Profitability retrospective: What have we learned?*

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March 14, 2025

Abstract

A lot! Profitability subsumes all of "quality" investing, explaining both the performance of the strategies that industry markets and the factors that academics employ. It also has striking power pricing "defensive equity" strategies that overweight low-beta or low-volatility stocks. Profitability tilts explain all the abnormal performance of popular "alternative value" strategies, including those adjusted for "intangibles," and half of value's post-2007 underperformance. Profitability is crucial for pricing a wide array of seemingly unrelated anomalies, yielding a more parsimonious understanding of the cross section of expected returns.

JEL classification: G10, G12
Keywords: Profitability, quality, value, defensive equity.

*Novy-Marx provides consulting services to Dimensional Fund Advisors, an investment firm headquartered in Austin, Texas with strong ties to the academic community. The thoughts and opinions expressed in this article are those of the authors alone, and no other person or institution has any control over its content. For helpful comments and suggestions, we thank Savina Rizova and Milena Novy-Marx.

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1. Introduction

Novy-Marx (2013) documents that profitability, broadly measured, has as much power as relative price predicting cross-sectional differences in expected returns. Profitability has quickly become a prominent theme in asset pricing research, perhaps best illustrated by Fama and French's (2015) inclusion of a profitability factor in their five-factor extension of the Fama and French (1993) three-factor model. It is also now a standard component of many investment strategies, often as part of so-called "quality" considerations.

This paper shows that profitability provides a unifying framework for understanding several seemingly disparate phenomena, yielding a more parsimonious understanding of the cross section of expected returns. We show that profitability completely subsumes the entire "quality" space, drives the success of "defensive equity" strategies, and explains all the abnormal performance of "alternative" value strategies. It also explains half of value's post-2007 underperformance.

Studies of "quality" investing show that the stocks of companies with strong fundamentals tend to outperform those with weak fundamentals, especially after controlling for value (Piotroski, 2000; Hou, Xue, and Zhang, 2015; Asness, Frazzini, and Pedersen, 2019). We show that broad notions of "quality investing" are completely subsumed by profitability. Profitability both prices the quality factors used in academia and explains the performance of quality strategies marketed by industry. That is, while practitioners often treat quality as a distinct investment style, it does not represent a new dimension of expected returns. Quality metrics merely provide an indirect means to tilt towards profitability, and sometimes other known factors, and these tilts drive all the performance of other quality investments.

Research on "defensive" equity strategies documents that low-risk stocks tend to outperform their riskier counterparts, seemingly violating basic risk-return relations (Black, Jensen, and Scholes, 1972; Fama and Macbeth, 1973; Ang, Hodrick, Xing, and Zhang, 2006). We resolve this "low-risk anomaly" by showing that defensive equity strategies—those based on low beta or low volatility—derive all of their performance by tilting towards profitable companies, particularly those that invest conservatively.

Finally, traditional value strategies have experienced an extended period of underperformance since the “quant crisis” of 2007. This has sparked debate over whether the value premium is “dead,” or if reports of its demise have “been greatly exaggerated” (Arnott, Harvey, Kalesnik, and Linnainmaa, 2021). It has also generated various “alternative” value strategies, all promoted with claims that they perform “better” than traditional value. We show that accounting for profitability largely resolves recent debates around value, consistent with profitability’s characterization by Novy-Marx (2013) as the “other side of value.” Profitability tilts drive “alternative” value strategies’ abnormal performance relative to traditional value. These strategies’ “better” performance simply reflects “factor rotations,” which add other factors to traditional value. These factor rotations do not, however, yield any actual improvements in the investment opportunity set. Investors can achieve superior outcomes by trading traditional value in conjunction with profitability directly. Probability’s remarkable performance since the publication of Novy-Marx (2013), in conjunction with value’s negative exposure to profitability, also explains half of value’s late-sample underperformance.

For the asset pricing literature, the fact that multiple widely-studied, seemingly disparate anomalies can be largely explained by a small number of factors suggests markets may be more efficient than a cursory review of the anomalies literature would indicate. Rather than representing distinct phenomena requiring different explanations, many documented patterns in returns simply reflect different manifestations of a few underlying factors.

For practitioners, the fact that seemingly distinct investment styles overlap more than commonly recognized suggests potential benefits from more parsimonious portfolio construction. Investment managers should carefully consider their portfolios’ exposure to profitability, as it is a key driver of returns across multiple investment classes. Our results also suggest that explicitly targeting profitability, rather than relying on indirect proxies, is more efficient.

The remainder of the paper is organized as follows. Section 2 shows that profitability subsumes the entire “quality” space. Section 3 documents the striking power profitability has pricing “defensive equity,” i.e., strategies that over-weight stocks with low market beta or low volatility and are not obviously related to profitability. Section 4 shows that accounting for profitability tilts explains all the abnormal performance of “alternative” value metrics. It also shows that accounting for profitability explains half of value strategies’ dramatic underperformance since the Great Recession of 2007. Section 5 concludes.

2. Understanding "quality"

Industry classifies profitability as a "quality strategy," a class that has recently experienced robust inflows.[1] Unfortunately the term "quality" is not well defined, with many distinct metrics used to quantify firm "quality." "Value" is also quantified in different ways, but almost always using some measure of relative price, and strategies based on different value metrics all basically bet on the same thing.[2] In contrast, there is little agreement on exactly what quality means. "Quality" is really a marketing term popularized around the Nasdaq deflation to capture outflows from underperforming growth funds in the mid-2000s, and exploited more recently to capture outflows from underperforming value funds.

"Quality" is variously used to describe stocks with high return-on-equity, stable earnings, low leverage, or high values for composite "roll-ups" of all three; high net payouts or return on invested capital; high composite measures of "financial strength;" or low measures of financial distress or bankruptcy risk. It is sometimes used to encompass "defensive stocks" with low market betas or volatilities. It is also the bucket into which industry places profitability.

While profitability is considered a quality strategy, the more interesting question is whether there is anything to quality beyond profitability. That is, do other notions of quality add anything to an investor that can directly trade profitability? The answer here is a resounding "no." That is, not only is profitability a quality strategy, it also explains the performance of quality quite generally. None of the the other popular notions of "quality" generate reliable abnormal returns relative to profitability, but profitability earns highly significant abnormal returns relative to all other notions of quality.

2.1. Understanding broad notions of "quality"

Before considering the quality factors employed in asset pricing models, we first analyze a broad range of measures that have been used, either in academia or in industry, to capture

[1] As of December 2024, "quality" equity mutual funds and ETFs tracked by Morningstar (i.e, those in their Quality Strategic Beta Group or with names containing the term "quality") have seen five-year net inflows of almost $80 billion, pushing their total assets under management to roughly $170 billion.

[2] While every relative-price measure makes large, obvious bets on value, many "alternative value" measures also make significant bets on profitability. Doing so dramatically improves their stand-alone performance but never expands the investment opportunity set for an investor that can also trade profitability directly. This "factor rotation" problem is analyzed in greater detail in Section 4.

Table 1. Quality measures.
This tables summarizes quality strategies proposed by academia or commonly employed in industry. Appendix A.1 provides the full details of each sorting variable's construction.

Strategy name	Sorting variable	Reference
Profitability	$\frac{\text{REVT}-\text{COGS}-(\text{XSGA}-\text{XRD})-\text{XINT}}{\text{BE}+\text{MIB}}$	This paper
ROE	Return-on-book equity	GMO (2004)
EPS stability	Earnings-per-share volatility	GMO (2004)
Leverage	Book equity-to-book assets	GMO (2004)
Q-Score	z-score combination of ROE, EPS stability, and leverage	GMO (2004); MSCI (2013)
Net payout	Fraction of operating profits paid to share holders	Asness et al. (2019)
ROIC	Return-on-invested capital	Greenblatt (2010)
F-score	Financial strength	Piotroski (2000)
Distress	Failure probability	Campbell et al. (2011)
O-score	Bankruptcy probability	Ohlson (1980)
G-score	Graham's quality metrics	Novy-Marx (2014*a*)
Low beta	Market beta	Black (1972); Frazzini and Pedersen (2014)
Low vol.	Volatility	Ang et al. (2006); Baker et al. (2011)

a "quality dimension." Table 1 summarizes these and provides references to the works promoting them. Full details of each measure's construction are provided in Appendix A.1.

Figure 1 shows the performance of quality factors based on each quality metric. Each factor is constructed like HML, but on the basis of the corresponding quality measure instead of book-to-market. The blue bars are the t-statistics on the quality factors' average returns. The red bars are the t-statistics on the factors' four-factor alphas, which indicate the significance of their performance relative to the model against which they were initially evaluated.[3,4] Full regression results are provided in Appendix A.2.

The figure shows that the strategy based on profitability (PROF) earned highly significant average excess returns (t-statistic of 6.26 on 45 bps/month), and an even more significant

[3] We include UMD as an explanatory factor because the distress risk measure of Campbell et al. (2011) predicts failure using, among other things, a firm's stock price and its last 12 months of stock returns, and consequently loads significantly on momentum.

[4] These t-statistics are roughly the strategies' Sharpe ratios (or information ratios relative to the Fama and French (1993) three-factor model plus UMD) scaled by the square-root of the sample size. With the roughly 50 year sample used here, this implies Sharpe ratios (or four-factor IRs) of roughly one-seventh the t-statistics presented in Figure 1.

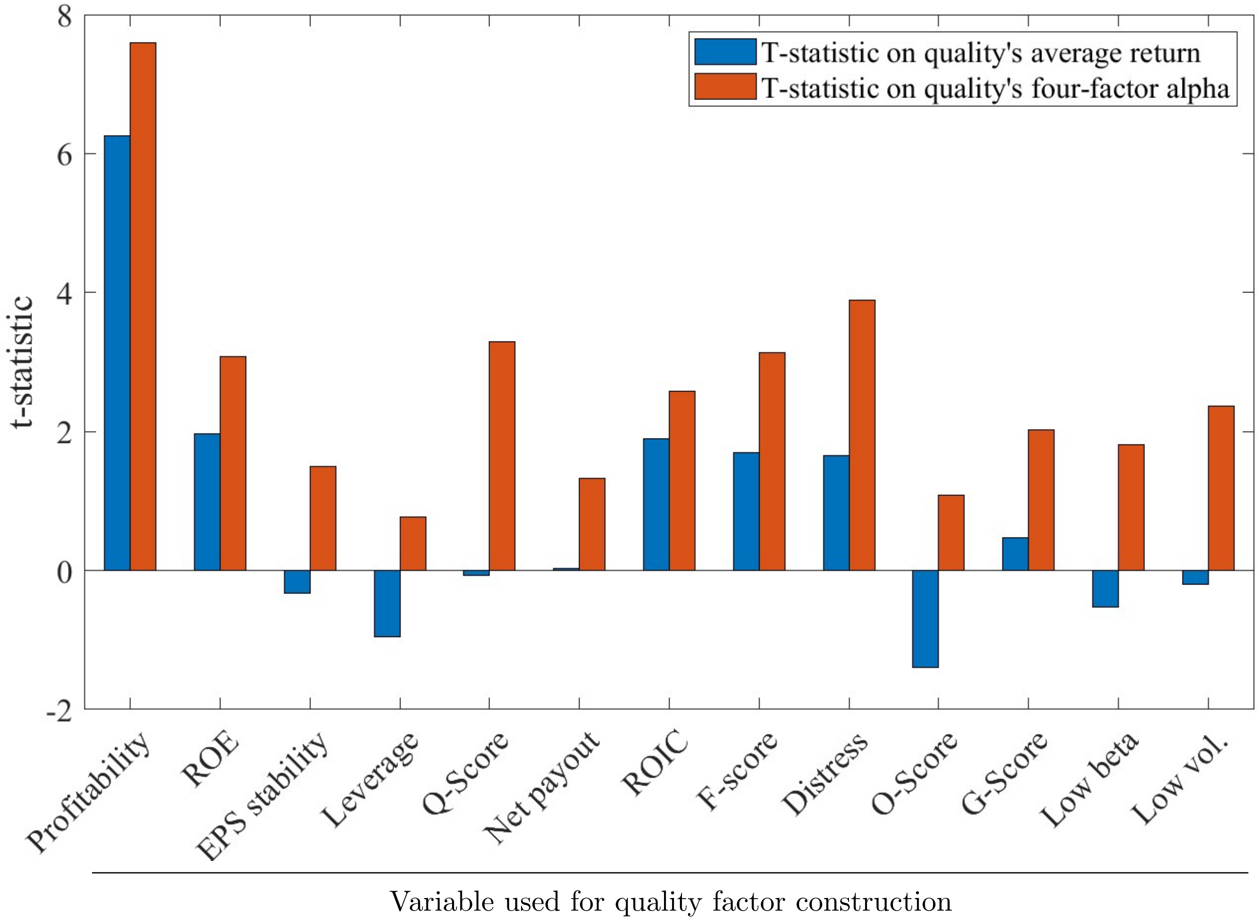

Fig. 1. Quality strategy performance. This figure shows the t-statistics on the intercepts from regressions of the form

$$\begin{aligned} \text{Quality} &= \alpha + \epsilon \\ \text{Quality} &= \alpha + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \beta_{\text{UMD}}\text{UMD} + \epsilon. \end{aligned}$$

Each quality factor is constructed like HML but on the basis of the corresponding quality metric instead of book-to-market. UMD is included as an explanatory factor because the distress risk measure of Campbell et al. (2011) predicts failure using, among other things, a firm's stock price and its last 12 months of stock returns, and consequently loads significantly on momentum. The sample covers July 1974 to December 2023, with the start date determined by the data required to construct some of the quality strategies.

four-factor alpha (t-statistic of 6.96 on 48 bps/month).[5] None of the other quality strategies

[5]Our PROF is based on a slightly broader notion of profitability than Fama and French's (2015) similarly constructed RMW. Specifically, we do not punish profitability for the most important of the "expensed investments" discussed in Novy-Marx (2013), R&D expenditures. Compustat's "Financial Statement Balancing Model" incorporates these expenditures (XRD) into selling, general, and administrative expenses (XSGA). We consequently subtract XRD form XSGA before calculating our-equity level measure of profitability, a construction Fama and French (2016a) explicitly consider. Ball, Gerakos, Linnainmaa, and Nikolaev (2015, 2016) also include this adjustment in their asset-level measures of accruals- and cash-based operating profitability. Appendix A.3 provides a direct comparison of the perfrormance of RMW and PROF.

earned significant average excess returns, though all did generate positive four-factor alphas. These four-factor alphas are significant for seven of the other 12 quality measures.

Figure 2 shows results of spanning tests employing profitability and other notions of quality. That is, results from regressions of the form

$$\begin{aligned} \text{PROF} &= \alpha + \beta_{\text{Quality}}\text{Quality} + \boldsymbol{\beta}'\mathbf{x} + \epsilon, \\ \text{Quality} &= \alpha + \beta_{\text{PROF}}\ \text{PROF} + \boldsymbol{\beta}'\mathbf{x} + \epsilon, \end{aligned}$$

where $\mathbf{x}$ are the remaining Fama and French (2015) factors (MKT, SMB, HML, and CMA) and momentum (UMD). The blue bars show the t-statistics on the alphas from regressions of profitability onto each of the quality factors plus controls; the red bars show the t-statistics on the alpha from regressions of each of the quality factors onto profitability plus controls. Full regression results, including factor loadings, are provided in Appendix Table A2.

The figure shows that none of the quality factors generate significant positive alpha relative to profitability, the other Fama and French factors, and momentum. The only significant alpha obtained regressing the quality strategies onto profitability is the negative alpha on the ROE strategy, despite this factor generating the largest return spread of all the quality metrics other than profitability. The pricing of these quality factors is primarily through significant positive loadings on PROF. With the exception of the low-leverage strategy, which tilts strongly to growth but not to high profitability, all of the quality strategies have positive, highly significant loadings on PROF averaging close to one-half. Eight of the 12 strategies load more on profitability than on any other factor.[6]

In contrast, the t-statistic on PROF's alpha in these spanning tests is always around six, implying information ratios of roughly 0.85 relative to quality, the other Fama and French factors, and momentum. That is, profitability always significantly expands the investment

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Appendix B reviews profitability measures proposed by the literature since Novy-Marx (2013). It also provides evidence that our operating profitability unpunished for R&D has more power predicting returns, profitability growth, and earnings growth than all these other measures, including popular cash-based profitability measures first advocated by Ball et al. (2016).

Appendix C replicates all the paper's results employing PROF using canonical RMW. We explicitly flag the two instances in the paper where results using PROF differ significantly from those using RMW.

[6]The net payout and low-beta strategies tilt more strongly to conservative investment than to profitability, while the Ohlson's O-score strategy tilts more strongly towards growth. For net payouts and O-score, these tilts are by construction. Net payouts are $\frac{\text{IB}-\Delta\text{BE}}{\text{OP}} = \frac{\text{IB}}{\text{OP}} - \left(\frac{\text{BE}}{\text{OP}}\right)\frac{\Delta\text{BE}}{\text{BE}}$, so decreasing in investment measured by book-equity growth. The O-score uses high return-on-assets and low leverage to predict low bankruptcy risk, and these are associated with higher valuations.

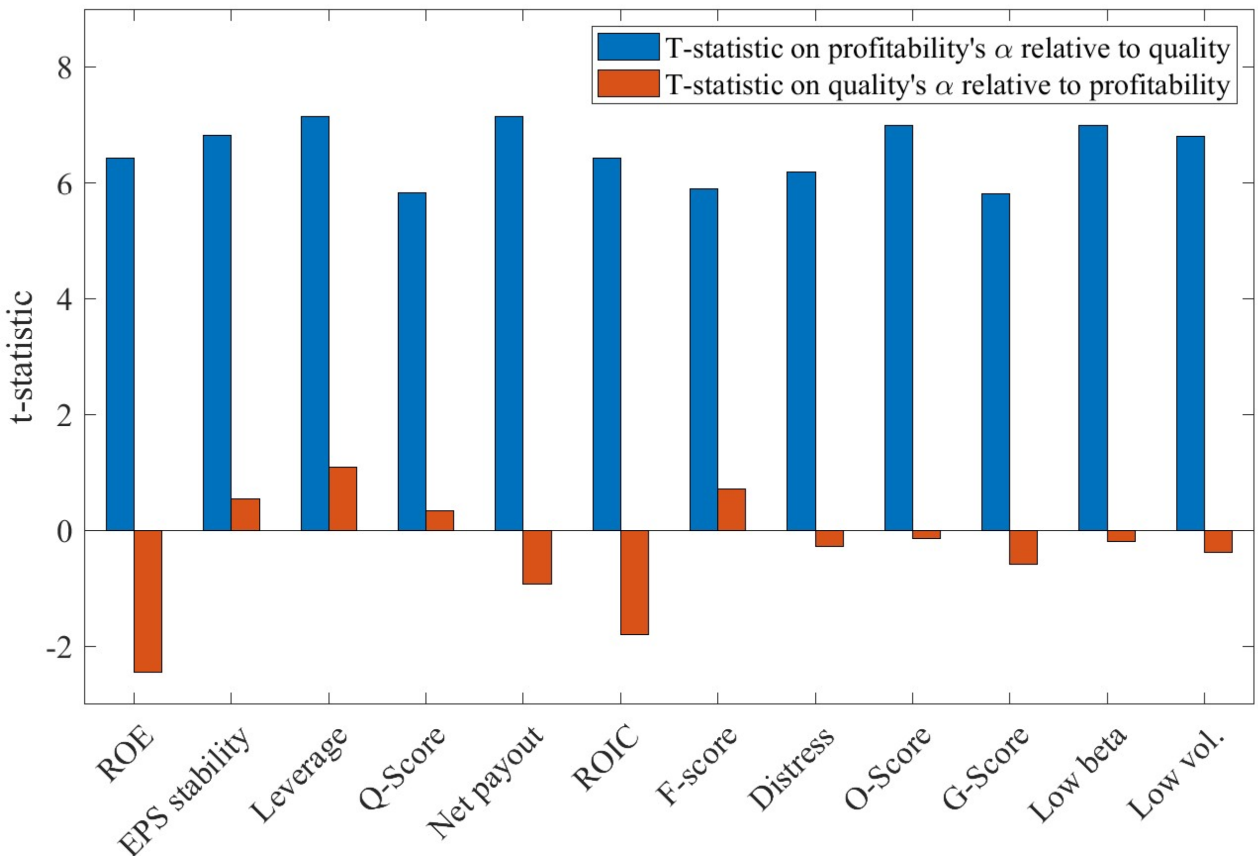

Fig. 2. Spanning tests employing profitability and other measures of quality. This figure shows the t-statistics on the alphas from regressions of the form

$$\begin{aligned} \text{PROF} &= \alpha + \beta_{\text{Quality}}\text{Quality} + \boldsymbol{\beta}'\mathbf{x} + \epsilon \\ \text{Quality} &= \alpha + \beta_{\text{PROF}}\ \text{PROF} + \boldsymbol{\beta}'\mathbf{x} + \epsilon, \end{aligned}$$

where $\mathbf{x}$ are other commonly used factors, those from the Fama and French (2015) five-factor model (excluding RMW) and UMD. The sample covers July 1974 to December 2023, with the start date determined by the data required to construct some quality strategies.

frontier relative to "quality," regardless of how quality is measured. In contrast, an investor that can directly trade profitability never benefits from trading any other notion of quality. Profitability subsumes the whole quality space. Broad notions of quality can tilt an investor towards higher profitability, but these tilts fully explain the benefits of quality, and tilting this way is less efficient than simply buying profitable stocks directly.

2.2. Understanding the quality factors used in asset pricing models

The best-known "quality factor" is Asness et al.'s (2019) "quality-minus-junk" (QMJ). QMJ is based on a composite "quality score," constructed as the sum of z-scores for sub-composite measures of "profitability," "growth," and "safety." The sub-composites are themselves constructed by summing z-scores of gross profits-to-assets, return-on-equity, return-on-assets, cash flow-to-assets, gross margin, and accruals (calculated as depreciation-minus-changes in working capital)-to-assets (the "profitability score"); the five-year growth per-share in the first five of its profitability measures, each expressed as a residual income (the "growth-score"); and low beta, low leverage, low bankruptcy risk measured using both Ohlson's (1980) O-Score and Altman's (1968) Z-Score, and low earnings volatility (the "safety score"). This construction raises red flags. The strategy combines elements of Novy-Marx's (2013) profitability, Sloan's (1996) accruals, Ball and Brown's (1968) fundamental momentum, and Black's (1972) beta-arbitrage, all strategies previously documented in the literature that back-test well. It is hardly surprising that combining strategies with significant return spreads generates a significant return spread.[7] Even so, QMJ is prevalent in the literature and thus presents a test asset for factor models trying to explain "quality."

Hou et al. (2015) introduce another well-known "quality" factor as part of their q-factor model, which they argue "outperforms the Fama-French and Carhart models in capturing many (but not all) of the significant anomalies" (p. 685). The model's "ROE factor," based on firms' most recently announced quarterly earnings, captures "price momentum, earnings surprise, and financial distress" (p. 663), so is another obvious "quality" test asset.

Panel A of Table 2 presents results from time-series regressions using the returns to QMJ and ROE. Both factors load heavily on earnings surprises by construction, so these regressions include a post-earnings-announcement drift factor, PEAD, as an explanatory variable.[8] Specifications (1) and (2) show that QMJ earned a highly significant 39 bps/month

[7] Novy-Marx (2015*a*) discusses econometric issues associated with testing strategies based on multiple signals. He documents the ease with which signals with no predictive power can be used to construct strategies that look "highly significant" in standard backtests. These tests fail to account for the degrees of freedom in multi-signal strategy design, which can be used to over-fit data using in-sample information.

[8] The profitability and growth sub-composites of the quality score used to construct QMJ depend positively on earnings-to-book equity and its five-year growth; the safety sub-composite depends negatively on quarterly earnings volatility and positively on earnings-to-book and earnings growth (through Ohlson's O-score and Altman's Z-score). The quarterly earnings surprises underlying PEAD are positively correlated with earnings-to-book and its growth, but negatively correlated with earnings volatility. These issues are even more acute for the ROE factor, because the cross-sectional variation in the most recently announced quarterly earnings used in its construction is driven more by year-over-year changes in quarterly earnings (i.e., earnings surprises) than by persistent long-run profitability. For more details, see Novy-Marx (2015*b*,*c*). The PEAD factor we consequently employ as a control is constructed like Fama and French's UMD factor, but based on standardized unexpected earnings (SUE) instead of recent stock performance.

Table 2. Quality factor spanning tests.
This table reports results from time-series regressions of the form $y = \alpha + \beta_{\mathbf{x}}\mathbf{x} + \epsilon$. Dependent variables are the quality-minus-junk (QMJ) factor of Asness et al. (2019) or the ROE factor of Hou et al. (2015) (Panel A), and PROF (Panel B). Explanatory factors include these, the Fama and French (2015) factors MKT, SMB, HML, and CMA, and a post-earnings-announcement drift factor (PEAD) constructed like UMD but based on standardized unexpected earnings (SUE) instead of stock performance. The sample covers July 1974 through June 2024, with the start date determined by the availability of the data used to construct SUE.

	y = QMJ					y = ROE				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: y = QMJ or ROE										
α	0.39	0.64	-0.01	-0.17	0.08	0.54	0.71	0.15	-0.20	-0.07
	[3.98]	[8.16]	[-0.11]	[-2.36]	[1.45]	[4.92]	[7.13]	[1.60]	[-2.75]	[-0.97]
PROF			0.89	0.80	0.79			0.86	0.69	0.63
			[20.8]	[19.9]	[25.5]			[16.8]	[17.4]	[16.2]
PEAD				0.40	0.23				0.83	0.78
				[9.83]	[7.60]				[21.1]	[20.2]
MKT		-0.22			-0.21		-0.09			-0.05
		[-12.9]			[-17.2]		[-4.04]			[-3.04]
SMB		-0.32			-0.17		-0.36			-0.18
		[-11.9]			[-9.56]		[-10.7]			[-7.92]
HML		-0.12			0.02		-0.15			0.07
		[-4.86]			[1.02]		[-4.78]			[2.26]
CMA					0.01					-0.12
					[0.29]					[-2.65]
Adj.-R^2 (%)		40.1	42.2	50.2	74.4		21.5	32.3	61.3	66.6
Panel B: y = PROF										
α	0.45	0.52	0.27	0.29	0.16	0.25	0.33	0.35	0.23	0.17
	[6.26]	[7.59]	[4.76]	[5.15]	[3.15]	[4.12]	[5.45]	[5.73]	[4.22]	[3.41]
QMJ			0.48	0.50	0.67				0.36	0.56
			[20.8]	[19.9]	[25.5]				[11.4]	[17.7]
ROE						0.38	0.49	0.49	0.14	0.17
						[16.8]	[17.4]	[16.2]	[4.99]	[5.63]
PEAD				-0.07	-0.08		-0.27	-0.27		-0.19
				[-2.18]	[-2.62]		[-6.41]	[-6.22]		[-5.42]
MKT		-0.00			0.14			0.02		0.12
		[-0.03]			[11.1]			[1.60]		[10.0]
SMB		-0.15			0.05			-0.00		0.07
		[-6.40]			[2.99]			[-0.11]		[3.93]
HML		-0.17			-0.06			-0.10		-0.07
		[-7.48]			[-3.10]			[-4.12]		[-3.48]
CMA					-0.06			-0.03		-0.04
					[-1.96]			[-0.63]		[-1.24]
Adj.-R^2 (%)		12.5	42.2	42.5	59.6	32.3	36.5	41.2	44.4	61.6

average excess return (t-statistic of 3.98) and an even larger 64 bps/month three-factor alpha (t-statistic of 8.16) over the sample. Specification (3) shows that despite the remarkable significance of its three-factor alpha, QMJ fails to deliver any abnormal returns relative to the PROF factor alone (-1 bp/month with a t-statistic of -0.11). Specification (4) shows that PROF and PEAD jointly explain more than half of QMJ's variation, with QMJ loading half as heavily on PEAD as on PROF. Specification (5) shows that QMJ also tilts towards low-beta and large-cap stocks (again by construction). The tilts to profitability and PEAD still price QMJ, however, and these four factors explain three-quarters of QMJ's variation (in specification 5, QMJ does not load significantly on HML and CMA).[9]

Specifications (6) through (10) replicate these tests using ROE instead of QMJ. Like QMJ, ROE generates a significant average excess return (54 bps/month with a t-statistic of 4.92) and three-factor alpha (71 bps/month with a t-statistic of 7.13), but fails to earn abnormal returns relative to PROF (specification 6 through 8). Strikingly, the ROE factor loads more heavily on PEAD than PROF in regressions including both as explanatory factors (specifications 9 and 10). ROE is a "dirty" version of PEAD, and its exposure to PEAD explains its high average returns (in untabulated results, ROE's alpha to just PEAD is only 4 bps/month with a t-statistic of 0.46, and PEAD alone explains 41.5% of its return variation, considerably more than the 32.3% explained by PROF). The full model prices ROE well. Its alpha relative to the model that includes profitability, PEAD, and the other most common factors, MKT, SMB, HML, and CMA, is an insignificant -7 bps/month (t-statistic of -0.97).

Panel B of Table 2 repeats the exercise, swapping QMJ or ROE with PROF on the two sides of the regressions. Here, the results are very different. PROF always loads significantly on both QMJ and ROE, but still earns highly significant abnormal returns in every specification, including those that employ both QMJ and ROE as explanatory factors. That is, profitability explains the performance of both the quality-minus-junk and ROE factors, but these factors cannot explain the performance of profitability.[10]

[9] Using Fama and French's (2015) RMW instead of our PROF yields material differences in these results. RMW has lower average returns than PROF and covaries less strongly with QMJ because it is based on a narrower definition of profitability. As a result, RMW cannot fully price QMJ, but is itself priced by QMJ. For details, see Appendix Table C2.

[10] PROF also has highly significant alphas relative to both the full Hou et al. (2015) and Hou, Mo, Xue, and Zhang (2021) four- and five-factor models. For details, see Appendix A.4.

3. Understanding "defensive equity"

While defensive characteristics are sometimes included as elements of firm quality, "defensive equity" is often treated as a distinct investment class.[11] These strategies over- and under-weight "safe" and "risky" stocks, respectively, where these are typically defined by a stock's market beta or volatility. They also represent the most striking examples of "away game wins" for asset pricing models incorporating profitability, and consequently deserve more attention here.[12] Profitability and investment seem unrelated to "low beta" and "low vol.," at least superficially. Nevertheless, including profitability and investment factors dramatically improves model performance pricing defensive strategies.

Defensive strategies' popularity has been encouraged by the convergence of two factors: a growing academic literature documenting a weak or negative relation between equities' risks and returns, and an equity market that delivered two severe bear markets over the first decade of the twenty-first century. Low-beta and low-volatility strategies are now common with institutional investors, pension funds, and insurance companies. Retail defensive equity funds also compete with "quality" as the new factor-based strategies most favored by active managers.[13] Their prevalence in academia and on Wall Street has some raising them into the canon of "most important market anomalies." For example, Frazzini and Pedersen (2014) claim that the return to their betting-against-beta strategy "rivals those of all the standard asset pricing factors (e.g., value, momentum, and size) in terms of economic magnitude, statistical significance, and robustness." Baker et al. (2011) go even further, opining that

[11] Morningstar now includes "Volatility" and "Quality" as two distinct elements of its "Factor Profile," which "shows an equity portfolio's exposure to seven standard investment factors that are broadly accepted in the investment industry as being important drivers of risk and return." Similarly, MSCI now includes "Low volatility" and "Quality" seperately in its "Factor Box" "classification standard and framework for evaluating, implementing and reporting style factors in equity portfolios," which "includes factors that have historically demonstrated excess market returns over the long run."

[12] Fama and French (2012) note that "models are playing home games" when used to price test assets formed using the same characteristics employed to construct the model's factors. Away games, i.e., tests employing test assets constructed using different characteristics than those used for factor construction, present a much stiffer model test. For example, the Fama and French (1993) model's away-game success pricing DeBondt and Thaler's (1985) Long Run Reversals provides more compelling evidence of the model's wide utility than its home-game success pricing the 25 size- and value-sorted portfolios.

[13] As of December 2024, the global pool of "defensive" equity mutual funds and ETFs tracked by Morningstar has total assets under management of roughly $124 billion, though they have seen outflows of almost $60 billion over the preceding five years. Specifically, these are surviving equity funds whose names contain "defensive," "low vol," or "low beta," or are in the "Risk Oriented" Strategic Beta Group.

"among the many candidates for the greatest anomaly in finance, a particularly compelling one is the long-term success of low-volatility and low-beta stock portfolios."

Previous works, including Blitz and van Vliet (2007) and Asness, Frazzini, and Pedersen (2014), explicitly reject the hypothesis that defensive strategy performance is driven by common factors. These papers fail to properly account for profitability, however, and profitability is an essential ingredient for understanding defensive strategy performance.[14]

3.1. Understanding low beta

Low beta strategies were first suggested by Black (1972), who unsuccessfully lobbied Wells Fargo to establish a levered low beta fund in the early 1970s as a way to exploit the relatively "flat" Securities Market Line documented in Black et al. (1972). Practitioners realized low-beta strategies tilt towards large value stocks, but these tilts only explain a fraction of their performance, leaving significant Fama and French (1993) three-factor alphas. Interest in low-beta strategies has surged recently, spurred by Frazzini and Pedersen's (2014) introduction of "betting-against-beta," a sophisticated dynamic version of Black's beta-arbitrage that generates a much more significant three-factor alpha, at least on paper.[15]

Table 3 presents results of time-series regressions employing the returns to NYSE beta quintiles. We estimate these betas each month from daily returns over the previous year (252 trading days) using Dimson's (1979) correction to account for asynchronous trading. The table shows the performance of these portfolios evaluated against several factor models. Consistent with Novy-Marx (2014*b*) and Fama and French (2016*b*), the beta-sorted portfolios are well-priced by accounting for profitability and investment.

Panel A gives portfolio average excess returns. The high-beta portfolio earns higher average returns than the low-beta portfolio, but the 12 bps/month spread is insignificant (t-statistic of 0.55). Panel B shows the portfolios' CAPM alphas. The high-beta portfolio has a

[14] Blitz, van Vliet, and Baltussen (2020) explicitly argue that "low-risk is distinct from the profitability effect," rejecting the evidence of Novy-Marx (2014*b*) and Fama and French (2016*b*) on the basis that "the alpha of low-risk stocks cannot be explained by the alpha on high-profitability stocks." Appendix A.5 shows that long-only low-beta and low-volatility portfolios can be closely approximated by a long-only portfolio that holds 80% stocks of profitable firms that invest conservatively and 20% T-bills. Low-risk stocks have no alpha relative to this portfolio.

[15] Novy-Marx and Velikov (2022) document multiple empirical issues associated with the construction of Frazzini and Pedersen's (2014) "betting-against-beta" factor.

Table 3. Performance of beta quintiles.
The table reports the time-series performance of NYSE beta quintiles. Returns are in excess of the one-month US Treasury bill rate. Betas is estimated each month from daily returns over the previous year (252 trading days) using Dimson's (1979) correction to account for asynchronous trading. Portfolio returns are value-weighted and rebalanced monthly. The sample covers July 1963 to December 2023.

	Beta quintile					
	High	4	3	2	Low	L−H
Panel A: Average monthly excess return (%)						
r^e	0.65	0.71	0.63	0.59	0.52	-0.12
	[2.37]	[3.49]	[3.74]	[4.02]	[4.22]	[-0.55]
Panel B: CAPM regression results						
α	-0.21	0.06	0.09	0.13	0.19	0.40
	[-2.07]	[0.83]	[1.55]	[2.22]	[2.47]	[2.52]
MKT	1.51	1.15	0.95	0.79	0.59	-0.92
	[66.1]	[77.3]	[71.1]	[59.1]	[35.0]	[-26.2]
Adj.-R^2 (%)	85.8	89.2	87.4	82.8	62.8	48.7
Panel C: Fama-French three-factor regression results						
α	-0.19	0.00	0.02	0.06	0.10	0.29
	[-2.03]	[0.06]	[0.43]	[1.06]	[1.36]	[1.97]
MKT	1.42	1.18	1.00	0.84	0.64	-0.78
	[64.3]	[76.4]	[77.5]	[65.4]	[38.9]	[-23.0]
SMB	0.36	-0.02	-0.09	-0.08	-0.07	-0.43
	[11.2]	[-0.93]	[-4.91]	[-4.33]	[-2.76]	[-8.62]
HML	-0.12	0.14	0.21	0.22	0.26	0.39
	[-3.81]	[6.43]	[11.1]	[11.8]	[11.0]	[7.79]
Adj.-R^2 (%)	88.2	89.8	89.7	86.1	68.6	57.4
Panel D: Five-factor regression results						
α	0.05	-0.05	-0.10	-0.07	-0.04	-0.09
	[0.54]	[-0.75]	[-1.75]	[-1.31]	[-0.49]	[-0.59]
MKT	1.36	1.16	1.00	0.86	0.67	-0.69
	[62.2]	[73.1]	[76.0]	[65.6]	[40.4]	[-20.5]
SMB	0.33	0.02	-0.05	-0.05	-0.04	-0.37
	[10.7]	[0.75]	[-2.51]	[-2.56]	[-1.69]	[-7.81]
HML	0.00	0.23	0.24	0.19	0.15	0.14
	[0.09]	[7.76]	[9.70]	[7.87]	[4.71]	[2.27]
PROF	-0.27	0.17	0.23	0.20	0.13	0.40
	[-5.09]	[4.25]	[7.16]	[6.22]	[3.13]	[4.86]
CMA	-0.53	-0.12	0.05	0.17	0.34	0.87
	[-8.55]	[-2.66]	[1.46]	[4.72]	[7.16]	[9.10]
Adj.-R^2 (%)	89.5	90.1	90.2	86.9	70.7	62.3

market beta 0.92 higher than the low-beta portfolio, yielding a highly significant low-minus-high CAPM alpha of 40 bps/month (t-statistic of 2.52). Panel C shows results employing the Fama and French (1993) three-factor model. Consistent with the practitioner-recognized tilt towards large value stocks, the low-beta strategy has negative SMB and positive HML loadings. The model-predicted impacts of these tilts on expected returns largely offset, however, so the three-factor alpha is still 29 bps/month (t-statistic of 1.97).

Panel D shows time-series regression results using the five-factor model that includes profitability and investment factors. The five-factor model does a remarkable job pricing the beta-sorted portfolios. None of the portfolios earn significant abnormal five-factor returns, and the root mean square pricing error is only 7 bps/month. The model accurately prices the low-minus-high beta return spread primarily through a large, highly significant profitability factor loading of 0.40 and an even larger, more significant investment factor loading of 0.87.[16]

3.2. Understanding low volatility

Ang et al. (2006) document a negative relation between idiosyncratic volatility and subsequent stock returns, the so-called "idiosyncratic volatility puzzle." Subsequent work by Blitz and van Vliet (2007) and Baker et al. (2011) analyzing strategies based on total volatility is highly influential in industry. These "low-volatility" defensive strategies, which exhibit large three-factor alphas, present a greater challenge to standard factor models.

Figure 3 replicates the first figure in Baker et al. (2011), extending the sample both earlier and later. It shows the performance of value-weighted volatility quintiles formed each month using "name-breaks" (i.e., 20% of all firms) on the basis of volatility estimated over the previous year (252 trading days) of daily returns. The figure is undeniably striking, with the risky high volatility quintile underperforming T-Bills over the Baker et al. (2011) sample.[17] It also points, however, to serious sample selection issues. First, the start-date of

[16]The investment factor is closely related to value. The "conservative" and "aggressive" investors on the long and short sides of CMA tend to be those with high and low costs-of-capital, respectively. A firm's cost-of-capital depends directly on its expected stock return, and thus on its relative price. Less expensive value firms on average have higher costs-of-capital, and thus tend to appear in the long sides of CMA as well as HML. The converse is true for growth stocks.

[17]We always show performance net of funding costs charged at the one-month Treasury bill rate. This comes closer to reflecting a strategy's real returns, which are more economically meaningful than its nominal returns. A strategy that realizes a cumulative excess return less than 1.00 is consequently one that delivers lower cumulative average returns than one-month Treasury bills.

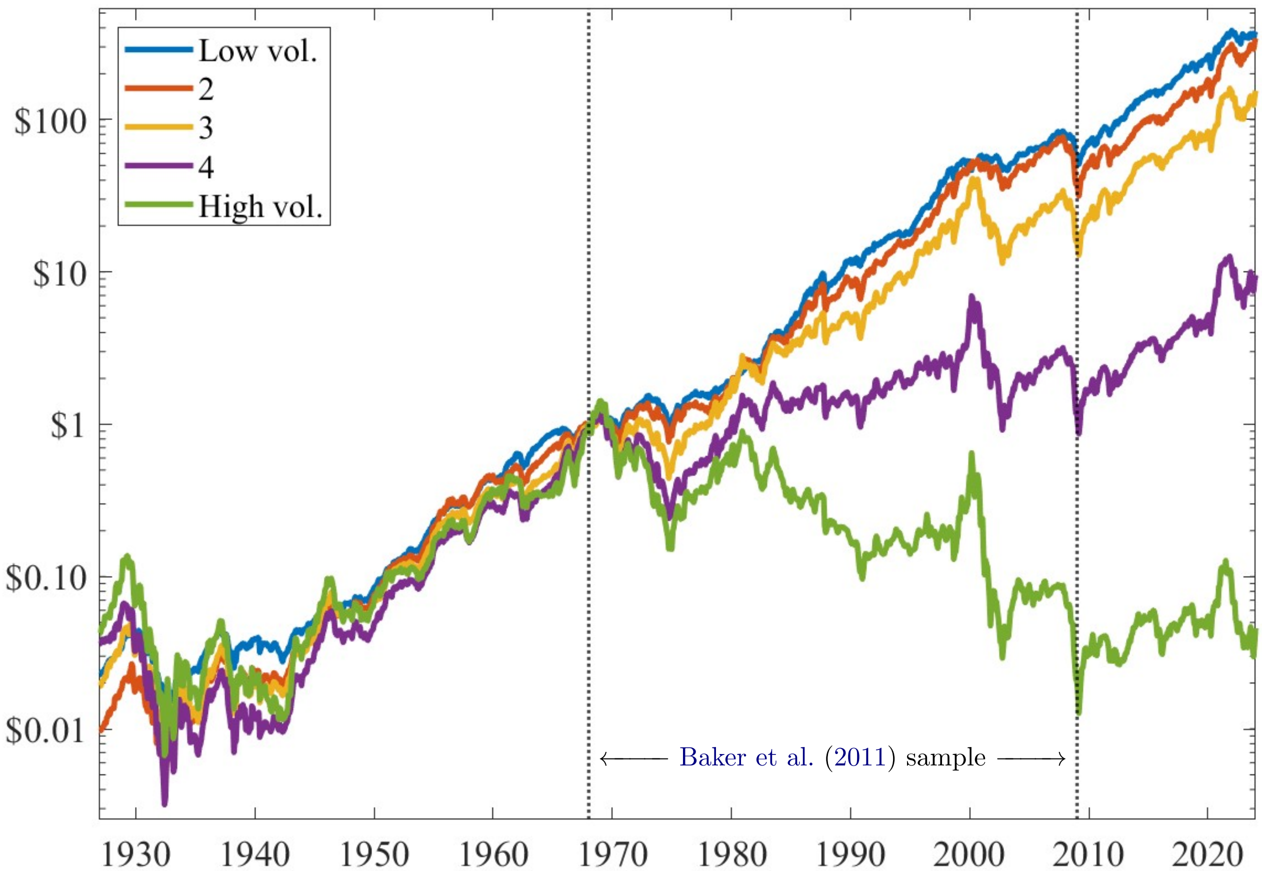

Fig. 3. Volatility portfolio performance. This figure replicates Figure 1 of Baker et al. (2011), extending the sample both earlier and later. It shows the performance of value-weighted volatility quintiles formed each month using name-breaks (i.e., 20% of all firms) on the basis of volatility estimated over the previous year (252 trading days) of daily returns. The sample covers January 1927 through December 2023.

1968 seems selected purely to maximize the result strength. There are no data restrictions or good economic reasons to pick 1968 as a start date. Second, the so-called "low volatility" effect is really all about high volatility. The striking feature of the figure is not low volatility's outperformance, but high volatility's underperformance. Finally, even the striking underperformance of the high-volatility quintile has limited economic significance. The high-volatility 20% of names represents on average only 1.3% of total market capitalization, and is comprised of stocks that are among the most expensive to trade.[18]

It is also important to ask why high-volatility stocks might underperform, and in par-

[18]Novy-Marx and Velikov (2016) document that volatility is an even more reliable predictor of effective spreads than size, and that the two together explain on average almost two-thirds of the cross-sectional variation in trading costs. Small, volatile stocks are the most expensive to trade.

Table 4. Volatility correlates.
The table reports monthly Fama and Macbeth (1973) regressions of volatility onto variables known to predict cross-sectional variation in returns. Volatility is measured in percent/year and estimated each month using the previous year (252 trading days) of daily returns. Independent variables are trimmed at the 1% and 99% levels. Test statistics use Newey-West standard errors with 60 monthly lags. All accounting variables are as of latest fiscal-year end, and book-to-market is scaled by year-end market equity. The sample covers July 1963 through December 2023.

Size (ln(ME))	-6.39					-5.48
	[-11.8]					[-10.0]
Valuation (ln(BE/ME))		-0.41				-4.64
		[-0.55]				[-8.60]
Profitability $\left(\frac{\text{GP}-(\text{XSGA-XRD})-\text{XINT}}{\text{BE+MIB}}\right)$			-26.5			-15.5
			[-10.7]			[-14.8]
Asset growth ($\ln(\text{AT}/\text{AT}_{-1})$)				-11.7		1.12
				[-4.85]		[1.31]
Leverage (ln(BE/AT))					2.60	-1.62
					[2.18]	[-1.48]
Mean-R^2 (%)	26.2	2.6	11.0	2.4	2.1	36.8

ticular what sorts of characteristics might be associated with high volatility. The minimal market coverage of the high-volatility 20% of names suggests volatile stocks tend to be small. It also seems reasonable that highly profitable stocks have steadier returns, so should come as no surprise that high-volatility stocks tend to be less profitable. What other characteristics might be cross-sectionally correlated with volatility? Table 4 answers this question, presenting results of Fama and Macbeth (1973) regressions of volatility onto variables known to predict cross-sectional variation in returns: size, relative price, profitability, and investment. It also includes leverage as a potential explanatory variable because industry frequently employs low leverage as an additional "defensive signal."

Specification (1) shows a highly significant negative correlation between volatility and size, explaining why stocks picked on the basis of high volatility tend to be small. Specification (2) shows that there is no significant univariate relation between volatility and valuations. Specification (3) shows that volatility has a significant negative univariate relation with profitability, suggesting low volatility strategies should tilt towards high profitability. Specifications (4) and (5) show that asset growth and leverage have modest but significant univariate power explaining volatility.

Specification (6) employs all five explanatory variables. Its most interesting features are that high profitability is the most reliable predictor of low volatility, and that valuations, after controlling for size and profitability, become a highly significant correlate of volatility. Not only do high-volatility stocks tend to be small, they also tend to be unprofitable and expensive. The insignificant univariate coefficient on valuations in specification (2) results from failing to control for profitability. While higher valuation growth stocks are on average more volatile holding all else equal, they also tend to be bigger and more profitable, characteristics associated with lower volatility. These size and profitability tilts obscure the true magnitude of the role value plays in defensive strategies. Specification (6) also shows that asset growth and leverage, while significant univariate predictors, do not play a significant role predicting volatility after accounting for size, valuations, and profitability. Controlling for these effects is consequently crucial for understanding the performance of defensive strategies.

Table 5 shows results of time-series regressions using the returns to NYSE volatility quintiles. These more accurately reflect portfolios that might be traded in practice, with the high-volatility quintile holding a more economically significant time-series average of 7.1% of total market capitalization. Panel A shows that the return spread between the high and low quintiles is negligible and insignificant. Panel B shows that the high-volatility portfolio has market beta 0.94 higher than the low-volatility portfolio, a spread slightly exceeding that achieved in Table 3 by sorting on estimated betas directly. This yields a highly significant low-minus-high volatility CAPM alpha of 60 bps/month (t-statistic of 3.04).

Panel C shows Fama and French (1993) three-factor model regressions results. The loadings are consistent with the correlations in Table 4, with the low-volatility strategy tilting towards large value. The model-predicted impact of these loadings on expected returns is close to zero, but SMB and HML explain a significant portion of the return variation unexplained by the market, yielding a better identified and thus more significant alpha (56 bps/month with a t-statistic of 3.93). As a result, low-volatility, unlike low-beta, has a higher information ratio relative to the three-factor model than it does to the CAPM.

Panel D shows results employing the five-factor model that includes profitability and investment factors. Unlike the three-factor model, this model accurately prices all the volatility portfolios; none of the portfolios has a significant five-factor alpha, and the root mean square pricing error is only 5 bps/month. The model performs remarkably well pricing the

Table 5. Performance of volatility quintiles.
The table reports the time-series performance of NYSE volatility quintiles. Volatility is estimated monthly using the previous year (252 trading days) of daily returns. Portfolio returns are value-weighted and rebalanced monthly. The sample covers July 1963 to December 2023.

	Volatility quintile					
	High	4	3	2	Low	L−H
Panel A: Average monthly excess return (%)						
r^e	0.50	0.74	0.72	0.63	0.56	0.06
	[1.58]	[3.09]	[3.63]	[3.74]	[4.31]	[0.25]
Panel B: CAPM regression results						
α	-0.44	-0.03	0.07	0.09	0.16	0.60
	[-2.84]	[-0.33]	[1.29]	[1.60]	[2.82]	[3.04]
MKT	1.64	1.35	1.14	0.95	0.70	-0.94
	[48.4]	[74.9]	[89.7]	[79.7]	[54.2]	[-21.6]
Adj.-R^2 (%)	76.3	88.5	91.7	89.7	80.2	39.2
Panel C: Fama-French three-factor regression results						
α	-0.44	-0.05	0.03	0.04	0.13	0.56
	[-3.87]	[-0.74]	[0.48]	[0.83]	[2.63]	[3.93]
MKT	1.43	1.28	1.15	1.01	0.77	-0.66
	[54.4]	[75.7]	[87.5]	[91.3]	[68.8]	[-19.9]
SMB	0.93	0.36	0.03	-0.17	-0.25	-1.19
	[24.3]	[14.4]	[1.58]	[-10.6]	[-15.5]	[-24.4]
HML	-0.16	0.01	0.12	0.16	0.15	0.31
	[-4.31]	[0.38]	[6.41]	[9.80]	[9.15]	[6.46]
Adj.-R^2 (%)	87.4	91.1	92.2	92.2	86.8	68.5
Panel D: Five-factor regression results						
α	-0.04	0.04	-0.04	-0.09	-0.00	0.03
	[-0.32]	[0.52]	[-0.65]	[-1.91]	[-0.09]	[0.22]
MKT	1.37	1.24	1.14	1.01	0.79	-0.59
	[53.1]	[72.2]	[84.6]	[90.4]	[69.3]	[-17.9]
SMB	0.85	0.35	0.06	-0.13	-0.22	-1.07
	[23.3]	[14.5]	[3.36]	[-8.04]	[-13.8]	[-23.3]
HML	-0.22	0.07	0.18	0.19	0.15	0.37
	[-4.59]	[2.22]	[7.31]	[8.94]	[6.95]	[6.05]
PROF	-0.61	-0.06	0.17	0.23	0.19	0.81
	[-9.67]	[-1.39]	[5.16]	[8.43]	[6.87]	[10.0]
CMA	-0.46	-0.29	-0.08	0.09	0.17	0.63
	[-6.31]	[-5.97]	[-2.09]	[2.76]	[5.31]	[6.84]
Adj.-R^2 (%)	89.0	91.6	92.5	92.7	87.6	72.6

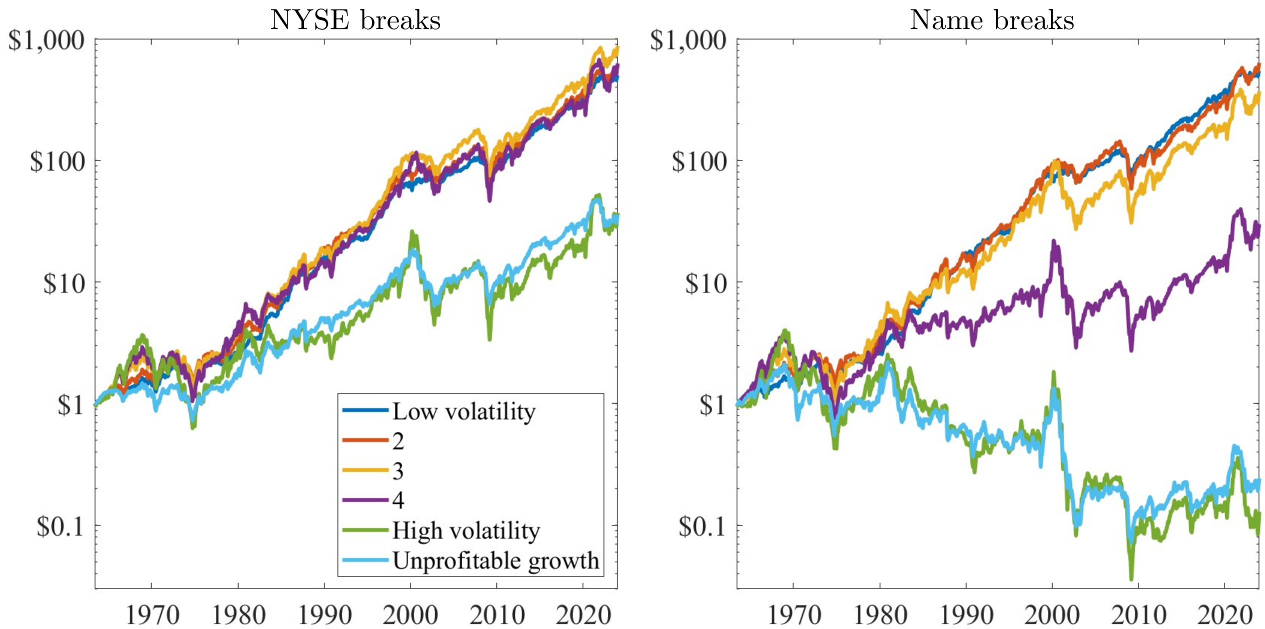

Fig. 4. Performance of volatility quintiles and unprofitable growth. This figure shows the performance of volatility portfolios quintile sorted using NYSE breaks (left panel) and name breaks (right panel). It also shows the performance of unprofitable growth stocks, defined as those with both below NYSE median book-to-market and profitability (left panel) or those in the bottom 30% by both book-to-market and profitability (right panel). These unprofitable growth portfolios contain time-series averages of 12.4% and 1.5% of total market capitalization, similar to the 7.1% and 1.3% held on average by the high volatility portfolios. The sample covers July 1963 through December 2023, with the start date determined by the availability of the Fama and French (2015) factors employed in Table 5.

low-minus-high volatility spread (five-factor alpha of 3 bps/month with a t-statistic of 0.22), achieving this primarily through a large, highly significant loading of 0.81 on the profitability factor, and significant though smaller loadings on the value factors, HML and CMA.

Appendix A.6 replicates the analysis on volatility quintiles constructed using the name breaks employed by Baker et al. (2011). This extreme construction yields a low-volatility strategy that earns a three-factor alpha of almost 15%/year (t-statistic of 5.94). Even so, the model that includes profitability and investment prices the strategy, which fails to generate a significant five-factor alpha.[19]

[19] This is the other place where using Fama and French's (2015) RMW instead of our preferred PROF yields a material difference in results. The extreme name-break high-volatility quintile has a significantly negative canonical five-factor alpha (−50 bps/month, t-statistic of −3.11). As a result, the low-minus-high volatility strategy earns a significant alpha of 48 bps/month (t-statistic of 2.72). This alpha is completely driven by the short side, i.e., from shorting small, unprofitable growth stocks, exactly the kind of stocks that we know the five-factor model struggles to price. It consequently does not represent a distinct anomaly, but simply reflects a repackaging of a well-known model failure. Details of these results are in Appendix A.6.

Figure 4 shows that high-volatility portfolios perform remarkably similarly to the unprofitable growth stocks they tend to hold. It shows the performance of volatility quintiles constructed using both NYSE breaks (left panel) and name breaks (right panel), together with the performance of unprofitable growth stocks, defined as those with both below NYSE median book-to-market and profitability (left panel) or those in the bottom 30% by both book-to-market and profitability (right panel). These unprofitable growth portfolios on average contain 12.4% and 1.5% of total market capitalization, respectively, similar to the 7.1% and 1.3% of market capitalization held on average by the high-volatility portfolios.

Finally, Appendix A.7 shows that profitability's striking power pricing "defensive" strategies extends beyond US markets. Both low-beta and low-volatility strategies generate large, highly significant one- and three-factor abnormal returns in developed markets outside the US, but are well priced by the five-factor model because they load heavily on PROF and CMA. Neither strategy earns significant average returns or any alphas in emerging markets.

4. Understanding value

While academics most commonly quantify value using book-to-market, virtually any relative-price variable is a value metric. In fact, in his seminal "The Intelligent Investor," Graham (1949) puts earnings-to-price on equal footing with book-to-price. Value is a persistent characteristic, however, so should be measured using a persistent variable. Book-to-market is the most persistent of the common relative-price metrics. Value strategies based on book-to-market consequently have lower average portfolio turnover, requiring less trading and incurring lower transaction costs.

Nevertheless, both academics and money managers promote alternative value measures they claim "work better," which typically means they earn higher average returns than, or significant alphas relative to, book-to-market based value. Introduction of these alternative measures has accelerated in response to value's poor performance, increasingly promoted on the basis that they would have underperformed less in the post-2007 period.

Unfortunately, the basis on which these strategies have been evaluated ignores the practical concerns of typical investors. Whether an "alternative value" strategy generates higher returns, or even higher Sharpe ratios, is itself largely irrelevant. What matters is how the strategy impacts the performance of an investor's overall portfolio, and the efficiency with which it can be implemented in practice.

4.1. Alternative value measures and the factor rotation problem

The problem of evaluating alternative value performance on a stand-alone basis, or even relative to book-to-market based value, can be characterized as a "factor rotation" issue.[20] Suppose we create a new strategy that picks stocks on the basis of both low relative price and high profitability. This new strategy, which we could label "improved value," has a higher Sharpe ratio than traditional value, relative to which it earns significant abnormal returns. It is not a better strategy, however, at least for an investor that can trade profitability directly. Given a portfolio that holds both this "improved value" and profitability, a smaller position in traditional value and a larger position in profitability achieves the same investment outcome. The original factors, profitability and value, and the "rotated factors," profitability and "improved value," span the same investment frontier. In conjunction with profitability, either value factor is equally good for achieving the same investment objective.

An "alternative value" strategy is only truly superior insofar as it expands the overall investment frontier of an investor relative to whatever else they can also trade. Alternative value strategies should therefore be evaluated not by their Sharpe ratios, or their alphas relative to book-to-market based value, but by the reliability of their alphas relative to common factors including profitability.

Table 6 describes 12 alternative value metrics proposed by academia or used in industry (for more detailed descriptions, see Appendix B). These include relative-price measures incorporating income statement information (e.g., cash flow-to-price and EBIDTA-to-enterprise value); analyst forecast (e.g., forecast earnings-to-price); and increasingly popular "intangibles-adjustments" to book equity (two different versions). For comparison, we also include a simple, transparent "rotation" of profitability and value, profits-to-price.

Figure 5 shows the t-statistics on these alternative value-minus-growth (VMG) strategies'

[20] We use factor rotation in the common statistical sense to denote a change-of-basis operation. This term is also unfortunately sometimes used in the money management industry to denote strategies that attempt to time factor premia by "rotating" through different factor exposures over time.

Table 6. Alternative value measures.
This tables summarizes popular "alternative" value metrics used in industry and proposed by the academic literature, and includes a brief description of any derived variables used in their construction. For a more detailed description of all the the variables and any data restrictions, see Appendix A.8.

Panel A: Alternative value metrics

Metric name	Variable construction	Reference
Earnings-to-price	$\frac{\text{IB}}{\text{ME}}$	Graham (1949)
Cash flow-to-price	$\frac{\text{IB+DP}}{\text{ME}}$	Lakonishok et al. (1994)
Free cash flow-to-price	$\frac{\text{NI+DP}-\text{WCAPCH}-\text{CAPX}}{\text{ME}}$	Novy-Marx (2013)
Sales-to-price	$\frac{\text{REVT}}{\text{ME}}$	Barbee et al. (1996)
EBITDA-to-enterprise value	$\frac{\text{EBITDA}}{\text{EV}}$	Loughran and Wellman (2011)
Net payouts-to-price	$\frac{\text{Net payouts to equity}}{\text{ME}}$	Boudoukh et al. (2007)
Clean surplus yield	$\frac{\text{IB}-(\text{BE}-\text{BE}_{-1})}{\text{ME}}$	This paper
Retained earnings-to-price	$\frac{\text{RE}}{\text{ME}}$	Ball et al. (2020)
Forward earnings-to-price	$\frac{\text{Shares}\times\text{Forecast-EPS}}{\text{ME}}$	Elgers et al. (2001)
Intangibles-adjusted B/M	$\frac{\text{BE+KC+OC}}{\text{ME}}$	Arnott et al. (2021); Rizova and Saito (2021)
Goodwill & intangibles-adjusted B/M	$\frac{\text{BE}+(\text{IC}-\text{GDWL})}{\text{ME}}$	Eisfeldt et al. (2022)
Profits-to-price	$\frac{\text{GP}-(\text{XSGA}-\text{XRD})-\text{XINT}}{\text{ME}}$	This paper

Panel B: Constructed variables used in alternative value metrics

Variable names	Variable construction
Enterprise value	$\text{EV} = \text{ME} + \text{DLC} + \text{DLTT} + \text{PSTKRV} - \text{CHE}$
Net payouts to equity	$\text{DVC} + (\text{PRSTKC} - \text{SSTK}) + (\text{PSTKRV} - \text{PSTKRV}_{-1})$
Forecast-EPS	I/B/E/S median analyst forecast of one-year ahead EPS
Knowledge capital	$\text{KC}_{it} = (1-\delta_{\text{KC}})\text{KC}_{i,t-1} + \frac{\text{XRD}_{it}}{\text{CPI}_t}$ where $\delta_{\text{KC}} = 0.15$
Organizational capital	$\text{OC}_{it} = (1-\delta_{\text{OC}})\text{OC}_{i,t-1} + 0.3\left(\frac{\text{XSGA}_{it}-\text{XRD}_{it}-\text{RDIP}_{it}}{\text{CPI}_t}\right)$ where $\delta_{\text{OC}} = 0.2$
Intangible capital	$\text{IC}_{it} = (1-\delta_{\text{IC}})\text{IC}_{i,t-1} + \frac{\text{XSGA}_{it}}{\text{CPI}_t}$ where $\delta_{\text{IC}} = 0.2$

alphas from three- and five-factor regressions of the form

$$\begin{aligned}
\text{VMG} &= \alpha + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \epsilon, \\
\text{VMG} &= \alpha + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \beta_{\text{PROF}}\text{PROF} + \beta_{\text{CMA}}\text{CMA} + \epsilon.
\end{aligned}$$

All the strategies have positive three-factor alphas; none earns significant returns relative to the five-factor model that includes profitability.

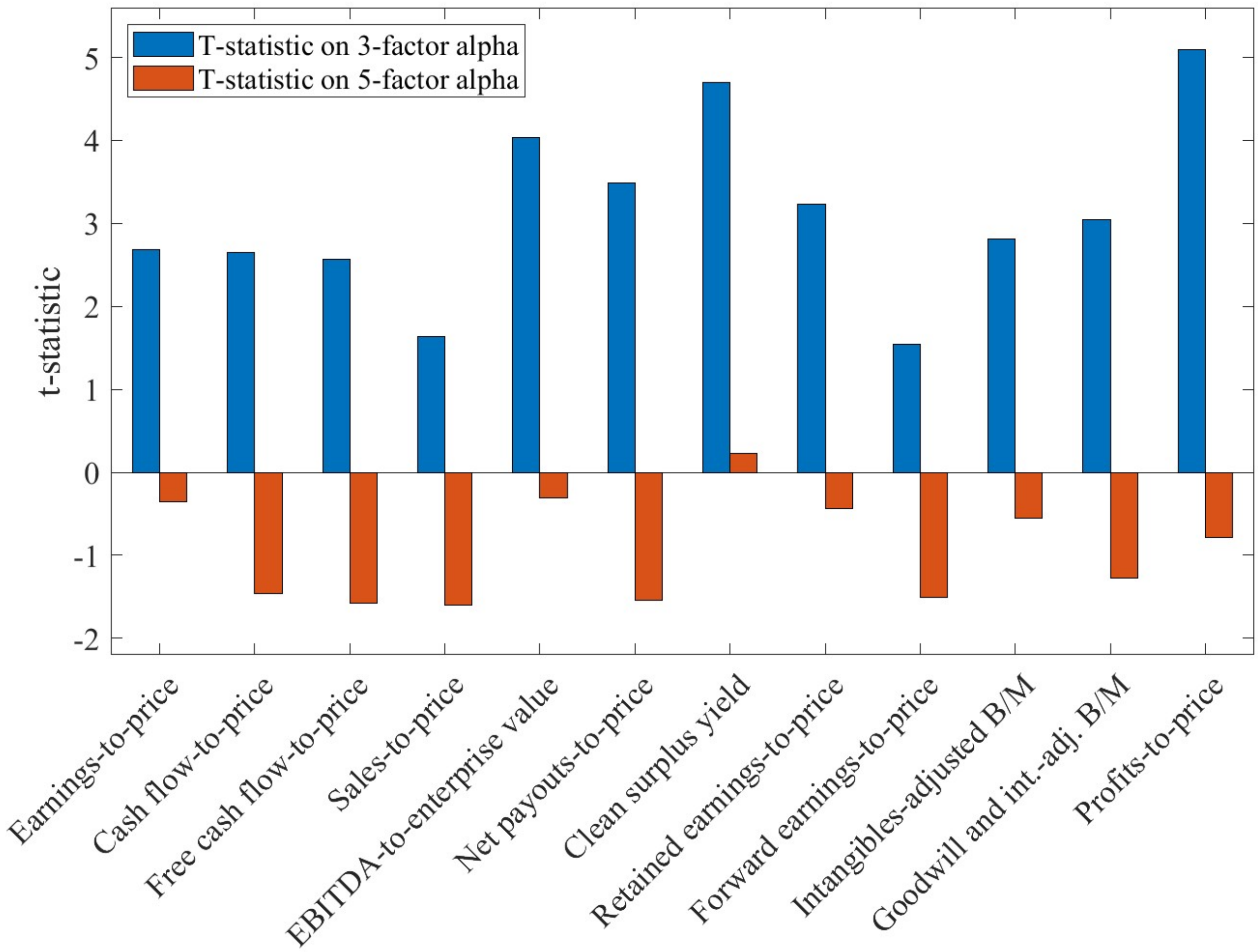

Fig. 5. Information ratios on alternative value metrics. This figure shows the three- and five factor information rations on value factors constructed like HML using alternative relative-price measures. That is, it shows the t-statistics on the alphas from regressions of the form

$$\begin{aligned}\mathrm{VMG} &= \alpha + \beta_{\mathrm{MKT}}\mathrm{MKT} + \beta_{\mathrm{SMB}}\mathrm{SMB} + \beta_{\mathrm{HML}}\mathrm{HML} + \epsilon,\\ \mathrm{VMG} &= \alpha + \beta_{\mathrm{MKT}}\mathrm{MKT} + \beta_{\mathrm{SMB}}\mathrm{SMB} + \beta_{\mathrm{HML}}\mathrm{HML} + \beta_{\mathrm{PROF}}\mathrm{PROF} + \beta_{\mathrm{CMA}}\mathrm{CMA} + \epsilon.\end{aligned}$$

The sample covers July 1963 to December 2023 except for the forward earnings-to-price strategy, which starts on July 1976 due to the availability of analyst forecasts.

That is, adding one of these alternative value factors typically significantly improves the investment frontier of an investor already trading only the market, size, and book-to-market based value, but none of them significantly improve the investment frontier of an investor that can also trade profitability and investment. The "best" alternative value metric, in the sense that it delivers the most significant average return and three-factor alpha, is profits-to-price, an obvious mechanical rotation of value and profitability. However, even this strategy's five-factor alpha is negligible and insignificant.

Table 7. Spanning tests of value strategies.
This table shows results from time-series regressions employing the returns to alternative value strategies. All strategies are a 50/50 mix of large- and small-cap value-minus-growth strategies. The size breakpoint is the NYSE median while relative price breakpoints are the 30th and 70th NYSE percentiles. Portfolios are rebalanced at the end of June and returns are value weighted. Appendix A.8 provides the full details of relative price measures' construction. The sample covers July 1963 to December 2023, except for the forward earnings-to-price strategy, which starts in July 1976 due to availability of data on analysts' forecasts.

Value strategy	r^e	α_{FF3}	α	MKT	SMB	HML	PROF	CMA	Adj.-R^2(%)
Earnings-to-price	0.29	0.19	-0.02	-0.13	-0.15	0.94	0.49	-0.19	72.9
	[2.48]	[2.68]	[-0.36]	[-8.48]	[-7.13]	[32.7]	[13.6]	[-4.48]	
Cash flow-to-price	0.36	0.18	-0.10	-0.04	-0.07	0.85	0.51	0.12	72.4
	[3.05]	[2.65]	[-1.46]	[-2.50]	[-3.06]	[29.8]	[13.9]	[2.73]	
Free cash flow-to-price	0.21	0.19	-0.11	-0.08	-0.22	0.56	0.53	0.11	60.1
	[2.07]	[2.57]	[-1.58]	[-4.76]	[-9.67]	[18.6]	[14.0]	[2.37]	
Sales-to-price	0.38	0.11	-0.11	0.09	0.19	0.66	0.37	0.18	61.3
	[3.76]	[1.64]	[-1.60]	[5.91]	[8.69]	[22.5]	[9.94]	[4.12]	
EBITDA-to-enterprise value	0.38	0.25	-0.02	-0.06	-0.04	0.76	0.51	0.04	73.1
	[3.79]	[4.03]	[-0.30]	[-4.59]	[-2.01]	[31.0]	[16.4]	[1.12]	
Net payouts-to-price	0.24	0.23	-0.09	-0.16	-0.32	0.65	0.49	0.37	79.8
	[1.87]	[3.48]	[-1.54]	[-11.4]	[-15.8]	[24.6]	[14.4]	[9.30]	
Clean surplus yield	0.33	0.30	0.01	-0.12	-0.19	0.46	0.41	0.34	74.1
	[3.10]	[4.70]	[0.23]	[-9.39]	[-9.72]	[19.1]	[12.6]	[8.84]	
Retained earnings-to-price	0.37	0.20	-0.03	-0.06	-0.11	0.85	0.40	0.13	76.0
	[3.12]	[3.23]	[-0.44]	[-4.15]	[-5.33]	[31.8]	[11.8]	[3.33]	
Forward earnings-to-price	0.21	0.13	-0.13	-0.09	-0.14	0.94	0.53	-0.20	69.5
	[1.51]	[1.55]	[-1.51]	[-4.91]	[-4.86]	[27.2]	[11.5]	[-3.75]	
Intangibles-adjusted B/M	0.43	0.16	-0.03	0.09	0.28	0.52	0.26	0.31	68.7
	[4.67]	[2.81]	[-0.55]	[7.44]	[15.8]	[21.7]	[8.60]	[8.64]	
Goodwill and int.-adj. B/M	0.44	0.20	-0.08	0.08	0.25	0.55	0.44	0.28	63.9
	[4.69]	[3.04]	[-1.28]	[5.48]	[12.8]	[20.9]	[13.3]	[7.13]	
Profits-to-price	0.47	0.28	-0.03	-0.01	0.04	0.82	0.58	0.10	84.7
	[4.67]	[5.09]	[-0.79]	[-1.38]	[2.65]	[44.6]	[24.8]	[3.44]	

Table 7 shows how these strategies deliver significant three-factor alphas while failing to deliver any five-factor alpha. The table reports full results from five-factor time-series regressions. While all the strategies tilt strongly towards value (mean HML loading of 0.71), they also all tilt strongly and significantly towards profitability. In fact, the strategies' mean PROF loading of 0.46 is larger than the mean PROF loading on the 12 "quality" strategies in Figure A2. While marketed as alternative versions of value, it is these strategies' profitability tilts that generate most of their three-factor alphas.

All the strategies get their significant profitability loadings by construction. The first nine explicitly include components of operating profitability in the numerator of their relative-price measures. The tenth and eleventh include adjustments to their numerators for "knowledge," "organizational," and "intangible" capital, all of which are constructed as depreciating stocks of capitalized components of profitability.[21] The last strategy, profits-to-price, is a transparent rotation of the two factors.

4.2. Understanding value's late-sample underperformance

Profitability also helps explain value's post-Great Recession drawdown. Over the 17 years between January 2007 and December 2023, the Fama-French value factor, HML, averaged an excess return of −17 bps/month. While not itself significant (t-statistic of −0.72), it is significantly lower than the 47 bps/month average return HML earned between July 1963 and December 2006 (64 bps/month lower with a t-statistic of 2.59). It is informative, however, to evaluate this performance jointly with profitability. According to Novy-Marx (2013),

> "Strategies based on gross profitability generate value-like average excess returns, even though they are growth strategies that provide an excellent hedge for value. The two strategies share much in common philosophically, despite being highly

[21]The net payouts-to-price, clean surplus yield, and both intangibles-adjusted book-to-market strategies also tilt strongly towards conservative investment, with CMA loadings around 0.3. This is, again, by construction. Net payouts-to-price is higher for firms paying large dividends or retiring equity, and cash returned to equity holders cannot be used to acquire assets. The clean surplus yield is $\frac{\text{IB}-\Delta\text{BE}}{\text{ME}} = \left(\frac{\text{BE}}{\text{ME}}\right)\left(\frac{\text{IB}}{\text{BE}} - \frac{\Delta\text{BE}}{\text{BE}}\right)$, which looks like standard value with tilts to high profitability (as measured by earnings-to-price) and conservative investment (as measured by book-equity growth). The intangibles adjustments both include capitalized R&D expenditures. High-R&D firms tend to have high relative prices (so low HML loadings), but depend less on physical capital so invest conservatively in components captured by book assets (so high CMA loadings).

> dissimilar in both characteristics and covariances. While traditional value strategies finance the acquisition of inexpensive assets by selling expensive assets, profitability strategies exploit a different dimension of value, financing the acquisition of productive assets by selling unproductive assets. Because the two effects are closely related, it is useful to analyze profitability in the context of value." (p. 1)

The converse is also true; it is always useful to analyze value in the context of profitability. Doing so explains a significant portion of value's underperformance since 2007.

While value underperformed over this period, profitability outperformed. PROF earned an average return of 31 bps/month from July 1963 to December 2006 (t-statistic of 3.96), but 60 bps/month over the subsequent 17 years (t-statistic of 4.84). That is, PROF's average return is 30 bps/month higher over the late-sample and the difference is significant (t-statistic of 2.02). This late-sample outperformance is particularly remarkable given Mclean and Pontiff's (2016) results on average post-publication underperformance, and the fact that the late sample coincides closely with the out-of-sample period following the publication of Novy-Marx (2013). Over the late sample, HML's loading on PROF is -0.57. This exposure consequently represents a 35 bps/month drag on HML's returns over the period. Profitability's exceptional late-sample performance, over which it realized a Sharpe ratio of 1.16, is unsustainable, suggesting value's short exposure to profitability should provide less drag on value going forward.

Value's short exposure to profitability is not enough, however, to fully explain its late-sample underperformance. It is also partially driven by large industry tilts, particularly value's short exposure to the tech sector, and thus the "Magnificent Seven" driving a disproportionate fraction of the market's extraordinary performance over the period. While this exposure also provided a significant drag on value's recent returns, these firms' historic performance was unexpected and is likewise unsustainable. We consequently should not expect industry exposure to represent the same drag on value's future performance.

The impact of industry tilts on value's performance can be seen in the left panel of Figure 6, which provides a "clean" decomposition of value into intra- and inter-industry components. It shows the performance of value-minus-growth NYSE quintiles (value; red line); industry-hedged value, which hedges the simple value strategy of its exposure to the

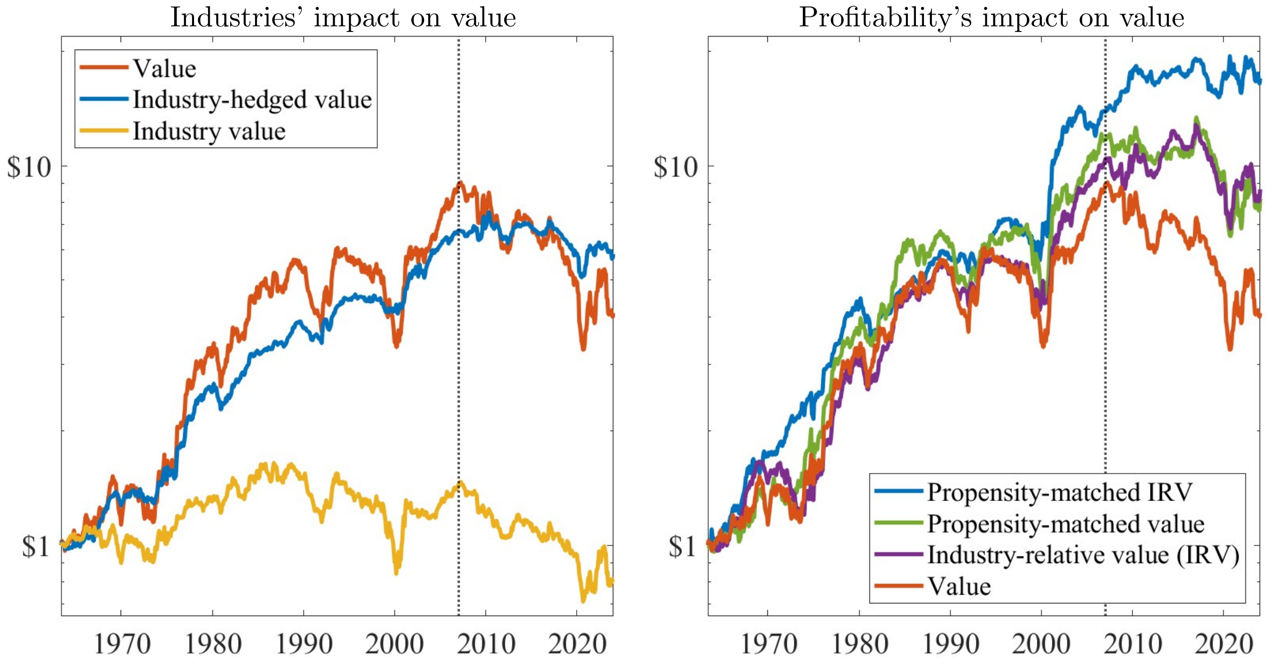

Fig. 6. Understanding value's underperformance. This figure shows the performance of value strategies from July 1963 through December 2023. The left panel shows simple value (high-minus-low value-weighted book-to-market quintiles using NYSE breaks), and a decomposition of this strategy into industry-hedged value (by taking an offsetting position in each stock's value-weighted industry portfolio) and industry value (the hedge). The right panel also shows simple value along with industry-relative value (IRV, from sorts on book-to-market relative to industry book-to-market using NYSE breaks), propensity-matched value (from sorts on book-to-market among groups of five stocks with similar profitability) and propensity-matched IRV.

Fama and French (1997) 49 industries (IHV; blue line); and the industry value strategy used as the hedge (IV; yellow line).[22]

The simple value strategy's underperformance since 2007 is pronounced. The figure shows, however, that most of the negative returns are driven by industry tilts. Over the full sample, industry tilts drive around 80% of the variation in the strategy's realized returns but none of its average returns.[23] As a result, the industry-hedged value strategy earns similar average returns while running at less than half the volatility.

The expected value premium is a mechanical implication of market prices reflecting dis-

[22]Specifically, industry-hedged hedges each stock held long or short in the value strategy with an offsetting position in the stock's value-weighted industry portfolio. The industry hedge replaces each stock with a long position in the stock's value-weighted industry portfolio. This decomposition is "clean" because the two strategies add to the simple value strategy exactly and consequently jointly explain 100% of its returns.

[23]Univariate tests of the simple value strategy produce an R^2 of 80.8% when regressed onto the industry hedge but only 63.8% when regressed on industry-hedged value.

counted expectations of future cash flows (e.g., Fama and French, 2006). Higher required rates of return reduce the present value of future cash flows, and consequently market prices, so low market prices are a visible expression of high expected returns. The "price-signal" in a firm's book-to-market is consequently informative about its expected returns, with lower relative prices on average indicating higher expected returns. The left panel of Figure 6 suggests, however, that book-to-market is not only informative about expected returns (the intra-industry value effect, with lower relative-price associated with higher average returns) but also the mix of inputs in an industry's production function (the industry tilts, with lower relative-price associated with firms in industries more dependent on balance sheet assets). Low relative-prices can also indicate low future expected cash flows, further obscuring the signal in relative prices regarding expected returns.

This suggests that the price-signal can be made more informative about expected returns by controlling for industries and profitability, both of which drive variation in book-to-market unrelated to discount rates. Panel B of Figure 6 shows the performance of simple value, together with value strategies constructed to make the price-signal more informative by controlling for industries and profitability.

To control for industry variation in book-to-market, we construct industry-relative value (IRV) as value-minus-growth NYSE quintiles from a sort on firms' log book-to-market relative to the log book-to-market of their Fama and French 49 industries. To control for expected cash-flow variation in book-to-market, we use the propensity-matched sorting technique of Novy-Marx (2015*b*). Profitability is informative about future cash flows, so differences in prices should be more informative about expected returns among stocks with similar profitability. We consequently match stocks into groups of five on the basis of profitability, and then assign one stock from each group into five different portfolios on the basis of relative price. Propensity-matched value (PMV) is constructed as the value-minus-growth quintiles from sorting on book-to-market after propensity matching on profitability; propensity-matched industry-relative value (PMIRV) is constructed as the value-minus-growth quintiles from sorting on industry-relative book-to-market after propensity matching on profitability.

The right panel of Figure 6 shows that controlling for either industries or profitability makes the price-signal more informative about expected returns. Industry-relative value

Table 8. Understanding value's underperformance. This table shows the average monthly returns to value strategies constructed as high-minus-low NYSE book-to-market quintiles (Value); value hedged of its exposure to the Fama and French (1997) 49 industries (IHV); and the industry value strategy used for hedging (IV); high-minus-low NYSE industry-relative book-to-market quintiles (IRV); and high-minus-low quintiles formed by first propensity-matching into groups of five stocks on the basis of profitability and then assigning stocks from each group into portfolios on the basis of either book-to-market (PMV) or industry-relative book-to-market (PMIRV). It shows this over the full sample, July 1963 through December 2023, and in early and late sub-periods split on the start of value's long-term underperformance, the start of 2007.

Period	Value	IHV	IV	IRV	PMV	PMIRV
Full	0.25	0.26	-0.00	0.33	0.34	0.42
	[1.92]	[3.96]	[-0.04]	[3.25]	[2.85]	[4.73]
Early	0.47	0.38	0.10	0.48	0.52	0.54
	[3.07]	[4.97]	[0.93]	[4.00]	[3.71]	[5.13]
Late	-0.31	-0.05	-0.26	-0.05	-0.12	0.12
	[-1.27]	[-0.44]	[-1.56]	[-0.25]	[-0.54]	[0.72]
Difference	-0.79	-0.43	-0.36	-0.53	-0.64	-0.42
	[-2.70]	[-3.01]	[-1.81]	[-2.33]	[-2.42]	[-2.11]

(IRV) and propensity-matched value (PMV) both outperform the simple value-strategy constructed without controls. Industry-relative value propensity-matched on profitability (PMIRV), which controls for both, does better still.

Improving the price-informativeness of book-to-market has a particularly large impact in the late sample. This is apparent in the right panel of Figure 6 and can also be seen in Table 8, which reports the average returns to all six value strategies over the early- and late samples, split at 2007. The average monthly return to the simple value strategy is 47 bps/month over the early sample (t-statistic of 3.07), but -31 bps/month over the late sample (t-statistic of -1.27), which is significantly lower than its early-sample performance (79 bps/month lower with a t-statistic of 2.70). Controlling for either industries or profitability improves value's performance in both periods, but more so in the late sample, reducing the underperformance (relative average underperformance of 53 bps/month for IRV and 64 bps/month for PMV, with t-statistics of 2.33 and 2.42, respectively). Controlling for both improves the late-sample performance of PMIRV to the point where it is slightly positive, though not significant (12 bps/month with a t-statistic of 0.72). It still significantly underperforms relative to the early sample, but less than any of the other value strategies and only half as much as simple value

(42 bps/month lower with a t-statistic of 2.11).[24]

5. Conclusion

Profitability provides a unifying framework for understanding a broad array of seemingly disparate phenomena in asset pricing. Properly accounting for profitability completely subsumes the quality investing space, explains the performance of defensive equity strategies, and drives all of the "superior performance" of alternative value strategies. Its exceptional post-publication returns, combined with value's negative exposure to profitability, also explains half of value's dramatic late-sample underperformance. Rather than representing distinct phenomena requiring different explanations, many documented return patterns simply reflect different manifestations of a few underlying factors.

For academics, these findings have broad implications for asset pricing and the factor models we use. Accounting for profitability yields a more parsimonious understanding of the cross section of expected returns, imposing some much needed order on the "factor zoo." Properly accounting for profitability more broadly provides a promising avenue for explaining more anomalies, and thus bringing more order and clairity to how we understand the world.

For practitioners, these findings suggest potential benefits from more parsimonious portfolio construction approaches. Investment managers should carefully consider their portfolios' exposure to profitability, as it is a key driver of returns across multiple investment classes. Explicitly targeting specific exposures, rather than relying on indirect proxies, should improve portfolio design and consequently investor outcomes.

[24]The t-statistics on these differences fall less than the spreads themselves because the controls for industry and profitability also reduce strategy volatility. The volatilites of IRV, PMV, and PMIRV are 9.6%, 11.2%, and 8.3% respectively, compared to 12.3% for simple value.

A. Appendix: Additional details and results

A.1. Details of quality strategy construction, performance, and spanning tests

This section provides detailed descriptions of how we construct the quality metrics employed in Section 2 and summarized in Table 1. It also gives complete results of the time-series regressions underlying Figure 1 (which shows the *t*-statistics on the quality strategies' average excess returns and four-factor alphas) and Figure 2 (which shows the *t*-statistics from spanning tests employing quality strategies and PROF).

In addition to profitability, we consider the following quality metrics:

1. Return-on-equity, defined as annual Income Before Extraordinary Items (IB) scaled by book equity (BE) (requires positive book equity).

2. Earnings-per-share (EPS) stability, defined as the inverse of the standard deviation of the year-over-year change in quarterly earnings per share (EPSPXQ) over the last eight quarters (requires at least six quarterly observations).

3. Leverage, defined as assets (AT) scaled by book equity (requires positive book equity).

4. Q-score, defined following GMO (2004) as a composite of the preceding three signals. We use the sum of their z-scores, a construction common in industry (e.g., the MSCI Quality index).

5. Net payout-to-profit, defined as income before extraordinary items (IB) plus year-over-year change in book equity all scaled by operating profits (which for consistency is not punished for R&D expenditures).

6. Return on invested capital (ROIC), defined as annual earnings before interest and taxes (EBIT) scaled by property, plant, and equipment (PPEGT) plus working capital (WCAP).

7. The F-score "financial strength" measure of Piotroski (2000), constructed as a sum of nine binary variables related to profitability, financial conditions and funding sources, and operating efficiency.

8. The distress risk measure of Campbell et al. (2011), which estimates firms' failure probabilities using accounting and market variables.

9. The O-score of Ohlson (1980), which estimates firms' bankruptcy probabilities using financial ratios.

10. The G-score measure of Novy-Marx (2014*a*) inspired by the quality metrics in Graham (1949), defined as the sum of indicator variables for strong financial conditions (current ratio > 2), earnings stability (10 straight years of positive earnings), dividend record (10 straight years of positive payouts to shareholders through dividends and/or repurchases), and earnings growth (10-year EPS growth of at least 33.3%).

11. Beta, estimated at the end of each June from daily returns over the previous year (252 trading days) using Dimson's (1979) correction to account for asynchronous trading.

12. Volatility estimated at the end of each June from daily returns over the previous year (252 trading days).

A.2. Quality strategy performance details

Table A1 shows details of the tests that use these quality definitions underlying Figure 1. The table shows full results of time-series regressions of the form

$$\begin{aligned} \text{Quality} &= \alpha + \epsilon \\ \text{Quality} &= \alpha_{FF4} + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \beta_{\text{UMD}}\text{UMD} + \epsilon. \end{aligned}$$

The t-statistics on these alphas are depicted in Figure 1.

Table A2 shows details of the tests underlying Figure 2. The table shows full results of the spanning tests employing PROF and other quality factors, i.e., time-series regressions of the form

$$\begin{aligned} \text{PROF} &= \alpha + \beta_{\text{Quality}}\text{Quality} + \boldsymbol{\beta}'\mathbf{x} + \epsilon \\ \text{Quality} &= \alpha + \beta_{\text{PROF}}\ \text{PROF} + \boldsymbol{\beta}'\mathbf{x} + \epsilon, \end{aligned}$$

where $\mathbf{x}$ are the other most commonly used factors, those from the Fama and French (2015) five-factor model (excluding RMW) and UMD. The t-statistics on these alphas are depicted in Figure 2.

Table A1. Quality spreads and four-factor regression results. This table shows results from time-series regressions of the form

$$\begin{aligned} \text{Quality} &= \alpha + \epsilon \\ \text{Quality} &= \alpha_{FF4} + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \beta_{\text{UMD}}\text{UMD} + \epsilon. \end{aligned}$$

where **x** are the other most commonly used factors, those from the Fama and French (2015) five-factor model (excluding RMW) and UMD. The sample covers July 1974 to December 2023, with the start date determined by the data required to construct some strategies.

Quality factor	α	α_{FF4}	MKT	SMB	HML	UMD	Adj.-R^2(%)
Profitability	0.45	0.48	0.01	0.15	-0.15	0.05	13.8
	[6.26]	[6.96]	[0.66]	[-6.51]	[-6.52]	[3.10]	
ROE	0.19	0.27	-0.03	-0.37	-0.02	0.03	22.5
	[1.96]	[3.01]	[-1.65]	[-12.2]	[-0.52]	[1.34]	
EPS stability	-0.02	0.10	-0.13	-0.06	-0.15	0.02	17.1
	[-0.33]	[1.49]	[-8.23]	[-2.45]	[-6.83]	[1.23]	
Leverage	-0.10	0.06	-0.05	0.18	-0.58	-0.01	54.1
	[-0.95]	[0.77]	[-3.17]	[7.01]	[-23.7]	[-0.45]	
Q-Score	-0.01	0.21	-0.13	-0.14	-0.44	0.02	48.6
	[-0.07]	[3.30]	[-9.25]	[-6.57]	[-21.0]	[1.66]	
Net payout	0.00	0.08	-0.15	-0.18	0.22	0.01	49.0
	[0.03]	[1.33]	[-11.7]	[-9.37]	[11.8]	[0.66]	
ROIC	0.19	0.25	-0.01	-0.34	0.01	0.02	16.8
	[1.90]	[2.57]	[-0.50]	[-10.5]	[0.24]	[0.98]	
F-score	0.15	0.25	-0.11	-0.27	-0.01	0.04	23.4
	[1.70]	[3.13]	[-5.86]	[-9.84]	[-0.44]	[2.21]	
Distress	0.23	0.35	-0.23	-0.40	-0.33	0.35	60.1
	[1.65]	[3.88]	[-11.1]	[-13.2]	[-11.2]	[16.4]	
O-Score	-0.10	0.07	-0.10	-0.14	-0.26	-0.03	25.7
	[-1.39]	[1.09]	[-6.72]	[-6.39]	[-12.0]	[-1.64]	
G-Score	0.04	0.15	-0.15	-0.24	0.10	0.05	36.1
	[0.47]	[2.02]	[-9.21]	[-8.09]	[3.81]	[2.50]	
Low beta	-0.10	0.19	-0.58	-0.46	0.40	0.16	71.0
	[-0.52]	[1.80]	[-24.3]	[-13.1]	[11.6]	[6.38]	
Low vol.	-0.04	0.28	-0.51	-0.78	0.43	0.10	70.2
	[-0.19]	[2.37]	[-19.2]	[-19.7]	[11.2]	[3.79]	

Table A2. Spanning tests of profitability and quality. This table shows results from time-series regressions of the form

$$\begin{aligned} \text{PROF} &= \alpha + \beta_{\text{Quality}}\text{Quality} + \boldsymbol{\beta}'\mathbf{x} + \epsilon \\ \text{Quality} &= \alpha + \beta_{\text{PROF}}\ \text{PROF} + \boldsymbol{\beta}'\mathbf{x} + \epsilon \end{aligned}$$

where $\mathbf{x}$ are the other most commonly used factors, those from the Fama and French (2015) five-factor model (excluding RMW) and UMD. The sample covers July 1974 to December 2023, with the start date determined by the data required to construct some strategies.

Quality factor	α	MKT	SMB	HML	PROF	CMA	UMD	Adj.-R^2(%)
Panel A: Regressing quality onto profitability, Quality $= \alpha + \beta_{\text{PROF}}\text{PROF} + \boldsymbol{\beta}'\mathbf{x} + \epsilon$								
ROE	-0.14	-0.07	-0.21	0.28	0.96	-0.28	0.00	69.3
	[-2.45]	[-5.50]	[-11.0]	[11.2]	[29.0]	[-7.35]	[0.07]	
EPS stability	0.04	-0.14	-0.02	-0.06	0.19	-0.14	0.02	21.4
	[0.54]	[-9.10]	[-1.04]	[-1.99]	[4.80]	[-3.17]	[1.15]	
Leverage	0.09	-0.04	0.15	-0.66	-0.08	0.08	-0.01	53.8
	[1.09]	[-2.51]	[5.77]	[-19.8]	[-1.86]	[1.66]	[-0.48]	
Q-Score	0.02	-0.15	-0.08	-0.29	0.46	-0.16	0.01	63.3
	[0.34]	[-11.9]	[-4.11]	[-12.1]	[14.4]	[-4.42]	[0.86]	
Net payout	-0.05	-0.12	-0.17	0.10	0.10	0.38	-0.02	57.2
	[-0.92]	[-9.36]	[-9.09]	[4.21]	[3.31]	[10.6]	[-1.45]	
ROIC	-0.13	-0.05	-0.19	0.33	0.91	-0.35	-0.00	56.8
	[-1.80]	[-3.16]	[-7.89]	[10.6]	[22.2]	[-7.29]	[-0.23]	
F-score	0.05	-0.14	-0.18	0.22	0.52	-0.28	0.03	41.4
	[0.71]	[-8.24]	[-7.44]	[6.89]	[12.3]	[-5.75]	[1.89]	
Distress	-0.02	-0.21	-0.30	-0.29	0.67	0.23	0.30	69.8
	[-0.28]	[-11.3]	[-10.8]	[-8.19]	[14.4]	[4.30]	[15.9]	
O-Score	-0.01	-0.10	-0.13	-0.21	0.16	0.00	-0.03	28.2
	[-0.14]	[-6.46]	[-5.75]	[-7.55]	[4.26]	[0.05]	[-2.15]	
G-Score	-0.04	-0.16	-0.16	0.13	0.40	0.17	0.03	44.5
	[-0.58]	[-9.76]	[-6.00]	[4.06]	[8.69]	[3.41]	[1.67]	
Low beta	-0.02	-0.54	-0.43	0.36	0.28	0.35	0.12	72.8
	[-0.19]	[-22.7]	[-12.2]	[7.98]	[4.64]	[4.99]	[5.05]	
Low vol.	-0.04	-0.49	-0.69	0.55	0.56	0.20	0.07	72.7
	[-0.37]	[-18.5]	[-17.8]	[10.9]	[8.39]	[2.54]	[2.43]	

Table A2 (cont.)

Quality factor	α	MKT	SMB	HML	Quality	CMA	UMD	Adj.-R^2(%)
Panel B: Regressing profitability onto quality, PROF $= \alpha + \beta_{\text{Quality}}\text{Quality} + \boldsymbol{\beta}'\mathbf{x} + \epsilon$								
ROE	0.29	0.04	0.08	-0.20	0.61	0.13	0.02	64.1
	[6.42]	[4.08]	[4.69]	[-10.0]	[29.0]	[4.01]	[2.12]	
EPS stability	0.47	0.03	-0.12	-0.06	0.20	-0.08	0.05	15.8
	[6.82]	[1.52]	[-5.09]	[-2.03]	[4.80]	[-1.69]	[3.11]	
Leverage	0.50	-0.01	-0.12	-0.12	-0.07	-0.11	0.06	13.0
	[7.15]	[-0.34]	[-4.79]	[-3.10]	[-1.86]	[-2.23]	[3.36]	
Q-Score	0.36	0.08	-0.05	0.11	0.57	0.01	0.04	35.3
	[5.84]	[5.49]	[-2.42]	[3.68]	[14.4]	[0.22]	[2.47]	
Net payout	0.50	0.02	-0.10	-0.09	0.18	-0.18	0.06	14.1
	[7.15]	[1.05]	[-3.80]	[-2.99]	[3.31]	[-3.50]	[3.57]	
ROIC	0.34	0.02	0.03	-0.20	0.50	0.11	0.03	52.5
	[6.42]	[2.02]	[1.37]	[-8.73]	[22.2]	[3.08]	[2.66]	
F-score	0.38	0.05	-0.03	-0.15	0.40	0.02	0.03	30.5
	[5.90]	[3.45]	[-1.28]	[-5.24]	[12.3]	[0.49]	[2.15]	
Distress	0.38	0.08	0.02	0.05	0.39	-0.17	-0.08	35.3
	[6.18]	[5.24]	[0.90]	[1.95]	[14.4]	[-4.22]	[-4.44]	
O-Score	0.49	0.02	-0.10	-0.03	0.19	-0.11	0.06	15.1
	[7.00]	[0.94]	[-4.16]	[-1.07]	[4.26]	[-2.34]	[3.73]	
G-Score	0.38	0.08	-0.04	-0.18	0.36	-0.20	0.01	34.2
	[5.81]	[4.86]	[-1.63]	[-5.70]	[8.69]	[-4.07]	[0.55]	
Low beta	0.49	0.07	-0.07	-0.12	0.13	-0.15	0.04	15.6
	[6.99]	[3.03]	[-2.61]	[-3.77]	[4.64]	[-3.22]	[2.33]	
Low vol.	0.46	0.09	0.02	-0.17	0.19	-0.14	0.04	21.9
	[6.80]	[4.80]	[0.67]	[-5.52]	[8.39]	[-3.07]	[2.39]	

A.3. Spanning tests of RMW and PROF

Table A3 shows spanning tests of RMW and PROF in the US, developed ex-US, and emerging markets. PROF is constructed in the same manner as RMW, except we use operating profitability unpunished for R&D. Specifically, PROF is a 50/50 mix of large- and small cap profitability strategies from 2×3 sorts on size and operating profitability unpunished for R&D.[25] In the US, the size breakpoint is the NYSE median and the profitability breakpoints are the 30th and 70th NYSE percentiles. Outside the US, large caps are the top 90% of total market capitalization and the profitability breakpoints are the regional 30th and 70th percentiles among large caps. Portfolios are rebalanced annually at the end of June and portfolio returns are value weighted.

Over our US sample, PROF earns a higher and more reliable average excess return than RMW (0.28% vs. 0.39% per month with t-statistics of 3.44 and 5.91). PROF also generates a larger three-factor abnormal return because of its negative, significant loading on HML, with which RMW is largely uncorrelated. PROF's negative HML loading is in line with Novy-Marx (2013), who finds that "Profitable firms tend to be growth firms, in the sense of having low book to-markets, and unprofitable firms tend to be value firms, with high book-to-market," (p. 6) and concludes that "the resulting strategy is a growth strategy as measured by either characteristics (valuation ratios) or covariances (HML loadings)" (p. 16). Lastly, RMW does not earn positive abnormal return relative to PROF, while the converse is not true: PROF earns highly significant abnormal returns relative to RMW and the remaining Fama and French (2015) factors.

Similar results hold outside the US. PROF earns highly significant average excess returns in both developed ex-US and emerging markets (t-statistics of 5.38 and 4.41). These are larger and more reliable than those earned by RMW (t-statistics of 4.87 and 4.01), as are its three-factor abnormal returns. In both developed ex-US and emerging markets RMW is within the span of PROF, but PROF is not within the span of RMW and the remaining factors.

[25] In August 2018, the definition of operating profits-to-book equity on Ken French's website was revised to include minority interest (MIB) in the denominator. Our PROF factor also adds MIB to book equity, and we require book equity plus minority interest to be positive.

Table A3. Spanning tests of PROF and RMW. This table shows spanning tests for the Fama and French (2015) robust-minus-weak (RMW) operating profitability factor, based on REVT − COGS − XSGA − XINT, and a similarly constructed factor (PROF) based on REVT−COGS−(XSGA−XRD)−XINT, where in both cases profits are scaled by BE + MIB. Both factors are a 50/50 mix of profitable-minus-unprofitable strategies among small and large caps. Size breakpoints are NYSE median (US), or top 90%/bottom 10% of market cap for the entire region (ex. US). Profitability breakpoints are the 30th and 70th percentiles by either NYSE breaks (US); or among large caps separately for Europe, Japan, and Asia-Pacific-ex Japan (developed ex-US); or among large caps separately for Latin America, Asia, Europe, and Middle East/Africa (Emerging). Portfolios are rebalanced annually at the end of June and returns are value weighted. In the US and developed ex-US markets, the remaining factors are from Ken French's website. In emerging markets, we construct the remaining factors similar to PROF. The samples are July 1963 through December 2023 (US), July 1990 through December 2023 (developed ex-US), and July 1994 through December 2023 (Emerging).

	US			Developed ex-US			Emerging		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: y = RMW									
α	0.28	0.35	-0.12	0.33	0.45	-0.04	0.39	0.54	-0.02
	[3.44]	[4.63]	[-2.70]	[4.87]	[7.59]	[-1.60]	[4.01]	[5.71]	[-0.45]
MKT		-0.03	-0.04		-0.09	-0.01		-0.02	-0.01
		[-0.07]	[-2.71]		[-6.98]	[-2.48]		[-1.38]	[-2.31]
SMB		-0.29	-0.14		-0.07	-0.01		0.06	-0.01
		[-11.0]	[-9.47]		[-2.16]	[-0.48]		[1.60]	[-0.49]
HML		0.00	0.28		-0.25	0.05		-0.19	0.00
		[0.17]	[14.4]		[-10.0]	[3.25]		[-6.53]	[0.16]
PROF			1.03			0.95			0.95
			[40.1]			[44.4]			[50.6]
CMA			-0.09			0.03			0.01
			[-0.24]			[1.60]			[0.54]
Adj.-R^2 (%)		17.2	74.1		25.8	88.1		11.0	89.9
Panel B: y = PROF									
α	0.39	0.47	0.24	0.38	0.52	0.12	0.43	0.58	0.09
	[5.91]	[7.63]	[6.70]	[5.38]	[8.95]	[5.09]	[4.41]	[6.20]	[2.66]
MKT		-0.00	-0.02		-0.07	0.00		-0.01	0.01
		[-1.93]	[-4.23]		[-6.08]	[-0.71]		[-0.47]	[1.30]
SMB		-0.13	0.06		-0.06	-0.01		0.07	0.01
		[-5.94]	[4.94]		[-2.02]	[-0.71]		[1.88]	[1.08]
HML		-0.21	-0.22		-0.33	-0.08		-0.20	-0.02
		[-9.97]	[-14.2]		[-13.4]	[-5.85]		[-7.06]	[-1.77]
RMW			0.67			0.87			0.93
			[40.1]			[44.4]			[50.6]
CMA			-0.01			-0.07			-0.04
			[-2.90]			[-3.75]			[-2.28]
Adj.-R^2 (%)		14.2	73.6		33.8	89.7		12.2	90.2

Table A4. Profitability's alpha to the q-factor model.
This table reports results from time-series regressions of the form

$$\text{PROF} \;=\; \alpha + \beta_{\mathbf{x}}\mathbf{x} + \epsilon.$$

Explanatory factors are those in the Hou et al. (2015) and Hou et al. (2021) four- and five-factor models, and a post-earnings-announcement drift factor (PEAD) constructed like the Fama and French UMD factor but based on standardized unexpected earnings (SUE) instead of past stock performance. The sample covers July 1974 through June 2024, with the start date determined by the availability of the data used to construct PEAD.

	(1)	(2)	(3)	(4)	(5)
α	0.45	0.30	0.14	0.36	0.19
	[6.26]	[4.88]	[2.22]	[5.90]	[3.15]
MKT		0.02	0.05	0.02	0.05
		[1.65]	[3.65]	[1.40]	[3.59]
ME		-0.02	0.01	-0.01	0.02
		[-0.85]	[0.37]	[-0.44]	[0.94]
I/A		-0.20	-0.19	-0.18	-0.17
		[-6.72]	[-6.86]	[-6.19]	[-6.29]
ROE		0.39	0.31	0.49	0.41
		[17.1]	[12.1]	[17.1]	[13.9]
E_g			0.23		0.25
			[6.75]		[7.39]
PEAD				-0.23	-0.25
				[-5.53]	[-6.28]
Adj.-R^2 (%)		38.3	42.7	41.3	46.2

A.4. Profitability's alpha relative to the q-factor model

Table 2 shows that PROF has significant abnormal returns relative to Hou et al.'s 2015 ROE factor, both alone and in conjunction with the Fama and French (2015) factors MKT, SMB, HML, and CMA and a PEAD factor. This section shows that it also has a large, highly significant alpha relative to the full Hou et al. (2015) four-factor the Hou, Mo, Xue, and Zhang (2019) five-factor models.

Specification (2) and (3) of Table A4 shows results of time-series regressions of PROF using the Hou et al. (2015) four- and Hou et al. (2019) five-factor models. PROF earns a highly significant alpha relative to the four-factor model (30 bps/mo. with a t-stat of 4.88), and a smaller though still significant alpha relative to the five-factor model (14 bps/mo. with a t-stat of 2.22). These models partially price PROF by implicitly attributing some of its returns to PEAD, however, despite the fact that PROF is basically free of fundamental momentum. They do so because PROF is correlated with the ROE factor through the persistent long-run profitability channel, but most of the high average returns to the ROE factor are driven by its large, highly significant exposure to PEAD. Explicitly accounting for this fact by additionally including PEAD as an explanatory factor increases the abnormal average returns earned by PROF relative to both models. The alpha of PROF is 36 bps/mo. with a t-statistic of 5.90 relative to the Hou et al. (2015) four-factor model augmented with a PEAD factor, and 19 bps/mo. with a t-statistic of 3.15 relative to the Hou et al. (2019) five-factor model augmented with PEAD.

A.5. Understanding long-only low-risk strategies

Blitz et al. (2020) claim that "[A]lthough the short side of a low-risk strategy (i.e., high risk) can be explained by the short side of the new Fama-French factors (e.g., poor profitability), the long-side is not explained [...] In a long-only setting, which is the preferred approach of many investors in practice [...] low-risk clearly stands out as a distinct factor" (p. 11). This section shows, contrary to these claims, that long-only low-risk strategies are easily spanned by long-only portfolios that tilt to the common factors, particularly profitability.

Tables 3 and 5 show that the performance of long/short low-risk strategies are explained by large tilts to PROF and CMA, suggesting that long-only low-risk strategies should tilt towards profitable firms with conservative investment policies. Frazzini and Pedersen (2014) ground their Betting Against Beta story in the idea that some "constrained agents need high unleveraged returns" and "therefore overweight risky securities" with high "embedded leverage." The analogous implicit deleveraging of low-risk stocks suggests that the long-only low-risk strategies should resemble a deleveraged position in these profitable firms with conservative investment policies.

Figure A1 shows the performance of low-risk stocks, using both the low-beta and low-volatility NYSE quintiles from Tables 3 and 5, and the performance of a deleveraged position in the stocks of high-profitability, low-investment firms (HPLI). The HPLI firms are those with both above NYSE median profitability and below NYSE median asset growth (value-weighted and rebalanced annually at the end of each June). The figure shows the performance of an 80/20 mix of these stocks and T-bills. Despite not being fully invested in equities, the

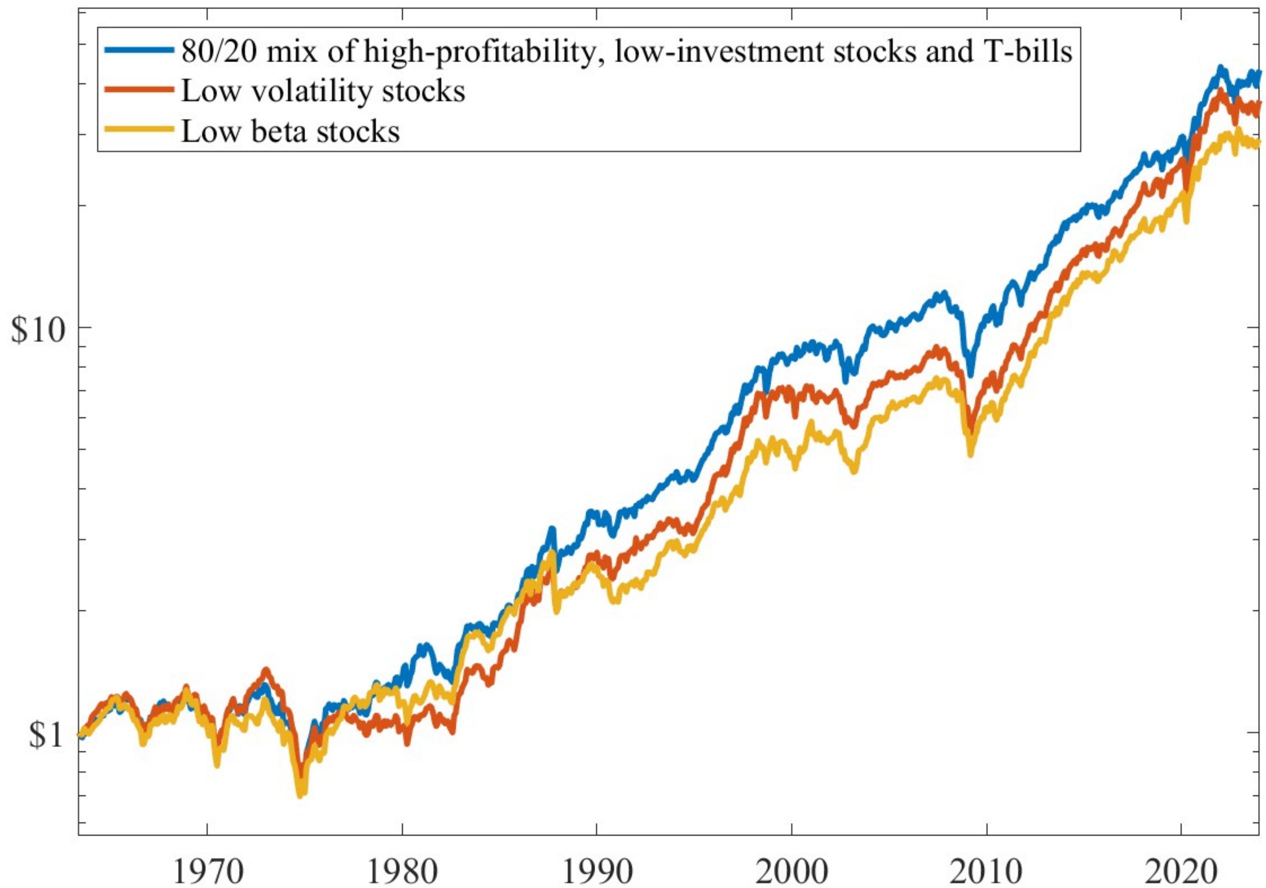

Fig. A1. Long-only "low-risk" equity strategies' cumulative excess returns. This figure shows the performance of low-risk stocks, using both the low-beta and low-volatility NYSE quintiles from Tables 3 and 5, and the performance of a deleveraged position in the stocks of high-profitability, low-investment firms (HPLI). The sample covers July 1963 through December 2023.

80/20 mix of high-profitability, low-investment firms and T-bills outperformed both the low-beta and low-volatility portfolios.

Table A5 shows results of time-series regressions employing the returns to these strategies. The low-beta portfolio earned average excess returns of 52 bps/month, slightly lower than the 57 bps/month earned by the market. It did so, however, with an average volatility of only 11.6%, compared to 15.6% for the market, and consequently realized a significantly higher Sharpe ratio (0.54 vs. 0.44). The low-volatility portfolio did even better, earning average excess returns of 56 bps/month while realizing an average volatility of 12.1%, yielding an even higher Sharpe ratio (0.56). The 80/20 mix of high-profitability, low-investment firms and T-bills, earned an even higher premium, 58 bps/month despite its 20% cash position, while running a volatility of 11.6%, so realized a still higher Sharpe ratio (0.60). The returns

Table A5. Performance of long-only "low-risk" equity strategies.
The table reports the time-series performance of low-risk stocks, both the low-beta and low-volatility NYSE quintiles from Tables 3 and 5, and the performance of a deleveraged position in the stocks of high-profitability, low-investment firms (HPLI). The sample covers July 1963 through December 2023.

	0.8×HPLI	Low beta			Low vol.		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
α	0.58	0.52	0.04	-0.04	0.56	0.00	-0.00
	[4.68]	[4.22]	[0.59]	[-0.49]	[4.31]	[0.05]	[-0.09]
0.8×HPLI			0.83			0.96	
			[40.0]			[61.8]	
MKT				0.67			0.79
				[40.4]			[69.3]
SMB				-0.04			-0.22
				[-1.69]			[-13.8]
HML				0.15			0.15
				[4.71]			[6.95]
PROF				0.13			0.19
				[3.13]			[6.87]
CMA				0.34			0.17
				[7.16]			[5.31]
Adj.-R^2 (%)			68.8	70.7		84.0	87.6

to the high-profitability, low-investment firms and those to the low beta and low volatility stocks are 83% and 92% correlated. This latter correlation exceed that between the low beta and low volatility stocks' returns with each other (90%). As a result, in time series-regressions the low risk stocks load heavily on the the 80/20 mix of the HPLI portfolio and T-bills, and these loadings explain essentially all of the low risk strategies' returns. The low beta and low volatility stocks' loadings on the deleveraged high-profitability, low-investment portfolios, are 0.83 and 0.96, respectively, and relative to this portfolio they earn negligible abnormal returns (4 bps/month and 0 bps/month, respectively, with t-statistics of 0.59 and 0.05). That is, the low-risk stocks achieve market-like returns with below average equity exposure by tilting to profitable firms and those with conservative investment policies, stocks that have high expected average return. Contrary to the claims of Blitz et al. (2020), they do not "clearly stand out," even in a long-only setting, as a "distinct factor."

A.6. Performance of volatility portfolios constructed using name breaks

The five-factor model also performs well pricing the extreme name-break volatility quintiles of Baker et al. (2011) shown in Figure 3 and the right panel of Figure 4. Table A6 shows time-series regression results using the excess returns to these portfolios.

Panel A shows that the low volatility-minus-high volatility spread is a significant 68 bps/month (t-statistic of 2.10), far higher than the insignificant -12 bps/month spread in Table 5. This difference is driven almost entirely be the negative excess average returns earned by the high volatility quintile, which holds on average only 1.3% of market capitalization. Panel B shows that the market beta-spread between these portfolios exceeds one, yielding a CAPM alpha on the low-volatility strategy of 126 bps/month (t-statistic of 4.46). Panel C shows that in Fama and French (1993) three-factor regressions, the low-volatility strategy also tilts strongly to large stocks (SMB loading -1.69, primarily driven by shorting the 1.45 SMB loading of the high volatility quintile that holds on average only 1.3% of total market capitalization) and modestly towards value (HML loading of 0.37). Its three-factor alpha is almost undiminished (123 bps/month) and even more significant (t-statistic of 5.94).

Panel D shows that adding the PROF and CMA factors reduces this alpha by almost 75%. The strategy loads heavily on PROF (1.59) and significantly on both value factors (0.68 on HML and 0.58 on CMA), and as a consequence its abnormal five-factor returns are insignificant (33 bps/month with a t-statistic of 1.65). Panel E shows that the canonical Fama and French (2015) five-factor model also performs well, though not quite as well, pricing the extreme name-breaks version of the low-volatility strategy. Using RMW instead of PROF, the strategy's five-factor alpha is 48 bps/month. All of this alpha (50 of the 48 bps/month) comes from shorting the high volatility quintile, stocks that tilt strongly to small, unprofitable growth stocks, exactly the stocks the Fama and French model is well known to misprice. These stocks have large, negative Fama and French (2015) five-factor alphas, so shorting these stocks mechanically yields the "low volatility" strategy's positive five-factor alpha. That is, even relative to the canonical model, this alpha does not indicate a distinct anomaly, but reflects a repackaging of an old, well-known failing of the standard asset pricing model.

Table A6. Performance of volatility quintiles with name-breaks.
The table reports the time-series performance of name-break volatility quintiles. Volatility is estimated monthly using the previous year (252 trading days) of daily returns. Portfolio returns are value-weighted and rebalanced monthly. The sample covers July 1963 to December 2023.

	Volatility quintile					
	High	4	3	2	Low	L−H
Panel A: Average monthly excess return (%)						
r^e	-0.10	0.47	0.68	0.66	0.58	0.68
	[-0.27]	[1.50]	[2.77]	[3.51]	[4.21]	[2.10]
Panel B: CAPM regression results						
α	-1.11	-0.46	-0.10	0.04	0.14	1.26
	[-4.55]	[-2.99]	[-1.10]	[0.87]	[2.81]	[4.46]
MKT	1.77	1.64	1.37	1.10	0.77	-1.01
	[32.8]	[48.0]	[69.3]	[111.6]	[67.4]	[-16.2]
Adj.-R^2 (%)	59.8	76.1	86.9	94.5	86.2	26.5
Panel C: Fama-French 3-factor regression results						
α	-1.12	-0.41	-0.08	-0.00	0.11	1.23
	[-6.10]	[-3.59]	[-1.10]	[-0.00]	[2.64]	[5.94]
MKT	1.45	1.42	1.27	1.10	0.83	-0.61
	[33.8]	[53.8]	[72.3]	[109.0]	[87.9]	[-12.8]
SMB	1.45	0.90	0.43	0.03	-0.24	-1.69
	[23.2]	[23.2]	[16.5]	[2.31]	[-17.3]	[-24.0]
HML	-0.23	-0.31	-0.12	0.10	0.14	0.37
	[-3.65]	[-8.13]	[-4.66]	[6.71]	[10.4]	[5.29]
Adj.-R^2 (%)	77.5	87.4	90.8	94.8	91.5	60.9
Panel D: Five-factor regression results (PROF)						
α	-0.35	-0.06	0.10	-0.04	-0.02	0.33
	[-1.98]	[-0.52]	[1.26]	[-0.99]	[-0.58]	[1.65]
MKT	1.39	1.38	1.23	1.10	0.85	-0.54
	[33.9]	[51.4]	[69.4]	[105.1]	[88.9]	[-11.9]
SMB	1.25	0.81	0.40	0.05	-0.21	-1.45
	[21.6]	[21.4]	[15.8]	[3.59]	[-15.2]	[-22.5]
HML	-0.52	-0.39	-0.07	0.14	0.17	0.68
	[-6.69]	[-7.75]	[-2.19]	[7.00]	[9.23]	[7.90]
PROF	-1.38	-0.54	-0.22	0.12	0.21	1.59
	[-13.7]	[-8.19]	[-4.94]	[4.51]	[9.12]	[14.1]
CMA	-0.45	-0.37	-0.35	-0.05	0.12	0.58
	[-3.88]	[-4.87]	[-6.89]	[-1.69]	[4.63]	[4.43]
Adj.-R^2 (%)	81.3	88.2	91.6	95.0	92.2	67.8

Table A6 (cont.)

	Volatility quintile					
	High	4	3	2	Low	L−H
Panel E: Fama and French (2015) model 5-factor regression results						
α	-0.50	-0.06	0.10	-0.02	-0.02	0.48
	[-3.11]	[-0.57]	[1.37]	[-0.52]	[-0.55]	[2.72]
MKT	1.33	1.34	1.22	1.10	0.86	-0.47
	[34.7]	[53.6]	[70.1]	[104.6]	[97.5]	[-11.2]
SMB	1.05	0.70	0.35	0.06	-0.16	-1.21
	[18.8]	[19.1]	[13.8]	[4.14]	[-12.6]	[-19.8]
HML	-0.13	-0.22	-0.00	0.11	0.10	0.23
	[-1.80]	[-4.62]	[-0.10]	[5.51]	[5.92]	[2.89]
RMW	-1.38	-0.68	-0.28	0.09	0.26	1.65
	[-18.3]	[-13.9]	[-8.22]	[4.46]	[15.1]	[19.9]
CMA	-0.58	-0.46	-0.38	-0.04	0.16	0.74
	[-5.36]	[-6.43]	[-7.77]	[-1.50]	[6.30]	[6.22]
Adj.-R^2 (%)	83.9	89.9	92.0	95.0	93.4	73.5

A.7. Defensive strategies in non-US markets

In contrast to the other "quality" strategies we consider (Section 2), "defensive" strategies only require return data so can be studied over relatively long samples with good coverage outside the US. Tables A7 and A8 show beta- and volatility-sorted portfolio performance in non-US developed markets; Tables A9 and A10 do the same in emerging markets. Portfolios are from quintile sorts using regional large-cap breakpoints and are rebalanced monthly.[26]

The results for developed-ex US markets resemble the US results shown in Section 3. The extreme quintiles earn significant CAPM and three-factor alphas of opposite signs but exhibit insignificant five-factor alphas, and the five-factor model prices the long-short strategies which load heavily on PROF and CMA. In emerging markets, neither the extreme quintiles nor the long-short strategies earn significant alphas.

[26]In non-US developed markets, our methodology closely follows Fama and French (2017). Large caps are the top 90% of total market capitalization across all countries; all other breakpoints are regional among large caps, where the regions are Canada, Europe (Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Sweden, and United Kingdom), Asia ex-Japan (Australia, Hong Kong, New Zealand, and Singapore), and Japan; and portfolio weights use total market capitalization. We apply a similar methodology in emerging markets, where the regions are Latin America (Brazil, Chile, Colombia, Peru, and Mexico), Asia (China, Taiwan, India, Indonesia, Malaysia, Philippines, Korea, and Thailand), Europe (Czech Republic, Hungary, and Poland), and Middle East/Africa (Turkey, United Arab Emirates, Kuwait, Qatar, Saudi Arabia, Egypt, and South Africa), and where the portfolio weights use free-float market capitalization.

Table A7. Performance of beta quintiles: Developed ex-US.
This table reports the time-series performance of beta quintiles in developed ex-US markets. The breakpoints are set among large caps and are regional, where the regions are Europe, Japan, and Asia-Pacific ex-Japan. Large caps are the top 90% of total market cap across all countries. Beta is estimated each month as the sum of the slopes on the current and lagged market excess returns using the preceding 60 months (24 minimum). Portfolios are rebalanced monthly. Portfolio returns are value weighted using total market cap and are in US dollars. Data are from Bloomberg. The sample covers January 1991 to December 2023.

	Beta quintile					
	High	4	3	2	Low	L−H
Panel A: Average monthly excess return (%)						
r^e	0.27	0.41	0.50	0.45	0.46	0.18
	[0.82]	[1.48]	[2.09]	[2.07]	[2.53]	[0.78]
Panel B: CAPM regression results						
α	-0.27	-0.06	0.10	0.09	0.18	0.45
	[-2.59]	[-1.04]	[2.30]	[1.52]	[2.21]	[2.52]
MKT	1.35	1.15	1.01	0.88	0.69	-0.66
	[60.1]	[99.3]	[112.3]	[69.3]	[39.9]	[-17.3]
Adj.-R^2 (%)	90.1	96.2	97.0	92.4	80.1	43.0
Panel C: Fama-French three-factor regression results						
α	-0.28	-0.10	0.06	0.06	0.17	0.45
	[-2.66]	[-1.89]	[1.56]	[0.98]	[2.08]	[2.50]
MKT	1.36	1.16	1.01	0.88	0.68	-0.68
	[60.2]	[101.0]	[116.7]	[69.3]	[39.0]	[-17.6]
SMB	0.18	0.05	-0.07	-0.05	-0.08	-0.26
	[3.31]	[1.82]	[-3.22]	[-1.61]	[-1.92]	[-2.81]
HML	-0.02	0.11	0.11	0.10	0.05	0.07
	[-0.56]	[4.82]	[6.57]	[4.10]	[1.32]	[0.93]
Adj.-R^2 (%)	90.4	96.4	97.3	92.7	80.3	43.9
Panel D: Five-factor regression results						
α	-0.03	-0.08	0.08	-0.01	0.00	0.03
	[-0.23]	[-1.43]	[1.70]	[-0.15]	[0.03]	[0.15]
MKT	1.26	1.12	1.01	0.92	0.76	-0.50
	[52.5]	[91.9]	[102.1]	[65.9]	[41.6]	[-12.3]
SMB	0.12	0.03	-0.07	-0.03	-0.03	-0.15
	[2.34]	[1.19]	[-3.11]	[-0.90]	[-0.87]	[-1.78]
HML	0.11	0.26	0.07	0.00	-0.11	-0.23
	[2.00]	[8.82]	[3.04]	[0.03]	[-2.58]	[-2.36]
PROF	-0.46	-0.03	-0.03	0.12	0.30	0.76
	[-5.32]	[-0.68]	[-0.74]	[2.31]	[4.49]	[5.20]
CMA	-0.61	-0.33	0.06	0.29	0.53	1.14
	[-7.77]	[-8.34]	[1.94]	[6.39]	[8.95]	[8.67]
Adj.-R^2 (%)	91.8	96.9	97.3	93.4	83.7	53.6

Table A8. Performance of volatility quintiles: Developed ex-US.
This table reports the time-series performance of volatility quintiles in developed ex-US markets. The breakpoints are set among large caps and are regional, where the regions are Europe, Japan, and Asia-Pacific ex-Japan. Large caps are the top 90% of total market cap across all countries. Volatility is estimated each month using the preceding 60 months (24 minimum). Portfolios are rebalanced monthly. Portfolio returns are value weighted using total market cap and are in US dollars. Data are from Bloomberg. The sample covers January 1991 to December 2023.

	Volatility quintile					
	High	4	3	2	Low	L−H
Panel A: Average monthly excess return (%)						
r^e	0.20	0.34	0.43	0.45	0.52	0.32
	[0.63]	[1.19]	[1.67]	[1.97]	[2.82]	[1.47]
Panel B: CAPM regression results						
α	-0.32	-0.14	-0.01	0.07	0.23	0.55
	[-3.08]	[-2.41]	[-0.19]	[1.50]	[3.15]	[3.24]
MKT	1.30	1.18	1.08	0.95	0.72	-0.57
	[58.6]	[96.4]	[126.2]	[101.8]	[46.8]	[-15.9]
Adj.-R^2 (%)	89.7	95.9	97.6	96.3	84.7	38.9
Panel C: Fama-French three-factor regression results						
α	-0.26	-0.17	-0.05	0.03	0.20	0.46
	[-2.74]	[-2.98]	[-1.24]	[0.69]	[2.88]	[2.93]
MkT	1.32	1.19	1.09	0.94	0.71	-0.61
	[65.4]	[97.2]	[130.6]	[113.1]	[47.6]	[-18.1]
SMB	0.37	0.10	0.01	-0.14	-0.19	-0.56
	[7.59]	[3.35]	[0.47]	[-6.83]	[-5.19]	[-6.88]
HML	-0.27	0.06	0.11	0.14	0.12	0.39
	[-6.76]	[2.53]	[6.59]	[8.73]	[4.25]	[5.96]
Adj.-R^2 (%)	91.8	96.1	97.8	97.2	86.2	49.3
Panel D: Five-factor regression results						
α	0.01	-0.03	-0.05	-0.03	0.02	0.01
	[0.06]	[-0.44]	[-1.07]	[-0.63]	[0.22]	[0.07]
MKT	1.22	1.15	1.08	0.96	0.78	-0.44
	[58.0]	[85.0]	[113.0]	[104.2]	[49.7]	[-12.6]
SMB	0.31	0.07	0.00	-0.12	-0.14	-0.45
	[6.93]	[2.56]	[0.25]	[-6.25]	[-4.32]	[-6.15]
HML	-0.14	0.05	0.15	0.10	0.04	0.18
	[-2.87]	[1.63]	[6.39]	[4.33]	[0.93]	[2.17]
PROF	-0.48	-0.27	0.00	0.09	0.34	0.82
	[-6.29]	[-5.46]	[-0.04]	[2.81]	[5.92]	[6.50]
CMA	-0.58	-0.17	-0.08	0.16	0.42	1.00
	[-8.49]	[-3.79]	[-2.62]	[5.33]	[8.13]	[8.83]
Adj.-R^2 (%)	93.3	96.4	97.8	97.4	88.5	59.1

Table A9. Performance of beta quintiles: Emerging markets.
This table reports the time-series performance of beta quintiles in emerging markets. The breakpoints are set among large caps and are regional, where the regions are Latin America, Asia, Europe, and Middle East/Africa. Large caps are the top 90% of total market cap across all countries. Beta is estimated each month as the sum of the slopes on the current and lagged market excess return using the preceding 60 months (24 minimum). Portfolios are rebalanced monthly. Portfolio returns are value weighted using free-float market cap and are in US dollars. Data are from Bloomberg. The sample covers January 1995 to December 2023.

	Beta quintile					
	High	4	3	2	Low	L−H
Panel A: Average monthly excess return (%)						
r^e	0.51	0.61	0.53	0.46	0.45	-0.06
	[1.18]	[1.59]	[1.59]	[1.62]	[1.91]	[-0.24]
Panel B: CAPM regression results						
α	-0.12	0.04	0.03	0.05	0.13	0.24
	[-0.95]	[0.46]	[0.45]	[0.53]	[1.23]	[1.33]
MKT	1.28	1.14	1.00	0.84	0.66	-0.63
	[61.5]	[71.5]	[80.9]	[56.6]	[38.7]	[-20.6]
Adj.-R^2 (%)	91.6	93.6	95.0	90.2	81.2	55.0
Panel C: Fama-French three-factor regression results						
α	-0.12	0.07	0.03	0.03	0.14	0.26
	[-0.99]	[0.84]	[0.46]	[0.39]	[1.37]	[1.36]
MKT	1.29	1.15	1.00	0.84	0.66	-0.63
	[64.5]	[82.6]	[92.7]	[64.6]	[40.8]	[-20.3]
SMB	0.08	-0.06	-0.09	0.01	0.04	-0.04
	[1.73]	[-1.79]	[-3.43]	[0.32]	[0.97]	[-0.61]
HML	0.05	0.02	0.06	0.05	0.01	-0.04
	[1.34]	[0.73]	[2.94]	[2.18]	[0.21]	[-0.76]
Adj.-R^2 (%)	92.4	95.3	96.3	92.5	83.0	54.5
Panel D: Five-factor regression results						
α	-0.06	-0.02	0.01	0.02	0.17	0.23
	[-0.46]	[-0.23]	[0.09]	[0.20]	[1.61]	[1.14]
MKT	1.27	1.14	1.00	0.87	0.69	-0.57
	[58.1]	[76.7]	[84.4]	[62.8]	[40.6]	[-17.4]
SMB	0.08	-0.07	-0.09	0.02	0.05	-0.03
	[1.76]	[-2.30]	[-3.56]	[0.52]	[1.35]	[-0.46]
HML	0.08	0.08	0.07	0.00	-0.07	-0.15
	[1.89]	[2.68]	[3.23]	[-0.07]	[-2.27]	[-2.42]
PROF	-0.06	0.18	0.05	-0.03	-0.12	-0.06
	[-0.75]	[3.52]	[1.14]	[-0.68]	[-2.00]	[-0.54]
CMA	-0.15	-0.08	-0.02	0.18	0.22	0.36
	[-2.39]	[-1.93]	[-0.48]	[4.66]	[4.42]	[3.86]
Adj.-R^2 (%)	92.5	95.6	96.3	93.0	84.3	56.5

Table A10. Performance of volatility quintiles: Emerging markets.
This table reports the time-series performance of volatility quintiles in emerging markets. The breakpoints are set among large caps and are regional, where the regions are Latin America, Asia, Europe, and Middle East/Africa. Large caps are the top 90% of total market cap across all countries. Volatility is estimated each month using the preceding 60 months (24 minimum). Portfolios are rebalanced monthly. Portfolio returns are value weighted using free-float market cap and are in US dollars. Data are from Bloomberg. The sample covers January 1995 to December 2023.

	Volatility quintile					
	High	4	3	2	Low	L−H
Panel A: Average monthly excess return (%)						
r^e	0.44	0.50	0.56	0.53	0.49	0.05
	[1.04]	[1.28]	[1.57]	[1.73]	[1.91]	[0.18]
Panel B: CAPM regression results						
α	-0.13	-0.04	0.06	0.11	0.15	0.28
	[-1.00]	[-0.49]	[0.88]	[1.49]	[1.66]	[1.46]
MKT	1.24	1.18	1.08	0.92	0.73	-0.51
	[57.9]	[87.2]	[91.0]	[77.4]	[49.6]	[-16.1]
Adj.-R^2 (%)	90.6	95.6	90.0	94.5	87.6	42.5
Panel C: Fama-French three-factor regression results						
α	-0.11	-0.12	0.05	0.12	0.07	0.18
	[-0.91]	[-1.50]	[0.71]	[1.68]	[0.80]	[1.00]
MKT	1.26	1.18	1.08	0.92	0.73	-0.54
	[62.3]	[88.6]	[90.1]	[77.2]	[50.4]	[-17.9]
SMB	0.34	0.00	-0.05	-0.10	-0.11	-0.46
	[7.12]	[0.15]	[-1.94]	[-3.45]	[-3.35]	[-6.42]
HML	-0.06	0.11	0.02	-0.01	0.12	0.19
	[-1.68]	[4.49]	[0.94]	[-0.39]	[4.48]	[3.29]
Adj.-R^2 (%)	91.8	95.9	96.0	94.7	88.5	49.4
Panel D: Five-factor regression results						
α	-0.03	-0.08	0.02	0.09	0.02	0.04
	[-0.21]	[-0.90]	[0.26]	[1.11]	[0.18]	[0.23]
MKT	1.24	1.17	1.07	0.93	0.77	-0.47
	[56.1]	[80.2]	[82.2]	[71.3]	[52.1]	[-14.8]
SMB	0.35	0.01	-0.06	-0.10	-0.11	-0.45
	[7.21]	[0.26]	[-2.18]	[-3.49]	[-3.40]	[-6.59]
HML	-0.04	0.12	0.05	-0.02	0.04	0.08
	[-0.83]	[4.15]	[2.13]	[-0.80]	[1.53]	[1.29]
PROF	-0.09	-0.05	0.07	0.04	0.00	0.09
	[-1.17]	[-1.11]	[1.67]	[0.83]	[-0.01]	[0.81]
CMA	-0.18	-0.05	-0.06	0.07	0.29	0.47
	[-2.78]	[-1.30]	[-1.74]	[1.87]	[6.95]	[5.17]
Adj.-R^2 (%)	91.9	95.9	96.1	94.7	90.0	52.8

A.8. Details of alternative value metric construction

This section provides detailed descriptions of how we construct the alternative value metrics summarized in Table 6 and employed in Subsection 4.1. Market equity (ME) values are as of the latest December end and we do not require positive values for earnings, cash flow, sales, EBITDA, either measure of payouts, retained earnings, or earnings forecasts.

1. Earnings-to-price: Income before extraordinary items (IB) scaled by ME.
2. Cash flow-to-price: IB plus depreciation and amortization (DP) scaled by ME.
3. Free cash flow-to-price: Net income (NI) plus DP minus change in working capital ($\text{WCAP} - \text{WCAP}_{-1}$) minus capital expenditures (CAPX) all scaled by ME.
4. Sales-to-price: Revenue (REVT) scaled by ME.
5. EBITDA-to-enterprise value (Loughran and Wellman, 2011): EBITDA scaled by enterprise value, defined as ME plus the sum of short- and long-term debt (DLC + DLTT) plus the redemption value of preferred stock (PSTKRV) minus cash and cash equivalents (CHE). Requires positive enterprise value.
6. Net payouts-to-price: Net payouts scaled by ME, where net payouts are dividends on common/ordinary shares (DVC) plus net expenditure on purchase of common and preferred stock (PRSTKC minus SSTK) minus any change in the redemption value of preferred stocks ($\text{PSTKRV} - \text{PSTKRV}_{-1}$, set to zero if missing).
7. Clean-surplus payouts-to-price: IB minus the change in book equity ($\text{BE} - \text{BE}_{-1}$) scaled by ME. Requires positive book equity (both latest and lagged).
8. Retained earnings-to-market (Ball et al., 2020): RE scaled by ME.
9. Forward earnings-to-price: $\widehat{\text{EPS}}_{1\text{Y}} \times \text{AdjShr}$ scaled by ME, where $\widehat{\text{EPS}}_{1\text{Y}}$ is the consensus median analyst forecast of one-year earnings-per-share as of the prior month from the I/B/E/S Unadjusted Summary database, while AdjShr is shares outstanding from CRSP adjusted for splits between the release date and the end of the month. Forecasts are required to be in USD. Starts in July 1976 due to availability of analysts' forecasts.
10. Intangibles-adjusted book-to-market (Arnott et al., 2021): BE plus "knowledge capital" (KC) plus "organizational capital" (OC) scaled by ME. Requires positive numerator.

Following Peters and Taylor (2017), KC is the capitalized value of real R&D and OC is the capitalized value of a fraction of real reported SG&A,

$$\begin{aligned} \mathrm{KC}_{it} &= (1-\delta_{\mathrm{R\&D}})\mathrm{KC}_{i,t-1} + \tfrac{\mathrm{XRD}_{it}}{\mathrm{CPI}_t}, \\ \mathrm{OC}_{it} &= (1-\delta_{\mathrm{SG\&A}})\mathrm{OC}_{i,t-1} + \theta\tfrac{\widehat{\mathrm{SG\&A}}_{it}}{\mathrm{CPI}_t}, \end{aligned}$$

where CPI is the consumer price index (set to 1 at the end of the sample) and $\widehat{\mathrm{SG\&A}}$ = XSGA − XRD − RDIP.[27, 28] For OC, we set $\theta = 0.3$, $\delta_{\mathrm{SG\&A}} = 0.2$, and we replace missing $\widehat{\mathrm{SG\&A}}$ with zero. For KC, we set $\delta_{\mathrm{R\&D}} = 0.15$ and replace missing XRD with zero. We define the starting values as $\mathrm{OC}_{i0} = \theta\frac{\widehat{\mathrm{SG\&A}}_{i1}/\mathrm{CPI}_1}{g+\delta_{\mathrm{SG\&A}}}$ and $\mathrm{KC}_{i0} = \frac{\mathrm{XRD}_{i1}/\mathrm{CPI}_1}{g+\delta_{\mathrm{R\&D}}}$ with $g = 0.1$, where $\widehat{\mathrm{SG\&A}}_{i1}$ and XSGA_{i1} are a firm's first non-missing values.[29]

11. Goodwill & intangible capital-adjusted book-to-market (Eisfeldt et al., 2022): BE plus "intangible capital" (IC) minus goodwill (GDWL) scaled by ME. We set missing GDWL to zero and require a positive numerator. IC is the capitalized value of real XSGA,

$$\mathrm{IC}_{it} = (1-\delta_{\mathrm{IC}})\mathrm{IC}_{i,t-1} + \tfrac{\mathrm{XSGA}_{it}}{\mathrm{CPI}_t},$$

where $\delta_{\mathrm{IC}} = 0.2$. We replace missing XSGA with zero. The starting value is $\mathrm{IC}_{i0} = \frac{\mathrm{XSGA}_{i1}/\mathrm{CPI}_1}{g+\delta_{\mathrm{IC}}}$ with $g = 0.1$, where XSGA_{i1} is a firm's first non-missing XSGA.

12. Profits-to-price: Operating profits unpunished for R&D (REVT − COGS − (XSGA − XRD) − XINT) scaled by ME.

[27] Peters and Taylor (2017) isolate reported SG&A expenses unrelated to R&D by subtracting both XRD and RDIP (In Process R&D Expense) from Compustat's XSGA. When XSGA is non-missing, missing values for XRD and RDIP are set to zero. When XRD exceeds XSGA but is less than COGS, SG&A equals Compustat's XSGA without adjustment. RDIP captures externally-acquired R&D on products not yet being sold. Compustat codes RDIP as a negative number and includes in XSGA only the part of R&D not captured by RDIP. The RDIP adjustment has almost no practical effect because it is populated and non-zero for less than 1% of firm-years in Compustat.

[28] The CPI adjustment is used to increase the relative importance of estimated intangibles. Book assets are the depreciated stock of accumulated tangible investments, which go onto the balance sheet at nominal, not CPI-adjusted, values. The CPI base-year choice consequently has a material impact on the importance of estimated intangibles relative to book assets.

[29] Peters and Taylor (2017) also assume $\theta = 0.3$ and $\delta_{\mathrm{SG\&A}} = 0.2$, as is common in the literature (e.g., Eisfeldt and Papanikolaou, 2013). For $\delta_{\mathrm{R\&D}}$, they rely on estimated industry-specific R&D depreciation rates from the Bureau of Economic Analysis (BEA; see Li and Hall, 2020) and set $\delta_{\mathrm{R\&D}} = 0.15$ for industries not covered by the BEA. They state, however, that "Our results are virtually unchanged if we apply a 15% depreciation rate to all industries" (p. 14), which is the value we use. For the starting values, KC_{i0} and OC_{i0}, Peters and Taylor use estimates based on firms' pre-IPO Compustat data (when available), but show that their results are robust to assuming starting values of zero or based on the simple formulas we apply.

B. Appendix: Profitability measures

This appendix reviews popular profitability measures proposed in the literature since Novy-Marx (2013). It also shows that operating profitability unpunished for R&D has the most power predicting both returns and the long-term growth in profitability. The latter is important because expected returns should depend on the entire stream of current and expected future cash flows. Formally, re-write Fama and French's (2006) expression for the market-to-book ratio in the dividend discount model as

$$\begin{aligned}\frac{M_t}{B_t} &= \sum_{\tau=0}^{\infty} \frac{\mathbf{E}_t[Y_{t+\tau} - \mathrm{d}B_{t+\tau}]/B_t}{(1+r)^\tau} \\ &= \left(\frac{1+r}{r}\right)\frac{Y_t}{B_t} + \sum_{\tau=0}^{\infty} \frac{1}{(1+r)^\tau}\left(\frac{\mathbf{E}_t[Y_{t+\tau} - Y_t]}{B_t} - \frac{\mathbf{E}_t[\mathrm{d}B_{t+\tau}]}{B_t}\right),\end{aligned} \tag{B1}$$

where Y_t is equity earnings, $\mathrm{d}B_t = B_t - B_{t-1}$ is the one-period change in book equity, and r is the required rate of return. Holding all else equal, higher current profitability (Y_t/B_t) and higher expected growth in profitability ($\mathbf{E}_t[Y_{t+\tau} - Y_t]/B_t$) imply higher required returns. Profitability measures that predict the long-term growth in profitability should be informative about expected returns.

B.1. Profitability measures in the literature

Table B1 shows an overview of the literature since Novy-Marx (2013). He argues that "Gross profits [i.e., revenue minus costs of goods sold] is the cleanest accounting measure of true economic profitability" and that "The farther down the income statement one goes, the more polluted profitability measures become" (p. 2-3). Ball et al. (2015) argue that firms' classification of costs of goods sold versus SG&A expenses is largely arbitrary. Moreover, they note that Compustat's SG&A variable contains R&D expenditures, but argue that "Whereas selling, general, and administrative expenses are expenses the company incurs primarily for generating the current period's revenue, research and development expenditures are largely about generating future revenue" (p. 237). Hence, they define operating profits as gross profits minus SG&A, where the latter is as reported, not pooled with R&D. In concurrent work, Fama and French (2015) define equity-level operating profits by subtracting both SG&A and interest expense from gross profits, though without undoing Compustat's adjustment to SG&A. Ball et al. (2016) argue that a cash-based version of their operating profits, which undoes the effects of accruals accounting, has more power predicting returns. Fama and French (2018) define a cash-based version of their equity-level operating profits by subtracting accruals, again with no adjustment to Compustat's SG&A, which is also studied by Detzel, Novy-Marx, and Velikov (2022).[30]

Below, we confirm that undoing Compustat's addition of R&D to SG&A significantly improves profitability's power predicting returns. In contrast, we show that undoing accruals accounting has limited additional impact on return predictability and, in fact, dramatically attenuates current profitability's power predicting the long-term growth in profitability, which, according to Eqn. (B1), is an important determinant of expected returns.

B.2. Predicting returns with profitability components

Before comparing the profitability measures directly, it is instructive to analyze how the components of profitability predict returns (Ball et al., 2015). Table B2 shows results from Fama and Macbeth (1973) cross-section regressions of monthly returns on revenue, costs of goods sold, SG&A (including and excluding R&D), interest expense, and accruals.[31] All components are scaled by book equity plus minority interest. Controls are asset growth, book-to-market, market capitalization, and past performance over the prior 12-to-2 months and one month. To avoid disproportionate influence of micro and nano caps, we use weighted least squares (WLS) with market capitalization as weight.[32] To avoid undue influence of outliers, we trim the independent variables at the 1% and 99% levels every month.

The first and second specifications show that undoing Compustat's inclusion of R&D into SG&A more than doubles the t-statistic on SG&A. It also implies noticeably higher t-

[30] Fama and French (2016*a*), a draft of Fama and French (2018), considers both operating profits and cash-based operating profits before R&D, i.e., while undoing Compustat's adjustment to SG&A.

[31] Ball et al. (2016) define the accruals adjustment to operating profits as the change in accounts receivables, plus the change in inventory, plus the change in prepaid expenses, minus the change in deferred revenue, minus the change in trade accounts payable, minus the change in accrued expenses: $\Delta\text{RECT} + \Delta\text{INVT} + \Delta\text{XPP} - \Delta(\text{DRC} + \text{DRLT}) - \Delta\text{AP} - \Delta\text{XACC}$, where changes are year-on-year and missing changes are replaced with zeros.

[32] For the same reason, Fama and French (2008), Ball et al. (2015, 2016), and others estimate cross section regressions separately for all-but-micro caps (top four NYSE size quintiles) and micro caps. WLS has the benefit of always using the entire cross section (Hou et al., 2019). Fama and French (2019) estimate cross section regressions at the portfolio level using value-weighted average returns and characteristics.

Table B1. Profitability measures.
This tables provides an overview of popular profitability measures considered in the literature since Novy-Marx (2013). The following variables are as in Compustat: REVT is revenue; COGS is costs of goods sold; XSGA is selling, general, and administrative (SG&A) expenses; XRD is research and development (R&D) expense; and XINT is interest expense. ACC is accruals (Ball et al., 2016).

Profit measure	Logic/Notes	Source
Gross profits GP = REVT − COGS	Unaffected by less persistent items. Does not punish SG&A and R&D. Scaled by total assets. Excludes financials.	Novy-Marx (2013)
Operating profits before R&D and interest GP − (XSGA − XRD)	Split between COGS and SG&A is arbitrary. Compustat's XSGA includes R&D, but R&D is about future revenue. Scaled by total assets. Excludes financials.	Ball et al. (2015)
Operating profits after R&D and interest GP − XSGA − XINT	Equity-level operating profits. No adjustment to Compustat's XSGA. Scaled by book equity.	Fama and French (2015)
Cash profits before R&D and interest GP − (XSGA − XRD) − ACC	Cash profits, which undo accruals accounting, appear more informative about returns. Scaled by average total assets. Excludes financials.	Ball et al. (2016)
Cash profits after R&D and interest GP − XSGA − ACC − XINT	Equity-level cash profits. No adjustment to Compustat's XSGA. Scaled by book equity.	Fama and French (2018); Detzel et al. (2022)
Operating profits before R&D minus interest GP − (XSGA − XRD) − XINT	Equity-level operating profits unpunished for R&D. Accruals adjustment has limited additional impact on return predictability and attenuates the power predicting long-term profitability. Scaled by book equity.	Fama and French (2016*a*); Jagannathan et al. (2023); This paper.

statistics on all of revenue, costs of goods sold, and interest expense. The third specification shows why: the coefficients on R&D and SG&A have opposite signs (positive for R&D) and markedly different magnitudes, yet both are significant. This suggests that adding R&D to SG&A is a misspecification for the purpose of predicting returns. The last three specifications show that controlling for accruals has virtually no impact on these findings.

Table B2. Cross section regressions of returns on components of operating profits. This table shows monthly Fama and Macbeth (1973) cross-section regressions to predict returns. We use weighted least squares WLS with market capitalization as weight. The components of operating profits are as follows (with Compustat mnemonics): Revenue (REVT); Costs of Goods Sold (COGS); Research and Development, or R&D, expenses (XRD, set to zero when missing); Selling, General, and Administrative, or SG&A, expenses (XSGA, which includes XRD); and Interest Expense (XINT). Following Ball et al. (2016), Accruals are defined using the balance sheet approach. All components of profits are scaled by book equity (BE) plus minority interest (MIB). Market equity (ME) is as of latest December-end in BE/ME. Independent variables are trimmed at the 1% and 99% levels each month. The sample is July 1963 through December 2023.

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Revenue	0.53	0.77	0.60	0.54	0.78	0.62
	[3.91]	[6.44]	[4.36]	[3.92]	[6.45]	[4.43]
Costs of Good Sold	-0.56	-0.79	-0.61	-0.57	-0.79	-0.62
	[-4.08]	[-6.54]	[-4.39]	[-4.08]	[-6.54]	[-4.43]
SG&A (incl. R&D)	-0.33			-0.34		
	[-2.06]			[-2.07]		
SG&A (excl. R&D)		-0.67	-0.48		-0.68	-0.49
		[-4.45]	[-2.95]		[-4.43]	[-2.98]
R&D			1.09			1.18
			[2.07]			[2.26]
Interest Expense	-1.42	-1.84	-1.60	-1.26	-1.70	-1.41
	[-2.72]	[-3.61]	[-3.09]	[-2.22]	[-3.05]	[-2.48]
Accruals				-0.48	-0.52	-0.51
				[-3.34]	[-3.69]	[-3.67]
$\ln(AT/AT_{-1})$	-0.41	-0.41	-0.43	-0.20	-0.19	-0.20
	[-3.16]	[-3.10]	[-3.24]	[-1.41]	[-1.32]	[-1.42]
ln(BE/ME)	0.18	0.20	0.21	0.18	0.21	0.22
	[2.69]	[3.07]	[3.21]	[2.72]	[3.09]	[3.27]
ln(ME)	-0.06	-0.07	-0.06	-0.06	-0.07	-0.06
	[-1.87]	[-2.18]	[-2.11]	[-1.85]	[-2.17]	[-2.09]
$r_{12,2}$	0.81	0.84	0.82	0.80	0.83	0.81
	[4.82]	[4.99]	[4.92]	[4.76]	[4.93]	[4.87]
$r_{1,0}$	-3.56	-3.51	-3.60	-3.58	-3.52	-3.62
	[-8.24]	[-8.13]	[-8.51]	[-8.28]	[-8.16]	[-8.54]
Adj.-R^2 (%)	9.4	9.3	10.2	9.6	9.6	10.4
Avg. N	2,373	2,373	2,362	2,362	2,362	2,353

B.3. Predicting returns with profitability measures

Table B3 shows cross section regressions of monthly returns on profitability measures. In addition to Fama and French's (2015) operating profits (OP), we consider operating profits unpunished for R&D ($OP_{R\&D}$), cash-based operating profits that undo accruals accounting

Table B3. Cross-section regressions of returns on profitability measures.
This table shows monthly Fama and Macbeth (1973) cross-section regressions to predict returns. We use WLS with market capitalization as weight. Operating profits are defined following Fama and French (2015) as OP = REVT − COGS − XSGA − XINT, where missing expenses are set to zero provided one is non-missing and where XSGA includes R&D expenditures (XRD). $\text{OP}_{\text{R\&D}}$ = OP + XRD is operating profits unpunished for R&D. COP = OP − ACC is cash-based operating profits, where ACC is accruals, defined using the balance sheet approach of Ball et al. (2016). $\text{COP}_{\text{R\&D}}$ = COP + XRD is cash-based operating profits unpunished for R&D. XRD is set to zero when missing. All profit measures are scaled by book equity (BE) plus minority interest (MIB). Market equity (ME) is as of latest December-end in BE/ME. Independent variables are trimmed at the 1% and 99% level each month. The sample is July 1963 through December 2023. See Table D1 in the Internet Appendix for sub-period results.

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OP	0.88				-1.00		
	[5.85]				[-1.96]		
$\text{OP}_{\text{R\&D}}$		1.10			1.99	1.09	0.90
		[7.91]			[4.11]	[6.99]	[5.69]
COP			0.35			0.04	
			[4.57]			[0.42]	
$\text{COP}_{\text{R\&D}}$				0.47			0.22
				[6.60]			[2.57]
$\ln(\text{AT}/\text{AT}_{-1})$	-0.44	-0.41	-0.29	-0.24	-0.41	-0.31	-0.26
	[-3.41]	[-3.10]	[-2.12]	[-1.75]	[-3.17]	[-2.38]	[-1.99]
ln(BE/ME)	0.19	0.25	0.13	0.16	0.26	0.25	0.25
	[2.77]	[3.76]	[2.16]	[2.63]	[4.10]	[3.80]	[3.72]
ln(ME)	-0.08	-0.08	-0.07	-0.07	-0.08	-0.08	-0.08
	[-2.73]	[-2.84]	[-2.41]	[-2.51]	[-2.73]	[-2.81]	[-2.91]
$r_{12,2}$	0.81	0.86	0.76	0.78	0.85	0.85	0.84
	[4.45]	[4.71]	[4.15]	[4.27]	[4.79]	[4.67]	[4.65]
$r_{1,0}$	-3.40	-3.30	-3.40	-3.35	-3.41	-3.36	-3.35
	[-7.66]	[-7.42]	[-7.63]	[-7.50]	[-7.81]	[-7.57]	[-7.55]
Adj.-R^2 (%)	8.1	8.1	8.0	7.9	8.9	8.4	8.3
Avg. N	3,371	3,371	3,368	3,368	3,362	3,345	3,345

(COP), and cash-based operating profits unpunished for R&D ($\text{COP}_{\text{R\&D}}$). All profit variables are scaled by book equity plus minority interest.

Specifications one to four show that $\text{OP}_{\text{R\&D}}$ has the most power predicting returns. Specifications five and six show that $\text{OP}_{\text{R\&D}}$ subsumes both OP and COP. The last specification shows that $\text{COP}_{\text{R\&D}}$ has incremental power predicting returns controlling for $\text{OP}_{\text{R\&D}}$, though much less than $\text{OP}_{\text{R\&D}}$ (t-statistics of 5.69 and 2.57).

Table D1 in the Internet Appendix repeats the regression in Table B3 for two sub-periods split at the year 2000. It shows results similar to those for the full sample in the early period but even stronger results in the late period, during which $\text{OP}_{\text{R\&D}}$ fully subsumes $\text{COP}_{\text{R\&D}}$.

Tables D2 and D3 in the Internet Appendix repeat the regression in Table B3 in non-US developed and emerging markets. They show that $\text{OP}_{\text{R\&D}}$ again has the most power predicting returns in these markets and that it subsumes OP, COP, and $\text{COP}_{\text{R\&D}}$.

B.4. Predicting the long-term growth in profitability

Of the profit measures we consider, operating profits unpunished for R&D has the most power predicting its own long-term growth. In fact, undoing accruals accounting, as is the case for cash-based profits, introduces significant mean reversion in the profitability measure.

Table B4 shows cross-section regressions of the three- and ten-year growth in each of OP, $\text{OP}_{\text{R\&D}}$, or $\text{COP}_{\text{R\&D}}$ on its current level. These regressions are similar to those considered by Novy-Marx (2013, Appendix A.5). We scale current profits (on the left-hand side) and future profit growth (on the right-hand side) by current book equity plus minority interest. The regressions are estimated annually using WLS with market capitalization as weight. We trim the dependent and independent variables at the 1% and 99% levels each year. Controls are total asset growth, book-to-market, market capitalization, and past performance over the prior 12 months. All market variables are as of fiscal-year ends. Test statistics use Newey and West (1987) standard errors with two or nine lags.

Univariately, both OP and $\text{OP}_{\text{R\&D}}$ predict their own three- and ten-year growth with a positive and significant coefficient, though the coefficient for $\text{OP}_{\text{R\&D}}$ is nearly twice as large (0.19 vs. 0.10) and more reliable (t-statistics of 5.54 vs. 3.07). With controls, both measures lose their positive predictive power at the three-year horizon, but $\text{OP}_{\text{R\&D}}$ retains it at the ten-year horizon (coefficient of 0.35 with a t-statistic of 2.59). The latter is in line with Ball et al.'s (2015) intuition that R&D is largely about generating long-term profits. In contrast, undoing accruals accounting dramatically attenuates profitability's positive power predictiving its own long-term growth. Alone, $\text{COP}_{\text{R\&D}}$ predicts its three-year growth with a negative, significant coefficient, but not its ten-year growth. With controls, $\text{COP}_{\text{R\&D}}$ predicts its own three- and ten-year growth with large, negative, highly significant coefficients.

Tables D4 and D5 in the Internet Appendix show that qualitatively similar, albeit noisier results hold in the shorter samples outside the US.

Table B4. Cross-section regressions of profitability growth on profitability.
This table shows annual Fama and Macbeth (1973) cross-section regressions to predict three- or 10-year growth in profitability using current profitability. We use weighted least squares (WLS) with market capitalization as weight. Following Fama and French (2015), operating profits are OP = REVT − COGS − XSGA − XINT, where missing expenses are set to zero provided one is non-missing and where XSGA includes R&D expenses (XRD). $OP_{R\&D}$ = OP + XRD is operating profits before R&D. $COP_{R\&D}$ = OP − ACC + XRD is cash-based operating profits before R&D, where ACC is accruals, defined using the balance sheet approach of Ball et al. (2016). XRD is set to zero when missing. Profit level and growth are scaled by current book equity (BE) plus minority interest (MIB). Dependent and independent variables are trimmed at the 1% and 99% levels. Test statistics use Newey-West standard errors with two or nine lags. The sample covers fiscal years ending between 1962 and 2023.

Independent variable	$\frac{OP_{t+\tau}-OP_t}{BE_t+MIB_t}$ (1)	(2)	$\frac{OP_{R\&D,t+\tau}-OP_{R\&D,t}}{BE_t+MIB_t}$ (3)	(4)	$\frac{COP_{R\&D,t+\tau}-COP_{R\&D,t}}{BE_t+MIB_t}$ (5)	(6)
Panel A: Predicting 3-year growth ($\tau = 3$)						
OP	0.10	-0.07				
	[3.07]	[-3.74]				
$OP_{R\&D}$			0.19	-0.04		
			[5.54]	[-1.72]		
$COP_{R\&D}$					-0.20	-0.40
					[-4.48]	[-14.2]
$\ln(AT/AT_{-1})$		0.03		0.06		0.14
		[1.42]		[2.89]		[4.78]
ln(BE/ME)		-0.08		-0.10		-0.16
		[-16.0]		[-17.4]		[-14.2]
ln(ME)		0.00		0.00		0.01
		[-0.43]		[-1.40]		[1.77]
$r_{12,1}$		0.05		0.06		0.03
		[4.64]		[4.84]		[2.33]
Adj-R^2 (%)	3.0	9.1	5.2	11.3	5.2	14.7
Avg. N	3,421	3,014	3,421	3,014	3,421	3,012
Panel B: Predicting 10-year growth ($\tau = 10$)						
OP	0.53	0.16				
	[3.23]	[1.51]				
$OP_{R\&D}$			0.84	0.35		
			[4.77]	[2.59]		
$COP_{R\&D}$					-0.04	-0.33
					[-0.25]	[-4.56]
$\ln(AT/AT_{-1})$		0.37		0.49		0.63
		[3.57]		[4.20]		[4.68]
ln(BE/ME)		-0.24		-0.30		-0.41
		[-28.2]		[-23.9]		[-21.3]
ln(ME)		-0.05		-0.05		-0.03
		[-11.7]		[-12.6]		[-4.52]
$r_{12,1}$		0.12		0.13		0.10
		[2.35]		[2.08]		[1.61]
Adj-R^2 (%)	3.6	10.2	5.6	12.9	2.5	12.1
Avg. N	2,284	2,029	2,285	2,029	2,284	2,027

B.5. Predicting the long-term growth in earnings

In addition to being the strongest predictor of its own long-term growth, operating profits unpunished for R&D also has the most power predicting the long-term growth in earnings.

Table B5 shows results from cross-section regressions of the three- and ten-year growth in earnings (IB) on OP, $OP_{R\&D}$, and $COP_{R\&D}$. We scale earnings growth and current profitability by current book equity plus minority interest. The regressions are estimated annually using WLS with market capitalization as weight. Dependent and independent variables are trimmed at the 1% and 99% levels each year. Controls are current earnings, total asset growth, book-to-market, market capitalization, and past performance over the prior 12 months. All market variables are as of fiscal-year ends. Test statistics use Newey and West (1987) standard errors with two or nine lags.

The first three specifications show that the univariate effects of all three measures are positive and significant at both the three- and ten-year horizons. The fourth and fifth specifications show that $OP_{R\&D}$ subsumes the power of OP and $COP_{R\&D}$ predicting earnings growth at either horizon. The last specification shows that $OP_{R\&D}$ retains its power predicting earnings growth alongside the controls. The negative, significant coefficient on current earnings at either horizon when controlling for $OP_{R\&D}$ is in line with the findings of Novy-Marx (2013, Table A7).

Table B5. Cross-section regressions of earnings growth on profitability.
This table shows annual Fama and Macbeth (1973) cross-section regressions to predict the growth in earnings: $\frac{\text{IB}_{t+\tau}-\text{IB}_t}{\text{BE}_t+\text{MIB}_t}$. We use WLS with market capitalization as weight. OP is operating profits (Fama and French, 2015). $\text{OP}_{\text{R\&D}}$ and $\text{COP}_{\text{R\&D}}$ are operating profits and cash profits unpunished for R&D. Earnings and profits are scaled by current book equity (BE) plus minority interest (MIB). Market equity (ME) and past performance ($r_{12,1}$) are as of fiscal-year ends. Dependent and independent variables are trimmed at 1% and 99% levels. Test statistics use Newey-West standard errors with two or nine lags. The sample covers fiscal years ending between 1962 and 2023.

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Predicting 3-year earnings growth ($\tau = 3$)						
OP	0.04			-0.14		
	[2.13]			[-2.85]		
$\text{OP}_{\text{R\&D}}$		0.06		0.18	0.05	0.13
		[3.00]		[3.58]	[1.97]	[5.73]
$\text{COP}_{\text{R\&D}}$			0.05		0.01	
			[5.59]		[1.59]	
Earnings						-0.46
						[-8.95]
$\ln(\text{AT}/\text{AT}_{-1})$						-0.04
						[-2.60]
ln(BE/ME)						-0.05
						[-9.34]
ln(ME)						0.01
						[2.94]
$r_{12,1}$						0.03
						[3.77]
Adj.-R^2 (%)	2.2	2.6	1.8	4.6	3.1	15.1
Avg. N	3,215	3,215	3,212	3,208	3,194	2,827
Panel B: Predicting 10-year earnings growth ($\tau = 10$)						
OP	0.22			-0.44		
	[2.59]			[-3.46]		
$\text{OP}_{\text{R\&D}}$		0.27		0.64	0.28	0.12
		[3.90]		[5.59]	[2.97]	[3.05]
$\text{COP}_{\text{R\&D}}$			0.13		-0.01	
			[3.15]		[-0.52]	
Earnings						-0.35
						[-2.86]
$\ln(\text{AT}/\text{AT}_{-1})$						0.12
						[2.35]
ln(BE/ME)						-0.15
						[-23.91]
ln(ME)						-0.01
						[-2.64]
$r_{12,1}$						0.01
						[0.65]
Adj.-R^2 (%)	3.5	3.9	1.7	5.3	4.2	11.1
Avg. N	2,162	2,162	2,160	2,158	2,148	1,916

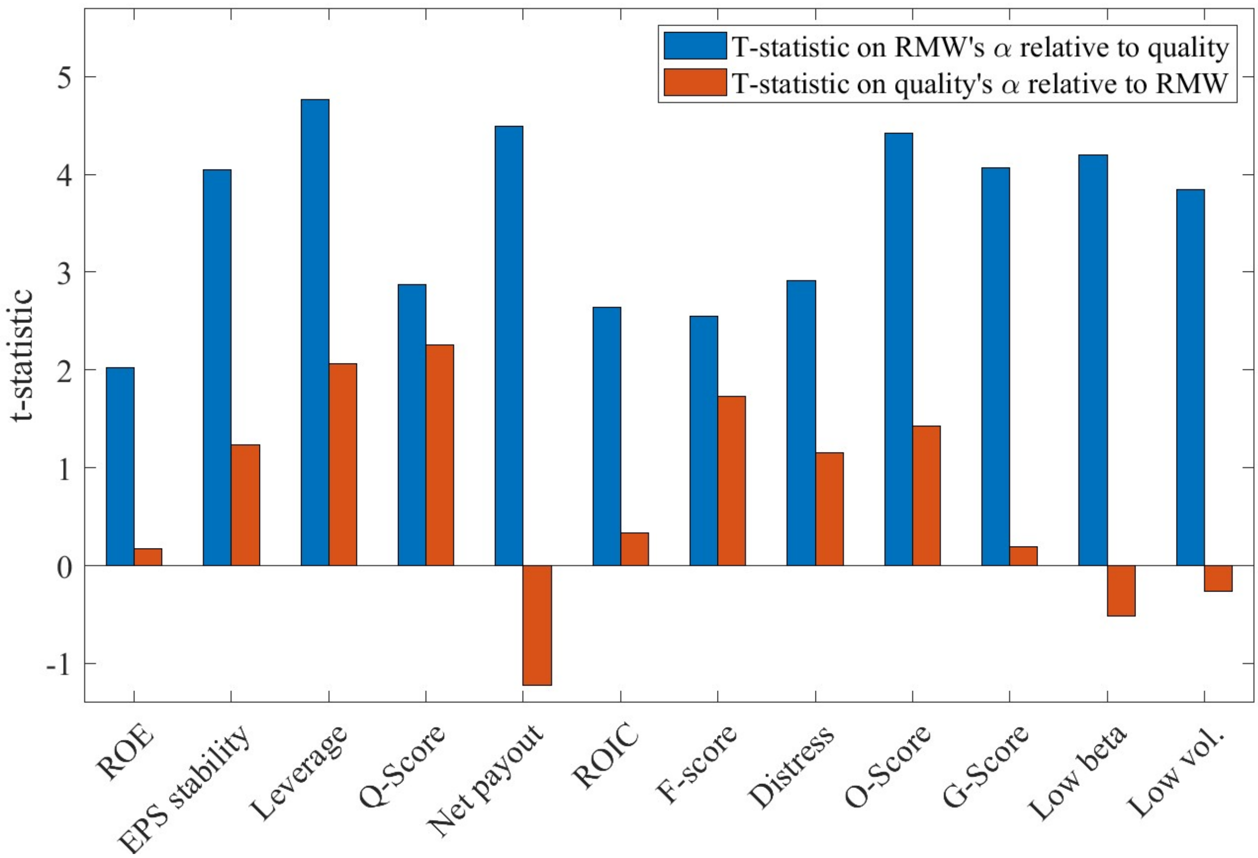

Fig. C1. Spanning tests employing RMW and other measures of quality. This figure shows the t-statistics on the alphas from regressions of the form

$$\begin{aligned} \text{RMW} &= \alpha + \beta_{\text{Quality}}\text{Quality} + \boldsymbol{\beta}'\mathbf{x} + \epsilon \\ \text{Quality} &= \alpha + \beta_{\text{RMW}}\ \ \text{RMW}\ \ + \boldsymbol{\beta}'\mathbf{x} + \epsilon, \end{aligned}$$

where $\mathbf{x}$ are the other most commonly used factors, those from the Fama and French (2015) five-factor model (excluding RMW) and UMD. The sample covers July 1974 to December 2023, with the start date determined by the data required to construct some of the quality strategies.

C. Appendix: Results using canonical RMW

This appendix replicates all the paper's results that employ PROF instead using RMW.

C.1. Quality results employing RMW

Figure C1 replicates Figure 2. The standard five-factor model prices all the quality factors except for marginally significant 5-factor alpha on leverage and Q-score. Table C1 provides full results of the time-series regression underlying the figure.

Table C2 replicates the main results of Table 2, the spanning tests employing QMJ, ROE,

Table C1. Spanning tests of profitability and quality. This table shows results from time-series regressions of the form

$$\begin{aligned} \text{RMW} &= \alpha + \beta_{\text{Quality}} \text{Quality} + \boldsymbol{\beta}'\mathbf{x} + \epsilon \\ \text{Quality} &= \alpha + \beta_{\text{RMW}}\ \text{RMW} + \boldsymbol{\beta}'\mathbf{x} + \epsilon, \end{aligned}$$

where $\mathbf{x}$ are the other most commonly used factors, those from the Fama and French (2015) five-factor model (excluding RMW) and UMD. The sample covers July 1974 to December 2023, with the start date determined by the data required to construct some strategies.

Quality factor	α	MKT	SMB	HML	RMW	CMA	UMD	Adj.-R^2(%)
Panel A: Regressing quality onto profitability, $\text{Quality} = \alpha + \beta_{\text{PROF}}\text{PROF} + \boldsymbol{\beta}'\mathbf{x} + \epsilon$								
ROE	0.01	-0.03	-0.08	0.02	0.86	-0.23	0.01	80.7
	[0.17]	[-3.03]	[-4.74]	[0.97]	[41.1]	[-7.52]	[0.50]	
EPS stability	0.09	-0.14	-0.01	-0.10	0.12	-0.14	0.02	20.4
	[1.24]	[-8.64]	[-0.44]	[-3.29]	[3.90]	[-3.10]	[1.37]	
Leverage	0.15	-0.06	0.08	-0.59	-0.28	0.04	0.00	58.4
	[2.07]	[-3.45]	[2.93]	[-18.4]	[-8.31]	[0.87]	[0.17]	
Q-Score	0.13	-0.14	-0.04	-0.39	0.31	-0.16	0.02	59.5
	[2.25]	[-10.2]	[-2.06]	[-15.2]	[11.5]	[-4.04]	[1.42]	
Net payout	-0.06	-0.11	-0.13	0.05	0.17	0.40	-0.02	59.8
	[-1.23]	[-8.93]	[-6.84]	[2.32]	[7.06]	[11.5]	[-1.83]	
ROIC	0.02	-0.01	-0.07	0.08	0.79	-0.30	0.00	63.6
	[0.34]	[-0.94]	[-2.89]	[2.92]	[26.4]	[-6.89]	[0.11]	
F-score	0.12	-0.11	-0.09	0.07	0.51	-0.24	0.03	49.6
	[1.73]	[-7.28]	[-3.93]	[2.24]	[16.5]	[-5.35]	[2.01]	
Distress	0.09	-0.18	-0.21	-0.46	0.58	0.27	0.31	71.7
	[1.15]	[-10.1]	[-7.39]	[-13.4]	[16.2]	[5.06]	[16.8]	
O-Score	0.10	-0.10	-0.17	-0.21	-0.06	-0.03	-0.02	26.5
	[1.43]	[-6.58]	[-7.02]	[-7.28]	[-2.01]	[-0.62]	[-1.31]	
G-Score	0.01	-0.15	-0.15	0.08	0.33	0.16	0.03	43.1
	[0.19]	[-9.11]	[-5.23]	[2.32]	[7.90]	[3.10]	[1.59]	
Low beta	-0.05	-0.52	-0.33	0.24	0.44	0.40	0.11	75.8
	[-0.52]	[-22.9]	[-9.40]	[5.59]	[9.82]	[6.05]	[4.93]	
Low vol.	-0.03	-0.46	-0.56	0.35	0.69	0.26	0.06	77.3
	[-0.27]	[-18.8]	[-14.8]	[7.58]	[14.3]	[3.71]	[2.33]	

Table C1 (cont.)

Quality factor	α	MKT	SMB	HML	Quality	CMA	UMD	Adj.-R^2(%)
Panel B: Regressing profitability onto quality, RMW $= \alpha + \beta_{\text{Quality}}\text{Quality} + \boldsymbol{\beta}'\mathbf{x} + \epsilon$								
ROE	0.09	0.01	-0.01	0.04	0.86	0.15	0.01	79.6
	[2.02]	[1.37]	[-0.67]	[1.93]	[41.1]	[4.77]	[0.98]	
EPS stability	0.36	-0.02	-0.29	0.23	0.21	-0.15	0.05	23.0
	[4.05]	[-0.95]	[-9.93]	[6.02]	[3.90]	[-2.57]	[2.53]	
Leverage	0.40	-0.07	-0.24	-0.03	-0.38	-0.15	0.05	29.3
	[4.76]	[-3.40]	[-8.31]	[-0.65]	[-8.31]	[-2.67]	[2.70]	
Q-Score	0.23	0.04	-0.22	0.41	0.60	-0.06	0.04	35.6
	[2.88]	[2.06]	[-7.95]	[10.6]	[11.5]	[-1.05]	[1.90]	
Net payout	0.38	0.00	-0.22	0.17	0.46	-0.36	0.06	27.2
	[4.49]	[0.17]	[-7.11]	[4.63]	[7.06]	[-5.76]	[3.20]	
ROIC	0.16	-0.01	-0.09	0.04	0.68	0.12	0.03	63.9
	[2.64]	[-0.94]	[-4.24]	[1.51]	[26.4]	[2.88]	[1.80]	
F-score	0.19	0.04	-0.15	0.11	0.62	0.02	0.02	46.0
	[2.55]	[2.01]	[-5.62]	[3.25]	[16.5]	[0.43]	[1.16]	
Distress	0.22	0.06	-0.10	0.40	0.53	-0.27	-0.12	45.3
	[2.91]	[3.37]	[-3.57]	[11.6]	[16.2]	[-5.41]	[-5.92]	
O-Score	0.39	-0.06	-0.32	0.19	-0.11	-0.19	0.06	21.5
	[4.42]	[-2.87]	[-10.4]	[4.70]	[-2.01]	[-3.17]	[2.67]	
G-Score	0.30	0.06	-0.11	-0.03	0.36	-0.18	0.02	22.1
	[4.06]	[3.20]	[-3.81]	[-0.89]	[7.90]	[-3.42]	[0.88]	
Low beta	0.35	0.12	-0.15	0.11	0.32	-0.29	0.01	32.1
	[4.19]	[4.72]	[-4.91]	[2.89]	[9.82]	[-5.11]	[0.70]	
Low vol.	0.30	0.13	-0.02	0.03	0.37	-0.24	0.02	41.3
	[3.85]	[6.08]	[-0.49]	[0.81]	[14.3]	[-4.59]	[1.21]	

Table C2. QMJ and ROE regression results using RMW. This table reports results from time-series regressions of the form

$$y = \alpha + \beta_{\mathbf{x}} \mathbf{x} + \epsilon.$$

The dependent variable is Asness et al.'s (2019) QMJ, Hou et al.'s (2015) ROE, or Fama and French's (2015) RMW. Explanatory factors include these variables, the other Fama and French (2015) factors, and a post-earnings-announcement drift factor (PEAD) constructed like the Fama and French UMD factor but based on standardized unexpected earnings (SUE) instead of past stock performance. The sample covers July 1974 through June 2024, with the start date determined by the availability of the data used to construct SUE.

	y = QMJ		y = ROE		y = RMW			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
α	0.16	0.26	0.30	0.04	0.05	-0.03	0.01	0.15
	[2.23]	[4.38]	[3.55]	[0.60]	[0.77]	[-0.43]	[0.16]	[2.24]
RMW	0.73	0.60	0.76	0.60				
	[24.4]	[22.0]	[21.4]	[20.0]				
QMJ					0.69	0.76		
					[24.4]	[22.0]		
ROE							0.57	0.68
							[21.4]	[20.0]
PEAD		0.22		0.75		-0.04		-0.37
		[6.76]		[20.7]		[-1.07]		[-7.68]
MKT		-0.18		-0.02		0.11		-0.01
		[-14.0]		[-1.46]		[6.96]		[-0.81]
SMB		-0.09		-0.08		-0.11		-0.13
		[-4.23]		[-3.40]		[-4.54]		[-5.60]
HML		-0.16		-0.10		0.21		0.17
		[-6.44]		[-3.72]		[7.77]		[5.94]
CMA		0.04		-0.08		-0.14		-0.07
		[0.96]		[-1.79]		[-3.25]		[-1.54]
Adj.-R^2 (%)	50.2	70.5	43.4	71.3	50.2	60.0	43.4	56.6

and PROF. The Fama and French (2015) five-factor model augmented with PEAD prices ROE (specification 4), but cannot price QMJ (specification 2).

PROF prices QMJ while RMW fails to do so because PROF earns higher average returns and, because it is based on a broader measure of profitability, also covaries more strongly with QMJ. While QMJ cannot price PROF (Table 2), it can explain the lower average returns earned by RMW (specifications 5 and 6). ROE also appears to price RMW on its own (specification 7), but implicitly does so by attributing a significant fraction of RMW's average returns to PEAD; controlling for PEAD, ROE cannot price RMW (specification 8).

C.2. Defensive equity results employing RMW

Table C3 replicates Panel D of Tables 3 and 5. The Fama and French (2015) five-factor model performs well pricing NYSE quintiles formed on both beta and volatility.

Table C3. Fama-French five-factor performance of risk-sorted portfolios.
The table reports results of time-series regressions of NYSE beta quintiles (Panel A) and NYSE volatility quintiles (Panel B) on the five Fama and French (2015) factors. Betas and volatilities are estimated each month from daily returns over the previous year (252 trading days), betas using Dimson's (1979) correction to account for asynchronous trading. Portfolio returns are value-weighted and rebalanced monthly. The sample covers July 1963 to December 2023.

	Beta quintile					
	High	4	3	2	Low	L−H
Panel A: Beta sorted portfolios						
α	0.01	-0.06	-0.11	-0.08	-0.07	-0.08
	[0.14]	[-0.86]	[-2.03]	[-1.62]	[-1.03]	[-0.60]
MKT	1.35	1.17	1.01	0.87	0.69	-0.67
	[61.5]	[75.0]	[81.8]	[70.1]	[42.3]	[-20.1]
SMB	0.30	0.05	0.01	0.00	0.01	-0.29
	[9.28]	[2.38]	[0.30]	[0.04]	[0.35]	[-5.97]
HML	0.08	0.18	0.16	0.12	0.09	0.02
	[1.86]	[6.03]	[7.01]	[5.36]	[3.04]	[0.26]
RMW	-0.25	0.22	0.31	0.28	0.25	0.50
	[-5.82]	[7.20]	[12.6]	[11.4]	[7.79]	[7.66]
CMA	-0.55	-0.09	0.10	0.21	0.38	0.93
	[-8.85]	[-2.04]	[2.72]	[6.06]	[8.29]	[9.92]
Adj.-R^2 (%)	89.6	90.6	91.4	88.3	72.6	64.0
	Volatility quintile					
	High	4	3	2	Low	L−H
Panel B: Volatility sorted portfolios						
α	-0.08	0.02	-0.03	-0.09	-0.01	0.07
	[-0.80]	[0.32]	[-0.60]	[-1.99]	[-0.28]	[0.55]
MKT	1.34	1.24	1.15	1.03	0.80	-0.54
	[54.4]	[71.6]	[86.7]	[97.4]	[74.8]	[-17.8]
SMB	0.75	0.35	0.10	-0.08	-0.18	-0.93
	[20.8]	[13.8]	[4.99]	[-5.28]	[-11.3]	[-20.8]
HML	-0.04	0.08	0.13	0.11	0.08	0.13
	[-0.94]	[2.56]	[5.30]	[5.82]	[4.17]	[2.22]
RMW	-0.66	-0.04	0.21	0.28	0.26	0.93
	[-13.6]	[-1.04]	[7.86]	[13.6]	[12.5]	[15.4]
CMA	-0.53	-0.29	-0.06	0.12	0.21	0.74
	[-7.61]	[-5.89]	[-1.47]	[4.11]	[6.84]	[8.57]
Adj.-R^2 (%)	90.1	91.6	92.9	93.6	89.1	76.5

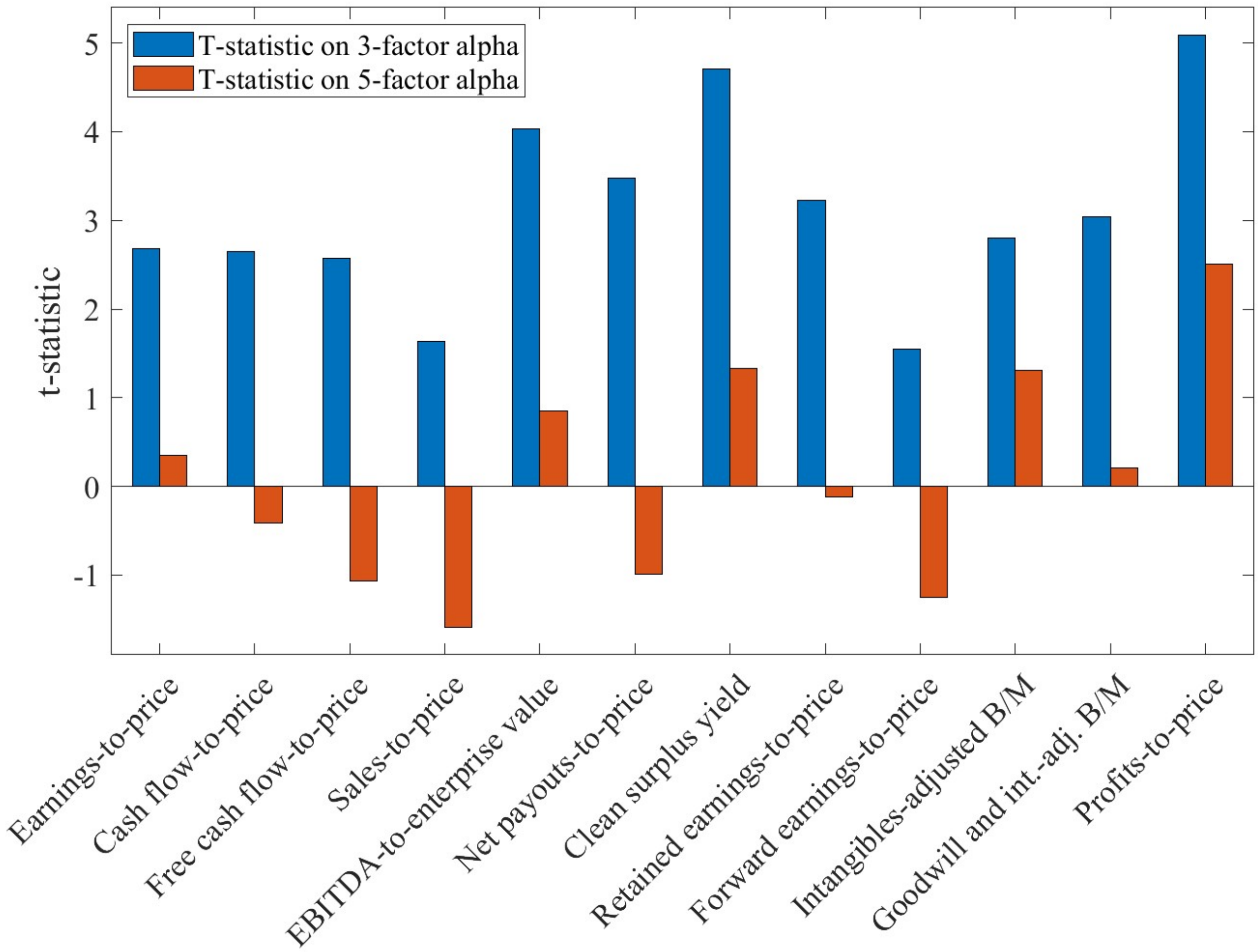

Fig. C2. Information ratios on alternative value metrics. This figure shows the three- and five factor information rations on value factors constructed using alternative relative-price measures to book-to-market. That is, it shows the t-statistics on the alphas from regressions of the form

$$\begin{aligned} \text{VMG} &= \alpha + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \epsilon, \\ \text{VMG} &= \alpha + \beta_{\text{MKT}}\text{MKT} + \beta_{\text{SMB}}\text{SMB} + \beta_{\text{HML}}\text{HML} + \beta_{\text{RMW}}\text{RMW} + \beta_{\text{CMA}}\text{CMA} + \epsilon. \end{aligned}$$

The sample covers July 1963 to December 2023 except for the forward earnings-to-price strategy, which starts on July 1976 due to limitations in the analyst forecast data.

C.3. Value results employing RMW

Figure C2 and Table C4 replicate Figure 5 and Table 7, which analyze the performance of alternative value metrics, using RMW instead of PROF. The standard five-factor model prices all the alternative value strategies except for profits-to-price, which is based on our measure of profitability that has more power predicting cross-sectional difference in avereage returns than the operating profitability underlying RMW.

Table C4. Spanning tests of value strategies.
This table shows results from time-series regressions employing the returns to alternative value strategies. All strategies are a 50/50 mix of large- and small-cap value-minus-growth strategies. The size breakpoint is the NYSE median while relative price breakpoints are the 30th and 70th NYSE percentiles. Portfolios are rebalanced at the end of June and returns are value weighted. Appendix A.8 provides the full details of relative price measures' construction. The sample covers July 1963 to December 2023, except for the forward earnings-to-price strategy, which starts in July 1976 due to availability of data on analysts' forecasts.

Value strategy	r^e	α_{FF3}	α	MKT	SMB	HML	RMW	CMA	Adj.-R^2(%)
Earnings-to-price	0.29	0.19	0.02	-0.11	-0.09	0.79	0.54	-0.12	77.9
	[2.48]	[2.68]	[0.35]	[-7.60]	[-4.24]	[30.3]	[19.7]	[-2.97]	
Cash flow-to-price	0.36	0.18	-0.03	-0.02	-0.01	0.71	0.49	0.18	75.0
	[3.05]	[2.65]	[-0.42]	[-1.21]	[-0.56]	[26.0]	[16.9]	[4.33]	
Free cash flow-to-price	0.21	0.19	-0.06	-0.05	-0.14	0.39	0.59	0.19	68.3
	[2.07]	[2.57]	[-1.07]	[-3.46]	[-6.88]	[14.7]	[20.8]	[4.70]	
Sales-to-price	0.38	0.11	-0.10	0.11	0.26	0.54	0.46	0.25	67.7
	[3.76]	[1.64]	[-1.59]	[7.91]	[12.2]	[20.1]	[16.1]	[6.20]	
EBITDA-to-enterprise value	0.38	0.25	0.04	-0.04	0.03	0.61	0.52	0.11	78.5
	[3.79]	[4.03]	[0.85]	[-3.16]	[1.49]	[27.7]	[22.7]	[3.36]	
Net payouts-to-price	0.24	0.23	-0.05	-0.14	-0.25	0.50	0.53	0.45	84.1
	[1.87]	[3.48]	[-0.99]	[-10.9]	[-13.5]	[21.4]	[21.5]	[12.5]	
Clean surplus yield	0.33	0.30	0.07	-0.11	-0.12	0.35	0.42	0.37	78.1
	[3.10]	[4.70]	[1.33]	[-8.65]	[-6.43]	[15.5]	[17.3]	[10.5]	
Retained earnings-to-price	0.37	0.20	-0.01	-0.04	-0.04	0.72	0.48	0.21	80.8
	[3.12]	[3.23]	[-0.12]	[-2.88]	[-2.29]	[30.1]	[18.8]	[5.66]	
Forward earnings-to-price	0.21	0.13	-0.09	-0.06	-0.03	0.77	0.59	-0.16	75.9
	[1.51]	[1.55]	[-1.25]	[-3.68]	[-1.05]	[25.0]	[17.8]	[-3.28]	
Intangibles-adjusted B/M	0.43	0.16	0.07	0.09	0.27	0.47	0.08	0.30	66.0
	[4.67]	[2.81]	[1.31]	[7.04]	[14.0]	[18.9]	[3.21]	[7.89]	
Goodwill and int.-adj. B/M	0.44	0.20	0.01	0.09	0.28	0.43	0.36	0.32	63.5
	[4.69]	[3.04]	[0.20]	[6.35]	[13.8]	[16.4]	[12.9]	[7.92]	
Profits-to-price	0.47	0.28	0.12	-0.00	0.06	0.69	0.38	0.12	79.8
	[4.67]	[5.09]	[2.51]	[-0.17]	[3.33]	[32.3]	[17.1]	[3.73]	

D. Internet Appendix

D.1. Cross-section regressions of returns on profitability measures: Sub-periods

Table D1. Cross-section regressions of returns on profitability measures: Sub-periods. This table shows monthly Fama and Macbeth (1973) cross-section regressions to predict returns by sub-periods. We use weighted least squares (WLS) with market capitalization as weight. Operating profits are defined following Fama and French (2015) as OP = REVT − COGS − XSGA − XINT, where missing expenses are set to zero provided one is non-missing and where XSGA includes R&D expenses (XRD). $\text{OP}_{\text{R\&D}}$ = OP + XRD is operating profits before R&D. COP = OP − ACC is cash-based operating profits, where ACC is accruals, defined using the balance sheet approach of Ball et al. (2016). $\text{COP}_{\text{R\&D}}$ = COP + XRD is cash-based operating profits before R&D. XRD is set to zero when missing. All profit measures are scaled by book equity (BE) plus minority interest (MIB). Controls are asset growth ($\ln(\text{AT}/\text{AT}_{-1})$), book-to-market (ln(BE/ME), where ME is as of latest December-end), size (ln(ME)), and past performance over the prior 12-to-2 months ($r_{12,2}$) one month ($r_{1,0}$). Independent variables are trimmed at the 1% and 99% levels each month.

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: July 1963 through December 1999							
OP	1.18				-1.06		
	[5.78]				[-1.38]		
$\text{OP}_{\text{R\&D}}$		1.42			2.35	1.27	1.10
		[7.21]			[3.19]	[5.66]	[4.86]
COP			0.50			0.22	
			[4.84]			[1.77]	
$\text{COP}_{\text{R\&D}}$				0.63			0.37
				[6.31]			[3.09]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.-R^2 (%)	7.6	7.7	7.6	7.5	8.5	8.0	7.9
Avg. N	3,215	3,215	3,212	3,212	3,207	3,186	3186
Panel B: January 2000 through December 2023							
OP	0.41				-0.92		
	[1.94]				[-1.64]		
$\text{OP}_{\text{R\&D}}$		0.61			1.45	0.80	0.61
		[3.43]			[2.97]	[4.22]	[2.97]
COP			0.11			-0.24	
			[1.04]			[-2.05]	
$\text{COP}_{\text{R\&D}}$				0.23			-0.02
				[2.42]			[-0.17]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj.-R^2 (%)	8.9	8.7	8.6	8.5	9.6	9.1	8.9
Avg. N	3,608	3,608	3,606	3,606	3,597	3,587	3,587

D.2. Predicting returns with different profitability measures: international evidence

Table D2. Cross-section regressions of returns on profitability: Developed ex-US. This table shows results from monthly Fama and Macbeth (1973) cross-section regressions to predict returns in developed ex-US markets. We use WLS with market capitalization as weight. Independent variables are transformed to country-specific percentiles of cumulative total market capitalization. Operating profit, OP, is revenue minus costs of goods sold minus selling, general, and administrative expenses (including R&D expenses) minus interest expense. $\text{OP}_{\text{R\&D}} = \text{OP} + \text{XRD}$ is operating profits before R&D (XRD). $\text{COP} = \text{OP} - \text{ACC}$ is cash-based operating profits, where ACC is accruals, defined as the change in accounts receivable plus the change in inventory minus the change in accounts payable, where changes are year-over-year and missing changes are set to zero. $\text{COP}_{\text{R\&D}} = \text{COP} + \text{XRD}$ is cash-based operating profits before R&D. XRD is set to zero when missing. All profit measures are scaled by book equity (BE) plus minority interest (MIB). Market equity (ME) is as of latest December end in BE/ME. Data are from Bloomberg. The sample covers July 1990 through December 2023.

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OP	0.60				-0.20		
	[5.60]				[-0.80]		
$\text{OP}_{\text{R\&D}}$		0.67			0.85	0.65	0.59
		[6.21]			[3.39]	[5.03]	[4.52]
COP			0.49			0.03	
			[5.36]			[0.31]	
$\text{COP}_{\text{R\&D}}$				0.57			0.10
				[6.05]			[1.07]
$\ln(\text{AT}/\text{AT}_{-1})$	-0.16	-0.15	-0.08	-0.07	-0.14	-0.14	-0.13
	[-1.57]	[-1.47]	[-0.77]	[-0.68]	[-1.38]	[-1.37]	[-1.31]
ln(BE/ME)	0.65	0.68	0.57	0.61	0.66	0.68	0.68
	[3.86]	[4.11]	[3.54]	[3.78]	[3.96]	[4.08]	[4.11]
ln(ME)	-0.08	-0.11	-0.07	-0.10	-0.11	-0.11	-0.12
	[-0.56]	[-0.81]	[-0.49]	[-0.73]	[-0.78]	[-0.82]	[-0.86]
$r_{12,2}$	0.56	0.57	0.56	0.56	0.56	0.56	0.57
	[2.49]	[2.48]	[2.45]	[2.45]	[2.49]	[2.48]	[2.48]
$r_{1,0}$	-0.63	-0.62	-0.61	-0.61	-0.63	-0.62	-0.62
	[-3.80]	[-3.76]	[-3.72]	[-3.70]	[-3.83]	[-3.78]	[-3.77]
Adj-R^2 (%)	6.0	6.0	5.9	5.9	6.3	6.2	6.1
Avg. N	10,929	10,929	10,929	10,929	10,929	10,929	10,929

Table D3. Cross-section regressions of returns on profitability: Emerging markets. This table shows results from monthly Fama and Macbeth (1973) cross-section regressions to predict returns in emerging markets. We use WLS with free-float market capitalization as weight. Independent variables are transformed to country-specific percentiles of cumulative free-float market capitalization. Operating profits, OP, are revenue minus costs of goods sold minus selling, general, and administrative expenses (including R&D expenses) minus interest expense. $\text{OP}_{\text{R\&D}} = \text{OP} + \text{XRD}$ is operating profits unpunished for R&D (XRD). $\text{COP} = \text{OP} - \text{ACC}$ is cash-based operating profits, where ACC is accruals, defined as the change in accounts receivable plus the change in inventory minus the change in accounts payable, where changes are year-over-year and missing changes are set to zero. $\text{COP}_{\text{R\&D}} = \text{COP} + \text{XRD}$ is cash-based operating profits unpunished for R&D. XRD is set to zero when missing. All profit measures are scaled by book equity (BE) plus minority interest (MIB). Market equity (ME) is as of latest December-end in BE/ME. Data are from Bloomberg. The sample covers January 1994 through December 2023.

Independent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
OP	0.72				-1.36		
	[4.50]				[-1.65]		
$\text{OP}_{\text{R\&D}}$		0.79			2.12	0.81	0.68
		[4.88]			[2.51]	[4.20]	[3.31]
COP			0.55			-0.03	
			[3.58]			[-0.18]	
$\text{COP}_{\text{R\&D}}$				0.63			0.12
				[4.04]			[0.63]
$\log(\text{AT}/\text{AT}_{-1})$	-0.25	-0.24	-0.18	-0.17	-0.24	-0.25	-0.23
	[-1.77]	[-1.75]	[-1.25]	[-1.20]	[-1.74]	[-1.74]	[-1.59]
log(BE/ME)	0.81	0.85	0.71	0.75	0.83	0.84	0.85
	[4.58]	[4.83]	[4.11]	[4.35]	[4.74]	[4.82]	[4.83]
log(ME)	-0.08	-0.10	-0.04	-0.07	-0.09	-0.10	-0.11
	[-0.46]	[-0.55]	[-0.23]	[-0.36]	[-0.49]	[-0.53]	[-0.59]
$r_{12,2}$	0.94	0.94	0.94	0.94	0.91	0.95	0.94
	[4.19]	[4.19]	[4.20]	[4.18]	[4.09]	[4.23]	[4.19]
$r_{1,0}$	-0.22	-0.22	-0.22	-0.22	-0.25	-0.23	-0.23
	[-1.09]	[-1.09]	[-1.11]	[-1.13]	[-1.24]	[-1.13]	[-1.13]
Adj.-R^2 (%)	4.2	4.2	4.2	4.2	4.5	4.4	4.4
Avg. N	8,087	8,087	8,087	8,087	8,087	8,087	8,087

D.3. Predicting profitability growth: international evidence

Table D4. Cross-section regressions of profitability growth on profitability: Developed ex-US. This table shows annual Fama and Macbeth (1973) cross-section regressions to predict three- or 10-year growth in profitability using current profitability. We use WLS with total market capitalization as weight. Dependent and independent variables are transformed to country-specific percentiles of cumulative total market capitalization. Operating profits, OP, are revenue minus costs of goods sold minus selling, general, and administrative expenses (including R&D expenses) minus interest expense. $OP_{R\&D} = OP + XRD$ is operating profits unpunished for R&D. COP = OP − ACC is cash-based operating profits, where ACC is accruals. $COP_{R\&D} = COP + XRD$ is cash-based operating profits unpunished for R&D. XRD is set to zero when missing. All profit measures are scaled by current book equity (BE) plus minority interest (MIB). Data are from Bloomberg. The sample covers fiscal years ending between 1989 and 2023.

Independent variable	$\frac{OP_{t+\tau}-OP_t}{BE_t+MIB_t}$ (1)	(2)	$\frac{OP_{R\&D,t+\tau}-OP_{R\&D,t}}{BE_t+MIB_t}$ (3)	(4)	$\frac{COP_{R\&D,t+\tau}-COP_{R\&D,t}}{BE_t+MIB_t}$ (5)	(6)
Panel A: Predicting 3-year growth ($\tau = 3$)						
OP	0.01	-0.22				
	[0.45]	[-3.68]				
$OP_{R\&D}$			0.07	-0.05		
			[2.47]	[-1.51]		
$COP_{R\&D}$					-0.11	-0.23
					[-5.12]	[-9.88]
$\log(AT/AT_{-1})$		0.00		0.02		0.12
		[0.39]		[1.84]		[8.52]
log(BE/ME)		-0.11		-0.17		-0.20
		[-6.04]		[-10.06]		[-12.07]
log(ME)		0.27		0.09		0.12
		[6.60]		[5.76]		[8.33]
$r_{12,1}$		0.05		0.06		0.02
		[3.37]		[3.77]		[1.21]
Adj.-R^2 (%)	1.10	6.92	1.87	7.00	2.38	11.16
Avg. N	7,747	7,248	7,747	7,248	7,746	7,247
Panel B: Predicting 10-year growth ($\tau = 10$)						
OP	0.01	-0.22				
	[0.16]	[-2.75]				
$OP_{R\&D}$			0.04	-0.08		
			[0.69]	[-1.81]		
$COP_{R\&D}$					-0.10	-0.23
					[-2.48]	[-7.76]
$\log(AT/AT_{-1})$		0.00		0.02		0.08
		[0.13]		[0.93]		[4.92]
log(BE/ME)		-0.10		-0.17		-0.21
		[-2.45]		[-7.82]		[-10.64]
log(ME)		0.26		0.09		0.12
		[8.38]		[1.55]		[2.65]
$r_{12,1}$		0.02		0.03		0.03
		[2.36]		[3.73]		[4.77]
Adj.-R^2 (%)	2.44	7.64	2.40	8.44	2.44	11.32
Avg. N	5,363	5,023	5,363	5,023	5,363	5,023

Table D5. Cross-section regressions of profitability growth on profitability: Emerging markets. This table shows annual Fama and Macbeth (1973) cross-section regressions to predict three- or 10-year growth in profitability using current profitability. We use WLS with free-float market capitalization as weight. Dependent and independent variables are transformed to country-specific percentiles of cumulative free-float market capitalization. Operating profits, OP, are operating income plus depreciation and amortization minus interest expense. $OP_{R\&D} = OP + XRD$ is operating profits before R&D. $COP = OP - ACC$ is cash-based operating profits, where ACC is accruals. $COP_{R\&D} = COP + XRD$ is cash-based operating profits before R&D. XRD is set to zero when missing. All profit measures are scaled by the sum of book equity (BE) and minority interest (MIB). Data are from Bloomberg. The sample covers fiscal years ending between 1994 and 2023.

	$\frac{OP_{t+\tau}-OP_t}{BE_t+MIB_t}$		$\frac{OP_{R\&D,t+\tau}-OP_{R\&D,t}}{BE_t+MIB_t}$		$\frac{COP_{R\&D,t+\tau}-COP_{R\&D,t}}{BE_t+MIB_t}$	
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Predicting 3-year growth ($\tau = 3$)						
OP	0.14	-0.08				
	[4.38]	[-1.41]				
$OP_{R\&D}$			0.11	-0.04		
			[2.50]	[-0.87]		
$COP_{R\&D}$					-0.02	-0.18
					[-0.45]	[-4.38]
$\log(AT/AT_{-1})$		0.02		0.03		0.10
		[1.27]		[1.75]		[6.81]
log(BE/ME)		-0.09		-0.12		-0.14
		[-3.13]		[-8.97]		[-10.23]
log(ME)		0.22		0.17		0.20
		[5.09]		[7.26]		[7.32]
$r_{12,1}$		0.05		0.06		0.06
		[3.36]		[3.76]		[4.68]
Adj.-R^2 (%)	3.4	9.3	3.8	10.6	2.6	12.8
Avg. N	6,649	6,160	6,649	6,160	6,642	6,155
Panel B: Predicting 10-year growth ($\tau = 10$)						
OP	0.17	-0.10				
	[5.46]	[-6.45]				
$OP_{R\&D}$			0.14	-0.03		
			[3.27]	[-2.09]		
$COP_{R\&D}$					0.06	-0.10
					[1.40]	[-4.86]
$\log(AT/AT_{-1})$		0.05		0.07		0.11
		[3.44]		[3.65]		[8.33]
log(BE/ME)		-0.11		-0.16		-0.15
		[-4.26]		[-6.53]		[-8.57]
log(ME)		0.27		0.19		0.20
		[13.77]		[9.99]		[10.14]
$r_{12,1}$		-0.02		-0.02		0.00
		[-2.25]		[-1.61]		[-0.21]
Adj.-R^2 (%)	4.0	9.9	3.5	10.9	2.3	11.7
Avg. N	4,766	4,384	4,766	4,384	4,762	4,381

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