Online Appendix for “Operating Hedge and Gross Profitability Premium”

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A. Moments in SMM estimation

Table A1 provides details on the construction of empirical moments in SMM.

B. Sensitivity of estimated parameters to moments

In this section, we report the identification of the model's structural parameters. In Figure A1, we plot the Andrews, Gentzkow, and Shapiro (2017) measure of sensitivity of parameters to moments. We report the measure in elasticity form,

$$\hat{\lambda}_{i,j} = \lambda_{i,j} \frac{\Psi^j(p)}{p^i}, \tag{C.1}$$

where $\lambda_{i,j}$ is the element of the sensitivity matrix Λ that corresponds to parameter i and moment j. The matrix Λ is computed as

$$\Lambda = -(G'WG)^{-1}G'W \tag{C.2}$$

where G is the numerical gradient of the sample moments $g(p) = \Psi - \frac{1}{S}\sum_{i=1}^{S} \hat{\Psi}_i(p)$ and W is the weighting matrix.

The simulated method of moment (SMM) estimation is a complex optimization problem, and the moments are mostly interconnected with each other. When we change the value of one parameter, most moments would change simultaneously so that other parameters would need to adjust accordingly. It is almost impossible to claim that the parameter ABC can be pinned down by the moment XYZ. Nevertheless, Figure A1 offers some insights on the identification of certain important parameters in the model. For instance, the two key parameters in our production-based model are the elasticity of substitution between capital and variable inputs (η) and the cyclicality of input price with respect to the aggregate profitability (p_1). Figure A1 shows that the average aggregate sales/COGS ratio and the elasticity of aggregate variable input prices with respect to aggregate revenues are very informative about p_1 (the cyclicality of variable input prices), and the average aggregate sales/COGS ratio and the relative volatility of aggregate sales and GP are par-

ticularly informative about η (the elasticity of substitution between capital and variable inputs). This should not be surprising because these moments are linked to the core mechanism of the operating hedge.

On the other parameters, the volatility of aggregate profitability σ_x is mostly affected by the aggregate sales volatility, as it is directly related to firm's production. The volatility of aggregate investment shocks σ_ξ and the capital adjustment cost coefficient θ are mostly affected by the average logBM, because these parameters determine the asset composition between assets-in-place and growth options. The level of input price p_0 is closely related to the average sales-to-COGS ratio and the volatility of aggregate gross profits relative to the volatility of aggregate sales. Holding p_1 constant, a higher p_0 strengthens the operating hedge effect and lowers both the average sales-to-COGS ratio and volatility of gross profits. The GP/A factor volatility has the most impact on the effective leverage ratio ϕ.

The two prices of risk parameters are simultaneously affected by many target moments. It is instructive to see how these parameters are identified, as this illustrates how individual parameters are generally identified by multiple moments. For the price of risk for the aggregate profitability shock γ_x, the most important moments are the market Sharpe ratio, the average GP/A, the average logBM, and the AR(1) coefficient of aggregate investment rate. For the price of risk for the aggregate investment shock γ_ξ, the most important determinants are the average logBM, the average and AR(1) coefficient of aggregate investment rate, and the volatility of GP/A and value factors. One may have expected the Sharpe ratios of various factors to be the dominant sources of information, but in finite samples Sharpe ratios are subject to significant sampling errors. Instead, the SMM estimator relies heavily on valuation ratios, which contain forward-looking information about expected returns. This is intuitive, and aligns with our general understanding of how one may estimate expected returns based on market prices and cash flow data. In particular, the average logBM is determined by both the current and expected cash flows and discount rates. The average GP/A is informative about the current cash flow, whereas the average and AR(1) coefficient of aggregate investment rate contribute additional information about the expected cash flows in the long run. Thus, controlling for the average GP/A and the average and AR(1) coefficient

of the aggregate investment rate, the average logBM is informative about the discount rates. The discount rates, in turn, can also be affected by the quantity of risk of the aggregate profitability shock and the aggregate investment shock. Therefore, controlling for the volatility of GP/A and value factors helps to further disentangle prices of risk from the discount rates.

C. Alternative log project arrival rate $\bar{a}$

The parameter $\bar{a}$ measures the average log project arrival rate and determines the average number of projects per firm. Since the project profitability shocks are perfectly correlated within a firm, the value of $\bar{a}$ does not have a significant impact on the moments we consider. To see this, Table A2 considers three alternative values of $\bar{a}$, corresponding to an average of 75, 92, and 168 projects per firm, respectively. The result shows that all 28 moments are quantitatively close to those from the benchmark parameterization ($\bar{a} = 0.3$), and the difference is mainly numerical due to more or less projects being simulated. We chose $\bar{a} = 0.3$ to balance the need to have sufficient number of projects in a firm and the computational cost in the SMM estimation.

D. Unconditional and within industry GP/A portfolios

Novy-Marx (2013) documents that the gross profitability premium is stronger within industries, because industries can differ in other dimensions that may affect gross profitability but not risk premium. To see if this result also holds in our sample, we conduct a horse race between the unconditional GP/A premium and the within-industry GP/A premium within Fama and French 30 industries.

The unconditional GP/A quintiles are created by sorting firms unconditionally on their gross profitability. Panel A, Table A3, we run time series regressions of unconditional GP/A portfolio returns on the market factor and a within-industry GP/A factor, which is the return of the long-short portfolio from Panel A. We find that the abnormal return of the GP/A premium is only 1.12% per year and statistically insignificant from zero. In contrast, when we regress the within-

industry GP/A portfolios onto the market factor and an unconditional GP/A factor in Panel B, the abnormal return of the within-industry GP/A premium remains statistically significant at 2.93% per year. Therefore, our results show that the unconditional GP/A premium is subsumed by the within-industry GP/A premium, indicating potential industry heterogeneity in technology.

E. GP/A portfolios among manufacturing firms

In this section, we create GP/A quintile portfolios within manufacturing firms. The definition of manufacturing firms is based on standardized industry classification (SIC) codes of Fama and French 10 industries in Kenneth French's data library. Panel A, Table A4 reports the characteristics of these GP/A quintiles. The results show that GP/A is negatively correlated with book-to-market ratio and positively correlated with gross margin. Panel B, Table A4 reports the average returns, CAPM, and Fama-French 3-factor model test results for both value-weighted and equally-weighted portfolios. The value-weighted GP/A premium in manufacturing firms is 1.79% per year, but once Fama and French 3 factors are controlled, the annualized premium (α) becomes 5.85% per year. The equally-weighted portfolio results are even stronger. The average return, CAPM alpha, and Fama-French 3-factor model alpha of the long-short portfolio (Hi-Lo) is 7.08%, 8.00%, and 9.41% per year, respectively.

F. logBM portfolios within Fama and French 30 industries

In the model estimation, we target moments of unconditional logBM portfolios. In this section, we analyze the logBM portfolios sorted within Fama and French 30 industries. As we will see, while the characteristics are quantitatively similar to the unconditional sorts, the value premium is smaller controlling for industries.

Panel A of Table A5 reports the average characteristics of within industry logBM quintiles. Like the unconditional sorts, value stocks within industries have lower gross profitability and gross margin, but higher financial and operating leverages. Panel B reports the portfolio returns

and CAPM test results. Controlling for Fama and French 30 industries, the value premium becomes only 2.85%, as compared to 4.21% from the unconditional sorts. The CAPM alpha is 3.65%, again smaller than 4.93% from the unconditional sorts. These results indicate that unlike gross profitability premium, the heterogeneity across industries plays a smaller role for the value premium. Panel C shows that the correlation between the within industry GP/A factor and logBM factor is now lower at -0.29, lower than -0.4 for the correlation between within-industry GP/A factor and unconditional logBM factorin the main text. Therefore, by using the moments from unconditional logBM portfolios, we have chosen a higher target of our SMM estimation.

G. Cash flow betas to the aggregate profitability shocks and aggregate investment shocks: model based simulations

In Panel A of Table A6, we repeat Table 9 of the paper and calculate cash flow betas using the aggregate profitability shock from model simulations. For the individual GP/A quintiles, the X beta of sales is always lower than X beta of cost of goods sold. As a result of this operating hedging effect, the X shock beta is lower compared with revenue beta. Therefore, the lower COGS beta than REVT beta in the high GP/A quintile in Table 8 is because in addition to the X shock exposure the GP/A factor is also driven by the aggregate investment shock. Furthermore, consistent with the model mechanism that the operating hedge effect decreases with firm GP/A, the gross profit beta increases from low to high GP/A quintiles in the simulated data.

In Panel B of Table A6, we report the cash flow exposures of GP/A quintiles to the aggregate investment shock. None of these GP/A quintiles has a statistically significant aggregate investment shock beta. Therefore, the patterns of cash flow exposure to the GP/A factor in Table 9 of the paper mainly reflects the pattern of exposure to the aggregate profitability shock.

H. Cash flow betas to the aggregate COGS growth

In Table A7, we repeat Table 10 of the paper and calculate cash flow betas with respect to the aggregate COGS growth. The result shows that firm-level COGS tends to respond more to the aggregate COGS growth than firm-level revenues. This operating hedge effect gives rise to a lower aggregate COGS beta for firm-level gross profits. Furthermore, the operating hedge effect decreases with gross profitability, and therefore, the exposure of gross profit to the aggregate COGS growth increases with gross profitability. The difference in the gross profit beta between high and low profitability firms is statistically significant when $K = 1$ and $K = 2$.

References

Andrews, Isaiah, Matthew Gentzkow, and Jesse M Shapiro, 2017, Measuring the sensitivity of parameter estimates to estimation moments, *The Quarterly Journal of Economics* 132, 1553–1592.

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

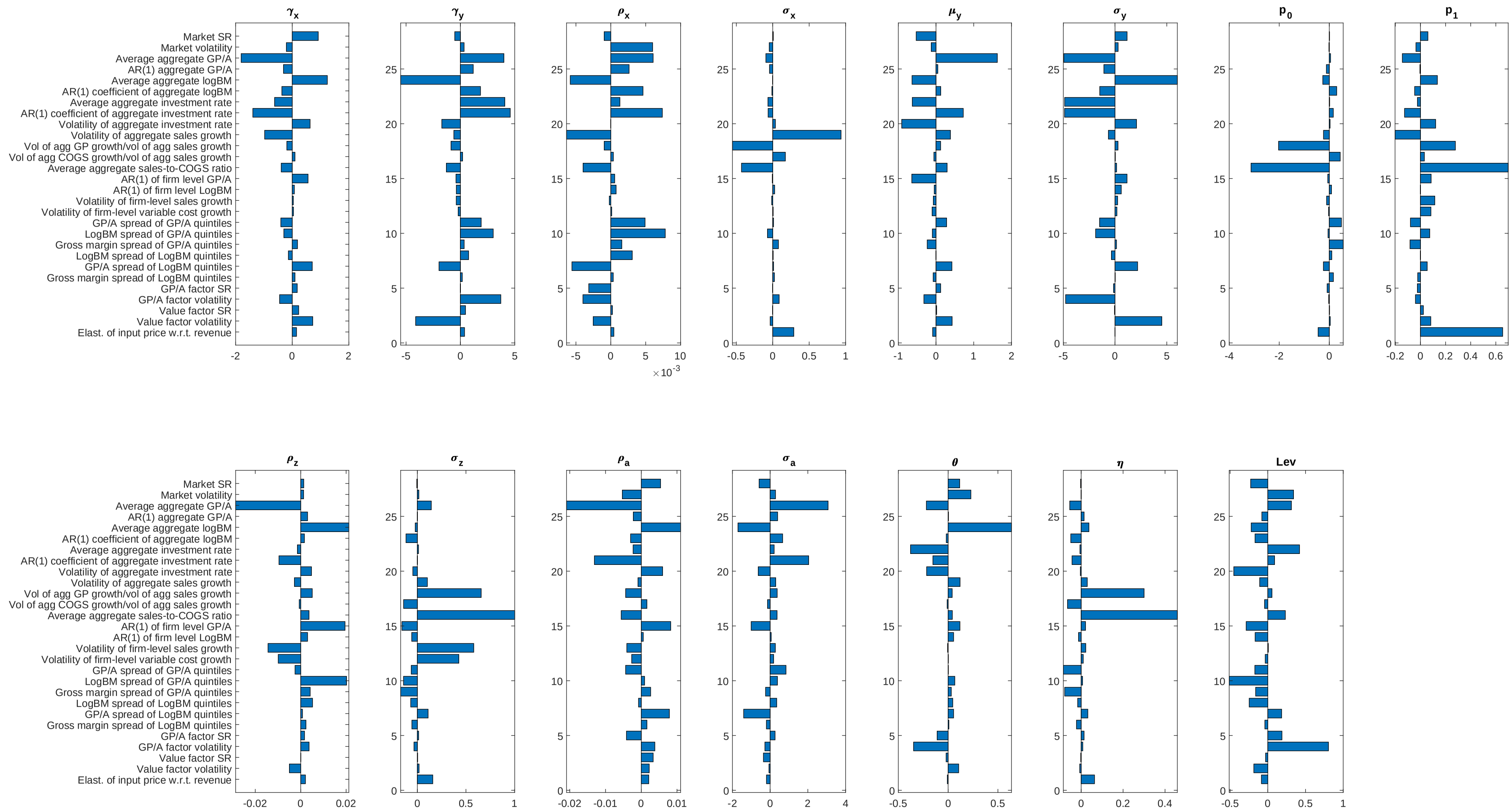

Figure A1: We report the Andrews, Gentzkow, and Shapiro (2017) sensitivity measure of the estimated parameters to moments. We report the measure in elasticity form, $\lambda_{i,j}\frac{\Psi^j}{\theta^i}$, where $\lambda_{i,j}$ is the element of the sensitivity matrix Λ that corresponds to parameter i and moment j.

Table A1: Empirical moments

This table provides details on how the empirical moments in SMM estimation are constructed. The moments on stock returns are based on the monthly sample from July 1963 to December 2019. The moments on characteristics and quantities are based on annual sample from 1964 to 2019. We only keep common shares (SHRCD = 10 or 11) in NYSE/AMEX/NASDAQ but exclude financial firm. For moments on quanties, we also restrict the fiscal year end (FYR) to be December to align variable timing.

Moments	Description
Elasticity of aggregate input price w.r.t. aggregate revenues	Time series regression coefficient of growth rate of aggregate CPI-deflated intermediate input price onto growth rate of aggregate CPI-deflated gross outputs. The annual data of intermediate input price and gross outputs are from the GDP by industry account at U.S. Bureau of Economic Analysis (BEA).
Average aggregate GP/A	The average of aggregate gross profits divided by aggregate total assets
AR(1) coefficient of aggregate GP/A	AR(1) of annual aggregate GP/A
Average aggregate logBM	Average of log aggregate BM, defined as aggregate book equity divided by aggregate market cap
AR(1) coefficient of aggregate logBM	AR(1) of annual aggregate logBM
Average aggregate investment rate	Average aggregate investment rate, defined as aggregate CAPX divided by lagged aggregate PPEGT
AR(1) coefficient of aggregate investment rate	AR(1) of annual aggregate investment rate
Volatility of aggregate investment rate ($\times 10$)	Standard deviation of annual aggregate investment rate
Volatility of aggregate sales growth	Standard deviation of aggregate REVT growth
Volatility of aggregate gross profit growth/volatility of aggregate sales growth	Standard deviation of aggregate GP growth/Standard deviation of aggregate REVT growth
Volatility of aggregate variable cost growth/volatility of aggregate sales growth	Standard deviation of aggregate COGS growth/Standard deviation of aggregate REVT growth
Average ratio aggregate sales to aggregate variable costs	Average aggregate REVT/aggregate COGS
AR(1) coefficient of firm-level GP/A	Time series average of AR(1) estimates of firm-level GP/A from cross-sectional regressions
AR(1) coefficient of firm-level LogBM	Time series average of AR(1) estimates of firm-level logBM from cross-sectional regressions
Volatility of firm-level sales growth	Pooling standard deviation of firm-level REVT growth
Volatility of firm-level variable cost growth	Pooling standard deviation of firm-level COGS growth
GP/A spread of GP/A quintiles	Time series average of difference in median GP/A between high and low within-industry GP/A quintiles
LogBM spread of GP/A quintiles	Time series average of difference in median logBM between high and low within-industry GP/A quintiles
Gross margin spread of GP/A quintiles	Time series average of difference in median GM between high and low within-industry GP/A quintiles
LogBM spread of LogBM quintiles	Time series average of difference in median logBM between high and low within-industry logBM quintiles
GP/A spread of LogBM quintiles	Time series average of difference in median GP/A between high and low within-industry logBM quintiles
Gross margin spread of LogBM quintiles	Time series average of difference in median GM between high and low within-industry logBM quintiles
Sharpe ratio of market factor	Annualized Sharpe ratio of market factor
Volatility of market factor	Annualized volatility of market factor
Sharpe ratio of GP/A factor	Annualized Sharpe ratio of GP/A factor. GP/A factor is long-short portfolio within-FF30 GP/A quintiles
Volatility of GP/A factor	Annualized volatility of GP/A factor
Sharpe ratio of value factor	Annualized Sharpe ratio of value factor. Value factor is long-short portfolio logBM quintiles
Volatility of value factor	Annualized volatility of logBM factor

Table A2: Alternative log project arrival rate $\bar{a}$

This table reports the mean moments from simulations using alternative values of log project arrival rate $\bar{a}$ while keeping other parameters unchanged from the benchmark parameterization. We solve and simulate the model at a monthly frequency, and report all statistics at an annual frequency. We simulate 100 independent samples from the model, with each sample representing 1,000 firms over 600 months. Standard deviations of all returns are in percent.

$\bar{a}$	0.3 (benchmark)	0.2	0.4	1
Average number of projects per firm	83.302	75.379	92.051	167.75
Moments				
Beta of input price w.r.t. revenue	0.333	0.333	0.333	0.333
Average aggregate gross profitability	0.255	0.255	0.255	0.255
AR(1) coefficient of aggregate gross profitability	0.892	0.892	0.893	0.893
Average aggregate ln(BM)	-0.858	-0.860	-0.857	-0.849
AR(1) coefficient of aggregate ln(BM)	0.852	0.852	0.851	0.851
Average aggregate investment rate	0.059	0.059	0.059	0.059
AR(1) coefficient of aggregate investment rate	0.884	0.884	0.884	0.885
Volatility of aggregate investment rate	0.013	0.013	0.013	0.013
Volatility of aggregate gross profit growth/volatility of aggregate sales growth	0.063	0.063	0.063	0.063
Volatility of aggregate variable cost growth/volatility of aggregate sales growth	0.820	0.820	0.820	0.820
Std of aggregate COGSG/Std of aggregate SaleG	1.110	1.110	1.110	1.110
Average ratio of aggregate sales to aggregate variable costs	1.504	1.504	1.504	1.504
AR(1) coefficient of firm-level gross profitability	0.754	0.753	0.754	0.757
AR(1) coefficient of firm-level Log(BM)	0.887	0.888	0.886	0.882
Volatility of firm-level sales growth	0.418	0.419	0.418	0.415
Volatility of firm-level variable cost growth	0.377	0.378	0.376	0.374
Gross profitability spread of gross profitability quintiles	0.422	0.422	0.422	0.422
Log(BM) spread of gross profitability quintiles	-0.314	-0.314	-0.313	-0.313
Gross margin spread of gross profitability quintiles	0.120	0.120	0.120	0.120
Log(BM) spread of Log(BM) quintiles	0.810	0.814	0.805	0.784
Gross profitability spread of Log(BM) quintiles	-0.149	-0.148	-0.149	-0.153
Gross margin spread of Log(BM) quintiles	-0.048	-0.048	-0.048	-0.049
Sharpe ratio of market factor	0.473	0.472	0.472	0.473
Volatility of market factor (%)	17.263	17.270	17.261	17.273
Sharpe ratio of GPA factor	0.532	0.534	0.533	0.537
Volatility of GPA factor (%)	8.117	8.128	8.117	8.098
Sharpe ratio of value factor	0.355	0.357	0.355	0.333
Volatility of value factor (%)	9.060	9.110	9.049	8.985

Table A3: Unconditional and within industry GP/A premia

This table report the result from the horse race between the unconditional GP/A premium and within-industry GP/A premium. In Panel A, the excess return of GP/A quintiles are regressed onto the market factor and the within-industry GP/A factor, and the abnormal returns (α) are reported. In Panel B, the excess returns of within-industry GP/A quintiles are regressed onto the market factor and the GP/A factor, and the abnormal returns (α) are reported. Panel C reports the correlation coefficient between the within-industry GP/A factor and logBM factor. The sample is from July of 1963 to December of 2019. Newey-West t-statistics computed with 4 lags given in parentheses adjust for heteroskedasticity and autocorrelation.

Panel A: Abnormal returns of GP/A portfolios controlling for within-industry GP/A factor

	Lo	2	3	4	Hi	Hi-Lo
α	-0.46	-0.19	1.31	-0.49	0.67	1.12
	(-0.56)	(-0.23)	(2.20)	(-0.68)	(0.82)	(0.89)

Panel B: Abnormal returns of within-industry GP/A portfolios controlling for GP/A factor

	Lo	2	3	4	Hi	Hi-Lo
α	-1.53	-0.06	0.88	-0.13	1.40	2.93
	(-2.13)	(-0.11)	(1.60)	(-0.24)	(2.48)	(2.98)

Table A4: Gross profitability portfolios for manufacturing firms

This table reports the characteristics and returns of quintile portfolios sorted by gross profitability (GP/A) for manufacturing firms. Panel A reports the time series average of the cross-sectional median of characteristics for each GP/A quintile, including gross profitability (GP/A), log book-to-market (logBM), gross profit margin (GM), market-based financial leverage (FLev), operating leverage (OLev), and Tobin's Q (Q). Panel B reports the mean, standard deviation, CAPM test result, and Fama-French three-factor model test result of the quintile GP/A portfolios. Panel B1 uses value-weighted portfolios and Panel B2 uses equally-weighted portfolios. The sample is from July of 1963 to December of 2019. Newey-West t-statistics computed with 4 lags given in parentheses adjust for heteroskedasticity and autocorrelation.

Panel A: Portfolio characteristics

Portfolio	GP/A	logBM	GM	FLev	OLev	Q
Lo	0.15	-0.03	0.18	0.34	0.56	0.86
2	0.26	-0.20	0.24	0.29	0.52	1.00
3	0.33	-0.34	0.28	0.24	0.57	1.26
4	0.42	-0.50	0.32	0.18	0.61	1.65
Hi	0.61	-0.69	0.42	0.11	0.70	2.34

Panel B: Portfolio returns, CAPM, and Fama-French 3-factor model test

	Panel B1: Value-weighted portfolios						Panel B2: Equally-weighted portfolios					
	Lo	2	3	4	Hi	Hi-Lo	Lo	2	3	4	Hi	Hi-Lo
Mean	5.89	7.46	6.98	6.35	7.69	1.79	4.94	10.04	10.35	11.74	12.02	7.08
Std	20.60	20.21	18.53	17.71	16.34	14.17	23.56	21.25	20.57	20.21	19.43	10.92
α	-1.51	0.05	0.00	-0.45	1.82	3.33	-2.97	2.53	3.04	4.44	5.02	8.00
	(-0.89)	(0.03)	(0.00)	(-0.40)	(1.49)	(1.70)	(-1.33)	(1.43)	(1.85)	(2.83)	(3.24)	(4.81)
MKT	1.14	1.14	1.08	1.05	0.90	-0.24	1.22	1.16	1.13	1.12	1.08	-0.14
	(23.55)	(27.56)	(34.99)	(44.43)	(23.25)	(-4.22)	(24.01)	(23.71)	(25.40)	(27.24)	(26.76)	(-4.02)
α	-3.84	-1.86	-1.54	-0.80	2.01	5.85	-6.41	-0.79	-0.03	2.04	3.00	9.41
	(-2.57)	(-1.39)	(-1.24)	(-0.74)	(1.74)	(3.31)	(-3.91)	(-0.70)	(-0.03)	(2.12)	(3.17)	(5.88)
MKT	1.17	1.18	1.10	1.04	0.91	-0.26	1.12	1.08	1.04	1.01	0.96	-0.16
	(30.81)	(36.92)	(36.47)	(45.80)	(24.34)	(-4.93)	(29.37)	(33.15)	(38.43)	(42.13)	(34.39)	(-4.43)
HML	0.46	0.39	0.30	0.06	-0.03	-0.49	0.55	0.55	0.50	0.35	0.28	-0.28
	(7.22)	(5.05)	(4.33)	(1.38)	(-0.42)	(-6.98)	(7.80)	(8.42)	(7.92)	(7.24)	(4.78)	(-4.15)
SMB	0.20	0.10	0.12	0.10	-0.05	-0.25	0.90	0.78	0.80	0.83	0.78	-0.12
	(2.93)	(1.32)	(1.64)	(2.77)	(-1.04)	(-3.16)	(10.66)	(8.55)	(8.73)	(12.55)	(11.25)	(-3.04)

Table A5: Log Book-to-market portfolios within Fama and French 30 industries

This table reports the characteristics and value-weighted returns of quintile portfolios sorted by the log book-to-market equity ratio (logBM) within Fama and French 30 industries. Panel A reports the time series average of the cross-sectional median of characteristics for each within-industry logBM quintile, including gross profitability (GP/A), log book-to-market (logBM), gross profit margin (GM), financial leverage (Ffev), operating leverage (Olev), and Tobin's Q (Q). Panel B reports the mean, standard deviation, CAPM test result of the quintile logBM portfolios. The sample is 196307-201912. Newey-West *t*-statistics computed with 4 lags given in parentheses control for heteroskedasticity and autocorrelation.

Panel A: Portfolio characteristics

portfolio	GP/A	logBM	GM	Flev	Olev	Q
Lo	0.39	-1.60	0.38	0.07	0.62	6.54
2	0.36	-0.86	0.35	0.13	0.62	3.14
3	0.33	-0.46	0.32	0.19	0.64	2.01
4	0.30	-0.09	0.31	0.26	0.67	1.30
Hi	0.27	0.43	0.28	0.38	0.74	0.64

Panel B: Portfolio returns and CAPM test

	Lo	2	3	4	Hi	Hi-Lo
Mean	5.81	6.58	7.19	7.22	8.66	2.85
Std	16.72	15.11	15.03	15.31	16.00	10.68
α	-1.04	0.34	1.04	1.11	2.61	3.65
	(-1.37)	(0.61)	(1.66)	(1.30)	(2.60)	(2.38)
MKT	1.05	0.96	0.95	0.94	0.93	-0.12
	(67.67)	(62.00)	(64.16)	(40.99)	(34.32)	(-3.24)

Panel C: Correlation between within-industry GP/A and logBM factors

	Correlation
Est.	-0.29

Table A6: Cash flow betas of gross profitability quintiles with aggregate profitability shocks and aggregate investment shocks: model-based simulations

This table reports the cash flow exposures of GP/A quintile portfolios to the aggregate profitability shock (Panel A) and aggregate investment shock (Panel B) using the simulated data. We regress the cumulative growth rate of gross profits, sales, and cost of goods sold of the quintile portfolios from year t to $t+K$ onto the aggregate profitability or investment shock in year t. We consider $K = 0,\ 1$, and 2, where $K = 0$ corresponds to contemporaneous annual regressions. We simulate 100 independent samples from the model, with each sample representing 1,000 firms over 600 months. We standardize the aggregate profitability shock to have a unit standard deviation. The Newey-West t-statistics are computed with $K + 4$ lags to adjust for heteroskedasticity and autocorrelation.

Panel A: Risk exposures to aggregate profitability shocks

			Exposures of gross profits			
$K=$	Lo	2	3	4	Hi	Hi-Lo
0	0.82	1.86	2.24	2.60	3.07	2.25
	(0.99)	(2.23)	(2.93)	(3.40)	(3.78)	(1.95)
1	2.46	3.80	4.43	5.06	5.87	3.41
	(1.88)	(3.25)	(3.76)	(4.19)	(4.69)	(2.13)
2	3.07	4.17	4.74	5.14	5.87	2.81
	(1.84)	(2.70)	(3.24)	(3.28)	(3.60)	(1.46)
			Exposures of sales			
0	2.53	3.26	3.51	3.76	4.05	1.52
	(3.35)	(4.26)	(4.61)	(4.88)	(4.81)	(1.71)
1	5.18	6.18	6.67	7.11	7.70	2.52
	(4.36)	(5.38)	(5.61)	(5.69)	(5.82)	(2.06)
2	5.52	6.37	6.80	7.07	7.61	2.09
	(3.44)	(3.97)	(4.31)	(4.20)	(4.33)	(1.41)
			Exposures of cost of goods sold			
0	3.12	3.84	4.09	4.33	4.63	1.51
	(4.12)	(4.93)	(5.17)	(5.40)	(5.28)	(1.87)
1	6.23	7.22	7.72	8.15	8.74	2.51
	(5.15)	(6.03)	(6.21)	(6.21)	(6.30)	(2.24)
2	6.51	7.35	7.78	8.04	8.58	2.07
	(3.87)	(4.34)	(4.62)	(4.50)	(4.60)	(1.53)

Panel B: Risk exposures to aggregate investment shocks

$K=$	Lo	2	3	4	Hi	Hi-Lo
Exposures of gross profits						
0	-0.09	0.03	0.02	0.09	-0.10	-0.01
	(-0.10)	(0.03)	(0.02)	(0.14)	(-0.13)	(-0.03)
1	0.12	0.37	0.45	0.49	0.27	0.15
	(0.11)	(0.26)	(0.37)	(0.41)	(0.11)	(0.05)
2	0.36	0.58	0.80	0.77	0.66	0.30
	(0.21)	(0.37)	(0.57)	(0.53)	(0.34)	(0.15)
Exposures of sales						
0	-0.02	0.06	0.04	0.10	-0.07	-0.04
	(-0.05)	(0.05)	(0.03)	(0.13)	(-0.07)	(-0.06)
1	0.25	0.44	0.51	0.54	0.35	0.09
	(0.21)	(0.33)	(0.36)	(0.41)	(0.17)	(0.04)
2	0.50	0.67	0.85	0.81	0.72	0.22
	(0.30)	(0.39)	(0.52)	(0.49)	(0.35)	(0.15)
Exposures of cost of goods sold						
0	0.00	0.06	0.05	0.10	-0.04	-0.04
	(-0.03)	(0.06)	(0.04)	(0.12)	(-0.04)	(-0.06)
1	0.29	0.47	0.54	0.56	0.39	0.10
	(0.23)	(0.34)	(0.36)	(0.41)	(0.20)	(0.05)
2	0.55	0.71	0.87	0.83	0.75	0.21
	(0.31)	(0.38)	(0.48)	(0.46)	(0.35)	(0.15)

Table A7: Cash flow betas of gross profitability quintiles with aggregate COGS shocks This table reports the cash flow exposures of the GP/A quintile portfolios within the Fama-French 30 industries to the growth rate of aggregate variable cost (COGS). We regress the cumulative growth rate of gross profits, sales, and cost of goods sold of the quintile portfolios from year t to $t + K$ onto the aggregate COGS growth in year t. We consider $K = 0,\ 1$, and 2, where $K = 0$ corresponds to contemporaneous annual regressions. We standardize the aggregate COGS growth to have a unit standard deviation. The Newey-West t-statistics are computed with $K + 4$ lags to adjust for heteroskedasticity and autocorrelation. The sample is annual from 1964 to 2019.

$K=$	Lo	2	3	4	Hi	Hi-Lo
			Exposures of gross profits			
0	2.93	3.01	2.53	3.28	3.99	1.06
	(3.02)	(9.12)	(5.27)	(10.91)	(10.88)	(1.23)
1	0.76	1.65	1.74	2.29	3.56	2.80
	(0.52)	(2.43)	(2.01)	(3.30)	(5.47)	(2.36)
2	-0.14	1.08	0.60	1.98	2.96	3.10
	(-0.08)	(1.29)	(0.65)	(2.60)	(3.42)	(2.05)
			Exposures of sales			
0	4.40	3.97	4.08	4.85	4.98	0.58
	(7.89)	(14.21)	(10.14)	(16.68)	(8.64)	(0.56)
1	4.21	4.33	4.40	5.12	5.08	0.87
	(4.48)	(5.58)	(7.15)	(5.32)	(5.98)	(0.86)
2	3.62	3.81	4.09	4.93	4.71	1.09
	(3.30)	(4.34)	(5.29)	(4.00)	(3.43)	(0.80)
			Exposures of cost of goods sold			
0	4.70	4.31	4.74	5.70	5.60	0.90
	(6.19)	(11.99)	(9.45)	(13.98)	(7.31)	(0.62)
1	4.97	5.29	5.53	6.61	6.05	1.08
	(4.94)	(5.97)	(8.33)	(5.84)	(6.08)	(0.83)
2	4.46	4.79	5.58	6.39	5.80	1.35
	(3.90)	(4.28)	(5.83)	(4.08)	(3.29)	(0.82)