existence of the labor leverage mechanism: labor share is countercyclical, is associated with greater sensitivity of operating profits to shocks, and is positively cross-sectionally related to average realized returns. In this section, we present evidence that this last finding originates from a positive relation between labor shares and the exposure of firms' output to systematic risk.

Table 7 reports the time-series averages of average firm-level conditional factor betas of portfolios of firms sorted on our measures of labor share, *LS* (Panel A), *ELS* (Panel B), and *CLS* (Panel C). We use a total of six risk factors: four derived from asset pricing models and two based on macro-economic series. The first proxy for aggregate risk is the market risk factor (*MKT*) described in Fama and French (1993) and obtained from Kenneth French's website. *ME*, *IA*, and *ROE* are the size, investment, and profitability factors of the q-factor model by Hou, Xue, and Zhang (2015) and obtained from the authors.¹³ The *q-factors* are derived from a production-based asset pricing model, which makes them a natural choice for the analysis of labor leverage. The table also includes conditional betas with respect to non-tradable macroeconomic factors that are closely related to the business cycle: real GDP growth and TFP growth. Conditional betas are estimated with monthly returns for the tradable factors *MKT*, *ME*, *IA*, and *ROE* and with quarterly returns for the macroeconomic factors *TFP* and *GDP* over rolling windows of five years. We provide more details on the construction of the firm-level conditional betas used in the tests in Appendix A.5.

Table 7 shows that the average firm-level conditional betas with respect to *MKT*, *ME*, *GDP*, and *TFP* are increasing across the labor share quintiles and positive and significant for the H-L portfolios. The average conditional betas with respect to the investment q-factor *IA* show no

¹³The market factor *MKT* is used in several asset pricing models, including the CAPM and the q-factor model.

clear trend across the labor share quintiles. A possible reason for this last finding is that betas with respect to the *IA* factor are more closely related to sources of risk that do not directly affect contemporaneous operating cash flows (e.g., investment specific shocks). The average conditional betas with respect to the profitability q-factor *ROE* show no clear trend across the *LS* and *ELS* quintiles, but are negative and significantly decreasing across the *CLS* quintiles. Note that this last finding is not inconsistent with our proposed mechanism: The proposed labor leverage mechanism implies that firms output's exposure to systematic risk, irrespective its sign, should be increasing in magnitude in labor share.¹⁴

The use of risk factors derived from asset pricing models does not imply that the labor leverage mechanism relies on the validity of these models. In fact, our theoretical motivation is agnostic about the true source(s) of systematic risk in the economy. The only additional assumption required for the tests presented in this section is that the risk factors are merely correlated to the true source(s) of risk in the economy. Under this assumption, empirical estimates of factor betas should be positively related to the (possibly not directly observable) true systematic risk loadings.

<< *Table 7 here* >>

2.5.3. *Factor Regressions*

Our theory shows that the predicted relation between labor leverage and expected returns is explained by the amplification of existing systematic risk exposure of firm level output. Consistent with the theory, the findings presented in Table 7 suggest that the positive relation between labor shares and expected returns documented in Table 6 arises from the amplifying effect of labor leverage on systematic risk exposure. In particular, the table shows that the loadings on the market (*MKT*), size (*ME*), and profitability (*ROE*) factors of the q-factor model are increasing in magnitude in labor share (there is no significant trend in the investment factor, *IA*, loadings). Although

¹⁴The effect of labor leverage on negative exposures to risk is analogous to the effect of borrowing and levering up a position in a negative beta asset.

outside the scope of our theoretical framework, a natural question is whether the q-factor model, which includes these four factors simultaneously, is able to explain the returns of the quintile labor share portfolios as well as the returns of the H-L labor share portfolio. To test the model, we follow the procedure in Hou et al. (2015) and run the factor regressions given by

$$r_t^i - r_t^f = \alpha_q^i + \beta_{MKT}^i MKT_t + \beta_{ME}^i ME_t + \beta_{IA}^i IA_t + \beta_{ROE}^i ROE_t + \varepsilon^i, \quad (16)$$

where the index i represents each of our six labor-share portfolios (i.e., EW and VW portfolios for each of our three labor share measures), β_x^i denotes the unconditional beta with respect to q-factor x of portfolio i , and the intercept α_q^i is the unexplained component of portfolio i 's average realized returns.

Based on our theoretical motivation, we expect the estimated betas from Eq. (16) to be increasing in magnitude over the labor share quintiles. Table 8 shows the results of the q-factor regression tests. The estimated betas indeed tend to be increasing in magnitude across the labor share quintiles. These findings are qualitatively similar to those shown in Table 7, despite the very different specifications used in these tables: While Table 7 reports average *conditional* factor betas estimated from *firm-level* regressions, Table 8 reports *unconditional* factor betas estimated from *portfolio-level* regressions.

As previously discussed, our theory is agnostic about the true sources of risk in the economy and is thus silent on the relation between the estimated unexplained component of average returns α_q and labor share. In particular, the test of whether the unexplained component of portfolio H-L's returns is significantly different from zero is a test of multiple null hypotheses: (1) the null hypothesis that returns are related to labor share, (2) the null hypothesis that the theoretical q-factor model spans all sources of risk that affect firms' output, and (3) the null hypothesis that the empirical implementation of the q-factor model spans the true factors predicted by the theory. Table 8 shows that the unexplained component of returns α_q of the statistically different from zero

for the equally-weighted H-L *LS* and *ELS* portfolios but not for any of the value-weighted H-L portfolios. One possible explanation for this finding is that there is greater measurement error in the estimation of betas of equally-weighted portfolios among high-labor share firms so that systematic risk loadings of these firms are underestimated.

<< *Table 8 here* >>

3. Model

The results from the previous section uncover an empirical link between a firm's labor share and its expected return. We now rationalize those results by reproducing them in a structural partial equilibrium model. The model is a specific application of the more general framework presented in Section 1. In particular, we impose some additional assumptions that allow us to estimate moments for quantities and prices and compare them to their empirical analogs. Despite its simplicity, the model is successful at explaining our main empirical findings. We first describe the model setup, we then derive labor leverage and firm value in the context of our model, and, at the end of the section, we describe and discuss the results of the model calibration procedure.

3.1. Setup

We take the stochastic discount factor (SDF) as exogenous. The dynamics of the SDF, which we denote by Λ , are given by

$$\frac{d\Lambda_t}{\Lambda_t} = -rdt - \eta dZ_t^\Lambda, \tag{17}$$

where $r > 0$ is the instantaneous risk-free rate, dZ^Λ is a Wiener process that represents the single source of systematic risk in the economy, and η represents the aggregate price of risk.

We assume perfect competition, so that the firm takes as given both its output price and the real wage it must pay its employees. The dynamics of the real wage W are given by

$$\frac{dW_t}{W_t} = \mu_w dt + \sigma_w \rho_w dZ_t^\Lambda + \sigma_w \sqrt{1 - \rho_w^2} dZ_t^W, \quad (18)$$

where dZ^W is a Wiener process orthogonal to dZ^Λ (i.e., $E[dZ^W dZ^\Lambda] = 0$); μ_w and σ_w are the drift and volatility of the wage growth process, respectively; and ρ_w is the priced portion of the wage growth risk.

The firm's productive technology is represented by a constant elasticity of substitution (CES) production function. Value added is given by

$$Y_t = X_t (\alpha L_t^\rho + (1 - \alpha) K_t^\rho)^{\frac{1}{\rho}}, \quad (19)$$

where L and K denote the labor and capital employed in production, $\alpha \in (0, 1)$ captures the relative importance of labor in total production, X denotes the level of total factor productivity (TFP), and the parameter ρ determines the elasticity of substitution between capital and labor, $\gamma \equiv \frac{1}{1-\rho}$. The limit $\rho \rightarrow -\infty$ represents the case in which capital and labor are perfect complements, while the other extreme case, $\rho = 1$, represents the case in which capital and labor are perfect substitutes. The case in which $\rho \rightarrow 0$ represents the Cobb-Douglas production function. We focus on the empirically relevant case in which labor and capital are strictly complements ($\rho < 0$). Multiple studies estimate values for the elasticity of substitution between capital and labor γ to be .7 or lower, which implies values for ρ lower than -0.4. See Klump et al. (2012) and references therein to find studies that support the strict complementarity between labor and capital in a number of countries around the world. See Oberfield and Raval (2014) for a recent study about the US manufacturing sector that finds an average elasticity of .5. As demonstrated in that paper (and following the

insight of Houthakker (1955)), the micro-level elasticity of substitution (which is relevant for our mechanism) may differ substantially from the macro-level elasticity of substitution. To focus on the implications of the labor share for firm risk, we abstract away from investment and depreciation so that capital K is fixed.

It is convenient to further decompose the firm's TFP X into two components: aggregate TFP (X^A) and the idiosyncratic component of TFP (X^I), such that $X = X^A X^I$. Aggregate TFP X^A follows the diffusion process

$$\frac{dX_t^A}{X_t^A} = \mu_X dt + \sigma_X \rho_X dZ_t^A, \quad (20)$$

while the idiosyncratic component of TFP X^I follows the diffusion process

$$\frac{dX_t^I}{X_t^I} = \sigma_X \sqrt{1 - \rho_X^2} dZ_t^X, \quad (21)$$

where dZ^X is orthogonal to both dZ^A and dZ^W (i.e., $E[dZ^X dZ^A] = 0$ and $E[dZ^X dZ^W] = 0$).

In addition to idiosyncratic TFP shocks, each firm faces a risk of death, in which the productivity and value of the firm both fall to zero. The main purpose of this additional source of idiosyncratic shocks is to stabilize the distribution of firms when the model is simulated. Firm death is modeled as a Poisson event with mean arrival rate λ .

Profit maximization drives the firm to set its labor demand L^D such that the marginal profitability of labor ($\frac{dY}{dL}$) is equated to the real wage (W). Solving out yields the following Labor demand L^D :

$$L_t^D = (1 - \alpha)^{1/\rho} \left(\left(\frac{W_t}{\alpha X_t} \right)^{\frac{\rho}{1-\rho}} - \alpha \right)^{-\frac{1}{\rho}}. \quad (22)$$

Eq. (22) implies that, consistent with intuition, the firm will demand more labor when its produc-

tivity is high relative to the real wage. In what follows, we always assume that the firm sets labor optimally.

We define labor share S as the ratio of labor costs to value added, $S \equiv \frac{L^D W}{Y}$. Intuitively, labor share is a measure of how value added is split between workers and the firm (capital) owners. Using Ito's Lemma we find the dynamics of S :

$$\frac{dS_t}{S_t} = \mu_S dt + \sigma_{S\Lambda} dZ_t^\Lambda + \sigma_{SW} dZ_t^W + \sigma_{SX} dZ_t^X, \quad (23)$$

where:

$$\mu_S \equiv - \left(\frac{\rho}{\rho-1} \right) (\mu_a - \mu_w - \sigma_a^2) + \left(\frac{\rho}{\rho-1} \right)^2 \left(\frac{\sigma_x^2}{2\rho} - \rho_w \rho_x \sigma_w \sigma_x + \frac{\sigma_w^2}{2\rho} \right), \quad (23a)$$

$$\sigma_{S\Lambda} \equiv - \left(\frac{\rho}{\rho-1} \right) (\rho_x \sigma_x - \rho_w \sigma_w), \quad (23b)$$

$$\sigma_{SW} \equiv \left(\frac{\rho}{\rho-1} \right) \sigma_w \sqrt{1 - \rho_w^2}, \quad \text{and} \quad (23c)$$

$$\sigma_{SX} \equiv - \left(\frac{\rho}{\rho-1} \right) \sigma_x \sqrt{1 - \rho_x^2}. \quad (23d)$$

Eq. (23) implies that labor share is affected differently by shocks to wages and shocks to productivity. In the empirically relevant case in which labor and capital are strictly complements ($\rho < 0$), labor share S is decreasing in idiosyncratic productivity (i.e., $\sigma_{SX} < 0$).¹⁵ Eq. (23) also shows that, despite the fact that labor demand decreases with wages, the labor share S is increasing in wages (i.e., $\sigma_{SW} > 0$) because the price effect dominates the quantity effect. Fig. 1 illustrates the negative relationship between labor share and idiosyncratic productivity and shows the positive relationship between labor share and wages.¹⁶ Finally, the effect of aggregate productivity (i.e., the priced shock λ) on the labor share reflects a combination of the two effects described above. On the one

¹⁵For completeness, it is worth mentioning the two cases that are not considered in this paper. Labor share is constant in the standard Cobb-Douglas production function (i.e., when $\rho \rightarrow 0$) and equals α . When labor and capital are strictly substitutes (i.e., when $\rho > 0$), labor share is decreasing in wages and increasing in productivity.

¹⁶A labor share greater than unity is possible in theory and would simply imply negative operating profits. As we discuss later, shareholders will choose to temporarily suspend operations in such states, so that labor share is effectively bounded by 1 for *active* firms.

hand, higher aggregate productivity leads to a lower labor share; but on the other hand, higher aggregate productivity is associated with a higher real wage (according to ρ_w), which increases the labor share. The overall effect is negative (i.e., $\sigma_{SA} < 0$), provided that real wage response is not too large, which is the empirically relevant case.

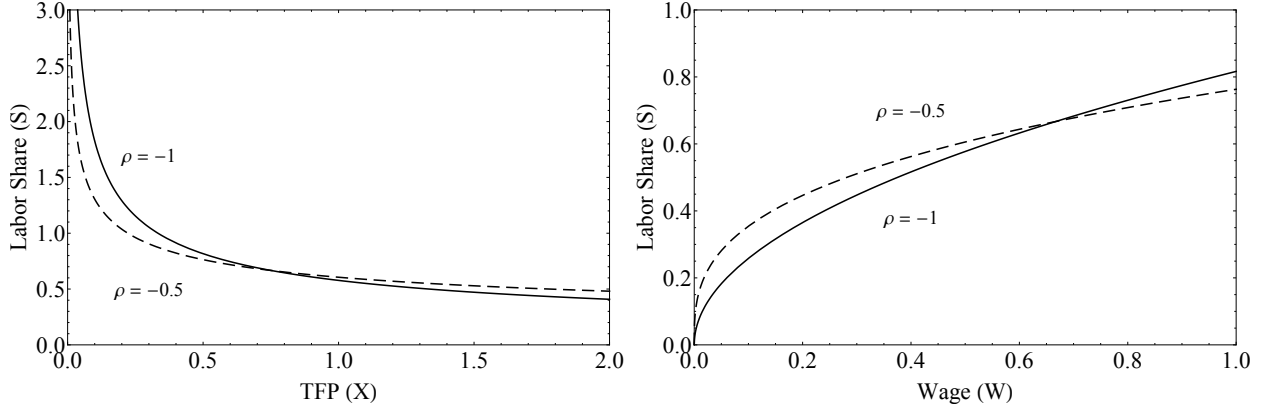


Fig. 1. Determinants of labor share. Labor share as a function of productivity and wages in the production model. The figure shows the numerical solution for the firm’s labor share as a function of productivity and wages. The left panel shows that labor share is decreasing in productivity. The right panel shows that labor share is increasing in economy-wide wages. The chosen values for ρ result in elasticities of substitution of .5 and .7, values in the range of what many empirical studies find for the elasticity of substitution between capital and labor. Parameter values used in numerical solution: $\alpha = 0.67$, $W = 0.5$ (left panel), and $X = 1$ (right panel).

Operating profits are defined as the residual cash flows of the firm after labor expenses are paid, $\Pi \equiv Y - LW$. We assume that firms can frictionlessly suspend and resume production (and thus operating costs) over time.¹⁷ Operating profits under the optimal labor demand can then be expressed as a function of productivity X and labor share S :

$$\Pi_t = \begin{cases} (1 - \alpha)^{\frac{1}{\rho}} X_t K (1 - S_t)^{\frac{\rho-1}{\rho}}, & \text{if } S_t < 1, \\ 0, & \text{if } S_t \geq 1, \end{cases} \quad (24)$$

where the second region reflects the fact that the firm will optimally suspend production before

¹⁷An interesting extensions is to incorporate costs of shutdown which would lead to an option value component.

operating profits become negative, which happens when $S \geq 1$. Fig. 2 shows the negative relation between labor share and operating profits (holding productivity X fixed). For instance, an increase in the real wage leads to an increase in labor share and a decrease in operating profits.¹⁸ On the other hand, higher productivity increases operating profits by increasing total output directly (according to Eq. (24)). The dynamics of profit growth are given by:

$$\frac{d\Pi_t}{\Pi_t} = \mu_\Pi[S_t]dt + \sigma_{\Pi\Lambda}[S_t]dZ_t^\Lambda + \sigma_{\Pi W}[S_t]dZ_t^W + \sigma_{\Pi X}[S_t]dZ_t^X, \quad (25)$$

where:

$$\mu_\Pi[S_t] \equiv \left(\frac{1}{1-S_t} \right) \left(\mu_X - S_t\mu_W + \left(\frac{\rho}{1-\rho} \right) \left(\frac{S_t}{1-S_t} \right) \left(\frac{\sigma_X^2}{2} - \rho_W\rho_X\sigma_W\sigma_X + \frac{\sigma_W^2}{2} \right) \right), \quad (25a)$$

$$\sigma_{\Pi\Lambda}[S_t] \equiv \left(\frac{1}{1-S_t} \right) (\rho_X\sigma_X - \rho_W\sigma_W S_t), \quad (25b)$$

$$\sigma_{\Pi W}[S_t] \equiv - \left(\frac{S_t}{1-S_t} \right) \left(\sqrt{1-\rho_W^2}\sigma_W \right), \quad \text{and} \quad (25c)$$

$$\sigma_{\Pi X}[S_t] \equiv \left(\frac{1}{1-S_t} \right) \left(\sqrt{1-\rho_X^2}\sigma_X \right). \quad (25d)$$

Eq. (25) shows that, since the capital stock is fixed, the dynamics of operating profits follow only from systematic and idiosyncratic TFP shocks and from shocks to the real wage. It also shows that the sensitivity of profit growth to the three shocks (dZ^Λ , dZ^W , and dZ^X) are increasing in *magnitude* in labor share S . This gives rises to the connection between labor share and labor-induced operating leverage, to which we now turn.

¹⁸The firm also reacts to the higher real wage by reducing labor demand, but the effect this has on operating profits is zero (to a first order) according to the Envelope theorem (i.e., labor is set optimally).

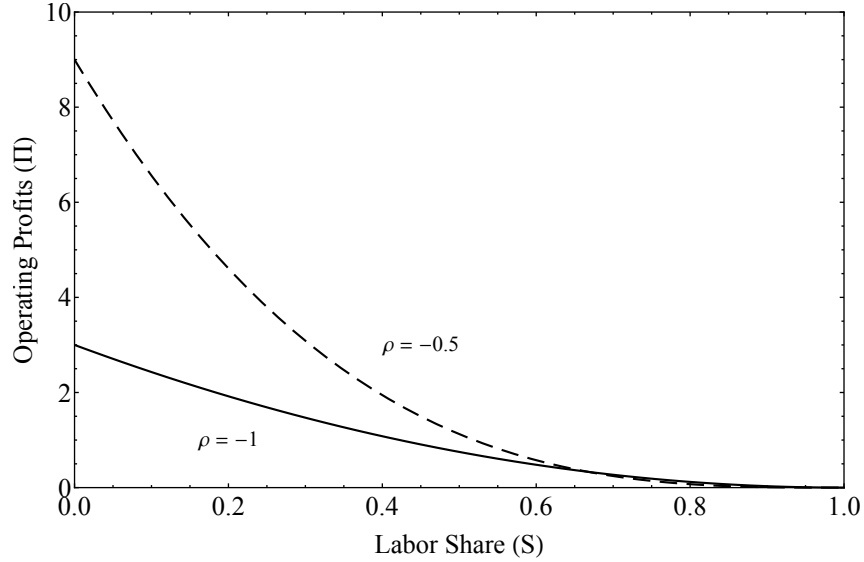


Fig. 2. Operating profits and labor share. Operating profits as a function of labor share in the production model. Parameter values used in numerical solution: $W = 0.5$, $\alpha = 0.67$, $K = 1$, $\sigma_x = 0.2$, $\rho_x = 0.5$, $\sigma_w = 0.05$, and $\rho_w = 0.1$.

3.2. Labor Leverage

Having derived the dynamics of cash flows, we can now formalize the labor leverage mechanism. The *traditional* operating leverage arises from the existence of fixed operating expenses. In contrast, the labor leverage mechanism is not based on the existence of fixed costs - labor is fully adjustable. Instead, the labor leverage mechanism is based on the relative smoothness of wages and the imperfect correlation between wages and productivity.

To see this, note that the response of profits to the aggregate productivity shock (i.e., the priced shock λ) equals $\left(\frac{1}{1-S}\right)(\rho_x\sigma_x - \rho_w\sigma_w S)$ according to Eq. (25), hence in the special case in which wages respond one-for-one to productivity (i.e., $\rho_x\sigma_x = \rho_w\sigma_w$), the response of operating profits to the shock is the same for all firms: profits respond one-to-one to productivity. In contrast, in the case in which wages respond less than one-for-one to productivity shocks (i.e., $\rho_x\sigma_x > \rho_w\sigma_w$), the response of operating profits to the shock is greater than unity for all firms. Smooth wages leverage up cash flow shocks, making operating profits more procyclical. Moreover, this operating leverage effect is larger when the labor share S is larger.

The assumption $\rho_x \sigma_x > \rho_w \sigma_w$ is consistent with standard stylized facts. In aggregate data, corporate profits (or earnings) are highly procyclical and more volatile than total factor productivity (TFP) or GDP. It is well understood that an important reason for this fact is that labor compensation is relatively smooth and weakly correlated with TFP or GDP growth.¹⁹

To quantify the effect of labor share on firm risk amplification, we define two measures of the sensitivity of operating profits to each of its two sources of shocks: productivity and wages. The first is a measure of the sensitivity of cash flow growth to TFP shocks, Θ , which we denote simply as *operating leverage*. Operating leverage, Θ , can be defined generally (see for instance Donangelo (2014)) as the covariance of equilibrium operating profit growth and TFP growth minus one (i.e., $\Theta \equiv \text{Cov} \left[\frac{d\Pi}{\Pi}, \frac{dX}{X} \right] / \text{Var} \left[\frac{dX}{X} \right] - 1$).²⁰ Given the results of the previous section, operating leverage

$$\Theta[S_t] = \frac{S_t}{1 - S_t} \left(1 - \frac{\rho_w \rho_x \sigma_w}{\sigma_x} \right). \quad (26)$$

Eq. (26) shows that the sensitivity of operating profits to TFP shocks is positive and monotonically increasing in labor share S , as long as TFP is more volatile than the component of wage growth correlated with TFP growth.²¹ This result is summarized in the proposition below:

Proposition 5 (Monotonic relationship between operating leverage and labor share)

The condition $\sigma_x > \rho_w \rho_x \sigma_w$ implies that operating leverage is positive and increasing in labor share S :

$$\Theta[S_t] > 0 \text{ and } \frac{d\Theta[S_t]}{dS_t} \geq 0.$$

Proposition 5 follows directly from Eq. (26). The main message of Proposition 5 is that, under

¹⁹For instance, Longstaff and Piazzesi (2004) hypothesize that the reason for the extreme volatility and procyclicality of corporate earnings is that stockholders are residual claimants to corporate cash flows. Thus, the compensation of workers is a senior claim to cash flows. See also Gomme and Greenwood (1995).

²⁰Alternatively, Θ is defined as the slope of a regression of operating profit growth on TFP growth minus one. The subtraction by 1 is a simple rescaling so that Θ is 0 when there is no risk amplification in the transmission of shocks.

²¹We anticipate that the assumption is fairly weak. For instance, we document that aggregate wage growth is less volatile and not highly correlated with aggregate TFP growth.

strict complementarity of labor and capital, labor share can be used as a proxy for the degree of labor leverage experienced by the firm.

We also define a related measure Θ^W as the sensitivity of operating profits to changes in economy-wide wages (i.e., $\Theta^W \equiv \text{Cov} \left[\frac{d\Pi}{\Pi}, \frac{dW}{W} \right] / \text{Var} \left[\frac{dW}{W} \right] - 1$). The measure Θ^W is given by

$$\Theta^W[S_t] = -\frac{1}{1-S_t} \left(1 - \frac{\rho_w \rho_x \sigma_x}{\sigma_w} \right). \quad (27)$$

Eq. (27) shows that the sensitivity of operating profits to wages shocks is negative, and its magnitude is monotonically increasing in labor share S . This result is summarized in the corollary below:

Corollary 1 (Sensitivity of operating profits to wage shocks)

The condition $\sigma_x > \rho_w \rho_x \sigma_w$ implies that the sensitivity of operating profit growth to wage growth is negative and increasing in magnitude in labor share S :

$$\Theta^W[S_t] < 0 \text{ and } \frac{d\Theta^W[S_t]}{dS_t} \leq 0.$$

Corollary 27 follows directly from Eq. (27).

Fig. 3 illustrates the relation of labor share to the exposure of operating profits to the two sources of uncertainty: productivity and wages. The figure shows that the magnitudes of the positive sensitivity of operating profits to productivity and the negative sensitivity of operating profits to wage shocks is increasing in labor share. This effect, which is directly related to labor leverage, is an intuitive result: Higher labor share is related to lower profit margins, which buffer the firm against either type of shocks. Productivity is positively related to operating profits, so that the exposure to productivity shocks is always positive and increasing in labor share. Labor expenses are negatively related to operating profits, so that the exposure to wages shocks is always negative, and its magnitude is increasing in labor share.

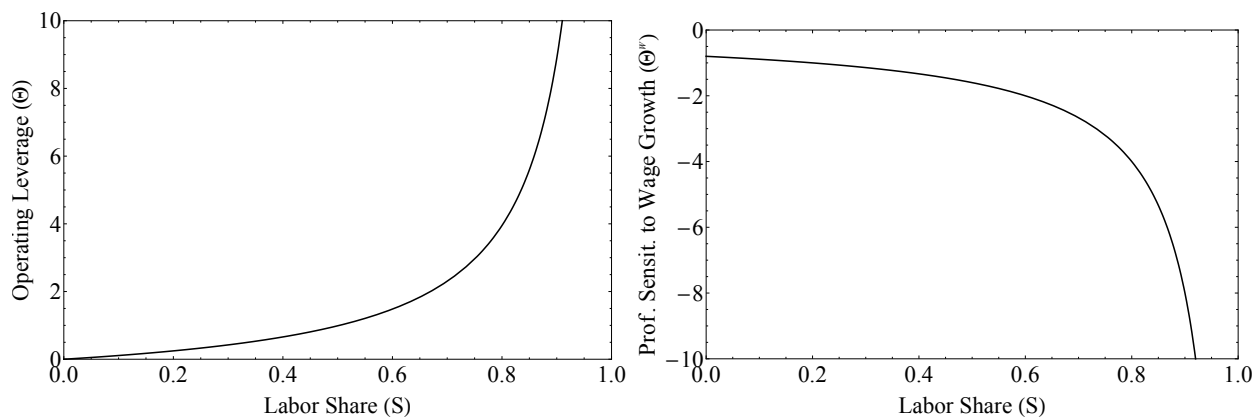


Fig. 3. Labor leverage and labor share. Sensitivity of operating profits to productivity and wage shocks in the production model. The figure shows the relation of labor share to the exposure of operating profits to the two sources of uncertainty: productivity and wages. The figure shows that the magnitudes of the positive sensitivity of operating profits to productivity and the negative sensitivity of operating profits to wage shocks is increasing in labor share. Parameter values used in numerical solution: $W = 0.5$, $\alpha = 0.67$, $K = 1$, $\sigma_x = 0.2$, $\rho_x = 0.5$, $\sigma_w = 0.05$, and $\rho_w = 0.1$.

3.3. Valuation and Expected Returns

In equilibrium, firm value (V) equals the value of the discounted stream of optimized operating profits:

$$V_t = E_t \left[\int_t^\infty \frac{\Lambda_s}{\Lambda_t} \Pi_s ds \right]. \quad (28)$$

Under technical conditions, the solution to Eq. (28) exists, and it is given by

$$V_t = (1 - \alpha)^{1/\rho} X_t K v[S_t], \quad (29)$$

where v is a monotonically decreasing function of labor share, such that $\lim_{S \rightarrow 0} v[S] = 1$ and $\lim_{S \rightarrow \infty} v[S] = 0$. The explicit solution is given in the Appendix.

The solution for the firm value is intuitive. First, when labor costs become negligible relative to the value added generated by the firm ($S \rightarrow 0$), the value of the firm converges to that of a firm with a perpetual dividend governed by a geometric Brownian motion, in which the current dividend

equals $(1 - \alpha)^{1/\rho} AK$. As the cost of labor increases relative to the value added generated by the firm, the dividend falls and, consistently, the value of the firm falls. When labor costs equal the value added ($S \rightarrow 1$), operating profits are zero, so the firm shuts down production and all firm value arises from the option to resume production when operating profits become positive again. As $S \rightarrow \infty$ the probability that the firm will ever operate again goes to zero, and the value of the firm consequently becomes zero.

The negative relation between labor share and firm value is driven by two complementary channels: a cash flow channel and a discount rate channel. The cash flow channel consists in labor intensive firms having lower operating profits due to higher labor expenses per unit produced (i.e., higher marginal profitability of labor). The discount flow channel is related to the higher loading on systematic risk of a labor-intensive firm relative to a capital-intensive one. Fig. 4 illustrates the negative relation between labor share and firm value.

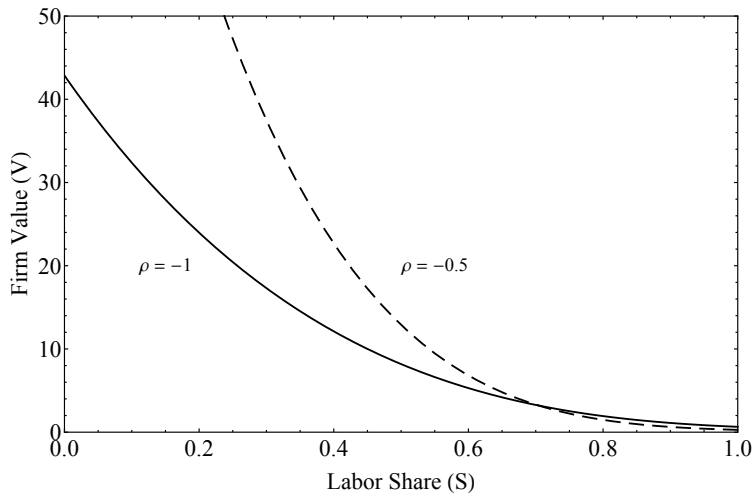


Fig. 4. Firm value and labor share. Firm value as a function of labor share in the production model. Parameter values used in numerical solution: $W = 0.5$, $\alpha = 0.67$, $K = 1$, $\mu_x = 0$, $\sigma_x = 0.2$, $\rho_x = 0.5$, $\mu_w = 0$, $\sigma_w = 0.05$, $\rho_w = 0.1$, $r = 0.02$, $\eta = 0.5$, and $\lambda = 0$.

Expected returns are the instantaneous drift of the gains process that reinvests dividends, $E_t[\mathcal{R}_t] \equiv$

$E_t \left[\frac{dV_t + \Pi_t^* dt}{V_t} \right]$, and are given by:

$$E_t[R_t] = r - \lambda + \eta \sigma_x \rho_x + S_t \frac{v'[S_t]}{v[S_t]} \frac{\rho}{1 - \rho} (\rho_x \sigma_x - \rho_w \sigma_w). \quad (30)$$

We show in the Appendix that $v'(S_t) < 0$ holds for all parameter values where a feasible solution for Eq. (29) exists. Thus, Eq. (30), in conjunction with our assumption that $\rho < 0$, implies that the relationship between risk and labor share depends on the sign of $\rho_x \sigma_x - \rho_w \sigma_w$. This is formalized below:

Proposition 6 (Asset returns and labor share)

For $S_t \in (0, 1)$, $\rho_x \sigma_x > \rho_w \sigma_w$ is a sufficient condition for $\frac{dE_t[R_t]}{dS_t} \geq 0$.

If the condition is satisfied, wages are less procyclical than productivity, and labor intensive-firms have higher exposure to systematic risk (and narrower profit margins).

Eq. (30) shows that the firm's excess returns over the risk-free rate depends on two sources of priced risk. The first source is a premium paid for the riskiness coming from the covariance between the firm's productivity and the stochastic discount factor ($\rho_x \sigma_x$). We call this source of risk *productivity risk*. Productivity risk affects expected returns both directly, through its impact on overall productivity, and indirectly, through its impact on the relative productivity of capital and labor. It is this second, indirect, component that depends on the firm's labor share. The direct impact of productivity risk for an average firm will be positive in good times, as the average firm produces more, or finds that the prices of its products increase. The indirect impact is also positive, since our assumption about complementarity between labor and capital implies that a positive shock to the firm's productivity will amplify the impact on profits.

The second source of risk captures the firm's exposure to aggregate wages ($\rho_w \sigma_w$). We call this component the *wage hedge*, as it depends only on the firm's exposure to wages and will likely *reduce* risk for the average firm. The wage hedge is linked to labor share, since variations in wages

will have a larger effect on firms with large labor costs. This component is a hedge because, on average, wages fall in bad times, which is precisely when a firm's profits are also falling due to systematic decreases in its own productivity.

Combining the two sources of risk—one positive, the other a hedge—delivers the relation between the firm's labor share and expected returns. This relation will be positive if the firm's systematic component of productivity is procyclical enough relative to wages. For instance, the systematic risk loadings of a firm whose productivity is uncorrelated with the stochastic discount factor ($\rho_x = 0$) is decreasing in its labor share. This is because, in this case, the hedge effect of wages is uncontested: Wages go up in good times, so profits fall; wages go down in bad times, so the firm's profits increase.

The hedging impact of wages, though, is muted when the firm's productivity is sufficiently procyclical ($\rho_x \sigma_x > \rho_w \sigma_w$). In this case, even though wages are a hedge, the procyclical variation in the firm's sales price dominates, making the firm riskier as its labor share increases.

Fig. 5 shows that asset betas are increasing in labor shares. The figure also shows that the positive relation between betas and labor share implies a positive relation between betas and wages and implies a negative relation between betas and productivity. The last panel shows that betas are insensitive to productivity once we control for labor share.

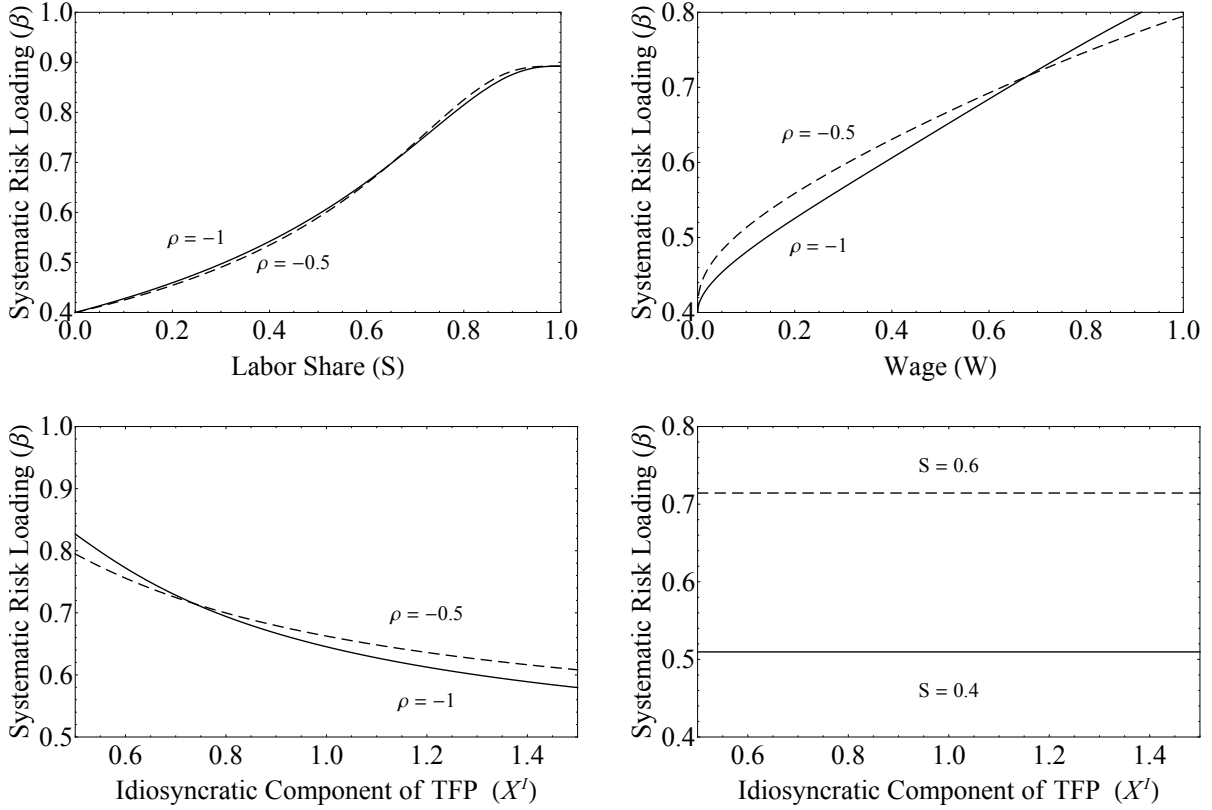


Fig. 5. Betas, productivity, wages and labor share. Betas as a function of labor share, productivity, and wages in the production model. Parameter values used in numerical solution: $X^I = 1$, $X^A = 1$, $W = 0.5$, $\alpha = 0.67$, $K = 1$, $\mu_X = 0$, $\sigma_X = 0.2$, $\rho_X = 0.5$, $\mu_W = 0$, $\sigma_W = 0.05$, $\rho_W = 0.1$, $r = 0.02$, $\eta = 0.5$, and $\lambda = 0$.

3.4. Quantitative Analysis of the Model

Our model represents a proof-of-concept for the theory developed in the Section 1. In this section, we take a step further and investigate the quantitative properties of the model via a calibration exercise. By simultaneously simulating the dynamics of many different firms—their labor share, cash flow, valuations, and expected returns endogenously varying over time—we impose discipline on our parameter choice so that relevant moments for the distribution of firms’ characteristics match the data. We can then further analyze the model’s implications for the cross-section of stock returns, as well as validate some of our additional results from the empirical section. We find that, despite its qualitative nature, our model is able to generate results that are consistent with

many of our empirical findings.

3.4.1. Calibration procedure

The calibration exercise is as follows. We use a given set of parameters to generate time-series paths for 10,000 firms over 1,200 months. Firms are identical at the beginning of each simulation. We record firm characteristics and valuations on the penultimate month, and we record returns and volatilities using changes that occurred between the penultimate month and last month in the simulation. Next, we calculate relevant moments for the distribution of firm characteristics and returns, and perform cross-sectional regressions similar to those conducted in Section 2. We repeat this process 10,000 times and then average the resulting moments and coefficients from the regressions. Finally, we compare the moments used for the calibration with the moments found in the data using a loss function and then use a Simulated Annealing algorithm to find parameters that minimize the value of the loss function.²²

One challenge in the calibration of the model is that the distribution of firm valuations and characteristics is not constant. We deal with this issue in two ways. First, we include a Poisson process for death of firms to the model solution. When a firm dies, it exits the market and it is replaced by a new firm with the same original characteristics that all firms had a time zero. Once we add this feature to the model, long-term distributions will be stationary. Second, the simulated time period is purportedly long to ensure that the distribution of firms becomes stable.

Table 9 shows the target moments used in the calibration. We target macroeconomic moments, firm-level cash flows moments, and firm-level average unlevered stock returns.²³ We choose the

²²The loss function is defined as the weighted average of the squared differences between targets model-generated moments. We only use the last year of simulated data in the analysis to ensure we are measuring the heterogeneity that arises only from differences in the idiosyncratic shock paths. The number of firms chosen for the simulation is set so it is at the same order of magnitude of the average number of publicly traded firms in the United States in the last century. The number of simulations is chosen so that the moments obtained from the simulation are stable enough for the optimal-parameter-seeking algorithm to deliver stable results.

²³Unlevered returns are constructed as $ret_t^m = ret_t \times (1 - leverage_{t-1})$.

macroeconomic moments to ensure that the aggregate behavior of our simulated firms corresponds to well-known aggregate moments of the US economy. In particular, we target the volatilities of GDP, aggregate TFP, and aggregate wage growth. Since covariances are key components of asset prices, we also target the correlations between GDP growth and aggregate TFP growth, the correlation between GDP growth and aggregate wage growth, and the correlation between aggregate TFP growth and aggregate wage growth.

The firm-specific moments we target are those that link labor shares with expected returns through leverage, namely the sensitivity of cash flows to GDP and TFP growth, as well as the change in the sensitivity of cash flows to GDP and TFP growth as a function of labor share.

The asset-pricing moments we target are those that link differences in expected asset returns to labor share. Given that, in the empirical section, we report returns for quintiles of stocks ranked by labor share, we target the average return for the low-labor-share quintile portfolio, the high-labor-share quintile portfolio, as well as the difference in returns between these two portfolios.

Table 9 reports the weights attached to each of the moments targeted in the calibration. We give the highest weight to the aggregate volatility of our simulated firms—with half as much weight on their correlations. We assign a high weight to the cross-sectional standard deviation of value-added growth, given the relatively low number of other firm-level moments. We set a relatively low weight to the slope coefficients from the regressions, since these are subject to significantly more serious estimation problems. Finally, we give a relatively high weight to the return of the low-labor-share quintile portfolio to obtain realistic stock returns, and we give a lower weight to the spread in portfolio returns between high and low labor share firms, given that this difference also suffers from potential estimation problems.

<< *Table 9 here* >>

3.4.2. Calibration results

Table 10 shows the resulting parameters that are required to match the moments discussed above. Consider first the implications for the representative technology in the economy; in particular the elasticity of substitution between capital and labor, given the wide attention it has received in the literature. The parameter value used, .40, is squarely in the range of values obtained by different estimations documented in the literature and discussed in the introduction.

The calibration delivers the expected results for the observed shocks and drift for wage growth and productivity growth in the U.S., but it yields interesting results related to unobservable variables: in particular, the priced portion of wage and productivity shocks. The implied priced portion of wage shocks with the stochastic discount factor is .519, a value that, combined with a wage volatility of .017 and a price of risk of .84, implies a risk-premium for a claim to aggregate wages of a bit less than 1%. This result is consistent with the common assumption about human capital being a *low-risk* asset, and similar to what others have estimated (for example, see Lustig, Van Nieuwerburgh, and Verdelhan (2013), and Palacios (2014)). The implied priced portion of productivity shocks, .377, suggests that the largest component of the productivity shocks received by firms is purely idiosyncratic.

Finally, the calibration implies a risk-free rate of 1% and a Sharpe ratio of .84. These values, particularly the risk-free rate, fall within the range of their widely-used estimates. Note that the only asset pricing moments we used were the average returns of the low- and high-labor-share portfolios. So we consider it a success that the calibration aligns with empirical observations for the risk-free rate and the market price of risk.

<< *Table 10 here* >>

Beyond point estimates for certain parameters, the calibration can be used to investigate the model's capacity to replicate other relevant data. Table 11 contrasts a large number of moments

derived from the calibration with those found in the data. Those explicitly targeted in the calibration are presented in bold, while the remaining ones are not targeted.

Table 11, Panel A, contrasts moments for macroeconomic variables in the data and in the model. We highlight the result for the comovement—captured as a slope coefficient—of wage and GDP growth. The model delivers a coefficient of .150, which implies that wages are relatively smooth in the model, just as they are in the data (coefficient of .142). This is relevant because wage smoothness is one of the conditions we identify in Section I as being conducive to labor leverage.

Panels B and C contain moments related to the cross-section of firm cash flows. Since we target the cross-sectional standard deviation of firm-level value-added growth, it is not surprising that the resulting moment in the model is close to that one in the data. We do not explicitly target the average and the standard deviation of labor share, which is a moment our model must match in order to be credible. Fortunately, Panel C shows that our model does match this. Panel D contrasts the sensitivities relevant to the labor leverage mechanism generated by the model with those from the data.

Finally, Panel E links asset prices related to labor leverage found in the data with those found in the model. The model and the data imply asset returns of 2.83% and 2.88% for the low labor share portfolio and asset returns of 6.24% and 5.88% for the high labor share portfolio, respectively. Panel E closes our exercise by closely replicating the returns of portfolios sorted by labor share.

Taken as a whole, the results summarized in Table 11 imply that our simple, partial equilibrium model for firm dynamics, relating labor share and asset returns via a labor leverage mechanism, succeeds in explaining the patterns for returns observed in the data.

<< *Table 11 here* >>

4. Conclusion

This paper argues that the labor share is an important firm characteristic that generates cross-sectional variation in expected returns. We develop a simple model to study the labor leverage mechanism. The model provides theoretical motivation for the use of labor share as a firm-level measure of the degree of labor leverage. The model shows that two sufficient conditions for the use of labor share as a proxy for labor leverage are: (a) Labor and capital are strict complements, and (b) economy-wide wages are smoother than aggregate productivity. These two sufficient conditions are generally supported in the data. Moreover, this paper provides model-agnostic empirical evidence that validates labor share as a measure of labor leverage: the sensitivity of operating profits to shocks is cross-sectionally increasing in labor share. We finally confirm a positive relation between labor leverage and expected asset returns. For instance, average realized stock returns and average loadings on traditional systematic risk factors are increasing in labor share.

There are many important avenues for future work. International evidence that relates the strength of labor leverage to the properties of productivity and wages in each country could be assembled. Time variation in the importance of labor leverage in the United States could also be studied. A more general model that encompasses key labor market frictions could be developed to add to our frictionless model. Finally, the implications for asset prices when workers are partially insured are also an important potential extension.

A. Data Sources

A.1. Compustat and CRSP Data

A.1.1. Sample Construction

Accounting and financial data comes from the CRSP–Compustat merged dataset. We include firms with common shares (`shrcd= 10 and 11`) and stocks traded on NYSE, AMEX, and NASDAQ (`exchcd=1, 2, and 3`). The sample is from January 1973 to June 2016 so that it is represented throughout by firms from all three exchanges.²⁴ As standard, we omit firms whose primary standard industry classification (SIC) is between 4900 and 4999 (regulated firms) or between 6000 and 6999 (financial firms).

Size is defined as the market value of equity (Compustat variables `prc times shrout`). The book-to-market ratio is defined as book value of equity over size. Book value is defined as shareholders' equity (Compustat `SEQ`) divided by the market value of equity. Firm-year observations with missing monthly returns in the current or previous year or with missing or negative lagged or twice-lagged measures of labor share, size, book-to-market, investment-to-assets, or return on equity are excluded from the the sample associated to the measure of labor share. Firm-year observations in which the measure of labor share is negative or greater than one are also excluded. Variables are Winsorized at the 0.5% level in each sample year to reduce the potential influence of outliers.

A.1.2. More details about the construction of the *LS* and *ELS* measures

The *LS* and *ELS* are measures of labor share based on publicly-available Compustat data. The definitions of both measures are consistent with the theoretical definition of labor share presented in Section 1. The measures are based on the ratio of a proxy for labor costs and a proxy for value

²⁴NASDAQ was founded in 1971 but enters the CRSP sample in December of 1972.

added, all at firm level.

The proxy for labor costs used in the *LS* measure is the *XLR* variable from Compustat. The proxy for labor costs used in the *ELS* measure is imputed and defined as the product of $(EMP_{t-1} + EMP_t)/2$ and the average of the ratio of *XLR* to *EMP* in the industry as defined by the 17-industry classification from Kenneth French's data library.

The proxies for value added in the *LS* and *ELS* measures attempt to emulate the theoretical definition of value added used in Section 1. With ideal data and in a neoclassical frictionless setting, we would construct an empirical measure of value added simply as sales minus the cost of materials. The first challenge is that the Compustat dataset does not disentangle the costs of materials from other operating costs. We address this challenge by using a proxy for the cost of materials as operating costs minus the proxy for labor costs. Note that sales minus the proxy for the cost of materials equals operating profits plus the proxy for labor costs. The second challenge is that value added is created at the time of production and not at the time of sale of a good. To address this second challenge, we add to sales the growth in the inventory of final goods. This last adjustment takes into account the fact that some of goods sold in a given year were not produced on that year and were instead in inventory and also that some goods that were produced on a given year were not sold on that year and were incorporated to the inventory instead.

A.2. *Census Data*

We use confidential establishment-level data from the Annual Survey of Manufactures (ASM) collected by the U.S. Census Bureau and supplant them with the *KLEMS Multifactor Productivity Tables by Industry for Manufacturing Industries* provided by the Bureau of Labor Statistics (BLS).

The U.S. Census Bureau collects annual data on manufacturing establishments in the ASM since 1972. The 50 to 60 thousand establishments comprise large establishments sampled with certainty every year (about half of the overall sample) and small establishments sampled with a

lower probability but for five consecutive years. The sampling design of the ASM is aimed at a data set that accurately reflects manufacturing employment and output while maintaining a representative age distribution: exiting establishments are replaced with a set of new and incumbent establishments so that the age distribution reflects that in the business register. We follow conventional practice and drop all observations which are imputed from administrative records ($AR=1$) or which are not part of the *tabbed sample* (i.e., observations with such a low quality and relevance that Census ignores them when publishing official tabulations). These establishments are also small enough to be considered unimportant for economic aggregates.

Following common practice among researchers working with the ASM, we correct industry codes as proposed in Davis, Haltiwanger, and Schuh (1998), transform the 1972-based SIC codes into 1987-based codes and all pre-1997 SIC codes into 6-digit NAICS codes to obtain a consistent industry classification for each establishment. This will be necessary to merge industry-level data by the BLS (see below).

The labor share is generally defined as the ratio of labor expenses and value added. The following section describes how we measure both of these.

A.2.1. Measuring labor costs

We define the following items as labor costs: salaries and wages (item *SW*), involuntary labor costs (item *ILC*) such as unemployment insurance or social security contributions netted out from wages, and voluntary labor costs (item *VLC*) such as health, retirement and other benefits paid to employees. Labor input comprises both full-time employees and temporary workers, a distinction visible in Census data since 2002. Before that year, instructions to establishments how to report the workforce and labor cost are ambiguous, but studying the development of employment and labor expenses before and after 2002 suggests most establishments included all worker compensation (both permanent and temporary) in their reported statistics.

Our labor expenses measure lacks any non-monetary compensation or ownership rights which have monetary value to an employee. Stock options, for example, are counted as labor income for tax purposes once a manager exercises the option but not at the point in time when the manager acquires the option. This downward bias of our labor share measure is likely uncorrelated with two-years ahead stock returns and thus won't impact our results below.

A.2.2. *Measuring value added*

Value added in the Census data is measured as sales less inventory investment for final and work-in-progress goods, resales, material inputs and energy expenditures.²⁵ Unlike in industry-level BLS data, purchased services, another intermediate input, are not reported in the Census data. To account for that, we reduce the value of an establishment's production by the industry-year-specific share of purchased services in sales computed from the 3-digit NAICS industry-level BLS data.

A.2.3. *Constructing firm labor shares*

Merging the ASM data to the Compustat panel requires aggregating establishments to the firm level. Our definition of a firm is based on the employer identification number (*EIN*) which we obtain from the Standard Statistical Establishment List (SSEL). In a given year, we sum labor expenses and value added of all establishments with the same *EIN* and take the ratio of these two variables to obtain the firm labor share:

$$CLS = \frac{\text{labor expenses}}{\text{value added}}. \tag{A.1}$$

Since the ASM is not a comprehensive panel of all establishments, we do not observe all labor

²⁵We subtract resales so that an establishment's value added is defined by its production activities (as opposed to its trading activities).

costs and the full value added of a firm. Only if establishments not sampled in the ASM have (1) a considerably different labor share than the establishments in the ASM *and* (2) are large enough to change the firm-level labor share, would our labor share measure be distorted. Fundamentally, the second point is already mute because, by construction, all large, economically significant establishments are covered in the ASM. So even significantly different labor shares of the not sampled establishments would not make a difference. Lastly, mismeasured labor shares at the firm level would not impact our analysis unless this measurement error was correlated with objects in our analysis such as stock market returns or operating profits. Following common practice, we truncate firms with a negative labor share and those in the top decile of labor shares. Negative labor shares usually arise when gross profits are negative, i.e. when value added does not suffice to pay for labor expenses let alone capital costs. Unreasonably large labor shares arise if a firm's value added is close to zero. While such firms carry essentially no relevance for aggregate outcomes because their weight in aggregate value added is negligible, their huge labor shares could bias firm-level analysis based on linear regressions and averages by bins. Like other researchers we smooth any hiccups in 1997 (transition to 1997 NAICS industry classification) and 2002 (switch in permanent establishment identifier) by replacing their values for the labor share with the average of the labor shares in that and the preceding year. Our resulting panel of Census firms has labor shares in the unit interval like in the Compustat panel, and the distribution of *CLS* closely resembles that of *LS*. Abiding with Census disclosure rules compels us to limit attention to observations with non-missing values in any variable needed for analysis in any of the statistical tables and regressions.²⁶ This means we are left with a panel of about 572,700 year-firm observations from 1972-2009 where we observe the levels and growth rates of the labor share, non-labor operating costs, total operating costs and profits. That sample underlies the analysis using *CLS* as the labor share measure in Tables 3 (Panel B), 4 and 5 (Panel B, right half).

²⁶Part of Census disclosure requirements mean that only rounded number of observations are disclosed.

When aggregating our firm-level labor shares to the manufacturing sector, it is very close in level and dynamic properties to the manufacturing labor share calculated from sectoral data in the BLS and BEA.

A.2.4. Matching Census and Compustat data

The key analysis is to relate the Census labor share to the Compustat stock market returns. Of the roughly 100 thousand year-firm observations in the Compustat panel, we can match about 14 thousand observations to firms in our panel of Census firms using the *EIN*. Using that variable gives us a higher match rate than using the Compustat bridge which extends only until 2005. The unmatched observations consist of years outside the ASM sample (before 1973/after 2009), non-manufacturing firms, firms with foreign ownership but no physical manufacturing operation in the U.S. and missing information on the matching variables. This matched panel underlies Tables 5 (Panel B, left half), 6, 7 and 8. Regressing the growth rate of operating income before depreciation growth on labor shares creates missing values, so that the sample underlying Table 6 (using *CLS* in Panel A) only comprises about 10 thousand observations. By Census disclosure requirement this was also the sample underlying the summary statistics in Panel C of Table 1 and Panel B (left half) of Table 5.

In the matched Compustat-Census sample, we have several measures for the labor share. *LS* is directly measured in the Compustat data but only available for few observations, *CLS* is directly measured in the Census data and available for nearly all observations. *ELS*, in contrast, was imputed for those observations in the Compustat sample where we could not compute *LS*. The two natural questions are (a) how well the two direct measures of the labor share line up and (b) how valid the imputation procedure is to obtain *ELS*. This is especially important to know for researchers that want to work with the labor share in Compustat but do not have access to the Census data.

Table A–1: Correlation between labor share measures

	<i>CLS</i>	No. obs.
<i>LS</i>	0.561 (0.020)	1,700
<i>ELS</i>	0.552 (0.007)	14,100

Table A–1 displays the pooled correlation coefficients between the labor share measures. To convey a sense of economic importance, we weigh observations with their value added in a given year. The results show that both the directly measured *LS* and the imputed *ELS* are positively and significantly related to the labor share measured in the Census data. Given that the high quality of employment and labor compensation in the Census data, we hence conclude that analyzing labor shares in Compustat data using our imputation methods is a good approximation of the true labor share.

A.3. *Macroeconomic Data*

The GDP growth series is taken from Table 1.1.3 of the National Income and Product Accounts of the Bureau of Economic Analysis (www.bea.gov). The real wage series and total factor productivity growth series are annualized, based on the quarterly seasonally adjusted series from the Bureau of Labor Statistics Major Sector Productivity and Costs program (www.bls.gov/lpc). The series cover the non-farm business sector. Following Arias, Hansen, and Ohanian (2007), we compute TFP growth as $\Delta \text{Log}[TFP] = \Delta \text{Log}[Y] - \frac{2}{3} \Delta \text{Log}[H]$, where $\Delta \text{Log}[Y]$ is the real output series and $\text{Log}[H]$ is the hours of all persons series. The real wage series is real hourly compensation. This measure is based on the BEA estimates for labor compensation, and it includes benefits. As a result, our measures of real wages and productivity are comparable in sectoral coverage and in construction.

A.4. *Portfolio Sorts Details*

For each of our labor share measures, we use two different sets of yearly breakpoints that define labor share portfolios. The first set of breakpoints, which defines equally-weighted portfolios, is denoted *all-but-micro breakpoints*. These breakpoints are defined as the 20th, 40th, 60th, and 80th labor share measure percentiles of the stocks with non-missing values for the labor share measure that have market values above the 20th size percentile among all NYSE-listed stocks. The second set of breakpoints, which defines value-weighted portfolios, is denoted *NYSE breakpoints*. These breakpoints are defined as the 20th, 40th, 60th, and 80th labor share measure percentile among NYSE-listed stocks and with non-missing labor share measure observations. The labor share and market size values used in the construction of the breakpoints for year t are measured at the end of calendar year $t-1$ (CRSP/Compustat samples) or year $t-2$ (merged CRSP/Census sample). Due to the sampling design of the Census data, *CLS* is lagged by two years to avoid the use of information not available to market participants on a given date. After constructing the breakpoints, portfolios are formed with the following procedures. For portfolios based on the merged CRSP/Compustat sample, we use the timing convention from Fama and French (1993). We use the breakpoints at year t to classify stocks in our sample based on the labor share measured at the end calendar year $t-1$ (i.e., the timing of the *LS* and *ELS* measures is the same as the one used to construct the breakpoints). We then hold each portfolio from July of year t until the end of June of year $t+1$. For portfolios based on the merged CRSP/Census sample, we use the breakpoints at year t to classify stocks in our sample based on the labor share measured at the end calendar year $t-2$ (i.e., the timing of the *CLS* measure is the same as the one used to construct the breakpoints). We then hold each portfolio from the end of December of year t until the end of December of year $t+1$.²⁷

²⁷The results of the portfolio sorts are qualitatively unchanged when we use the *CLS* measure at the end of year $t-1$ (i.e., when we follow the same procedure used in the portfolio sort tests based on CRSP/Compustat data).

A.5. Beta Construction Details

Conditional betas are estimated with monthly returns for the tradable factors MKT , ME , IA , and ROE over rolling one-year windows. Conditional betas are estimated with quarterly returns rates for the macroeconomic growth series of TFP and GDP over rolling five-year windows. We correct conditional betas for nonsynchronous price movements using the methodology proposed by Dimson (1979) and discussed by Lewellen and Nagel (2006): We include one-period lagged factors in the regressions and define betas as the sum of the slopes on the contemporaneous and lagged factor return or growth.

B. Theoretical Motivation Details

B.1. Derivation of Propositions 1 to 4 and Corollary 1

Capital is fixed, so the firm maximizes its profits solely by optimizing labor as given by

$$\Pi[X, W] = \max_L \{XF[K, L] - WL\}. \quad (\text{B.2})$$

After applying the envelope theorem to Equation (B.2), we obtain

$$\frac{\partial \text{Log} [\Pi]}{\partial \text{Log} [X]} = \frac{1}{1 - S}, \quad (\text{B.3a})$$

$$\frac{\partial \text{Log} [\Pi]}{\partial \text{Log} [W]} = -\frac{S}{1 - S}, \quad (\text{B.3b})$$

where $S \equiv wL/y$ is the labor share. The overall effect of a change in productivity (i.e., taking into account the effect on the wage) is given by

$$\frac{d \text{Log} [\Pi]}{d \text{Log} [X]} = \frac{\partial \text{Log} [\Pi]}{\partial \text{Log} [X]} + \frac{\partial \text{Log} [\Pi]}{\partial \text{Log} [W]} \frac{\partial \text{Log} [W]}{\partial \text{Log} [X]} = \frac{1 - S\theta}{1 - S}, \quad (\text{B.4})$$

where $\theta \equiv \partial \text{Log}[W] / \partial \text{Log}[X]$ is the elasticity of the wage to productivity.

Optimal labor $L[X, W]$ is defined implicitly by the first-order condition:

$$XF_L[K, L[X, W]] - W = 0. \quad (\text{B.5})$$

Differentiating Equation (B.5) leads to

$$\frac{\partial \text{Log}[L]}{\partial \text{Log}[X]} = \frac{\gamma}{1 - S}, \quad (\text{B.6a})$$

$$\frac{\partial \text{Log}[L]}{\partial \text{Log}[W]} = -\frac{\gamma}{1 - S}, \quad (\text{B.6b})$$

where $\gamma \equiv \frac{F_K[K, L]F_K[K, L]}{F[K, L]F_{KL}[K, L]}$ is the elasticity of substitution between capital and labor. Equations (B.6a) and (B.6b) follow from the constant return to scale property of the function F .

The overall effect of a productivity shock on labor demand is hence

$$\frac{d \text{Log}[L]}{d \text{Log}[X]} = \gamma \frac{1 - \theta}{1 - S}. \quad (\text{B.7})$$

The effects on output, which are obtained by differentiation of $Y = XF[K, L]$, are given by

$$\frac{\partial \text{Log}[Y]}{\partial \text{Log}[X]} = 1 + \frac{\gamma S}{1 - S}, \quad (\text{B.8a})$$

$$\frac{\partial \text{Log}[Y]}{\partial \text{Log}[W]} = -\frac{\gamma S}{1 - S}, \quad (\text{B.8b})$$

so that the overall effect is given by

$$\frac{d \text{Log}[Y]}{d \text{Log}[X]} = 1 + \frac{\gamma S(1 - \theta)}{1 - S}. \quad (\text{B.9})$$

Combining Equations (B.4) and (B.9) yields the expression in Proposition 1:

$$\ell \equiv \frac{\frac{d\text{Log}[\Pi]}{d\text{Log}[X]}}{\frac{d\text{Log}[Y]}{d\text{Log}[X]}} - 1 = \frac{(1-\gamma)S(1-\theta)}{1-S} \cdot \frac{1}{1 + \frac{\gamma S(1-\theta)}{1-S}}. \quad (\text{B.10})$$

Proposition 2 and Corollary 1 follow directly from Equation (B.10).

After differentiating labor share S , we obtain

$$\frac{\partial \text{Log}[S]}{\partial \text{Log}[X]} = \frac{\partial \text{Log}[L]}{\partial \text{Log}[X]} - \frac{\partial \text{Log}[Y]}{\partial \text{Log}[X]} = \gamma - 1, \quad \text{and} \quad (\text{B.11a})$$

$$\frac{\partial \text{Log}[S]}{\partial \text{Log}[W]} = 1 + \frac{\partial \text{Log}[L]}{\partial \text{Log}[W]} - \frac{\partial \text{Log}[Y]}{\partial \text{Log}[W]} = 1 - \gamma. \quad (\text{B.11b})$$

Equations (B.11a) and (B.11b) show that labor share S is increasing in productivity X (and decreasing in the wage W) if and only if $\gamma < 1$.

To derive Proposition 3, we first introduce the two assumptions discussed in the text: (1) there are two periods, $t = 0$ and $t = 1$, and (2) X_1, W_1 , and M_1 are jointly log-normally distributed. For convenience, we also approximate log profit with its log linearized transformation, as given by

$$\text{Log}[\Pi_1] = \text{Log}[\Pi[X_1, W_1]] \quad (\text{B.12a})$$

$$\begin{aligned} &\simeq \text{Log}[\Pi[X_0, W_0]] + \frac{\partial \text{Log}[\Pi[X_0, W_0]]}{\partial \text{Log}[X]} (\text{Log}[X_1] - \text{Log}[X_0]) \\ &+ \frac{\partial \text{Log}[\Pi[X_0, W_0]]}{\partial \text{Log}[W]} (\text{Log}[W_1] - \text{Log}[W_0]). \end{aligned} \quad (\text{B.12b})$$

The gross asset return is

$$R_1 = \frac{\Pi_1}{P_0}, \quad (\text{B.13})$$

where

$$P_0 \equiv \mathbf{E}_0[M_1 \Pi_1] \quad (\text{B.14})$$

is the price of the firm defined as the expected discounted profit. From Equations (B.13) and (B.14), we have that the expected excess asset return over the risk-free rate is given by

$$\frac{\mathbf{E}_0[R_1]}{r_F} = \frac{\mathbf{E}_0[\Pi_1] \mathbf{E}_0[M_1]}{\mathbf{E}_0[M_1 \Pi_1]}. \quad (\text{B.15})$$

Using the log linear approximation in Equation (B.12b) and the assumption about the joint log-normality of X_1 , W_1 , and M_1 , we obtain

$$\text{Log}[\mathbf{E}_0[\Pi_1]] = \mathbf{E}_0[\text{Log}[\Pi_1]] + \frac{1}{2}V \text{Log}[\Pi_1], \quad (\text{B.16a})$$

$$\text{Log}[\mathbf{E}_0[M_1]] = \mathbf{E}_0[\text{Log}[M_1]] + \frac{1}{2}V \text{Log}[M_1], \quad (\text{B.16b})$$

$$\text{Log}[\mathbf{E}_0[M_1 \Pi_1]] = \mathbf{E}_0[\text{Log}[\Pi_1]] + \mathbf{E}_0[\text{Log}[M_1]] + \frac{1}{2}V \text{Log}[\Pi_1] + \frac{1}{2}V \text{Log}[M_1] + \text{Cov}(\text{Log}[M_1], \text{Log}[\Pi_1]), \quad (\text{B.16c})$$

hence the following standard expression for the excess return on the firm:

$$\text{Log} \left[\frac{\mathbf{E}_0[R_1]}{R_f} \right] \simeq \text{Cov}(\text{Log}[M_1], \text{Log}[\Pi_1]). \quad (\text{B.17})$$

Proposition 3, which follows from Equations (B.3a) and (B.3b) and from the log linear approximation in Equation (B.12b), is given by

$$\begin{aligned} \text{Cov}(\text{Log}[M_1], \text{Log}[\Pi_1]) &\simeq \frac{\partial \text{Log}[\Pi[X_0, W_0]]}{\partial \text{Log}[X]} \text{Cov}(\text{Log}[M_1], \text{Log}[X_1]) \\ &+ \frac{\partial \text{Log}[\Pi[X_0, W_0]]}{\partial \text{Log}[W]} \text{Cov}(\text{Log}[M_1], \text{Log}[W_1]), \end{aligned} \quad (\text{B.18a})$$

$$\simeq \frac{1}{1-S} \beta_x - \frac{S}{1-S} \beta_w, \quad (\text{B.18b})$$

$$\simeq \beta_x + (\beta_x - \beta_w) \frac{S}{1-S}, \quad (\text{B.18c})$$

where $\beta_x \equiv \text{Cov}(\text{Log}[M_1], \text{Log}[X_1])$ and $\beta_w \equiv \text{Cov}(\text{Log}[M_1], \text{Log}[W_1])$. Finally, Proposition 4 follows directly from Proposition 3 and from Assumption 3.

B.2. Extension with fixed costs and traditional operating leverage

In this section we incorporate fixed operating costs in the previous model to illustrate how traditional operating leverage affects our analysis.

Fixed operating costs are given by fK , so that optimized operating profits are now given by

$$\Pi^f = \max_L \{XF[K, L] - LW - fK\}, \quad (\text{B.19})$$

where the superscript f in Π^f denotes operating profits when under fixed operating costs. Note that we can define the share of fixed costs to profits net of labor costs, $S^f \equiv fK/Y(1-S)$, where $S = WL/XF[K, L]$ is the labor share (not including fixed costs), so that

$$\Pi^f = Y(1-S)(1-S^f) \quad (\text{B.20a})$$

$$= \Pi(1-S^f), \quad (\text{B.20b})$$

where Π are operating profits in the otherwise identical case without fixed costs. Overall operating leverage includes components from labor leverage and from *traditional* operating leverage as given by

$$1 + \text{Operating Leverage} = \frac{d\text{Log}[\Pi^f]/d\text{Log}[X]}{d\text{Log}[Y]/d\text{Log}[X]}, \quad (\text{B.21a})$$

$$= \frac{d\text{Log}[\Pi]/d\text{Log}[X] \left(1 + \frac{1}{1-S^f}\right)}{d\text{Log}[Y]/d\text{Log}[X]}, \quad (\text{B.21b})$$

$$= \underbrace{\frac{1 + \frac{S}{1-S}(1-\theta)}{1 + \gamma \frac{S}{1-S}(1-\theta)}}_{\text{Labor Lev.}} \underbrace{\left(1 + \frac{1}{1 - \frac{fK}{\Pi}}\right)}_{\text{Traditional Op. Lev.}}. \quad (\text{B.21c})$$

Expression (B.21c) shows how labor leverage and traditional leverage interact and magnify each other.

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Table 1

Summary Statistics

Panels A, B and C report time series averages of median (for A and B) or average (for C) characteristics of portfolios of firms sorted on labor share (*LS*), the extended measure of labor share (*ELS*), and the Census measure of labor share (*CLS*), respectively. *LS* is ratio of labor expenses over the sum of labor expenses, operating profits, and the change in inventories of final goods. The construction of *ELS* is identical to that of *LS*, except that it uses the product of the number of employees in the firm and the average wage in the industry as proxy for labor expenses. The Census measure of the labor share, *CLS*, is the ratio of labor costs over value added described in detail in the appendix. *Log. L/K* is the logarithm of the ratio of the number of employees over PPE. *B/M* is the shareholders' book value of equity divided by the market value of equity. *Log. Size* is the logarithm of market value of equity. *Log. Asset* is the logarithm of the book value of assets. *Tang.* is tangibility, and is defined as the ratio of plant, property, and equipment (PPE) over assets. *Org. Cap* is organizational capital, constructed as in Eisfeldt and Papanikolaou (2013). *Lev.* is leverage, and is defined as the ratio of the book value of debt minus cash and marketable securities over the book value of assets minus cash and marketable securities. *ROE* and *Inv/Asset* are the measures of profitability (return on equity) and investment-to-assets from Hou et al. (2015). All variables are adjusted for inflation as measured by the Consumer Price Index. The Compustat-based sample covers all industries in Compustat, except Financials, over the period 1973–2016. The matched Compustat–Census sample covers firms in manufacturing industries over the period 1973-2009.

Table 1 (*continued*)

Column	1a	1b	2	3	4	5	6	7	8	9	10	11
Port.	<i>LS</i>	<i>ELS</i>	Log. L/K	B/M	Log. Size	Log. Asset	Tang.	Org. Cap.	Lev.	ROE	Inv/ Asset	Obs/ Year
Panel A: <i>LS</i> -Quintile Portfolios (Compustat Sample)												
<i>full sample</i>												
All	0.60	0.62	2.78	0.80	6.48	7.26	0.32	0.61	0.65	0.12	0.05	384.9
<i>all-but-micro breakpoints</i>												
L	0.30	0.28	1.33	0.77	7.23	8.19	0.42	0.25	0.71	0.14	0.04	61.3
2	0.43	0.42	1.62	0.77	6.95	7.90	0.43	0.45	0.67	0.13	0.05	70.6
3	0.56	0.58	2.66	0.69	6.79	7.32	0.28	0.67	0.59	0.13	0.05	78.3
4	0.67	0.70	3.04	0.80	6.28	6.91	0.30	0.70	0.60	0.11	0.05	80.9
H	0.81	0.85	3.52	0.91	5.64	6.47	0.29	0.69	0.59	0.08	0.05	93.8
<i>NYSE breakpoints</i>												
L	0.30	0.29	1.33	0.77	7.19	8.16	0.43	0.26	0.71	0.14	0.04	65.8
2	0.44	0.43	1.62	0.78	6.92	7.86	0.43	0.45	0.67	0.13	0.05	77.3
3	0.57	0.59	2.62	0.71	6.76	7.30	0.28	0.67	0.60	0.13	0.05	81.2
4	0.68	0.72	3.08	0.78	6.39	6.92	0.30	0.71	0.57	0.11	0.05	76.4
H	0.82	0.86	3.55	0.92	5.58	6.45	0.29	0.70	0.59	0.07	0.05	84.2
Panel B: <i>ELS</i> -Quintile Portfolios (Compustat Sample)												
<i>full sample</i>												
All	0.59	0.70	3.13	0.75	5.72	6.16	0.25	0.97	0.53	0.10	0.05	2338.0
<i>all-but-micro breakpoints</i>												
L	0.34	0.28	0.70	0.69	7.04	7.50	0.48	0.29	0.60	0.13	0.06	320.7
2	0.50	0.49	2.38	0.62	6.54	6.84	0.25	0.66	0.55	0.13	0.05	361.8
3	0.61	0.63	2.95	0.65	6.13	6.39	0.22	0.90	0.51	0.12	0.05	407.7
4	0.70	0.74	3.23	0.73	5.71	6.08	0.24	1.05	0.51	0.11	0.05	476.9
H	0.80	0.88	3.71	0.94	4.75	5.39	0.25	1.33	0.51	0.06	0.04	771.0
<i>NYSE breakpoints</i>												
L	0.34	0.29	0.80	0.69	7.02	7.45	0.47	0.32	0.60	0.13	0.06	344.9
2	0.52	0.51	2.51	0.62	6.48	6.76	0.24	0.71	0.54	0.13	0.05	421.4
3	0.63	0.66	3.02	0.67	6.04	6.31	0.22	0.93	0.51	0.12	0.05	442.8
4	0.72	0.77	3.30	0.76	5.58	6.01	0.24	1.10	0.51	0.10	0.05	473.0
H	0.81	0.89	3.76	0.97	4.64	5.32	0.25	1.37	0.51	0.05	0.04	656.0

Table 1 (continued)

Column	1a	1b	1c	2	3	4	5	6	7	8	9	10	11
Port.	<i>LS</i>	<i>ELS</i>	<i>CLS</i>	Log. L/K	B/M	Log. Size	Log. Asset	Tang.	Org. Cap.	Lev.	ROE	Inv/ Asset	Obs/ Year
Panel C: <i>CLS</i> -Quintile Portfolios (Matched Compustat–Census Sample)													
<i>full sample</i>													
All	0.61	0.67	0.49	2.96	0.73	6.62	6.70	0.30	1.34	0.44	0.12	0.06	268.0
<i>all-but-micro breakpoints</i>													
L	0.53	0.59	0.20	2.77	0.56	7.36	7.10	0.29	1.78	0.43	0.16	0.07	48.8
2	0.60	0.65	0.39	2.90	0.69	6.68	6.67	0.30	1.36	0.43	0.13	0.07	58.7
3	0.61	0.68	0.52	2.98	0.76	6.44	6.55	0.30	1.22	0.44	0.11	0.06	62.2
4	0.63	0.71	0.65	3.04	0.83	6.38	6.63	0.30	1.20	0.46	0.09	0.06	65.1
H	0.67	0.73	0.75	3.12	0.86	6.36	6.67	0.30	1.20	0.47	0.09	0.06	33.2
<i>NYSE breakpoints</i>													
L	0.50	0.51	0.13	2.45	0.35	9.50	8.98	0.31	1.72	0.48	0.22	0.07	25.4
2	0.56	0.52	0.26	2.33	0.37	9.50	9.01	0.33	1.49	0.48	0.21	0.07	33.6
3	0.60	0.57	0.40	2.49	0.51	9.10	8.90	0.31	1.22	0.49	0.19	0.07	62.2
4	0.61	0.62	0.56	2.64	0.60	8.70	8.71	0.31	1.03	0.51	0.18	0.06	86.5
H	0.67	0.67	0.72	2.79	0.65	8.61	8.80	0.30	1.98	0.55	0.07	0.06	60.3

Table 2

Smoothness and Cyclicity of Aggregate Wages and Aggregate Profits

This table reports measures of association of aggregate profit growth, aggregate GDP, TFP, and wage growth. The top panel reports the correlation of these variables. The bottom panel reports the volatility of each variable, the volatility normalized by that of GDP growth, and the slope coefficient of the regression

$$x_t = \beta_0 + \beta_1 \text{gdp}_t^g.$$

gdp^g is annualized growth calculated as the change of the logarithm of real GDP. tfp^g is annualized growth calculated as the change of the logarithm of TFP. wage^g is annualized growth calculated as the change of the logarithm of real wages. profit^g is annualized growth in corporate profits from the National Income and Product Accounts. The sample covers the period 1948–2016.

Variable	gdp^g	tfp^g	wage^g	profit^g
gdp^g	1.000			
tfp^g	0.868	1.000		
wage^g	0.268	0.393	1.000	
profit^g	0.586	0.413	-0.094	1.000
σ	0.031	0.019	0.017	0.104
$\sigma / \sigma^{\text{gdp}}$	1.000	0.622	0.531	3.331
Slope on gdp^{g*}	1.000	0.540	0.142	1.950

Table 3

Smoothness of Labor Costs

This table reports estimates of panel data regressions of changes of costs on changes in sales. Δlc and $lc^g(\%)$ are the \$ and % changes of staff expenses. Δnlc and $nlc^g(\%)$ are the \$ and % changes of the sum of operating expenses (SG&A and COGS) minus staff expenses in Panel A (Compustat data); they are the summed expenses for intermediate and energy inputs in Panel B (Census data). Dependent variables are Winsorized at the [2.5%, 97.5%] levels yearly. Δtc and $tc^g(\%)$ are the \$ and % changes of the sum of operating expenses (SG&A and COGS) in Panel A; they are the expenses for labor compensation, intermediate and energy inputs in Panel B. Standard errors clustered by year are shown in parentheses. Significance levels are denoted by (* = 10% level), (** = 5% level), and (***) = 1% level). The Compustat-based sample covers all industries in Compustat, except Financials, over the period 1973–2016. The Census sample covers manufacturing industries over the period 1973–2009.

	Cost (Dependent Variable)					
	Δlc	Δnlc	Δtc	$lc^g(\%)$	$nlc^g(\%)$	$tc^g(\%)$
Panel A: Compustat Sample						
$\Delta sale$	0.16*** (0.05)	0.39*** (0.14)	0.55*** (0.10)			
$sale^g(\%)$				0.53*** (0.12)	1.08*** (0.23)	0.82*** (0.13)
Firm FE	Y	Y	Y	Y	Y	Y
R-sq. (%)	21.87	19.92	38.84	0.01	6.89	34.95
Obs.	9,365	9,365	9,365	9,365	9,365	9,365
Panel B: Census Sample						
$\Delta sale$	0.03* (0.01)	0.84*** (0.06)	0.86*** (0.04)			
$sale^g(\%)$				0.69*** (0.002)	0.99*** (0.002)	0.89*** (0.001)
Firm FE	Y	Y	Y	Y	Y	Y
R-sq. (%)	14.8	87.4	88.8	48.6	60.2	75.4
Obs.	572,700	572,700	572,700	572,700	572,700	572,700

Table 4

Cyclicality of Labor Share

This table reports estimates and standard errors of panel data regressions of log. growth of measures of labor share (*LS*, *ELS*, and *CLS*) on growth in business cycle indicators. gdp_t^g is the change of the logarithm of real GDP. tfp_t^g is the change of the logarithm of TFP. mkt_t^g is the lagged annualized excess return of the market factor described in Fama and French (1993) and obtained from Kenneth French's website. Dependent variables are Winsorized at the [2.5%,97.5%] levels yearly. Standard errors clustered by year are shown in parentheses. Significance levels are denoted by (* = 10% level), (** = 5% level), and (***) = 1% level). The sample underlying *LS* and *ELS* covers firms in all industries in Compustat, except Financials, over the period 1973–2016. The sample underlying *CLS* covers firms in manufacturing industries in the Census data set over the period 1973-2009.

Column	1	2	3	4	5	6	7	8	9
	Proxy for Labor Share (S)								
Shock	<i>LS</i>			<i>ELS</i>			<i>CLS</i>		
gdp_t^g	-0.56*** (0.18)			-0.53*** (0.12)			-0.52*** (0.02)		
tfp_t^g		-0.44 (0.33)			-0.63*** (0.21)			-0.60*** (0.03)	
MKT_t			-0.07*** (0.02)			-0.08*** (0.03)			-0.07*** (0.02)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sq. (%)	0.83	0.18	0.50	0.46	0.23	0.44	0.30	0.10	0.20
Obs.	14,107	14,107	14,107	87,714	87,714	87,714	572,700	572,700	572,700

Table 5**Labor Share and Sensitivity of Operating Profits to Aggregate Shocks**

This table reports estimates and standard errors of panel data regressions of measures of real operating income before depreciation growth (OP^g) on an aggregate shock (GDP, TFP, or wage growth), lagged labor share, and interaction between lagged labor share and the aggregate shock. gdp^g , tfp^g , and mkt^g are defined in Table 4. LS , ELS , and CLS are standardized so that the cross-sectional standard deviation is one in every year. Standard errors clustered by year are shown in parentheses. Significance levels are denoted by (* = 10% level), (** = 5% level), and (***) = 1% level). The sample underlying LS and ELS covers firms in all industries in Compustat, except Financials, over the period 1973–2016. The Compustat–Census matched sample covers firms in manufacturing industries over the period 1973–2009. The Census sample covers firms in manufacturing industries over the period 1973–2009.

Panel A: LS and ELS						
S	LS			ELS		
	Compustat			Compustat		
Shock Proxy	gdp^g	tfp^g	mkt^g	gdp^g	tfp^g	mkt^g
Shock	2.14*** (0.51)	2.36** (0.93)	0.19** (0.09)	1.96*** (0.39)	1.58** (0.60)	0.20** (0.08)
Shock \times S	0.59** (0.28)	0.87** (0.42)	0.05 (0.05)	0.52*** (0.17)	0.74** (0.36)	0.05* (0.03)
S	0.21*** (0.03)	0.21*** (0.03)	0.21*** (0.03)	0.21*** (0.01)	0.21*** (0.01)	0.22*** (0.01)
Firm FE	Y	Y	Y	Y	Y	Y
R-sq. (%)	8.47	6.70	6.08	5.45	4.43	4.57
Obs.	15,100	15,100	15,100	88,519	88,519	88,519
Panel B: CLS						
S	CLS			CLS		
	Compustat–Census			Census		
Shock Proxy	gdp^g	tfp^g	mkt^g	gdp^g	tfp^g	mkt^g
Shock	2.30*** (0.20)	2.21*** (0.37)	0.24*** (0.03)	2.66*** (0.05)	2.71*** (0.08)	0.35*** (0.01)
Shock \times S	0.53*** (0.17)	0.77*** (0.28)	0.06** (0.03)	0.46*** (0.05)	0.45*** (0.09)	0.06*** (0.01)
S	0.02* (0.01)	0.02* (0.01)	0.03*** (0.01)	0.64*** (0.00)	0.64*** (0.00)	0.65*** (0.00)
Firm FE	Y	Y	Y	Y	Y	Y
R-sq. (%)	2.40	0.90	1.20	23.00	22.50	22.80
Obs.	10,400	10,400	10,400	572,700	572,700	572,700

Table 6

Average Monthly Stock Returns of Firms Sorted on Labor Share

This table reports monthly excess stock returns of equal- and value-weighted portfolios of firms sorted on *LS*, *ELS*, and *CLS*. H-L is the zero net investment portfolio long high labor share (H) stocks and short low labor share (L) stocks. Quintile thresholds in equal-weighted sorts are based on a sample that excludes micro-cap stocks, which are defined as stocks with market values below the bottom NYSE 20% percentile. Quintile thresholds that define value-weighted portfolios are solely based on the sample of stocks listed on NYSE on a given year. Newey-West standard errors estimated with five lags are shown in parentheses. Significance levels are denoted by (* = 10% level), (** = 5% level), and (***) = 1% level). The sample underlying *LS* and *ELS* covers realized monthly stock returns from July 1974 to June 2016 and covers industries in the matched Compustat–CRSP sample dataset, except Financials. The sample underlying *CLS* covers realized monthly stock returns from July 1974 to June 2011 and covers manufacturing industries in the matched Compustat–Census sample.

	Portfolio					
	L	2	3	4	H	H-L
<i>Equally-Weighted Returns</i>						
LS	0.61*** (0.21)	0.74*** (0.17)	0.91*** (0.21)	0.94*** (0.23)	1.15*** (0.26)	0.53*** (0.18)
ELS	0.79*** (0.20)	0.96*** (0.22)	1.05*** (0.24)	1.14*** (0.26)	1.24*** (0.28)	0.45*** (0.15)
CLS	0.71*** (0.12)	0.99*** (0.19)	1.08*** (0.21)	1.09*** (0.24)	1.05*** (0.27)	0.35* (0.19)
<i>Value-Weighted Returns</i>						
LS	0.42* (0.23)	0.65*** (0.18)	0.76*** (0.23)	0.48* (0.27)	0.78*** (0.23)	0.36* (0.20)
ELS	0.64*** (0.19)	0.69*** (0.20)	0.71*** (0.21)	0.79*** (0.22)	0.92*** (0.25)	0.29* (0.16)
CLS	0.51*** (0.18)	0.64** (0.24)	0.63*** (0.17)	0.67*** (0.19)	0.83*** (0.16)	0.43* (0.24)

Table 7**Risk Factor Loadings**

This table reports time-series averages of average conditional factor betas of portfolios of firms sorted on labor share *LS*, *ELS*, and *CLS*. *MKT* is the market risk factor described in Fama and French (1993) and obtained from Kenneth French's website. *ME*, *IA*, and *ROE* are the size, investment, and profitability factors of the q-factor model proposed by Hou et al. (2015). *TFP* and *GDP* are total factor productivity growth and real gross domestic product growth, respectively. Appendix A.5 provides details of the construction of the conditional factor betas. H-L is the zero net investment portfolio long high labor share (H) stocks and short low labor share (L) stocks. Newey-West standard errors estimated with one lag are shown in parentheses. Significance levels are denoted by (* = 10% level), (** = 5% level), and (***) = 1% level). The sample underlying *LS* and *ELS* covers conditional factor betas from 1974 to 2016 and covers industries in the matched Compustat–CRSP sample dataset, except Financials. The sample underlying *CLS* covers factor betas from 1974 to 2010 and covers manufacturing industries in the matched Compustat–Census sample.

Factor	Portfolio					
	L	2	3	4	H	H-L
Panel A: Average Conditional Factor Betas of Stocks Sorted on <i>LS</i>						
MKT	0.87*** (0.09)	0.88*** (0.07)	1.04*** (0.04)	1.15*** (0.05)	1.27*** (0.06)	0.40*** (0.10)
ME	0.11 (0.18)	0.23* (0.14)	0.40*** (0.14)	0.44*** (0.10)	0.82*** (0.09)	0.71*** (0.21)
IA	0.36 (0.22)	0.21 (0.23)	0.20 (0.20)	0.04 (0.20)	-0.14 (0.21)	-0.51 (0.36)
ROE	-0.34* (0.19)	-0.14 (0.15)	0.03 (0.23)	-0.35* (0.19)	-0.31 (0.20)	0.03 (0.23)
TFP	2.18* (1.09)	2.34** (1.04)	3.17*** (1.07)	4.44*** (0.95)	5.74*** (1.22)	3.56*** (0.66)
GDP	-0.06 (1.14)	0.31 (0.98)	0.68 (0.93)	1.05 (0.93)	2.27* (1.18)	2.32*** (0.39)

Table 7 (continued)

Factor	Portfolio					
	L	2	3	4	H	H-L
Panel B: Average Conditional Factor Betas of Stocks Sorted on <i>ELS</i>						
MKT	1.03*** (0.05)	1.23*** (0.05)	1.33*** (0.06)	1.38*** (0.06)	1.39*** (0.08)	0.36*** (0.06)
ME	0.36*** (0.09)	0.53*** (0.08)	0.66*** (0.06)	0.89*** (0.06)	1.23*** (0.11)	0.87*** (0.15)
IA	0.15 (0.17)	-0.01 (0.10)	-0.04 (0.09)	0.07 (0.10)	0.03 (0.13)	-0.12 (0.17)
ROE	-0.23* (0.13)	-0.14* (0.08)	-0.24** (0.10)	-0.18* (0.10)	-0.29** (0.14)	-0.06 (0.16)
TFP	4.12*** (1.23)	5.24*** (1.07)	5.76*** (1.21)	6.60*** (1.30)	7.79*** (1.37)	3.66*** (0.49)
GDP	1.19 (1.14)	1.64* (0.93)	1.99* (1.02)	2.58** (1.04)	3.15*** (1.07)	1.97*** (0.49)
Panel C: Average Conditional Factor Betas of Stocks Sorted on <i>CLS</i>						
MKT	0.95*** (0.03)	1.05*** (0.02)	1.04*** (0.03)	1.07*** (0.02)	1.07*** (0.03)	0.12*** (0.03)
ME	0.48*** (0.04)	0.74*** (0.04)	0.76*** (0.04)	0.77*** (0.03)	0.81*** (0.03)	0.33*** (0.04)
IA	-0.06 (0.06)	0.03 (0.07)	0.00 (0.07)	-0.02 (0.07)	-0.01 (0.07)	0.04 (0.06)
ROE	-0.01 (0.05)	-0.10** (0.05)	-0.17*** (0.05)	-0.20*** (0.04)	-0.22*** (0.05)	-0.20*** (0.05)
TFP	5.41*** (1.44)	6.05*** (1.65)	6.48*** (1.81)	6.10*** (1.78)	6.80*** (1.71)	1.40** (0.57)
GDP	1.91 (1.16)	2.48* (1.35)	2.59* (1.42)	2.43* (1.37)	3.07** (1.32)	1.16** (0.48)

Table 8**Q-Factor Regressions**

The table below shows the results of estimates of the q -factor model from Hou et al. (2015) on the returns of the quintile portfolios of firms sorted on LS (Panel A), ELS (Panel B), and CLS (Panel C). Newey-West standard errors estimated with five lags are shown in parentheses. Significance levels are denoted by (* = 10% level), (** = 5% level), and (***) = 1% level). The samples underlying *LS* and *ELS* cover realized monthly stock returns from July 1974 to June 2016 and the industries in the matched Compustat–CRSP sample dataset, except Financials. The sample underlying *CLS* covers realized monthly stock returns from July 1974 to June 2011 and the manufacturing industries in the matched Compustat–Census sample.

Panel A: Average Conditional Factor Betas of Portfolios Sorted on <i>LS</i>													
Factor	Equally-Weighted Returns						Factor	Value-Weighted Returns					
	L	2	3	4	H	H-L		L	2	3	4	H	H-L
α_q	-0.06 (0.17)	0.16 (0.14)	0.03 (0.12)	0.16 (0.11)	0.36** (0.16)	0.42** (0.21)	α_q	-0.22 (0.17)	-0.05 (0.12)	-0.22 (0.14)	-0.27* (0.15)	0.00 (0.19)	0.22 (0.24)
β_{MKT}	0.82*** (0.06)	0.83*** (0.05)	0.91*** (0.04)	0.94*** (0.04)	0.94*** (0.04)	0.12* (0.07)	β_{MKT}	0.95*** (0.06)	0.98*** (0.05)	1.10*** (0.06)	1.13*** (0.04)	1.14*** (0.05)	0.19** (0.07)
β_{ME}	0.12* (0.07)	0.19** (0.08)	0.35*** (0.07)	0.45*** (0.11)	0.66*** (0.09)	0.53*** (0.06)	β_{ME}	-0.22*** (0.06)	-0.19*** (0.05)	-0.03 (0.09)	0.03 (0.12)	0.02 (0.10)	0.24*** (0.09)
$\beta_{I/A}$	0.50*** (0.09)	0.35*** (0.09)	0.40*** (0.09)	0.39*** (0.10)	0.42*** (0.11)	-0.08 (0.10)	$\beta_{I/A}$	0.64*** (0.13)	0.44*** (0.08)	0.45*** (0.13)	0.37*** (0.13)	0.51*** (0.13)	-0.13 (0.17)
β_{ROE}	-0.12* (0.07)	-0.05 (0.06)	0.09 (0.07)	-0.02 (0.07)	-0.22** (0.09)	-0.10 (0.08)	β_{ROE}	0.06 (0.08)	-0.01 (0.06)	-0.01 (0.10)	-0.02 (0.10)	-0.22** (0.09)	-0.28** (0.13)

Panel B: Average Conditional Factor Betas of Portfolios Sorted on <i>ELS</i>													
Factor	Equally-Weighted Returns						Factor	Value-Weighted Returns					
	L	2	3	4	H	H-L		L	2	3	4	H	H-L
α_q	0.15** (0.07)	0.24*** (0.07)	0.25*** (0.08)	0.38*** (0.11)	0.47*** (0.14)	0.32** (0.16)	α_q	0.13** (0.06)	0.02 (0.06)	-0.01 (0.09)	0.04 (0.10)	0.07 (0.13)	-0.06 (0.15)
β_{MKT}	0.92*** (0.03)	1.00*** (0.03)	0.99*** (0.03)	0.98*** (0.03)	0.94*** (0.04)	0.02 (0.04)	β_{MKT}	0.97*** (0.02)	1.06*** (0.02)	1.07*** (0.02)	1.09*** (0.03)	1.12*** (0.05)	0.15*** (0.06)
β_{ME}	0.31*** (0.07)	0.56*** (0.07)	0.68*** (0.08)	0.76*** (0.10)	0.85*** (0.12)	0.55*** (0.07)	β_{ME}	-0.21*** (0.03)	-0.09** (0.04)	0.12** (0.06)	0.22** (0.09)	0.41*** (0.14)	0.63*** (0.13)
$\beta_{I/A}$	0.25*** (0.07)	0.08 (0.06)	0.22*** (0.08)	0.26*** (0.09)	0.32** (0.13)	0.07 (0.13)	$\beta_{I/A}$	0.12** (0.05)	0.05 (0.06)	0.14* (0.08)	0.14 (0.09)	0.27*** (0.10)	0.14 (0.12)
β_{ROE}	-0.11** (0.05)	-0.08* (0.04)	-0.09* (0.05)	-0.19*** (0.06)	-0.33*** (0.09)	-0.23** (0.09)	β_{ROE}	-0.05 (0.03)	0.00 (0.04)	0.06 (0.06)	0.02 (0.06)	-0.05 (0.09)	0.00 (0.10)

Panel C: Average Conditional Factor Betas of Portfolios Sorted on <i>CLS</i>													
Factor	Equally-Weighted Returns						Factor	Value-Weighted Returns					
	L	2	3	4	H	H-L		L	2	3	4	H	H-L
α_q	0.24* (0.12)	0.25** (0.10)	0.32*** (0.12)	0.22* (0.12)	0.15 (0.11)	-0.09 (0.15)	α_q	0.01 (0.16)	0.13 (0.19)	0.30* (0.16)	0.50** (0.21)	-0.01 (0.16)	-0.02 (0.21)
β_{MKT}	0.98*** (0.03)	1.05*** (0.03)	1.06*** (0.03)	1.08*** (0.04)	1.06*** (0.03)	0.08*** (0.02)	β_{MKT}	0.93*** (0.04)	0.98*** (0.05)	1.06*** (0.04)	1.01*** (0.04)	1.14*** (0.03)	0.21*** (0.05)
β_{ME}	0.38*** (0.07)	0.55*** (0.07)	0.57*** (0.09)	0.63*** (0.11)	0.72*** (0.09)	0.36*** (0.05)	β_{ME}	-0.23*** (0.06)	-0.14** (0.06)	-0.12** (0.06)	-0.10 (0.09)	0.23*** (0.06)	0.46*** (0.08)
$\beta_{I/A}$	0.10 (0.08)	-0.04 (0.09)	0.10 (0.10)	0.28** (0.12)	0.12 (0.08)	0.03 (0.08)	$\beta_{I/A}$	0.07 (0.11)	-0.04 (0.12)	-0.18 (0.13)	-0.43** (0.20)	0.10 (0.12)	0.03 (0.15)
β_{ROE}	-0.13* (0.07)	-0.25*** (0.09)	-0.11 (0.07)	-0.19* (0.10)	-0.20*** (0.07)	-0.08 (0.07)	β_{ROE}	0.05 (0.10)	0.06 (0.08)	0.02 (0.07)	-0.14 (0.12)	-0.07 (0.10)	-0.12 (0.14)

Table 9

Target Moments in Calibration

This table shows the target moments and the loss function weights used in the calibration of the model.

Moment	Target Moment	LF Weight
<i>Moments from Macroeconomic Variables</i>		
Volatility of GDP growth	0.031	0.095
Volatility of aggregate TFP growth	0.019	0.095
Volatility of aggregate wage growth	0.017	0.095
Correlation between GDP growth and agg. TFP growth	0.868	0.048
Correlation between GDP growth and agg. wage growth	0.268	0.048
Correlation between agg. TFP growth and agg. wage growth	0.393	0.048
<i>Moments from Firm-Level Cash Flows</i>		
Mean Labor Share	0.594	0.583
Cross-Sectional Std. Dev. of Value-Added Growth	0.131	0.048
Cross-Sectional Std. Dev. of Labor Share	0.186	0.048
Slope of GDP growth from regression (15)	2.140	0.024
Slope of TFP growth from regression (15)	2.360	0.024
Slope of interaction $LS \times$ GDP growth from regression (15)	0.590	0.024
Slope of interaction $LS \times$ TFP growth from regression (15)	0.870	0.024
<i>Moments from Firm-Level Unlevered Stock Returns</i>		
Return of Low-Labor-Share Quintile Portfolio	2.830	0.095
Return of High-Labor-Share Quintile Portfolio	4.720	0.095
Return of High- minus Low-Labor-Share Quintile Portfolio	1.890	0.095

Table 10

Parameter Calibration

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

Parameter	Symbol	Value
<i>Productive Technology</i>		
K-L elasticity of substitution	$\frac{1}{1-\rho}$	0.400
Weight of labor in productive technology	α	0.814
<i>Shocks</i>		
Volatility of wage shocks	σ_w	0.017
Drift of wage shocks	μ_w	0.029
Priced portion of wage shocks	ρ_w	0.519
Volatility of productivity shocks	σ_A	0.076
Drift of productivity shocks	μ_A	0.034
Priced portion of productivity shocks	ρ_A	0.377
Initial productivity level over wage level	A_0/W_0	2.078
Annual firm death rate	λ	0.010
<i>Stochastic Discount Factor</i>		
Risk-free rate	r	0.010
Price of risk	η	0.840

Table 11

Moments from the Data and from the Model

This table compares moments from our calibrated model with those from the data. Simulated data from the model are generated from 10,000 panels of 10,000 firms over 1,200 months (only the last year is used in the analyses). Targeted moments from the data are in bold.

	Data*				Model			
Panel A: Smoothness and Cyclicalities of Macroeconomic Variables								
Variable	gdp ^g	tfp ^g	wage ^g	profit ^g	gdp ^g	tfp ^g	wage ^g	profit ^g
gdp ^g	1.000				1.000			
tfp ^g	0.868	1.000			0.988	1.000		
wage ^g	0.268	0.393	1.000		0.275	0.367	1.000	
profit ^g	0.586	0.413	-0.094	1.000	0.997	0.973	0.222	1.000
σ	0.031	0.019	0.017	0.104	0.030	0.024	0.016	0.036
Slope on gdp ^g	1.000	0.540	0.142	1.950	1.000	0.775	0.150	1.188
Panel B: Cross-Sectional Standard Deviation of Firm-Level Value-Added Growth								
	0.131				0.152			
Panel C: Mean and Cross-Sectional Standard Deviation of Labor Share								
Mean	0.594				0.582			
σ	0.186				0.183			
Panel D: Sensitivity of Operating Profit Growth to GDP and TFP Shocks								
	gdp ^g		tfp ^g		gdp ^g		tfp ^g	
gdp _t ^g	2.14				1.94			
$S_{it-1} \times \text{gdp}_t^g$	0.59				0.86			
tfp _t ^g			2.36				2.34	
$S_{it-1} \times \text{tfp}_t^g$			0.87				0.98	
S_{it-1}	0.21		0.21		-0.01		-0.01	
Panel E: Portfolio Sorts (Unlevered Stock Returns / Asset Returns)								
L	2.88				2.83			
2	3.53				3.52			
3	4.69				4.06			
4	4.56				4.74			
H	5.88				6.24			
H-L	2.99				3.41			