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Abstract

We study the use of firms' book-to-market ratios (B/M) in value investing and its implications for comovements in firms' stock returns and trading volumes. We show B/M has become increasingly detached from common alternative valuation ratios over time while also becoming worse at forecasting future returns and growth in both an absolute and relative sense. Despite these trends, some major U.S. stock indexes and institutional funds continue relying on B/M when identifying value stocks and selecting index weights. Consistent with this reliance shaping market outcomes, we find firms' stock returns and trading volumes comove with B/M-peers (i.e., firms with similar B/M) in excess of their fundamentals, particularly among stocks held by value-oriented funds. A shift in the economy toward firms investing in knowledge and organizational capital and increasing shareholder payouts contribute to these trends. Finally, we highlight simple adjustments to B/M that mitigate these issues.

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1. Introduction

In this study, we examine the use of firms' book-to-market (B/M) ratios in value investing strategies and its implications for the cross-section of stock returns and trading activity. Our study is motivated by secular trends within the U.S. economy in recent decades that distort firms' reported book values (i.e., the shareholders' equity reported on firms' balance sheets) as an estimate of the residual liquidation value available to shareholders. Despite these trends, popular U.S. stock indexes have maintained a long-standing reliance on firms' B/M ratios when identifying value stocks and selecting index weights. Our study examines the implications of this reliance on equity market outcomes.

Our analyses proceed in two stages. First, to set the stage for our main tests, we show that B/M has gradually detached from common alternative valuation ratios over time, and that B/M has become worse at forecasting future returns and fundamental growth in both an absolute and a relative sense. Second, in our main tests, we provide evidence that stocks continue to trade as if B/M outperforms other ratios as an indicator of firms' future performance, despite the opposite being true. Specifically, we show firms' stock returns and trading volumes predictably comove along B/M in excess of fundamentals, particularly among stocks held by value-oriented funds. Together, our findings suggest some institutions have been slow to adapt to the declining relevance of book values for selecting value stocks and, in doing so, helping to shape the cross-section of stock returns and trading activity.

Dating at least as far back as Graham and Dodd (1934), academics and practitioners have used the B/M ratio to measure how cheaply firms' net assets could be acquired. Influential studies in financial economics such as Fama and French (1992) likely contributed to the prominence of B/M by highlighting a robust positive relation between B/M and firms' future stock returns. Due to the time these influential studies were written, a notable feature is that they rely on vintages of data that are now several decades old.

In recent decades, however, book values have become a less relevant valuation anchor. One reason is that, with the shift to a knowledge-based economy, public companies' most valuable "assets" are often related to intellectual property, brand recognition, and customer loyalty, which are typically omitted from firms' balance sheets.[1] For example, under GAAP accounting, firms are required to expense research and development (R&D) and advertising expenditures, which lower book values by reducing retained earnings, regardless of whether the expenditures are expected to generate net assets. Thus, when omitting key "assets" for some firms, the ratio of book values to market prices (i.e., B/M) can provide a distorted view of the value proposition of buying firms' net assets (Lev and Gu, 2016). Another distortive factor is the growing trend in shareholder payouts, for example due to share repurchases, which lower both book value and market capitalization. Because most stocks have a B/M below one, cash payouts to shareholders tend to lower a firm's B/M even if the firm's expected returns and growth prospects are unchanged.[2] Thus, similar firms can have varying B/M ratios due to different payout policies.

At the time of this writing, major stock indexes and investment firms report using B/M to identify value stocks, reflecting the continuation of a practice that has been in place for several decades (e.g., see Appendix B and C). For instance, the FTSE Russell, the top provider of style indexes in the U.S., uses B/M in determining the Russell Value 3000/2000/1000. Its methodology for identifying value stocks places 50% weight on B/M, by far the most heavily weighted input. Similarly, Barra, one of the top risk and performance tracking data providers, focuses exclusively on B/M in some of its value/growth indexes (Boyer, 2011).

Institutional investors commonly construct their product offerings to mimic or benchmark against branded indexes such as the Russell Value 3000 to attract and retain capital. Our central hypothesis is that this phenomenon causes investor demands for stocks within a given

[1]Relative to the 1950's, the value-added by manufacturing firms to the U.S. GDP fell by more than half, whereas the value-added by nontraditional sectors such as professional and business services increased increased more than three-fold (see, e.g., data compiled by the Bureau of Economic Analysis: www.bea.gov/industry/gdpbyind_data.htm).

[2]For any dividend or repurchase amount $r > 0$ and $B, M > 0$, $\frac{B}{M} > \frac{B-r}{M-r}$ *if and only if* $\frac{B}{M} < 1$.

B/M portfolio to move in concert. In turn, we expect these correlated demand shocks to result in stocks trading like their B/M peers, despite B/M losing its informativeness about similarities between firms in terms of their expected returns and growth.

Our hypotheses are motivated by prior evidence of 'style investing' in which investors trade baskets of stocks without scrutinizing the underlying securities (e.g., Barberis and Shleifer, 2003; Barberis et al., 2005). As noted in Boyer (2011), style investing is not limited to retail traders. It is common among derivative traders, index funds, and exchange-traded funds written on an index, as well as more active managers who benchmark to, and mimic, an index for protection against underperformance.

To assess the role of investors' reliance on B/M, we identify cases where B/M significantly deviates from other relative value measures that we refer to as 'benchmarks.' We intentionally select specific ratios as benchmarks of comparison that serve a similar purpose as B/M, but whose numerators are less likely affected by the secular trends in the economy that motivate our study. Specifically, our benchmarks include: sales-to-price, denoted S/P; gross-profit-to-price, denoted G/P; net payouts to shareholders-to-price, denoted N/P; and a composite, denoted COMP. By identifying significant deviations between B/M and these benchmarks, we can study how investors price and trade stocks when facing conflicting value signals.

Our empirical analysis begins by showing that the correlations between B/M and our benchmarks steadily declined over time, consistent with B/M becoming a noisier signal of stocks' value status. For example, the average cross-sectional correlation between B/M and COMP fell from approximately 0.7 to 0.45 during our 1980 to 2017 sample period. This trend of gradual detachment between the ratios coincides with a steady increase in firms' off-balance-sheet intangible assets, goodwill, and stock issuances and repurchases.

We also show that B/M has become worse at forecasting firms' returns and fundamental growth in both an absolute and a relative sense. On an absolute basis, B/M has lost its ability to forecast stock returns in recent years, whereas the same is not true of our benchmark ratios.

To assess relative performance, we identify cases where B/M substantially differs as a signal of value. In June of each year, we rank the cross-section of firms into quintiles based on B/M, and again independently rank firms into quintiles using our benchmarks. We then calculate the absolute spread in each firm's B/M ranking relative to its ranking based on our benchmarks, denoted *RatioSpread*. Higher values of *RatioSpread* correspond to cases where firms appear as value firms in terms of B/M but as glamour firms in terms of our benchmarks, or as glamour firms in terms of B/M but as value firms in terms of our benchmarks. We show extreme values of *RatioSpread* have become increasingly prevalent over time.

When *RatioSpread* is large, B/M performs predictably worse in forecasting future stock returns and growth in firms' fundamentals. These findings illustrate that B/M has become a noisier measure of expected returns and growth, particularly in cases where it deviates from benchmark valuation ratios. Thus, in the absence of the frictions we hypothesize, investors should substitute away from B/M for value investing, especially when B/M differs from other ratios. Our results suggest, however, that the opposite is true on average.

The main result of the paper is that B/M better explains variation in market outcomes than our benchmarks. Specifically, firms' stock returns are more correlated with the contemporaneous returns of B/M-similar stocks than the returns of benchmark-similar stocks. These empirical patterns are also present in trading volumes. A striking finding is that our results actually strengthen for larger values of *RatioSpread*. These results suggest that investors, on average, anchor on B/M in pricing and trading stocks, even as B/M deviates further from other value signals and becomes a predictably noisier signal.

Our next tests explore two implications of the hypothesis that our findings stem from institutional reliance on B/M within value investing. First, we show that excess comovements in firms' returns and trading volumes are strongest among stocks held by more value-oriented funds that trade based on B/M. These findings are consistent with value-oriented institutions responding to fund inflows and outflows by trading baskets of stocks grouped by B/M.

Additionally, we show our main findings concentrate in cases where firms appear as a value stock in terms of B/M (and hence a candidate to buy) but as a glamour stock in terms of our benchmarks. These results are intuitive because index tracking funds are far more likely to buy value stocks than short glamour stocks due to short-sale constraints and/or contractual mandates against shorting. Thus, our findings are consistent with our main results stemming from price pressure from long-biased index tracking funds.

In the absence of price pressure from long-biased funds, we also expect that investors will price and trade stocks along our benchmark ratios. This is because our benchmarks better signal firms' expected returns and growth prospects. Consistent with this prediction, we find firms' returns and trading volumes correlate more with benchmark-peers (i.e., firms with similar benchmark ratios) compared to B/M-peers, in cases where the firms appear as a value stock in terms of our benchmarks but as a glamour stock in terms of B/M.

We also provide evidence consistent with the institutional reliance on B/M having a distortionary effect on some firms' costs of capital. Specifically, firms' annual stock returns are predictably lower in cases where the firm appears as a value stock in terms of B/M but as a glamour stock in terms of our benchmarks. These findings are consistent with buying pressure from value-index tracking funds artificially inflating prices among some firms.

In the final section of our paper, we provide evidence on the source of noise in B/M and explain the implications for B/M's use as a value signal. We first show B/M is predictably low relative to benchmarks for firms that invest heavily in off-balance-sheet intangible assets [i.e., expenditures on R&D or SG&A or what Peters and Taylor (2017) refers to as investments in knowledge and organizational capital] and those that engage in greater shareholder payouts. Conversely, we show B/M is predictably high relative to benchmarks for firms with high levels of goodwill intangible assets. These findings illustrate how the realignment of the economy and secular changes in corporate finance decisions contribute to the growing spread between B/M and alternative valuation ratios.

We conclude the paper by demonstrating how, with appropriate adjustments, investors can improve the usefulness of B/M in value strategies. First, we corroborate our main findings when replacing our benchmarks with an estimate of what B/M would look like after adjusting book value for investments (i.e., capitalizing expenditures) in intellectual and brand capital, and goodwill. These findings highlight the efficacy of adding back assets omitted from firms' book values to mitigate noise in B/M as a value signal.[3]

We also show that our main findings are preserved when replacing our benchmarks with a intrinsic-value-to-price ratio constructed using a linear combination of B/M and price-scaled discounted future residual income (Frankel and Lee, 1998). This finding is not surprising: the residual-income valuation model is algebraically equivalent to a discounted cash flow model, and distortions in accounting do not impact expected future cash flows.[4] Collectively, these results mitigate concerns that our inferences are sensitive to the choice of benchmarks used in our main tests, while also underscoring the usefulness of understanding accounting-based valuation models and financial reporting rules for value investors.

A central contribution of our paper is in studying how the continued use of B/M for value investing shapes outcomes of interest to financial economists. Our findings are thus related to Boyer (2011) who shows that arbitrary changes in Barra's value/growth index elicit comovements in firms' returns in excess of fundamentals. We complement and extend the findings in Boyer (2011) by highlighting increased noise in firms' book values as an additional driver of changes in stock comovements. Thus, our findings highlight market distortions specifically attributable to the delayed adaptation to changes in firms' book values rather than those attributable to changes to a given index.[5]

[3]These adjustments are also consistent with the adjustments by some practitioners. For example, in 2020, Institutional Shareholder Services (ISS) introduced a new performance measure, economic value-added, which will be used to help evaluate firm performance. To compute this measure, the ISS adjusts total assets by capitalizing R&D and SG&A expenses and depreciating these intangible investments over time. Credit Suisse's HOLT group performs similar adjustments.

[4]Downward distortions in book value, for example due to expensing of investments, are compensated for in the residual-income model through higher expected return on equity, and vice versa for upward distortions.

[5]An extensive literature in economics has examined how inefficient standards can persist over time (David, 1985) and why institutions may be slow to adopt or update standards (Clements, 2005).

Our findings point to a form of institutional inertia or path dependence in financial markets, where some key market participants continue to rely on signals that previously worked well, despite a steady decline in signal content. A likely explanation for this phenomenon is that some market participants, such as index providers, are reluctant to modify products due to costs of recalibrating performance around methodological changes. This reluctance is likely to be especially strong when it is uncertain whether the change would meaningfully boost revenues or whether the performance gains from the change are likely transitory.

Our study also relates to research highlighting the increased difficulty of inferring firms' economic profits and values from financial statements within the modern economy (e.g., Lev and Gu, 2016; Rouen et al., 2021). Related studies also point specifically to noise in firms' book values and the declining returns to value investing (e.g., Chan et al., 2001; McNichols et al., 2014; Fama and French, 2015; Ball et al., 2020; Lev and Srivastava, 2020). Our findings complement and extend these studies by highlighting excess correlations in market outcomes that result from the apparent failure of some market participants to substitute away from B/M, despite the presence of adjusted value signals that better reflect expected returns.

2. Empirical Results

The primary dataset for our analyses stems from publicly available sources: we obtain financial statement data from Compustat, market data from CRSP, and mutual fund holdings data from the Thomson Reuters S12 database. We first take ordinary common stocks with positive book values and are traded on NYSE, Amex, and NASDAQ. Following Edelen et al. (2016), we exclude financial firms and firms with share prices less than $5, although our main inferences are not sensitive to these choices. We require the stock to have at least ten months of observations to compute the past 12-month returns and adjust for delisting returns following Shumway and Warther (1999). The final sample consists of 84,837 firm-year observations from 1980 to 2017.

2.1. Book-to-Market and Benchmarks of Comparison

To assess the role of investors' reliance specifically on B/M, we identify cases where B/M significantly deviates from benchmark measures of relative value: sales-to-price ("S/P"), gross-profit-to-price ("G/P"), net payouts-to-price ("N/P"), and a composite based on the first principal component of the three multiples ("COMP").[6] We intentionally select these specific ratios as benchmarks of comparison for B/M because they also measure market prices relative to fundamentals but are less affected by some of the secular changes that motivate our study. For instance, growing R&D and SG&A expenditures likely add noise to book values as net asset estimates; in such cases, book values fail to capture firms' intellectual and organizational capital. By contrast, sales and gross profit are not prone to this issue. We also use net payouts-to-price to identify firms that return high amounts of cash to shareholders relative to market prices. Whereas higher payout yields suggest a more attractive value proposition for investors, they also result in distortions (declines) in B/M, leading to potential deviations between N/P and B/M.

We calculate each ratio at the end of June each year using data from firms' most recent 10K filings. We conservatively require a minimum six-month gap between firms' fiscal period end and the June portfolio formation date to mitigate potential look-ahead bias. We scale each measure by firms' market capitalization in December of the prior year following Fama and French (1992). We then rank firms each year into quintiles based on B/M and again independently rank firms into quintiles using our benchmarks (i.e., S/P, G/P, N/P, and COMP) using NYSE breakpoints following Lettau et al. (2018).

Figure 1, Panel A, shows that the correlation between B/M and our benchmarks has steadily declined over time. For example, the average cross-sectional correlation between B/M and COMP fell from approximately 75% to 45% during our 1980 to 2017 sample period.

[6] We compute the principal component each year. It is is essentially a weighted average of S/P, G/P, and N/P, with average weights of 43%, 43%, and 13% weights, respectively, and it explains 60% of the total variance on average.

Related evidence in Figure 1, Panels B through D, shows that this trend coincides with a steady increase in firms' off-balance-sheet intangible assets, goodwill, and stock issuances and repurchases. These findings are consistent with B/M becoming a noisier signal of stocks' value status due, in part, to changes in firm behavior.[7]

A key variable in our analysis is the extent to which B/M differs from benchmark ratios. This variable plays a key role for two reasons. First, we expect more significant deviations from our benchmarks signal noise in B/M, and thus that B/M does a poorer job in forecasting firms' future stock returns and growth. Second, by identifying significant deviations between B/M and our benchmarks, we examine how investors price and trade stocks when faced with discordant signals about a stock's value proposition.

For each firm, we calculate the spread in the firm's benchmark ranking relative to its corresponding B/M ranking, denoted *RatioSpread*. Specifically, we define *RatioSpread* as the absolute difference between the quintile rankings of B/M and the given benchmark. For example, if a firm ranks in the same quintile of B/M and a given benchmark, *RatioSpread* equals zero. Higher values of *RatioSpread* correspond to cases where firms appear as value firms in terms of B/M but as glamour firms in terms of our benchmarks or vice versa.

As noted in the Introduction, our study is motivated by secular trends within the U.S. economy that have changed the nature of firms' reported book values. Consistent with this motivation, Panel A of Table 1 and Figure 1 highlight a gradual shift in the distribution of *RatioSpread* away from zero. For example, the frequency and total market capitalization of cases where *RatioSpread* takes on extreme values steadily increase over our sample period. Moreover, relative to the total number of firms, the proportion of firms with extreme values (*RatioSpread* of 3 or 4) has increased from 6.7% in the 1980-1991 period to 8.1% and 11% in the 1992-2004 and 2005-2017 periods. Similarly, relative to the total market capitalization

[7]Practitioners and journalists have increasingly pointed to this form of noise in firms' book values (e.g., Fairchild, 2018). Another potential source of noise in firms' book values stems from the depreciation of long-term assets that retain value but are absent from firms' balance sheets. For example, firms with significant real estate investments likely depreciate these assets on their balance sheet regardless of whether they increased in value.

of firms, the proportion of firms with extreme values has increased from 3.7% in the 1980-1991 period to 4.9% and 7.9% in the 1992-2004 and 2005-2017 periods. We depict these trends in Figure 2. Together, these findings indicate that B/M has gradually decoupled from alternative valuation ratios and investors are increasingly faced with valuation ratios that make opposite predictions about the value proposition of buying a firm's stock.

Table 1, Panel B, provides descriptive statistics for each *RatioSpread* portfolio. The top half of the panel reports pooled means of firms' background characteristics and the bottom half of the panel reports pooled correlations between B/M and our benchmark valuation ratios. Firms with higher values of *RatioSpread* tend to have lower market capitalization and recent return momentum, but appear quite similar in terms of their average asset base, share turnover, and firm age. The negative link between *RatioSpread* and firm size is important because it suggests that B/M is poorer at predicting future returns when *RatioSpread* is high despite market frictions being larger among small firms. The bottom rows of Panel B also highlight that, by construction, the correlations between B/M and our benchmarks decline with *RatioSpread* and become negative for more extreme values.

2.2. Signal Content of B/M

Our next tests examine the signal content of B/M by testing its predictive power for firms' future returns and fundamental growth over time. Table 1, Panel C, compares the return predictability of B/M and our composite benchmark COMP over time. We measure returns over the 12-months following portfolio formation in June of each year, and estimate Fama-MacBeth regressions of one-month-ahead returns on the quintile rankings of the valuation ratio for three sub-periods in our sample (as in Panel A).

Table 1 shows that although B/M quintiles exhibit positive and significant (at the 5% levels) coefficients for the 1980-1991 and 1992-2004 periods, the coefficient is substantially attenuated and statistically insignificant at the 10% level in the 2005-2017 period. In contrast, COMP quintiles exhibit positive and significant coefficients for all three sub-periods, suggesting that stocks with high fundamentals relative to prices (i.e., value stocks) consistently outperform stocks with low fundamentals to prices (i.e., glamour stocks). Together, these findings point to a time-series decline in the signal content of B/M, rather than the overall efficacy of value investing disappearing.

To supplement our time-series tests, we also explore how the signal content of B/M varies cross-sectionally. Table 2, Panel A, examines the link between B/M and future returns in Fama-MacBeth regressions conditional upon its divergence from our benchmarks. To the extent *RatioSpread* signals B/M as a noisier measure of value, we expect B/M's return forecasting ability to deteriorate when as *RatioSpread* increases. In columns (1) through (4), we find that the main effect of B/M on future returns is positive and statistically significant at the 1% level. This suggests that when *RatioSpread* is 0 (when B/M is a relatively precise value signal), B/M positively predicts future returns. However, the negative and statistically significant (at the 1%) coefficient on the interaction term between B/M and *RatioSpread* illustrates that B/M becomes predictably noisier as a measure of expected returns when *RatioSpread* is large. By contrast, column (5) of Table 2, Panel A, shows that while the main effect of our composite benchmark, COMP, on future returns is also positive and statistically significant at the 1% level, the interaction effect is statistically insignificant at the 10% level. Corroborating evidence in Figure 3 plots the time-series of returns to each strategy, which shows that the time-series decline in B/M's predictive power is driven primarily by cases where *RatioSpread* is large.

Table 2, Panel B, examines the link between B/M and future growth in firms' fundamentals and how this relation varies with *RatioSpread*. We focus on sales growth following Lakonishok et al. (1994) as a measure of fundamental growth, which avoids complications arising from measuring earnings growth for firms with negative or zero earnings. A common interpretation of B/M is that it captures expectations over firms' growth potential, where lower values of B/M reflect firms' greater ability to grow retained earnings (and thus book value). Consistent with this idea, in columns (1) through (4), we find that the main effect of B/M on future growth is positive and statistically significant at the 1% level, suggesting that when *RatioSpread* is 0 (when B/M is a relatively precise value signal), B/M negatively predicts future growth. However, these specifications also highlight the consistently positive and statistically significant (at the 1%) coefficient on the interaction term between B/M and *RatioSpread*, suggesting that the main effect of B/M on future growth in firms' fundamentals predictably weakens as *RatioSpread* takes on larger values. Mirroring the results in Panel A, Table 2, the main effect of COMP is negative and statistically significant at the 1% level; however, we do not find a statistically significant coefficient (at the 10% level) on the interaction term.

Together, the results of Table 2 jointly illustrate that B/M is a particularly noisy measure of expected returns and growth when it significantly deviates from our benchmark valuation ratios. Thus, in the absence of the frictions we hypothesize, we would expect investors to substitute away from B/M for value investing, particularly in cases where B/M deviates substantially from other ratios (i.e., when *RatioSpread* is large).

2.3. Comovements in Returns and Trading Volumes

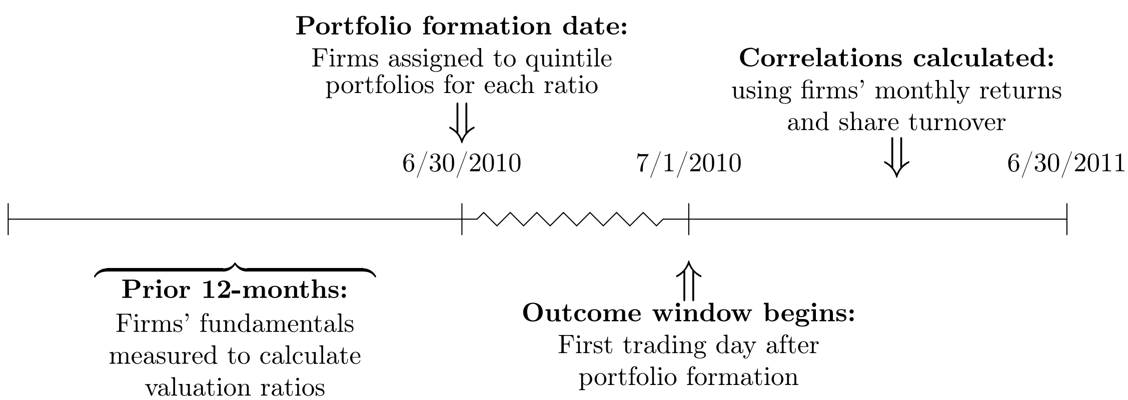
Major stock indexes and investment firms continue using B/M to identify value stocks despite the decline in B/M's signal content highlighted above. Our central hypothesis is that this behavior causes investor demands for stocks within a given B/M portfolio to move in concert. In turn, we expect these correlated demand shocks to result in stocks trading like their B/M peers. We test this prediction by first examining whether firms' stock returns are more correlated with the contemporaneous returns of stocks with similar B/M (i.e., B/M-peers) than those with similar benchmark ratios (i.e., benchmark-peers).

For each stock i, we calculate its corresponding B/M, S/P, G/P, N/P, and COMP portfolio returns. Stock i's corresponding portfolio consists of peer stocks within the same quintile of a given valuation ratio. For example, we compare the returns of a stock with a B/M below the 20th percentile of the sample distribution against the average return of *other* firms in the lowest B/M quintile. We form portfolios at the end of June in year t and exclude the stock itself when calculating the return of its corresponding portfolio to avoid a mechanical correlation (Wahal and Yavuz, 2013).

Table 3 tests the extent to which stock i's returns are better explained by (i.e., correlated with) the contemporaneous returns of stocks with similar B/M versus a given benchmark (i.e., S/P, G/P, N/P, and COMP). To measure these correlations for each benchmark, we construct the firm-year measure *CorrelationSpread* as follows:

$$CorrelationSpread_{i,t} = \rho_{i,t}(Ret_{i,m},\ PortRet_{i,m}^{B/M}) - \rho_{i,t}(Ret_{i,m}, PortRet_{i,m}^{Benchmark})$$

where $\rho_{i,t}(Ret_{i,m},\ PortRet_{i,m}^{B/M})$ refers to the year t correlation between stock i's monthly returns (indexed by m) and the contemporaneous value-weighted returns of its corresponding B/M portfolio. $\rho_{i,t}(Ret_{i,m}, PortRet_{i,m}^{Benchmark})$ is defined analogously for each benchmark.



A point of emphasis is that we construct *CorrelationSpread* by using stock returns in the 12-months *after* the valuation ratios are observed and stocks are assigned to portfolios. We rely on post-assignment returns to study how investors price stocks conditional upon observing the underlying ratios we study. For example, as depicted in the timeline above, *CorrelationSpread* for firm i in the year 2010 corresponds to value signals observed in June of 2010, and the monthly returns used to calculate the correlations are measured from July of 2010 to June of 2011.

Panel A of Table 3 shows that *CorrelationSpread* is positive on average and increases nearly monotonically with *RatioSpread* for all four benchmark ratios. Firms' stock returns actually covary more with the benchmark portfolio in cases where B/M and the benchmark both identify the stock in the same quintile (i.e., *RatioSpread* equals zero). However, as *RatioSpread* increases, firms' stock returns increasingly covary more with their B/M-peers than their benchmark-peers. In economic terms, for example, among cases where B/M and COMP are in opposite extremes (i.e., *RatioSpread* equals four), their returns have a correlation that is approximately 0.015 higher with the returns of B/M-peers than the returns of COMP-peers. The results corresponding to COMP suggest an economically large effect: a one-unit increase in *RatioSpread* results in *CorrelationSpread* roughly doubling on average.[8]

A central inference in our paper is that stocks display correlations in returns in excess of fundamentals. To help illustrate this point, Figure 4 plots two series depicting average correlations as a function of *RatioSpread*. The first series (shown in blue) plots the results from Panel A of Table 3, which shows that stocks' returns become relatively more correlated with their B/M peer as *RatioSpread* increases. The second series (shown in red) plots an analogous series based on the correlations between the valuation ratios and future fundamental growth. The downward trend in the second series illustrates that B/M becomes relatively poorer, compared to COMP, in explaining realized growth in firms' sales. The conflicting trends in Figure 4 help illustrate that investors weigh B/M more heavily in forming portfolios, even as it becomes a significantly worse signal of firms' fundamentals.

To account for firm- and year-specific effects that may drive correlations in firms' stock returns, we also run panel regressions of the following form in Panel B of Table 3:

$$CorrelationSpread_{i,t} = \beta_1 RatioSpread_{i,t} + \sum_{i,t,j} \beta_j Controls_{i,t} + \gamma_i + \psi_t + \epsilon_{i,t} \tag{1}$$

[8]The coefficient on *RatioSpread* is 0.0036 (0.0022) in Table 3 (Table 4) between B/M and COMP. Given that the mean *CorrelationSpread* (*CorrTurnSpread*) between B/M and COMP is 0.0027, this represents approximately 133% (122%) increase with one unit increase in *RatioSpread*.

where γ_i and ψ_t reflect firm- and year-fixed effects, respectively. We also include controls for firm size and historical return volatility. The results in Panel B, Table 3, show a robust positive β_1 coefficient on *RatioSpread*, suggesting that investors on average more heavily anchor on B/M in pricing, even as B/M deviates further from our benchmarks and becomes a predictably noisier signal for value investing.

Figure 5 provides corroborating evidence when measuring comovements using firms' return betas estimated from monthly returns in place of return correlations. Specifically, the figure plots the coefficients of the following regression across three subsamples of *RatioSpread*:

$$Ret_{i,m,t} = \beta_1 PortRet^{B/M}_{i,m,t} + \beta_2 PortRet^{COMP}_{i,m,t} + \gamma_i + \psi_t + \epsilon, \tag{2}$$

where $Ret_{i,m,t}$ refers to firm i's return at month m of year t and $PortRet^{B/M}_{i,m,t}$ ($PortRet^{COMP}_{i,m,t}$) refers to firm i's corresponding book-to-market (composite valuation signal) portfolio return at month m of year t. The estimated β coefficients thus capture the relative degree of comovement between a stock and the two portfolios.

In Figure 5, the red-striped bars show stocks' betas with respect to their corresponding B/M portfolio return increase with *RatioSpread*. By contrast, the blue bars show stocks' betas with respect to their corresponding benchmark portfolio return decrease with *RatioSpread*. Moreover, F-tests indicate that stocks trade significantly more like benchmark peers when *RatioSpread* is zero, but become more closely aligned with B/M-peers as *RatioSpread* grows. The reversal of betas across groupings of *RatioSpread* reinforces the inference that investors shape the cross-section of returns by grouping stocks based on B/M.

To the extent institutions group and trade stocks based on B/M, we also expect this behavior to shape comovements in firms' trading activity. Building upon our tests regarding return correlations, Table 4 contains analogous tests that study comovements in stocks' share turnover, measured as the monthly trading volume scaled by total shares outstanding. The main dependent variable in Table 4 measures correlations in firms' turnover relative to the average turnover of their corresponding portfolios:

$$CorrTurnSpread_{i,t} = \rho_t(Turn_{i,m}, PortTurn_{i,m}^{B/M}) - \rho_t(Turn_{i,m}, PortTurn_{i,m}^{Benchmark})$$

where $\rho_{i,t}(Turn_{i,m},\ PortTurn_{i,m}^{B/M})$ refers to the correlation in year t between stock i's monthly turnover (indexed by m) and the contemporaneous average turnover of its corresponding B/M portfolio. Similarly, $\rho_{i,t}(Turn_{i,m}, PortTurn_{i,m}^{Benchmark})$ is defined analogously for each benchmark.

Both univariate and multivariate tests in Table 4 show stocks' share turnover comove relatively more with its B/M peers when investors are faced with a disagreement among signals of relative value. As *RatioSpread* increases, stocks' trading activity tends to become increasingly aligned with the trading activity of stocks with similar B/M rather than the trading activity of stocks with similar benchmark valuation ratios. These results relate to prior evidence of investors grouping stocks based on price levels or index inclusions (e.g., Boyer (2011), Green and Hwang (2009)) that deviate from the predictions of frictionless models. Taken together, the results in this section suggest investors on average more heavily anchor on B/M when forming portfolios and trading stocks, even as B/M deviates further from other ratios and becomes a predictably noisier signal for value investing.

3. Mechanisms

This section explores two implications of the hypothesis that our findings stem from institutional reliance on B/M when value investing.

3.1. Fund Holdings Tests

To assess the role of institutions in driving our main findings, we exploit cross-sectional variation in institutional holdings. Specifically, we focus on the extent to which a stock is held by institutional funds that appear to group stocks by, and trade on, firms' B/M. The intuition for these tests is that more significant holdings by these funds cause stocks' returns and trading volumes to comove with B/M peers as the funds expand and contract their portfolios in response to fluctuations in capital inflows and outflows.

To identify funds that trade specifically on B/M, we follow the approach detailed in Lettau et al. (2018). Specifically, Lettau et al. (2018) constructs characteristics of funds by assigning a characteristic score of the individual stocks and computing the portfolio-weighted average of the characteristic scores of the stocks in the fund's portfolio. We compute the characteristic score of a given fund f as of June in year t, $C_{f,t}$ as:

$$C_{f,t} = \Sigma w_{f,i,t} C_{i,t}$$

where $w_{f,i,t}$ is the weight of stock i in the portfolio of fund f in year t, and $C_{i,t} = j,\ j \in \{1, 2, 3, 4, 5\}$ is the assigned characteristic score of stock i in year t based on the quintile rank j with respect to the multiple. For instance, if a particular fund holds only high B/M-value stocks (i.e., $C_{i,t} = 5$) in a given year, then the fund is assumed to be following a B/M-oriented value strategy. We define funds in the top tercile of the fund characteristic score as those that trade on a given valuation ratio (i.e., B/M, S/P, G/P, N/P, and COMP).

To facilitate our analyses, we derive a measure that allows us to hone in specifically on the impact of holdings from funds that appear to emphasize B/M, rather than value strategies as a whole. We estimate the extent to which B/M-oriented funds hold a given stock in excess of the holdings by funds that trade based on our benchmark ratios (i.e., S/P, G/P, N/P, and COMP). We calculate this spread in holdings for each stock i in June of year t as follows:

$$HoldingsSpread_{i,t} = \frac{(FundHoldings_{i,t}^{B/M} - FundHoldings_{i,t}^{Benchmark})}{SharesOutstanding_{i,t}}$$

where $FundHoldings_{i,t}^{B/M}$ and $FundHoldings_{i,t}^{Benchmark}$ denote the total number of shares of stock i held of B/M-oriented funds and the number of shares of stock i held by funds oriented to a given benchmark, respectively, and $SharesOutstanding_{i,t}$ denotes firms' total shares outstanding. Higher values of $HoldingsSpread_{i,t}$ indicate that a greater fraction of stock i's shares are held by funds that trade stocks specifically based on B/M.

Table 5 shows that our main results on excess return and turnover correlations concentrate in cases where $HoldingsSpread_{i,t}$ is large. Specifically, the positive interaction effect between *RatioSpread* and $HoldingsSpread_{i,t}$ indicate that excess comovements in firms' returns (Panel A) and trading volumes (Panel B) are strongest among stocks held by more value-oriented funds that trade based on B/M.[9] These findings are consistent with our findings being driven in part by institutional reliance on B/M for value investing. Specifically, they suggest that value-oriented institutions responding to fund inflows and outflows by trading baskets of stocks grouped by B/M.

In Table 6, we provide another test of the institutional reliance on B/M. Specifically, we show our main findings on excess return and turnover correlations concentrate in cases where firms appear as a value stock in terms of B/M (and hence a candidate to buy) but as a glamour stock in terms of our benchmarks. For example, the column heading in Table 6 indicating "B/M » Benchmark" denotes the subsample where firms appear more attractive as a value stock based on B/M than based on the corresponding benchmark. Columns (1) through (4) of both Panels A and B show that our main findings on excess correlations in returns and trading volumes tend to concentrate in cases where firms are ranked in a higher quintile of B/M than our benchmarks. These results are intuitive because index-tracking funds tend to 'long-biased' in that they are far more likely to buy value stocks than short glamour stocks due to short-sale constraints or contractual mandates.

In the absence of price pressure from long-biased funds, we also expect investors to trade stocks based on our benchmark ratios. This is because our benchmarks better signal firms'

[9]Interpreting the economically magnitude of the estimates from Panel A, column 8, increasing the holdings by B/M funds relative to COMP funds by 1% leads to an increase in the effect of *RatioSpread* by 0.001 ($= 0.137 \times 0.01$). Considering that the main effect on *RatioSpread* is 0.003, this represents approximately 33% increase in the effect of *RatioSpread* on $CorrelationSpread$.

expected returns and growth prospects. Consistent with this prediction, columns (5) through (8) of Table 6 show that firms' returns and trading volumes correlate more with benchmark peers (i.e., firms with similar benchmark ratios) compared to B/M-peers, in cases where the firms appear as a value stock in terms of our benchmarks but as a glamour stock in terms of B/M (i.e., the "B/M « Benchmark" subsample).

Finally, if our main results are driven by price pressure from long-biased funds, we expect return reversals when B/M is particularly noisy (i.e., *RatioSpread* is high). In Table 7, we examine the association between *RatioSpread* and future stock returns in the 13 to 24 months, 25 to 36 months, and 37 to 48 months after portfolio formation for two subsamples: the "B/M » Benchmark" subsample in which we expect greater price pressures from long-biased funds that are B/M oriented and the "B/M « Benchmark" in which we do not expect these price pressures. Consistent with our hypothesis, columns (1) and (2) report negative and statistically significant (at the 5% levels) coefficients on *RatioSpread* for the "B/M » Benchmark" subsample, suggesting long-term return reversals when B/M is particularly noisy and stocks are more likely to be subject to the price pressures of B/M-oriented funds. In contrast, columns (4) through (6) report both statistically and economically insignificant coefficients on *RatioSpread* for the "B/M « Benchmark" subsample. Taken together, the results in this section provide suggest that our main results are driven by price pressure from long-biased who rely on B/M when forming value-oriented portfolios.

4. Drivers of book values and simple adjustments

In the final section of our paper, we establish the links between our main findings and firm behavior as well as secular changes in the economy. We also illustrate approaches for adjusting firms' book values to remove noise in B/M as a signal of value.

4.1. Links to Firm Behavior and Secular Changes

In Table 8, we examine how firm-level characteristics relate to the spread between B/M and our benchmark ratios. For these tests, we measure the *signed* difference between a firm's quintile ranking in B/M and its quintile ranking in our composite measure, COMP. We focus on the signed difference because many of the drivers we consider have a clear prediction on whether it will raise or lower firms' book values in a relative sense. In Table 8, we estimate the following pooled OLS regression:

$$Quintile_{i,t}^{COMP} - Quintile_{i,t}^{B/M} = \beta_1 Know_{i,t} + \beta_2 Org_{i,t} + \beta_3 Gdwl + \beta_4 ShareholderPayouts_{i,t} + \beta_5 Leverage_{i,t} + \gamma_i + \psi_t + \epsilon_{i,t} \tag{3}$$

where $Quintile_{i,t}^{COMP}$ denotes firms quintile ranking along COMP and $Quintile_{i,t}^{B/M}$ denotes firms quintile ranking along B/M. *Gdwl*, *Shareholder Payouts*, and *Leverage* represent the extent of goodwill, cumulative net shareholder payouts, and long-term debt reported in firms' financial statements and scaled by total assets. *Know* and *Org* refers to measures of firms' knowledge and organizational capital following Peters and Taylor (2017), where knowledge capital equals the accumulation of past R&D spending, and organizational capital is a fraction of SG&A spending using the perpetual inventory method.[10] We include firms' leverage in the regression to control for firms financing their operations via debt.

In Table 8, we test three predictions regarding the drivers of the spread between B/M and COMP. First, we expect that greater expensing of investments in R&D and organizational capital artificially suppresses B/M relative to our benchmark ratios. That is, the more firms make these investments, which lower book values by reducing retained earnings, the more likely they appear expensive in terms of B/M relative to our benchmarks. Second,

[10] Peters and Taylor (2017) assume that 30% of SG&A (net of R&D expense) is invested towards organizational capital, which includes human capital, brand, and customer relationships. We additionally compare the reported advertising expense with the calculated organizational expense and take the higher of the two numbers. The correlation between our measure and the original measure for organizational capital is 0.94. Our results are unchanged when we replace our modified organizational measure with the Peters and Taylor (2017) measure.

we expect that larger amounts of goodwill on the balance sheet, which has been relatively inflated and untimely impaired since SFAS 142 (Li and Sloan, 2017), artificially inflates B/M by retaining synergy-related assets created through acquisitions, rather than expensing them through retained earnings. Thus, we expect that firms with more goodwill will appear cheaper in B/M than our benchmarks. Finally, we expect that greater shareholder payouts will disproportionately lower B/M relative to other benchmarks. This is because most stocks have a B/M below 1 and shareholder payouts (which lower both book values and total market capitalization mechanically lower B/M even if expected returns and growth are unchanged. Thus, otherwise similar firms that engage in a greater degree of payouts will appear relatively expensive in terms of B/M.

In Table 8, we show B/M is predictably high relative to our benchmarks for firms that invest heavily in knowledge and organizational capital and those that engage in more significant shareholder payouts. Conversely, we show B/M is predictably low relative to our benchmarks for firms with high levels of goodwill intangible assets. These findings help illustrate how the realignment of the economy and secular changes in corporate finance decisions contributed to the growing spread between B/M and alternative valuation ratios.

The evidence in Tables 6, 7, and 8 may lead readers to initially conclude that growing levels of investments in intangible assets and repurchases do not play a significant role in driving our main results. This is because both types of actions tend to lower B/M relative to our benchmarks, and our results concentrate in cases where B/M is higher than our benchmarks (e.g., B/M » S/P). This conclusion would likely be correct if value investing involved evaluating a given firm in isolation. However, value investing typically involves ranking firms in the cross-section and buying firms that appear *relatively* cheap. As a result, changes in one firm's book values affect the likelihood that a different firm is selected as a value stock by altering their cross-sectional rankings. Thus, greater repurchases and investments in intangibles likely play an important role in our setting by adding noise to B/M rankings as a signal of the relative value proposition from buying firms' net assets.

4.2. Simple adjustments to B/M

We conclude the paper by illustrating that, with appropriate adjustments, B/M can remain a useful part of investors' value investing signals. We do so using two approaches for removing the influence of the distortions in B/M highlighted above. In the first, we construct an adjusted B/M ratio (denoted B^*/M) that accounts for assets related to knowledge and organization capital and goodwill. Specifically, we construct an adjusted measure of book value, denoted B^*, as firms' reported book values after capitalizing knowledge and organization capital using the perpetual inventory method and subtracting goodwill (i.e., $B^*_{i,t} = B_{i,t} + Know_{i,t} + Org_{i,t} - Gdwl_{i,t}$) as defined in Eq. (3) following Peters and Taylor (2017), Eisfeldt et al. (2020), and Park (2020).

Another way we adjust for the potential distortions in B/M is to compute a V/P ratio using the residual income valuation (RIV) model (Ohlson, 1995; Frankel and Lee, 1998). By assuming the clean-surplus accounting relation holds (i.e., change in book value equals the difference between net income and dividends), RIV re-expresses the dividend-discount model and implies that the intrinsic-value to stock price ratio is as follows:

$$\frac{V_{i,t}}{P_{i,t}} = \frac{B_{i,t}}{P_{i,t}} + \frac{1}{P_{i,t}} \sum_{\tau=1}^{\infty} \frac{\left(\frac{\mathbb{E}_t[NI_{i,t+\tau}]}{\mathbb{E}_t[B_{i,t+\tau-1}]} - r_e\right) \times \mathbb{E}_t[B_{i,t+\tau-1}]}{(1+r_e)^\tau}, \tag{4}$$

where $V_{i,t}$ and $P_{i,t}$ are firm i's intrinsic and market values at time t, $NI_{i,t+\tau}$ is its net income at $t+\tau$, $B_{i,t+\tau-1}$ is its book value at $t+\tau$, and r_e is the required rate of return.

V/P adjusts B/M by adding a scaled discounted sum of abnormal profitability. To see why such an adjustment would undo distortions in book value, Eq. (4) shows that when book value (and thus B/M) is artificially deflated, the V/P ratio offsets the lower book values through higher future profitability (i.e., the ratio of expected future earnings to expected future book value). Conversely, when book value (and thus B/M) is artificially inflated, the V/P ratio offsets the higher book values through lower future profitability. An alternative way to understand why V/P compensates for accounting distortions is to recall that the RIV model is a mathematical re-expression of the dividend discount model, and the distortions in reported book values do not change future cash flows and thus intrinsic value. To highlight the usefulness of V/P, we estimate intrinsic value using a two-period version of the RIV model as in Eq. (3.2) of Frankel and Lee (1998) using discount rates of 11%, and cross-sectional earnings forecasts following Hou et al. (2012).

A trade-off exists between using B^*/M versus V/P as adjusted versions of B/M. A key appeal of using B^*/M that it is relatively straightforward to calculate and is designed to account for some of the secular increases in distortions to retained earnings that motivate our study. A drawback of B^*/M is that it does not address noise in contributed capital, for example, distortions in B/M driven by net repurchases. By contrast, V/P implicitly accounts for both types of distortions, but is less straightforward to calculate because it relies on earnings forecasts, which may be noisy, and requires a number of additional assumptions (e.g., on the required rate of return and long-term growth rates). Our tests illustrate the efficacy of both approaches while noting that the choice of using B^*/M versus V/P ultimately depends on how users weigh these trade-offs.

Table 9 shows that we reach similar inferences as our main tests when comparing firms' B/M values against B^*/M or V/P. We again find evidence of stocks comoving more along B/M than B^*/M or V/P in excess of fundamentals, particularly for stocks held by value-oriented funds. These tests underscore the efficacy of simple adjustments to firms' book values to mitigate noise in B/M as a value signal, while also mitigating concerns that our main findings are sensitive to the choice of benchmarks.

5. Conclusion

We study the use of firms' book-to-market ratios in value investing and its implications for comovements in firms' returns and trading activity. We show B/M has become increasingly detached from common alternative valuation ratios over time, while also becoming worse at forecasting returns and growth in both an absolute and relative sense. Despite these trends, some major U.S. stock indexes and funds continue to rely on B/M when identifying value stocks and forming portfolios. Consistent with this reliance shaping market outcomes, we find firms' stock returns and trading volumes comove along B/M in excess of comovement in their fundamentals. Taken together, our findings highlight a form of institutional inertia in financial markets, where some key participants shape market outcomes by continuing to rely on signals that previously worked well, despite a steady decline in signal content.

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Appendix A. Variable Definitions

B/M	Book value of equity (*ceq*) divided by the market value of equity at the end of December of prior year.
S/P	Sales (*sale*) divided by the market value of equity.
G/P	Sales (*sale*) minus cost of goods sold (*cogs*) divided by market value of equity.
N/P	Net payouts to shareholders divided by the market value of equity. We compute net payouts to shareholders following Fried and Wang (2019).
$COMP$	Composite valuation signal, measured as the first principal component of S/P, G/P, and N/P.
B^*/M	Sum of book value of equity, knowledge capital, organizational capital, minus goodwill, divided by market value of equity.
V/P	Intrinsic value value divided by market value of equity. We compute intrinsic value using the residual income model in Frankel and Lee (1998), and forecast future earnings using the cross-sectional prediction technique from Hou et al. (2012).
$Ret_{i,t+1}$	1-year future returns of firm i starting from year t to $t+1$.
$SalesGrowth_{i,t+5}$	5-year geometric average growth rate of sales for firm i starting from year t.
$RatioSpread_{i,t}$	Absolute difference between firm i's B/M quintile and the benchmark quintile as of year t.
$CorrelationSpread_{i,t+1}$	Correlation between firm i's 12-month returns and its corresponding value-weighted B/M portfolio returns, minus the correlation between a firm's 12-month returns and its corresponding benchmark portfolio returns. Returns are measured from July of year t to June of year $t+1$.
$CorrTurnSpread_{i,t+1}$	Correlation between firm i's 12-month turnover and its corresponding value-weighted B/M portfolio turnover, minus the correlation between a firm's 12-month turnover and its corresponding benchmark portfolio turnover. Turnover is measured from July of year t to June of year $t+1$.

Appendix A. Variable Definitions (continued)

$HoldingsSpread_{i,t}$	Number of firm i's shares held by B/M-oriented funds minus number of shares held by benchmark-oriented funds, divided by number of outstanding shares as of June in year t. We identify funds that is oriented to a particular valuation signal by computing fund's characteristic score following Lettau et al. (2018), and define funds in the top tercile as oriented to that signal. Fund characteristic score is computed as the value-weighted average of quintile rankings of stocks in a fund's portfolio with respect to a particular signal.
Size	Natural logarithm of market value of equity of a firm at December of prior year.
Momentum	Cumulative past 12-month stock returns prior to portfolio formation.
Volatility	Past 12-month stock return volatility prior to portfolio formation.
Know	Knowledge capital defined by Peters and Taylor (2016), divided by total assets (at). Knowledge capital is computed as the accumulated past R&D spending using the perpetual inventory method.
Org	Organizational capital defined by Peters and Taylor (2016), divided by total assets (at). Organizational capital is computed as the accumulated past fraction of SG&A spending using the perpetual inventory method.
Off-BS Intangibles	Sum of *Know* and *Org*.
Gdwl	Goodwill ($gdwl$) divided by total assets (at).
Leverage	Total long term debt ($dltt + dd1$) divided by total assets (at).
Shareholder Payouts	Net repurchases and dividends ($prstkc - sstk + dvc$), divided by total assets (at).

Appendix B. Russell Value/Growth indexes Construction Methodology

FTSE Russell

Section 8

Determining Style

8.0 Determining Style

8.1.1 FTSE Russell uses a "non-linear probability" method to assign stocks to the growth and value style valuation indexes and to assign stocks to the defensive and dynamic Russell Stability Indexes®.

8.2 **Russell Growth and Value Indexes**

8.2.1 FTSE Russell uses three variables in the determination of growth and value. For value, book-to-price (B/P) ratio is used, while for growth, two variables—I/B/E/S forecast medium-term growth (2-year) and sales per share historical growth (5-year) are used.

8.2.2 The term "probability" is used to indicate the degree of certainty that a stock is value or growth, based on its relative book-to-price (B/P) ratio, I/B/E/S forecast medium-term growth (2 year), and sales per share historical growth (5 year). This method allows stocks to be represented as having both growth and value characteristics, while preserving the additive nature of the indexes.

8.2.3 The process for assigning growth and value weights is applied separately to the stocks in the Russell 1000 and Russell 2000 and to the smallest 1,000 stocks in the Russell Microcap Index Research indicates that on average, valuations of small stocks differ from those of large stocks. Treating the Russell 1000, Russell 2000 and smallest Russell Microcap stocks separately prevents the possible distortion to relative valuations that may occur if the Russell 3000E is used as the base index.

8.2.4 For each base index (the Russell 1000 and Russell 2000, and the smallest 1,000 in Russell Microcap), stocks are ranked by their book-to-price ratio (B/P), their I/B/E/S forecast medium-term growth (2 year) and sales per share historical growth (5 year). These rankings are converted to standardized units, where the value variable represents 50% of the score and the two growth variables represent the remaining 50%. They are then combined to produce a composite value score (CVS). Stocks are then ranked by their CVS, and a probability algorithm is applied to the CVS distribution to assign growth and value weights to each stock. In general, a stock with a lower CVS is considered growth, a stock with a higher CVS is considered value and a stock with a CVS in the middle range is considered to have both growth and value characteristics, and is weighted proportionately in the growth and value index. Stocks are always fully represented by the combination of their growth and value weights; e.g., a stock that is given a 20% weight in a Russell value index will have an 80% weight in the corresponding Russell

Appendix C. Dimensional Fund Advisor's Value Fund Prospectus

Prospectus dated 02/28/2020 for

U.S. Large Cap Value Portfolio

Prospectus: Table of Contents

Principal Investment Strategies

The U.S. Large Cap Equity Portfolio purchases a broad and diverse group of readily marketable securities of U.S. companies that Dimensional Fund Advisors LP (the "Advisor") determines to be large capitalization companies within the U.S. Universe. A company's market capitalization is the number of its shares outstanding times its price per share. The Advisor generally defines the U.S. Universe as a market capitalization weighted portfolio of U.S. operating companies listed on a securities exchange in the United States that is deemed appropriate by the Advisor. As of the

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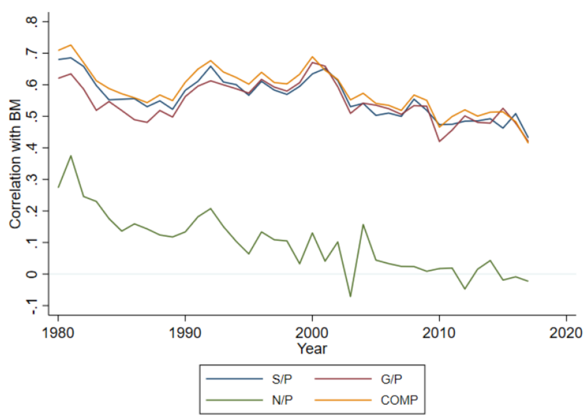
date of this Prospectus, for purposes of the Portfolio, the Advisor considers large cap companies to be companies whose market capitalizations are generally in the highest 90% of total market capitalization within the U.S. Universe or companies whose market capitalizations are larger than or equal to the 1,000th largest U.S. company within the U.S. Universe, whichever results in the higher market capitalization break. Under the Advisor's market capitalization guidelines described above, based on market capitalization data as of December 31, 2019, the market capitalization of a large cap company would be $6,482 million or above. This threshold will change due to market conditions. As a non-fundamental policy, under normal circumstances, the U.S. Large Cap Equity Portfolio will invest at least 80% of its net assets in equity securities of large cap U.S. companies.

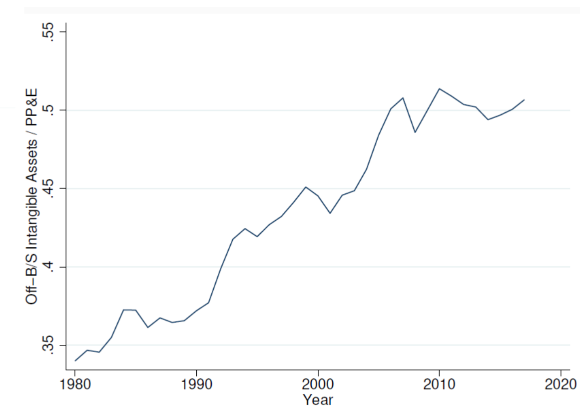
In addition, the Advisor may consider a company's size, value, and/or profitability relative to other eligible companies when making investment decisions for the U.S. Large Cap Equity Portfolio. Securities are considered value stocks primarily because a company's shares have a low price in relation to their book value. In assessing value, the Advisor may consider additional factors such as price to cash flow or price to earnings ratios. In assessing profitability, the Advisor may consider different ratios, such as that of earnings or profits from operations relative to book value or assets. The criteria the Advisor uses for assessing value or profitability are subject to change from time to time. The Advisor may also adjust the representation in the U.S. Large Cap Equity Portfolio of an eligible company, or exclude a company, after considering such factors as free float, momentum, trading strategies, liquidity, size, value, profitability, and other factors that the Advisor determines to be appropriate. The Advisor may also adjust the representation in the Portfolio of an eligible company, or exclude a company, that the Advisor believes to be negatively impacted by environmental, social or governance factors (including accounting practices and shareholder rights) to a greater degree relative to other issuers.

Figure 1. Trends in Correlations and Corporate Behavior

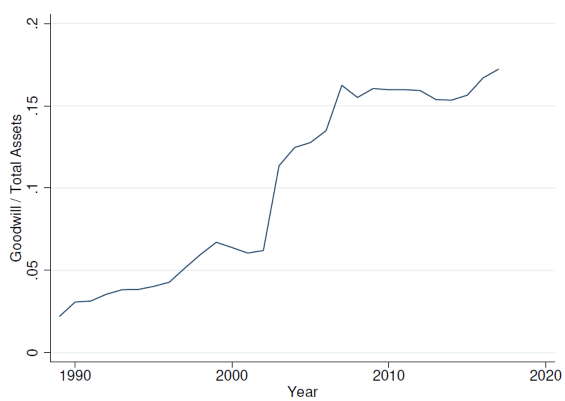
This figure plots the annual cross-sectional correlations between book-to-market (B/M) with other valuation signals and the time series of factors that affect the book value of equity. Panel (a) plots annual cross-sectional correlations between book-to-market (B/M) with other valuation signals: sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P), and the composite (COMP). We measure the numerator of each ratio using firms' most recently available 10K as of June of each year. We measure the denominator of each ratio using firms' trailing market capitalization as of December of each year. We measure B/M as shareholders' equity divided by market value of equity; S/P as total revenue divided market value of equity; G/P as Sales minus cost of goods sold divided by market value of equity; and N/P as net payouts to shareholders divided by the market value of equity. COMP is the first principal component of sales-to-price (S/P), gross profit-to-price (G/P), and net payouts-to-price (N/P). Panel (b) plots off-balance-sheet intangible assets (sum of knowledge capital and organizational capital scaled by property, plant, and equipment). Knowledge capital is computed by accumulating past R&D spending and organizational capital is computed by accumulating fraction of past SG&A spending using perpetual inventory method, following Peters and Taylor (2017). Panel (c) plots goodwill (scaled by total assets). Panel (d) plots the percentage of firms that engaged in either share repurchases or issuances. The sample for this analysis consists of 84,837 firm-year observations from 1980 to 2017.



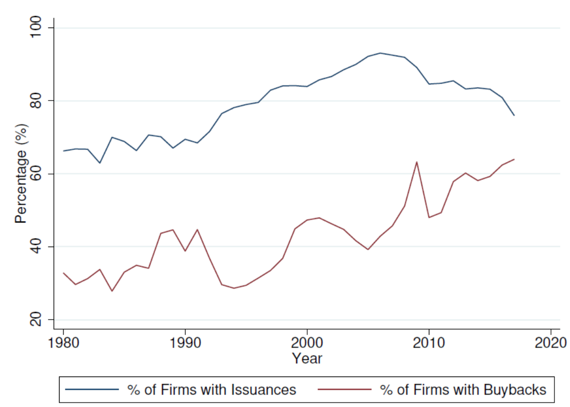
(a) Correlations



(b) Investments in Knowledge and Organizational Capital



(c) Goodwill

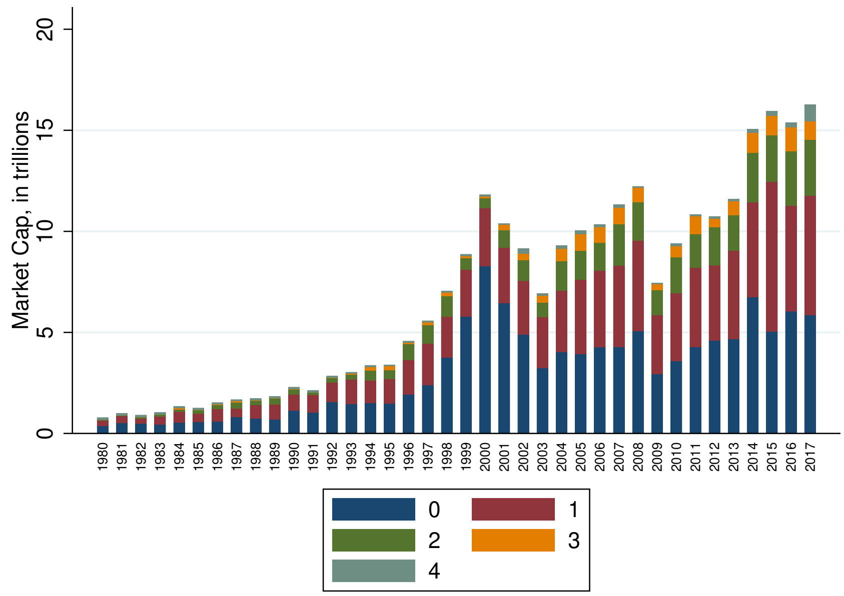


(d) Stock Issuances and Repurchases

Figure 2. Spread Between Valuation Ratios Over Time

This figure plots the yearly distribution of total market capitalization in our sample across values of *RatioSpread*. For this figure, we calculate *RatioSpread* at the firm-year level as the absolute difference between a firm's book-to-market (B/M) quintile rank versus the firm's composite valuation signal (COMP) quintile rank. COMP is the first principal component of sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P). Quintiles are formed for all firms each June. Panel A plots the yearly distribution for all firms across values of *RatioSpread*. The sample for this analysis consists of 84,837 firm-year observations from 1980 to 2017. Panel B plots the yearly trend in market capitalization for the subsample where *RatioSpread* is greater than or equal to 2. Refer to Appendix A for remaining variable definitions.

Panel A: Total Market Capitalization by *RatioSpread* (All Firms)



Panel B: Total Market Capitalization by *RatioSpread* (Subsample of *RatioSpread* ≥ 2)

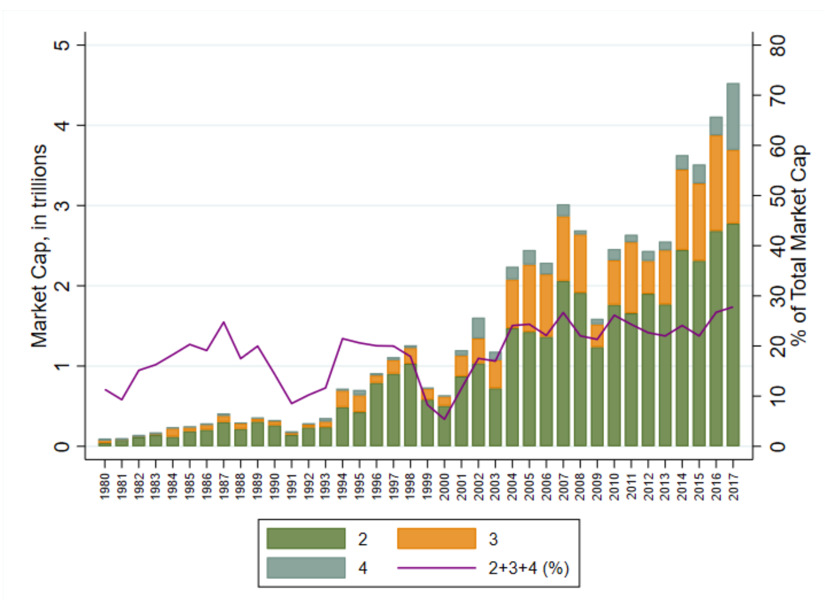
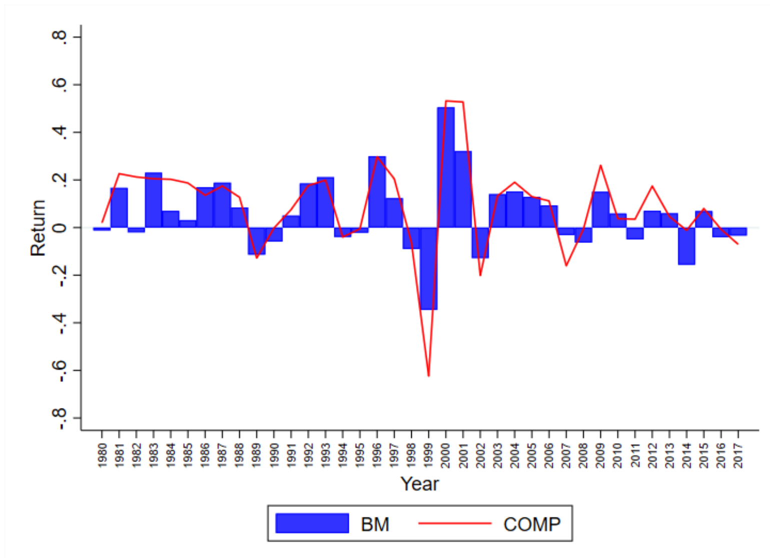


Figure 3. Annual Returns to Long-Short Strategies

This figure plots the annual value-weighted size-adjusted returns to value strategies based on B/M and COMP. Strategies are formed by taking a long position in the highest quintile and short position in the lowest quintile based on B/M and COMP at the end of each June. Quintiles are formed for all firms each June. B/M is firms' shareholders' equity divided by market capitalization. COMP is the first principal component of sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P). Panel A plots the yearly distribution for all firms. The sample for this analysis consists of 84,837 firm-year observations from 1980 to 2017. Panel B plots returns for the subsample where *RatioSpread* is greater than or equal to 2. For this figure, we calculate *RatioSpread* at the firm-year level as the absolute difference between a firm's book-to-market (B/M) quintile rank versus the firm's composite valuation signal (COMP) quintile rank. Refer to Appendix A for remaining variable definitions.

Panel A: Long-Short Strategy Returns (Full Sample)



Panel B: Long-Short Strategy Returns (Subsample of *RatioSpread* ≥ 2)

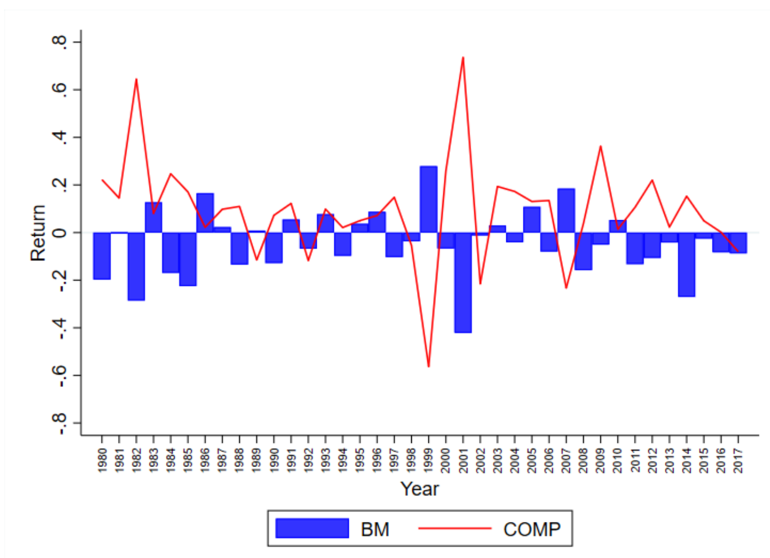


Figure 4. Correlations based on Future Returns and Fundamentals

This figure plots the mean *Return CorrelationSpread* and *Fundamentals CorrelationSpread* by *RatioSpread* groups. For this figure, we calculate *RatioSpread* at the firm-year level as the absolute difference between a firm's book-to-market (B/M) quintile rank versus the firm's composite valuation signal (COMP) quintile rank. COMP is the first principal component of sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P). Quintiles are formed for all firms each June. *Return CorrelationSpread* is computed as the correlation between firm's 12-month returns and its corresponding value-weighted B/M portfolio returns, minus the correlation between a firm's 12-month greturns and its corresponding COMP portfolio returns (i.e., ρ(Stock Return, B/M Portfolio Return) $-$ ρ(Stock Return, COMP Portfolio Return)). *Fundamentals CorrelationSpread* is computed as the correlation between B/M and 5-year geometric average growth rate in sales minus the correlation between COMP and 5-year sales growth rate (i.e., $\rho(\text{B/M}, \text{5-yr future sales growth}) \times (-1) - \rho(\text{COMP}, \text{5-yr future sales growth}) \times (-1)$). Refer to Appendix A for remaining variable definitions.

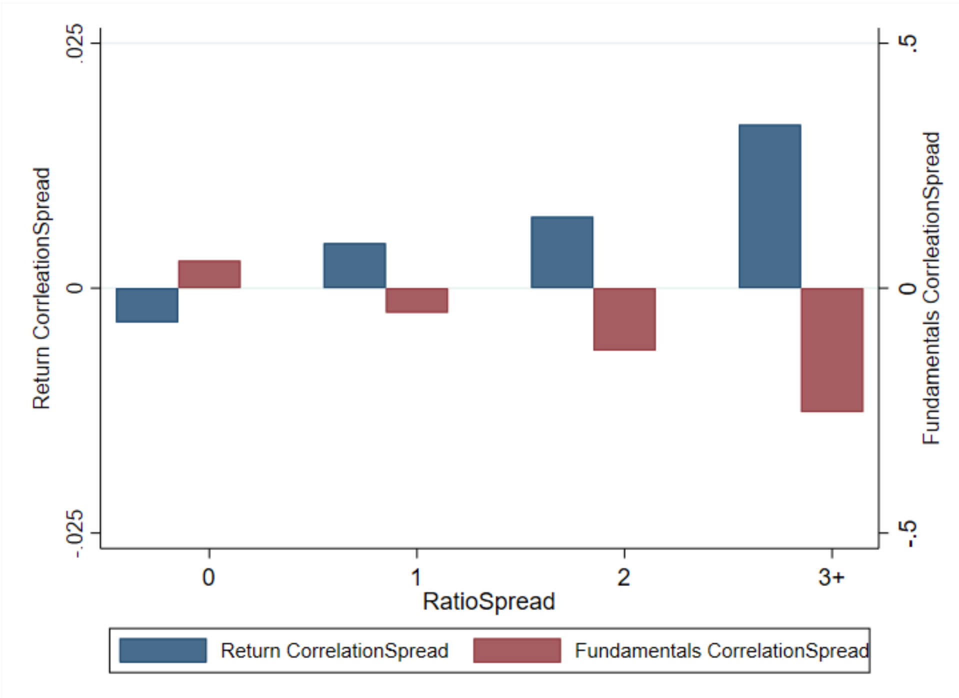


Figure 5. Comparison of Monthly Betas (B/M Portfolio vs. COMP Portfolio)

This figure plots the coefficients of the following regression across three subsamples of *RatioSpread*: $Ret_{i,m,t} = \beta_1 PortRet^{B/M}_{i,m,t} + \beta_2 PortRet^{COMP}_{i,m,t} + \gamma_i + \psi_t + \epsilon$. $Ret_{i,m,t}$ refers to firm i's return at month m of year t. $Ret^{B/M}_{i,m,t}$ ($Ret^{COMP}_{i,m,t}$) refers to firm i's corresponding book-to-market (composite valuation signal) portfolio return at month m of year t. We define *RatioSpread* as the absolute difference between firm's book-to-market quintile and the composite valuation signal quintile. We plot values of β_1 (red) and β_2 (blue) as bar graphs across three subsamples of *RatioSpread* ($RatioSpread < 2, RatioSpread = 2, RatioSpread > 2$), and report the F-tests of the difference between β_1 and β_2. Refer to Appendix A for remaining variable definitions.

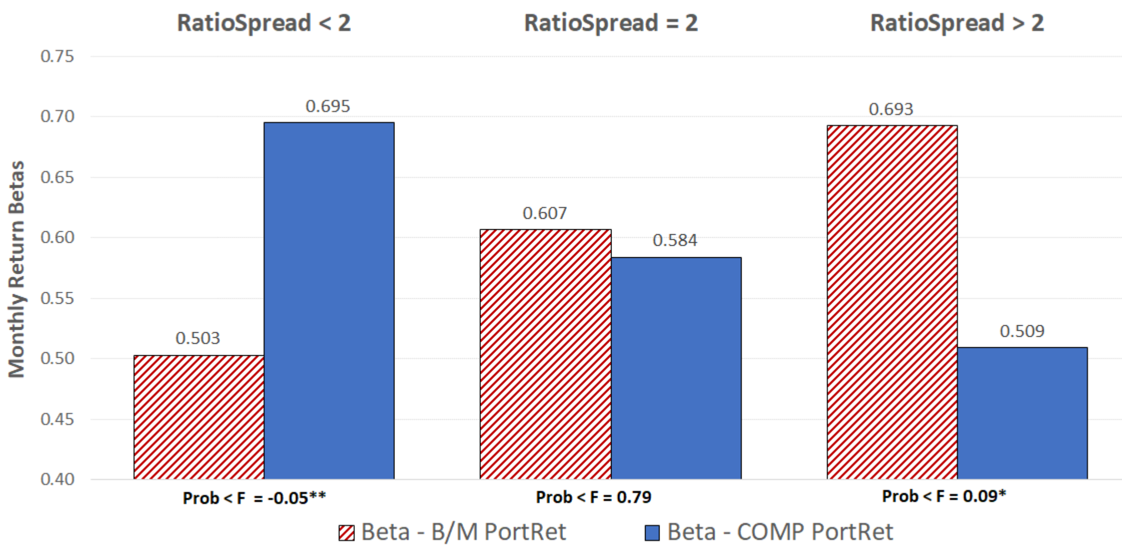


Table 1. Descriptive Statistics

This table presents the descriptive statistics for the sample of 84,837 firm-year observations from 1980 to 2017. For this table, we calculate *RatioSpread* at the firm-year level as the absolute difference between a firm's book-to-market (B/M) quintile rank versus the firm's composite valuation signal (COMP) quintile rank. COMP is the first principal component of sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P). Panel A presents the number of observations and total market capitalization in billions of firms by *RatioSpread* groups summed across three periods. Panel B presents key summary statistics by *RatioSpread*. *Total Assets* and *Market Cap* refer to the reported total assets and December market capitalization, respectively. *Momentum* refers to past 12-month returns, and *Avg Share Turnover* refers to the average monthly trading volume divided by number of outstanding shares in a year. *Age* is calculated as the number of years since the initial date the firm appears on Compustat. $\rho(B/M, Benchmark)$ refers to the correlation between book-to-market and the benchmarks. We use sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P), and the composite valuation signal (COMP) as benchmarks. COMP is the first principal component of S/P, G/P, and N/P. Panel C reports estimates from the following Fama-MacBeth regression: $Returns_{i,t+1} = \beta_1 Signal\ Quintile_{i,t} + \epsilon_{i,t}$. $Returns_{i,t+1}$ refers to firm i's size-adjusted 1-year future returns starting from year t. $Signal\ Quintile_{i,t}$ is the quintile raking of firm i in year t based on two valuation signals: B/M and COMP. Standard errors are Newey-West adjusted by three lags to control for time-series autocorrelation. Refer to Appendix A for variable definitions.

Panel A: Number of Firms & Market Value by RatioSpread, B/M vs. COMP

	Summed Number of Firms			Summed Market Capitalization ($ bn)		
RatioSpread	1980-1991	1992-2004	2005-2017	1980-1991	1992-2004	2005-2017
0	11,452	15,380	8,694	9,453	49,146	57,392
1	8,671	12,297	8,365	7,307	29,104	53,793
2	3,421	5,361	4,097	2,355	10,490	23,889
3	1,259	2,126	1,799	589	3,566	9,190
4	431	767	717	145	1,023	2,357
Total	25,234	35,931	23,672	19,849	93,329	146,621

Panel B: Summary Statistics by *RatioSpread*

RatioSpread	Total Assets (mm)	Market Cap (mm)	Momentum	Avg Share Turnover	Age (Years)
0	2,367	3,248	0.24	0.14	15.73
1	2,913	3,118	0.16	0.13	18.22
2	3,132	2,854	0.15	0.14	17.44
3	3,306	2,432	0.11	0.14	15.72
4	3,580	1,967	0.08	0.15	15.16

RatioSpread	$\rho(B/M, S/P)$	$\rho(B/M, G/P)$	$\rho(B/M, N/P)$	$\rho(B/M, COMP)$
0	0.841	0.861	0.599	0.800
1	0.514	0.545	0.304	0.428
2	0.082	0.110	0.063	-0.026
3	-0.311	-0.299	-0.096	-0.413
4	-0.632	-0.650	-0.482	-0.703

Panel C: Return Predictability of B/M and COMP by Sub-period

Dependent Variable: $Returns_{i,t+1}$

Signal =	B/M			COMP		
	1980-1991	1992-2004	2005-2017	1980-1991	1992-2004	2005-2017
	(1)	(2)	(3)	(4)	(5)	(6)
Signal Quintile	0.0164**	0.0248***	0.00385	0.0291**	0.0277**	0.0116**
	(2.50)	(3.63)	(0.86)	(2.89)	(2.59)	(2.18)
N	23,041	35,635	26,161	23,041	35,635	26,161
R-sq	0.016	0.020	0.005	0.024	0.035	0.009

Table 2. Future Returns and Growth Conditioning on *RatioSpread*

Panel A reports estimates from the following Fama-MacBeth regressions: $Ret_{i,t+1} = \alpha + \beta_1 LN(B/M)_{i,t} + \beta_2 LN(B/M)_{i,t} \times RatioSpread_{i,t} + \beta_3 RatioSpread_{i,t} + \beta_4 Size_{i,t} + \beta_5 Momentum_{i,t} + \epsilon_{i,t}$. $Ret_{i,t+1}$ refers to firm i's 1-year future return starting from year t. $LN(B/M)_{i,t}$ is the natural logarithm of firm i's book-to-market as of year t. We define $RatioSpread_{i,t}$ as the absolute difference between firm i's book-to-market (B/M) quintile and the benchmark quintile in year t. We use sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P), and the composite valuation signal (COMP) as benchmarks. COMP is the first principal component of S/P, G/P, and N/P. Panel B reports estimates from the following Fama-MacBeth regressions: $SalesGrowth_{i,t+5} = \alpha + \beta_1 B/M_{i,t} + \beta_2 B/M_{i,t} \times RatioSpread_{i,t} + \beta_3 RatioSpread_{i,t} + \epsilon_{i,t}$. $SalesGrowth_{i,t+5}$ refers to the 5-year geometric average growth rate of sales for firm i starting from year t. Standard errors are Newey-West adjusted by three lags to control for time-series autocorrelation. Refer to Appendix A for variable definitions.

Panel A: Return Predictability Conditioning on RatioSpread

Dependent Variable: 1-year future returns

B/M vs.	S/P	G/P	N/P	COMP	
	(1)	(2)	(3)	(4)	(5)
LN(B/M)	0.050***	0.055***	0.055***	0.054***	
	(4.53)	(5.09)	(4.43)	(5.04)	
LN(B/M) × RatioSpread	-0.020***	-0.025***	-0.014***	-0.026***	
	(-3.44)	(-4.64)	(-4.24)	(-4.58)	
COMP					0.034***
					(4.04)
COMP × RatioSpread					-0.002
					(-0.66)
N	84,837	84,837	84,837	84,837	84,837
R-sq	0.042	0.042	0.040	0.042	0.041
Controls	YES	YES	YES	YES	YES

Panel B: Forecasting Fundamental Growth

Dependent Variable: 5-year future sales growth ($SalesGrowth_{i,t+5}$)

B/M vs.	S/P	G/P	N/P	COMP	
	(1)	(2)	(3)	(4)	(5)
LN(B/M)	-0.074***	-0.075***	-0.077***	-0.075***	
	(-15.16)	(-16.64)	(-19.76)	(-16.48)	
LN(B/M) × RatioSpread	0.029***	0.027***	0.017***	0.031***	
	(11.38)	(13.62)	(18.20)	(14.03)	
COMP					-0.046***
					(-14.89)
COMP × RatioSpread					0.002
					(1.21)
N	84,837	84,837	84,837	84,837	84,837
R-sq	0.107	0.107	0.103	0.102	0.099
Controls	YES	YES	YES	YES	YES

Table 3. Comovements in Returns

This table presents the univariate and multivariate analysis of the relation between *RatioSpread* and *CorrelationSpread*. Panel A presents the mean *CorrelationSpread* by *RatioSpread* groups. Panel B reports estimates from the following regression: $CorrelationSpread_{i,t+1} = \beta_1 RatioSpread_{i,t} + \beta_2 Size_{i,t} + \beta_3 Volatility_{i,t} + \gamma_i + \psi_t + \epsilon_{i,t}$. We define *RatioSpread* as the absolute difference between firm's B/M quintile and the benchmark quintile. We use sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P), and the composite valuation signal (COMP) as benchmarks. COMP is the first principal component of S/P, G/P, and N/P. $CorrelationSpread_{i,t+1}$ refers to the correlation between a firm i's 12-month returns and its corresponding value-weighted B/M portfolio returns, minus the correlation between a firm's 12-month returns and its corresponding benchmark portfolio returns during year *t+1*. (i.e., $\rho_{i,t+1}(Ret_{i,m}, PortRet^{B/M}_{i,m} - \rho_{i,t+1}(Ret_{i,m}, PortRet^{COMP}_{i,m})$. The parentheses contain t-statistics based on standard errors clustered by firm. *, **, *** indicate statistical significance at less than 10%, 5%, and 1%, respectively. Refer to Appendix A for variable definitions.

Panel A: Univariate Analysis

	CorrelationSpread			
B/M vs.	S/P	G/P	N/P	COMP
RatioSpread	(1)	(2)	(3)	(4)
All	0.0022	0.0038	0.0033	0.0027
	(4.88)	(8.16)	(5.84)	(5.78)
0	-0.0013	-0.0014	-0.0041	-0.0035
	(-2.42)	(-2.32)	(-3.74)	(-6.30)
1	0.0020	0.0059	0.0028	0.0046
	(2.61)	(7.39)	(3.01)	(5.70)
2	0.0051	0.0060	0.0071	0.0073
	(3.50)	(4.44)	(6.01)	(4.98)
3	0.0201	0.0140	0.0065	0.0183
	(7.41)	(5.59)	(3.81)	(6.84)
4	0.0058	0.0163	0.0151	0.0151
	(1.08)	(3.88)	(5.96)	(3.09)

Panel B: Multivariate Analysis

Dependent Variable: Excess return correlation ($CorrelationSpread_{i,t+1}$)

B/M vs.	S/P		G/P		N/P		COMP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RatioSpread	0.0027***	0.0020***	0.0034***	0.0033***	0.0027***	0.0017***	0.0043***	0.0036***
	(4.53)	(2.84)	(5.91)	(4.73)	(5.26)	(2.79)	(7.24)	(5.07)
N	84,837	84,837	84,837	84,837	84,837	84,837	84,837	84,837
R-sq	0.013	0.133	0.012	0.128	0.026	0.141	0.013	0.129
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	YES	NO	YES	NO	YES	NO	YES	NO
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Table 4. Comovements in Trading Volumes

This table presents the univariate and multivariate analysis of the relation between *RatioSpread* and *CorrTurnSpread*. Panel A presents the mean *CorrTurnSpread* by *RatioSpread* groups. Panel B reports estimates from the following regression: $CorrTurnSpread_{i,t+1} = \beta_1 RatioSpread_{i,t} + \beta_2 Size_{i,t} + \beta_3 Volatility_{i,t} + \gamma_i + \psi_t + \epsilon_{i,t}$. We define *RatioSpread* as the absolute difference between firm's B/M quintile and the benchmark quintile. We use sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P), and the composite valuation signal (COMP) as benchmarks. COMP is the first principal component of S/P, G/P, and N/P. $CorrTurnSpread_{i,t+1}$ refers to the correlation between a firm i's 12-month turnover and its corresponding value-weighted B/M portfolio turnover, minus the correlation between a firm's 12-month turnover and its corresponding benchmark portfolio turnover during year *t+1*. (i.e., $\rho_{i,t+1}(Turn_{i,m}, PortTurn^{B/M}_{i,m} - \rho_{i,t+1}(Turn_{i,m}, PortTurn^{COMP}_{i,m})$. The parentheses contain t-statistics based on standard errors clustered by firm. *, **, *** indicate statistical significance at less than 10%, 5%, and 1%, respectively. Refer to Appendix A for variable definitions.

Panel A: Univariate Analysis

	CorrTurnSpread			
B/M vs.	S/P	G/P	N/P	COMP
RatioSpread	(1)	(2)	(3)	(4)
All	0.0019	0.0031	0.0057	0.0027
	(3.43)	(5.51)	(8.88)	(4.82)
0	-0.0004	0.0011	-0.0002	0.0008
	(-0.57)	(1.55)	(-0.17)	(1.14)
1	0.0005	0.0041	0.0057	0.0014
	(0.54)	(4.10)	(5.53)	(1.46)
2	0.0062	0.0042	0.0084	0.0073
	(3.71)	(2.56)	(5.87)	(4.28)
3	0.0114	0.0021	0.0100	0.0046
	(3.60)	(0.69)	(4.89)	(1.44)
4	0.0136	0.0185	0.0113	0.0230
	(2.08)	(3.38)	(3.47)	(3.76)

Panel B: Multivariate Analysis

Dependent Variable: Excess turnover correlation ($CorrTurnSpread_{i,t+1}$)

B/M vs.	S/P		G/P		N/P		COMP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RatioSpread	0.0023***	0.0032***	0.0012*	0.0028***	0.0018***	0.0016**	0.0022***	0.0022***
	(3.52)	(3.79)	(1.84)	(3.47)	(3.22)	(2.43)	(3.27)	(2.70)
N	84,837	84,837	84,837	84,837	84,837	84,837	84,837	84,837
R-sq	0.006	0.114	0.005	0.110	0.007	0.111	0.005	0.110
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES
Industry FE	YES	NO	YES	NO	YES	NO	YES	NO
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Table 5. Conditioning on Fund Holdings

This table reports estimates from the following regression: $CorrelationSpread_{i,t+1}$ ($CorrTurnSpread_{i,t+1}$) $= \beta_1 RatioSpread_{i,t} + \beta_2 RatioSpread_{i,t} \times HoldingsSpread_{i,t} + \beta_3 HoldingsSpread_{i,t} + \beta_4 Size_{i,t} + \beta_5 Volatility_{i,t} + \gamma_i + \psi_t + \epsilon_{i,t}$. Panel A presents the results using $CorrelationSpread_{i,t+1}$ as the dependent variable, and Panel B presents the results using $CorrTurnSpread_{i,t+1}$ as the dependent variable. We define *RatioSpread* as the absolute difference between firm's B/M quintile and the benchmark quintile. We use sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P), and the composite valuation signal (COMP) as benchmarks. COMP is the first principal component of S/P, G/P, and N/P. $CorrelationSpread_{i,t+1}$ ($CorrTurnSpread_{i,t+1}$) refers to the correlation between a firm i's 12-month returns (turnover) and its corresponding B/M portfolio returns (turnover), minus the correlation between a firm's 12-month returns (turnover) and its corresponding benchmark portfolio returns (turnover) during year *t+1*. $HoldingsSpread_{i,t}$ refer to the number of firm i's shares held by B/M-oriented funds minus the number of shares held by benchmark-oriented funds, divided by number of outstanding shares as of June in year t. We identify funds that is oriented to a particular valuation signal by computing fund's characteristic score following Lettau et al. (2018), and define funds in the top tercile as oriented to that signal. The parentheses contain t-statistics based on standard errors clustered by firm. *, **, *** indicate statistical significance at less than 10%, 5%, and 1%, respectively. Refer to Appendix A for variable definitions.

Panel A: Excess return correlation

Dependent Variable: $CorrelationSpread_{i,t+1}$

B/M vs.	S/P		G/P		N/P		COMP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RatioSpread	0.003***	0.002***	0.003***	0.003***	0.002***	0.001	0.003***	0.003***
	(4.18)	(2.61)	(4.75)	(3.96)	(2.84)	(0.96)	(4.99)	(3.65)
RatioSpread × *HoldingsSpread*	0.268***	0.190***	0.269***	0.202***	0.039***	0.034***	0.195***	0.137***
	(8.37)	(5.50)	(8.08)	(5.71)	(4.59)	(3.75)	(6.61)	(4.28)
HoldingsSpread	-0.094**	-0.063	-0.148***	-0.147***	0.029*	0.030	-0.034	0.003
	(-2.44)	(-1.47)	(-3.55)	(-3.13)	(1.65)	(1.38)	(-0.93)	(0.07)
N	84,837	84,837	84,837	84,837	84,837	84,837	84,837	84,837
R-sq	0.014	0.133	0.013	0.129	0.027	0.142	0.014	0.130
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Excess turnover correlation

Dependent Variable: $CorrTurnSpread_{i,t+1}$

B/M vs.	S/P		G/P		N/P		COMP	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RatioSpread	0.002***	0.003***	0.001	0.003***	0.001	0.001	0.002**	0.002**
	(3.34)	(3.65)	(1.46)	(3.25)	(1.42)	(0.77)	(2.36)	(2.10)
RatioSpread × *HoldingsSpread*	0.119***	0.096**	0.087**	0.040	0.034***	0.033***	0.084**	0.062*
	(3.20)	(2.43)	(2.18)	(0.95)	(3.71)	(3.36)	(2.54)	(1.68)
HoldingsSpread	-0.034	-0.029	0.037	0.054	-0.003	-0.045**	-0.043	-0.042
	(-0.74)	(-0.57)	(0.72)	(0.94)	(-0.15)	(-1.97)	(-0.98)	(-0.82)
N	84,837	84,837	84,837	84,837	84,837	84,837	84,837	84,837
R-sq	0.006	0.114	0.005	0.110	0.007	0.112	0.005	0.110
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE	YES	NO	YES	NO	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES

Table 6. Subsample Tests

This table reports estimates from the following regression: $CorrelationSpread_{i,t+1}$ ($CorrTurnSpread_{i,t+1}$) $= \beta_1 RatioSpread_{i,t} + \beta_2 Size_{i,t} + \beta_3 Volatility_{i,t} + \gamma_i + \psi_t + \epsilon_{i,t}$ based on "B/M » Benchmark" and "B/M « Benchmark" subsamples. Panel A presents the results using $CorrelationSpread_{i,t+1}$ as the dependent variable, and Panel B presents the results using $CorrTurnSpread_{i,t+1}$ as the dependent variable. B/M » («) Benchmark denotes the subsample where firms appear more attractive as a value (glamour) stock based on B/M than the benchmark. We define *RatioSpread* as the absolute difference between firm's B/M quintile and the benchmark quintile. We use sales-to-price (S/P), gross profit-to-price (G/P), net payouts-to-price (N/P), and the composite valuation signal (COMP) as benchmarks. COMP is the first principal component of S/P, G/P, and N/P. $CorrelationSpread_{i,t+1}$ ($CorrTurnSpread_{i,t+1}$) refers to the correlation between a firm i's 12-month returns (turnover) and its corresponding B/M portfolio returns (turnover), minus the correlation between a firm's 12-month returns (turnover) and its corresponding benchmark portfolio returns (turnover) during year *t+1*. The parentheses contain t-statistics based on standard errors clustered by firm and year. *, **, *** indicate statistical significance at less than 10%, 5%, and 1%, respectively. Refer to Appendix A for variable definitions.

Panel A: Excess Return Correlation

Dependent Variable: $CorrelationSpread_{i,t+1}$

Subsample	B/M » Benchmark				B/M « Benchmark			
Benchmark =	S/P	G/P	N/P	COMP	S/P	G/P	N/P	COMP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RatioSpread	0.0098***	0.0088***	0.0011	0.0064***	-0.0047**	-0.0069***	0.0031**	-0.0070***
	(6.13)	(5.74)	(0.93)	(4.27)	(-2.34)	(-3.88)	(2.25)	(-3.72)
N	28,692	27,355	36,995	28,447	20,199	23,538	29,236	20,864
R-sq	0.225	0.214	0.235	0.243	0.186	0.180	0.170	0.201
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Excess Turnover Correlation

Dependent Variable: $CorrTurnSpread_{i,t+1}$

Subsample	B/M » Benchmark				B/M « Benchmark			
Benchmark =	S/P	G/P	N/P	COMP	S/P	G/P	N/P	COMP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RatioSpread	0.0061***	0.0062***	0.0043***	0.0048**	-0.0025	-0.0030	-0.0022	-0.0023
	(3.17)	(3.41)	(3.04)	(2.57)	(-1.04)	(-1.39)	(-1.48)	(-0.95)
N	28,692	27,355	36,995	28,447	20,199	23,538	29,236	20,864
R-sq	0.179	0.174	0.181	0.201	0.177	0.177	0.161	0.195
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 7. Reversals of Stock Returns by *RatioSpread*

This table presents estimates from the following Fama-MacBeth regression: $FutureReturns_{n,n+1} = \beta_1 RatioSpread_{i,t} + \beta_2 LN(B/M)_{i,t} + \beta_3 Size_{i,t} + \beta_4 Momentum_{i,t} + \beta_5 RatioSpread_{i,t-1} + \epsilon_{i,t}$. $FutureReturns_{n,n+1}$ is measured over four horizons: first 12 months after portfolio formation ($t_1\_t_2$), months 13 to 24 ($t_2\_t_3$), and months 25 to 36 ($t_3\_t_4$). We define *RatioSpread* as the absolute difference between firm's B/M quintile and COMP quintile. COMP is the first principal component of S/P, G/P, and N/P. Standard errors are adjusted by three lags to control for time-series correlation. Refer to Appendix A for variable definitions.

Dependent Variable: $FutureReturns_{n,n+1}$						
Subsample:	BM » COMP			BM « COMP		
	$t_1\_t_2$	$t_2\_t_3$	$t_3\_t_4$	$t_1\_t_2$	$t_2\_t_3$	$t_3\_t_4$
	(1)	(2)	(3)	(4)	(5)	(6)
RatioSpread	-0.0182**	-0.0172***	-0.00877	0.00718	0.00736	-0.00347
	(-2.52)	(-3.17)	(-1.08)	(1.45)	(0.84)	(-0.53)
N	24,227	20,824	18,848	18,000	16,062	14,741
R-sq	0.044	0.039	0.043	0.038	0.037	0.041
Controls	YES	YES	YES	YES	YES	YES

Table 8. Links to Firm Behavior

This table reports OLS estimates from estimating Eq., (3). $Quintile_{i,t}^{COMP} - Quintile_{i,t}^{B/M}$ refers to firm i's quintile rank based on the composite signal (COMP) minus quintile rank based on book-to-market (B/M) in year t. COMP is the first principal component of sales-to-price (S/P), gross profit-to-price (G/P), and net payouts-to-price (N/P). *Off-BS Intangibles* refers to the sum of *Know* and *Org*. *Know* (*Org*) is defined as accumulated past R&D (fraction of SG&A) spending using the perpetual inventory method following Peters and Taylor (2017), divided by total assets. *Gdwl* is reported goodwill divided by total assets. *Shareholder Payouts* refers to accumulated net repurchases and dividends divided by total assets. The parentheses contain t-statistics based on standard errors clustered by industry. *, **, *** indicate statistical significance at less than 10%, 5%, and 1%, respectively. Refer to Appendix A for variable definitions.

Dependent Variable: $Quintile_{i,t}^{COMP} - Quintile_{i,t}^{B/M}$				
	(1)	(2)	(3)	(4)
Off-BS Intangibles	0.852***			
	(6.23)			
Know		0.394***	0.729***	0.618***
		(5.94)	(9.24)	(7.13)
Org		1.374***	1.235***	1.436***
		(10.52)	(8.87)	(9.98)
Gdwl	-0.725***	-0.637***	-0.675***	-1.156***
	(-6.96)	(-5.87)	(-5.92)	(-10.92)
Shareholder Payouts			0.421***	0.394***
			(6.03)	(4.60)
Leverage				2.263***
				(14.13)
N	84,837	84,837	84,837	84,837
R-sq	0.582	0.585	0.589	0.614
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Table 9. Robustness Tests using B*/M and V/P

This table presents the analyses of Table 3, Table 4, Table 5, Table 7, and Table 8 using adjusted book-to-market (B*/M) and intrinsic value-to-price (V/P) as benchmarks, where adjusted book value (B*) is calculated as the sum of book value of equity, knowledge capital, and organizational capital, minus goodwill. We compute intrinsic value using the residual income model in Frankel and Lee (1998), and forecast future earnings using the cross-sectional prediction technique from Hou et al. (2012). Panel A presents the estimates from the following Fama-MacBeth regression: $Ret_{i,t+1}(SalesGrowth_{i,t+5}) = \alpha + \beta_1 B/M_{i,t} + \beta_2 B/M_{i,t} \times RatioSpread_{i,t} + \beta_3 RatioSpread_{i,t} + \beta_4 Size_{i,t} + \beta_5 Momentum_{i,t} + \epsilon_{i,t}$. Panel B reports estimates from the following regression: $CorrelationSpread_{i,t+1} = \beta_1 RatioSpread_{i,t} + \beta_2 Size_{i,t} + \beta_3 Volatility_{i,t} + \gamma_i + \psi_t + \epsilon_{i,t}$. Panel C reports estimates from the following regression: $CorrelationSpread_{i,t+1} = \beta_1 RatioSpread_{i,t} + \beta_2 RatioSpread \times HoldingsSpread + \beta_3 HoldingsSpread + \beta_4 Size + \beta_5 Volatility + \gamma_i + \psi_t + epsilon_{i,t}$. We define *RatioSpread* as the absolute difference between firm's B/M quintile and B*/M quintile. $CorrelationSpread_{i,t+1}$ ($CorrTurnSpread_{i,t+1}$) refers to the correlation between a firm i's 12-month returns (turnover) and its corresponding B/M portfolio returns (turnover), minus the correlation between a firm's 12-month returns (turnover) and its corresponding benchmark portfolio returns (turnover) during year *t+1*. $HoldingsSpread_{i,t}$ refer to the number of firm i's shares held by B/M-oriented funds minus the number of shares held by benchmark-oriented funds, divided by number of outstanding shares as of June in year t. We identify funds that is oriented to a particular valuation signal by computing fund's characteristic score following Lettau et al. (2018), and define funds in the top tercile as oriented to that signal. The parentheses contain t-statistics. *, **, *** indicate statistical significance at less than 10%, 5%, and 1%, respectively. Panel D presents the estimates from the regressions using subsamples, where B/M » («) Benchmark denotes cases where firms appear more attractive as a value (glamour) stock based on B/M than the benchmark. Refer to Appendix A for variable definitions.

Panel A: Returns & Sales Growth Predictability

Dependent Variable:	12- mo future returns	12- mo future returns	5-yr Sales Growth	5-yr Sales Growth
Benchmark =	B*/M	V/P	B*/M	V/P
	(1)	(2)	(3)	(4)
LN(B/M)	0.0489***	0.0431***	-0.0733***	-0.0795***
	(5.11)	(3.96)	(-14.85)	(-14.85)
LN(B/M) × *RatioSpread*	-0.0287***	-0.0056**	0.0240***	0.0158***
	(-5.93)	(-2.28)	(5.98)	(10.93)
N	84,837	84,837	84,837	84,837
R-sq	0.039	0.038	0.113	0.117
Controls	YES	YES	YES	YES

Panel B: Excess Correlation Test

Dependent Variable: $CorrelationSpread_{i,t+1}$

Benchmark =	B*/M	V/P	B*/M	V/P
	(1)	(2)	(3)	(4)
RatioSpread	0.0041***	0.0024***	0.0042***	0.0026***
	(6.25)	(4.97)	(5.53)	(4.94)
N	84,837	84,837	84,837	84,837
R-sq	0.008	0.007	0.119	0.127
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	NO	NO	YES	YES
Industry FE	YES	YES	NO	NO

Table 9. Robustness Tests using B*/M and V/P (continued)

Panel C: CX-test based on Fund Holdings				
Dependent Variable: $CorrelationSpread_{i,t+1}$				
Benchmark =	B*/M	V/P	B*/M	V/P
	(1)	(2)	(3)	(4)
RatioSpread	0.004***	0.002***	0.004***	0.003***
	(6.24)	(5.08)	(5.54)	(4.92)
RatioSpread × *HoldingsSpread*	0.128***	0.114***	0.083*	0.069***
	(2.76)	(5.17)	(1.66)	(2.99)
HoldingsSpread	0.0379	0.124***	0.0187	0.130***
	(0.86)	(3.72)	(0.39)	(3.51)
N	84,837	84,837	84,837	84,837
R-sq	0.008	0.009	0.120	0.128
Year FE	YES	YES	YES	YES
Industry FE	NO	YES	NO	YES
Firm FE	YES	NO	YES	NO
Controls	YES	YES	YES	YES