

Measuring Operating Leverage

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We examine a simple measure of operating leverage: the ratio of fixed costs (measured by depreciation and amortization plus selling, general, and administrative expenses) to the market (or book) value of assets. We find that this measure of operating leverage positively predicts returns. This operating leverage measure is not explained by common factors and

Rubinstein (1973) and Lev (1974). More recently, Carlson, Fisher, and Giammarino (2004) argue that the book-to-market effect can be driven by the operating leverage effect. In their model, operating leverage is measured by the present value of fixed costs over the market value of assets. They assume that fixed costs are proportional to book assets, and therefore the book-to-market ratio should capture operating leverage and be positively correlated with expected returns. In the absence of a mechanism, such as operating leverage, growth stocks are typically viewed as having more growth options and should therefore have higher risk and returns. Cooper (2006), Sagi and Seasholes (2007), Obreja (2013), Ozdagli (2012), and Zhang (2005), among others, explore related mechanisms in the research.

Although this idea is appealing, measuring operating leverage is not trivial. The most widely used measure of operating leverage is provided in Mandelker and Rhee (1984) and has been utilized more recently in García-Feijóo and Jorgensen (2010), Chen, Kacperczyk, and Ortiz-Molina (2011), and Cao (2015), who measure operating leverage by estimating a time-series

those that a firm must incur even when it does not produce or sell any products. Depreciation should fall within the fixed costs category, since machinery depreciates even when a firm is not producing any products. While some may argue that investment in property, plant, and equipment (PPE) is a sunk cost, we view depreciation and amortization as a proxy for the difference between investment cost and resale value; thus, investment in PPE is not typically entirely a sunk cost. While part of depreciation may be related to production, vintage is often the most important determinant of resale value. In this paper, we provide evidence that firms' resale value decreases when DA increases. SGA typically covers company overhead costs that are not product specific. For example, SGA includes accounting expenses, research and development costs, corporate expenses, labor and related expenses, and marketing expenses. A firm is likely to incur much of these costs even when it is not producing or selling any products. On the contrary, COGS, cost of goods sold, is recorded only when a product is produced and sold. In the extreme event of low demand for the products leading to no production or sales, COGS would also drop to zero.

Results from our analyses are consistent with the notion that DA and SGA are more likely to be fixed costs, while COGS is more of a variable cost. We calculate the ratio of aggregate DA over total assets and find it to be relatively stable over time. The same pattern is found for the ratio of aggregate SGA over total assets. On the other hand, COGS as a fraction of total assets varies widely over time. Further, in a time-series regression of aggregate DA, SGA, and COGS on revenues and total assets, the coefficient for revenues for COGS is about one, which is higher than the coefficients for DA and SGA. The results on the firm-level data are the same. Furthermore, we provide evidence that firms encounter more difficulty cutting DA and SGA than in cutting COGS, especially when sales decrease.

We then test whether the empirical measure of operating leverage can explain the return over and above known factors. Our primary variable is market operating leverage: the sum of DA and SGA over the market value of assets. Our use of market value as the denominator is a direct implication of all of the theoretical models, as the market value of assets, rather than book assets, provides a better proxy for the present value of all future operating profits. We find that market operating leverage predicts higher returns. A Fama-MacBeth (1973) regression and a portfolio analysis show that market operating leverage has predictive power over and above common factors.

To further examine this issue, we examine book operating leverage (the ratio of fixed costs over book assets). Because market operating leverage consists of information about book operating leverage and book-to-market assets, examining book operating leverage amounts to examining the part of

market operating leverage that is not mechanically related to book-to-market. We find that book operating leverage is negatively correlated with book-to-market, yet positively predicts returns, contrary to the predictions of the Fama-French three-factor model. Furthermore, in Fama-MacBeth regressions, we cannot reject the hypothesis that the coefficient for the log book operating leverage equals the coefficient for the log book-to-market ratio. These results suggest that market operating leverage contains information over and above book-to-market and therefore may be the more fundamental variable. We also find that the return spread of a long-short portfolio sorted by operating leverage is persistently positive before and after formation, consistent with the risk explanation.

We then examine whether operating leverage helps explain the returns of portfolios sorted by the book-to-market ratio. We find that in return regressions, the coefficients for book operating leverage and the book-to-market ratio are similar in magnitude. Further, using value-weighted and equal-weighted portfolios sorted by the book-to-market ratio, the GRS test cannot reject a two-factor model with the market return and the operating leverage factor. These results suggest that operating leverage helps explain the book-to-market effect.

Finally, we explore the performance of a two-factor model with the market return factor and the operating leverage factor. We find that the two-factor model performs at least as well as the Fama and French five-factor model in terms of squared Sharpe ratio tests and numbers of anomalies explained. However, the two-factor model does not subsume the French five-factor model, as it explains the size, value, and investment factors, but not the profitability factors. When the profitability factor from Hou, Xue, and Zhang (2015) is added to our two-factor model, the three-factor model is at least as good as the q -factor model from Hou, Xue, and Zhang (2015).

Our paper builds on earlier work, including that of García-Feijóo and Jorgensen (2010) and Novy-Marx (2011). García-Feijóo and Jorgensen (2010)

i_A / V^i), than

it is for operating leverage ($(V_A^i / V^i)(\beta_R^i - \beta_C^i)$), and thus implicitly assumes that the level of gearing and the degree of operational inflexibility are uncorrelated across firms.” We present evidence that DA and SGA behave like fixed costs, while COGS is closer to variable costs than fixed costs.¹ We also differ from [Novy-Marx \(2011\)](#) in that our primary variable is scaled by market value instead of book value. Because market value is a better proxy for the present value of all future profits, all theoretical models point to market value as the right scaling variable; we therefore scale by market value in our primary variable but do study book value as a scaling variable in robustness checks. Our measure differs from that in [Chen, Harford, and Kamara \(2019\)](#) in that we include depreciation and amortization as a source of fixed costs, in addition to selling, general, and administrative costs. Machinery depreciates even when a firm is not producing any products. We view depreciation and amortization as a proxy for the difference between investment cost and resale value, and vintage is often the most important determinant of resale value. Therefore, we do not view depreciation and amortization as entirely a sunk cost.²

We note that our measure of operating leverage is motivated by theory that is consistent with the conditional capital asset pricing model (CAPM). However, we believe the conditional CAPM is a sufficient, but not a necessary, condition for operating leverage to matter. An analogy can be made about financial leverage. Financial leverage certainly matters in magnifying risk and returns in a model of conditional CAPM, but because its intuition is clear, we expect financial leverage to matter even in a more general setting, for example, in a multifactor model. Operating leverage is similar. While operating leverage certainly works in these models with conditional CAPM, it is likely to hold in a more general setting. Given the evidence in the literature (e.g., [Lewellen and Nagel 2006](#); [Clementi and Palazzo 2019](#)), we do not believe that the conditional CAPM is literally true. Nonetheless, our evidence suggests that empirical measures of operating leverage are important predictors of returns.

¹ Our measure of fixed costs is related to the gross profitability measure in [Novy-Marx \(2013\)](#). We find that fixed costs and the part of gross profitability not made up of fixed costs exhibits different cross-sectional properties. In particular, the effect of fixed costs on stock returns is greater among small stocks, while the effect of the part of gross profitability not made up of fixed costs is greater among large stocks. The [Internet Appendix](#) presents the results.

² In a seminal paper, [Eisfeldt and Papanikolaou \(2013\)](#) show that firms with higher organizational capital have higher returns. Their measure of organizational capital is derived from the cumulative deflated value of SGA, which is related to our measure of operating leverage. In their model, organizational capital is firm specific and should not be related to systematic risk. We believe that our results are not explained by organizational capital because of the following three findings. First, we find that another fixed cost component, DA, also positively predicts stock returns, with the predictive power on the same order of magnitude as that of SGA. Second, while we also find a lack of correlation between our measure and the earnings-GDP sensitivities at the firm level, once we mitigate estimation errors and estimate the sensitivities at the portfolio level, high book operating leverage is associated with higher systematic risk. Third, the return predictability of our measure of operating leverage remains significant in the cross-sectional Fama-MacBeth regressions controlling for organizational capital.

1. Data

We collect monthly stock returns from CRSP and both annual and quarterly accounting data from Compustat. We include only U.S. common stocks (CRSP share code of 10 or 11) with nonmissing SIC codes and exclude financial stocks (SICCD: 6000–6999) and utility stocks (SICCD: 4900–4999). Our sample covers the period July 1963 to June 2016.

The key explanatory variable in this paper is the operating leverage measure. Our main operating leverage measure is defined as fixed costs over the market value of assets, where we use the sum of DA (depreciation and amortization) and SGA (selling, general, and administrative expenses) as a measure of fixed costs during the previous fiscal year, and the market value of assets at the previous fiscal year-end (book assets plus market equity, minus book equity). We refer to this measure as market operating leverage, or simply, operating leverage. To address the concern regarding a potential price effect in the denominator of our operating leverage measure, we also examine results by using book operating leverage, that is, the ratio of fixed costs over the book value of assets.

In our analysis of the operating leverage effect on stock returns, we also control for other well-known variables related to stock returns. Monthly returns, in percentages, from July of year t to June of year $t + 1$ are matched with accounting variables for fiscal years that end in year $t - 1$. *Size* is the capitalization of the firm at the end of June. *BM* is the book-to-market ratio of equity. *FL* is financial leverage, which is defined as total liabilities over total book assets.³ *gBA* is the annual growth rate of total book assets. *Accrual* is the change in current assets, minus the change in current liability, minus depreciation, all scaled by lagged total book assets, as in Sloan (1996). *IK* is the investment-to-capital ratio. *Momentum* is the past 6-month cumulative returns (skipping a month). We also control for firm's age, *lnAGE*, which is defined as the log of one plus the number of years since the firm's first appearance in CRSP.

Table 1 presents simple summary statistics for our sample. Specifically, we calculate the cross-sectional mean, median, standard deviation, 1st and 99th percentiles, and the number of observations for each month. We then average these cross-sectional measures over time. For example, the average monthly stock return is 1.24%, and the average cross-sectional standard deviation of stock returns is 15.21%. Our market operating leverage measure has a mean of 0.265 and a cross-sectional standard deviation of 0.212. Book operating leverage has a mean of 0.355 and a standard deviation of 0.242. The average number of observations is 2,686 for *Market OL* and *Book OL* and ranges

³ In a robustness check, we also include market beta as a control variable, which is the measured stock's five-year rolling window market beta. We require a firm to have 24 valid monthly returns to compute beta. The results are qualitatively the same.

Table 1
Summary statistics

| | Avg. obs. | Mean | Median | SD | p1 | p99 |
|--------------------|-----------|---------|--------|----------|---------|------------|
| <i>Return (%)</i> | 2,921 | 1.242 | 0.120 | 15.212 | -67.005 | 229.419 |
| <i>Market OL</i> | 2,686 | 0.265 | 0.206 | 0.212 | 0.025 | 1.173 |
| <i>Book OL</i> | 2,686 | 0.355 | 0.296 | 0.242 | 0.047 | 1.294 |
| <i>NMOL</i> | 2,689 | 1.246 | 1.078 | 0.837 | 0.097 | 4.877 |
| <i>Size</i> | 2,901 | 1570.83 | 170.51 | 7,502.16 | 1.22 | 183,836.42 |
| <i>BM</i> | 2,882 | 0.886 | 0.692 | 0.754 | 0.061 | 4.423 |
| <i>FL</i> | 2,928 | 0.455 | 0.458 | 0.203 | 0.045 | 0.914 |
| <i>gBA</i> | 2,806 | 0.194 | 0.085 | 0.453 | -0.385 | 2.842 |
| <i>Accrual</i> | 2,800 | -0.019 | -0.029 | 0.115 | -0.345 | 0.456 |
| <i>IK</i> | 2,761 | 0.377 | 0.235 | 0.477 | 0.015 | 3.250 |
| <i>Momentum</i> | 2,916 | 0.068 | 0.027 | 0.336 | -0.573 | 1.390 |
| <i>lnAGE</i> | 2,928 | 2.445 | 2.444 | 0.854 | 0.699 | 4.146 |
| <i>ln(BA/BE)</i> | 2,928 | 0.693 | 0.591 | 0.492 | 0.042 | 2.684 |
| <i>ln(ME/MA)</i> | 2,882 | -0.567 | -0.459 | 0.534 | -2.413 | 0.463 |
| <i>DA/BA</i> | 2,920 | 0.043 | 0.037 | 0.029 | 0.003 | 0.167 |
| <i>SGA/BA</i> | 2,689 | 0.311 | 0.255 | 0.239 | 0.017 | 1.229 |
| <i>COGS/BA</i> | 2,925 | 0.923 | 0.761 | 0.732 | 0.025 | 4.162 |
| <i>ln(SGA/TC1)</i> | 2,688 | -1.469 | -1.401 | 0.713 | -3.512 | -0.155 |
| <i>ln(FC/TC2)</i> | 2,685 | -1.301 | -1.267 | 0.611 | -3.037 | -0.128 |
| <i>ln(TC1/BA)</i> | 2,689 | -0.012 | 0.063 | 0.713 | -2.387 | 1.569 |
| <i>ln(TC2/BA)</i> | 2,685 | 0.049 | 0.103 | 0.657 | -1.986 | 1.579 |

This table reports summary statistics. The summary statistics (average number of observations, mean, median, standard deviation, and 1st and 99th percentiles) are calculated for each month, and the cross-sectional measures are then averaged over time. The sample covers all U.S. common stocks with nonmissing SIC codes, excluding financial and utility stocks, from July 1963 to June 2016. Return is the stock's monthly raw return in percentage. *Market OL*

from 2,685 ($\ln(FC/TC2)$, $\ln(TC2/BA)$) to 2,928 (FL , $\ln AGE$, and $\ln(BA/BE)$) for other variables.⁴

2. Our Measures of Operating Leverage

2.1 Theoretical motivation

Carlson, Fisher, and Giammarino (2004) derive a simple formula for firm beta under the assumption of the capacity constraints and no variable cost in their Proposition 2 as follows:

$$\beta_t^i = 1 + \frac{V_i^G}{V_i}(v - 1) + \frac{V_i^F}{V_i}, \quad (1)$$

where $\frac{V_i^G}{V_i}$ denotes the fraction of the value of a growth option in the firm value, v is a constant, i denotes the firm stage (0 for juvenile, 1 for adolescent, and 2 for mature), and $\frac{V_i^F}{V_i}$ denotes the ratio of the present value of fixed costs to the firm value. The firm's revenue beta is normalized to one. This model is a dynamic version of [Rhee \(1986\)](#), who shows a similar formulation that includes financial leverage. These analyses suggest that we measure operating

aware of this, and he acknowledges that “our empirical proxy for operating leverage, operating costs over book assets, is a better proxy for gearing (V_A^i/V^i), than it is for operating leverage ($((V_A^i/V^i)(\beta_R^i - \beta_C^i))$), and thus implicitly assumes that the level of gearing and the degree of operational inflexibility are uncorrelated across firms.” Noxy-Marx (2011) attempts to go deeper into the mechanisms of how production costs affect a firm’s risk profile. We impose simplifying assumptions here to obtain a working empirical measure.

We therefore proceed to measure operating leverage as the ratio of fixed costs to the market value of assets. We also explore a version of our model in which we scale fixed costs by the book value of assets. For parsimony, we do not attempt to compute the present value of future fixed costs. Because market value is a better proxy for the present value of all future profits, all theoretical models point to market value as the right scaling variable; we therefore use market operating leverage as our primary variable.⁶

2.2 Fixed cost measures

As explained in the introduction, production costs typically include DA, SGA, and COGS. We view DA as largely fixed costs because machinery depreciates even when a firm is not producing any products. DA is a proxy for the difference between investment cost and resale value, and vintage is often the most important determinant of resale value. Therefore, we do not view DA as a purely sunk cost. SGA typically covers company overhead costs that are not product specific. A firm must incur these costs even when it is not producing or selling any products. Conversely, COGS is recorded only when a product is actually produced and sold.⁷ Our premise is that depreciation and selling, general, and administrative expenses are more likely fixed costs, while the cost of goods sold is a variable cost. To examine whether this assumption is reasonable, we look at the ratio of aggregate costs (across firms) as a fraction of total assets over time, the sensitivities of costs to sales revenue, and the stickiness of DA, SGA, and COGS.

Figure 1 plots aggregate DA (depreciation and amortization), SGA (selling, general, and administrative expenses), COGS (cost of goods sold), and REVT (total revenue) as fractions of total assets in each year between 1963 and 2015. As is clear from Figure 1, depreciation and amortization are almost a constant fraction of total assets. Selling, general, and administrative

⁶ In Section 5.1, we also find that in return regressions, the coefficients for the book-to-market ratio and book operating leverage are almost the same, and the difference is not statistically significant. Additionally, these results are consistent with the notion that market operating leverage drives the empirical performance of the book-to-market effect and the book operating leverage effect.

⁷ In financial statements, some companies do not list depreciation as a separate item in expenses but break depreciation into SGA or COGS (or both). These cases raise the concern of double counting when we add DA and SGA to measure fixed costs. However, Compustat makes an adjustment that eliminates the possibility of double counting in Compustat XSGA, COGS, and DA. For details, see Section 2.1 of the Internet Appendix.

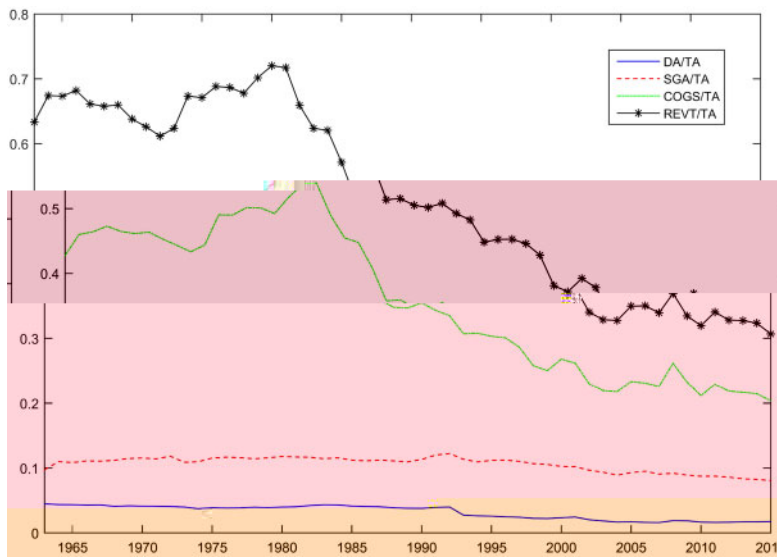


Figure 1
Costs and revenues as fractions of total assets over time
This figure plots aggregate DA (depreciation and amortization), SGA (selling, general, and administrative expenses), COGS (cost of goods sold), and REVT (total revenue) as fractions of TA (total assets) in each year between 1963 and 2015. The ratios are the sums of respective items over the sum of total assets across firms.

costs are also very stable over time as a fraction of total assets. Cost of goods sold and total revenue, on the other hand, vary significantly over time as fractions of total assets. This figure is consistent with the view that DA and SGA are more likely fixed costs, whereas COGS can be viewed as a variable cost.

Panel A of Table 2 reports time-series ordinary least squares (OLS) regressions of aggregate DA (depreciation and amortization), SGA (selling, general, and administrative expenses), and COGS (cost of goods sold) on aggregate REVT (total revenue) and on aggregate TA (total assets) as well as firm-level panel analysis. Simply adding these accounting variables across firms may be problematic since firms may enter and exit the market. To address this issue, we follow Chen (2017) and compute these quantities across time for a \$100 initial investment. This procedure first computes the portfolio value-weighted return with and without dividends. This approach allows us to compute the price series over time; we then multiply the fundamental-to-price ratio by this price series to obtain fundamental values that are comparable over time. We also control for the time trend in the regressions. The results in panel A show that the coefficients for market-level regressions on $\ln(\text{REVT})$ for DA, SGA, and COGS are -0.108 , 0.468 , and 1.191 , respectively. Columns 4 to 6 of panel A produce the firm-level counterparts to columns 1 to 3 and show that the respective coefficients are 0.429 , 0.438 ,

and 0.984. Both market-level analysis and firm-level analysis show that COGS is more positively correlated with REVT, with a larger slope coefficient and a higher significance relative to DA and SGA. Moreover, we investigate the sensitivities of various costs to decreases in sales revenue in columns 7 to 9 of panel A. The coefficient for the interactor of $\ln(\text{REVT})$ and the dummy for decreasing revenue (β_2) is significantly negative for DA (-0.053 , t -statistic = -3.26) and SGA (-0.047 , t -statistic = -5.27). However, the estimated β_2 is statistically indistinguishable from zero for COGS. These results indicate that DA and SGA are less sensitive to sales revenue than COGS, especially when sales decrease.

We then follow [Chen, Harford, and Kamara \(2019\)](#) to test the stickiness of DA, SGA, and COGS by using the logarithmic change of costs and sales in the regressions and report the results in panel B of [Table 2](#). In this specification, the estimated coefficient for $\Delta \ln(\text{REVT})$, β_3 , is a measure of how much the costs respond to changes in sales. The closer the estimate of β_3 is to zero, the stickier are the costs. When β_3 is positive, the negative β_4 (the estimated coefficient for the interactor term of $\Delta \ln(\text{REVT})$ and the dummy variable for decreasing revenue) indicates that the firm cannot decrease its costs when its sales decrease as much as the firm increases them when its sales increase. In univariate regressions of logarithmic change in costs on logarithmic change in sales, as shown in columns 1 to 3, the estimated β_3 is 0.6185 for DA, 0.5448 for SGA, and 0.9377 for COGS, indicating that DA and SGA are stickier than COGS. In columns 4 to 6, the estimated β_4 is -0.441 for DA and -0.172 for SGA, much larger in magnitude than that for COGS (-0.0498). These results suggest that it is more difficult for firms to cut DA and SGA rather than COGS when facing declining sales. Overall, these results indicate higher stickiness of DA and SGA relative to COGS and are consistent with the view that COGS is a variable cost and that DA and SGA are more likely to be fixed costs.

If parts of DA and SGA are variable costs, then our measure may be viewed as the true fixed costs plus some noise, which may lead to some attenuation bias.

2.3 Depreciation and amortization cost and resale value

In this paper, we view depreciation and amortization (DA) as a proxy for the difference between investment cost and resale value, while some may argue that investment in PPE is a sunk cost. Meanwhile, the results in the previous section show that DA is more likely to be a fixed cost, meaning that operational flexibility would be less for firms with higher DA.⁸ Thus, we conjecture that, *ceteris paribus*, an increase in DA is associated with a decline in resale

⁸ In Section 1.3 of the [Internet Appendix](#), we explore a simple extension of the theoretical model with depreciation, and we find that DA is equivalent to other fixed costs, using the cash-flow-based approach for estimating a firm's value and asset beta, under the condition of asset resaleability.

Table 2
Regressions of costs on revenue

A. Regressions of log costs on log revenue

| | Market-level regressions | | | Firm-level regressions | | | | | |
|------------------------|--------------------------|------------------|--------------------|------------------------|-------------------|--------------------|-------------------|-------------------|--------------------|
| | ln(DA) 1 | ln(SGA) 2 | ln(COGS) 3 | ln(DA) 4 | ln(SGA) 5 | ln(COGS) 6 | ln(DA) 7 | ln(SGA) 8 | ln(COGS) 9 |
| $\ln(REVT) (\beta_1)$ | -0.1081 (-0.70) | 0.4680 (3.66) | 1.1911 (26.31) | 0.4288 (30.45) | 0.4377 (35.43) | 0.9842 (104.89) | 0.4462 (28.65) | 0.4530 (34.79) | 0.9886 (97.28) |
| $\ln(REVT)$ | | | | | | | -0.0533 | -0.0470 | -0.0135 |
| *Decrease(β_2) | | | | | | | (-3.26) | (-5.27) | (-1.58) |
| $\ln(TA)$ | 0.5274 (2.50) | 0.2977 (2.68) | -0.1399 (-3.23) | 0.4996 (38.68) | 0.3175 (38.00) | -0.0065 (-0.82) | 0.4963 (38.19) | 0.3145 (37.12) | -0.0073 (-0.91) |
| Year | 0.0147 (2.04) | 0.0086 (2.43) | -0.0017 (-2.49) | | | | | | |
| $\beta_1 + \beta_2$ | | | | | | | 0.393 | 0.406 | 0.9751 |
| p-value | | | | | | | .0000 | .0000 | .0000 |
| Obs. | 53 | 53 | 53 | 147,275 | 147,275 | 147,275 | 147,275 | 147,275 | 147,275 |
| Adj. R^2 | .975 | .993 | .999 | .509 | .610 | .832 | .510 | .610 | .832 |

B. Stickiness of DA, SGA, and COGS

| | Dependent variables | | | | | |
|---------------------------------------|-----------------------|------------------------|-------------------------|-----------------------|------------------------|-------------------------|
| | $\Delta \ln(DA)$ 1 | $\Delta \ln(SGA)$ 2 | $\Delta \ln(COGS)$ 3 | $\Delta \ln(DA)$ 4 | $\Delta \ln(SGA)$ 5 | $\Delta \ln(COGS)$ 6 |
| $\Delta \ln(REVT) (\beta_3)$ | 0.6185 (29.86) | 0.5448 (44.45) | 0.9377 (148.69) | 0.7592 (30.81) | 0.5997 (38.45) | 0.9536 (122.81) |
| $\Delta \ln(REVT)*Decrease (\beta_4)$ | | | | -0.4412 (-11.86) | -0.1723 (-8.61) | -0.0498 (-3.48) |
| $\beta_3 + \beta_4$ | | | | 0.3180 | 0.4274 | 0.9038 |
| p-value | | | | .0000 | .0000 | .0000 |
| Obs. | 130,791 | 130,791 | 130,791 | 130,791 | 130,791 | 130,791 |
| Adj. R^2 | .273 | .411 | .730 | .292 | .417 | .730 |

Panel A report regressions of various costs on revenues. Columns 1 to 3 report the time-series OLS regressions of the log of DA (depreciation and amortization), SGA (selling, general, and administrative expenses), and COGS (cost of goods sold) of the market portfolio, on the log of REVT (total revenue) of the market portfolio, the log of TA (total assets) of the market portfolio, and a time trend. We follow [Chen \(2017\)](#) to calculate the annual DA, SGA, COGS, REVT, and TA of the value-weighted market portfolio with an initial investment of \$100. Reported in parentheses are [Newey and West \(1987\)](#) *t*-statistics adjusted for heteroscedasticity and autocorrelation. Columns 4 to 9 report the firm-level panel regressions of the detrended log of DA, SGA, and COGS, on the detrended log of REVT and TA. Decrease equals one for decreasing REVT and zero otherwise. In panel B, we follow [Chen, Harford, and Kamara \(2019\)](#) to test the stickiness of DA, SGA, and COGS. Firm-specific variables are winsorized at the 1% and 99% levels every year. Standard errors are adjusted by two-way clustering in the dimensions of firm and year. We also report the *p*-values for the tests of $H_0: \beta_1 + \beta_2 = 0$ in panel A and $H_0: \beta_3 + \beta_4 = 0$ in panel B. Costs, revenue, and assets are adjusted to real values by the PCE deflator. Time fixed effects are controlled for in columns 4–9 in panel A and all columns in panel B. The sample is from 1963 to 2015.

value. In practice, we collect firms' asset redeployability score from [Kim and Kung \(2017\)](#).

We first test the correlation of depreciation and amortization to the asset redeployability score in Table IA.2 in the [Internet Appendix](#). We find that DA/BA is negatively correlated with the asset redeployability score with an

overall Pearson coefficient of -0.127 and an overall Spearman coefficient of -0.116. The cross-sectional correlation is stronger in magnitude with an average cross-sectional Pearson coefficient of -0.153 and an average cross-sectional Spearman coefficient of -0.139.

We then follow [Kim and Kung \(2017\)](#) to examine the effect of the changes in aggregate uncertainty on corporate investment conditional on firms' depreciation and amortization-to-asset ratio. Our hypothesis is that when uncertainty increases, corporate investment would decrease more for firms with less resalable assets, meaning higher DA/BA in this circumstance, since firm managers would delay investment if liquidating capital is costly. In [Table 3](#), we examine the effect of firms' depreciation and amortization-to-asset ratio on the response of corporate investment to changes in aggregate uncertainty. The First Gulf War and the 9/11 terrorist attacks are two exogenous shocks to uncertainty for analysis in columns 1 to 3 and columns 4 to 6, respectively. The dependent variable is the corporate investment measured by capital expenditure scaled by lagged total assets. For each event, *After* is a dummy variable that equals one for quarters ending after the occurrence of the event, and zero otherwise. Tobin's q , sales growth, and cash flow are controlled in all specifications. In columns 1 and 4, we find that the corporate investment ratio decreases by 0.211 and 0.337 percentage points after the shocks of the First Gulf War and 9/11 terrorist attacks, respectively. When we include the variable DA/BA in the regressions, as shown in columns 2, 3, 5, and 6, the coefficients for the interactor of *After* and DA/BA are negative and statistically significant at the 10% level with or without control variables, meaning that corporate investment decreases more for firms with higher DA/BA . In addition, we use two continuous measures, the VIX index and the economic policy uncertainty (*EPU*) index developed by [Baker, Bloom, and Davis \(2016\)](#), as proxies for aggregate economic uncertainty. The results are reported in columns 7 to 10. The coefficient for the interactor of *VIX* and DA/BA is -21.599 with a t -statistic of -4.32 in column 8 and for the interactor of *EPU* and DA/BA is -4.272 with a t -statistic of -4.79 in column 10. These results indicate that corporate investment would decrease more for firms with higher DA/BA when uncertainty increases, consistent with the conjecture that firms' resale value decreases when DA increases.

In cross-sectional analyses, we focus on within-industry variation in costs for the following two reasons. First, in equilibrium models (e.g., [Novy-Marx 2011](#)), within-industry and across-industry market structures may be different, and cost behavior within and across industries may have different pricing implications. Second, different industries may have different accounting practices regarding how to classify certain cost items into different categories. We therefore follow [Novy-Marx \(2011\)](#) and [Eisfeldt and Papanikolaou \(2013\)](#) and focus on within-industry variations. Nonetheless, we report in the [Internet Appendix](#) that the main results are the qualitatively the same if we do not use industry adjustment.

each operating-leverage-sorted portfolio and for each month between July and the following June.

Panel A of Table 4 shows results from 10 market operating-leverage-sorted deciles. As we move from decile 1 to decile 10, market operating leverage increases from 0.060 to 0.686. These 10 deciles have different returns. The value-weighted portfolio returns are almost monotonically increasing in operating leverage, and the return spread between portfolio 10 (H) and portfolio 1 (L) is 0.771% per month with a *t*-statistic of 3.83. For the equal-weighted portfolio returns, the return spread is even greater at 1.430% per month between high and low operating leverage deciles with a *t*-statistic of 8.55. This return spread is both statistically and economically significant and shows a positive relation between firms' operating leverage and their stock returns.

The above analysis uses market operating leverage defined as fixed costs over the market value of assets. Readers might be legitimately concerned that our operating leverage effect on stock returns is simply driven by prices in the denominator of market operating leverage. To address this concern, we redo all of the above analysis using book operating leverage, in which prices play no direct role.

Panel B of Table 4 reports results for portfolios sorted by book operating leverage. As we move from decile 1 to decile 10, book operating leverage increases from about 0.103 to 0.814. Book operating leverages are typically higher than market operating leverages because the book value of assets is typically lower than the market value of assets. Sorting on book operating leverage also produces dispersion in returns, although the dispersion tends to be smaller. The return spread between the high and low book operating leverage deciles is 0.527% per month for value-weighted deciles and 0.603% per month for equal-weighted deciles, and both are statistically and economically significant, albeit smaller than the return spread of the market operating leverage deciles.

We also examine the return persistence of long-short portfolios sorted by our operating leverage measures surrounding portfolio formation. Figure 2 plots the long-short decile portfolio return spread. In Figure 2, panel A, we find that the return spread of long-short portfolios sorted by market operating leverage is mostly positive from 6 months prior to formation to 18 months after formation. The relative high return spreads 6 months prior to and 7 months after formation are likely due to the January effect. We find a similar result that the long-short spread is persistently positive before and after formation for book operating-leverage-sorted portfolios in Figure 2, panel B. The persistence of the long-short portfolio return spread surrounding formation is consistent with the risk explanation, if we believe that the return spread is compensation for persistent risk instead of transitory mispricing.

Table 4.
Operating-leverage-sorted deciles

A. Portfolios sorted by market operating leverage

| Decile | L | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | H | H-L |
|-----------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|--------------------|
| Market OL | 0.060 (28.16) | 0.103 (31.24) | 0.136 (33.23) | 0.167 (34.65) | 0.201 (36.08) | 0.240 (37.62) | 0.287 (39.05) | 0.349 (40.49) | 0.443 (42.42) | 0.686 (43.78) | 0.626 (41.81) |
| VWRet(%) | 0.713 (3.11) | 0.767 (4.00) | 0.917 (4.98) | 0.933 (5.16) | 1.151 (5.94) | 1.065 (5.98) | 1.278 (6.43) | 1.124 (5.60) | 1.288 (5.86) | 1.484 (5.96) | 0.771 (3.83) |
| EWRet(%) | 0.545 (1.96) | 0.803 (3.05) | 0.962 (3.79) | 1.072 (4.19) | 1.190 (4.52) | 1.210 (4.66) | 1.454 (5.44) | 1.560 (5.60) | 1.641 (5.60) | 1.975 (5.96) | 1.430 (8.55) |
| Size | 3,189 (7.27) | 2,682 (7.51) | 2,745 (6.70) | 2,418 (6.66) | 1,827 (7.06) | 1,266 (7.00) | 750 (7.34) | 435 (9.46) | 293 (8.69) | 114 (12.68) | -3,074 (-7.10) |
| lnSize | 5.496 (37.18) | 5.420 (38.38) | 5.342 (37.64) | 5.163 (38.40) | 4.965 (39.64) | 4.726 (39.33) | 4.449 (40.08) | 4.144 (39.63) | 3.794 (40.50) | 3.118 (36.80) | -2.378 (-28.71) |
| NMOL | 0.823 (36.72) | 0.945 (52.24) | 1.036 (55.35) | 1.094 (60.20) | 1.171 (57.21) | 1.252 (61.77) | 1.338 (66.63) | 1.429 (71.22) | 1.565 (76.56) | 1.827 (92.01) | 1.004 (59.66) |

B. Portfolios sorted by book operating leverage

| Decile | L | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | H | H-L |
|----------|------------------|-------------------|-------------------|------------------|------------------|------------------|------------------|------------------|------------------|-------------------|--------------------|
| Book OL | 0.103 (76.04) | 0.163 (105.07) | 0.208 (107.03) | 0.249 (98.96) | 0.292 (94.73) | 0.336 (91.69) | 0.389 (83.01) | 0.456 (75.06) | 0.557 (65.80) | 0.814 (48.91) | 0.711 (40.76) |
| VWRet(%) | 0.706 (3.52) | 0.833 (3.91) | 0.827 (4.22) | 0.907 (4.77) | 0.934 (4.79) | 0.956 (5.06) | 1.114 (6.06) | 1.086 (5.45) | 1.016 (4.75) | 1.233 (5.51) | 0.527 (3.52) |
| EWRet(%) | 0.885 (3.34) | 1.025 (3.94) | 1.127 (4.36) | 1.149 (4.54) | 1.290 (5.03) | 1.260 (4.78) | 1.315 (4.89) | 1.396 (4.99) | 1.440 (4.95) | 1.489 (4.37) | 0.603 (3.52) |
| Size | 2,270 (6.42) | 1,894 (7.06) | 2,289 (6.50) | 2,222 (6.18) | 2,051 (7.77) | 1,919 (7.89) | 1,144 (8.71) | 933 (8.83) | 684 (9.31) | 359 (8.68) | -1,910 (-6.02) |
| lnSize | 5.098 (37.12) | 5.095 (39.25) | 5.042 (37.61) | 4.961 (37.32) | 4.852 (38.34) | 4.721 (38.75) | 4.590 (39.41) | 4.414 (40.30) | 4.179 (42.70) | 3.702 (39.32) | -1.396 (-18.19) |
| NMOL | 0.771 (45.10) | 0.930 (52.23) | 1.028 (59.02) | 1.097 (54.40) | 1.178 (56.61) | 1.247 (56.24) | 1.310 (60.80) | 1.429 (66.67) | 1.572 (77.81) | 1.911 (105.96) | 1.140 (95.10) |

We sort stocks into 10 deciles in June of year t according to their operating leverage measures within each of the Fama and French (1997) 17 industries. Monthly returns are from July of year t to June of year $t+1$. Accounting variables are for fiscal years that end in year $t-1$. The measures are calculated for each operating-leverage-sorted decile and for each month. Finally, we average over time to get the average values for each operating-leverage-sorted decile. Panel A reports results for portfolios sorted by market operating leverage (*market OL*, the ratio of fixed costs to market assets). Panel B reports results for portfolios sorted by book operating leverage (*book OL*, the ratio of fixed costs to book assets). Fixed costs are defined as the sum of DA (depreciation and amortization) and SGA (selling, general, and administrative expenses). *VWRet* (*EWRet*) is the value-weighted (equal-weighted) average portfolio return in percentage. *Size* is the capitalization of the firm at the end of June (in \$M). *NMOL* is the operating leverage measure from Novy-Marx (2011), which is the ratio of SGA and COGS to book assets. Reported in parentheses are Newey and West (1987) t -statistics adjusted for heteroscedasticity and autocorrelation.

One noteworthy finding in Table 9 is that our operating leverage measures decrease with size and increase with the operating leverage measure from Novy-Marx (2011). We will compare our operating leverage measures with the operating leverage measure from Novy-Marx (2011) in Section 7.1.

3.2 Evidence from cross-sectional regressions

In the previous section, we have shown that returns are higher for stocks with higher market and book operating leverages. However, our operating leverage measures might simply be proxies for other existing predictors of stock

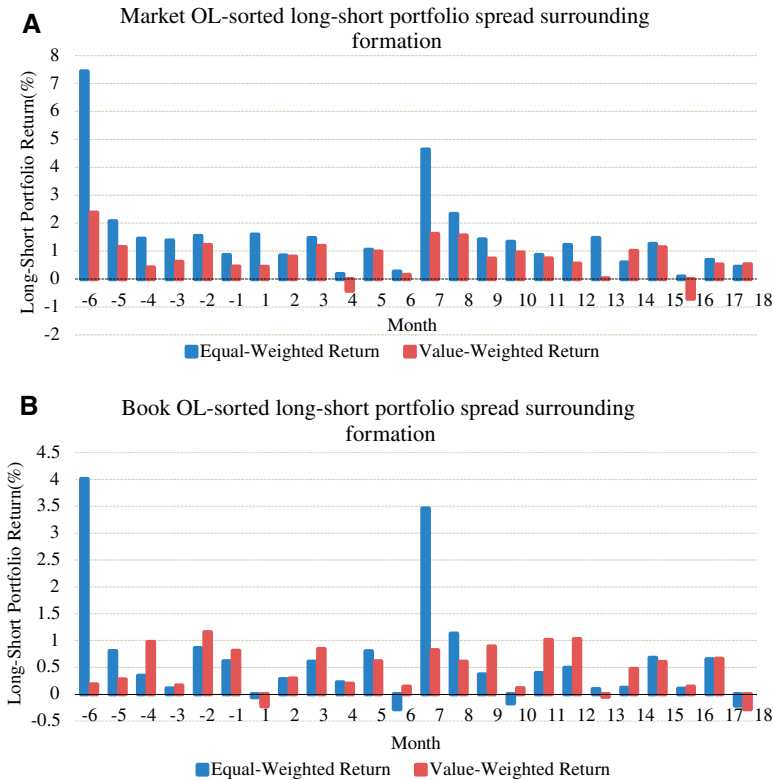


Figure 2

Persistence of long-short return spread surrounding formation

This figure plots the return spread of long and short decile portfolios sorted by market operating leverage (*Market OL*) and book operating leverage (*Book OL*). *Market OL* is operating leverage, defined as fixed costs divided by the market value of assets (book assets plus market equity, minus book equity), where we use the sum of DA (depreciation and amortization) and SGA (selling, general, and administrative expenses) in the previous year as a measure of fixed costs. *Book OL* is book operating leverage, which is the ratio of fixed costs to total book assets. We sort stocks into 10 deciles in June of year t according to their operating leverage measures within each of the Fama and French (1997) 17 industries. We calculate the value-weighted and equal-weighted return spreads between the highest decile and the lowest decile from 6 months prior to the formation to 18 months after the formation. Then we plot the average return spread in the figures. The sample period is from July 1963 to June 2016.

returns. We now control for other variables that are known to predict returns, such as size, book-to-market, and momentum. To do so, we estimate cross-sectional regressions of returns on operating leverage, while controlling for other variables.

Table 5 reports the results of Fama-MacBeth cross-sectional regressions. For each month (from July in year t to June in year $t+1$), we estimate a regression of stock returns on operating leverages, which uses accounting information from year $t-1$. To capture the influence of intra-industry differences in operating leverage on stock returns, we include the industry fixed

effect in all specifications. We then report average coefficients and t -statistics from such cross-sectional regressions. Unless stated otherwise, all t -statistics in this paper are adjusted using the Newey-West (1987) pr

stocks and value stocks have higher returns. In column 3, we jointly estimate a regression of returns on market operating leverage, $\ln Size$, and $\ln BM$. Comparing columns 1 and 3 gives us two more important results. First, the operating leverage measure is still significant even after controlling for size and the book-to-market ratio. Second, both the operating leverage and book-to-market coefficients become smaller in column 3. This result indicates that operating leverage is positively correlated with the book-to-market ratio. At the same time, operating leverage still has additional explanatory power beyond that of the book-to-market ratio. We further control for financial leverage, asset growth, accrual, investment, momentum, and firm age in column 4. The results show that the operating leverage effect is still highly significant, with a coefficient of 0.703 and a t -statistic of 3.82, after controlling for all the other variables. This magnitude means that a one-standard-deviation increase in market operating leverage is associated with a 1.79% increase in annualized returns.

Columns 5 through 7 present the Fama-MacBeth regression results using book operating leverage. Similar to the market operating leverage results in column 1, book operating leverage is associated with higher returns. The average coefficient is positive at 0.673, which suggests that if book operating leverage increases, stock returns tend to increase as well. The effect is statistically significant in the univariate regression with a t -statistic of 3.43. Moreover, controlling for size and the book-to-market ratio makes the effect of book operating leverage larger: the coefficient increases from 0.673 (column 5) to 0.797 (column 6), and the t -statistic increases from 3.43 to 4.96. Furthermore, the coefficient for book operating leverage remains significant, 0.565 (t -statistic = 3.72), after controlling for other predictors of returns (column 7). This magnitude means that a one-standard-deviation increase in book operating leverage is associated with a 1.51% increase in annualized returns.

Considering that depreciation and amortization costs are included in our fixed costs, we scale fixed costs by the market value of assets in the previous fiscal year as an alternative market operating leverage measure and by the book value of assets in the previous fiscal year as an alternative book operating leverage measure. In columns 8 and 9, the coefficient decreases from 0.703 to 0.405 for the alternative market operating leverage and decreases from 0.565 to 0.503 for the alternative book operating leverage, and both remain statistically significant. The results verify the robustness of our operating leverage measure, although the economic magnitude for alternative measures of operating leverage declines somewhat.

3.3 Evidence from time-series regressions

We now use a different methodology to examine whether operating leverage is subsumed by the known factors, such as the Fama-French three factors.

Specifically, we estimate factor models on our operating-leverage-sorted deciles and examine the alphas.

We first examine deciles sorted by market operating leverage within each industry. Panel A of Table 6 presents, for the value-weighted highest decile and lowest decile as well as the high-minus-low portfolio,⁹ the excess return, one-factor ($MktRf$) alpha, Fama-French (1993) three-factor ($MktRf$, SMB , HML) alpha, four-factor (three-factor plus UMD) alpha, five-factor (four-factor plus liquidity factor $LIQT$) alpha, Fama-French (2015) five-factor (three-factor plus RMW and CMA) alpha, q -factor (MKT , ME , IA , and ROE) alpha, and Misp-factor ($MktRf$, SMB , $MGMT$, $PERF$) alpha. The $LIQT$ is the tradable liquidity factor from Pástor and Stambaugh (2003). The q -factor model is from Hou, Xue, and Zhang (2015).¹⁰ The Misp-factor model is with mispricing factors from Stambaugh and Yuan (2017). Column 1 shows that deciles sorted by market operating leverage exhibit increasing returns (shown previously in panel A of Table 4). The difference between high-minus-low market operating leverage is 0.771% per month and is statistically significant. Column 2 shows that CAPM does not explain the returns of market operating leverage portfolios. The difference between the alphas of the high and low market operating leverage portfolios increases slightly to 0.783% per month and remains statistically significant. When we use Fama-French three factors, the alpha of the high-minus-low (H-L) market operating leverage portfolio decreases to 0.427% per month but is still statistically significant. The differences in alphas for the four-factor, five-factor, FF5-factor, q -factor, and Misp-factor models are somewhat smaller than that for the three-factor model, but they are all statistically significant. These results suggest that value-weighted portfolios sorted by market operating leverages are not explained by common factor models.

Panel B reports results for the equal-weighted portfolios sorted by market operating leverage. The alpha for the equal-weighted H-L portfolio is higher than that for the value-weighted portfolio. The alpha spread across all models exceeds 1% per month and is highly statistically significant (t -statistics of all models exceed six).

Panel C of Table 6 also shows that market operating leverage contains information that cannot be completely explained by the common factors. Specifically, one can view market operating leverage as containing information about book operating leverage and book-to-market assets. The book-to-market assets are mechanically related to book-to-market equity, but book operating leverage is likely to include information about market operating leverage that is not captured by book-to-market. We therefore examine portfolios sorted by book operating leverage in panel C. Similar to previous

⁹ We report the excess returns and time-series regression alphas for each decile sorted by market or book operating leverage in Table IA.3 in the Internet Appendix.

¹⁰ We thank the authors for kindly providing us with the data.

Table 6

Alphas of portfolios sorted by operating leverages

| Deciles | Excess return | 1-factor Alpha | 3-factor alpha | 4-factor alpha | 5-factor alpha | FF5-factor alpha | <i>q</i> -factor alpha | Misp-factor alpha |
|--|------------------|--------------------|--------------------|--------------------|--------------------|--------------------|------------------------|--------------------|
| <i>A. Value-weighted deciles sorted by market OL</i> | | | | | | | | |
| L | 0.3169 (1.36) | -0.2615 (-2.68) | -0.0698 (-0.97) | 0.0182 (0.26) | 0.0111 (0.15) | 0.0353 (0.45) | 0.0573 (0.55) | 0.0720 (0.71) |
| H | 1.0881 (4.35) | 0.5214 (3.37) | 0.3568 (2.89) | 0.3438 (2.65) | 0.3150 (2.23) | 0.3948 (3.29) | 0.4234 (2.86) | 0.4171 (3.33) |
| H-L | 0.7712 (3.83) | 0.7829 (3.73) | 0.4266 (2.94) | 0.3256 (2.17) | 0.3039 (1.89) | 0.3595 (2.60) | 0.3661 (2.08) | 0.3451 (2.26) |
| <i>B. Equal-weighted deciles sorted by market OL</i> | | | | | | | | |
| L | 0.1487 (0.53) | -0.5080 (-3.82) | -0.5495 (-6.50) | -0.2967 (-3.40) | -0.3250 (-3.59) | -0.3902 (-3.24) | -0.2092 (-1.38) | -0.1243 (-1.01) |
| H | 1.5789 (4.72) | 1.0179 (4.57) | 0.7396 (5.13) | 0.9070 (5.52) | 0.9067 (5.19) | 0.8337 (5.54) | 1.1902 (5.82) | 0.9462 (5.21) |
| H-L | 1.4303 (8.55) | 1.5260 (8.68) | 1.2891 (8.31) | 1.2037 (7.50) | 1.2317 (7.26) | 1.2240 (7.60) | 1.3994 (7.44) | 1.0705 (6.47) |
| <i>C. Value-weighted deciles sorted by book OL</i> | | | | | | | | |
| L | 0.3102 (1.52) | -0.2101 (-2.42) | -0.2319 (-2.74) | -0.1444 (-1.82) | -0.1057 (-1.24) | -0.1554 (-1.74) | -0.0404 (-0.41) | -0.0136 (-0.17) |
| H | 0.8371 (3.68) | 0.2953 (2.58) | 0.3135 (2.99) | 0.2841 (2.78) | 0.2149 (2.05) | 0.3083 (2.58) | 0.2669 (2.00) | 0.2590 (2.26) |
| H-L | 0.5270 (3.52) | 0.5055 (3.26) | 0.5453 (4.13) | 0.4285 (3.49) | 0.3206 (2.44) | 0.4636 (3.04) | 0.3073 (1.83) | 0.2727 (2.01) |
| <i>D. Equal-weighted deciles sorted by book OL</i> | | | | | | | | |
| L | 0.4895 (1.83) | -0.1026 (-0.76) | -0.3488 (-4.15) | -0.1330 (-1.69) | -0.1573 (-1.88) | -0.3378 (-3.23) | -0.1177 (-0.82) | -0.1047 (-1.12) |
| H | 1.0929 (3.18) | 0.4808 (2.17) | 0.3367 (2.34) | 0.5689 (3.18) | 0.5478 (2.97) | 0.5305 (3.09) | 0.8825 (3.27) | 0.7029 (3.19) |
| H-L | 0.6034 (3.52) | 0.5834 (3.47) | 0.6854 (4.56) | 0.7019 (4.12) | 0.7051 (4.00) | 0.8683 (5.42) | 1.0002 (3.76) | 0.8076 (3.81) |

This table reports the excess returns (raw returns minus the risk-free rate) of operating leverage (*market OL* and *book OL*) sorted deciles as well as the time-series regression alphas from (1) one-factor (*MktRf*); (2) three-factor (*MktRf SMB HML*); (3) four-factor (*MktRf SMB HML UMD*); (4) five-factor (*MktRf SMB HML UMD LIQT*); (5) Fama-French five-factor (*MktRf SMB HML RMW CMA*) models; (6) *q*-factors from [Hou, Xue, and Zhang \(2015\)](#); and (7) mispricing factors from [Stambaugh and Yuan \(2017\)](#). We sort stocks into 10 deciles in June of year *t* according to their operating leverage measures within each of the [Fama and French \(1997\)](#) 17 industries. Monthly returns are in percentages from July of year *t* to June of year *t*+1. Market operating leverage (*market OL*) is defined as fixed costs divided by the market value of assets. Fixed costs are defined as the sum of depreciation and amortization and selling, general, and administrative expenses. Book operating leverage (*book OL*) is defined as fixed costs divided by the book value of assets. *LIQT* refers to the tradable liquidity factor from [Pástor and Stambaugh \(2003\)](#). The sample period is from July 1963 to June 2016. Panels A and B report results for portfolios sorted by *market OL*. Panels C and D report results for portfolios sorted by *book OL*. Panels A and C are for value-weighted portfolios, and panels B and D are for equal-weighted portfolios. Reported in parentheses are [Newey and West \(1987\)](#) *t*-statistics adjusted for heteroscedasticity and autocorrelation.

panels, we present for each book operating leverage decile (value-weighted) the excess return, one-factor (*MktRf*), three-factor (*MktRf, SMB, HML*), four-factor (three-factor plus *UMD*), five-factor (four-factor plus liquidity factor *LIQT*), FF5-factor (three-factor plus *RMW* and *CMA*), *q*-factor (*MKT, ME, IA, and ROE*), and Misp-factor (*MktRf, SMB, MGMT*,

PERF) alphas. Column 1 of panel C shows that the excess return of the high-minus-low (H-L) book operating leverage portfolio is positive at 0.527% per month and statistically significant. The alpha of the H-L portfolio from the CAPM is similar at 0.506% per month. Once the *SMB* and *HML* factors are included, the alphas become slightly larger. For the H-L portfolio, the three-factor alpha is 0.545% per month (t -statistic = 4.13). The fact that the three-factor alpha is larger than the one-factor alpha is interesting (we explore that fact later in Table 7). The four-factor, five-factor, FF5-factor, q -factor, and Misp-factor alphas are 0.429%, 0.321%, 0.464%, 0.307%, and 0.273% per month, respectively.

Panel D shows that the results are even stronger for equal-weighted book operating leverage deciles: the H-L portfolio excess return is 0.603% and statistically significant (t -statistic = 3.52). The H-L portfolio has a CAPM alpha of 0.583% per month and is statistically significant (t -statistic = 3.47). Just like the value-weighted portfolios, including *SMB* and *HML* actually increases the alpha. The three-factor alpha for the H-L book operating leverage portfolio is 0.685% per month (t -statistic = 4.56). The four-factor, five-factor, FF5-factor, and Misp-factor alphas are 0.702% (t -statistic = 4.12), 0.705% (t -statistic = 4.00), 0.868% (t -statistic = 5.42), and 0.808% (t -statistic = 3.81) per month, respectively. The q -factor alpha is even larger at 1.000% (t -statistic = 3.76).

In Table 7, we present the Fama-French three-factor loadings for each operating leverage decile. Panel A reports the results for the value-weighted portfolio sorted by market operating leverage relative to industry peers. The portfolio with high market operating leverage has a higher *SMB* loading, consistent with the finding in Table 4 that operating leverage decreases with firms' size. Decile 10 has an *SMB* loading of 0.61, and decile 1 has an *SMB* loading of -0.02. The difference is 0.63 and statistically significant (t -statistic = 7.64). The portfolio with high market operating leverage also has a higher *HML* loading. Decile 10 has an *HML* loading of 0.22, and decile 1 has an *HML* loading of -0.44. The difference is 0.66 and statistically significant (t -statistic = 8.00). These results suggest that stocks with higher market operating leverage are likely to be small and value stocks.

Panel B shows the results for equal-weighted portfolios sorted by market operating leverage. Again, the portfolio with high market operating leverage has higher *SMB* and *HML* loadings. Decile 10 has an *SMB* loading of 1.23, and decile 1 has an *SMB* loading of 0.78. The difference is 0.45 and statistically significant (t -statistic = 5.19). Decile 10 has an *HML* loading of 0.32, and decile 1 has an *HML* loading of -0.11. The difference is 0.43 and statistically significant (t -statistic = 5.93).

Panel C of Table 7 reports Fama-French three-factor loadings for the value-weighted portfolios sorted by book operating leverage relative to industry peers. The results are different from those for market operating leverage. The portfolio with high book operating leverage has higher *SMB* but

Table 7

Three-factor loadings of portfolios sorted by operating leverages

| Deciles L | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | H | H-L | |
|--|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| <i>A. Value-weighted deciles sorted by market OL</i> | | | | | | | | | | | |
| <i>Alpha</i> | -0.0698 (-0.97) | -0.0760 (-1.23) | 0.0645 (1.05) | 0.0317 (0.54) | 0.2693 (2.85) | 0.1126 (1.49) | 0.3409 (4.41) | 0.1117 (1.29) | 0.2260 (2.35) | 0.3568 (2.89) | 0.4266 (2.94) |
| <i>MktRf</i> | 1.0850 (37.71) | 0.9897 (46.00) | 0.9872 (45.43) | 0.9749 (52.91) | 0.9501 (37.24) | 0.9729 (54.05) | 0.9783 (35.00) | 1.0072 (37.21) | 1.0829 (30.90) | 1.0449 (35.53) | -0.0401 (-1.00) |
| <i>SMB</i> | -0.0164 (-0.40) | -0.0399 (-1.81) | -0.0490 (-1.37) | 0.0265 (0.91) | 0.1416 (2.29) | 0.1212 (4.48) | 0.1759 (2.95) | 0.2456 (4.58) | 0.3820 (6.85) | 0.6115 (10.10) | 0.6279 (7.64) |
| <i>HML</i> | -0.4406 (-7.51) | -0.1147 (-2.81) | -0.0766 (-1.99) | 0.0342 (0.94) | -0.0591 (-0.82) | 0.1244 (3.09) | 0.0390 (0.73) | 0.1723 (2.77) | 0.1193 (2.18) | 0.2200 (4.26) | 0.6606 (8.00) |
| Adj. R^2 | .9031 | .8887 | .8967 | .9055 | .8535 | .8735 | .8373 | .8240 | .8131 | .7762 | .3317 |
| <i>B. Equal-weighted deciles sorted by market OL</i> | | | | | | | | | | | |
| <i>Alpha</i> | -0.5495 (-6.50) | -0.3410 (-4.77) | -0.1916 (-2.84) | -0.1025 (-1.49) | -0.0231 (-0.32) | 0.0121 (0.16) | 0.2382 (3.17) | 0.3150 (3.59) | 0.4031 (3.77) | 0.7396 (5.13) | 1.2891 (8.31) |
| <i>MktRf</i> | 1.1344 (31.00) | 1.1056 (38.54) | 1.0863 (41.78) | 1.0665 (41.20) | 1.0661 (40.19) | 1.0271 (36.62) | 1.0114 (36.83) | 1.0144 (38.27) | 0.9936 (34.11) | 0.9242 (26.81) | -0.2102 (-5.99) |
| <i>SMB</i> | 0.7822 (8.20) | 0.7817 (8.54) | 0.7787 (9.03) | 0.8343 (10.73) | 0.8713 (10.65) | 0.9110 (10.99) | 0.9989 (14.67) | 1.0462 (15.88) | 1.0484 (16.77) | 1.2313 (20.54) | 0.4491 (5.19) |
| <i>HML</i> | -0.1110 (-1.26) | 0.0742 (1.08) | 0.1316 (1.99) | 0.1873 (3.30) | 0.2763 (4.43) | 0.2634 (4.41) | 0.2831 (5.08) | 0.3335 (5.69) | 0.3402 (5.51) | 0.3200 (4.59) | 0.4310 (5.93) |
| Adj. R^2 | .8891 | .9094 | .9064 | .9197 | .9010 | .9028 | .8964 | .8767 | .8504 | .7920 | .2731 |
| <i>C. Value-weighted deciles sorted by book OL</i> | | | | | | | | | | | |
| <i>Alpha</i> | -0.2319 (-2.74) | -0.1119 (-1.71) | -0.0452 (-0.65) | 0.0211 (0.30) | 0.0889 (1.40) | 0.1460 (2.35) | 0.2853 (3.68) | 0.2619 (3.78) | 0.1815 (2.18) | 0.3135 (2.99) | 0.5453 (4.13) |
| <i>MktRf</i> | 1.0589 (35.08) | 1.0717 (61.39) | 0.9969 (43.31) | 1.0008 (50.58) | 1.0326 (44.47) | 0.9571 (47.91) | 0.9603 (40.13) | 0.9935 (59.11) | 1.0005 (39.72) | 0.9694 (37.40) | -0.0894 (-2.23) |
| <i>SMB</i> | -0.0437 (-1.41) | 0.0415 (1.45) | 0.0591 (1.49) | 0.0182 (0.57) | -0.0547 (-1.85) | -0.0167 (-0.63) | -0.0742 (-2.04) | 0.0398 (1.20) | 0.1165 (2.24) | 0.4279 (10.60) | 0.4716 (11.10) |
| <i>HML</i> | 0.0620 (1.43) | 0.0096 (0.26) | -0.1008 (-1.52) | -0.0431 (-1.13) | -0.1613 (-3.67) | -0.1756 (-3.73) | -0.0912 (-1.58) | -0.2225 (-5.49) | -0.2514 (-4.63) | -0.1554 (-2.79) | -0.2174 (-2.78) |
| Adj. R^2 | .8662 | .8966 | .8599 | .8760 | .8944 | .8806 | .8304 | .8703 | .8247 | .8346 | .2311 |
| <i>D. Equal-weighted deciles sorted by book OL</i> | | | | | | | | | | | |
| <i>Alpha</i> | -0.3488 (-4.15) | -0.1862 (-2.34) | -0.0789 (-1.03) | -0.0340 (-0.54) | 0.0937 (1.47) | 0.0809 (1.18) | 0.1426 (1.80) | 0.2119 (2.68) | 0.2501 (2.65) | 0.3367 (2.34) | 0.6854 (4.56) |
| <i>MktRf</i> | 1.0849 (35.21) | 1.0680 (38.86) | 1.0643 (40.87) | 1.0486 (40.41) | 1.0567 (44.91) | 1.0407 (38.55) | 1.0224 (43.06) | 1.0406 (33.15) | 1.0234 (34.68) | 0.9839 (24.54) | -0.1010 (-3.32) |
| <i>SMB</i> | 0.7829 (8.61) | 0.8163 (9.61) | 0.8272 (9.90) | 0.8415 (10.24) | 0.8887 (12.37) | 0.9125 (12.89) | 0.9841 (15.40) | 0.9833 (13.16) | 1.0484 (15.94) | 1.1917 (16.47) | 0.4088 (5.76) |
| <i>HML</i> | 0.3640 (5.25) | 0.3007 (4.59) | 0.2849 (4.44) | 0.2336 (3.50) | 0.2310 (3.96) | 0.1886 (3.74) | 0.1509 (2.43) | 0.1598 (2.77) | 0.1589 (2.55) | 0.0189 (0.19) | -0.3451 (-3.36) |
| Adj. R^2 | .8974 | .9101 | .9032 | .9051 | .9114 | .9136 | .8950 | .8929 | .8688 | .7725 | .2149 |

We estimate time-series regressions of portfolio excess returns (raw returns minus the risk-free rate) on Fama-French three factors: the market factor (*MktRf*), small-minus-big (*SMB*), and high-minus-low (*HML*). We sort stocks into 10 deciles in June of year t according to their operating leverage measures within each of the [Fama and French \(1997\)](#) 17

lower *HML* loadings. Decile 10 has an *SMB* loading of 0.43, and decile 1 has an *SMB* loading of -0.04. The difference is 0.47 and statistically significant (t -statistic = 11.10). However, decile 10 has an *HML* loading of -0.16, and decile 1 has an *HML* loading of 0.06. The difference is -0.22 and statistically significant (t -statistic = -2.78). Therefore, stocks with higher book operating leverage are likely to be low book-to-market stocks. The results for equal-weighted returns for portfolios sorted by book operating leverage in panel D also show that book operating leverage is likely to be negatively correlated with book-to-market. For equal-weighted portfolios, decile 10 has an *HML* loading of 0.02 and decile 1 has an *HML* loading of 0.36. The difference is -0.35 and statistically significant (t -statistic = -3.36).

The negative association between book operating leverage and book-to-market allows us to examine whether book-to-market or operating leverage is more fundamental. If book-to-market were the fundamental variable, then the Fama-French three-factor model suggests that stocks with higher book operating leverage should earn lower returns. But our earlier results show that stocks with higher book operating leverage actually earn higher returns than stocks with low book operating leverage. We make two remarks regarding this finding. First, this finding explains why the Fama-French three-factor model does a worse job than the CAPM in explaining the returns of portfolios sorted by book operating leverage. Second, this finding suggests that operating leverage is likely to be a more fundamental variable than book-to-market because part of the variation in operating leverage that is negatively correlated with book-to-market (book operating leverage) still predicts higher returns.¹¹

In sum, we find that both market and book operating leverages predict higher returns. The returns of both value-weighted and equal-weighted portfolios sorted by operating leverage cannot be explained by common factors, even after adjustment for nonsynchronous price movements.¹² More important, the information contained in market operating leverage that is not mechanically related to book-to-market—that is, book operating leverage—cannot be explained by book-to-market. Therefore, we conclude that the association between operating leverage and returns cannot be fully explained by common factors, including the book-to-market effect.

4. Can Operating Leverage Help Explain the Book-to-Market Effect?

We now examine whether operating leverage can help explain the book-to-market effect and other promising anomalies in the literature. We first

¹¹ Previous papers suggest that book-to-market simply may be a proxy for financial leverage (D/ME). However, financial leverage does not pass this test. We can view financial leverage as the product of book leverage and book-to-market ($D/ME = D/BE \cdot BE/ME$). Part of the variation in financial leverage that is not directly related to book-to-market (D/BE) actually predicts lower returns (see Fama and French 1992).

¹² For details, see Section 4 of the Internet Appendix.

provide tests from the operating leverage decomposition and then examine whether an operating leverage factor can explain returns of portfolios sorted by book-to-market.

4.1 Evidence from decomposing operating leverage

In the previous section, we have shown that book operating leverage predicts higher returns despite its negative association with book-to-market. If operating leverage is indeed the fundamental variable, then there is a quantitative restriction of the relative magnitude of the book operating leverage effect and the book-to-market effect. To show this, we decompose our logarithm of market operating leverage into four components:

$$\ln\left(\frac{FC}{MA}\right) = \ln\left(\frac{FC}{BA}\right) + \ln\left(\frac{BE}{ME}\right) + \ln\left(\frac{BA}{BE}\right) + \ln\left(\frac{ME}{MA}\right). \quad (4)$$

The above equation says that log market operating leverage is related to log book operating leverage, book-to-market equity, and two terms related to financial leverage (book financial leverage and market financial leverage). If book-to-market equity affects stock returns only to the extent that it affects market operating leverage, then the above decomposition implies that the coefficients for $\ln(FC/BA)$ and $\ln(BM)$ should be the same. We make no predictions about the signs of the other two variables that are related to financial leverages because financial leverages may affect stock returns on their own. We now test this implication in the Fama-MacBeth regressions.

Table 8 presents the results. Column 1 estimates univariate regressions of returns on log market operating leverage. The average coefficient is 0.533 with a t -statistic of 8.43. Column 2 estimates univariate regressions of returns on log book operating leverage. The average coefficient is 0.302 with a t -statistic of 4.31. Column 3 shows that the univariate effect of log book-to-market equity is 0.447 and is also highly statistically significant (t -statistic = 7.31).

In column 4, we estimate bivariate regressions of returns on log book operating leverage and log book-to-market equity. The coefficient for log book operating leverage is 0.406, and the coefficient for log book-to-market is 0.494. These two coefficients are similar in magnitude. The difference is -0.088 and is statistically indistinguishable from zero. In column 5, we use all four variables in the above decomposition. The coefficient for log book operating leverage is 0.404, and the coefficient for log book-to-market is 0.585. These coefficients are on the same order of magnitude, although the difference of -0.181 is statistically significant. In column 6, we further control for other variables, such as size. The coefficient for log book operating leverage is 0.270, and the coefficient for log book-to-market is 0.340. The difference is -0.069 and is statistically insignificant with a t -statistic of -0.98. Again, the coefficients for log of operating leverage measures are still significant in

Table 8
Fama-MacBeth return regressions: Decomposition of market OL

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|------------------------|------------------|------------------|------------------|--------------------|--------------------|--------------------|------------------|--------------------|
| $\ln(FC/MA)$ | 0.5330 (8.43) | | | | | | | |
| $\ln(FC/BA)$ | | 0.3017 (4.31) | | 0.4061 (5.68) | 0.4036 (5.58) | 0.2701 (5.22) | | |
| $\ln(FC/\text{lag}MA)$ | | | | | | | 0.3461 (6.29) | |
| $\ln(FC/\text{lag}BA)$ | | | | | | | | 0.2743 (5.60) |
| $\ln BM$ | | | 0.4468 (7.31) | 0.4943 (7.96) | 0.5848 (7.25) | 0.3396 (4.85) | | 0.3589 (4.60) |
| $\ln(BA/BE)$ | | | | | 0.2659 (2.12) | 0.0244 (0.24) | | 0.0640 (0.52) |
| $\ln(ME/MA)$ | | | | | 0.2051 (1.98) | 0.0572 (0.64) | | 0.1283 (0.99) |
| $\ln Size$ | | | | | | -0.0867 (-2.48) | | -0.0962 (-2.63) |
| gBA | | | | | | -0.2911 (-3.80) | | -0.6648 (-5.96) |
| $Accrual$ | | | | | | -0.8016 (-4.08) | | -0.7544 (-2.73) |
| IK | | | | | | -0.1576 (-3.05) | | -0.1095 (-1.53) |
| $Momentum$ | | | | | | 0.2496 (1.12) | | 0.1028 (0.42) |
| $\ln AGE$ | | | | | | 0.0055 (0.15) | | 0.0152 (0.38) |
| Avg. obs. | 2,509 | 2,509 | 2,509 | 2,509 | 2,509 | 2,509 | 2,388 | 2,388 |
| Adj. R^2 | .0267 | .0249 | .0285 | .0303 | .0343 | .0538 | .0324 | .0503 |
| $\ln(FC/BA)-\ln BM$ | | | | -0.0882 (-1.28) | -0.1811 (-2.14) | -0.0694 (-0.98) | | |

This table reports Fama-MacBeth return regression results. Monthly returns in percentages from July of year t to June of year $t+1$ are matched with accounting variables for fiscal years that end in year $t-1$. Here, we break the logarithm of market operating leverage $\{ \ln OL = \ln[(DA+SGA)/MA] \}$ into log book operating leverage $\ln(FC/BA) = \ln[(DA+SGA)/BA]$, log book financial leverage $\ln(BA/BE)$, log book-to-market $\ln(BE/ME)$, and log market financial leverage $\ln(ME/MA)$. DA is depreciation and amortization; SGA is selling, general, and administrative expenses; BA is total book assets; BE is book equity; ME is the same as the size measure; and MA is the market value of assets at the fiscal year-end. We then test whether the two components $\ln(FC/BA)$ and $\ln(BE/ME)$ have equal coefficients in the Fama-MacBeth regression. *Size* is the capitalization of the firm at the end of June (in \$M). *BM* is the book-to-market equity ratio. *FL* is financial leverage, which is defined by the ratio of total liabilities to total book assets. *gBA* is the annual growth rate of total book assets. *Accrual* is measured as in Sloan (1996). *IK* is the investment-to-capital ratio. *Momentum* is the past 6-month cumulative returns (skipping a month). *lnAGE* is the log of one plus the number of years since the firm's first appearance in CRSP. Note that we take logarithms for both the size and the book-to-market-equity in the regressions. In column 7, *lagMA* is the market value of assets at the end of fiscal year $t-2$. In column 8, *lagBA* is the book value of assets at the end of fiscal year $t-2$. The sample covers the period from July 1963 to June 2016. The industry fixed effect is controlled in all specifications. We use the 17-industry classification in Fama and French (1997). Explanatory variables are winsorized at the 1% and 99% levels every month. Reported in parentheses are Newey and West (1987) t -statistics adjusted for heteroskedasticity and autocorrelation.

columns 7 and 8 when using the market value and book value of assets in the previous fiscal year as scaling variables for alternative market and book operating measures, respectively.

By and large, we conclude that the effect of book operating leverage is similar in magnitude to the book-to-market effect. In other words, this test supports the view that book operating leverage and book-to-market matter

to the extent that they affect operating leverage, and operating leverage is the fundamental variable.

4.2 Evidence from time-series regressions

We now examine whether the return spread of the high-minus-low operating leverage portfolios can serve as a factor and explain the returns of portfolios that are sorted by the book-to-market ratio. We describe the construction of the operating leverage factor (*OLFactor*) later in Section 6. In this test, we use the book-to-market deciles as our testing portfolios.

We test whether the 10 value-weighted or equal-weighted returns of portfolios sorted by book-to-market can be explained by our operating leverage factor. We use the market factor (*MktRf*) and our operating leverage factor to explain the returns of portfolios. Section 5.1 of the [Internet Appendix](#) (Table IA.5) reports the results, and we summarize the key findings here. The GRS test fails to reject the hypothesis that all 10 value-weighted or equal-weighted alphas are jointly zero. In other words, the market factor and our operating leverage factor help explain the returns of the book-to-market deciles.

Overall, the decomposition test in Section 5.1 shows that the coefficient for book operating leverage is similar in magnitude to that of book-to-market. The GRS test in Section 5.2 cannot reject the hypothesis that alphas are jointly zero for both value-weighted and equal-weighted portfolios. Therefore, we conclude that operating leverage helps explain the book-to-market effect.

5. Exploring Operating Leverage as a Factor

In this section, we empirically examine whether measures of operating leverage are important in explaining returns in a multifactor model. We view these tests as exploratory. To construct the operating leverage factor, we sort stocks into two groups, small and big, by the median NYSE size. We sort stocks into three groups (low 30%, middle 40%, and high 30%) independently by *market OL* within each of the industries in the 17-industry classification in [Fama and French \(1997\)](#). We calculate the equal-weighted return for the portfolios from the intersection of two size and three *market OL* groups.¹³ The operating leverage factor (*OLFactor*) is the return spread between the simple average of the returns on two high *market OL* groups and the simple average of the returns on two low *market OL* groups.

In choosing factors, researchers typically use the right-hand-side (RHS) approach, where they focus on comparing factors, or the left-hand-side

¹³ We report the results of the value-weighted OL factor in Section 5 of the [Internet Appendix](#). Also, as shown in Section 5.4 of the [Internet Appendix](#), to make better use of information from our operating leverage measure, we mainly report the equal-weighted operating leverage factor (*OLFactor*) in the main text. The factor is available at <https://sites.google.com/view/luafengjasonchen/home/operating-leverage>.

(LHS) approach, where they focus on the alpha from LHS portfolios (Fama and French 2018). We examine both approaches and start with the LHS approach.

We now employ the LHS approach and examine whether our factor models can explain the anomalies in the literature. This approach brings more economic content to the factor model tests.

To this end, we follow the procedure in Hou, Xue, and Zhang (2015) and construct the 80 anomaly variables because they comprehensively cover six categories of anomalies: momentum, value-versus-growth, investment, profitability, intangibles, and trading frictions. Table IA.10 of the Internet Appendix describes all 80 anomaly variables. Furthermore, the market operating leverage and book operating leverage in this paper are also included in the anomaly set. Finally, we select 39 anomaly variables in which the average return of the high-minus-low decile is significant at the 5% level during the sample period from July 1963 to June 2016.

Table 9 reports the excess returns and the intercepts from time-series regressions of CAPM, FF3, FF5, q -factor, OL2F, Misp-factor, and OL3F models. We find that 35 anomalies survive after being adjusted by the CAPM, 32 anomalies survive after being adjusted by the Fama and French three-factor model, and 25 anomalies survive after being adjusted by the Fama and French five-factor model. Ten anomalies survive after being adjusted by the q -factor model, and nine anomalies survive after being adjusted by the Misp-factor model.

Despite having only two factors in the OL2F model, 24 anomalies remain after being adjusted by the market factor and our market operating leverage factor. This means that the OL2F model's power in explaining anomalies is better than the Fama and French three-factor model (32 anomalies remain) and is at least as powerful as the Fama and French five-factor model (25 anomalies remain). In addition, after we add the ROE profitability factor, only 5 anomalies survive the OL3F model: cumulative abnormal returns around earnings announcements (Abr-1 and Abr-6), net operating assets (NOA), changes in property, plant, and equipment plus changes in inventory scaled by assets ($\Delta PI/A$), and inventory changes (IvC). These five anomalies also survive the Fama and French models and the q -factor model, and three of them survive the Misp-factor model.

The overall findings in this section suggest that a simple two-factor model (the market factor, $MktRf$, and our operating leverage factor, $OLFactor$) is at least as good as, but does not subsume, the Fama and French five-factor model in explaining anomalies. When the profitability factor (ROE) is added to the two-factor model, the three-factor model is at least as good as the q -factor model. Furthermore, when implementing GRS tests on portfolios sorted by 5*5 on any two variables of $Size$, BM , OP , and INV , we find a similar result that the two-

Table 9.
Significant anomalies in the broad cross-section

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 |
|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------------------------------|-------|-------|
| | SUE-1 | R6-1 | R6-6 | R6-12 | R11-1 | Abr-1 | Abr-6 | RE-1 | I-Mom | B/M | Rev | CF/P | NO/P | Dur | ACI | I/A | NOA | API/A | IG | NSI | CEI |
| <i>ExRet</i> | 0.38 | 0.74 | 0.93 | 0.65 | 1.29 | 0.81 | 0.36 | 0.72 | 0.64 | 0.44 | -0.47 | 0.39 | 0.55 | -0.40 | -0.34 | -0.39 | -0.59 | -0.55 | -0.48 | -0.66 | -0.51 |
| <i>t-stat</i> | 3.46 | 2.72 | 4.03 | 3.62 | 4.82 | 6.29 | 3.84 | 2.72 | 3.33 | 2.25 | -2.06 | 2.01 | 2.32 | -2.02 | -2.74 | -2.51 | -4.66 | -4.11 | -4.17 | -4.23 | -3.03 |
| <i>Alpha</i> | 0.45 | 0.89 | 1.00 | 0.69 | 1.42 | 0.84 | 0.37 | 0.75 | 0.70 | 0.48 | -0.47 | 0.48 | 0.79 | -0.55 | -0.32 | -0.50 | -0.61 | -0.61 | -0.53 | -0.76 | -0.73 |
| FF3 | 4.26 | 3.59 | 4.71 | 3.92 | 5.85 | 6.73 | 4.13 | 3.09 | 3.71 | 2.39 | -2.09 | 2.43 | 3.27 | -2.80 | -2.45 | -3.07 | -4.81 | -4.47 | -4.50 | -4.94 | -4.90 |
| <i>t-stat</i> | 0.50 | 1.04 | 1.18 | 0.91 | 1.62 | 0.92 | 0.44 | 0.94 | 0.77 | -0.12 | 0.03 | -0.04 | 0.43 | -0.03 | -0.32 | -0.18 | -0.69 | -0.45 | -0.35 | -0.61 | -0.53 |
| <i>Alpha</i> | 4.44 | 4.29 | 5.64 | 5.73 | 6.95 | 6.65 | 4.53 | 4.02 | 3.96 | -1.07 | 0.17 | 0.17 | 2.42 | -0.24 | -2.67 | -1.45 | -5.13 | -3.38 | -3.27 | -4.68 | -4.43 |
| FF5 | 0.37 | 0.84 | 1.08 | 0.87 | 1.39 | 0.93 | 0.50 | 0.65 | 0.67 | -0.18 | 0.05 | -0.13 | -0.01 | 0.09 | -0.28 | 0.03 | -0.66 | -0.39 | -0.21 | -0.30 | -0.26 |
| <i>t-stat</i> | 3.13 | 2.47 | 3.81 | 4.50 | 4.09 | 6.48 | 4.83 | 2.60 | 2.41 | 1.61 | 0.30 | -1.06 | 0.05 | -0.07 | -2.15 | 0.29 | -4.27 | -3.28 | -2.05 | -2.38 | -2.50 |
| <i>Alpha</i> | 0.09 | 0.03 | 0.32 | 0.20 | 0.41 | 0.75 | 0.32 | -0.08 | 0.11 | 0.12 | -0.21 | 0.05 | 0.12 | -0.07 | -0.12 | 0.02 | -0.55 | -0.30 | -0.13 | -0.25 | -0.30 |
| <i>q-factor</i> | 0.78 | 0.07 | 1.01 | 0.93 | 1.05 | 5.00 | 2.80 | -0.32 | 0.37 | 0.72 | -1.25 | 0.23 | 0.71 | -0.34 | -0.81 | 0.18 | -3.10 | -2.22 | -1.17 | -1.86 | -2.16 |
| OL2F | 0.47 | 0.80 | 0.99 | 0.81 | 1.35 | 1.00 | 0.48 | 0.99 | 0.48 | -0.36 | 0.26 | -0.31 | 0.09 | 0.17 | -0.32 | 0.16 | -0.54 | -0.32 | -0.15 | -0.33 | -0.28 |
| <i>t-stat</i> | 3.33 | 2.80 | 4.19 | 4.85 | 4.32 | 7.14 | 4.64 | 3.39 | 2.08 | -2.07 | 1.22 | -1.71 | 0.51 | 0.99 | -1.93 | 1.19 | -3.83 | -2.14 | -1.33 | -2.55 | -2.08 |
| Misp-factor | 0.17 | -0.29 | 0.10 | 0.26 | 0.07 | 0.68 | 0.31 | 0.31 | -0.13 | -0.12 | 0.18 | 0.00 | -0.25 | 0.11 | -0.12 | 0.21 | -0.22 | -0.14 | -0.11 | -0.08 | -0.11 |
| <i>t-stat</i> | 1.26 | -1.09 | 0.47 | 1.45 | 0.30 | 4.50 | 2.77 | 1.06 | -0.69 | -0.81 | 0.92 | 0.02 | -1.59 | 0.66 | -0.86 | 1.73 | -1.93 | -0.99 | -0.97 | -0.68 | -0.99 |
| OL3F | 0.14 | -0.03 | 0.31 | 0.19 | 0.38 | 0.83 | 0.36 | 0.08 | 0.00 | 0.12 | -0.38 | -0.15 | -0.15 | 0.05 | -0.24 | -0.01 | -0.47 | -0.47 | -0.20 | -0.10 | -0.18 |
| <i>t-stat</i> | 1.05 | -0.08 | 0.97 | 0.86 | 0.98 | 5.29 | 2.86 | 0.36 | -0.01 | 0.61 | -1.67 | -0.65 | -0.59 | 0.20 | -1.25 | -0.08 | -2.88 | -3.10 | -1.58 | -0.55 | -1.07 |
| | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | | | |
| | IvG | IvC | OA | POA | PTA | ROE | ROA | GP/A | F | TES | RS | NEI | OC/A | Ad/M | RD/M | OL | MOL | BOL | Number of Significant Alphas | | |
| <i>ExRet</i> | -0.36 | -0.58 | -0.30 | -0.40 | -0.37 | 0.69 | 0.62 | 0.37 | 0.56 | 0.42 | 0.30 | 0.33 | 0.61 | 0.69 | 0.63 | 0.40 | 0.77 | 0.53 | | | |
| <i>t-stat</i> | -2.88 | -4.51 | -2.47 | -3.02 | -2.99 | 2.79 | 2.85 | 2.67 | 2.21 | 2.90 | 2.01 | 2.92 | 5.05 | 2.78 | 2.36 | 2.44 | 3.83 | 3.52 | | | |
| <i>Alpha</i> | -0.44 | -0.64 | -0.34 | -0.47 | -0.48 | 0.86 | 0.80 | 0.37 | 0.79 | 0.28 | 0.29 | 0.33 | 0.67 | 0.73 | 0.43 | 0.33 | 0.78 | 0.51 | | 35 | |
| <i>t-stat</i> | -3.75 | -4.79 | -2.75 | -3.62 | -4.03 | 3.60 | 3.91 | 2.57 | 3.49 | 1.93 | 1.90 | 2.95 | 5.19 | 2.85 | 1.69 | 1.87 | 3.73 | 3.26 | | | |
| FF3 | -0.27 | -0.51 | -0.35 | -0.29 | -0.30 | 1.03 | 0.97 | 0.53 | 0.68 | 0.46 | 0.55 | 0.52 | 0.61 | 0.14 | 0.23 | 0.37 | 0.43 | 0.55 | | 32 | |
| <i>t-stat</i> | -2.32 | -3.81 | -3.01 | -2.66 | -2.72 | 4.73 | 5.27 | 3.87 | 3.56 | 3.96 | 4.22 | 4.98 | 5.56 | 0.81 | 0.92 | 2.36 | 2.94 | 4.13 | | | |
| <i>Alpha</i> | -0.16 | -0.54 | -0.53 | -0.19 | -0.15 | 0.50 | 0.57 | 0.23 | 0.33 | 0.53 | 0.46 | 0.34 | 0.37 | -0.14 | 0.50 | 0.04 | 0.36 | 0.46 | | 25 | |
| FF5 | -1.46 | -4.55 | -4.47 | -1.74 | -1.40 | 3.44 | 3.85 | 1.91 | 1.79 | 4.08 | 3.14 | 3.30 | 3.31 | -0.75 | 1.93 | 0.30 | 2.60 | 3.04 | | | |
| <i>t-stat</i> | -1.46 | -4.55 | -4.47 | -1.74 | -1.40 | 3.44 | 3.85 | 1.91 | 1.79 | 4.08 | 3.14 | 3.30 | 3.31 | -0.75 | 1.93 | 0.30 | 2.60 | 3.04 | | | |
| <i>q-factor</i> | -0.03 | -0.45 | -0.54 | -0.16 | -0.23 | -0.08 | 0.06 | 0.13 | 0.18 | 0.28 | 0.17 | 0.04 | 0.18 | 0.05 | 0.72 | -0.02 | 0.33 | 0.36 | | 10 | |
| <i>t-stat</i> | -0.25 | -2.75 | -3.94 | -1.39 | -2.02 | -0.53 | 0.46 | 0.90 | 0.90 | 1.64 | 1.13 | 0.42 | 1.47 | 0.19 | 2.66 | -0.13 | 1.91 | 2.21 | | | |
| OL2F | -0.10 | -0.33 | -0.16 | -0.01 | -0.09 | 0.93 | 0.89 | 0.36 | 0.44 | 0.42 | 0.62 | 0.41 | 0.30 | -0.37 | 0.07 | 0.29 | -0.03 | 0.40 | | 24 | |
| <i>t-stat</i> | -0.86 | -2.48 | -1.25 | -0.08 | -0.77 | 4.05 | 4.37 | 2.49 | 2.44 | 2.80 | 3.83 | 3.39 | 2.35 | -1.61 | 0.24 | 1.56 | -0.18 | 2.35 | | | |

| | | | | | | | | | | | | | | | | | | | | |
|-------------|-----------|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|------|-------|------|-------|------|-------|------|------|---|
| Misp-factor | α | -0.01 | -0.28 | -0.39 | -0.17 | -0.05 | 0.31 | 0.26 | 0.05 | 0.22 | 0.43 | 0.36 | 0.23 | 0.19 | -0.01 | 0.07 | -0.09 | 0.35 | 0.27 | 9 |
| | t -stat | -0.11 | -2.11 | -2.90 | -1.49 | -0.52 | 1.70 | 1.53 | 0.37 | 1.16 | 2.80 | 2.61 | 2.00 | 1.55 | -0.02 | 0.32 | -0.73 | 2.26 | 2.01 | |
| OL3F | α | -0.12 | -0.49 | -0.28 | -0.04 | -0.14 | -0.19 | -0.11 | -0.08 | -0.17 | 0.24 | 0.18 | -0.07 | 0.04 | -0.08 | 0.63 | -0.03 | 0.12 | 0.31 | 5 |
| | t -stat | -0.92 | -2.82 | -1.74 | -0.23 | -0.90 | -1.15 | -0.74 | -0.56 | -0.81 | 1.24 | 1.15 | -0.63 | 0.27 | -0.27 | 1.81 | -0.15 | 0.57 | 1.52 | |

We construct the 80 anomaly variables¹⁶ from Hou, Xue, and Zhang (2015) and test the explanatory power of the three prominent asset pricing models and two base models in this paper on 37 significant anomaly variables as well as the market operating leverage (MOL) and book operating leverage (BOL). "Significant" in this table means statistical significance at the 5% level. The models include (1) CAPM; (2) FF3 ($MktRF$, SMB , HML); (3) FF5 ($MktRF$, SMB , HML , RMW , CMA); (4) q -factors from Hou, Xue, and Zhang (2015); (5) OL2F ($MktRF$, $OLFactor$); (6) Misp-factor (mispricing factors from Stambaugh and Yuan 2017); and (7) OL3F ($MktRF$, $OLFactor$, ROE). The operating leverage factor ($OLFactor$) is constructed as follows. In June of year t , we first sort stocks into two groups, small and big, by the median NYSE size. Independently, we sort stocks into three groups (low, 30%, middle 40%, and high 30%) by $market\ OL$ within each of the industries in the 17-industry classification in Fama and French (1997). Monthly returns are in percentages from July of year t to June of year $t+1$. We calculate the equal-weighted return for the portfolios from the intersection of two size and three $market\ OL$ groups. The operating leverage factor $OLFactor$ is the return spread between the simple average of the returns on two high $market\ OL$ groups and the simple average of the returns on two low $market\ OL$ groups. The models are presented from top to bottom in order of increasing squared Sharpe ratios, as reported in Table IA.9 of the Internet Appendix. $ExRet$ is the average return of the high-minus-low decile, and α is the intercept of asset pricing models of the high-minus-low decile. The q -factors cover the period from January 1967 to June 2016, and the other factors cover the period from July 1963 to June 2016. The t -statistics are adjusted for heteroscedasticity and autocorrelation following Newey and West (1987).

factor model (the market factor, $MktRf$, and our operating leverage factor, $OLFactor$) works at least as well as the Fama and French five-factor model.¹⁴

In addition to above LHS approach, we next provide a RHS approach to testing the explanatory power of our operating leverage factor by spanning regressions and pairwise tests of squared Sharpe ratios. To save space, we report the results of the RHS approach in Section 5.3 (Table IA.8) and 5.4 (Table IA.9) of the [Internet Appendix](#) and only discuss the main findings here. We first examine whether our operating leverage factor spans the prominent factors from [Barillas and Shanken \(2018\)](#). We find that the market factor and our operating leverage factor can explain the size factors, value factors, and investment factors reasonably well. The profitability factors and momentum factors also could be explained when the ROE factor is added to our model. Since [Barillas and Shanken \(2017\)](#) develop the insight that the maximum Sharpe ratio of tradable factors from an asset pricing model can be directly used to compare factor models, we then calculate the Sharpe ratios and follow [Barillas et al. \(2020\)](#) to perform pairwise tests of equality of the squared Sharpe ratios. The results suggest that the $OLFactor$ and the market factor have already performed as well as the Fama and French five-factor model. Overall, the results indicate that the OL2F does not subsume the Fama and French five-factor model as profitability is not explained by the OL2F. When the profitability factor ROE is added to the model, the OL3F model performs better than the q -factor model.

6. Relation to Previous Studies

6.1 Total operating costs

We know of two accounting-based measures of operating leverage that have been used in the literature on stock returns. [Novy-Marx \(2011\)](#) uses $(SGA+COGS)/BA$ in his tests for the operating leverage hypothesis. [Ferri and Jones \(1979\)](#) use the ratio of net fixed assets to total assets as a measure for operating leverage, which is also utilized in [García-Feijóo and Jorgensen \(2010\)](#) as a secondary measure.

In this section, we first compare the return predictability of our measure of operating leverage with the operating leverage measure from [Novy-Marx \(2011\)](#) using cross-sectional Fama-MacBeth regressions. [Table 10](#) reports the results. In column 1, $NMOL$ positively and significantly predicts future stock returns from the univariate regression with a coefficient of 0.189 (t -statistic = 5.48). The coefficient of $NMOL$ declines (0.115) and is still statistically significant with other control variables in column 2. Columns 3 and 4 report the regressions of stock returns on market operating leverage, repeated

¹⁴ Returns of the portfolios sorted by 5*5 on any two variables of *Size*, *BM*, *OP*, and *INV* are downloaded from Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. The results of GRS tests on bivariate-sorted portfolios, which are not reported for simplicity, are available on request.

from [Table 5](#). We then jointly estimate regressions of returns on *NMOL* and market operating leverage in columns 5 and 6. In column 5, the coefficient of market operating leverage is 1.626, which is almost the same as 1.615 in column 3. However, the coefficient of *NMOL* becomes -0.004 and statistically insignificant (*t*-statistic = -0.13). When all other variables are controlled in column 6, the coefficient of *market OL* is still positive and significant at

leverage is also significant at 0.504 (t -statistic = 2.17) without other control variables and 0.513 (t -statistic = 2.91) with all other control variables. Meanwhile, the coefficient of *NMOL* becomes smaller (0.118, t -statistic = 2.54) when only book operating leverage is added and becomes indistinguishable from zero (0.047, t -statistic = 1.21) when other control variables are included. These results suggest that our market operating leverage and book operating leverage measures are more robust predictors of future stock returns than *NMOL*. The results are similar when we employ the log of operating leverage measures, as shown in Table IA.12 in the [Internet Appendix](#). The overall results verify that market operating leverage and book operating leverage in this paper contain information over and above

Table 11
Fama-MacBeth regressions of returns on various costs

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|----------------|------------------|------------------|------------------|------------------|------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| $\ln(DA/BA)$ | 0.2333 (4.84) | | | 0.2127 (4.77) | 0.1988 (4.45) | 0.1268 (3.41) | | | 0.1045 (2.89) | 0.1027 (2.78) | | |
| $\ln(SGA/BA)$ | | 0.2186 (3.88) | | 0.2046 (3.76) | 0.1878 (3.10) | | 0.2102 (5.04) | | 0.2043 (4.97) | 0.2107 (4.67) | | |
| $\ln(COGS/BA)$ | | | 0.1210 (2.71) | | 0.0639 (1.24) | | | 0.0239 (0.66) | | -0.0294 (-0.73) | | |
| $\ln(SGA/TC1)$ | | | | | | | | | | | 0.2022 (3.74) | |
| $\ln(TC1/BA)$ | | | | | | | | | | | 0.2103 (4.76) | |
| $\ln(FC/TC2)$ | | | | | | | | | | | | 0.2682 (3.85) |
| $\ln(TC2/BA)$ | | | | | | | | | | | | 0.2697 (5.37) |
| $\ln BM$ | | | | | | 0.2566 (3.46) | 0.3385 (4.84) | 0.2479 (3.40) | 0.3362 (4.81) | 0.3381 (5.05) | 0.3370 (4.95) | 0.3400 (4.96) |
| $\ln(BA/BE)$ | | | | | | -0.0489 (-0.46) | 0.0223 (0.22) | -0.0655 (-0.62) | 0.0191 (0.19) | 0.0198 (0.20) | 0.0131 (0.13) | 0.0148 (0.14) |
| $\ln(ME/MA)$ | | | | | | 0.0230 (0.25) | 0.0583 (0.65) | 0.0175 (0.19) | 0.0530 (0.59) | 0.0544 (0.62) | 0.0559 (0.63) | 0.0568 (0.64) |
| $\ln Size$ | | | | | | -0.1183 (-3.23) | -0.0861 (-2.46) | -0.1161 (-3.11) | -0.0883 (-2.51) | -0.0889 (-2.52) | -0.0860 (-2.43) | -0.0859 (-2.44) |
| gBA | | | | | | -0.3616 (-4.67) | -0.3013 (-3.84) | -0.3688 (-4.67) | -0.2941 (-3.80) | -0.3026 (-3.97) | -0.3042 (-3.90) | -0.2926 (-3.81) |
| $Accrual$ | | | | | | -0.6764 (-3.43) | -0.9313 (-4.60) | -0.9516 (-4.86) | -0.7316 (-3.72) | -0.7324 (-3.95) | -0.9542 (-4.99) | -0.8459 (-4.62) |
| IK | | | | | | -0.1134 (-1.99) | -0.1553 (-2.85) | -0.1215 (-2.20) | -0.1384 (-2.52) | -0.1280 (-2.39) | -0.1460 (-2.71) | -0.1449 (-2.69) |
| $Momentum$ | | | | | | 0.2907 (1.31) | 0.2653 (1.19) | 0.2853 (1.28) | 0.2599 (1.17) | 0.2493 (1.13) | 0.2567 (1.16) | 0.2578 (1.16) |
| $\ln AGE$ | | | | | | 0.0161 (0.45) | -0.0001 (-0.00) | 0.0096 (0.29) | 0.0032 (0.09) | 0.0057 (0.17) | -0.0007 (-0.02) | 0.0047 (0.13) |

(continued)

Table 11
Continued

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|------------------------------|-------|-------|-------|------------------|------------------|-------|-------|-------|--------------------|--------------------|--------------------|--------------------|
| Avg. obs. | 2,490 | 2,490 | 2,490 | 2,490 | 2,490 | 2,490 | 2,490 | 2,490 | 2,490 | 2,490 | 2,490 | 2,490 |
| Adj. R^2 | .0245 | .0251 | .0248 | .0262 | .0279 | .0540 | .0541 | .0542 | .0546 | .0553 | .0547 | .0547 |
| $\ln(DA/BA) - \ln(SGA/BA)$ | | | | 0.0081 (0.14) | 0.0110 (0.18) | | | | -0.0998 (-2.25) | -0.1080 (-2.40) | | |
| $\ln(DA/BA) - \ln(COGS/BA)$ | | | | | 0.1349 (2.28) | | | | | 0.1321 (2.60) | | |
| $\ln(SGA/BA) - \ln(COGS/BA)$ | | | | | 0.1239 (1.51) | | | | | 0.2400 (4.27) | | |
| $\ln(SGA/TC1) - \ln(TC1/BA)$ | | | | | | | | | | | -0.0081 (-0.19) | |
| $\ln(FC/TC2) - \ln(TC2/BA)$ | | | | | | | | | | | | -0.0015 (-0.03) |

This table reports Fama-MacBeth return regression results. Monthly returns in percentages from July of year t to June of year $t+1$ are matched with accounting variables for fiscal years that end in year $t-1$. DA is depreciation and amortization; SGA is selling, general, and administrative expenses; COGS is cost of goods sold; fixed costs (FC) are defined as the sum of DA and SGA; the first total costs ($TC1$) are defined as the sum of SGA and COGS; the second total costs ($TC2$) are defined as the sum of DA, SGA, and COGS; BA is total book assets; BE is book equity; ME is the same as the size measure; and MA is the market value of assets at the fiscal year-end. We then test whether the ratios of different costs to total book assets have equal coefficients in the Fama-MacBeth regression. $Size$ is the capitalization of the firm at the end of June (in \$M). BM is the book-to-market equity ratio. FL is financial leverage, which is defined as the ratio of total liabilities to total book assets. $Accrual$ is measured as in Sloan (1996). IK is the investment-to-capital ratio. $Momentum$ is the past 6-month cumulative returns (skipping a month). $\ln AGE$ is the log of one plus the number of years since the firm's first appearance in CRSP. Note that we take logarithms for both size and book-to-market equity in the regressions. The sample covers the period from July 1983 to June 2016. The industry fixed effect is controlled in all specifications. We use the 17-industry classification in Fama and French (1997). Explanatory variables are winsorized at the 1% and 99% levels every month. Reported in parentheses are Newey and West (1987) t -statistics adjusted for heteroscedasticity and autocorrelation.

Next, we explore a different way to examine the relation between our measure and Novy-Marx's measure. Specifically, we decompose our log book operating leverage measure into two components:

$$\ln\left(\frac{FC}{BA}\right) = \ln\left(\frac{FC}{TC}\right) + \ln\left(\frac{TC}{BA}\right), \quad (5)$$

where TC is the total costs. Novy-Marx (2011) decomposes operating leverage into the level of gearing and operational inflexibility. His proxy for operating leverage, TC/BA , basically captures the level of gearing. Novy-Marx (2011) is aware of this and acknowledges that this measure does not explicitly account for operational inflexibility in his empirical analysis. Both analyses in Novy-Marx (2011) and in our Section 3 show that operational inflexibility can be captured by FC/TC . We explore two specifications of fixed costs and total costs. In the first specification, we follow Novy-Marx (2011) and only use SGA as fixed costs and SGA+COGS as total costs (denoted by $TC1$ in Table 11). In the second specification, we use DA+SGA as fixed costs and DA+SGA+COGS as total costs 2 (denoted by $TC2$ in Table 11). We then estimate Fama-MacBeth regressions of monthly returns on both operational inflexibility and level of gearing and examine whether the difference between our measure and Novy Marx's measure, $\ln(FC/TC)$, positively predicts returns and whether the coefficients for $\ln(FC/TC)$ and $\ln(TC/BA)$ are the same. The results are reported in columns 11 and 12 of Table 11. Column 11 shows that the coefficients for $\ln(SGA/TC1)$ and $\ln(TC1/BA)$ are both positive (coefficients = 0.202 and 0.210) and statistically significant (t -statistics = 3.74 and 4.76). The difference between the coefficients is -0.008, which is not statistically significant (t -statistic of -0.19). The results are similar when we include DA in fixed costs as well. Column 12 shows that the coefficients for $\ln(FC/TC2)$ and $\ln(TC2/BA)$ are both positive (coefficients = 0.268 and 0.270). The associated t -statistics are 3.85 and 5.37, respectively. The difference between the coefficients is -0.002, which is not statistically significant (t -statistic of -0.03). These results suggest that $\ln(FC/TC)$, the difference between our measure and Novy-Marx's measure, positively predicts returns. Furthermore, empirical results are consistent with the view that the coefficients for operational inflexibility, $\ln(FC/TC)$, and level of gearing, $\ln(TC/BA)$, are the same, and therefore what really matters simply may be $\ln(FC/BA)$, or fixed costs.

6.2 Net fixed assets

Next, we examine the relation between our measure and the measure used in Ferri and Jones (1979) and García-Feijóo and Jorgensen (2010): net fixed assets to total assets. To do so, we focus on DA, the part of fixed costs that is directly related to net PPE. We decompose $\ln(DA/BA)$ into $\ln(DA/PPE)$ and $\ln(PPE/BA)$, with the latter being the traditional measure of operating

leverage in [Ferri and Jones \(1979\)](#). Using these variables, we again estimate Fama-MacBeth regressions. To save space, we report the results in Table IA.17 in the [Internet Appendix](#) and summarize the main findings here. In the Fama-MacBeth regressions, $\ln(PPE/BA)$ becomes statistically significant only when we add $\ln(DA/PPE)$. If we believe that operating leverage should predict returns, then our measure is an improvement over the traditional measure of operating leverage.

6.3 Organizational capital and systematic risk

In a seminal paper, [Eisfeldt and Papanikolaou \(2013\)](#) show that firms with higher organizational capital have higher returns. Their measure of organizational capital is derived from the cumulative deflated value of SGA, which is closely related to our measure of operating leverage. They argue that their results on organizational capital are not explained by operating leverage because they find that the earnings of firms with high organizational capital do not exhibit a higher covariance with gross domestic product (GDP).

We believe that our results are not simply driven by organizational capital. First, their notion of organizational capital is measured by the cumulated value of SGA. However, in [Table 11](#), we find that another fixed cost component, DA, also positively predicts stock returns, with predictive power on the same order of magnitude as that of SGA.

Second, we now explore the relation between our operating leverage measure and systematic risk. We first attempt to redo the analysis in [table X](#) of [Eisfeldt and Papanikolaou \(2013\)](#) on firms sorted by our measure of book operating leverage. Table IA.18 in the [Internet Appendix](#) reports the results, which are qualitatively the same as those in [Eisfeldt and Papanikolaou \(2013\)](#). While firms with higher book operating leverage appear to have higher earnings-to-sales sensitivities, they do not seem to exhibit higher earnings-to-GDP sensitivities.

We conjecture that this result is driven by the fact that firm-level estimations of these sensitivities are noisy. To investigate this conjecture, we now compute the relevant quantities at the portfolio level and then reestimate the sensitivities. We follow [Chen \(2017\)](#) and compute the relevant accounting variables for an initial investment of \$100. Because we view depreciation as a cost, we do not add back depreciation to compute operating cash flows; rather, we compute EBIT. Because EBIT (ib) can be negative at the portfolio level, we use the transformation for logs of negative earnings from [Ljungqvist and Wilhelm \(2005\)](#): $\ln(1+ib)$ if ib is positive and $-\ln(1-ib)$ if ib is negative. We also examine dividends, which are never negative, for robustness. [Table 12](#) reports the results. Panel A1 shows that at the portfolio level, earnings are more sensitive to sales as book operating leverage increases. Panel A2 shows that once we estimate at the portfolio level, earnings of higher operating leverage portfolios do have higher sensitivities to GDP. Panel A3 displays

Table 12
Systematic risk

| Quintile | <i>A. Cash flow is measured by EBIT</i> | | | | | <i>B. Cash flow is measured by Dividend</i> | | | | |
|-----------------|---|--------|--------|---------|--------|---|--------|--------|--------|---------|
| | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| | <i>A1. $\ln(EBIT)$ on $\ln(Sale)$</i> | | | | | <i>B1. $\ln(Dividend)$ on $\ln(Sale)$</i> | | | | |
| <i>ln(Sale)</i> | 0.2117 | 0.4048 | 0.4482 | 0.6978 | 2.3745 | -0.1163 | 0.3703 | 0.4370 | 0.2332 | 0.7475 |
| | (0.33) | (2.20) | (3.73) | (7.98) | (2.46) | (-1.25) | (1.54) | (2.86) | (1.60) | (4.51) |
| Obs. | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 |
| Adj. R^2 | -.026 | .804 | .917 | .967 | .224 | .845 | .937 | .967 | .982 | .967 |
| | <i>A2. $\ln(EBIT)$ on $\ln(GDP)$</i> | | | | | <i>B2. $\ln(Dividend)$ on $\ln(GDP)$</i> | | | | |
| | 1 | 2 | 3 | 4 | 5 | 1 | 2 | 3 | 4 | 5 |
| | | | | | | | | | | |
| <i>ln(GDP)</i> | -0.8310 | 0.0550 | 0.0716 | -0.2888 | 2.2678 | -0.3574 | 0.2656 | 0.5164 | 0.2641 | 1.4164 |
| | (-0.79) | (0.21) | (0.30) | (-1.22) | (1.64) | (-1.60) | (1.00) | (2.23) | (1.64) | (10.98) |
| Obs. | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 |
| Adj. R^2 | - | | | | | | | | | |

estimates of the same regression using the difference specification. Panels B1 through B3 show that the results are robust when we change EBIT to dividends. In fact, the sensitivities often have higher statistical precision, probably because negative earnings create a specification difficulty. The specification in panel B2 is similar to that in [Bansal, Dittmar, and Kiku \(2009\)](#), who show that portfolios sorted by size and book-to-market equity differ in systematic risk. We find that portfolios sorted by fixed costs also differ in systematic risk.¹⁵

When we compare the return predictability of organizational capital with our measure of operating leverage, as shown in Table IA.19 in the [Internet Appendix](#), we find that our market operating leverage and book operating leverage measures are better at predicting stocks' future returns than organizational capital.

Overall, we conclude that once we estimate the sensitivities at the portfolio level, high book operating leverage is associated with higher systematic risk. But organizational capital is firm specific and should not be related to sys-

Table 13.
Fama-MacBeth regressions with regression-based operating leverage measure

| Model | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| <i>RBOL</i> | −0.0079 (−0.65) | 0.0073 (0.84) | −0.0012 (−0.16) | 0.0035 (0.42) | −0.0029 (−0.39) | 0.0028 (0.34) | −0.0036 (−0.48) |
| <i>Market OL</i> | | | | 0.8107 (4.02) | 0.5822 (3.11) | | |
| <i>Book OL</i> | | | | | | 0.6497 (3.50) | 0.4598 (2.74) |
| <i>lnSize</i> | | −0.0882 (−2.09) | −0.0888 (−2.43) | −0.0590 (−1.48) | −0.0675 (−1.94) | −0.0605 (−1.56) | −0.0700 (−2.06) |
| <i>lnBM</i> | | 0.3275 (4.60) | 0.2591 (3.87) | 0.2733 (3.74) | 0.2242 (3.28) | 0.3806 (5.55) | 0.2995 (4.54) |
| <i>FL</i> | | | −0.0743 (−0.32) | | −0.1036 (−0.44) | | −0.0585 (−0.25) |
| <i>gBA</i> | | | −0.4946 (−4.63) | | −0.4465 (−4.28) | | −0.4462 (−4.35) |
| <i>Accrual</i> | | | −1.3339 (−5.31) | | −1.2055 (−5.04) | | −1.2277 (−5.20) |
| <i>IK</i> | | | −0.0681 (−0.95) | | −0.0769 (−1.09) | | −0.0806 (−1.17) |
| <i>Momentum</i> | | | 0.0327 (0.13) | | 0.0012 (0.00) | | 0.0062 (0.02) |
| <i>lnAGE</i> | | | −0.0187 (−0.40) | | −0.0223 (−0.47) | | −0.0173 (−0.37) |
| Avg. obs. | 2,018 | 2,018 | 2,018 | 2,018 | 2,018 | 2,018 | 2,018 |
| Adj. R^2 | .0259 | .0407 | .0525 | .0417 | .0532 | .0417 | .0532 |

We first estimate cross-sectional regressions for each month (July 1972 to June 2016). Time series of the coefficients from the first-stage regressions are then used to calculate the average coefficients and the t -statistics. The adjusted R^2 and the number of observations are the averages of the cross-sectional regressions. Monthly returns in percentages from July of year t to June of year $t+1$ are matched with accounting variables for fiscal years that end in year $t-1$. *RBOL* is the regression-based measure of operating leverage. Similar to [García-Feijóo and Jørgensen \(2010\)](#), we estimate the coefficients in regressions of the detrended natural logarithm of quarterly EBIT on the detrended natural logarithm of quarterly sales in the previous 20 quarters for each firm at the end of each fiscal year. The estimations require nonmissing EBIT and sales data over the previous 20 quarters. Market operating leverage (*market OL*) is defined as fixed costs divided by the market value of asset. Fixed costs are defined as the sum of depreciation and amortization and selling, general, and administrative expenses. The book operating leverage (*book OL*) is defined as fixed costs divided by the book value of assets. *Size* is the capitalization of the firm at the end of June (in \$M). *BM* is the book-to-market equity ratio. *FL* is financial leverage, which is defined as the ratio of total liabilities to total book assets. *gBA* is the annual growth rate of total book assets. *Accrual* is measured as in [Sloan \(1996\)](#). *IK* is the investment-to-capital ratio. *Momentum* is the past 6-month cumulative returns (skipping a month). *lnAGE* is the log of one plus the number of years since the firm's first appearance in CRSP. Note that we take logarithms for both size and book-to-market equity in the regressions. The industry fixed effect is controlled in all specifications. We use the 17-industry classification in [Fama and French \(1997\)](#). Explanatory variables are winsorized at the 1% and 99% levels every month. Reported in parentheses are [Newey and West \(1987\)](#) t -statistics adjusted for heteroscedasticity and autocorrelation.

coefficient for our measure of book operating leverage (FC/BA) is also positive and significant at 0.650 (t -statistic = 3.50) with size and book-to-market ratio controlled and 0.460 (t -statistic = 2.74) with all other control variables.

Overall, the results suggest that fixed costs are positively associated with the sensitivity of earnings to output. However, directly estimating operating leverage from regressions is likely to be ridden with estimation error problems, and this problem is more severe at the firm level.

6.5 Further robustness checks

Our measure of fixed costs also might be related to the following literature: the gross profitability measure in [Novy-Marx \(2013\)](#), the operating profitability measure in [Fama and French \(2015\)](#), the cash-based operating profitability measure in [Ball et al. \(2016\)](#), the intangible assets effect ([Chan, Lakonishok, and Sougiannis 2001](#)), the retained earnings-to-market ratio in [Ball et al. \(2020\)](#), and the labor leverage ([Favilukis and Lin 2016](#); [Donangelo et al. 2019](#)). For robustness checks, we compare the predictive ability of our operating leverage measure with these variables. We report the results of these robustness tests in Sections 10 to 13 (Tables IA.20 to IA.23) of the [Internet Appendix](#). We find that book operating leverage and the remainder of gross profitability have different cross-sectional properties, that the effect of book operating leverage is greater in small stocks, whereas the effect of the rest of gross profitability is greater in large stocks. The operating profitability measure, the cash-based operating profitability measure, and the retained earnings-to-market ratio do not subsume the information from book operating leverage. In addition, the predictive ability of our operating leverage measure does not come from intangible intensity or labor costs.

Finally, we examine whether our results are sensitive to industry adjustments. We perform robustness tests for the raw operating leverage measure (not industry adjusted) and the industry-adjusted operating leverage measure that uses the 49-industry classification in [Fama and French \(1997\)](#), as in [Novy-Marx \(2011\)](#). We report the results in Tables IA.27 to IA.32 of the [Internet Appendix](#). The key regression coefficients of interest in the main text are qualitatively the same with no industry adjustment or with an adjustment from the 49-industry classification in [Fama and French \(1997\)](#).

7. Conclusion

Although the idea of operating leverage has long been associated with fixed costs, recent empirical examinations of the relation between operating leverage and stock returns have not directly utilized fixed costs. We examine a simple measure of operating leverage: the ratio of fixed costs to the market value of assets. We measure fixed costs as depreciation and amortization plus selling, general, and administrative expenses. We find that this measure of operating leverage positively predicts returns and that its predictive power is stronger than previous measures of operating leverage. Operating leverage is not explained by common factors. We also construct an operating leverage factor and find that it helps explain the returns of book-to-market portfolios. Furthermore, an exploratory two-factor model with the operating leverage factor works at least as well as, but does not subsume, the Fama and French five-factor model in explaining anomalies.

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