The Fundamental-to-Market Ratio and the Value Premium Decline

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Abstract

Recent evidence indicates the value premium declined over time. In this paper, we argue this decline happened because book equity, BE, is no longer a good proxy for fundamental equity, FE, defined as the equity value originating from expected cash flows (i.e., no discount rate differences across firms). Specifically, we estimate FE for public US firms (from 1973 to 2018) and find that the premium associated with the fundamental-to-market ratio, FE/ME, has been large and stable while the cross-sectional correlation between FE/ME and BE/ME decreased over time, inducing an apparent decline in the value premium. Our results echo recent findings in the corporate finance literature.

JEL Classification: C58; E44; G10; G11; G12.

Keywords: Value Premium; Book-to-Market; Valuation Ratios; The Cross Section of Expected Returns.

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Introduction

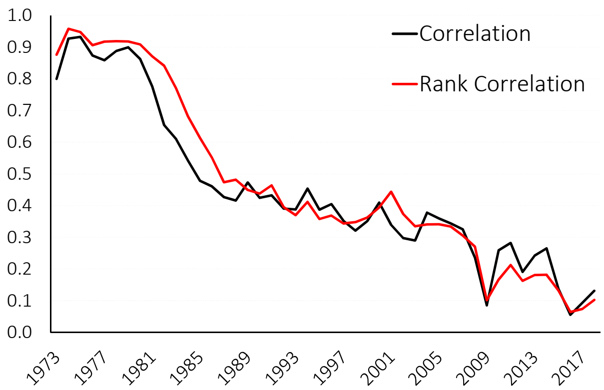
The value premium is one of the oldest and most studied cross-sectional asset pricing phenomena. It refers to the stylized fact that high book-to-market firms earn subsequent higher average returns than low book-to-market firms (e.g., Fama and French (1992)). For academics, it represents a fundamental pattern in the cross-section of stock returns that helps us better understand what drives investors' demand. For practitioners, it is a simple way to implement the value investing philosophy (Graham (1949) and Graham and Dodd (1934)). However, recent evidence indicates the value premium has been relatively low (or even non-existent) over the last decades (e.g., Fama and French (2020)).

In this paper, we argue that this apparent decline in the value premium happened because book equity, BE, is no longer a good proxy for fundamental equity, FE, defined as the equity value originating purely from expected cash flows (i.e., with no discount rate differences across firms). In fact, we find that while the value premium as traditionally defined using the book-to-market ratio, BE/ME, has declined, a strong and stable value premium re-emerges when we sort stocks by their fundamental-to-market ratio, FE/ME.

Our key point is straightforward. BE is simply one firm fundamental that can be used to scale prices and recover expected stock returns. It is successful to the extent that it properly captures firms' ability to generate cash flows going forward. While BE was a good measure of cash flow generation in the 70s and early 80s, this is no longer true. For instance, intangibles play a larger role in productive assets today than they used to (e.g., Peters and Taylor (2017)). Consequently we need a new fundamental to scale prices. Since any static firm fundamental is unlikely to consistently capture cash flow generation, we rely on the firm's FE, which we define as the present value of future cash flows under a common discount rate across firms.

Empirically, we estimate (annually from 1973 to 2018) expected payouts at the firm level using a vector autoregressive system and obtain (an out-of-sample measure of) FE for the cross-section of US firms. We then calculate FE/ME and compare it to BE/ME. As Figure 1(a) shows, we find that the two ratios were strongly correlated in the cross-section during

(a) **Cross-Sectional Cor$\left(\frac{BE}{ME}, \frac{FE}{ME}\right)$**



(b) **H-L Spread: $\frac{BE}{ME}$ and $\frac{FE}{ME}$**

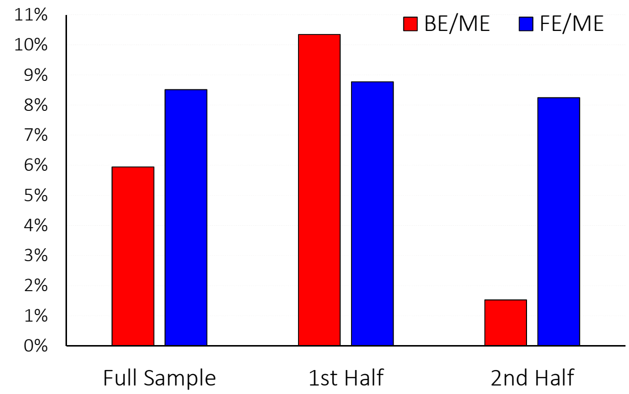


Figure 1
Main Results: BE/ME vs FE/ME

Figure (a) plots the annual cross-sectional correlation between $bm = log(BE/ME)$ and $fm = log(FE/ME)$ using both linear correlation (i.e., Pearson correlation) and rank correlation (i.e, Spearman correlation). Figure (b) displays the average return of the high-low spread portfolio based on decile sortings on bm and fm over our full sample (1973-2018) as well as over the first (1973-1995) and second (1996-2018) halves of our sample period, where years refer to the portfolio formation year. See Section 2 for further empirical details.

the 70s and early 80s, but that this correlation declined over time and has become quite weak during the 21s century. Consequently, as Figure 1(b) shows, the premium associated with BE/ME declined from the first to the second half of our sample period while the premium associated with FE/ME remained relatively stable.

While Figure 1 captures the essence of this paper, we provide more detailed evidence on the patterns described by exploring the identity $BE/ME = FE/ME \times BE/FE$, which implies $bm = fm + bf$, linking the (log) book-to-market ratio, bm, to the (log) fundamental-to-market ratio, fm, and the (log) book-to-fundamental ratio, bf.

We start by presenting two motivating facts. First, Fama-MacBeth regressions of stock returns on fm and bf indicate expected returns are linked to bm only through fm. Specifically, these regressions show that, statistically, fm is related to future returns while bf is not. Second, the strength of the link between bm and fm has declined over time, with their rank correlation dropping from 0.67 in the first half of our sample (henceforth, the "early sample") to 0.26 in the second half (henceforth, the "late sample").

These two basic facts suggest that the value premium is mainly driven by a premium associated with fm and raise the possibility that the apparently low value premium over the more recent decades is at least partially driven by a weaker correlation between bm and fm. To further explore these issues, we form decile portfolios sorted on bm, fm, and bf. The dynamics of these portfolios yield two key results.

First, the premium associated with fm is stronger, more persistent, and more stable than the premium associated with bm. In terms of strength and persistence, the average return on the (value-weighted) high-low fm is 8.5% per year and remains strong at 4.1% in the fifth year after the portfolio formation. In contrast, the analogous numbers for the bm portfolios are 5.9% and 0.8%. In terms of stability, the fm premium is relatively stable over time (8.8% in the early sample vs 8.2% in the late sample) and across size groups (8.5% in the overall sample and 6.9% in a sample focused on the largest firms). In contrast, the bm premium drops substantially over time (10.3% in the early sample vs 1.5% in the late sample) and as we move to larger firms (5.9% in the overall sample and 1.6% in a sample focused on the largest firms).

Second, the premium associated with bm disappears after we control for the correlation between bm and fm. Specifically, regressions of portfolio returns on portfolio deciles show that high bm portfolios no longer outperform low bm portfolios once we control for the average fm rank of the stocks in these portfolios. Moreover, we see little change in the premium associated with bm from the early to the late sample once we control for fm. That is, after controlling for fm, the premium associated with bm is statistically zero in both halves of our sample period. These results are equally valid when focusing on small or big firms as defined in the Fama and French (1993)'s value factor construction. Moreover, we also find that the bm and fm premia (as well as the bm premium decline) are mostly reflective of a within industry effect.

Given our FE construction, the mismatch between BE and FE is a consequence of BE no longer being a good proxy for cash flow generation. As such, the different behavior of the fm and bm value premia is a result of changes in the corporate environment over the years. To further understand this issue, we explore one particular aspect of the corporate environment that has changed drastically. Namely, we show that part (but not all) of the deterioration of BE as a measure of future cash flows is due to its inability to reflect intangible capital, which has grown in importance over the years. We start by adjusting BE for intangible capital as estimated in Peters and Taylor (2017) (and call the adjusted measure BE^*). Then, we show that the deviations of BE from BE^* explain basically none of the cross-sectional variability in the deviations of BE from FE in the 1970s, but about 30% of this variability towards the end of our sample. Finally, we show that the BE^*/ME value premium has declined less than the BE/ME value premium over time, but that it remains insignificant over both halves of our sample period after controlling for FE/ME.

In summary, we develop a novel firm-level measure of FE and use it to demonstrate that the value premium largely reflects a premium associated with the fundamental-to-market ratio since BE is a proxy for FE. Moreover, we show that the ability of BE to proxy for FE has deteriorated over time, which explains why the value premium appears to have declined over the years when measured based on BE/ME. Finally, we show that intangibles explain about 30% of the inability of BE to reflect FE over the recent years, and thus part (but not all) of the BE/ME value premium decline is due to intangibles.

Our results largely reflect the fact that BE no longer captures firms' ability to generate cash flows going forward. Given this cash flow connection, our paper is directly related to a recent literature in corporate finance that explores how corporate activity has dramatically changed over the years (see Kahle and Stulz (2017) for an overview). Some of the most important changes are the decline in the number of listed firms (Doidge, Karolyi, and Stulz (2017)), the aging of corporations and its impact on innovation activity (Hathaway and Litan (2014) and Loderer, Stulz, and Waelchli (2017)), the concentration of public firms and its effect on competition (Barkai (2020), DeAngelo, DeAngelo, and Skinner (2004), and Grullon, Larkin, and Michaely (2020)), the increase in R&D investment and its connection to firm's asset composition and capital structure (Bates, Kahle, and Stulz (2009), Corrado, Hulten, and Sichel (2009), Eisfeldt and Papanikolaou (2014), and Falato et al. (2020)), and the changing nature of Tobin's q (Lee, Shin, and Stulz (2018) and Peters and Taylor (2017)). Our work is an important contribution to this literature as it outlines a significant asset pricing implication of the changing corporate environment. Specifically, if corporate activity had been stable over the years, then book equity would remain a good proxy for fundamental equity and we would not see an apparent decline in the value premium. As such, while we focus on the relation between the book-to-market and fundamental-to-market ratios, the ultimate driver of this dynamic relation is the change in how firms are expected to produce cash flows, which indicates our results echo the recent findings in the corporate finance literature aforementioned.

This paper is also closely related to a few recent papers that document a decline in the value premium. In particular, Fama and French (2020) show that the value premium declined from the first to the second half of the 1963-2019 sample period, but that such decline is only statistically significant under the assumption that the function linking book-to-market to future returns is stable over the entire period. Amenc, Goltz, and Luyten (2020) and Park (2020) show that part of this value premium decline is related to the fact that BE does not reflect intangibles. Arnott et al. (2020) explore the influence of several factors on the weak value performance since 2007 and argue that a large component of the weak performance can be attributed to intangibles and also to an increase in the value spread between value and growth companies, suggesting that the conditional value premium is unusually high as of 2020. Binfaré, Brown, and Polk (2020) also explore different explanations for the decline in the value premium, with special emphasis on sample composition and the drop in the number of listed value and growth companies since 1997. We contribute to this new body of literature by showing that the underlying value premium book-to-market captured in the past has not declined. Instead, the ability of book-to-market to capture such a premium has deteriorated as BE is no longer a good proxy for FE. Our approach provides a substantial departure from the literature as we do not treat book-to-market as the underlying source of the value premium it delivers. Instead, we treat it as an imperfect measure of the fundamental-to-market ratio, which explains why it no longer yields the value premium it used to.

Our FE/ME measure is also connected to a separate strand of literature that provides alternative ways to measure valuation signals in an attempt to improve return predictability. In the context of aggregate return predictability, Kelly and Pruitt (2013) show that a single factor extracted from the cross-section of BE/ME ratios through a latent factor system performs much better in predicting aggregate returns than traditional valuation ratios. In terms of cross-sectional return predictability, Bartram and Grinblatt (2018) and Golubov and Konstantinidi (2019) create a measure of value, V, as the fitted value of a regression of ME on several firm fundamentals and show that V/ME, which they interpret as a mispricing measure, is a strong return predictor beyond BE/ME. Similarly, Souza (2020) and Wang (2020) show that valuation ratios measured from expected profitability and cash-based profitability, respectively, improve upon the BE/ME value premium. Our FE/ME measure is substantially different from all these alternative measures in that we build fundamental equity, FE, from a formally defined valuation equation in which we shut down cross-sectional variability in discount rates in order to capture cash flow generation. Moreover, our focus is not on designing a value measure that better predicts returns, but rather to demonstrate that BE/ME no longer captures the value premium because BE is no longer a good proxy for FE.

Finally, our work also has important implications for the literature attempting to explain the value premium through different economic channels. Specifically, the previous literature has provided explanations for the value premium based on behavioral biases (e.g., Lakonishok, Shleifer, and Vishny (1994)), reduced-form factor models (e.g., Fama and French (1996) and Hou, Xue, and Zhang (2015)), conditional asset pricing models (e.g., Lettau and Ludvigson (2001)), production and investment frictions (e.g, Zhang (2005)), cash flow duration (Gonçalves (2020) and Lettau and Wachter (2007)), among others. These explanations have the unifying feature that book-to-market proxies for some hard to measure characteristic of firms (e.g., the conditional consumption CAPM β in the framework of Lettau and Ludvigson (2001)). Our results impose a sharp restriction on these explanations. Specifically, the correlation between book-to-market and the relevant characteristic must have declined over time while the correlation between fundamental-to-market and the same characteristic must be relatively stable.

The rest of the paper is organized as follows. Section 1 defines fundamental equity and explains how it can be estimated. Section 2 details our empirical design. Section 3 studies the relation between bm, fm, and bf at the firm level while Section 4 explores the apparent value premium decline through portfolio sorts and Section 5 measures the impact of size, industry, intangibles on our results. Finally, Section 6 concludes. The Internet Appendix contains technical derivations.

1 Firms' Fundamental Equity

In this section, we define the fundamental equity of a firm (Subsection 1.1) and explain how it can be estimated (Subsection 1.2).

1.1 Defining a Firm's Fundamental Equity

Let $ME_{j,t}$ be the market equity of a firm and $\{PO_{j,t}^{(h)}\}_{h=1}^{\infty}$ represent the stream of equity payouts (Dividends + Repurchases - Issuances) the firm will deliver going forward. Then, the valuation equation gives (under no arbitrage):

$$\begin{aligned} ME_{j,t} &= \sum_{h=1}^{\infty} \mathbb{E}_t \left[SDF_{t,t+h} \cdot PO_{j,t+h} \right] \\ &= \sum_{h=1}^{\infty} \mathbb{E}_t \left[PO_{j,t+h} \right] \cdot e^{-h \cdot dr_{j,t}^{(h)}} \\ &= BE_{j,t} \cdot \sum_{h=1}^{\infty} \mathbb{E}_t \left[PO_{j,t+h} / BE_{j,t} \right] \cdot e^{-h \cdot dr_{j,t}^{(h)}} \end{aligned} \tag{1}$$

where $SDF_{t,t+h}$ is the growth in the Stochastic Discount Factor from t to $t+h$, BE is the firm's book-equity, and $dr_{j,t}^{(h)} = (1/h) \cdot log \left(\mathbb{E}[R_{j,t \to t+h}^{(h)}] \right)$ is the cash-flow discount rate with $R_{j,t \to t+h}^{(h)}$ representing the hold-to-maturity return for the claim to payout $PO_{j,t+h}$.

We define the fundamental equity of a firm, $FE_{j,t}$, as the portion of ME originating purely from expected cash flows (i.e., replacing $dr_{j,t}^{(h)}$ with a constant dr):

$$FE_{j,t} = BE_{j,t} \cdot \sum_{h=1}^{\infty} \mathbb{E}_t \left[PO_{j,t+h}/BE_{j,t}\right] \cdot e^{-h \cdot dr} \tag{2}$$

The entire challenge in obtaining $FE_{j,t}$ is in estimating $\mathbb{E}_t[PO_{j,t+h}/BE_{j,t}]$, a task we detail in the next subsection.

1.2 Estimating Firms' Fundamental Equity

Let clean surplus earnings be $CSE_{j,t} = PO_{j,t} + \Delta BE_{j,t}$, with Δ representing the difference operator. Then, substituting the CSE definition into $\mathbb{E}_t[PO_{j,t+h}]$ gives:

$$\begin{aligned} \frac{\mathbb{E}_t\left[PO_{j,t+h}\right]}{BE_{j,t}} &= \mathbb{E}_t\left[\left(1 + \frac{CSE_{j,t+h}}{BE_{j,t+h-1}} - \frac{BE_{j,t+h}}{BE_{j,t+h-1}}\right) \cdot \prod_{\tau=1}^{h-1} \frac{BE_{j,t+\tau}}{BE_{j,t+\tau-1}}\right] \\ &= \mathbb{E}_t\left[\left(e^{CSprof_{j,t+h} - BEg_{j,t+h}} - 1\right) \cdot e^{\sum_{\tau=1}^{h} BEg_{j,t+\tau}}\right] \end{aligned} \tag{3}$$

where the second equality follows from the definitions $CSprof_{j,t} = ln\left(1 + CSE_{j,t}/BE_{j,t-1}\right)$ and $BEg_{j,t} = ln(BE_{j,t}/BE_{j,t-1})$.

To estimate $\mathbb{E}_t[PO_{j,t+h}/BE_{j,t}]$ at the firm-level, we follow Campbell, Polk, and Vuolteenaho (2009) and Vuolteenaho (2002) and assume $s_{j,t}$ is a vector of firm-level characteristics (including a constant, $CSprof_{j,t}$, and $BEg_{j,t}$) that follows a Vector Autoregressive (VAR) system of order one:

$$s_{j,t} = \Gamma s_{j,t-1} + u_{j,t} \tag{4}$$

where $u_{j,t} \overset{i.i.d}{\sim} \mathcal{N}\left(0, \Sigma\right)$ with arbitrary cross-sectional covariance structure.

Using the VAR system in Equation 4, we have (see Internet Appendix A for the derivation):

$$\frac{\mathbb{E}_t\left[PO_{j,t+h}\right]}{BE_{j,t}} = \left[e^{(\mathbf{1}_{CSprof} - \mathbf{1}_{BEg})'\Gamma^h s_{j,t} + v_1(h)} - 1\right] \cdot e^{\mathbf{1}'_{BEg}\left(\sum_{\tau=1}^{h} \Gamma^\tau\right) \cdot s_{j,t} + h \cdot v_2(h)} \tag{5}$$

where $\mathbf{1}_x$ is a selector vector such that $\mathbf{1}'_x s_{j,t} = x_t$ and $v_k(h)$ are adjustments for Jensen's inequality that depend on Γ, Σ, and h, but not on the state vector.

Consequently, the fundamental equity of a firm is given by:[1]

$$FE_{j,t} = BE_{j,t} \cdot \sum_{h=1}^{\infty} \left[e^{(\mathbf{1}_{CSprof} - \mathbf{1}_{BEg})' \Gamma^h s_{j,t} + v_1(h)} - 1 \right] \cdot e^{\mathbf{1}'_{BEg} (\sum_{\tau=1}^{h} \Gamma^\tau) \cdot s_{j,t} + h \cdot v_2(h) - h \cdot dr} \tag{6}$$

We set $dr = \overline{dr}$ for all firms and years, with $\overline{dr}$ defined as the solution to the non-linear equation:

$$\overline{MB} = \sum_{h=1}^{\infty} \left[e^{(\mathbf{1}_{CSprof} - \mathbf{1}_{BEg})' \Gamma^h \overline{s} + v_1(h)} - 1 \right] \cdot e^{\mathbf{1}'_{BEg} (\sum_{\tau=1}^{h} \Gamma^\tau) \cdot \overline{s} + h \cdot v_2(h) - h \cdot \overline{dr}} \tag{7}$$

where $\overline{MB}$ and $\overline{s}$ are the unconditional averages implied by Γ, which is estimated on an expanding window such that our $FE_{j,t}$ only requires information that is publicly available by time t (details are provided in the next section).[2]

2 The Empirical Design

This section provides the empirical details associated with our analysis. Subsection 2.1 explains the main empirical tests we rely on, Subsection 2.2 details the sample construction and measurement of the variables needed for the estimation, Subsection 2.3 describes the estimation procedure, and Subsection 2.4 outlines our portfolio sorts.

2.1 The Empirical Tests

Our empirical analysis revolves around the fact that a firm's book-equity, $BE_{j,t}$, can be seen as a proxy for its fundamental equity, $FE_{j,t}$, for asset pricing purposes. Since we place special emphasis on the value premium, which is linked to valuation ratios, we focus on the book-to-market ratio, $BM_{j,t} = BE_{j,t}/ME_{j,t}$, and the fundamental-to-market ratio,

[1]Stationarity of the VAR system implies $\mathbb{E}_t[s_{t+H}] \overset{H\to\infty}{\longrightarrow} \mathbb{E}[s_t]$. As such, we deal with the infinite sum by assuming that $\mathbb{E}_t[s_{t+H}] = \mathbb{E}[s_t]$ for $H \geq 1,000$ years (Internet Appendix A provides the details).

[2]Strictly speaking, the unconditional averages implied by the VAR (and thus $\overline{dr}$) vary over time as the Γ estimate varies due to the expanding estimation window that assures our analysis is out-of-sample. However, $\overline{dr}$ does not vary across firms and our analysis is based on the cross-section of firms.

$FM_{j,t} = FE_{j,t}/ME_{j,t}$, instead of the $BE_{j,t}$ and $FE_{j,t}$ levels. Finally, to guide our empirical tests, we use the following identity:

$$\begin{aligned} \frac{BE_{j,t}}{ME_{j,t}} &= \frac{FE_{j,t}}{ME_{j,t}} \cdot \frac{BE_{j,t}}{FE_{j,t}} \\ &\Downarrow \\ bm_{j,t} &= fm_{j,t} \; + \; bf_{j,t} \end{aligned} \tag{8}$$

where $bm_{j,t} \equiv log(BE_{j,t}/ME_{j,t})$, $fm_{j,t} \equiv log(FE_{j,t}/ME_{j,t})$, and $bf_{j,t} \equiv log(BE_{j,t}/FE_{j,t})$.

We ask three sequential questions. First, we ask whether bm is linked to $\mathbb{E}[r]$ through fm or bf (or both). Specifically, we study return predictability using the cross-sectional regression:

$$r_{j,t+h} = a^{(h)} \; + \; b^{(h)}_{fm} \cdot fm_{j,t} \; + \; b^{(h)}_{bf} \cdot bf_{j,t} \; + \; \epsilon_{j,t+h} \tag{9}$$

which allows us to test our three hypothesis of interest:

1. bm is linked to $\mathbb{E}[r]$ only through $fm \Rightarrow H_0: \; b^{(h)}_{bf} = 0$;

2. bm is linked to $\mathbb{E}[r]$ only through $bf \Rightarrow H_0: \; b^{(h)}_{fm} = 0$;

3. The bm components are equally linked to $\mathbb{E}[r] \Rightarrow H_0: \; b^{(h)}_{bf} = b^{(h)}_{fm}$.[3]

Second, after finding that bm is linked to $\mathbb{E}[r]$ only through fm, we ask whether the relation between bm and fm is stable over time. To answer this question, we explore the cross-sectional correlation structure between bm, fm, and bf as well as how much fm and bf contribute to cross-sectional variability in bm. Overall, we find that $Cor(bm, fm)$ was strong in the 70s and early 80s, but declined over time.

Third, we explore the implications of the two previous findings to our understanding of the value premium. Specifically, we create portfolios sorted on bm, fm, and bf and calculate

[3]Note that, under this hypothesis, Equation 9 reduces to:

$$r_{j,t+h} = a^{(h)} \; + \; b^{(h)} \cdot bm_{j,t} \; + \; \epsilon_{j,t+h}$$

where $b^{(h)} \equiv b^{(h)}_{bf} = b^{(h)}_{fm}$.

the premium associated with each ratio to explore the unconditional value premium and to better understand why the value premium appears to have declined over the years.

2.2 The Sample Construction

We use data from the Center for Research in Security Prices (CRSP) monthly stock file and the COMPUSTAT annual file. We follow the literature and restrict the analysis to common stocks of firms incorporated in the United States (shrcd = 10 or 11) trading on NYSE, Amex, or Nasdaq (exchcd = 1,2 or 3). We exclude utilities (4900≤SIC≤4949) and financials (6000≤SIC≤6999) and require a minimum of two previous years in COMPUSTAT for a company to be included in our analysis with the objective of alleviating backfilling concerns (see Fama and French (1993)).

To estimate the VAR, we follow Gonçalves (2020) and form $s_{j,t}$ based on twelve state variable split among four broad categories:

(i) Valuation Measures:

- book-to-market: $bm_{j,t} = ln\,(BE_{j,t}/ME_{j,t})$;
- payout yield: $POy_{j,t} = ln\,(1 + PO_{j,t}/ME_{j,t})$;
- sales yield: $Yy_{j,t} = ln\,(Y_{j,t}/ME_{j,t})$;

(ii) Growth Measures:

- book-equity growth: $BEg_{j,t} = ln\,(BE_{j,t}/BE_{j,t-1})$;
- asset growth: $Ag_{j,t} = ln\,(A_{j,t}/A_{j,t-1})$;
- sales growth: $Yg_{j,t} = ln\,(Y_{j,t}/Y_{j,t-1})$;

(iii) Profitability Measures:[4]

- clean-surplus profitability: $CSprof_{j,t} = ln\left(1 + \frac{PO_{j,t}+\Delta BE_{j,t}}{BE_{j,t-1}}\right)$;
- return-on-equity: $Roe_{j,t} = ln\left(1 + \frac{E_{j,t}}{0.5BE_{j,t}+0.5BE_{j,t-1}}\right)$;
- gross profitability: $Gprof_{j,t} = ln\left(1 + \frac{GP_{j,t}}{0.5A_{j,t}+0.5A_{j,t-1}}\right)$;

(iv) Capital Structure Measures:

- market-leverage: $Mlev_{j,t} = B_{j,t}/\left(ME_{j,t} + B_{j,t}\right)$;
- book-leverage: $Blev_{j,t} = B_{j,t}/A_{j,t}$;
- cash-holdings: $Cash_{j,t} = C_{j,t}/A_{j,t}$.

where ME is market-equity from CRSP and all other variables are constructed from COMPUSTAT. BE is book equity following Davis, Fama, and French (2000); A is total assets (at); Y is total revenue ($revt$); PO is net payout following Boudoukh et al. (2007);[5] E is income before extraordinary items (ib); GP is gross profits ($revt - cogs$) following Novy-Marx (2013); B is total book debt ($dltt + dlc$ as long as one of the two is available); and C is cash

[4]For the denominator of return-on-equity (gross profitability) we use the average of initial and final book equity (total assets) over the fiscal period. This is a compromise between the two typical approaches of using either beginning of period (e.g., Hou, Xue, and Zhang (2015)) or end of period (e.g., Novy-Marx (2013) and Fama and French (2015)) book-equity/total assets to measure profitability. Profits are generated over the fiscal year so that neither the beginning nor the end of the period represents the basis for the profit generation, and thus we take the average between them. The definition of $CSprof$ in the calculation of $\mathbb{E}_t[PO_{j,t+h}/BE_{j,t}]$ does not allow us to use this approach for clean-surplus profitability, which requires beginning of period book equity.

[5]To define net payouts, PO, we start by defining book value of preferred stock ($BVPS$), which is given by redemption ($pstkrv$), liquidation ($pstkl$), or par value ($pstk$) of preferred stock in this order. Then, the net payout in any given fiscal year is equal to cash dividends (dvc) + net equity repurchases, which is given by the total expenditure on the purchase of common and preferred stocks ($prstkc_t$) - sale of common and preferred stock ($sstk$) + net issuances of preferred stocks ($BVPS_t - BVPS_{t-1}$). The COMPUSTAT data required to calculate net equity repurchases is only available starting in 1971. As such, for the earlier period, which is only used for the VAR estimation, we also follow Boudoukh et al. (2007) and use CRSP information on prices ($P_{j,t}$) and shares outstanding ($N_{j,t}$), $PO_{j,t} = P_{j,t} \cdot (N_{j,t} - N_{j,t-1})$.

and short-term investments (*che*).[6] All raw level quantities are deflated by the CPI index before calculating ratios.

From Equation 6, the identification of $FE_{j,t}$ comes from $BE_{j,t}$ and the the cross-sectional variability in $\mathbb{E}_t[PO_{j,t+h}/BE_{j,t}]$. Since $s_{j,t}$ represents the only source of cross-firm variation in $\mathbb{E}_t[PO_{j,t+h}/BE_{j,t}]$ (and state variables only matter to the extent that they predict $CSprof$ or BEg at some horizon), twelve state variables is a reasonable compromise between parsimony and achieving enough cross-firm variability to measure $FE_{j,t}$.

2.3 The Estimation Procedure

At June of year t (with t from 1973 to 2018), we estimate $FE_{j,t}$ for all firms in our sample (i.e., firms that have all variables in $s_{j,t}$ available) using Equation 6 and calculate our three log ratios of interest: $bm_{j,t}$, $fm_{j,t}$, and $bf_{j,t}$.[7] The VAR estimation uses data up to the fiscal year ending in calendar year $t-1$ and aligns accounting and market-equity information (so that the gap between $s_{j,t}$ and $s_{j,t-1}$ is always one year).[8] We then obtain $bm_{j,t}$, $fm_{j,t}$, and $bf_{j,t}$ by combining the VAR estimates with $ME_{j,t}$ as of December of year $t-1$ and the latest accounting information used in the VAR estimation (i.e., from fiscal year ending in calendar year $t-1$). This approach is consistent with the conventional alignment of market and accounting data used in the literature (see Fama and French (1992)).

We use the same Γ and Σ for all firms so that all cross-sectional variability used to identify

[6] We impose some minor screenings in the data used to get the state vector, $s_{i,t}$. We set any non-positive A, BE, ME, and Y to missing as well as any negative C, B, and cash dividends. We also set to missing any BE, C, and B higher than A. Similar to Vuolteenaho (2002), we set to missing any BE higher than $50 \times ME$ or below $(1/50) \times ME$ and set any profitability ratio to -99% when below this value so that the log transformation is always feasible and firms do not lose more than 100% their book equity (or assets). Finally, to avoid the effect of outliers, we winsorize each non-bounded variable in the state vector at 1% and 99% percentiles for each cross-section (this avoids any look-ahead bias in the winsorization).

[7] After estimating $FE_{j,t}$, we deal with outliers by bounding $FE_{j,t}$ at $(1/100) \cdot max(ME_{j,t}, BE_{j,t})$ from below and at $100 \cdot min(ME_{j,t}, BE_{j,t})$ from above. This approach to deal with outliers is analogous to bounding ME/BE at 1/100 from below and at 100 from above. Moreover, bounding $FE_{j,t}$ directly (instead of winsorizing $fm_{j,t}$ and $bf_{j,t}$ separately) assures that the identity in Equation 8 remains valid even at the bounded points.

[8] The first estimation of $FE_{j,t}$ is in June of 1973, which gives ten years of data (t from 1963 to 1972) for our initial estimation of the VAR parameters.

$FE_{j,t}$ comes only from $BE_{j,t}$ and $s_{j,t}$. We estimate the autoregressive matrix, Γ, equation by equation from Fama-MacBeth regressions and the covariance matrix, Σ, based on the sample analogue constructed from pooling observations of firm-demeaned residuals.[9] To minimize the effect of small stocks on the VAR parameters, we always exclude microcaps (firms below the 20% quantile of market equity based on NYSE breakpoints) when estimating Γ and Σ even when we estimate $FE_{j,t}$ for microcaps. The intercepts in the Γ matrix define the long-term behavior of $\mathbb{E}[CSProf]$ and $\mathbb{E}[BEg]$ and have no cross-sectional variability given the use of a common Γ across firms. To minimize the effect of extreme observations on the long-term expected profitability and growth, we select the intercepts to match the time-series average of cross-sectional medians for each of the variables in the state vector (using the same expanding window as for other parameters in Γ).

2.4 The Portfolio Sorts

We use portfolio sorts to estimate the premiums associated with bm, fm, and bf. At June of year t (with t from 1973 to 2018) we form ten (value-weighted and equal-weighted) decile portfolios by sorting stocks based on their bm, fm, and bf (which use information no later than December of year $t-1$). We then study the returns on these portfolios over the subsequent twelve months (so that portfolio returns go from July/1973 to June/2019). To capture predictability beyond a one-year investment horizon, we sort on lagged bm, fm, and bf. For example, using bm as of December of year $t-2$ in the June of year t sorting (and recording returns over the subsequent twelve months) provides a simple way to study predictability over the second year of a two-year investment horizon (this approach is analogous to how Jegadeesh and Titman (1993) originally studied momentum).

For value-weighted portfolios, we use NYSE breakpoints to define thresholds to assign stocks into portfolios, but form portfolios with all stocks in the sample (as in Fama and French (1993)). For equal-weighted portfolios, we follow Hou, Xue, and Zhang (2019) and

[9] As it is common in the literature, we weight each cross-section in the Fama-MacBeth regression by the number of firms in that cross-section.

completely exclude microcaps (defined as the firms below the 20% quantile of market equity based on NYSE breakpoints) to make sure results are not driven by these firms. We then define breakpoints and form decile portfolios with the remaining firms. For both value- and equal-weighted portfolios, we hold each stock for one year and repeat the procedure the following June (equal-weighted portfolios are rebalanced every month to keep equal weights for each stock). After stock delistings, we rebalance the portfolios to keep value- or equal-weighted returns across the available stocks.

3 Firm-level bm, fm, and bf: Two Motivating Facts

In this section, we provide two motivating facts that suggest the correlation between bm and fm is at least partially responsible for the apparent value premium decline. Subsection 3.1 introduces our sample, Subsection 3.2 shows that bm predicts future returns only through fm, and Subsection 3.3 demonstrates that the strength of the link between bm and fm has declined over the years, suggesting that bm is no longer a good proxy for fm.

3.1 The Sample Studied

Table 1 summarizes the sample of firms we study in this paper. The key point of this table is that the sample we rely on is comprehensive despite requiring the availability of the full state vector, $s_{j,t}$. Specifically, the average number of firms available in a given year is 2,554, which, on average, accounts for 88.2% of the market equity available in an analogous sample that requires only ME and BE to be non-missing. The other columns show the year by year cross-sectional distribution of our three key variables, $BM = BE/ME$, $FM = FE/ME$, and $BF = BE/FE$, demonstrating that the annual distribution of each variable is reasonable.

3.2 The Cross-Section of Expected Returns: bm, fm, and bf

Table 2 contains the results from Fama and MacBeth (1973) regressions of monthly returns ($\times 12$) on bm, fm, and bf at different lags to study return predictability at different horizons.

For instance, treating June/t as the bm measurement date, regressions based on ratios as of Dec/t-5 reflect returns over the fifth year after measuring bm. The bivariate regression reflects Equation 9, which effectively decomposes the $bm = fm + bf$ predictability into its fm and bf effects. To preserve the additivity of the decomposition, the coefficients are not normalized (i.e., a coefficient of 1% on bm implies an increase of $ln(2) \approx 0.7$ percentage points on annual expected returns as we double bm). We focus the description on value-weights (Panel A) and point out when there are relevant differences compared to equal weights (Panel B).

First, bm is only marginally related to future returns, with a coefficient of $b^{(1)} = 1.7\%$ ($t_{stat} = 1.56$) in the first year and non-significant coefficients beyond a one-year horizon (the effect is a bit stronger with equal-weights, but not much). In contrast, fm is strongly related to future returns ($b^{(1)} = 5.3\%$, $t_{stat} = 4.29$) and such link lasts for at least five years ($b^{(5)} = 2.8\%$, $t_{stat} = 2.32$). Since $bm = fm + bf$, these results point to a weak link between bf and future returns, which is confirmed by the fact that bf does not predict future returns at any horizon.

Second, when estimating the joint specification in Equation 9, we can easily reject the hypothesis that bm is linked to $\mathbb{E}[r]$ only through bf (i.e., $H_0 : b^{(h)}_{fm} = 0$) at all horizons, but not the hypothesis that bm is linked to $\mathbb{E}[r]$ only through fm (i.e., $H_0 : b^{(h)}_{bf} = 0$). Moreover, we tend to reject (at least weakly) the hypothesis that the bm components are equally linked to $\mathbb{E}[r]$ (i.e., $H_0 : b^{(h)}_{bf} = b^{(h)}_{fm}$). The overall evidence indicates bm predicts future returns only through fm.[10]

3.3 The Relation Between bm, fm, and bf

The previous results indicate that, for asset pricing purposes, BE serves as a proxy for FE (i.e., bm predicts future returns only through fm). To explore the quality of BE as a proxy

[10]Note that it is not necessary to separately estimate the specification

$$r_{j,t+h} = a^{(h)} + \theta^{(h)}_{fm} \cdot fm_{j,t} + \theta^{(h)}_{bm} \cdot bm_{j,t} + \epsilon_{j,t+h}$$

since the identify $bm = fm + bf$ implies $\theta^{(h)}_{bm} = b^{(h)}_{bf}$ and $\theta^{(h)}_{fm} = b^{(h)}_{fm} - b^{(h)}_{bf}$, which are already presented in Table 2.

for FE, Table 3 reports the fraction of bm cross-sectional variance explained by fm as well as the cross-sectional correlation between bm and fm. For the variance decomposition, we rely on

$$Var(bm) = Cov(bm\,,\ fm) + Cov(bm\,,\ bf) \tag{10}$$

which follows directly from Equation 8.

The first panel of Table 3 displays the variance decomposition results. fm explains, on average, 46.6% of the variation in bm, which indicates bm is generally a reasonable, but far from perfect, proxy for fm. However, the fraction of variation in bm explained by fm declined over time (59.2% over the early sample vs 33.9% over the late sample), which suggests bm has become a worse proxy for fm over the years.

While the variance decomposition is telling, it is still possible that bm is a good proxy for fm if $Cor(fm, bf)$ is strongly positive because, in this case, bm can be strongly correlated with fm. The second and third panels of Table 3 display the cross-sectional (linear and rank) correlations between bm, fm, and bf to explore this issue. We focus the description on rank correlations as they are more relevant in the context of our portfolio exercise (and more generally, to measuring the value premium).

Overall, $Cor(bm, fm) = 0.47$, confirming that bm is a reasonable, but imperfect, proxy for fm. Also similar to the variance decomposition results, $Cor(bm, fm)$ has declined over time (from 0.62 in the early sample to 0.27 in the late sample), indicating that bm became a worse proxy for fm over the more recent decades. This change happened not only because fm explains less of the variation in bm over the late sample, but also because $Cor(fm, bf)$ was weakly positive over the early sample but became strongly negative over the late sample. The aforementioned results are not driven by a small subset of years, but rather by a general declining pattern in $Cor(bm, fm)$, as can be seen in Figure 1(a) in the introduction.

4 Portfolios Sorted on bm, fm, and bf

The previous section shows that (i) bm predicts future returns only through fm and (ii) the correlation between bm and fm has declined over the years. These two results suggest an apparent decline in the value premium when measured by bm, which is driven by the fact that bm is no longer a good proxy for fm. We cannot explore this possibility further using cross-sectional regressions because, as pointed out by Fama and French (2020), the functional link between these ratios and subsequent returns can vary over time even if the value premium does not change (e.g., if the cross-sectional variance in bm changes). As such, this section explores portfolios sorted on bm, fm, and bf in order to study the apparent decline in the value premium. Subsection 4.1 summarizes the characteristics of the sorted portfolios studied, Subsection 4.2 studies the performance of these portfolios in a univariate sense, and Subsection 4.3 moves to a bivariate analysis to show that there is no value premium decline once we control for fm.

4.1 Characteristics of Decile Portfolios

Table 4 displays the characteristics of our decile portfolios sorted on bm, fm, and bf. To conserve space, we keep only deciles 1, 2, 3, 8, 9, and 10 as they provide the most relevant information to understand how firm characteristics vary across decile portfolios. Panel A shows that high bm firms are value firms, with low growth, low profitability, and high leverage. Panel B shows that high fm firms are also value firms with low growth, but, in contrast to high bm firms, they have high profitability and low leverage. Finally, the bf provide similar sorts to bm on valuation, growth, profitability, and capital structure, but the bf sorts are relatively stronger on the growth, profitability, and capital structure dimensions.

These results provide a general picture of the characteristics of firms in the different portfolios we study. However, they also demonstrate that the key difference between bm and fm is that a sort on bm induces a negative sort on profitability while a sort on fm induces a positive sort on profitability. This result is intuitive as FE reflects the present value of cash flows under a common discount rate, and thus firms need high profitability to achieve a high FE after accounting for size differences.

Given the above results, it is natural to ask whether fm provides a better (than bm) signal for variation in the future cash flow generation of firms, which is the basic premise of our fm estimation (but not necessarily true since we estimate our FE in an out-of-sample fashion). To explore this issue, we construct a measure of realized present value for each portfolio i at each time t as follows:

$$\text{Realized } \frac{FE_{i,t}}{ME_{i,t}} = \sum_{h=1}^{10} \left(e^{-h \cdot \overline{dr}} \cdot \frac{\sum_{j=1}^{N_{i,t}^{(h)}} PO_{j,t+h}}{\sum_{j=1}^{N_{i,t}^{(h)}} ME_{j,t}} \right) \tag{11}$$

where $N_{i,t}^{(h)}$ reflects the number of firms in portfolio i at time t that have PO_{t+h} available, with the firm identities fixed over the horizon summation ($h = 1, ..., 10$).

In simple words, we create an ex-post measure of cash flow present values (normalized by market equity) for each portfolio, with the caveat that we only consider cash flows paid for the ten years subsequent to the measurement of fm, bm, and bf. We stop at ten years to strike a balance between the fact that present values should reflect long-term cash flows and the fact that our realized present values are affected by an intrinsic survivorship bias that is stronger for longer-term cash flows.

Figure 2 displays the average realized FE/ME for the fm, bm, and bf decile portfolios. The clear observation from the figure is that FE/ME provides a good signal for realized FE/ME whereas BE/ME does not. As such, our FE measure indeed improves upon BE in capturing future firm cash flows. This fact has important implications for return predictability, as we demonstrate in the next two subsections.

4.2 Performance of Decile Portfolios

Table 5 summarizes the performance of (value- and equal-weighted) portfolios sorted on bm, fm, and bf. Again, to conserve space, we provide results only for deciles 1, 2, 3, 8, 9, and 10. The first three columns of each section of the table ($\overline{r}_{t+1}$, α_{FF}, and α_q) show annualized average returns as well as αs relative to the Fama and French (2015)'s 5-Factor model and the Hou, Xue, and Zhang (2015)'s q-Factor model. The subsequent two columns ($\overline{r}_{t+5}$ and r_{t+1}^{Large}) display annualized average returns, respectively, in the fifth year after portfolio formation and when portfolios are formed only with large firms (defined as the firms above the 80% quantile of market equity based on NYSE breakpoints). Finally, the last two columns ($\overline{r}_{t+1}^{Early}$ and r_{t+1}^{Late}) provide annualized average returns after splitting the sample into its early (formation years 1973 to 1995) and late (formation years 1996 to 2018) periods. We focus the description on value-weighted portfolios, but results for equal-weighted portfolios are similar.

The average returns indicate the premium associated with fm is stronger, more persistent, and more stable than the premium associated with bm. In terms of strength and persistence, the average return on the high-low fm is 8.5% ($t_{stat} = 3.96$) per year and remains strong at 4.1% ($t_{stat} = 1.89$) in the fifth year after portfolio formation. In contrast, the analogous numbers for the high-low bm spread are 5.9% ($t_{stat} = 1.90$) and 0.8% ($t_{stat} = 0.32$). In terms of stability, the premium associated with fm is relatively stable over time with a 8.8% ($t_{stat} = 2.87$) premium in the early sample and a 8.2% ($t_{stat} = 2.72$) premium in the late sample, contrasting with the premium associated with bm, which is strong during the early sample (10.3% with $t_{stat} = 2.58$) but much weaker during the late sample (1.5% with $t_{stat} = 0.33$). The fm premium is also more stable across size groups, with the premium remaining strong (6.9% with $t_{stat} = 2.93$) when we focus on large firms, which is not true for the premium associated with bm (1.6% with $t_{stat} = 0.56$). Finally, we find no premium associated with bf over the entire sample, within large firms, and in each of the sample periods studied.

The αs suggest the bm premium is fully captured by the Fama and French (2015)'s 5-Factor model and the Hou, Xue, and Zhang (2015)'s q-Factor model (as expected given the results in these papers). In contrast, the fm premium is not captured by these two factor models. Moreover, portfolios sorted on bf have no α relative to the factor models studied (if anything, there is a negative α relative to the Fama and French (2015)'s 5-Factor model).

4.3 Panel Regressions of Returns on Portfolio Deciles

The previous subsection demonstrates that the premium associated with fm dominates the premium associated with bm in a univariate sense (it is stronger, more persistent, and more stable). This subsection explores portfolio tests analogous to Equation 9 to demonstrate that, after controlling for fm, there is no premium associated with bm. Building on this result, this subsection also shows that there is no decline in the premium associated with bm after controlling for fm since bm delivers no premium in either sample period once we control for fm.

To explore a portfolio-level analysis analogous to Equation 9 (i.e., a bivariate cross-sectional regression), we rely on the method proposed in Gonçalves (2020). Specifically, we estimate panel regressions using portfolio returns on the left side and the average decile values as covariates. Consider the case in which fm and bf are included in the regression specification. We form 10 decile portfolios for fm and 10 for bf and assign each stock a fm decile number as well as a bf decile number (i.e., we create fm decile and bf decile as firm-level characteristics). Then, for each fm portfolio, we calculate the weighted average bf decile of its stocks and similarly for bf portfolios. At the end of this procedure, we have 20 decile portfolios with each portfolio having an average fm decile as well as an average bf decile. We then regress portfolio returns on portfolio deciles.

This procedure is a multivariate version of the typical average High-Low returns. To see this result, note that, with only one covariate (e.g., only 10 fm deciles), the OLS estimate, $\widehat{b}$, of this pooled panel regression is given by $9 \cdot \widehat{b} = \sum_{i=0}^{4} w_i \cdot (\overline{R}_{10-i} - \overline{R}_{1+i}) \cdot \frac{9}{9-2 \cdot i}$, where $w_i = (4.5-i)^2 \,/ \sum_{k=0}^{4} (4.5-k)^2$ are weights and $9 \cdot \widehat{b}$ provides an estimate for the High-Low portfolio predicted by the given regression model since there are nine decile increases between deciles one and ten. The predicted premium is a weighted average of several terms. The first term is the average return on the High-Low portfolio (when $i = 0$, we have $\overline{R}_{10} - \overline{R}_1$), which is the focus of the typical analysis. The second term, $(9/7) \cdot (\overline{R}_9 - \overline{R}_2)$, is the spread between the second set of most extreme portfolios scaled to have the same units as average return on the High-Low portfolio. All other terms are similar, with the last term being $9 \cdot (\overline{R}_6 - \overline{R}_5)$.

Of course, not all long-short portfolios provide the same level of information, with the most extreme deciles being more important. The OLS weights the terms accordingly (trough w_i) to incorporate information from all decile spreads in the appropriate manner.

Table 6 presents the results from these panel regressions of returns on portfolio deciles. We focus the description on value-weighted portfolios, but equal-weighted portfolios yield similar results. As expected, the univariate specifications deliver results that are very similar to the high-low average returns on the respective portfolios (presented in Tables 5). The multivariate specifications show, however, that there is no premium associated with bm at any horizon after controlling for fm. This is particularly clear from specification [5], which shows that the premium associated with bm is 3.6% ($t_{stat} = 1.25$) after controlling for fm while the premium associated with fm remains strong (at 8.7% with $t_{stat} = 4.29$). All of these results are also present when looking at returns three or five years after measuring the respective sorting variables.

Table 7 focuses on the claim that the value premium declined by comparing the early and late sample periods. The univariate value premium as measured by bm declines from 7.8% ($t_{stat} = 2.45$) to 0.5% ($t_{stat} = 0.15$) while the univariate fm premium remains strong in the second half of our sample period, moving from 9.3% ($t_{stat} = 3.76$) to 7.4% ($t_{stat} = 2.68$). However, the premium associated with bm is not significant in either sample period after controlling for fm. Specifically, specification [5] shows that the bm premium after controlling for fm is 4.3% ($t_{stat} = 0.91$) over the early sample and 1.5% ($t_{stat} = 0.36$) over the late sample. In contrast, the fm premium after controlling for bm actually increases slightly from 7.8% ($t_{stat} = 1.95$) to 8.7% ($t_{stat} = 3.47$). This result indicates that the decline in the correlation between bm and fm goes a long way in explaining the apparent decline in the value premium as measured by bm.

5 The Impact of Size, Industry, and Intangibles

This section explores how size, industry, and intangibles are related to our findings on the connection between the bm and fm premia. In a nutshell, Subsection 5.1 shows that our results are similar among big and small firms, Subsection 5.2 finds that most of the fm and bm premia come from a within industry effect, and Subsection 5.3 demonstrates that intangibles explain roughly 30% of the improvement of fm over bm.

5.1 The Impact of Size

The previous sections focus on bm and fm as univariate value signals as this approach allows us to cleanly study the relation between bm and fm and its implications to the value premium decline. However, since the well-known value factor in the 3-factor model of Fama and French (1993) controls for size, this subsection shows that our core results are similar whether we focus on big or small firms.

Table 8 provides panel regressions of portfolio returns on portfolio deciles using deciles that are formed only using big firms or only using small firms, with small and big firms defined as in Fama and French (1993) (i.e., based on the median market equity of firms trading on NYSE). Our discussion focuses on Panel A (i.e., value weighted portfolios) and we point out differences relative to Panel B (equal-weighted portfolios) when relevant.

To start, whether we focus on small or big firms, the fm premium is higher than the bm premium over the full sample and dominates it in the sense that the bm premium is small an insignificant after controlling for fm. Moreover, for both small and big firms, we see little change in the fm premium from the early to the late sample, but a large decline in the bm premium. Finally, there is little change in the bm premium (once we controlling for fm) from the early to the late sample as the bm premium is small and insignificant over both samples. The only exception to the aforementioned results is among small firms with value-weighted returns, in which case the bm premium (after we control for fm) is much larger in the first half of the sample, but it is statistically insignificant in both halves.

5.2 The Impact of Industry

While the previous sections demonstrate that the bm premium has declined as a consequence of its declining correlation with fm, it remains unclear whether this results is a manifestation of an across or within industry effect. This subsection demonstrates that most of bm and fm premia (as well as the bm premium decline) are driven by a within industry effect.

To study the impact of firm's industry in the context of decile portfolios, we start by constructing $bm_{j,t,ind}$ and $fm_{j,t,ind}$ for each firm j. In the case of $bm_{j,t,ind}$ (and analogously for $fm_{j,t,ind}$), we use $bm_{j,t,ind} = 0.999 \cdot \overline{bm}_{j,t,ind} + 0.001 \cdot bm_{j,t}$, where $bm_{j,t}$ is the firm's log book-to-market and $\overline{bm}_{j,t,ind}$ is the median $bm_{j,t}$ for firms in the same industry as firm j (with industries based on the 48 industry classification of Fama and French (1997)). We then form decile portfolios analogously to our $bm_{j,t}$ decile portfolios, but using $bm_{j,t,ind}$. The idea is to assign the industry median log book-to-market to each firm (through a large weight on $\overline{bm}_{j,t,ind}$) but to break ties in the portfolio construction based on the firm-specific log book-to-market (through a small weight on $bm_{j,t}$).

Table 8 provides panel regressions of portfolio returns on portfolio deciles using deciles formed based on fm, bm, fm_{ind}, and bm_{ind}. Our discussion focuses on Panel A (i.e., value weighted portfolios) and we point out differences relative to Panel B (equal-weighted portfolios) when relevant.

Starting from the full sample, it is clear that most of the value premium (whether measured based on fm or bm) is driven by a within industry effect. For instance, while the univariate fm and bm premia are 8.3% ($t_{stat} = 4.50$) and 4.2% ($t_{stat} = 1.75$) respectively, the fm_{ind} and bm_{ind} premia are roughly four percentage points lower at 4.4% ($t_{stat} = 2.52$) and 0.3% ($t_{stat} = 0.16$) respectively. Perhaps more importantly, fm_{ind} and bm_{ind} have no marginal effect after controlling for fm and bm, respectively.

In terms of the value premium decline, when the panel regression includes bm and bm_{ind} portfolios, the entire value premium decline is through the firm specific component, bm, with little change in the (negative and insignificant) marginal effect of bm_{ind}. At the same time, when the panel regression includes fm and fm_{ind} portfolios, we see no significant decline in the effect of either component under value-weighted returns. With equal-weighted returns, the marginal effect of fm significantly declines, but the effect of fm_{ind} increases substantially so that the overall fm premium declines little.

5.3 The Impact of Intangibles

The previous sections show that bm has become a weak signal for the value premium over the recent years and that such result is a consequence of BE no longer capturing future cash flows since fm (which replaces BE with FE to capture cash flows) remains a strong signal for the value premium. There are many potential channels for why BE is no longer a good proxy for cash flow generation and they tend to relate to changes in the corporate environment over the years. In this subsection, we explore one particular channel. Specifically, we show that part (but not all) of the deterioration of BE as a measure of future cash flows is due to its inability to reflect intangible capital, which has grown in importance over the years.

a) Adjusting BE for Intangibles

Following Park (2020), we define $BE^* = BE + K_{int} - K_{goodwill}$, where intangible capital is given by $K_{int} = K_{know} + K_{org}$ (with K_{know} and K_{org} reflecting knowledge and organizational capital) and $K_{goodwill}$ represents goodwill. Park (2020) argues that goodwill should be removed from BE because (i) it distorts the historical book cost of the firm's equity (which is the motivation for using BE when constructing value measures) and (ii) there is substantial subjectivity in estimating goodwill's current fair value.

To obtain BE^*, we use the K_{know} and K_{org} estimates from Peters and Taylor (2017).[11] We set K_{know} and/or K_{org} to zero whenever the respective measure is not available to assure the sample of firms we study in this section matches the sample of firms studied in the previous sections.

[11] We also explore tests that replace the estimates from Peters and Taylor (2017) with the estimates from Park (2020), but the results are omitted as they are almost identical. We thank the authors of these papers for sharing their data.

Figure 3(a) (which is analogous to Figure 1(a)) plots the cross-sectional correlation between $bm = log(BE/ME)$ and $bm^* = log(BE^*/ME)$. Clearly, there is a decline in the correlation between bm and bm^* over the years. For the rank correlation (which is more relevant in the context of portfolio sortings), the correlation declines from close to 100% in 1973 to about 70% in 2018.

If intangibles are important for the cash flow generation process of firms, then one would expect the declining $Cor(bm, bm^*)$ in Figure 3(a) to explain part of the declining $Cor(bm, fm)$ reported in Figure 1(a). Since such a decline is driven by the difference between be and fe, we explore this issue through the following identity:

$$be_{j,t} - fe_{j,t} \ = (be_{j,t} - be^*_{j,t}) \ + \ (be^*_{j,t} - fe_{j,t}) \tag{12}$$

which implies the cross-sectional variability in $be_{j,t} - fe_{j,t}$ can be decomposed into the effect of $be_{j,t} - be^*_{j,t}$ and $be^*_{j,t} - fe_{j,t}$ as follows:

$$Var\,(be - fe) \ = Cov\,(be - fe \ , \ be - be^*) \ + \ Cov\,(be - fe \ , \ be^* - fe) \tag{13}$$

Figure 3(b) displays the decomposition in Equation 13. In 1970s, be was a good proxy for fe (see Figure 1(a)) and intangible capital (i.e., the deviations of be^* from be) did not explain the existing deviations of fe from be. Over time, be became a worse proxy for fe and intangible capital is one of the channels responsible for such a result. For instance, towards the end of our sample, intangible capital explains about 30% of the deviations of be from fe, which indicates intangible capital is not the only reason why fe deviates from be, but it is an important component of it.

b) Adjusting the Value Premium for Intangibles

Given the importance of intangible capital in explaining the deviations of fe from be, it is natural to ask how much of the bm value premium decline can be explained by the inability of be to capture intangibles. In this context, Table 10 provides regressions of portfolio returns on portfolio deciles formed based on fm, bm, and bm^*. Our description focuses on value-weighted returns, but results are similar for equal-weighted returns.

Starting from the full sample results, adjusting bm for intangibles largely affects portfolio formation, with the value premium increasing from 4.2% to 7.0%, which is closer to the 8.3% value premium delivered from fm sorts. However, when controlling for fm deciles, the value premium from bm^* is weaker and statistically insignificant while the premium associated with fm changes little. As such, the results indicate intangibles are an important component of fundamental equity, but other components remain relevant so that fm is overall a better value measure than bm^*.

Moving to the value premium decline, bm^* produces a strong value premium in the early period but a weaker and statistically insignificant value premium in the late period. However, the bm^* value premium produced in the late period is much stronger than the bm value premium over the same period (around 4.2% with bm^* vs 0.5% with bm), which is in line with the finding that intangibles explain a portion of the deviation of be from fe.

Importantly, the bm^* sortings produce a statistically insignificant value premium in both the early and late sample periods once we control for fm deciles, which again indicates our estimated FE is a better measure of fundamental value than BE and that this result remains valid even if we account for intangibles in the BE measurement.

6 Conclusion

Recent research has shown an apparent decline in the value premium (e.g., Fama and French (2020)). In this paper, we argue that this decline happened because book equity, BE, is no longer a good proxy for fundamental equity, FE, defined as the equity value originating purely from expected cash flows (i.e., with no discount rate differences across firms). Empirically, we estimate FE for public US firms and find that the premium associated with the fundamental-to-market ratio, FE/ME, has remained relatively stable while the cross-sectional correlation between FE/ME and book-to-market, BE/ME, decreased over time, inducing an apparent value premium decline. In addition, after controlling for FE/ME, we no longer see a decline in the premium associated with BE/ME (i.e., the BE/ME premium has been consistently zero from a statistical standpoint).

Our results contribute to the recent literature studying the value premium decline. Specifically, we treat BE/ME as an imperfect measure of FE/ME and show that the underlying value premium captured by BE/ME comes from this relation. Since the ability of BE/ME to proxy for FE/ME has declined over the years, it follows that BE/ME no longer yields the value premium it used to.

Our findings also speak to the corporate finance literature. Specifically, we argue that book equity is no longer a good proxy for fundamental equity because corporate activity has dramatically changed over the years. This result outlines an important asset pricing implication from the drastic changes in the corporate environment observed over the last decades (see Kahle and Stulz (2017)).

Our results also open the door to new asset pricing research. Perhaps most obviously, our findings impose a sharp restriction on mechanisms attempt to explain the value premium. Specifically, the current value premium explanations have the unifying feature that book-to-market proxies for some hard to measure characteristic of firms. Our results indicate that, for an explanation to be viable, the correlation between book-to-market and the relevant characteristic must have declined over time while the correlation between fundamental-to-market and the same characteristic must be relatively stable.

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Table 1
Summary Statistics (Sample of Firms with FE Available)

The table reports sample statistics at June of selected years for all firms included in our analysis. N is the total number of sample firms; $\%ME$ represents the percentage of market equity in our sample relative to a comparable sample that requires only ME and BE availability; and $q^x_{p\%}$ represents the p-th quantile of variable x based on the respective cross-section of firms. The relevant variables are book-to-market, $BM = BE/ME$, fundamental-to-market, $FM = FE/ME$, and book-to-fundamentals, BE/FE.

Year	N	%ME	$q^{BM}_{10\%}$	$q^{BM}_{50\%}$	$q^{BM}_{90\%}$	$q^{FM}_{10\%}$	$q^{FM}_{50\%}$	$q^{FM}_{90\%}$	$q^{BF}_{10\%}$	$q^{BF}_{50\%}$	$q^{BF}_{90\%}$
1973	1,507	91.0%	0.25	0.80	1.71	0.74	1.27	2.22	0.33	0.64	0.85
1975	2,016	91.9%	0.74	2.13	5.05	1.18	2.57	5.07	0.56	0.84	1.06
1977	2,584	95.5%	0.47	1.18	2.45	0.79	1.43	2.43	0.55	0.82	1.13
1979	2,487	87.6%	0.48	1.17	2.46	0.80	1.42	2.31	0.55	0.84	1.16
1981	2,377	88.1%	0.27	0.94	2.29	0.58	1.14	2.00	0.41	0.83	1.28
1983	2,455	86.6%	0.27	0.85	1.91	0.49	1.05	1.68	0.43	0.83	1.52
1985	2,622	85.9%	0.31	0.80	1.63	0.49	1.07	1.59	0.42	0.80	1.56
1987	2,810	89.2%	0.24	0.67	1.45	0.26	0.90	1.52	0.35	0.79	2.34
1989	2,741	85.0%	0.27	0.71	1.52	0.37	1.00	1.66	0.34	0.76	2.01
1991	2,862	88.3%	0.26	0.89	2.47	0.38	1.09	2.16	0.31	0.87	2.70
1993	2,860	91.3%	0.18	0.59	1.54	0.35	0.92	1.78	0.23	0.67	2.07
1995	3,168	90.6%	0.19	0.57	1.37	0.29	0.92	1.70	0.25	0.68	2.11
1997	3,395	86.0%	0.16	0.50	1.30	0.25	0.90	1.66	0.22	0.62	2.37
1999	3,270	80.6%	0.16	0.58	1.56	0.32	0.92	1.78	0.21	0.67	2.27
2001	2,954	77.5%	0.19	0.74	2.61	0.27	0.99	2.09	0.25	0.79	3.52
2003	2,831	84.6%	0.25	0.73	2.05	0.34	0.97	1.89	0.28	0.78	2.95
2005	2,601	87.8%	0.17	0.43	0.94	0.38	0.86	1.43	0.22	0.54	1.40
2007	2,451	86.6%	0.17	0.43	0.94	0.40	0.86	1.41	0.22	0.52	1.45
2009	2,365	89.8%	0.28	0.84	2.62	0.18	1.05	2.15	0.26	0.81	7.71
2011	2,226	89.9%	0.18	0.50	1.17	0.41	0.93	1.64	0.21	0.56	1.77
2013	2,126	91.1%	0.19	0.56	1.40	0.34	0.94	1.74	0.21	0.63	2.62
2015	2,013	89.1%	0.14	0.43	1.18	0.31	0.85	1.45	0.17	0.52	2.55
2017	1,922	89.3%	0.14	0.42	1.12	0.19	0.78	1.46	0.18	0.56	3.65
2018	1,878	91.2%	0.12	0.40	1.10	0.21	0.75	1.36	0.17	0.55	3.37
Average	2,554	88.2%	0.25	0.73	1.79	0.43	1.06	1.90	0.31	0.70	2.18
1973-1995	2,547	89.7%	0.32	0.93	2.13	0.55	1.22	2.14	0.40	0.78	1.63
1996-2018	2,561	86.8%	0.17	0.53	1.44	0.30	0.89	1.65	0.21	0.62	2.74

Table 2

Fama-MacBeth Regressions: bm, fm, and bf

The table reports results from Fama and MacBeth (1973) cross-sectional regressions of stock returns on the log book-to-market ratio, $bm = log(BE/ME)$, the log fundamental-to-market ratio, $fm = log(FE/ME)$, and the log book-to-fundamental ratio, $bf = log(BE/FE)$, from July/1973 to June/2019. Each cross-section is weighted based on the number of firms to avoid overweighting earlier observations (results are similar either way). Panel A uses value-weights when estimating each cross-section while Panel B uses equal-weights. Statistical inference is robust to heteroskedasticity and autocorrelation (Newey and West (1987, 1994)) with t_{stat} in parentheses.

PANEL A: Value-Weighted (WLS)

Predictive	Ratios from Dec/t − 1				Ratios from Dec/t − 3				Ratios from Dec/t − 5			
Variable	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
bm	1.7%				0.8%				0.2%			
	(1.56)				(0.71)				(0.18)			
fm		5.3%		4.2%		4.0%		2.8%		2.8%		2.6%
		(4.29)		(2.87)		(3.16)		(2.29)		(2.32)		(2.29)
bf			1.8%	1.5%			1.2%	0.6%			0.2%	-0.5%
			(1.48)	(1.17)			(1.01)	(0.45)			(0.17)	(-0.43)
$b_{fm} - b_{bf}$				2.7%				2.2%				3.1%
				(1.64)				(1.58)				(2.29)

PANEL B: Equal-Weighted (OLS)

Predictive	Ratios from Dec/t − 1				Ratios from Dec/t − 3				Ratios from Dec/t − 5			
Variable	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
bm	2.4%				1.5%				0.8%			
	(2.19)				(1.50)				(0.82)			
fm		4.5%		4.3%		3.3%		2.7%		2.6%		2.2%
		(4.24)		(3.57)		(3.83)		(2.44)		(2.77)		(1.93)
bf			1.1%	1.3%			1.8%	0.6%			0.6%	-0.5%
			(0.91)	(1.08)			(1.79)	(0.54)			(0.57)	(-0.42)
$b_{fm} - b_{bf}$				3.0%				2.0%				2.7%
				(2.71)				(1.79)				(2.19)

Table 3
Relation Between bm, fm, and bf

The table reports the cross-sectional $\sigma^2(bm)$ decomposition and cross-sectional correlations at June of selected years for all firms included in our sample. The relevant variables are the log book-to-market ratio, $bm = log(BE/ME)$, the log fundamental-to-market ratio, $fm = log(FE/ME)$, and the log book-to-fundamental ratio, $bf = log(BE/FE)$. The variance decomposition is based on Equation 10. The linear correlation is the Pearson correlation and the rank correlation is the Spearman correlation.

	$\sigma^2(bm)$ Decomposition			Linear Correlation			Rank Correlation		
Year	$\sigma(bm)$	% fm	% bf	(bm, fm)	(bm, bf)	(fm, bf)	(bm, fm)	(bm, bf)	(fm, bf)
1973	0.55	48.3%	51.7%	0.80	0.82	0.31	0.88	0.83	0.52
1975	0.56	70.9%	29.1%	0.93	0.73	0.43	0.95	0.81	0.62
1977	0.41	66.2%	33.8%	0.86	0.65	0.17	0.92	0.80	0.54
1979	0.41	61.2%	38.8%	0.90	0.79	0.45	0.92	0.82	0.57
1981	0.69	53.7%	46.3%	0.78	0.73	0.13	0.87	0.83	0.52
1983	0.59	64.4%	35.6%	0.61	0.39	-0.49	0.77	0.69	0.18
1985	0.44	62.2%	37.8%	0.48	0.31	-0.68	0.61	0.61	-0.11
1987	0.56	61.2%	38.8%	0.43	0.29	-0.74	0.47	0.52	-0.38
1989	0.54	64.6%	35.4%	0.47	0.28	-0.71	0.45	0.54	-0.38
1991	0.81	51.8%	48.2%	0.43	0.41	-0.65	0.46	0.59	-0.31
1993	0.72	46.3%	53.7%	0.39	0.44	-0.66	0.37	0.60	-0.41
1995	0.60	55.3%	44.7%	0.39	0.32	-0.75	0.36	0.54	-0.48
1997	0.66	50.9%	49.1%	0.35	0.34	-0.76	0.34	0.54	-0.49
1999	0.78	40.4%	59.6%	0.35	0.48	-0.65	0.36	0.62	-0.40
2001	1.08	40.0%	60.0%	0.34	0.47	-0.67	0.44	0.63	-0.30
2003	0.70	37.9%	62.1%	0.29	0.44	-0.73	0.33	0.62	-0.42
2005	0.47	47.8%	52.2%	0.36	0.39	-0.72	0.34	0.58	-0.45
2007	0.46	43.6%	56.4%	0.33	0.41	-0.73	0.31	0.62	-0.44
2009	0.82	12.0%	88.0%	0.08	0.53	-0.80	0.10	0.66	-0.59
2011	0.56	35.3%	64.7%	0.28	0.47	-0.71	0.21	0.65	-0.50
2013	0.69	30.4%	69.6%	0.24	0.50	-0.72	0.18	0.65	-0.52
2015	0.77	16.7%	83.3%	0.14	0.57	-0.73	0.13	0.70	-0.50
2017	0.72	12.9%	87.1%	0.09	0.53	-0.79	0.07	0.67	-0.59
2018	0.78	17.3%	82.7%	0.13	0.53	-0.77	0.10	0.68	-0.54
Average	0.64	46.6%	53.4%	0.45	0.49	-0.49	0.47	0.66	-0.19
1973-1995	0.58	59.2%	40.8%	0.62	0.51	-0.27	0.67	0.68	0.08
1996-2018	0.70	33.9%	66.1%	0.27	0.47	-0.72	0.26	0.63	-0.47

Table 4
Characteristics of Firms in Sorted Portfolios: bm, fm, and bf

Portfolios are formed every June (1973 to 2018) from deciles based on the respective characteristics. The table reports median characteristics for the firms in each portfolio. All variables are defined in Subsections 2.1 and 2.2. Statistical inference is robust to heteroskedasticity and autocorrelation (Newey and West (1987, 1994)) with t_{stat} in parentheses. Section 2 provides further empirical details.

PANEL A: Portfolios Sorted on bm

bm			Valuation			Growth			Profitability			Capital Structure		
Decile	BM	$Size$	BE/M	PO/M	Y/M	BEg	Ag	Yg	$CSprof$	Roe	$Gprof$	$Mlev$	$Blev$	$Cash$
Low	0.19	20.16	0.189	0.002	-0.997	0.101	0.096	0.121	0.151	0.145	0.398	0.049	0.148	0.171
2	0.33	20.32	0.333	0.005	-0.433	0.099	0.082	0.093	0.143	0.146	0.372	0.094	0.164	0.122
3	0.44	20.10	0.442	0.008	-0.131	0.083	0.063	0.074	0.121	0.130	0.354	0.127	0.176	0.104
8	1.06	18.91	1.058	0.014	0.766	0.017	0.005	0.019	0.042	0.067	0.281	0.283	0.204	0.067
9	1.32	18.52	1.325	0.012	1.015	-0.001	-0.012	0.004	0.019	0.047	0.266	0.337	0.212	0.064
High	2.04	17.63	2.045	0.004	1.540	-0.041	-0.046	-0.029	-0.029	0.006	0.240	0.491	0.245	0.052
H-L	1.86	-2.53	1.856	0.003	2.536	-0.143	-0.142	-0.149	-0.180	-0.139	-0.158	0.442	0.097	-0.119
(t_{H-L})	(10.60)	(-12.87)	(10.60)	(1.09)	(27.20)	(-10.95)	(-15.07)	(-19.00)	(-25.82)	(-18.97)	(-19.68)	(15.15)	(7.35)	(-7.16)

PANEL B: Portfolios Sorted on fm

fm			Valuation			Growth			Profitability			Capital Structure		
Decile	FM	$Size$	BE/M	PO/M	Y/M	BEg	Ag	Yg	$CSprof$	Roe	$Gprof$	$Mlev$	$Blev$	$Cash$
Low	0.31	18.85	0.356	-0.004	-0.120	-0.115	0.004	0.049	-0.297	-0.381	0.193	0.242	0.292	0.090
2	0.61	19.96	0.497	0.003	0.193	0.050	0.057	0.071	0.066	0.072	0.251	0.259	0.285	0.062
3	0.75	20.02	0.563	0.006	0.220	0.051	0.048	0.063	0.079	0.091	0.269	0.244	0.261	0.060
8	1.28	19.40	0.853	0.017	0.373	0.038	0.023	0.039	0.076	0.096	0.347	0.206	0.184	0.092
9	1.47	19.06	0.986	0.016	0.501	0.033	0.015	0.033	0.069	0.090	0.372	0.196	0.150	0.109
High	1.97	18.18	1.379	0.011	0.877	0.017	-0.002	0.014	0.047	0.073	0.428	0.189	0.103	0.134
H-L	1.66	-0.67	1.023	0.014	0.997	0.132	-0.005	-0.035	0.344	0.454	0.236	-0.053	-0.190	0.043
(t_{H-L})	(3.95)	(-2.58)	(3.95)	(5.25)	(5.21)	(3.13)	(-0.25)	(-2.58)	(4.67)	(4.87)	(4.63)	(-0.66)	(-5.70)	(3.73)

PANEL C: Portfolios Sorted on bf

bf			Valuation			Growth			Profitability			Capital Structure		
Decile	BF	$Size$	BE/M	PO/M	Y/M	BEg	Ag	Yg	$CSprof$	Roe	$Gprof$	$Mlev$	$Blev$	$Cash$
Low	0.24	20.53	0.229	0.009	-0.784	0.133	0.108	0.120	0.200	0.196	0.523	0.031	0.088	0.196
2	0.37	20.08	0.393	0.008	-0.292	0.095	0.071	0.084	0.136	0.146	0.432	0.073	0.118	0.145
3	0.47	19.78	0.518	0.009	-0.003	0.073	0.048	0.062	0.108	0.124	0.383	0.107	0.138	0.118
8	1.06	18.93	1.118	0.011	0.895	0.005	-0.002	0.012	0.022	0.050	0.244	0.348	0.250	0.053
9	1.40	18.61	1.370	0.008	1.157	-0.021	-0.015	0.004	-0.011	0.021	0.220	0.455	0.293	0.044
High	3.92	17.88	1.401	0.000	1.170	-0.159	-0.063	-0.025	-0.267	-0.302	0.158	0.555	0.346	0.056
H-L	3.68	-2.65	1.172	-0.009	1.954	-0.292	-0.171	-0.144	-0.467	-0.498	-0.366	0.524	0.258	-0.140
(t_{H-L})	(6.38)	(-21.85)	(6.38)	(-3.17)	(12.97)	(-11.11)	(-15.62)	(-11.95)	(-12.97)	(-9.84)	(-12.78)	(19.93)	(14.47)	(-21.09)

Table 5
Performance of Portfolios Sorted on bm, fm, and bf

Portfolios are formed every June (1973 to 2018) from deciles based on $bm = log(BE/ME)$, $fm = log(FE/ME)$, and $bf = log(BE/FE)$. Columns $\overline{r}_{t+1}$, α_{FF}, and α_q show annualized average returns as well as αs relative to the Fama and French (2015)'s 5-Factor model and the Hou, Xue, and Zhang (2015)'s q-Factor model. Columns $\overline{r}_{t+5}$ and r_{t+1}^{Large} display annualized average returns, respectively, in the fifth year after portfolio formation and when portfolios are formed only with large firms (i.e., firms above the 80% NYSE market equity quantile). Columns $\overline{r}_{t+1}^{Early}$ and r_{t+1}^{Late} provide annualized average returns after splitting the sample into equal halves. Statistical inference is robust to heteroskedasticity and autocorrelation (Newey and West (1987, 1994)) with t_{stat} in parentheses. Section 2 provides empirical details.

PANEL A: Portfolios Sorted on bm

bm	Value-Weighted Portfolios							Equal-Weighted Portfolios						
Decile	$\overline{r}_{t+1}$	α_{FF}	α_q	$\overline{r}_{t+5}$	$\overline{r}_{t+1}^{Large}$	$\overline{r}_{t+1}^{Early}$	$\overline{r}_{t+1}^{Late}$	$\overline{r}_{t+1}$	α_{FF}	α_q	$\overline{r}_{t+5}$	$\overline{r}_{t+1}^{Large}$	$\overline{r}_{t+1}^{Early}$	$\overline{r}_{t+1}^{Late}$
Low	6.2%	0.5%	1.2%	8.4%	6.2%	3.6%	8.8%	5.7%	-0.8%	0.4%	9.0%	6.9%	3.7%	7.8%
2	7.3%	-0.5%	0.3%	7.4%	6.1%	6.6%	8.1%	7.5%	0.2%	1.9%	10.4%	6.9%	5.4%	9.6%
3	9.0%	0.2%	0.8%	10.0%	6.7%	8.2%	9.9%	9.7%	1.0%	2.8%	9.8%	7.4%	9.4%	10.1%
8	9.0%	-1.9%	0.1%	8.3%	7.2%	10.1%	8.0%	11.4%	-0.8%	1.6%	12.2%	9.4%	12.1%	10.7%
9	10.0%	-0.3%	1.9%	8.5%	8.7%	11.6%	8.4%	10.9%	-1.7%	0.5%	11.4%	9.5%	12.4%	9.5%
High	12.1%	-0.6%	3.2%	9.2%	7.8%	13.9%	10.4%	12.3%	-1.9%	1.5%	11.2%	9.6%	13.6%	11.0%
H-L	5.9%	-1.1%	2.1%	0.8%	1.6%	10.3%	1.5%	6.5%	-1.1%	1.1%	2.2%	2.7%	9.9%	3.2%
(t_{H-L})	(1.90)	(-0.55)	(0.84)	(0.32)	(0.56)	(2.58)	(0.33)	(2.41)	(-0.75)	(0.53)	(0.89)	(1.04)	(2.98)	(0.75)

PANEL B: Portfolios Sorted on fm

fm	Value-Weighted Portfolios							Equal-Weighted Portfolios						
Decile	$\overline{r}_{t+1}$	α_{FF}	α_q	$\overline{r}_{t+5}$	$\overline{r}_{t+1}^{Large}$	$\overline{r}_{t+1}^{Early}$	$\overline{r}_{t+1}^{Late}$	$\overline{r}_{t+1}$	α_{FF}	α_q	$\overline{r}_{t+5}$	$\overline{r}_{t+1}^{Large}$	$\overline{r}_{t+1}^{Early}$	$\overline{r}_{t+1}^{Late}$
Low	4.7%	-3.4%	-2.3%	8.3%	4.5%	3.8%	5.6%	3.9%	-5.3%	-2.1%	8.0%	6.0%	3.2%	4.7%
2	5.7%	-2.9%	-1.6%	7.9%	5.4%	4.6%	6.7%	7.5%	-3.1%	-1.4%	9.1%	5.7%	6.2%	8.8%
3	6.4%	-1.9%	-0.6%	7.4%	4.5%	6.7%	6.1%	8.6%	-2.1%	-0.1%	10.7%	6.3%	8.1%	9.1%
8	11.1%	3.6%	4.1%	9.2%	11.8%	11.4%	10.8%	13.0%	2.5%	4.3%	12.2%	11.4%	13.5%	12.5%
9	12.3%	3.0%	4.3%	11.1%	9.7%	12.2%	12.4%	13.1%	2.8%	4.5%	12.9%	10.5%	13.6%	12.5%
High	13.2%	3.9%	5.8%	12.3%	11.5%	12.6%	13.8%	12.9%	1.1%	2.9%	11.5%	10.9%	13.8%	12.0%
H-L	8.5%	7.3%	8.0%	4.1%	6.9%	8.8%	8.2%	8.9%	6.3%	4.9%	3.5%	5.0%	10.6%	7.3%
(t_{H-L})	(3.96)	(3.28)	(3.42)	(1.89)	(2.93)	(2.87)	(2.72)	(3.89)	(3.33)	(2.39)	(2.11)	(2.28)	(3.92)	(1.97)

PANEL C: Portfolios Sorted on bf

bf	Value-Weighted Portfolios							Equal-Weighted Portfolios						
Decile	$\overline{r}_{t+1}$	α_{FF}	α_q	$\overline{r}_{t+5}$	$\overline{r}_{t+1}^{Large}$	$\overline{r}_{t+1}^{Early}$	$\overline{r}_{t+1}^{Late}$	$\overline{r}_{t+1}$	α_{FF}	α_q	$\overline{r}_{t+5}$	$\overline{r}_{t+1}^{Large}$	$\overline{r}_{t+1}^{Early}$	$\overline{r}_{t+1}^{Late}$
Low	6.9%	1.5%	1.9%	8.3%	6.1%	5.2%	8.7%	8.6%	1.1%	2.1%	10.8%	7.1%	6.4%	10.7%
2	7.9%	-0.2%	0.7%	9.5%	7.0%	5.8%	9.9%	9.2%	1.2%	2.6%	9.5%	8.3%	7.1%	11.3%
3	9.2%	0.7%	1.6%	10.3%	6.7%	8.3%	10.1%	10.4%	1.5%	2.8%	11.2%	8.4%	9.2%	11.7%
8	8.5%	-3.0%	-1.6%	9.8%	8.2%	9.8%	7.3%	10.5%	-1.5%	0.6%	10.2%	9.0%	10.7%	10.3%
9	10.0%	-1.0%	1.1%	8.1%	7.4%	12.0%	8.0%	11.4%	-1.4%	1.4%	10.9%	8.8%	12.1%	10.7%
High	8.3%	-2.2%	1.3%	8.7%	8.1%	9.7%	6.9%	8.7%	-4.0%	0.1%	11.9%	8.5%	10.4%	7.0%
H-L	1.4%	-3.7%	-0.6%	0.4%	1.9%	4.5%	-1.8%	0.1%	-5.1%	-1.9%	1.1%	1.4%	4.0%	-3.7%
(t_{H-L})	(0.48)	(-1.89)	(-0.30)	(0.16)	(0.71)	(1.15)	(-0.42)	(0.05)	(-2.94)	(-0.97)	(0.44)	(0.53)	(1.26)	(-0.95)

Table 6
Panel Regressions of Portfolio Returns on Portfolio Deciles: bm, fm, and bf

Portfolios are formed every June (1973 to 2018) from deciles based on the respective characteristics, which are described in Section 2. The table reports results from panel regressions of portfolio returns on the lagged deciles for the respective variables. Subsection 4.3 provides details on the methodology. t_{stat} are in parentheses and statistical inference is based on the method in Driscoll and Kraay (1998), which is the natural generalization of Newey and West (1987, 1994) to a panel data setting and is robust to heteroskedasticity, autocorrelation, and cross-sectional correlation between portfolio returns.

PANEL A: Value-Weighted Portfolios

Sorting	Ratios from Dec/t − 1					Ratios from Dec/t − 3					Ratios from Dec/t − 5				
Variable	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
bm	4.2%				3.6%	2.4%				2.0%	0.6%				0.8%
	(1.75)				(1.25)	(1.10)				(0.68)	(0.27)				(0.25)
fm		8.3%		11.4%	8.7%		6.5%		9.3%	7.9%		3.6%		5.5%	4.7%
		(4.50)		(4.76)	(4.29)		(3.65)		(4.24)	(3.35)		(2.08)		(2.55)	(1.91)
bf			1.7%	5.4%				0.5%	2.9%				-0.5%	1.4%	
			(0.74)	(2.06)				(0.26)	(1.18)				(-0.23)	(0.55)	

PANEL B: Equal-Weighted Portfolios

Sorting	Ratios from Dec/t − 1					Ratios from Dec/t − 3					Ratios from Dec/t − 5				
Variable	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
bm	5.3%				3.3%	3.1%				1.3%	2.2%				1.0%
	(2.22)				(1.26)	(1.43)				(0.51)	(1.04)				(0.39)
fm		8.1%		9.0%	7.7%		5.1%		6.7%	6.0%		3.9%		4.7%	4.3%
		(4.58)		(4.12)	(3.62)		(3.74)		(4.39)	(3.17)		(2.76)		(2.77)	(2.05)
bf			0.8%	2.9%				1.8%	3.7%				0.7%	2.0%	
			(0.37)	(1.22)				(0.88)	(1.98)				(0.34)	(0.96)	

Table 7
Panel Regressions of Portfolio Returns on Portfolio Deciles: bm, fm, and bf (Early vs Late Sample)

Portfolios are formed every June (1973 to 2018) from deciles based on the respective characteristics, which are described in Section 2. The table reports results from panel regressions of portfolio returns on the lagged deciles for the respective variables. Subsection 4.3 provides details on the methodology. t_{stat} are in parentheses and statistical inference is based on the method in Driscoll and Kraay (1998), which is the natural generalization of Newey and West (1987, 1994) to a panel data setting and is robust to heteroskedasticity, autocorrelation, and cross-sectional correlation between portfolio returns.

PANEL A: Value-Weighted Portfolios

Sorting	1973 to 1995					1996 to 2018					Difference: Late - Early				
Variable	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
bm	7.8%				4.3%	0.5%				1.5%	-7.3%				-2.8%
	(2.45)				(0.91)	(0.15)				(0.36)	(-1.56)				(-0.44)
fm		9.3%		9.7%	7.8%		7.4%		13.9%	8.7%		-1.9%		4.1%	0.8%
		(3.76)		(3.55)	(1.95)		(2.68)		(2.52)	(3.47)		(-0.51)		(0.68)	(0.18)
bf			5.5%	4.6%				-2.1%	7.0%				-7.6%	2.3%	
			(1.68)	(1.38)				(-0.65)	(1.14)				(-1.66)	(0.34)	

PANEL B: Equal-Weighted Portfolios

Sorting	1973 to 1995					1996 to 2018					Difference: Late - Early				
Variable	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]	[1]	[2]	[3]	[4]	[5]
bm	8.7%				4.2%	1.9%				2.1%	-6.8%				-2.1%
	(3.02)				(1.32)	(0.52)				(0.55)	(-1.43)				(-0.42)
fm		9.9%		9.7%	7.7%		6.4%		7.0%	6.8%		-3.5%		-2.7%	-0.9%
		(4.22)		(3.93)	(2.87)		(2.42)		(2.08)	(2.42)		(-0.99)		(-0.65)	(-0.23)
bf			4.3%	2.9%				-2.7%	1.1%				-7.1%	-1.9%	
			(1.56)	(1.10)				(-0.82)	(0.27)				(-1.63)	(-0.40)	

Table 8
Panel Regressions of Portfolio Returns on Portfolio Deciles: The Impact of Size

Portfolios are formed every June (1973 to 2018) from deciles based on the respective characteristics, which are described in Section 2. Following Fama and French (1993), the table considers two samples for portfolio construction, with the first (associated with fm_{Big} and bm_{Big}) using only firms with market equity above the median NYSE market equity and the second (associated with fm_{Small} and bm_{Small}) using only firms with market equity below the median NYSE market equity (see Subsection 5.1 for details). The table reports results from panel regressions of portfolio returns on the lagged deciles for the respective variables. Subsection 4.3 provides details on the methodology. t_{stat} are in parentheses and statistical inference is based on the method in Driscoll and Kraay (1998), which is the natural generalization of Newey and West (1987, 1994) to a panel data setting and is robust to heteroskedasticity, autocorrelation, and cross-sectional correlation between portfolio returns.

PANEL A: Value-Weighted Portfolios

Sorting	Full Sample			1973 to 1995			1996 to 2018			Difference: Late - Early		
Variable	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]
fm_{Big}	6.4%	7.0%		7.8%	7.0%		5.0%	6.7%		-2.8%	-0.2%	
	(3.60)	(3.58)		(3.21)	(1.85)		(1.94)	(2.58)		(-0.80)	(-0.05)	
bm_{Big}	2.6%	2.9%		5.9%	3.1%		-0.7%	1.3%		-6.6%	-1.8%	
	(1.16)	(1.09)		(1.92)	(0.74)		(-0.24)	(0.28)		(-1.52)	(-0.30)	
fm_{Small}	8.7%		8.4%	9.9%		2.5%	7.5%		10.8%	-2.4%		8.3%
	(4.78)		(2.78)	(4.19)		(0.32)	(2.71)		(3.65)	(-0.68)		(0.99)
bm_{Small}	3.1%		2.5%	6.3%		7.8%	-0.1%		-0.2%	-6.5%		-8.0%
	(1.26)		(0.75)	(2.41)		(1.01)	(-0.03)		(-0.05)	(-1.33)		(-0.90)

PANEL B: Equal-Weighted Portfolios

Sorting	Full Sample			1973 to 1995			1996 to 2018			Difference: Late - Early		
Variable	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]
fm_{Big}	6.1%	5.9%		8.3%	6.3%		4.0%	4.4%		-4.3%	-1.9%	
	(3.61)	(2.98)		(3.52)	(2.24)		(1.65)	(1.72)		(-1.29)	(-0.50)	
bm_{Big}	4.0%	3.1%		7.2%	4.2%		0.7%	1.3%		-6.6%	-3.0%	
	(1.69)	(1.28)		(2.35)	(1.28)		(0.20)	(0.35)		(-1.42)	(-0.61)	
fm_{Small}	9.3%		9.1%	9.9%		8.1%	8.7%		9.3%	-1.2%		1.2%
	(4.37)		(3.55)	(3.79)		(2.93)	(2.59)		(2.58)	(-0.28)		(0.25)
bm_{Small}	5.4%		2.2%	8.6%		3.2%	2.2%		1.9%	-6.4%		-1.3%
	(2.02)		(0.73)	(2.85)		(0.99)	(0.51)		(0.40)	(-1.20)		(-0.24)

Table 9
Panel Regressions of Portfolio Returns on Portfolio Deciles: The Impact of Industry

Portfolios are formed every June (1973 to 2018) from deciles based on the respective characteristics, which are described in Section 2. In the case of bm_{ind} (and analogously for fm_{ind}), we use $bm_{ind} = 0.999 \cdot \overline{bm}_{ind} + 0.001 \cdot bm$, where bm is the firm's log book-to-market and $\overline{bm}_{ind}$ is the median bm for firms in the same industry as the given firm, with industries based on the 48 industry classification of Fama and French (1997) (see Subsection 5.2 for details). The table reports results from panel regressions of portfolio returns on the lagged deciles for the respective variables. Subsection 4.3 provides details on the methodology. t_{stat} are in parentheses and statistical inference is based on the method in Driscoll and Kraay (1998), which is the natural generalization of Newey and West (1987, 1994) to a panel data setting and is robust to heteroskedasticity, autocorrelation, and cross-sectional correlation between portfolio returns.

PANEL A: Value-Weighted Portfolios

Sorting	Full Sample			1973 to 1995			1996 to 2018			Difference: Late - Early		
Variable	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]
fm	8.3%	8.9%		9.3%	9.5%		7.4%	8.8%		-1.9%	-0.8%	
	(4.50)	(3.36)		(3.76)	(2.53)		(2.68)	(2.55)		(-0.51)	(-0.16)	
bm	4.2%		6.4%	7.8%		9.6%	0.5%		1.6%	-7.3%		-8.0%
	(1.75)		(2.41)	(2.45)		(2.09)	(0.15)		(0.51)	(-1.56)		(-1.42)
fm_{ind}	4.4%	1.8%		3.0%	1.2%		5.9%	3.1%		2.9%	1.9%	
	(2.52)	(0.83)		(1.21)	(0.32)		(2.36)	(1.34)		(0.83)	(0.45)	
bm_{ind}	0.3%		-2.8%	1.2%		-2.0%	-0.6%		-2.4%	-1.9%		-0.4%
	(0.16)		(-1.05)	(0.46)		(-0.45)	(-0.21)		(-0.80)	(-0.46)		(-0.08)

PANEL B: Equal-Weighted Portfolios

Sorting	Full Sample			1973 to 1995			1996 to 2018			Difference: Late - Early		
Variable	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]
fm	8.1%	7.2%		9.9%	10.5%		6.4%	3.9%		-3.5%	-6.6%	
	(4.58)	(4.06)		(4.22)	(4.91)		(2.42)	(1.42)		(-0.99)	(-1.88)	
bm	5.3%		5.7%	8.7%		9.5%	1.9%		2.1%	-6.8%		-7.5%
	(2.22)		(3.02)	(3.02)		(3.95)	(0.52)		(0.74)	(-1.43)		(-2.00)
fm_{ind}	3.7%	0.6%		3.1%	-1.5%		4.3%	2.8%		1.1%	4.4%	
	(2.60)	(0.47)		(1.49)	(-0.91)		(2.22)	(1.55)		(0.40)	(1.75)	
bm_{ind}	0.1%		-2.0%	2.1%		-2.2%	-1.9%		-2.3%	-4.1%		0.0%
	(0.05		(-0.99)	(0.80)		(-1.17)	(-0.46)		(-0.65)	(-0.83)		(-0.01)

Table 10
Panel Regressions of Portfolio Returns on Portfolio Deciles: The Impact of Intangibles

Portfolios are formed every June (1973 to 2018) from deciles based on the respective characteristics, which are described in Section 2. In the case of $bm^* = log(BE^*/ME)$, we adjust BE for intangibles using $BE^* = BE + K_{int} - K_{goodwill}$, with intangible capital data from Peters and Taylor (2017) (see Subsection 5.3 for details). The table reports results from panel regressions of portfolio returns on the lagged deciles for the respective variables. Subsection 4.3 provides details on the methodology. t_{stat} are in parentheses and statistical inference is based on the method in Driscoll and Kraay (1998), which is the natural generalization of Newey and West (1987, 1994) to a panel data setting and is robust to heteroskedasticity, autocorrelation, and cross-sectional correlation between portfolio returns.

PANEL A: Value-Weighted Portfolios

Sorting	Full Sample			1973 to 1995			1996 to 2018			Difference: Late - Early		
Variable	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]
fm	8.3%	8.7%	7.7%	9.3%	7.8%	7.8%	7.4%	8.7%	7.9%	-1.9%	0.8%	0.1%
	(4.50)	(4.29)	(3.30)	(3.76)	(1.95)	(1.75)	(2.68)	(3.47)	(2.93)	(-0.51)	(0.18)	(0.02)
bm	4.2%	3.6%		7.8%	4.3%		0.5%	1.5%		-7.3%	-2.8%	
	(1.75)	(1.25)		(2.45)	(0.91)		(0.15)	(0.36)		(-1.56)	(-0.44)	
bm^*	7.0%		5.2%	9.7%		5.4%	4.3%		3.5%	-5.4%		-2.0%
	(2.75)		(1.58)	(2.76)		(1.02)	(1.19)		(0.78)	(-1.06)		(-0.28)

PANEL B: Equal-Weighted Portfolios

Sorting	Full Sample			1973 to 1995			1996 to 2018			Difference: Late - Early		
Variable	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]	Univariate	[1]	[2]
fm	8.1%	7.7%	6.5%	9.9%	7.7%	6.8%	6.4%	6.8%	5.7%	-3.5%	-0.9%	-1.1%
	(4.58)	(3.62)	(2.90)	(4.22)	(2.87)	(2.46)	(2.42)	(2.42)	(1.91)	(-0.99)	(-0.23)	(-0.27)
bm	5.3%	3.3%		8.7%	4.2%		1.9%	2.1%		-6.8%	-2.1%	
	(2.22)	(1.26)		(3.02)	(1.32)		(0.52)	(0.55)		(-1.43)	(-0.42)	
bm^*	7.5%		4.8%	9.9%		5.6%	5.1%		3.8%	-4.8%		-1.7%
	(3.42)		(1.84)	(3.41)		(1.68)	(1.57)		(1.06)	(-1.11)		(-0.35)

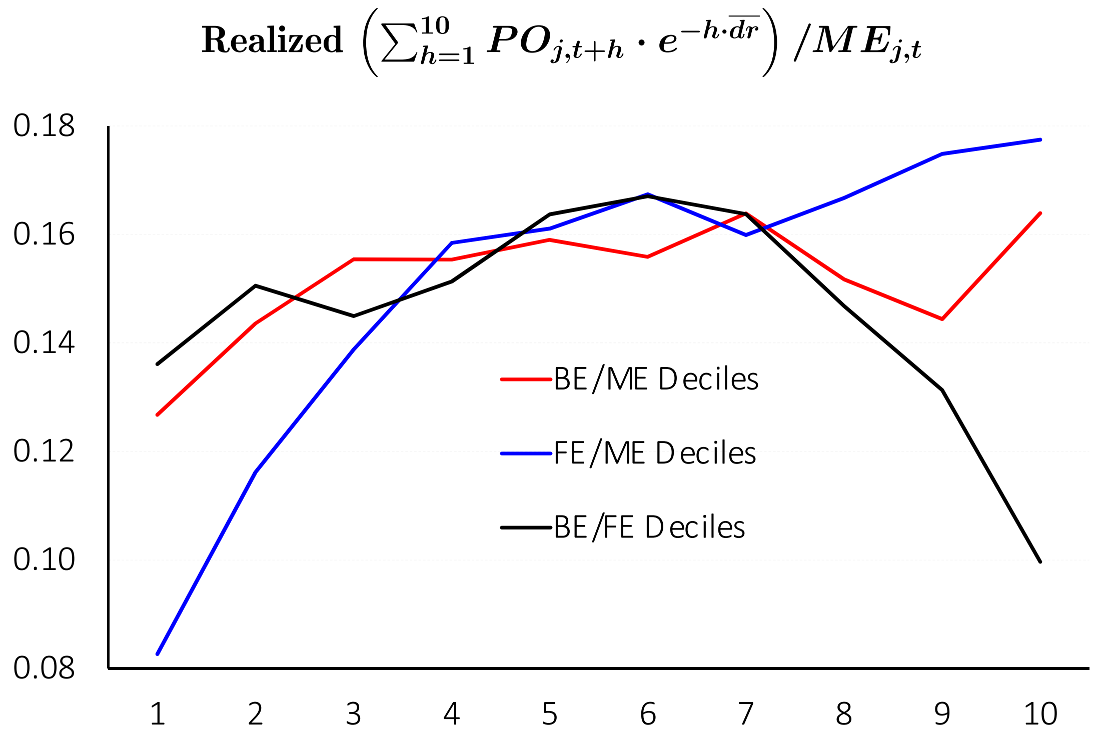
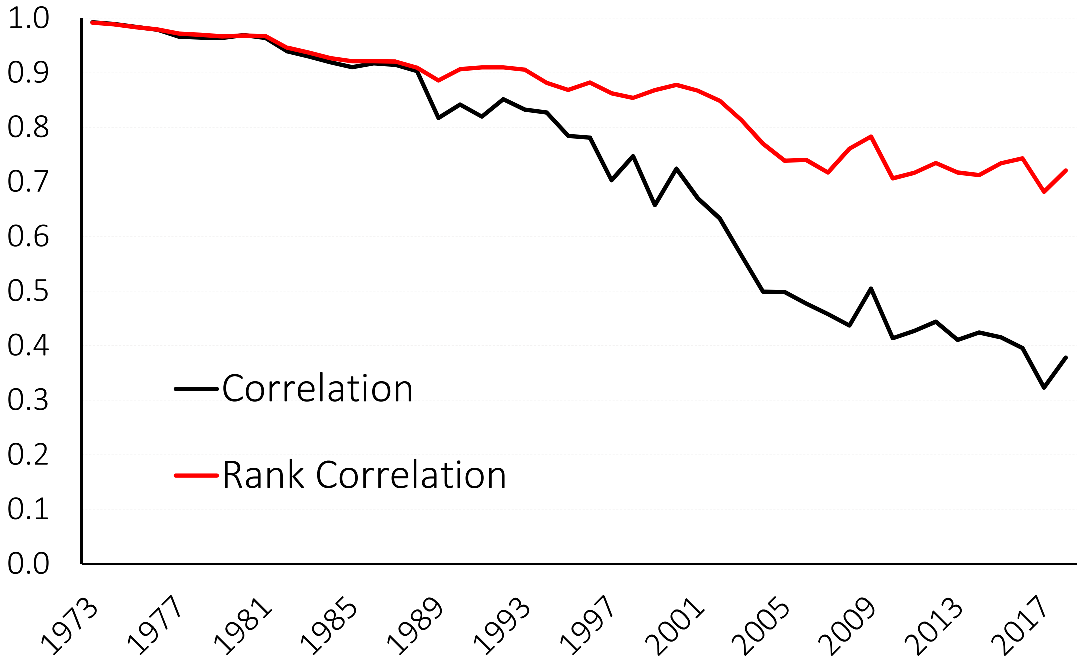


Figure 2
Realized Present Values from Firms at Different Portfolios

The graph plots the average realized FE/ME (defined in Equation 11) for decile portfolios based on the log book-to-market ratio, $bm = log(BE/ME)$, the log fundamental-to-market ratio, $fm = log(FE/ME)$, and the log book-to-fundamental ratio, $bf = log(BE/FE)$. Portfolios are formed every June (from 1973 to 2009), with the last portfolio formation year chosen to assure there are at least ten years after portfolio formation available in our sample. See Section 2 and Subsection 4.1 for further empirical details.

(a) Cross-Sectional $Cor(bm, bm^*)$



(b) Cross-Sectional $Var(be - fe)$ Decomposition

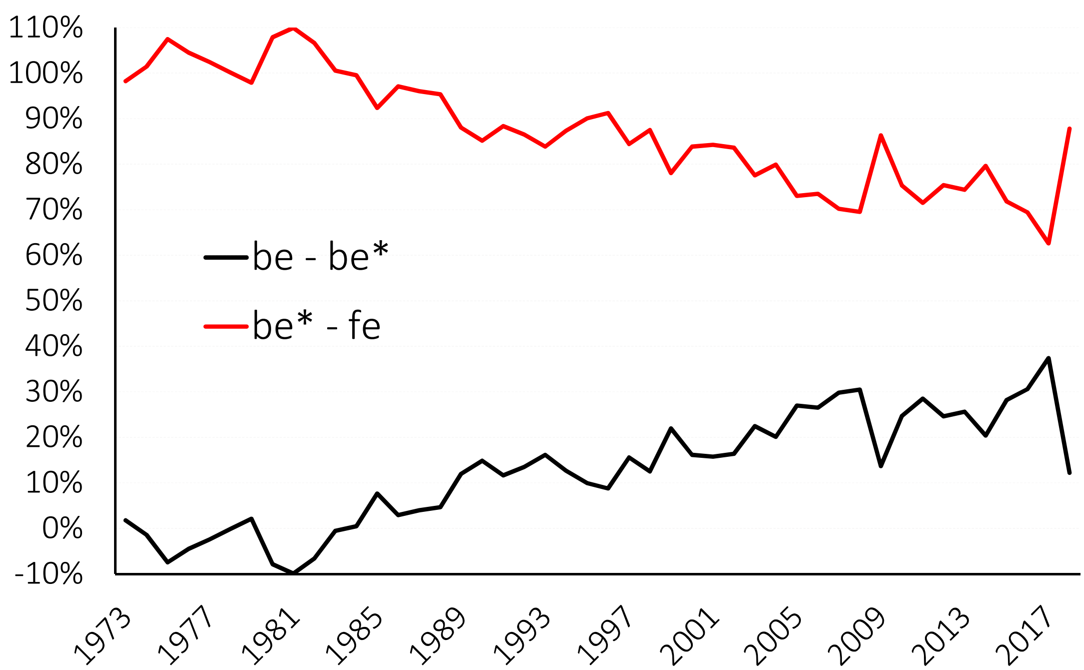


Figure 3
Cross-Sectional $Cor(bm, bm^*)$ and $Var(be - fe)$ Decomposition

Panel (a) plots the annual cross-sectional correlation between $bm = log(BE/ME)$ and $bm^* = log(BE^*/ME)$ using both linear correlation (i.e., Pearson correlation) and rank correlation (i.e, Spearman correlation). Panel (b) plots the cross-sectional decomposition $Var(be - fe) = Cov\,(be - fe\ ,\ be - be^*) + Cov\,(be - fe\ ,\ be^* - fe)$ annually, with $be = log(BE)$, $fe = log(FE)$, and $be^* = log(BE^*)$. In both panels, $BE^* = BE + K_{int} - K_{goodwill}$, with K_{int} reflecting intangible capital from Peters and Taylor (2017). See Section 2 and Subsection 5.3 for further empirical details.

Internet Appendix

"The Fundamental-to-Market Ratio"

By Andrei S. Gonçalves and Gregory Leonard

This Internet Appendix contains technical derivations required to support the analysis in the paper.

A Technical Derivations

This section omits firm's subscript, j, to simplify the notation during the derivations.

A.1 Using VAR to get $\mathbb{E}_t[PO_{t+h}]/BE_t$

From equation 3 and the conditional normality imposed by the VAR process in equation 4, we have:

$$
\begin{aligned}
\frac{\mathbb{E}_t\left[PO_{t+h}\right]}{BE_t} &= \mathbb{E}_t\left[\left(e^{CSprof_{t+h}-BEg_{t+h}+\sum_{\tau=1}^{h}BEg_{t+\tau}} - e^{\sum_{\tau=1}^{h}BEg_{t+\tau}}\right)\right] \\
&= e^{\mathbb{E}_t\left[CSprof_{t+h}-BEg_{t+h}+\sum_{\tau=1}^{h}BEg_{t+\tau}\right]+0.5\cdot Var_t\left[CSprof_{t+h}-BEg_{t+h}+\sum_{\tau=1}^{h}BEg_{t+\tau}\right]} \\
&\quad - e^{\mathbb{E}_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau}\right]+0.5\cdot Var_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau}\right]} \\
&= \left(e^{\mathbb{E}_t\left[CSprof_{t+h}-BEg_{t+h}\right]+0.5\cdot Var_t\left[CSprof_{t+h}-BEg_{t+h}\right]+Cov_t\left[CSprof_{t+h}-BEg_{t+h},\sum_{\tau=1}^{h}BEg_{t+\tau}\right]} - 1\right) \\
&\quad \times e^{\mathbb{E}_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau}\right]+0.5\cdot Var_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau}\right]} \\
&= \left[e^{(\mathbf{1}_{CSprof}-\mathbf{1}_{BEg})'\Gamma^{h}s_t+v_1(h)} - 1\right]\cdot e^{\mathbf{1}'_{BEg}\left(\sum_{\tau=1}^{h}\Gamma^{\tau}\right)\cdot s_t+h\cdot v_2(h)}
\end{aligned}
$$

which is equation 5 in subsection 1.2 with:

$$v_1(h) \;=\; 0.5\cdot Var_t\left[CSprof_{t+h}-BEg_{t+h}\right] + Cov_t\left[CSprof_{t+h}-BEg_{t+h},\sum_{\tau=1}^{h}BEg_{t+\tau}\right]$$

and

$$h\cdot v_2(h) = 0.5\cdot Var_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau}\right] = 0.5\cdot Cov_t\left[\sum_{\tau=1}^{h}BEg_{t+\tau},\sum_{\tau=1}^{h}BEg_{t+\tau}\right]$$

a) Deriving $v_1(h)$

Define $po = CSprof - BEg$ and $\mathbf{1}_{po} = \mathbf{1}_{CSprof} - \mathbf{1}_{BEg}$. Then, from the VAR structure, it is straightforward to get:

$$Var_t\left[CSprof_{t+h}-BEg_{t+h}\right] = Var_t\left[CSprof_{t+h-1}-BEg_{t+h-1}\right] + \mathbf{1}'_{po}\Gamma^{h-1}\Sigma\Gamma'^{h-1}\mathbf{1}_{po} \qquad \text{(IA.1)}$$

with boundary condition $Var_t\left[CSprof_{t+1}-BEg_{t+1}\right] = \mathbf{1}'_{po}\Sigma\mathbf{1}_{po}$.

For the other term in $v_1(h)$, which I label $Cov_1\,(h)$ for simplicity, we have $Cov_1\,(1) = Cov_t[po_{t+1}, BEg_{t+1}] = \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{BEg}$ and then:

$$\begin{aligned}
Cov_1\,(2) &= Cov_t\,[po_{t+2}, BEg_{t+1} + BEg_{t+2}] \\
&= Cov_t\,[po_{t+2}, BEg_{t+1}] + Cov_t\,[po_{t+2}, BEg_{t+2}] \\
&= Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma u_{t+1} + u_{t+2}), \mathbf{1}_{BEg}^{'}u_{t+1}\right] + Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma u_{t+1} + u_{t+2}), \mathbf{1}_{BEg}^{'}(\Gamma u_{t+1} + u_{t+2})\right] \\
&= \mathbf{1}_{po}^{'}\Gamma\Sigma\mathbf{1}_{BEg} + \mathbf{1}_{po}^{'}\Gamma\Sigma\Gamma^{'}\mathbf{1}_{BEg} + \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{BEg} \\
&= \mathbf{1}_{po}^{'}\Gamma\Sigma(\Gamma + \mathrm{I})^{'}\mathbf{1}_{BEg} + Cov_1\,(1)
\end{aligned}$$

and

$$\begin{aligned}
Cov_1\,(3) &= Cov_t\,[po_{t+3}, BEg_{t+1} + BEg_{t+2} + BEg_{t+3}] \\
&= Cov_t\,[po_{t+3}, BEg_{t+1}] + Cov_t\,[po_{t+3}, BEg_{t+2}] + Cov_t\,[po_{t+3}, BEg_{t+3}] \\
&= Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}_{BEg}^{'}u_{t+1}\right] \\
&\quad + Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}_{BEg}^{'}(\Gamma u_{t+1} + u_{t+2})\right] \\
&\quad + Cov_t\left[\mathbf{1}_{po}^{'}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3}), \mathbf{1}_{BEg}^{'}(\Gamma^2 u_{t+1} + \Gamma u_{t+2} + u_{t+3})\right] \\
&= \mathbf{1}_{po}^{'}\Gamma^2\Sigma(\Gamma^2 + \Gamma + \mathrm{I})^{'}\mathbf{1}_{BEg} + \mathbf{1}_{po}^{'}\Gamma\Sigma(\Gamma + \mathrm{I})^{'}\mathbf{1}_{BEg} + \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{BEg} \\
&= \mathbf{1}_{po}^{'}\Gamma^2\Sigma(\Gamma^2 + \Gamma + \mathrm{I})^{'}\mathbf{1}_{BEg} + Cov_1\,(2)
\end{aligned}$$

which generalizes to:

$$Cov_1\,(h) = \mathbf{1}_{po}^{'}\Gamma^{h-1}\Sigma F_1(h)^{'}\mathbf{1}_{BEg} + Cov_1\,(h-1) \tag{IA.2}$$

where $F_1(h) = F_1(h-1)\Gamma + \mathrm{I}$ with I representing an identity matrix.

Putting all terms together, we have:

$$v_1(h) = v_1(h-1) + 0.5 \cdot \mathbf{1}_{po}^{'}\Gamma^{h-1}\Sigma\Gamma^{'h-1}\mathbf{1}_{po} + \mathbf{1}_{po}^{'}\Gamma^{h-1}\Sigma F_1(h)^{'}\mathbf{1}_{BEg} \tag{IA.3}$$

with boundary condition $v_1(1) = 0.5 \cdot \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{po} + \mathbf{1}_{po}^{'}\Sigma\mathbf{1}_{BEg}$.

b) Deriving $v_2(h)$

Letting $Cov_t\left(BEg_{t+\tau}, BEg_{t+h}\right) = Cov^{BEg}_{\tau,h}$, we have $1 \cdot v_2(1) = 0.5 \cdot Cov^{BEg}_{1,1}$ and then:

$$\begin{aligned} 2 \cdot v_2\left(2\right) &= 0.5 \cdot Cov_t\left[BEg_{t+1} + BEg_{t+2}, BEg_{t+1} + BEg_{t+2}\right] \\ &= \; 0.5 \cdot (Cov^{BEg}_{1,1} + Cov^{BEg}_{2,2}) + Cov^{BEg}_{1,2} \end{aligned}$$

and

$$\begin{aligned} 3 \cdot v_2\left(3\right) &= 0.5 \cdot Cov_t\left[BEg_{t+1} + BEg_{t+2} + BEg_{t+3}, BEg_{t+1} + BEg_{t+2} + BEg_{t+3}\right] \\ &= \; 0.5 \cdot (Cov^{BEg}_{1,1} + Cov^{BEg}_{2,2} + Cov^{BEg}_{3,3}) + \left[Cov^{BEg}_{1,2} + Cov^{BEg}_{2,3} + Cov^{BEg}_{1,3}\right] \end{aligned}$$

which generalizes to:

$$h \cdot v_2\left(h\right) = \left(h-1\right) \cdot v_2\left(h-1\right) + 0.5 \cdot Cov^{BEg}_{h,h} + \sum_{i=1}^{h-1} Cov^{BEg}_{h-i,h} \tag{IA.4}$$

with boundary condition $v_2(1) = 0.5 \cdot Cov^{BEg}_{1,1}$

Hence, all we need is an expression for $Cov^{BEg}_{\tau,h}$ with $\tau = 1, 2, ..., h$. However, note that $BEg_{t+h} = u_{t+h} + \Gamma u_{t+h-1} + \Gamma^2 u_{t+h-2} + ... + \Gamma^{h-1} u_{t+1} + \Gamma^h s_t$, and thus:

$$\begin{aligned} Cov^{BEg}_{\tau,h} &= Cov_t\left(u_{t+\tau} + \Gamma u_{t+\tau-1} + ... + \Gamma^{\tau-1} u_{t+1}, u_{t+h} + \Gamma u_{t+h-1} + \Gamma^2 u_{t+h-2} + ... + \Gamma^{h-1} u_{t+1}\right) \\ &= Cov_t\left(u_{t+\tau} + \Gamma u_{t+\tau-1} + ... + \Gamma^{\tau-1} u_{t+1}, \Gamma^{h-\tau} u_{t+\tau} + \Gamma^{h-\tau+1} u_{t+\tau-1} + ... + \Gamma^{h-1} u_{t+1}\right) \\ &= \mathbf{1}'_{BEg}\left[\mathrm{I}\Sigma\Gamma'^{h-\tau} + \Gamma\Sigma\Gamma'^{h-\tau+1} + \Gamma^2\Sigma\Gamma'^{h-\tau+2} + ... + \Gamma^{\tau-1}\Sigma\Gamma'^{h-1}\right]\mathbf{1}_{BEg} && \text{(IA.5)} \\ &= \mathbf{1}'_{BEg} F_2(\tau, h) \mathbf{1}_{BEg} && \text{(IA.6)} \end{aligned}$$

with $F_2(\tau, h) = \Gamma F_2(\tau-1, h) + \mathrm{I}\Sigma\Gamma^{h-\tau}$ and boundary condition $F_2(0, h) = 0$

c) An Adjustment

The VAR implied long-term variance and covariance terms needed for $v_1(h)$ and $v_2(h)$ can be very noisy because a small estimation error in Γ or Σ can induce a substantial estimation error in such terms. As such, when estimating $v_1(h)$ and $v_2(h)$, we follow Gonçalves (2020) and replace Γ with $\Gamma_{adj} = \theta \cdot \Gamma + (1-\theta) \cdot \Gamma_{ss}$, where $\theta^{10} = 0.1$ (so $\theta \approx 0.8$) and the intercepts in

Γ_{ss} are the steady state values and all slopes being zero. This specification shrinks Γ towards the steady state to speed up the convergence of the variance/covariance terms.

A.2 The Infinite Sum in $FE_{j,t}$

While in principle the $FE_{j,t}$ in Equation 2 accounts for the present value of cash flows going to infinity, in practice (numerically) we need some approximation to deal with very long-term cash flows. We assume that cash flow growth already reached its limiting behavior at a maturity of $H = 1,000$ years. This means that (for $h \geq H$):

$$\frac{e^{-(h+1)\cdot dr} \cdot \mathbb{E}_t \left[PO_{j,t+h+1}\right] / BE_{j,t}}{e^{-h\cdot dr} \cdot \mathbb{E}_t \left[PO_{j,t+h}\right] / BE_{j,t}} = e^{\overline{BEg}+\overline{v}_2-dr} \tag{IA.7}$$

so that we can split the valuation equation into two terms:

$$\begin{aligned} FB_{j,t} &= \left(\sum_{h=1}^{H} \mathbb{E}_t \left[PO_{j,t+h}/BE_{j,t}\right] \cdot e^{-h\cdot dr}\right) + \left(\sum_{h=H+1}^{\infty} \mathbb{E}_t \left[PO_{j,t+h}/BE_{j,t}\right] \cdot e^{-h\cdot dr}\right) \\ &= \left(\sum_{h=1}^{H} \mathbb{E}_t \left[PO_{j,t+h}/BE_{j,t}\right] \cdot e^{-h\cdot dr}\right) + \mathbb{E}_t \left[PO_{j,t+H}/BE_{j,t}\right] \cdot e^{-H\cdot dr} \cdot \sum_{h=1}^{\infty} e^{h\cdot(\overline{BEg}+\overline{v}_2-dr)} \\ &= \left(\sum_{h=1}^{H} \mathbb{E}_t \left[PO_{j,t+h}/BE_{j,t}\right] \cdot e^{-h\cdot dr}\right) + \mathbb{E}_t \left[PO_{j,t+H}/BE_{j,t}\right] \cdot e^{-H\cdot dr} \cdot \overline{PV_{j,t}/CF_{j,t}} \end{aligned}$$

where $\overline{PV_{j,t}/CF_{j,t}} = e^{\overline{BEg}+\overline{v}_2-dr}/(1 - e^{\overline{BEg}+\overline{v}_2-dr})$, with $\overline{BEg}$ representing the steady-state growth in (log) book-equity (obtained from the VAR) and $\overline{v}_2$ reflecting $v_2(\infty)$, which we approximate as $v_2(H)$.

References for Internet Appendix

Gonçalves, A. S. (2020). “The Short Duration Premium”. In: *Journal of Financial Economics* Forthcoming.