Operating Leverage and Risk Premium *

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Abstract

We introduce an out-of-sample neural-network-based measure of firm-level operating leverage, which outperforms existing ones in capturing the elasticity of operating profits to gross profits. Strikingly, our analysis uncovers a non-monotonic—and potentially negative—relationship between operating leverage and the risk premium. This challenges conventional wisdom and contradicts explanations that link operating leverage to the value premium. A production-based asset pricing model incorporating both variable and fixed costs provides a possible rationale for these empirical findings. Furthermore, our analysis offers a fresh perspective on the idiosyncratic volatility premium by emphasizing the interplay between the operating hedge effect induced by variable costs and the operating leverage effect induced by fixed costs.

JEL Classifications: G12, E44

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Keywords: Operating leverage, operating hedge, variable costs, fixed costs, risk premium, value premium, idiosyncratic volatility

1 Introduction

Operating leverage is a fundamental concept in accounting, economics, and finance that reflects the extent to which a firm relies on fixed costs to generate profits. It is widely believed that higher operating leverage increases a firm's risk due to the rigidity of fixed costs, which, in turn, raises the firm's expected return. This mechanism has been proposed as an explanation for the value premium (e.g., Carlson, Fisher, and Giammarino (2004), Zhang (2005)). The idea is that firms with low productivity tend to have low valuation ratios (value firms), high operating leverage, and higher risk premiums, leading to a negative cross-sectional correlation between valuation ratios and risk premiums. However, empirical support for this mechanism remains limited, largely due to ongoing debate over the proper measurement of operating leverage.

In this paper, we introduce an out-of-sample neural-network-based firm operating leverage measure. Our new operating leverage measure, referred to as $\mathrm{OL}_{\mathrm{NN}}$, integrates information from key firm characteristics that are widely believed to influence operating leverage and several existing operating leverage measures. These include a firm's beta, book-to-market equity ratio, gross profitability, operating profitability, idiosyncratic volatility, and various established measures of operating leverage $\mathrm{OL}_{\mathrm{NM}}$ Novy-Marx (2011) (the sum of COGS and SG&A divided by total asset AT), $\mathrm{OL}_{\mathrm{CCLL}}$ Chen, Chen, Li, and Li (2022) (the sum of DP and SG&A divided by the market value of assets), $\mathrm{OL}_{\mathrm{CHK}}$ Chen, Harford, and Kamara (2019) (SG&A divided by AT), $\mathrm{OL}_{\mathrm{FJ}}$ Ferri and Jones (1979) (PPENT divided by AT), and a new flow-based operating leverage $\mathrm{OL}_{\mathrm{FL}}$ (SG&A divided by gross profit), which emerges from a production-based asset pricing model discussed in Section 4. The use of machine learning enables us to capture the nonlinear relationships between operating leverage and firm characteristics, as well as their interactions.

Both the neural-network-based ($\mathrm{OL}_{\mathrm{NN}}$) and flow-based ($\mathrm{OL}_{\mathrm{FL}}$) measures are positively correlated with but significantly outperform existing operating leverage measures in the literature in capturing the cross-sectional heterogeneity of the elasticity of operating profits to gross profits, thus more truthfully represent the operating leverage effect. Economically, a one-standard-deviation increase in $\mathrm{OL}_{\mathrm{NN}}$ and $\mathrm{OL}_{\mathrm{FL}}$ increases the elasticity of operating profits by 1.38 and 0.85, respectively. This leads to an increase in R^2 from 67.5% under the assumption of homogeneous elasticity to 73.9% and 71.5%, respectively, when the elasticity varies with our operating leverage measures. In comparison, a one-standard-deviation increase in the strongest existing operating leverage measure, $\mathrm{OL}_{\mathrm{CCLL}}$ from Chen, Chen, Li, and Li (2022), increases gross profit elasticity by 0.72, with the corresponding R^2 rising only to 69.1%. Extensive robustness checks suggest that the neural-network-based measure

(OL_{NN}) closely approximates the best possible measure.

Using these two new measures, we empirically examine the relationship between operating leverage and risk premiums. A one-way quintile portfolio sort based on operating leverage shows that the average stock excess return initially rises but then declines sharply as operating leverage increases. The difference in the average excess return between the lowest and highest operating leverage quintiles (low minus high) is 3.6% per year for the neural-network-based measure and 4.0% for the flow-based measure. While the market beta increases with operating leverage, both average returns and CAPM alphas exhibit negative correlations with operating leverage. These findings contradict the conventional view that fixed-cost-induced operating leverage should lead to a higher risk premium, as firms with high operating leverage instead exhibit lower average returns and CAPM alphas.

This finding also challenges the notion that the operating leverage mechanism explains the value premium. Our empirical findings demonstrate that although the book-to-market equity ratio exhibits positive correlations with the new operating leverage measures, the relationship is relatively weak. In cross-sectional regressions, the book-to-market ratio accounts for only 5.5% of the variation in the neural-network-based measure (OL_{NN}) and less than 1% in the flow-based measure (OL_{FL}). Moreover, adjusting for operating leverage actually strengthens the value premium rather than diminishing it, indicating that operating leverage is unlikely to be its primary driver.

Why doesn't operating leverage increase the risk premium? While multiple factors may influence the relationship between operating leverage and expected returns, we highlight one possible mechanism—the role of variable costs in firm production. Unlike fixed costs, variable costs tend to be more cyclical than revenues, creating an operating hedge effect that counteracts the impact of operating leverage. Kogan, Li, and Zhang (2023) further show that cross-sectional differences in the operating hedge effect contribute to the gross profitability premium (Novy-Marx (2013)).

To examine how variable costs influence the relationship between fixed-cost-induced operating leverage and risk premium, we develop a static production-based asset pricing model incorporating three types of production inputs: physical capital (e.g., properties, plants, and equipment), fixed (inflexible) inputs, and variable inputs. We model these inputs using a nested constant elasticity of substitution (CES) production function. Following existing literature, we first nest physical capital and fixed inputs, then combine this aggregate input with variable inputs, allowing for different substitution elasticities among them. In this setting, firms optimize their fixed and variable inputs to maximize their values, or equivalently, their operating profits. From the first-order condition of this optimization problem, key accounting variables—such as gross margin (or gross profitability) and a flow-based measure of operating leverage (OL_{FL})——naturally emerge.

The production-based model demonstrates that the operating leverage effect, induced by fixed costs on a firm's risk exposure, depends on the its gross profitability. When gross profitability is high, fixed costs amplify the exposure of operating profits to aggregate profitability shocks relative to gross profits, creating an operating leverage effect, as conventional wisdom suggests. However, when gross profitability is sufficiently low, fixed costs strengthen the operating hedge effect from variable inputs, which further reduces the firm's risk premium. We validate this prediction and find a more negative operating leverage premium among firms with low gross profitability in the data. The model-implied unconditional relationship between operating leverage and risk premium follows a hump-shaped curve, consistent with empirical finding.

The model also provides a novel explanation for the idiosyncratic volatility (IVOL) premium, an anomaly first documented by Ang, Hodrick, Xing, and Zhang (2006). The key idea is that while the interaction of variable and fixed costs reduces the risk premium of firms with high operating leverage through the operating hedge effect against aggregate profitability shocks, both types of costs create an operating leverage effect against firm-specific profitability shocks. As a result, firms with high IVOL tend to have low profitability and high operating leverage, leading to a low or even negative risk premium due to the operating hedge effect. Our empirical findings support this explanation. In a factor-spanning test, the operating leverage factor explains over 40% of the time series variation of IVOL factor returns. Furthermore, controlling for neural-network-based and flow-based operating leverage factors reduces the IVOL premium by more than 30%, respectively.

Our paper builds on the literature that explores the effects of production costs on asset pricing. A significant body of work focuses on the role of firms' fixed costs and the associated operating leverage effect on risk premiums. For example, Carlson, Fisher, and Giammarino (2004) and Zhang (2005) illustrate how operating leverage can generate a value premium within a neoclassical model of firm investments. Novy-Marx (2011) introduces an empirical measure of operating leverage and documents its positive relationship with cross-sectional stock returns. More recently, Kogan, Li, and Zhang (2023) emphasize the importance of variable inputs in reducing a firm's risk premium through an operating hedge effect, contributing to the gross profitability premium. Our empirical findings, based on newly proposed measures, challenge conventional wisdom regarding the relationship between operating leverage and risk premium, particularly in explaining the value premium. Our theoretical investigation highlights that the operating leverage effect can be significantly influenced by the presence of variable costs. To the best of our knowledge, we are the first to evaluate a broad range of operating leverage measures and analyze their impact on risk premiums from both theoretical and empirical perspectives.

A related strand of literature examines the effect of labor costs on stock returns, with a focus on wage rigidity as a source of operating leverage. For instance, Danthine and Donaldson (2002) show that wage rigidity can create strong labor leverage, improving the performance of asset pricing models by better matching aggregate market volatility and the equity premium. Favilukis and Lin (2015) quantify the effects of wage rigidity and labor leverage on both the equity and value premiums. Donangelo, Gourio, Kehrig, and Palacios (2019) find that firms with higher labor shares tend to have higher expected returns than those with lower labor shares. We find that although labor share increases with our new measures of operating leverage, it is less effective than our measures in capturing the elasticity of operating profits.

Finally, our paper contributes to the literature on the idiosyncratic volatility (IVOL) premium. From a risk perspective, the investment-based model of Kogan and Papanikolaou (2013) shows that IVOL increases with growth options in asset composition, leading to greater exposures of high-IVOL firms to investment-specific technology shocks and lower expected returns. Barinov and Chabakauri (2023) also examine asset compositions but attribute the IVOL premium to aggregate volatility risk. From a behavioral standpoint, Stambaugh, Yu, and Yuan (2015) explain the low returns of high-IVOL firms through arbitrage risk and asymmetry, where investors buy undervalued stocks but are reluctant to short overvalued ones. Our explanation connects IVOL to economic fundamentals such as production costs, demonstrating how the fixed-cost-induced operating leverage effect and the variable-cost-induced operating hedge effect jointly drive the IVOL premium.

The paper is structured as follows. In Section 2, we describe the construction of the flow-based operating leverage measure and the estimation of neural-network-based operating leverage measure. We discuss their properties and compare them to measures used in existing studies. In Section 3, we investigate the relationship between operating leverage and risk premium and assess the contribution of the operating leverage effect to the value premium. In Section 4, we present a model of firm production to show how fixed-cost-induced operating leverage can be influenced by the presence of variable costs. We also test the model's implications for risk premiums related to operating leverage, gross profitability, and idiosyncratic volatility. We conclude in Section 5.

2 Measuring Firm Operating Leverage

In this section, we discuss the construction of a simple flow-based measure ($\mathrm{OL_{FL}}$), which naturally emerges from the production-based asset pricing model introduced in Section 4, and the estimation of a machine-learning-based neural network measure of operating leverage (OL_{NN}). We examine the properties of these new measures and compare them with existing measures in the literature.

2.1 Construction of operating leverage measures

We begin with the flow-based measure (OL_{FL}) due to its simplicity and intuitive appeal. OL_{FL} is defined as the ratio of SG&A expenses—–a proxy for fixed costs—–to gross profit (GP), i.e., OL_{FL} = SG&A/GP. This ratio quantifies the proportion of gross profit allocated to fixed costs. Holding other factors constant, a higher OL_{FL} implies a greater amplification effect of fixed costs on firm performance. As shown in Section 4, OL_{FL} arises naturally from the first-order condition of a firm's production optimization.

Several existing measures of operating leverage have been proposed in the literature, including those by Novy-Marx (2011) (OL_{NM}), Chen, Chen, Li, and Li (2022) (OL_{CCLL}), Chen, Hartford, and Kamara (2019) (OL_{CHK}), and Ferri and Jones (1979) (OL_{FJ}). Table 1 summarizes these measures. Compared to prior approaches, OL_{FL} has two distinctive features. First, unlike OL_{NM}, OL_{FL} differentiates between the cost of goods sold (COGS) and SG&A expenses. As discussed in Section 4, these cost components exhibit different cyclical properties, and the effect of operating leverage is more relevant for production costs that are relatively "sticky", such as SG&A. Second, OL_{FL} uses gross profit as the denominator rather than total assets (book or market value) as in prior measures. This choice aligns with the production-based model in Section 4 and reflects the notion that operating leverage arises from fixed costs amplifying cash flow risks.

[Insert Table 1 Here]

Despite its simplicity, OL_{FL} has limitations. First, it is a static measure and does not account for a firm's dynamic trade-offs. Second, the operating leverage effect may depend not only on the level of fixed costs and gross profit but also on their relative cyclicalities. Third, the relationship between operating leverage and OL_{FL} is likely non-linear, with a stronger effect for firms with high fixed costs relative to gross profit.

To address these shortcomings, we introduce an out-of-sample neural-network-based measure of operating leverage (OL_{NN}). While OL_{NN} serves as our benchmark estimate, we also employ alternative machine learning techniques such as Ridge and LASSO regressions as robustness checks (see Section 3.2).

By definition, operating leverage captures the elasticity of operating profit with respect to gross profits:

$$\%\Delta \mathrm{OP}_{i,t+1} = \mathrm{OL}_{i,t} \times \%\Delta \mathrm{GP}_{i,t+1}, \tag{1}$$

where $\mathrm{OL}_{i,t}$ represents firm i's operating leverage at the end of year t and $\%\Delta\mathrm{OP}_{i,t+1}$ ($\%\Delta\mathrm{GP}_{i,t+1}$) denotes the growth rate of operating profits (gross profits) in year $t+1$. Since $\mathrm{OL}_{i,t}$ is unobservable, we estimate it using a neural network trained on firm-level inputs available at the end of year t. These inputs include five firm characteristics that potentially correlate with operating leverage: stock's market beta (Beta), idiosyncratic volatility (IVOL), book-to-market equity ratio (BM), gross profitability (GPA), operating profitability (OPE). Table 1 provides the definitions for these characteristics. Intuitively, firms with lower profitability typically exhibit higher operating leverage and lower valuation ratios. Furthermore, the operating leverage effect may amplify both systematic and idiosyncratic risks, measured by Beta and IVOL, respectively. We also include four existing operating leverage measures—$\mathrm{OL}_{\mathrm{NM}}$, $\mathrm{OL}_{\mathrm{FJ}}$, $\mathrm{OL}_{\mathrm{CHK}}$, and $\mathrm{OL}_{\mathrm{CCLL}}$—along with $\mathrm{OL}_{\mathrm{FL}}$, as additional neural network inputs. We update $\mathrm{OL}_{\mathrm{FL}}$, $\mathrm{OL}_{\mathrm{NM}}$, $\mathrm{OL}_{\mathrm{FJ}}$, $\mathrm{OL}_{\mathrm{CHK}}$, $\mathrm{OL}_{\mathrm{CCLL}}$, BM, GPA, and OPE using Compustat Quarterly data, while Beta and IVOL are updated monthly.

Constructing $\mathrm{OL}_{\mathrm{NN}}$ involves training neural networks in the cross section and making out-of-sample predictions. Each neural network has an input layer with 10 neurons corresponding to the 10 inputs. These inputs pass through a hidden layer with 32 neurons, each using a rectified linear unit (ReLU) activation function to capture the nonlinear relationship between characteristics and the elasticity of operating profits to gross profits. The output layer consists of two neurons with linear activation functions: one estimates firm-specific operating leverage, while the other serves as an intercept term, capturing the firm's exposure to aggregate operating profit growth. To improve stability and prevent overfitting, we use He initialization for weight normalization, apply l_1 regularization, and incorporate batch normalization. The network is optimized using the Adam optimizer.

This procedure introduces two hyperparameters: (1) l_1 regularization strength, and (2) learning rate, whose values are selected by minimizing mean validation loss through repeated five-fold cross-validation (five repetitions). In our benchmark estimation, the learning rate is chosen from $\{0.5, 0.05, 0.02, 0.01, 0.001\}$, and the l_1 penalty from $\{0.001, 0.0001\}$.

The training sample is annual and consists of firms with fiscal year ending in December (FYR = 12). Panel A of Figure 1 illustrates the timing of neural network training process. At the end of March in year $t+1$, after the annual reports for year-t have been disclosed, we train year-t neural network, denoted as $\mathrm{NN}^{(t)}(\cdot)$, using a loss function based on mean squared errors ($\epsilon_{i,t} \equiv \%\Delta\text{OP}_{i,t} - \text{NN}^{(t)}(X_{i,t-1}) \times \%\Delta\text{GP}_{i,t}$):

$$\mathcal{L}^{(t)} = \frac{1}{N}\sum_{i=1}^{N}\left(\epsilon_{i,t} - \frac{1}{N}\sum_{i=1}^{N}\epsilon_{i,t}\right)^2, \quad (2)$$

where $\%\Delta\text{OP}_{i,t}$ ($\%\Delta\text{GP}_{i,t}$) represents firm i's growth rate of operating profits (gross profits) in year t, and $X_{i,t-1}$ includes most updated inputs available at the end of year $t-1$. These inputs are standardized to have a zero mean and unit standard deviation in the cross section, with any missing value being imputed with the cross-sectional mean (see, Chen and McCoy (2024)). After hyperparameters are selected from repeated cross-validations, we re-train the neural network on the entire training sample of year t, denoted as $\hat{\text{NN}}^{(t)}(\cdot)$.

[Insert Figure 1 Here]

Using the annually estimated neural networks, we construct monthly out-of-sample predictions of OL_{NN} for all firms, regardless of fiscal year-end, in two steps.

In the first step, for each month between March of year $t+1$ and February of year $t+2$, we estimate operating leverage by applying the 10 most recent neural networks—$\hat{\text{NN}}^{(t)}(\cdot)$, $\hat{\text{NN}}^{(t-1)}(\cdot)$, ..., $\hat{\text{NN}}^{(t-9)}(\cdot)$—to the latest firm characteristics at the end of that month. To prevent data leakage, we normalize these characteristics using the means and standard deviations from the corresponding training samples. This process yields 10 different estimates of operating leverage for each firm in that month.

In the second step, to reduce measurement error, we take the average of these 10 estimates as the final OL_{NN} measure. For example, in Panel B of Figure 1, the predicted OL_{NN} for September of year $t+1$ is estimated as

$$\text{OL}_{\text{NN, Sep},t+1} = \frac{\hat{\text{NN}}^{(t)}(X_{\text{Sep},t+1}) + ... + \hat{\text{NN}}^{(t-9)}(X_{\text{Sep},t+1})}{10},$$

where $X_{\text{Sep},t+1}$ represents the most updated inputs at the end of September, year $t+1$. As a result, the estimated OL_{NN} begins in December 1978 due to the availability of Compustat Quarterly data.

2.2 Properties of operating leverage measures

Figure 2 plots the time series of median values of our newly constructed OL_{NN} and OL_{FL} from January 1979 to December 2021. Although our main focus is on the cross section, the figure shows that these two measures comove with each other and tend to rise following recessions (grey-shaded areas), which is consistent with the fact that gross profits fall more than fixed costs during economic downturns.

[Insert Figure 2 Here]

Table 2 presents the summary statistics, including the mean, median, standard deviation, the 1st, 25th , 75th , and 99th percentiles, and the 12-month autocorrelation (AR12), of the six operating leverage measures (the neural-network-based, the flow-based, and four existing) and the five firm characteristics used to construct the neural-network-based operating leverage measure. Compared to the existing measures, one prominent feature of OL_{NN} and OL_{FL} is that they are less persistent. For example, the existing measure with the lowest autocorrelation is OL_{CCLL}, whose estimated AR12 coefficient is 0.88. In contrast, the AR12 coefficient is only 0.65 for OL_{NN} and 0.63 for OL_{FL}. For the other firm characteristics, Table 2 shows that while market beta, book-to-market ratio, and gross profitability are relatively persistent, idiosyncratic volatility and operating profitability are much less persistent with an AR12 coefficient of 0.58 and 0.51, respectively.

[Insert Table 2 Here]

To evaluate how well our new measures capture the operating leverage effect compared to existing ones, we examine the elasticity of operating profits with respect to gross profits. Specifically, we estimate panel regressions of firm-level operating profit growth on gross profit growth, interacting the latter with different operating leverage measures one at a time. To facilitate comparison, all operating leverage measures are normalized to have unit standard deviations. The measure with the highest coefficient on the interaction term and the largest R^2 best captures the cross-sectional variation in the operating leverage effect.

Specification (1) serves as the benchmark, assuming constant elasticity across all firms. The results show that, on average, a 1% increase in gross profits is associated with a 5.17% increase in operating profits. The firm-level gross profit growth explains 67.5% of the variation in operating profit growth.

[Insert Table 3 Here]

Specifications (2)–(7) in Table 3 incorporate different operating leverage measures individually. The positive coefficients on OL_{NN}, OL_{FL}, OL_{NM}, OL_{CHK}, and OL_{CCLL} suggest that firms with higher values of these measures exhibit greater elasticity of operating profits, confirming that these measures capture cross-sectional heterogeneity in the operating leverage effect. Economically, a one-standard-deviation increase in OL_{NN}, OL_{FL}, OL_{NM}, OL_{CHK}, and

OL_{CCLL} corresponds to increases in operating profit elasticity by 1.38, 0.85, 0.19, 0.52, and 0.72, respectively.

Compared to Specification (1), the neural-network-based measure OL_{NN} and the flow-based measure OL_{FL} explain an additional 6.4% (73.9% – 67.5%) and 4% (71.5% – 67.5%) of the variation in operating profit growth, respectively. By contrast, the maximum additional explanatory power among existing measures is 1.6% (69.1% – 67.5%), achieved by OL_{CCLL}. Interestingly, Specification (5) reveals a negative coefficient on the interaction term involving OL_{FJ}, suggesting that the Ferri and Jones (1979) measure fails to properly capture operating leverage.

Specifications (8)–(12) conduct head-to-head comparisons between the neural-network-based measure OL_{NN} and existing measures. The inclusion of OL_{NN} substantially reduces the coefficients of other measures, which become statistically insignificant when controlling for OL_{NN}, while its own coefficient remains largely unaffected. A similar pattern emerges for the flow-based measure OL_{FL} in Specifications (13)–(17), where the coefficients of existing measures are substantially reduced.

Specification (18) directly compares OL_{FL} and OL_{NN}. While their coefficients weaken in each other's presence, both remain statistically significant, indicating that these two measures capture distinct information. Finally, Specification (19) includes all operating leverage measures in a single regression. The results highlight the superiority of the neural-network-based measure OL_{NN} in explaining the elasticity of operating profits.

2.3 Determinants of OL_{NN} and OL_{FL}

To better understand the drivers of OL_{NN} and OL_{FL}, we examine their relationships with existing operating leverage measures and firm characteristics——including Beta, IVOL, BM, GPA, and OPE——using Fama-MacBeth regressions. The results are presented in Table 4.

[Insert Table 4 Here]

Panel A of Table 4 reports results where the dependent variable is the neural-network-based operating leverage measure, OL_{NN}. OL_{FL} is also included as an independent variable. Specifications (1)-(9), where each independent variable is included separately, show that OL_{NN} is positively correlated with Beta, IVOL, BM, OL_{NM}, OL_{CHK}, OL_{CCLL}, and OL_{FL}, while it is negatively correlated with OPE and OL_{FJ}. The positive relationship with market beta and idiosyncratic volatility suggests that operating leverage amplifies risk. The positive coefficient on BM and negative coefficient on OPE align with the view that firms with low productivity tend to have higher BM ratios and higher operating leverage. Among existing operating leverage measures, all except OL_{FJ} are positively correlated with OL_{NN}. The three strongest determinants of OL_{NN} are OL_{FL}, OL_{CCLL}, and IVOL, explaining 49.2%, 20.5%, and 17.7% of its variation, respectively. When all 10 neural network inputs are included in Specification (11), they collectively explain 65.9% of OL_{NN}, suggesting that the remaining 34.1% is driven by non-linear interactions among these inputs.

Panel B presents results for the flow-based operating leverage measure, OL_{FL}. The univariate regressions in Specifications (1)-(10) yield qualitatively similar findings to those in Panel A. The top three determinants of OL_{FL} are OL_{CHK}, OL_{CCLL}, and OL_{FJ}, with OL_{CHK} alone explaining over 30% of its variation.

The positive coefficient on gross profitability (GPA) in Specification (4) is initially unexpected, as higher profitability is typically associated with lower operating leverage. However, the result from Table IA1 in the Internet Appendix shows that this positive correlation primarily arises from the cross section, likely due to differences in production technology across firms. In contrast, the within-firm time-series correlation between GPA and operating leverage is strongly negative. Moreover, when all nine independent variables are included in Specification (10), the coefficient on GPA turns significantly negative.

3 Operating leverage and risk premium

We now examine the relationship between firms' operating leverage and risk premium. In Section 3.1, we analyze the average returns of portfolios sorted by operating leverage using our newly introduced measures. Section 3.2 explores the robustness of these findings by considering alternative machine-learning-based measures of operating leverage. In Section 3.3, we assess the predictive power of operating leverage for long-horizon returns. Finally, Section 3.4 evaluates the role of operating leverage in explaining the value premium.

Our stock return data come from the Center for Research in Security Prices (CRSP) database. We include only stocks with a share code (CRSP item SHRCD) of 10 or 11 and an exchange code (CRSP item EXCHCD) of 1, 2, or 3. Firms in the financial sector (SIC codes 6000–6999) and utility sector (SIC codes 4950–4999) are excluded. Our benchmark sample period spans from January 1979 to December 2021.

3.1 Operating leverage sorted portfolios

We now examine the stock return predictability of the newly introduced operating leverage measures. At the end of each month, firms are sorted into quintiles based on the most recent values of OL_{NN} or OL_{FL}, with portfolios rebalanced monthly. The results of portfolio returns and asset pricing tests are reported in Table 5.

[Insert Table 5 Here]

Panel A of Table 5 presents the results based on the neural-network-based measure, OL_{NN}. The relationship between OL_{NN} and average stock returns follows a hump-shaped pattern rather than a monotonic trend. The average excess return rises from 9.72% per year for firms with low OL_{NN} to 10.21% in quintile 4, before sharply declining to 6.12% in the highest quintile. Although the difference in average returns between the high and low OL_{NN} quintiles (H-L) is –3.59% and statistically insignificant, the difference between the top two quintiles (H-4) is highly significant at –4.09%.

The portfolio market betas from the unconditional CAPM test exhibit a strong positive correlation with OL_{NN}, indicating that higher fixed costs amplify market exposure. Market beta increases from 1.05 for low OL_{NN} firms to 1.45 for high OL_{NN} firms. This rising pattern in market beta leads to an even greater abnormal return spread between the high and low OLNN quintiles (H-L), as well as between the highest and fourth quintiles (H-4). The CAPM alpha is –7.15% with a t-statistic of –2.83 for the H-L portfolio and –5.76% with a t-statistic of –2.92 for the H-4 portfolio.

The last four columns present results from the Fama-French three-factor model. The size factor beta increases with OL_{NN}, suggesting that firms with high OL_{NN} tend to be smaller. The value factor beta follows a hump-shaped pattern, indicating that the relationship between value effects and operating leverage may be fragile. This issue is explored further in Section 3.4.

Panel B of Table 5 reports results using the flow-based operating leverage measure, OL_{FL}. The average return pattern across OL_{FL} quintiles is qualitatively similar, also displaying a hump shape. The return spread between high and low OL_{FL} quintiles is –3.97%, while the spread between the top two OL_{FL} quintiles is –7.62%.[1] These findings contrast with the conventional belief that operating leverage should be positively associated with stock returns. As we show in Section 4, an alternative mechanism may explain the low returns of firms with high operating leverage.

3.2 Robustness tests

To test the robustness of our findings on the relationship between operating leverage and risk premium, we consider various alternative operating leverage measures derived from different

[1] In Table IA2 of the Internet Appendix, we confirm that the average return pattern of OL_{FL}-sorted portfolios holds over a longer sample period (July 1963–December 2021) and across two subperiods: July 1963–December 1991 and January 1992–December 2021.

machine learning specifications and techniques.

Table 6 compares the results across these alternative approaches. Specification (1) represents our benchmark OL_{NN}. Specifications (2)–(6) introduce modifications to the benchmark neural network, altering one aspect at a time. Specification (2) expands the range of parameter values for l_1. Specification (3) increases the hidden layer size to 64 neurons. Specification (4) incorporates 63 firm characteristics instead of 10, including the five operating leverage measures from Table 1, their annually updated counterparts, and 53 of the 212 stock return predictors from Chen and Zimmermann (2021) with at most 30% missing observations per year. Specification (5) employs a deeper neural network with three hidden layers (32, 16, and 8 neurons). Specification (6) augments OL_{NN} using a boosting method with second-stage ridge regressions on the above-mentioned 63 characteristics.

[Insert Table 6 Here]

Specifications (7) and (8) apply Ridge regressions with 10 and 63 characteristics, respectively, while Specifications (9) and (10) use LASSO regressions with the same sets of characteristics. Specification (11) employs the random Fourier feature method with 12,000 features generated from the 10 characteristics used in OL_{NN}. Finally, Specification (12) defines operating leverage as the average of the measures from Specifications (1), (7)–(11).

Panel A of Table 6 presents results from panel regressions of operating profit growth on gross profit growth and its interaction with one of the operating leverage measures, following Specifications (1)–(7) in Table 3. For brevity, we report only the interaction term coefficient, its t-statistic, and the regression R^2. The results indicate that all measures perform similarly in capturing the elasticity of operating profits. The weakest performance is observed in Specification (4), where 63 characteristics are used in the neural network estimation, yielding an interaction coefficient of 1.20 and an R^2 of 72.6%. The strongest measure comes from Specification (12), which ensembles six other measures, resulting in an interaction coefficient of 1.54 and an R^2 of 74.5%. Notably, Ridge and LASSO regressions in Specifications (7)–(10) produce results comparable to the benchmark measure OL_{NN}, suggesting that nonlinearity plays a limited role in operating leverage.

Panel B reports the average annualized value-weighted excess returns of quintile portfolios sorted by these operating leverage measures. Across most specifications, portfolio returns follow a non-monotonic, hump-shaped pattern. Crucially, firms with high operating leverage consistently exhibit lower average returns than those with low operating leverage. The return spread (H-L) ranges from –2.26% in Specification (3) to –8.33% in Specification (10), confirming that our findings remain robust across alternative machine learning techniques.

3.3 Operating leverage and return relation at long-horizons

The previous subsections document the stock return predictability of operating leverage over a one-month horizon. In this subsection, we extend the analysis to longer horizons to assess the persistence and economic significance of this relationship. This investigation is important for two reasons. First, it helps determine whether the absence of a strong positive operating leverage premium is a robust and economically meaningful phenomenon. As discussed in Van Binsbergen and Opp (2019), if a characteristic's return predictability is short-lived, its impact on investment decisions and firm value may be limited.

Second, we examine whether the low average returns of high operating leverage firms are driven by short-lived characteristics that exhibit strong return predictability. For instance, Table 4 identifies idiosyncratic volatility (IVOL) as a key determinant of operating leverage. Prior research (e.g., Rachwalski and Wen (2016)) suggests that the IVOL premium is substantial but short-lived, typically lasting only a few months. This raises the question of whether the observed negative correlation between operating leverage and average returns is primarily driven by IVOL.

The top panels of Figure 3 plot the average returns of quintile portfolios sorted by lagged operating leverage (OL_{NN} on the left and OL_{FL} on the right) for horizons ranging from 1 to 36 months. Across all horizons, we find no strong relationship between operating leverage and average stock returns. For most lags, returns exhibit a hump-shaped pattern, peaking in the fourth quintile.

[Insert Figure 3 Here]

The bottom panels of Figure 3 depict the return spread between high and low operating leverage quintiles as a function of the lag length, along with the 2.5%-97.5% confidence interval. Although the return spread turns positive after approximately one year, it remains statistically insignificant. Furthermore, the premium dissipates as the lag extends to 30 months.

In summary, our long-horizon analysis reinforces the persistent lack of a strong operating leverage premium. Meanwhile, the hump-shaped relationship between operating leverage and average returns appears to be a robust feature, even over extended horizons. In Section 4, we explore a potential explanation based on firms' production cost structures.

3.4 Operating leverage and value premium

In this subsection, we explicitly assess the contribution of operating leverage to the value premium. As we discussed in the introduction, the operating leverage mechanism is one of the most popular explanations for the value premium in the literature. If operating leverage were the primary mechanism driving the value premium, we would expect the value premium to be weakened by the control of operating leverage.

Panel A of Table 7 presents results for quintile portfolios sorted by book-to-market equity ratio (BM). Over the sample period from January 1979 to December 2021, the unconditional value premium is 2.55% per year, with a t-statistic of 0.98. While value stocks tend to have higher OL_{NN} than growth stocks, the relationship between BM and OL_{FL} across BM quintiles is weak. Additionally, value firms tend to be smaller and exhibit lower gross profitability.

[Insert Table 7 Here]

Panels B and C of Table 7 examine the value premium conditional on operating leverage. Firms are first sorted into 3-by-5 portfolios based on operating leverage (OL) and then BM, and we report the returns and characteristics of BM quintiles averaged across OL terciles. Conditional on operating leverage, the cross-sectional dispersion in BM remains largely unchanged, yet the value premium becomes stronger than its unconditional counterpart from Panel A. Specifically, the value premium increases to 4.22% per year (t-statistic = 1.52) when conditioned on OL_{NN} and to 5.19% per year (t-statistic = 1.88) when conditioned on OL_{FL}——representing increases of 65% and 104%, respectively, relative to the unconditional value premium. These results suggest that operating leverage is unlikely to be the primary driver of the value premium, challenging existing explanations that attribute the value premium to operating leverage.[2]

In an untabulated analysis, we explore the relationship between labor leverage and our operating leverage measures.[3] Donangelo, Gourio, Kehrig, and Palacios (2019) document that firms with a high labor share exhibit greater sensitivity of operating profits to economic shocks, leading to higher expected returns—a pattern consistent with labor-induced operating leverage. Following their methodology, we construct the firm-level extended labor share (ELS). Our analysis reveals that while ELS is strongly correlated with OL_{NN} and OL_{FL} (with correlation coefficients of 0.45 and 0.51, respectively), it is less effective in capturing the elasticity of operating profits. Specifically, a one-standard-deviation increase in ELS is associated with a 0.58 increase in the elasticity of operating profits, compared to 1.38 for OL_{NN} and 0.85 for OL_{FL} (Table 3). Consequently, the positive ELS premium aligns with the left (low operating leverage) region of the hump-shaped relationship between operating leverage and the risk premium documented in Table 5.

[2]In Table IA3 of the Internet Appendix, we show that these conclusions also hold for OL_{FL} over a longer sample period (July 1963 to December 2021). In this extended sample, the unconditional value premium is stronger at 3.74% per year (t-statistic = 1.71), and controlling for OL_{FL} further amplifies the value premium to 6.04% per year (t-statistic = 2.67).

[3]The results are available upon request.

4 Firm Production and Operating Leverage

In the previous section, we documented a negative correlation between operating leverage and average stock returns in the cross section, challenging the conventional understanding of the operating leverage effect. In this section, we explore a potential economic mechanism that could help explain this result. Specifically, we examine the role of variable costs and their impact on the relationship between operating leverage and risk premium.

Standard asset pricing studies on operating leverage focus primarily on fixed costs. However, as highlighted by Kogan, Li, and Zhang (2023), variable costs tend to be more cyclical than revenues, creating an operating hedge effect that contributes to the gross profitability premium. Using data from the NBER-CES Manufacturing Industry Database, we find that the elasticity of aggregate variable costs—measured by the total cost of materials, energy, and production workers' wages—with respect to aggregate revenue—measured by the total shipped value—is significantly greater than one (1.17). In contrast, the elasticity of aggregate fixed costs—measured by office workers' wages—is considerably lower than one (0.34) (see Panel A, Table 8). As a result, the variable-cost-induced operating hedge dampens the cyclicality of gross profits relative to revenues (0.68, statistically significant and below one), whereas fixed-cost-induced operating leverage amplifies the cyclicality of operating profits relative to gross profits (1.16).

[Insert Table 8 Here]

To explore how the interaction between fixed and variable costs affects a firm's risk premium, we develop a static, production-based asset pricing model. Before delving into the details of the model, it's important to note that our approach abstracts from dynamic features, such as capital accumulation and asset composition, which have been shown to have significant implications for asset pricing, as demonstrated in studies by Kogan and Papanikolaou (2013) and Kogan and Papanikolaou (2014). For example, Kogan and Papanikolaou (2013) show that low-profitability firms derive less value from assets in place and more from growth options, resulting in lower risk premiums—a finding that aligns with the empirical profitability premium. In contrast, models based on the operating leverage effect predict the opposite. Our static model, however, reveals that even when considering only assets in place, the relationships predicted by traditional models that focus exclusively on fixed costs and operating leverage may not hold.

4.1 The model

The economy comprises numerous profit-maximizing firms. Each firm produces its output (Y) using three inputs: physical capital (K), fixed inputs (A), and variable inputs (M). We assume a constant elasticity of substitution (CES) production function. Following the literature on production functions with multiple inputs, we adopt a nested specification by first combining physical capital (K) and fixed inputs (A) to obtain integrated inputs (V) with a constant elasticity of substitution ρ between K and A. We then combine integrated inputs (V) and variable inputs (M) with a constant elasticity of substitution θ.[4] Specifically, a firm's output Y is given by

$$Y = \left((ZM)^{\frac{\theta-1}{\theta}} + \left\{ \left[(UA)^{\frac{\rho-1}{\rho}} + (XK)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \right\}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \tag{3}$$

where U and Z represent idiosyncratic productivity for fixed and variable inputs, respectively, and X signifies capital-augmenting aggregate productivity.[5] Let V denote the firm's integrated inputs, which combine physical capital K and fixed inputs A, that is,

$$V = \left[(UA)^{\frac{\rho-1}{\rho}} + (XK)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}. \tag{4}$$

Firm's output Y can then be expressed as

$$Y = \left[(ZM)^{\frac{\theta-1}{\theta}} + V^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}. \tag{5}$$

Firms in our economy own physical capital, which is fixed, and their objective is to maximize operating profits (OP) by choosing variable inputs (M) and fixed inputs (A), taking input prices as given:

$$OP = \max_{M,A} GP - P_A A = \max_{M,A} Y - P_M M - P_A A, \tag{6}$$

where GP is gross profit, and P_M and P_A are the prices of variable and fixed inputs, respectively.

From the derivation detailed in the appendix, we arrive at the following two results. First, the effect of variable costs can be observed from the difference in the exposure of gross profits

[4]This structure has been widely validated as a good approximation of firm production behavior in several studies, including Carlstrom and Fuerst (2006), Bodenstein, Erceg, and Guerrieri (2011), and Kemfert (1998).

[5]Following Kogan, Li, and Zhang (2023), we model aggregate profitability X as multiplying the capital stock K to ensure that the optimal level of inputs is procyclical with respect to aggregate profitability.

and outputs to the aggregate profitability shock. Denoting $p_1^M \equiv \frac{\partial \log P_M}{\partial \log X}$ as the cyclicality of variable input price with respect to aggregate profitability X, and $GM \equiv 1 - \frac{P_M M}{Y}$ as the gross margin, we have the following proposition.

PROPOSITION 1. *With the production technology described above, the difference in the exposure of gross profits and outputs to the aggregate profitability shock, i.e., the effect of variable costs on the risk exposure, is given by*

$$\frac{\partial \log GP}{\partial \log X} - \frac{\partial \log Y}{\partial \log X} = p_1^M(\theta - 1)\frac{1 - GM}{GM}. \tag{7}$$

Proof: See the Appendix.

Proposition 1 suggests that when $\theta < 1$ and $p_1^M > 0$, a condition empirically confirmed by Kogan, Li, and Zhang (2023), variable costs consistently reduce the firm's systematic risk. In other words, the operating hedge effect exists regardless of whether we model fixed inputs in the production function. Furthermore, the strength of the operating hedge decreases with the gross margin, implying that more profitable firms are associated with a lower operating hedge effect. This finding aligns with the explanation for the gross profitability premium provided by Kogan, Li, and Zhang (2023).

The second result is new and represents the effect of fixed costs on risk premium, which can be observed from the difference between the exposures of operating profits and gross profits to the aggregate profitability shock. Denoting $p_1^A \equiv \frac{\partial \log P_A}{\partial \log X}$ as the cyclicality of fixed input price with respect to aggregate profitability X, and $OL \equiv \frac{P_A A}{GP}$ as the ratio of fixed costs to gross profit, we have the following proposition regarding the effect of fixed costs.

PROPOSITION 2. *With the production technology described above, the difference in the exposure of operating profits and gross profits to the aggregate profitability shock, i.e., the effect of fixed costs on the risk exposure, is given by*

$$\frac{\partial \log OP}{\partial \log X} - \frac{\partial \log GP}{\partial \log X} = (1 - \rho)\frac{OL}{1 - OL}\left[\left(p_1^M - p_1^A\right) - \frac{p_1^M}{GM}\right]. \tag{8}$$

Proof: See the Appendix.

Proposition 2 demonstrates that, when $\rho < 1$ and $p_1^A < 0 < p_1^M$, a condition we discuss further below, the effect of fixed costs on the risk premium is nuanced and depends on the firm's gross margin. When the gross margin is high, the term in the square bracket in Equation (8) is positive, indicating the presence of the conventional operating leverage effect. For instance, when the model abstracts from variable inputs (i.e., $GM = 1$), an assumption commonly made in theoretical models of operating leverage, the right-hand side of Equation (8) is positive, and therefore, the presence of fixed costs raises the firm's risk exposure. Furthermore, the operating leverage effect increases with OL.

However, when the gross margin is sufficiently low, $\left[\left(p_1^M - p_1^A\right) - \frac{p_1^M}{GM}\right]$ can turn negative. In this scenario, fixed costs lower, rather than raise, the risk premium. The intuition is that for firms with sufficiently low gross margins, the operating hedge from variable costs is so strong that the gross profits to become less risky (i.e., exhibit a lower aggregate profitability beta) than fixed costs. Consequently, any fixed cost will further reduce the firm's systematic risk. Note that OL measures how fixed costs amplify the risk of gross profits and serves as the basis for our flow-based measure of operating leverage ($\mathrm{OL_{FL}}$).

One condition for the above results is $\rho < 1$ and $p_1^A < 0 < p_1^M$. The complementarity between fixed inputs, such as labor, and physical capital ($\rho < 1$), has been documented in the macroeconomics literature. In a pioneering work, Arrow, Chenery, Minhas, and Solow (1961) found that the elasticity of substitution between capital and labor was below 0.6 in the United States from 1909 to 1949. This complementarity is also supported by empirical evidence at the sectoral level (see, e.g., Chirinko and Mallick (2017), Herrendorf, Herrington, and Valentinyi (2015)). In a more recent study based on data from the U.S. Census of Manufactures, Oberfield and Raval (2021) found that the plant-level elasticity of substitution between capital and labor lies between 0.3 and 0.5, and the aggregate elasticity for the U.S. manufacturing sector is in the range of 0.5–0.7.

The countercyclicality of fixed input prices ($p_1^A < 0$) is consistent with nominal wage rigidity from Keynesian theories, and there is empirical evidence in the literature supporting this condition.[6] For instance, Bernanke and Carey (1996) demonstrated that real wages were countercyclical in the interwar period using money supplies and aggregate demand shifters as instruments. Sumner and Silver (1989) documented that real earnings were countercyclical from 1948 to 1971. Swanson (2004) argued that testing theories of wage cyclicality should be done from the firm's perspective, deflating wages by the firm's output price rather than the consumer price index, and found that a vast majority of sectors show countercyclical real product wages.

Using the NBER-CES Manufacturing Industry Database, we estimate the cyclicality of input prices (p_1^A and p_1^M) from time series regressions of real input price growths on the aggregate profitability shock. We measure fixed input prices using the price index for office workers' wage rates and measure variable input prices using the value-weighted average of price indexes for materials, energy, and production workers' wage rates. In addition, Proposition 1 suggests that the difference in the growth rate of aggregate revenues (aggregate

[6]Abraham and Haltiwanger (1995) provide a comprehensive review of this literature.

shipped value) and aggregate gross profits (aggregate shipped value minus variable cost) is approximately proportional to and can be used as a proxy for the aggregate profitability shock. The regression results are reported in Panel B of Table 8. We find that the real price of variable inputs is procyclical with respect to aggregate profitability shocks, with an estimated elasticity of 0.38. In contrast, the real price of fixed inputs is found to be countercyclical, with an estimated elasticity of -0.87. Both elasticities are statistically significant from zero.

The intuitions from Propositions 1 and 2 on the effects of variable and fixed costs extend to the firm's overall risk exposure to the aggregate profitability shock, as summarized in the following proposition.

PROPOSITION 3. *With the production technology described above, the firm's risk exposure to the aggregate profitability shock is given by*

$$\beta \equiv \frac{\partial \log OP}{\partial \log X} = 1 + p_1^A + \frac{1}{1-OL}\left[\left(p_1^M - p_1^A\right) - \frac{p_1^M}{GM}\right]. \tag{9}$$

Proof: See the Appendix.

Proposition 3 has three key implications. First, when the variable input price is procyclical (i.e., $p_1^M > 0$) and the firm's operating leverage (OL) is held constant, a firm's beta to the aggregate profitability shock (β) increases with the firm's gross margin (GM) or gross profitability. Consequently, high profitability firms have greater exposure to the aggregate profitability shock, providing an explanation for the gross profitability premium.

Second, the positive relationship between gross profitability and aggregate profitability beta is more pronounced among firms with high operating leverage (OL). This suggests that operating leverage may amplify the gross profitability premium.

Third, the relationship between aggregate profitability beta and operating leverage can be either positive or negative, depending on gross profitability. For firms with high profitability, their exposure to the aggregate profitability shock increases with the firm's operating leverage. Conversely, when a firm's gross profitability is sufficiently low, the relationship between exposure to the aggregate profitability shock and operating leverage becomes negative.

4.2 Value and Policy Functions

Table 9 lists the parameter values we use for the model calibration, and the Figure 4 plots the firm's optimal fixed input (A) and variable input (M), gross profitability (GPA), operating leverage (OL), gross margin (GM), and operating profitability (OPA), against the firm-level productivity of fixed inputs ($u \equiv \log(U)$) and variable inputs ($z \equiv \log(Z)$). Since physical capital (K) is normalized to 1, OPA is also equal to operating profit and firm value.

[Insert Table 9 Here]

[Insert Figure 4 Here]

The top left and middle panels of Figure 4 show that the firm's optimal fixed inputs and variable inputs both increase with the productivity of variable inputs (z). However, their relation to the fixed input productivity (u) is more complex. While there is always a positive relation between the variable inputs (M) and the fixed input productivity (u), the relation between the optimal fixed inputs (A) and the fixed input productivity (u) depends on the level of variable input productivity (z). When variable input productivity (z) is low, the optimal fixed inputs (A) increase with fixed input productivity (u). At high levels of variable input productivity, the optimal fixed inputs (A) decrease with fixed input productivity (u). More generally, the relation between the optimal fixed inputs (A) and the fixed input productivity (u) can be non-monotonic.

The top right and bottom left panels of Figure 4 plot how a firm's gross profitability (GPA) and operating leverage (OL), respectively, vary with variable input productivity (z) and fixed input productivity (u). While firm gross profitability is mostly driven by variable input productivity (z), a firm's operating leverage is affected by both its variable input productivity (z) and fixed input productivity (u). Firms with both low variable input and fixed input productivities have high operating leverage. The bottom middle panel of Figure 4 shows that a firm's gross margin only depends on its variable input productivity (z). Therefore, gross profitability and gross margin are strongly correlated in the model. The bottom right panel plots the operating profitability (the firm value in our economy) against these two idiosyncratic input productivities. Despite a similar pattern to that of gross profitability (top right panel), we find that operating profitability (OPA) demonstrates a stronger relation to fixed input productivity (u) than gross profitability (GPA). This is especially true at high variable input productivity, i.e., high gross profitability.

An important question for asset pricing is how the risk premium varies across firms. Given the focus of our study, we are particularly interested in the relation of a firm's risk premium to its gross profitability and operating leverage. The top panel of Figure 5 shows the relation of the firm's aggregate profitability shock exposure (β) to fixed input productivity (u) and variable input productivity (z). We find that the firm's exposure to the aggregate profitability shock increases with its variable input productivity (z). However, the firm's aggregate profitability shock exposure increases with fixed input productivity (u) only when variable input productivity (z) is low. The relation reverses when the firm's variable input productivity (z) is high, with the firm's aggregate risk exposure decreasing with fixed input productivity.

[Insert Figure 5 Here]

More importantly, when we plot the firm's aggregate profitability shock exposure against the firm's gross profitability (GPA) and operating leverage (OL) in the bottom panel of Figure 5, the following patterns emerge. First, the firm's risk exposure to the aggregate profitability shock increases with the firm's gross profitability at all levels of the firm's operating leverage. Therefore, our model predicts a positive gross profitability premium. Furthermore, the profitability premium is stronger for firms with high operating leverage. In contrast, the relation between risk exposure and operating leverage depends on the firm's gross profitability. Specifically, the firm's risk exposure slightly increases with its operating leverage at high levels of firm profitability, but decreases with its operating exposure at low levels of firm profitability. This is consistent with the relation between a firm's risk exposure to the aggregate profitability shock and its operating leverage (OL) as shown in Equation (9). We test these predictions using characteristic-sorted portfolios in the next subsection.

4.3 Empirical evidence

To test the prediction of the production-based model on the relation between gross profitability, operating leverage, and risk premium, we double-sort stocks into portfolios based on their gross profitability and operating leverage.

In Table 10, Panel A, we split stocks into low and high operating leverage portfolios, and within each operating leverage portfolio, we form quintile portfolios based on their gross profitability. Panel A1 reports the average portfolio returns for the portfolios based on the neural-network-based measure OL_{NN} and Panel A2 reports the result for the portfolios based on the flow-based measure OL_{FL}. Conditional on operating leverage, the GPA premium is large in magnitude and statistically significant. Additionally, the GPA premium is much larger among firms with high operating leverage. The GPA premium is 5.86% among low OL_{NN} firms, which is smaller than 11.60% among firms with high OL_{NN}. The corresponding GPA premium is 5.19% and 8.17% when OL_{FL} is used.

[Insert Table 10 Here]

Consistent with the model prediction, we also find the negative operating leverage premium is more prominent for firms with low gross profitability. When we sequentially double-sort firms into 2-by-5 portfolios based on gross profitability and operating leverage (Panel B of Table 10), we find the relationship between operating leverage and average stock return demonstrates a hump shape for both firms with high and low gross profitability. However, the negative operating leverage premium (H-L) only exists in low GPA firms. For example, the operating leverage premium among low GPA firms is -4.78% when $\mathrm{OL_{NN}}$ is used (Panel B1) and -8.09% when $\mathrm{OL_{FL}}$ is used (Panel B2). In contrast, the operating leverage premium is close to zero among firms with high GPA. Intuitively, when gross profitability is low, the operating hedge effect from variable costs has a greater impact on the relationship between operating leverage and risk premium, and therefore, the expected return of high operating leverage firms is further reduced by the operating hedge.

Taken together, the interdependence of gross profitability, operating leverage, and average stock return lends support to the prediction of our production-based model. The finding also manifests the importance and imperativeness of simultaneously taking into account fixed and variable costs in production-based asset pricing models.

4.4 Idiosyncratic volatility premium

The production-based model provides a novel explanation for the idiosyncratic volatility (IVOL) premium documented by Ang, Hodrick, Xing, and Zhang (2006). Figure 6 plots the model-implied idiosyncratic volatility against firm-level productivities (top panel) and key characteristics, including gross profitability and operating leverage (bottom panel). In the model, we measure IVOL as $\sqrt{(z_{max}-z_{min})^2\beta_z^2+(u_{max}-u_{min})^2\beta_u^2}$, where β_z and β_u are the exposures of firm value to z and u, respectively. The plots indicate that IVOL decreases with firm productivity and gross profitability but increases with operating leverage. Consequently, high IVOL firms are strongly influenced by the operating hedge effect, which leads to lower risk premiums, as evident when comparing Figure 6 with Figure 5.

[Insert Figure 6 Here]

It is important to note that whether production costs induce operating leverage or operating hedge effect depend on the type of shock we focus on. For example, variable costs reduce risk premiums through the operating hedge effect because they have higher exposure to aggregate profitability shocks than revenues—a mechanism emphasized by Kogan, Li, and Zhang (2023). However, variable costs are more exposed to firm-specific profitability shocks than revenues, leading to an operating leverage effect. This asymmetry in response to firm-specific and aggregate shocks results in lower risk premiums for high IVOL firms, a discrepancy further amplified by the presence of fixed costs.

Empirical data support this intuition. Panel A of Table 11 presents the average returns and characteristics of quintile portfolios sorted by IVOL. Following Ang, Hodrick, Xing, and Zhang (2006), we estimate monthly IVOL as the standard deviation of residuals from regressing daily stock returns on the Fama-French three factors over each month. Panel A shows that high IVOL stocks tend to have lower gross profitability and higher operating leverage. These stocks also exhibit lower average returns compared to low IVOL stocks (0.25% vs. 9.98%).

[Insert Table 11 Here]

If operating leverage and operating hedge effects play a crucial role in explaining the IVOL premium, controlling for gross profitability and operating leverage should weaken the IVOL premium. This is precisely what we find. In Panel B of Table 11, we conduct a factor-spanning test by projecting the IVOL factor onto the operating leverage (OL) and gross profitability (GPA) factors. When controlling for the OL factor, the IVOL premium decreases in magnitude from –9.73% to –6.17% using the neural-network-based measure (Specification (2)) and to –6.58% using the flow-based measure of operating leverage (Specification (3)), representing reductions of over 30%. The OL factor explains more than 40% of the time-series variation in the IVOL factor. Controlling for the GPA factor in Specification (4) further reduces the IVOL premium by 66% to –3.27%. When both GPA and OL factors are included in Specifications (5) and (6), the IVOL factor's abnormal return becomes economically and statistically insignificant.

These findings are particularly noteworthy because IVOL is return-based, while gross profitability and operating leverage are derived from accounting data. Our proposed mechanism thus complements existing risk-based explanations of the IVOL premium. For example, Kogan and Papanikolaou (2013) show that high IVOL stocks tend to have more growth options relative to existing assets, making them more exposed to investment-specific technology (IST) shocks. Since IST shocks carry a negative risk premium, this results in a negative relationship between IVOL and expected returns. In contrast, our explanation is rooted in production costs and holds even in a static setting.

5 Conclusion

We examine operating leverage, a fundamental concept widely used in finance, accounting, and economics. Traditionally, fixed production costs are considered "sticky", creating to a positive link between operating leverage and the risk premium. However, using a production-based model that incorporates three types of inputs—–physical capital, fixed inputs, and variable inputs—–we reveal a more nuanced relationship. Specifically, the effect of fixed-cost-induced operating leverage is significantly influenced by variable production costs. This complexity is further exacerbated by the diverse operating leverage measures used in the literature, which can sometimes be negatively correlated. Therefore, identifying the most appropriate measures that accurately capture the elasticity of a firm's operating profits to its gross profits is essential.

To address this, we introduce an out-of-sample neural-network-based measure of firm-level operating leverage. In addition to key firm characteristics and existing operating leverage measures, this approach integrates insights from an intuitive flow-based operating leverage measure that naturally emerges from a production-based asset pricing model. We find that while our neural-network-based measure is positively correlated with existing ones, it significantly outperforms them in capturing the elasticity of operating profit to gross profit.

More importantly, we find the relationship between operating leverage and the risk premium is non-monotonic, exhibiting a hump-shaped pattern. Contrary to conventional wisdom, firms with high operating leverage tend to have lower, rather than higher, average returns compared to firms with low operating leverage. Our findings suggests that the well-documented value premium is unlikely to be driven by the difference in operating leverage between value and growth firms.

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Appendix: Solution to firm's optimization problem

Firm's production function is given by

$$Y = \left((ZM)^{\frac{\theta-1}{\theta}} + \left\{ \left[(UA)^{\frac{\rho-1}{\rho}} + (XK)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \right\}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \tag{A.1}$$

where U and Z represent idiosyncratic productivity shocks to fixed inputs and variable inputs, respectively. Let V denote the integrate capital of physical capital K and fixed inputs A: $V = \left[(UA)^{\frac{\rho-1}{\rho}} + (XK)^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}$, and firm's output Y can then be expressed as $Y = \left[(ZM)^{\frac{\theta-1}{\theta}} + V^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}}$.

Firm maximizes its operating profit OP by choosing fixed inputs A and variable inputs M:

$$OP = \max_{\{M,A\}} \{Y - P_M M - P_A A\}, \tag{A.2}$$

where P_M and P_A are the exogenous prices of variable and fixed inputs, respectively.

It can be shown from the first order conditions that:

$$P_M = \left[(ZM)^{\frac{\theta-1}{\theta}} + V^{\frac{\theta-1}{\theta}} \right]^{\frac{1}{\theta-1}} Z^{\frac{\theta-1}{\theta}} M^{-\frac{1}{\theta}}, \tag{A.3}$$

$$P_A = \left[(ZM)^{\frac{\theta-1}{\theta}} + V^{\frac{\theta-1}{\theta}} \right]^{\frac{1}{\theta-1}} \left[(UA)^{\frac{\rho-1}{\rho}} + (XK)^{\frac{\rho-1}{\rho}} \right]^{\frac{\theta-\rho}{(\rho-1)\theta}} U^{\frac{\rho-1}{\rho}} A^{-\frac{1}{\rho}}. \tag{A.4}$$

Furthermore, the ratios of variable cost to revenue and fixed cost to revenue are given by

$$\frac{P_M M}{Y} = \frac{(ZM)^{\frac{\theta-1}{\theta}}}{(ZM)^{\frac{\theta-1}{\theta}} + V^{\frac{\theta-1}{\theta}}}, \tag{A.5}$$

$$\frac{P_A A}{Y} = \frac{V^{\frac{\theta-1}{\theta}}}{(ZM)^{\frac{\theta-1}{\theta}} + V^{\frac{\theta-1}{\theta}}} \cdot \frac{(UA)^{\frac{\rho-1}{\rho}}}{(UA)^{\frac{\rho-1}{\rho}} + (K)^{\frac{\rho-1}{\rho}}}. \tag{A.6}$$

Proof of Proposition 1: Operating hedge effect

From equation (A.5), we can express gross profit GP as

$$GP = Y - P_M M = Y \cdot \frac{V^{\frac{\theta-1}{\theta}}}{(ZM)^{\frac{\theta-1}{\theta}} + V^{\frac{\theta-1}{\theta}}}. \tag{A.7}$$

Rearranging equation (A.7) and taking partial derivative of the logarithm of both sides of the equation with respect to $\log X$ yield

$$\frac{\partial \log GP}{\partial \log X} - \frac{\partial \log Y}{\partial \log X} = \frac{\theta-1}{\theta} \cdot \frac{\partial \log V}{\partial \log X} - \frac{\partial \log \left((ZM)^{\frac{\theta-1}{\theta}} + V^{\frac{\theta-1}{\theta}} \right)}{\partial \log X}. \tag{A.8}$$

Expanding the last partial derivative of equation (A.7) and after some algebra, we can show

$$\frac{\partial \log GP}{\partial \log X} - \frac{\partial \log Y}{\partial \log X} = \frac{\theta - 1}{\theta}(1 - GM)\left[-\frac{\partial \log M}{\partial \log X} + OL \cdot \frac{\partial \log A}{\partial \log X} + (1 - OL)\right], \tag{A.9}$$

where we have defined gross margin $GM = \frac{Y - P_M M}{Y}$ and operating leverage $OL = \frac{P_A A}{Y - P_M M}$.

Furthermore, $\frac{\partial \log M}{\partial \log X}$ and $\frac{\partial \log A}{\partial \log X}$ can be found by solving two linear equations from taking partial derivative of the logarithm of equations (A.3) and (A.4) with respect to $\log X$. Defining $p_1^M = \frac{\partial \log P_M}{\partial \log X}$, equation (A.9) can be further simplified to:

$$\frac{\partial \log GP}{\partial \log X} - \frac{\partial \log Y}{\partial \log X} = (\theta - 1)\frac{1 - GM}{GM} p_1^M. \tag{A.10}$$

Q.E.D.

Proof of Proposition 2: Operating leverage effect

Combining equations (A.2), (A.5), and (A.6), we can express operating profit OP as

$$OP = GP \cdot \frac{(XK)^{\frac{\rho-1}{\rho}}}{(UA)^{\frac{\rho-1}{\rho}} + (XK)^{\frac{\rho-1}{\rho}}}. \tag{A.11}$$

Rearranging equation (A.11) and taking partial derivative of the logarithm of both sides of the equation with respect to $\log X$ yield

$$\frac{\partial \log OP}{\partial \log X} - \frac{\partial \log GP}{\partial \log X} = \frac{\rho - 1}{\rho} - \frac{\partial \log\left((UA)^{\frac{\rho-1}{\rho}} + (XK)^{\frac{\rho-1}{\rho}}\right)}{\partial \log X}, \tag{A.12}$$

which, along with expressions of $\frac{\partial \log M}{\partial \log X}$ and $\frac{\partial \log A}{\partial \log X}$, can be simplified to:

$$\frac{\partial \log OP}{\partial \log X} - \frac{\partial \log GP}{\partial \log X} = (1 - \rho)\frac{OL}{1 - OL}\left(p_1^M - p_1^A - \frac{p_1^M}{GM}\right), \tag{A.13}$$

where we have defined $p_1^A = \frac{\partial \log P_A}{\partial \log X}$. Q.E.D.

Proof of Proposition 3: Risk exposure to aggregate profitability shocks

With the above results, we can quickly show that firm's exposure to aggregate profitability shocks is given by

$$\frac{\partial \log OP}{\partial \log X} = 1 + p_1^A + \frac{1}{1 - OL}\left(p_1^M - p_1^A - \frac{p_1^M}{GM}\right). \tag{A.14}$$

Q.E.D.

Table 1: Definition of variables

This table describes the construction of variables used in the paper.

Variable	Description	Definition
Beta	CAPM beta defined in Fama and MacBeth (1973)	Monthly CAPM beta from 60-month rolling window regression using monthly returns
IVOL	Idiosyncratic volatility defined in Ang, Hodrick, Xing, and Zhang (2006)	Standard deviation of residuals from regressing daily stock returns on Fama-French three factors over each month
BM	Book-to-market ratio defined in Rosenberg, Reid, and Lanstein (1985)	Ratio of book value of equity to December market value of equity
GPA	Gross profitability defined in Novy-Marx (2013)	Ratio of GP to AT
OPE	Operating profitability defined in Fama and French (2006)	Ratio of net income, (REVT - COGS - XSGA - XINT), to book value of equity
OL_{NM}	Operating leverage defined in Novy-Marx (2011)	Sum of COGS and XSGA divided by AT
OL_{FJ}	Operating leverage defined in Ferri and Jones (1979)	PPENT divided by AT
OL_{CHK}	Operating leverage defined in Chen, Hartford, and Kamara (2019)	XSGA divided by AT
OL_{CCLL}	Operating leverage defined in Chen, Chen, Li, and Li (2022)	Sum of DP and XSGA divided by market value of assets
OL_{FL}	Flow-based operating leverage	Ratio of XSGA to GP

Table 2: Summary statistics

This table reports means, medians, standard deviations, 1st, 25th , 75th , and 99th percentiles, and 12-month autocorrelations (AR12) of five firm characteristics that are potentially related to the operating leverage effect and are used in the construction of our neural-network-based operating leverage measure (OL_{NN}), and six measures of operating leverage. The five firm characteristics are: market beta (Beta), idiosyncratic volatility (IVOL), book-to-market ratio (BM), gross profitability (GPA), and operating profitability (OPE). The six measures of operating leverage include: the measure defined in Novy-Marx (2011) (OL_{NM}, the sum of COGS and SG&A divided by AT), the measure defined in Ferri and Jones (1979) (OL_{FJ}, PPENT divided by AT), the measure defined in Chen, Hartford, and Kamara (2019) (OL_{CHK}, SG&A divided by AT), and the measure defined in Chen, Chen, Li, and Li (2022) (OL_{CCLL}, the sum of DP and SG&A divided by market value of assets), the flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP), and the neural network measure of operating leverage (OL_{NN}). The sample period is from fiscal year 1978 to 2021.

	Mean	Median	Std.Dev	P1	P25	P75	P99	AR12
Beta	1.09	0.99	0.61	-0.03	0.66	1.42	3.05	0.88
IVOL	0.39	0.32	0.27	0.08	0.21	0.48	1.55	0.58
BM	0.74	0.60	0.63	-0.73	0.35	0.96	3.49	0.86
GPA	0.40	0.35	0.23	0.06	0.24	0.51	1.28	0.92
OPE	0.28	0.26	0.43	-1.63	0.15	0.38	2.50	0.51
OL_{NM}	1.06	0.91	0.72	0.08	0.59	1.32	4.11	0.94
OL_{FJ}	0.30	0.24	0.22	0.02	0.13	0.42	0.89	0.97
OL_{CHK}	0.26	0.21	0.21	0.01	0.11	0.35	1.12	0.93
OL_{CCLL}	0.21	0.17	0.16	0.02	0.10	0.27	0.91	0.88
OL_{FL}	0.63	0.62	0.28	0.09	0.45	0.77	1.79	0.63
OL_{NN}	2.36	2.01	1.12	0.77	1.56	2.88	5.27	0.65

Table 3: Elasticities of operating profits

This table reports the results of panel regressions of percentage change in firm-level operating profit on percentage change in firm-level gross profit and its interaction with six measures of operating leverage. The six measures of operating leverage include: the neural-network-based measure of operating leverage (OL_{NN}), the flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP), the measure defined in Novy-Marx (2011) (OL_{NM}, the sum of COGS and SG&A divided by AT), the measure defined in Ferri and Jones (1979) (OL_{FJ}, PPENT divided by AT), the measure defined in Chen, Hartford, and Kamara (2019) (OL_{CHK}, SG&A divided by AT), and the measure defined in Chen, Chen, Li, and Li (2022) (OL_{CCLL}, the sum of DP and SG&A divided by market value of assets). We normalize OL_{NN}, OL_{FL}, OL_{NM}, OL_{FJ}, OL_{CHK}, and OL_{CCLL} to have unit standard deviation. Firm- and year-fixed effects are applied in all specifications. We report t-statistics with firm clustering and year clustering. Variables are winsorized at 1% and 99%. The sample period is from fiscal year 1978 to 2021.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
%GP	5.17	3.49	4.14	5.17	5.17	5.03	4.94	3.50	3.46	3.50	3.51	3.47	4.14	4.13	4.15	4.11	4.04	3.45	3.41
	(14.46)	(14.44)	(14.48)	(14.28)	(14.23)	(13.89)	(14.29)	(14.16)	(14.41)	(14.25)	(14.43)	(14.71)	(14.42)	(14.86)	(14.35)	(14.55)	(15.56)	(14.89)	(15.42)
%GP×OL_{NN}		1.38						1.38	1.41	1.35	1.30	1.31						1.17	1.09
		(11.34)						(11.45)	(11.31)	(10.65)	(10.09)	(9.85)						(7.15)	(6.14)
%GP×OL_{FL}			0.85										0.85	0.87	0.81	0.76	0.79	0.26	0.28
			(8.59)										(8.84)	(8.54)	(8.69)	(8.83)	(8.45)	(2.42)	(2.89)
%GP×OL_{NM}				0.19				0.02				-0.11	-0.00				-0.23		-0.11
				(1.44)				(0.16)				(-1.57)	(-0.01)				(-3.42)		(-1.58)
%GP×OL_{FJ}					-0.24				0.14			0.19		0.10			0.16		0.22
					(-1.82)				(1.24)			(2.11)		(0.85)			(1.55)		2.50
%GP×OL_{CHK}						0.52				0.11		0.03			0.17		-0.05		-0.03
						(3.78)				(0.83)		(0.45)			(1.40)		(-0.69)		(-0.5)
%GP×OL_{CCLL}							0.72				0.27	0.32				0.46	0.60		0.35
							(4.25)				(1.52)	(1.90)				(2.91)	(3.82)		(2.04)
R^2(%)	67.5%	73.9%	71.5%	67.6%	67.7%	68.4%	69.1%	73.9%	74.0%	73.9%	74.1%	74.2%	71.5%	71.5%	71.6%	72.1%	72.3%	74.1%	74.5%

Table 4: Determinants of operating leverage

This table examines the determinants of the two new operating leverage measures. We report the results of Fama-MacBeth regressions of neural-network-based measure of operating leverage (OL_{NN}) in Panel A and flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP) in Panel B. The explanatory variables used in Panel A include five firm characteristics, including market beta (Beta), idiosyncratic volatility (IVOL), book-to-market ratio (BM), gross profitability (GPA), and operating profitability (OPE), and four measures of operating leverage: the measure defined in Novy-Marx (2011) (OL_{NM}, the sum of COGS and SG&A divided by AT), the measure defined in Ferri and Jones (1979) (OL_{FJ}, PPENT divided by AT), the measure defined in Chen, Hartford, and Kamara (2019) (OL_{CHK}, SG&A divided by AT), and the measure defined in Chen, Chen, Li, and Li (2022) (OL_{CCLL}, the sum of DP and SG&A divided by market value of assets), as well as the flow-based operating leverage (OL_{FL}). The explanatory variables used in Panel B include five firm characteristics: Beta, IVOL, BM, GPA, and OPE, and four measures of operating leverage: OL_{NM}, OL_{FJ}, OL_{CHK}, OL_{CCLL}. Newey-West t-statistics reported in parentheses control for autocorrelation and heteroskedasticity. All dependent and independent variables are winsorized at the 1st and 99th percentiles. The sample is annual from fiscal year 1978 to 2021.

Panel A: Determinants of OL_{NN}

	(1)	(2)	(3)	(4)	(5)	(6)	(9)	(7)	(8)	(10)	(11)
Beta	0.12										-0.03
	(5.01)										(-1.53)
IVOL		0.42									0.17
		(40.36)									(9.47)
BM			0.22								-0.01
			(10.53)								(-0.30)
GPA				-0.06							-0.38
				(-1.11)							(-13.97)
OPE					-0.19						0.02
					(-6.48)						(1.88)
OL_{NM}						0.14					0.02
						(6.33)					(0.81)
OL_{FJ}							-0.09				0.16
							(-5.77)				(5.06)
OL_{CHK}								0.24			0.08
								(4.70)			(1.75)
OL_{CCLL}									0.42		0.15
									(8.36)		(6.40)
OL_{FL}										0.70	0.67
										(29.53)	(33.85)
Adj. R^2(%)	2.4%	17.7%	5.5%	3.4%	6.6%	2.7%	1.2%	9.3%	20.5%	49.2%	65.9%

Panel B: Determinants of OL_{FL}

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Beta	0.12									0.03
	(3.33)									(2.95)
IVOL		0.26								0.07
		(14.45)								(7.28)
BM			0.06							0.00
			(3.15)							(-0.32)
GPA				0.30						-0.51
				(10.37)						(-17.44)
OPE					-0.19					-0.08
					(-8.15)					(-4.31)
OL_{NM}						0.29				-0.03
						(20.36)				(-4.46)
OL_{FJ}							-0.41			-0.24
							(-21.86)			(-19.76)
OL_{CHK}								0.56		0.86
								(22.78)		(18.00)
OL_{CCLL}									0.51	0.18
									(22.99)	(7.09)
Adj. R^2(%)	3.3%	7.2%	0.9%	10.2%	5.1%	8.6%	17.3%	32.7%	27.3%	56.0%

Table 5: Portfolios sorted on two new operating leverage measures

This table reports the average annualized value-weighted excess returns and the result of time-series asset pricing tests of quintile portfolios sorted on neural-network-based measure of operating leverage (OL_{NN}) in Panel A and flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP) in Panel B. Newey-West t-statistics reported in parentheses control for autocorrelation and heteroskedasticity. The sample is monthly from January 1979 to December 2021.

Panel A: OL_{NN} quintile portfolios

OL_{NN} quintile	Ret-RF	α_{CAPM}	β_{CAPM}	α_{FF3F}	β_{MKT}	β_{SMB}	β_{HML}
Low	9.72	0.27	1.05	1.12	1.02	0.02	-0.24
2	8.89	0.35	0.95	0.57	0.96	-0.09	-0.06
3	9.92	0.75	1.02	0.74	1.02	0.00	0.01
4	10.21	-1.11	1.27	-0.53	1.17	0.47	-0.19
High	6.12	-6.87	1.45	-5.29	1.26	0.80	-0.49
H-L	-3.59	-7.15	0.40	-6.41	0.24	0.78	-0.26
t-stat	(-1.29)	(-2.83)	(6.37)	(-2.89)	(4.09)	(10.36)	(-2.59)
H-4	-4.09	-5.76	0.19	-4.76	0.09	0.33	-0.30
t-stat	(-2.07)	(-2.92)	(4.43)	(-2.60)	(2.44)	(6.13)	(-4.41)

Panel B: OL_{FL} quintile portfolios

OL_{FL} quintile	Ret-RF	α_{CAPM}	β_{CAPM}	α_{FF3F}	β_{MKT}	β_{SMB}	β_{HML}
Low	8.32	-0.79	1.02	-0.73	1.03	-0.08	-0.01
2	9.89	1.11	0.98	1.63	0.97	-0.04	-0.14
3	9.76	0.72	1.01	1.33	0.98	0.05	-0.18
4	11.97	1.27	1.19	2.27	1.09	0.40	-0.31
High	4.35	-8.93	1.48	-7.06	1.27	0.83	-0.58
H-L	-3.97	-8.14	0.47	-6.33	0.25	0.91	-0.57
t-stat	(-1.13)	(-2.47)	(6.13)	(-2.23)	(3.74)	(10.27)	(-4.44)
H-4	-7.62	-10.20	0.29	-9.32	0.18	0.44	-0.27
t-stat	(-3.11)	(-4.34)	(6.01)	(-4.29)	(4.37)	(7.22)	(-3.31)

Table 6: Robustness tests

This table performs robustness checks on operating leverage measures based on alternative machine learning specifications or techniques. Specification (1) is for our benchmark OL_{NN}. Specifications (2) to (6) modify the benchmark neural network, one change at a time. Specification (2) uses a broader range of parameter value for l_1: $\{0.5, 0.05, 0.02, 0.01, 0.001\}$. Specification (3) uses 64 neurons in the hidden layer. Specification (4) uses 63 characteristics as neural network inputs described in Table IA4 of the Internet Appendix. Specification (5) consists of a deeper neural network with 3 hidden layers (32, 16, and 8 neurons). In Specification (6), OL_{NN} is augmented in a boosting method with second-stage ridge regressions on 63 characteristics. Specifications (7) to (12) are for operating leverage measures based on other machine learning techniques. Specifications (7) and (8) use Ridge regressions with 10 and 63 characteristics, respectively. Specifications (9) and (10) use LASSO regressions with 10 and 63 characteristics, respectively. Specification (11) uses Ridge regressions with 12,000 features generated from the random Fourier feature method (bandwidth parameter = 0.01) with 10 characteristics. The shrinkage parameters for both Ridge and LASSO regressions are selected from cross-validations over 100 values logarithmically spaced between 10^{-10} and 10^{10}. In specification (12), operating leverage is defined as the average of benchmark OL_{NN} and the measures from specifications (7) to (11). Panel A reports the results of panel regressions of percentage change in firm-level operating profit on percentage change in firm-level gross profit and its interaction with one of the alternative operating leverage measures. All operating leverage measures are normalized to have unit standard deviation. We report t-statistics with firm clustering and year clustering. The sample is annual from 1979 to 2021. Panel B reports the average annualized value-weighted excess returns of quintile portfolios sorted on alternative operating leverage measures. We report Newey-West t-statistics controlling for autocorrelation and heteroskedasticity. The sample is monthly from January 1979 to December 2021.

	Panel A1: Modifications of benchmark neural network						Panel A2: Alternative machine learning techniques					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Coeff	1.38	1.36	1.37	1.20	1.36	1.39	1.53	1.51	1.53	1.59	1.58	1.54
t-stat	(11.34)	(10.71)	(12.01)	(8.10)	(13.02)	(11.24)	(11.32)	(9.98)	(11.49)	(10.88)	(11.42)	(11.77)
R^2(%)	73.9%	73.7%	74.1%	72.6%	74.1%	74.0%	73.9%	73.6%	73.9%	74.1%	74.0%	74.5%

	Panel B1: Modifications of benchmark neural network						Panel B2: Alternative machine learning techniques					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Low	9.72	10.00	8.72	9.32	9.80	9.65	8.96	10.86	8.50	10.67	8.86	9.42
2	8.89	8.86	9.75	9.97	9.18	8.96	9.83	8.57	10.34	8.32	10.06	9.52
3	9.92	9.48	9.71	9.30	8.79	10.33	10.39	8.99	10.29	8.99	9.66	10.44
4	10.21	9.59	8.68	8.41	8.58	9.71	9.55	9.10	9.95	9.65	9.73	7.83
High	6.12	6.28	6.46	3.87	3.50	5.61	2.35	2.98	1.99	2.34	5.83	1.70
H-L	-3.59	-3.72	-2.26	-5.45	-6.31	-4.04	-6.61	-7.88	-6.51	-8.33	-3.03	-7.72
t-stat	(-1.29)	(-1.35)	(-0.78)	(-1.50)	(-2.01)	(-1.39)	(-1.94)	(-2.39)	(-1.84)	(-2.57)	(-0.93)	(-2.27)

Table 7: Portfolios sorted on book-to-market ratio

This table reports the average annualized value-weighted excess returns of quintile portfolios sorted on book-to-market ratio (BM), as well as the time-series means of median portfolio characteristics: flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP), the neural-network-based measure of operating leverage (OL_{NN}), logarithm of June end market capitalization (logME), logarithm of book-to-market ratio (logBM), gross profitability (GPA), and annualized idiosyncratic volatility (IVOL). Panel A reports the result for one-way quintiles unconditionally sorted on BM. Panel B (Panel C) reports the result for the BM portfolios conditional on OL_{NN} (OL_{FL}). Specifically, we sequentially double sort firms into 3-by-5 portfolios based on their OL and then BM, and report the average return and characteristics of each BM quinitle across three OL terciles. Newey-West t-statistics reported in parentheses control for autocorrelation and heteroskedasticity. The sample period is from January 1979 to December 2021.

Panel A: BM quintile portfolios

BM quintile	Ret-RF	OL_{FL}	OL_{NN}	logME	logBM	GPA	IVOL
Low	8.44	0.70	2.17	5.55	-1.85	0.45	0.40
2	9.22	0.65	1.92	5.81	-1.07	0.42	0.34
3	9.25	0.67	2.05	5.44	-0.59	0.37	0.33
4	9.37	0.70	2.40	4.85	-0.17	0.33	0.35
High	10.99	0.77	3.06	3.85	0.41	0.29	0.43
H-L	2.55	0.06	0.88	-1.69	2.26	-0.15	0.02
t-stat	(0.98)						

Panel B: BM quintle portfolios conditional on OL_{NN}

BM quintile	Ret-RF	OL_{FL}	OL_{NN}	logME	logBM	GPA	IVOL
Low	6.84	0.83	2.85	5.52	-1.86	0.44	0.43
2	7.70	0.76	2.81	5.51	-1.05	0.41	0.39
3	9.38	0.73	2.80	5.22	-0.57	0.38	0.38
4	10.65	0.71	2.81	4.86	-0.18	0.35	0.38
High	11.06	0.70	2.86	4.15	0.36	0.30	0.41
H-L	4.22	-0.14	0.01	-1.37	2.23	-0.14	-0.02
t-stat	(1.52)						

Panel C: BM quintile portfolios conditional on OL_{FL}

BM quintile	Ret-RF	OL_{FL}	OL_{NN}	logME	logBM	GPA	IVOL
Low	6.53	0.81	2.69	5.67	-1.88	0.44	0.41
2	9.11	0.74	2.69	5.58	-1.08	0.41	0.38
3	9.77	0.71	2.77	5.25	-0.58	0.38	0.37
4	9.86	0.71	2.92	4.85	-0.16	0.34	0.38
High	11.72	0.71	3.14	4.02	0.40	0.29	0.43
H-L	5.19	-0.10	0.45	-1.65	2.28	-0.15	0.01
t-stat	(1.88)						

Table 8: Cyclicality of gross profits, operating profits, variable and fixed costs

This table reports the cyclicality of aggregate variable cost, fixed cost, gross profit, and operating profit. Data come from NBER-CES Manufacturing Industry Database. Revenue (Rev) is the total value of shipments. Variable cost (VC) includes costs of materials, energy, and production worker wages. Fixed cost (FC) is measured by office worker wage. All values are deflated by the personal consumption expenditure (PCE) price index. Gross profit (GP) is Rev minus VC. Operating profit (OP) is GP minus FC. Panel A reports the result of time series regressions of annual growth rates of aggregate VC, FC, and GP on the annual growth rate of Rev, and the regression of annual growth rate of aggregate OP on the annual growth rate of GP. Panel B reports the result of time series regressions of price indexes for VC and FC on the aggregate profitability shock. The price index for VC is calculated as the value-weighted average of price indexes for materials, energy, and production worker wages. The aggregate profitability shock is measured as the difference in the annual growth rates of Rev and GP. All price indexes are adjusted by the PCE index. Newey-West t-statistics reported in parentheses control for autocorrelation and heteroskedasticity. The data are annual from 1958 to 2018.

Panel A: Elasticities of costs and profits

	$\beta^{\mathrm{V}}_{\mathrm{Rev}}(\mathrm{VC})$	$\beta^{\mathrm{V}}_{\mathrm{Rev}}(\mathrm{FC})$	$\beta^{\mathrm{V}}_{\mathrm{Rev}}(\mathrm{GP})$	$\beta^{\mathrm{V}}_{\mathrm{GP}}(\mathrm{OP})$
Est.	1.17	0.34	0.68	1.16
t-stat	(30.79)	(6.14)	(9.35)	(45.48)

Panel B: Cyclicalities of input prices

	p^{VC}	p^{FC}
Est.	0.37	-0.87
t-stat	(6.46)	(-7.17)

Table 9: Parameter values in model calibration

This table reports the parameter values used in model calibration at the annual frequency.

Symbol	Parameter description	Value
ρ	Elasticity of substitution b/w physical capital (K) and fixed inputs (A)	0.44
θ	Elasticity of substitution b/w K-A bundle and variable inputs (M)	0.55
x	Mean of aggregate profitability	1.38
z_{min}	Minimum value of firm-level variable input productivity shock	-0.15
z_{max}	Maximum value of firm-level variable input productivity shock	1.36
u_{min}	Minimum value of firm-level fixed input productivity shock	-0.90
u_{max}	Maximum value of firm-level fixed input productivity shock	1.03
P_M^0	Level of price of variable inputs	0.08
P_M^1	Elasticity of variable input price w.r.t. aggregate profitability shock	0.47
P_A^0	Level of price of fixed inputs	0.23
P_A^1	Elasticity of fixed input price w.r.t. aggregate profitability shock	-0.57

Table 10: Excess returns of portfolios double sorted on operating leverage and gross profitability

This table reports the average annualized value-weighted excess returns of portfolios doubled sorted on operating leverage and gross profitability (GPA). Panel A conducts sequential sorts first on operating leverage and then on GPA, and Panel B conducts sequential sorts first on GPA and then on operating leverage. Both the neural-network-based measure of operating leverage (OL_{NN}) and the flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP) are included. Newey-West t-statistics reported in parentheses control for autocorrelation and heteroskedasticity. The sample period is from January 1979 to December 2021.

Panel A: Portfolios sequentially sorted on OL first and then GPA

A1) neural-network-based measure OL_{NN}

	1	2	GPA	4	5	5-1	t-stat
Low OL_{NN}	5.15	9.89	9.86	9.68	11.00	5.86	(2.80)
High OL_{NN}	2.81	9.05	9.58	10.48	14.40	11.60	(3.73)

A2) Flow-based measure OL_{FL}

	1	2	GPA	4	5	5-1	t-stat
Low OL_{FL}	5.35	8.29	9.52	9.70	10.54	5.19	(2.42)
High OL_{FL}	3.30	8.71	9.74	11.31	11.46	8.17	(2.68)

Panel B: Portfolios sequentially sorted on GPA first and then OL

B1) neural-network-based measure OL_{NN}

	1	2	OL_{NN}	4	5	5-1	t-stat
Low GPA	7.93	7.57	8.16	5.88	3.15	-4.78	(-1.58)
High GPA	10.89	9.96	11.08	15.47	11.10	0.20	(0.06)

B2) Flow-based measure OL_{FL}

	1	2	OL_{FL}	4	5	5-1	t-stat
Low GPA	7.95	7.17	8.24	8.78	-0.15	-8.09	(-1.98)
High GPA	9.90	10.79	11.05	14.08	10.81	0.91	(0.25)

Table 11: Portfolios sorted on idiosyncratic volatility

Panel A reports the average annualized value-weighted excess returns of quintile portfolios sorted on idiosyncratic volatility (IVOL). Panel A also reports the time-series means of median portfolio characteristics: flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP), the neural-network-based measure of operating leverage (OL_{NN}), logarithm of June end market capitalization (logME), logarithm of book-to-market ratio (logBM), gross profitability (GPA), and annualized idiosyncratic volatility (IVOL). Panel B reports the results from factor spanning tests of the IVOL factor using the operating leverage and the gross profitability factors. Each factor is defined as the long-short portfolio return in the quintile portfolios sorted on the corresponding characteristic. We run time-series regressions of the IVOL factor under the following six specifications: Specification (1) includes only a constant, Specification (2) includes flow-based operating leverage (OL_{FL}) factor, Specification (3) includes neural network operating leverage (OL_{FL}) factor, Specification (4) includes the gross profitability (GPA) factor, Specification (5) includes both OL_{NN} and GPA factors, and Specification (6) includes both OL_{NN} and GPA factors. Newey-West t-statistics reported in parentheses control for autocorrelation and heteroskedasticity. The sample period is from January 1979 to December 2021.

Panel A: IVOL quintile portfolios

IVOL quintile	Ret-RF	OL_{FL}	OL_{NN}	logME	logBM	GPA	IVOL
Low	9.98	0.60	1.82	6.46	-0.62	0.37	0.16
2	9.45	0.63	1.88	5.93	-0.59	0.37	0.26
3	9.99	0.68	2.18	5.22	-0.57	0.37	0.37
4	6.59	0.76	2.80	4.48	-0.53	0.37	0.52
High	0.25	0.90	4.08	3.43	-0.44	0.35	0.87
H-L	-9.73	0.30	2.26	-3.03	0.18	-0.03	0.71
t-stat	(-2.52)						

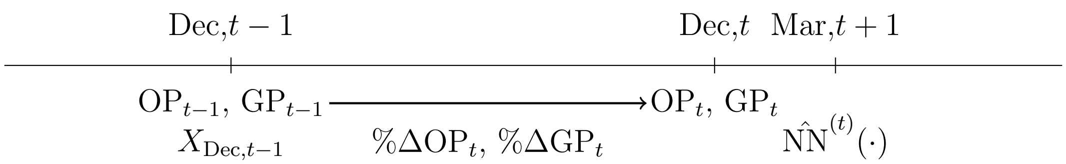
Panel B: IVOL factor spanning test

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	-9.73	-6.58	-6.17	-3.27	-0.97	-2.80
	(-2.52)	(-2.12)	(-2.27)	(-0.92)	(-0.37)	(-1.11)
OL_{FL} factor		0.79			0.76	
		(10.42)			(13.04)	
OL_{NN} factor			0.99			0.88
			(13.15)			(12.62)
GPA factor				-0.85	-0.76	-0.49
				(-7.01)	(-9.94)	(-7.18)
R^2(%)		42.0%	48.2%	19.7%	57.6%	54.3%

Figure 1: Timing for OL_{NN} construction

Panel A of this figure plots the timing for training a neural network for the training sample of year t. Panel B of this figure plots the timing for calculating predicted OL_{NN} for September of year $t+1$.

Panel A: Training model $\text{NN}^{(t)}$



Panel B: Predicting OL_{NN} for September, year $t+1$:

$$\text{OL}_{\text{NN, Sep},t+1} = \frac{\hat{\text{NN}}^{(t)}(X_{\text{Sep},t+1}) + ... + \hat{\text{NN}}^{(t-9)}(X_{\text{Sep},t+1})}{10}$$

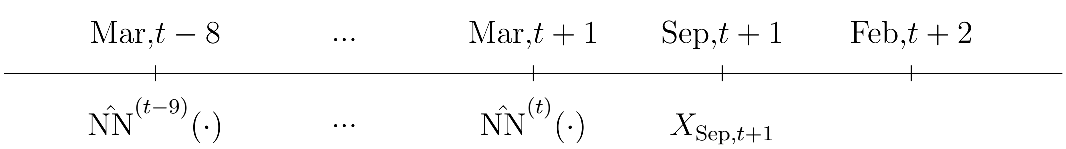


Figure 2: Time series of median operating leverage

This figure plots the time series of median values of the neural-network-based measure of operating leverage (OL_{NN}) and that of the flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP). The grey-shaded areas represent NBER recession periods. The sample period is from January 1979 to December 2021.

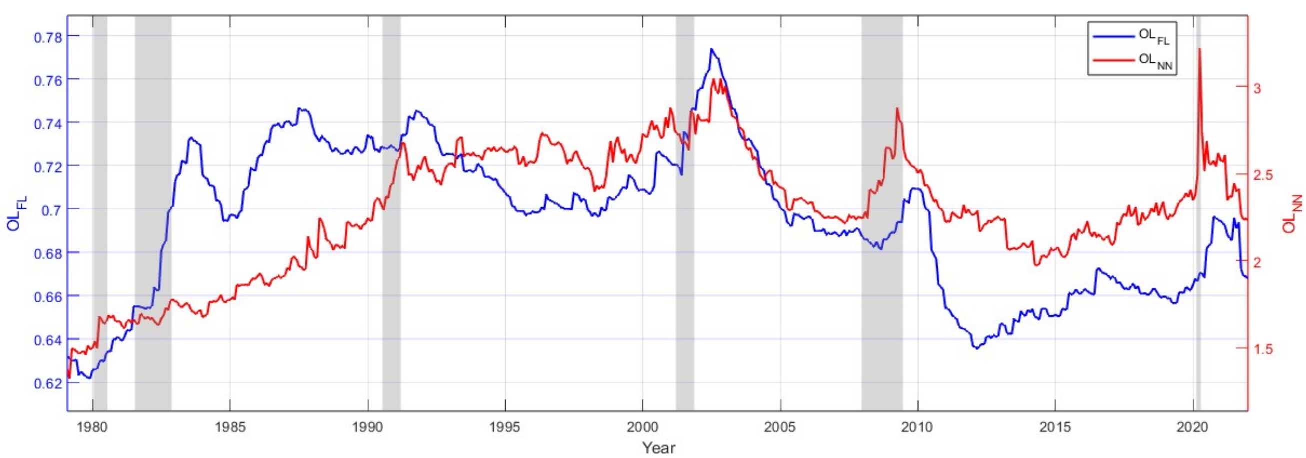


Figure 3: Long-horizon premium of operating leverage

The top two figures plot the average annualized value-weighted excess returns of five portfolios sorted on OL_{NN} and OL_{FL} across different lages of months between the availability of OL and portfolio formation. The lag of months being 1 corresponds to the standard sort, where portfolios are formed the next month after OL is available. The bottom two figures plot the average annualized long-short portfolio return in the quintile portfolios sorted on neural-network-based measure of operating leverage (OL_{NN}) and flow-based operating leverage (OL_{FL}, the ratio of SG&A to GP) against the lag of months between the availability of OL and portfolio formation. The grey-shaded area represents the 2.5%-97.5% confidence band of the premium. The sample period is from January 1979 to December 2021.

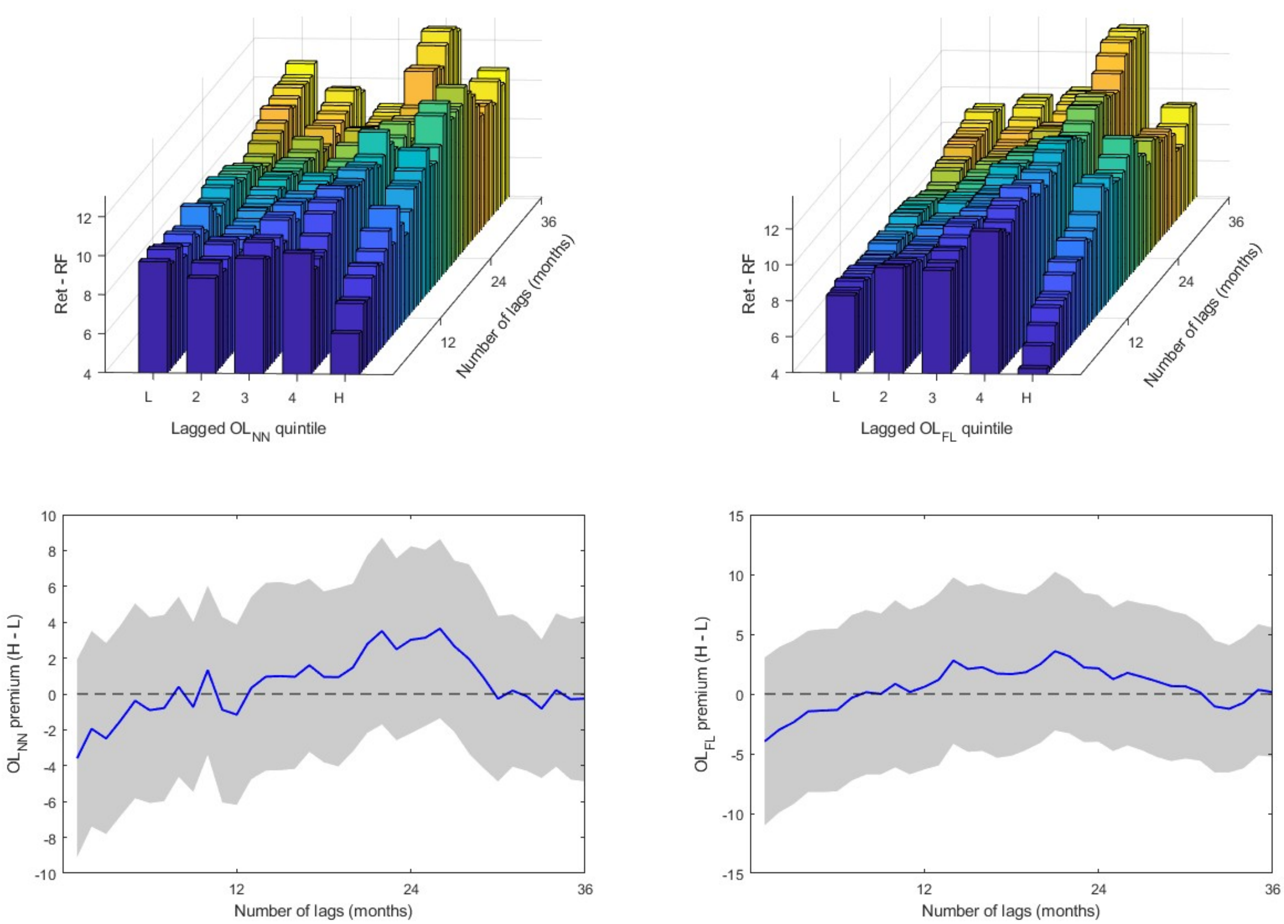


Figure 4: Value and policy functions

This figure plots the optimal policies for fixed input (A) and variable input (M), gross profitability (GPA), operating leverage (OL), gross margin (GM), and operating profitability (OPA, which is also equal to operating profit (OP) and firm value because physical capital is normalized to 1), against fixed input productivity (u) and variable input productivity (z).

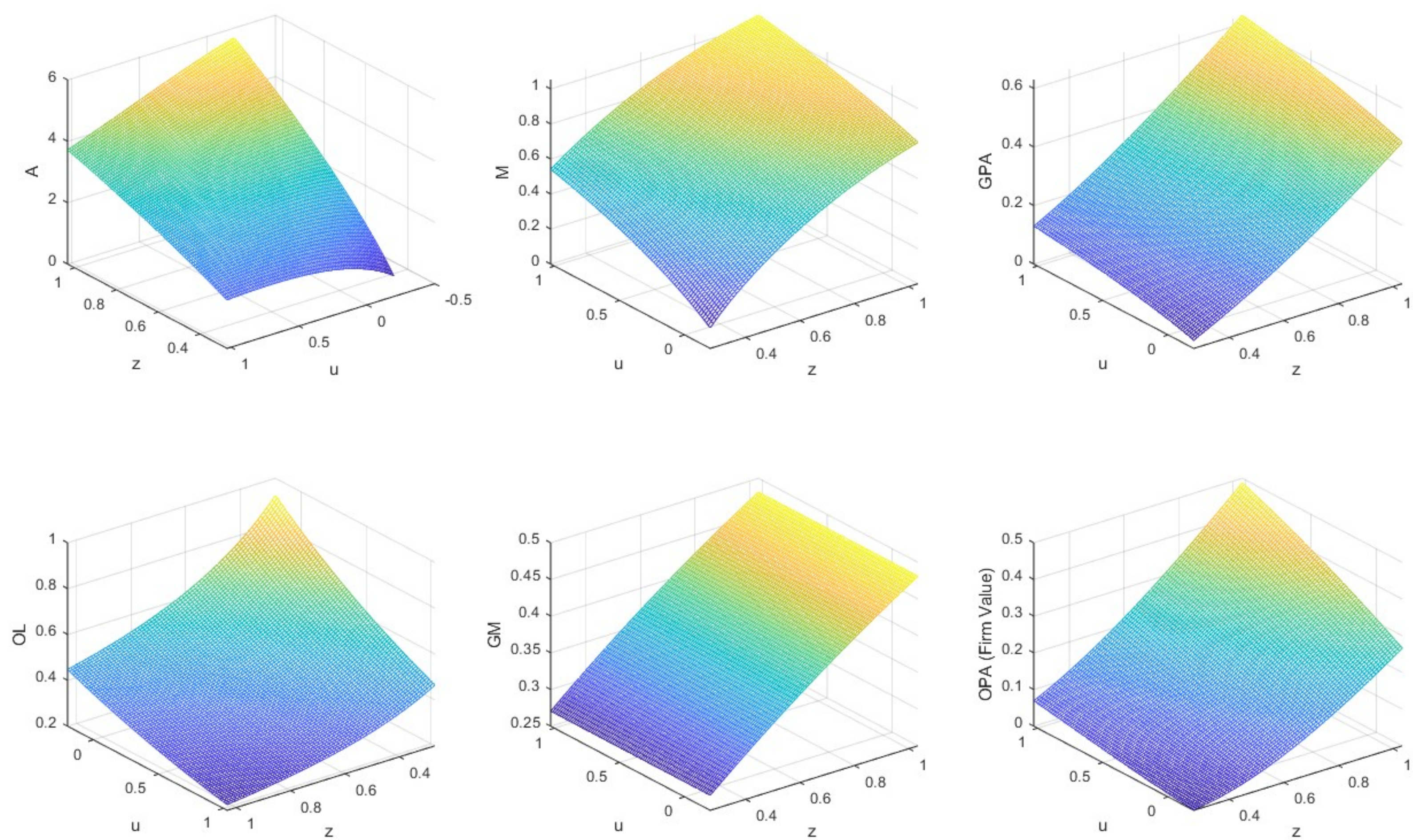
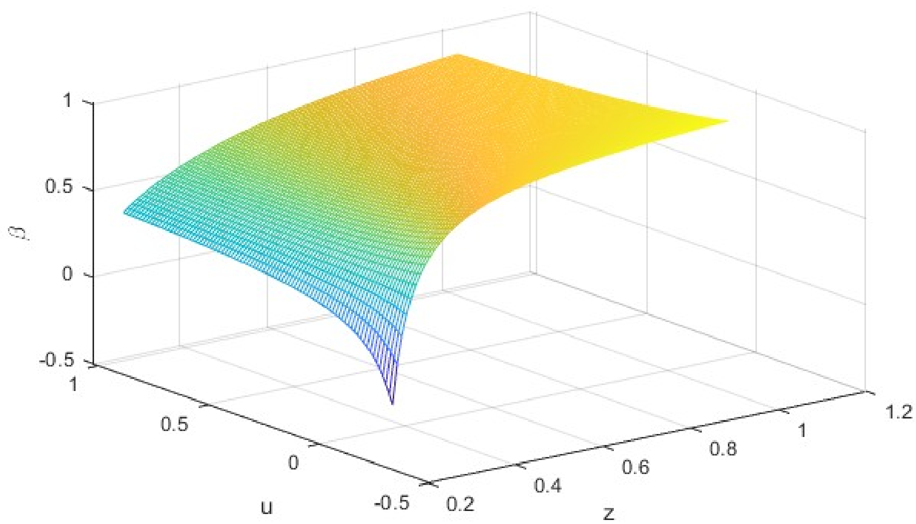


Figure 5: Systematic risk exposure

This figure plots firm's exposure to the aggregate profitability shock (beta) against the fixed input productivity (u) and the variable input productivity (z) in Panel A, and against gross profitability (GPA) and operating leverage (OL) in Panel B.



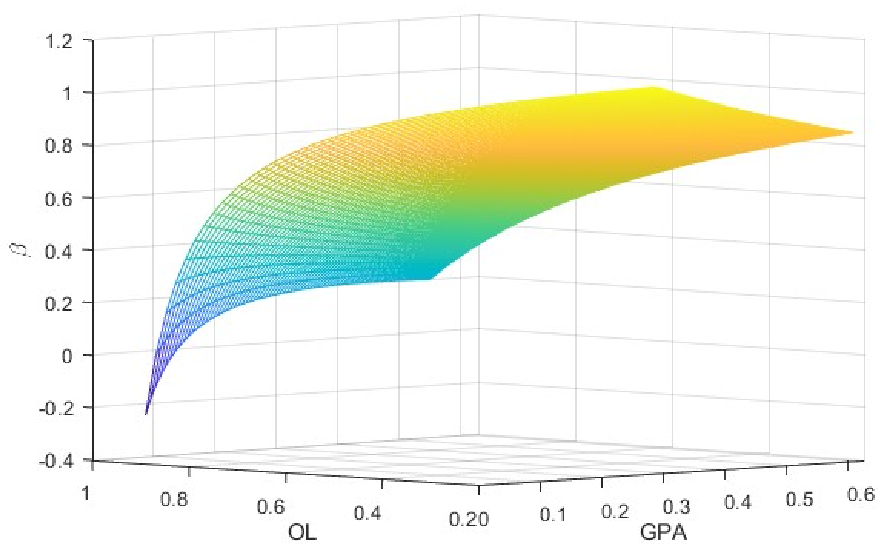


Figure 6: Model-implied idiosyncratic volatility

This figure plots the model-implied idiosyncratic volatility (IVOL) against the fixed input productivity (u) and the variable input productivity (z) in Panel A, and against gross profitability (GPA) and operating leverage (OL) in Panel B.