Waiting for the Next Factor Wave: Daily Rebalancing around Market Cycle Transitions

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KEY FINDINGS

- Historically, long-only factor investing relied heavily on a small number of periods with outsized returns to deliver factor premiums. These periods coincided with market cycle transitions when the makeup of market leadership changed dramatically.
- By rebalancing frequently—daily instead of every month or six months—during market cycle transitions, a factor investor would have achieved significantly higher factor premiums, effectively doubling the historically observed premiums. This finding holds true even after accounting for much higher transaction costs driven by the higher turnover.
- Our findings indicate that an ability to tell the right moment to rebalance more frequently may be central to harvesting factor premiums to their maximal potential.

ABSTRACT

To deliver historically observed factor premiums, long-only factor investing relied heavily on a small number of periods, when factors realized outsized returns in the midst of changing market leadership. This article shows that by rebalancing factor funds more frequently during these periods—rebalancing on a daily basis instead of monthly or biannually—investors would have achieved significantly higher factor premiums, effectively doubling the historically observed premiums of many factors. These findings indicate that to harvest factor premiums to their maximal potential, skill is needed on the part of the fund manager—an ability to tell the right moment to aggressively rebalance.

TOPICS

*Analysis of individual factors/risk premia, factor-based models, Factors, risk premia**

Over the last decade, the popularity of factor investing has grown dramatically. Today, by some estimates, over $1 trillion[1] is allocated to various factor funds dedicated to delivering factor premiums. A unique aspect of factor investing is how it seemingly straddles active and passive investing. On one hand, many factor funds run significant active risk against a market-capitalization-weighted index fund and frequently experience persistent out- or underperformance. On the other hand,

[1] This figure includes all US-domiciled funds included in the Morningstar Strategic Beta category as of December 2019.

factor funds have the appearance of a passive investment, because the funds are often anchored to a factor index that rebalances, at most, a few times in a given year.

Beneath this passive façade, however, all factor funds are fundamentally active at their core. Consider the following list of decisions any asset manager designing factor funds must make. At the initial design phase, the manager needs to determine relevant characteristics for the targeted factor, decide whether to prioritize factor scores above industry and/or market-capitalization concentrations, and decide how to translate the relative strengths of factor scores into the final portfolio weights. All of these represent decisions regarding *how* to be active rather than whether to be active. A corollary of these being active decisions is the substantial diversity of factor fund designs observed in the current marketplace. This diversity reflects the difference of opinion among asset managers on the best way to capture the return premium of the same target factor. This diversity in factor fund design stands in stark contrast to the near uniformity observed in the marketplace of market-cap-weighted index funds. Indeed, absent cash flow events or corporate actions, all market-cap-weighted index funds rebalance themselves without trading most of the time. On the other hand, any factor fund manager needs to determine when and how to rebalance the fund away from the market-cap-weighted index—left unrebalanced, every fund eventually converges to market-cap weighting—and closer to the ideal portfolio of the target factor, which we refer to as the *signal portfolio* hereafter.[2]

Despite the diversity in how factor funds rebalance, if the return property of factor investing were such that the returns accrued steadily over time, it may be reasonable to expect the return implication of different fund designs to be somewhat limited. In recent contributions, however, Fama and French (2018a) and Arnott et al. (2019) reminded us that factor returns over different time horizons are anything but consistent and steady. Indeed, the return distributions of most long-only factors show sizeable positive skewness and kurtosis. Thus, to deliver the historically observed premium, these factors leaned heavily on a small number of periods with outsized positive returns.

In this article, we set out to identify an optimal rebalancing approach for long-only factor funds. We are motivated by reconciling the obvious tension between the two established facts of factor investing discussed above: (1) There is an apparent diversity of fund design and rebalancing approaches that, in turn, reflects differences of opinion in the industry in how to be active in factor investing and (2) statistically speaking, successful factor investing requires being sure to harvest the premium when the fat right-tail returns show up in droves. This article makes four main contributions. First, based on the last 30 years of factor investing performance, we show that daily rebalancing of factor funds may not only be viable—despite the significant turnover budget required—but also potentially much more profitable than monthly or biannual rebalancing. To the best of our knowledge, this article is the first to document this fact.[3]

Second, we show that the efficacy of daily rebalancing is highly time varying, and significant outperformance is observed during periods of changing market leadership, when a bull market transitions to a bear market or vice versa—a type of market environment we call *market cycle transitions*[4] in this article. This finding suggests that harvesting a factor premium to its maximal potential requires skill on the part of the

[2] For most factors, the composition of the ideal factor portfolio changes on a daily basis. This is because factor portfolios are based on the characteristics (e.g., prices, valuation, profitability) of stocks, whose relative attractiveness changes over time along with the changing market environments, primarily through the change in price.

[3] The convention in this literature is to rebalance factor portfolios monthly at the highest frequency.

[4] We use the term *market cycles* in the same sense articulated by Marks (2011, 2018).

fund manager, an ability to tell the right moment to aggressively rebalance toward the signal portfolio.

Third, by illustrating the importance of optimal rebalancing, we contribute to the growing literature that articulates the attributes required for successful factor investing. Notably, to the often-cited patience (e.g., Fama and French 2018a and Arnott et al. 2019) and business cycle awareness (e.g., Hodges et al. 2017 and Amenc et al. 2019), we add agility in times of market cycle transitions. Taken together with the extant literature, and using the analogy of thrill-seeking adventures, we observe that factor investing is more akin to surfing (a high-skill adventure) than to riding a roller coaster (a low-skill adventure). Factor investing requires active monitoring of the market environment, patience to wait until the wave of outsized returns finally arrives, and, most importantly, the ability to decisively catch the wave to ride it from start to finish. From the viewpoint of skills required, surfing cannot be more different from riding a roller coaster at an amusement park, where all passengers can have more or less the same (net) enjoyable experience simply by fastening the seat belt and holding tight to the bars through the ups and downs of the ride—an analogy that appears fitting for investing in market-cap-weighted index funds.

Last, but not least, we provide an initial sketch of why and how higher-frequency rebalancing improves factor investing outcomes during market cycle transitions. Our hope is that this initial sketch will raise the importance of research utilizing daily frequency data, and that the researcher community will develop additional insights into the nature of factor premiums and appropriate return expectations from factor investing.

The rest of the article is organized as follows. We begin with a description of the data and our empirical setup for this study. Next, we compare the return distributions of factor portfolios rebalanced at different frequencies and identify the periods when daily rebalancing outperforms less frequent rebalancing. Finally, focusing on value and momentum factors in separate case studies, we investigate how the outperformance of daily rebalanced portfolio arose in notable market cycle transitions of the last 30 years.

EMPIRICAL SET UP AND DATA DISCUSSION

Portfolios and Data

In this article, we examine four long-only factor portfolios: momentum, value, quality, and a multifactor portfolio that equally weights the three aforementioned factors. We choose these factors because they represent the set of factors that has become commonly available in the factor fund marketplace. In addition, all single factors we consider have undergone years of extensive research in the academic and practitioner literature, a process that has consolidated insights into why the factor premium existed in the past and may persist into the future.[5]

Using the US equity universe data underlying Axioma's Risk Model AXUS4 (Axioma hereafter)—a universe of securities that largely overlaps with Russell 3000—our factor portfolios are created as follows. To construct any of the three single-factor portfolios, we select and equal weight the top 30% of securities by

[5] Fama and French (2018b) showed that a factor model that includes value, quality, and momentum generates the highest Sharpe ratio among leading academic factor models. Israel, Laursen, and Richardson (2020) provided a detailed analysis of the economic intuition and empirical evidence supporting the value premium. Novy-Marx (2013) documented the profitability premium, the key driver behind the quality factor. Geczy and Samonov (2016) used a 200-year data sample to provide robust empirical evidence about the momentum factor.

their respective strength in the characteristic of interest—factor score—across the cross section of Axioma universe, as determined by Axioma.[6] For example, to construct a momentum portfolio, we select the top 30% of securities in Axioma in the order of Axioma's medium-term momentum factor score and equal weight them; value and quality portfolios are constructed analogously.[7] The multifactor fund is constructed first by averaging the factor scores of momentum, value, and quality at the individual security level, which creates a cross section of composite multifactor scores; then, based on this composite score, we select the top 30% of securities and equal weight them.

At the outset, we acknowledge that there are multiple ways to design a fund that seeks to harvest the targeted factor. As discussed earlier, numerous configurations in fund design could arise because decisions can vary along the following dimensions: descriptor selection, prioritization decisions between factor score and industry and/or market-capitalization concentrations, and translation of relative factor score strengths into active weights. Having acknowledged this, we also note that these considerations are primarily about optimally designing factor funds, a topic we consider a logical sequel to the focal point of this article—identifying the role of optimal rebalancing in factor fund management. This also informs our decision to examine the relatively simple and pure long-only factor fund introduced earlier in this article, wherein the funds take the top 30% of securities and equally weight them without overengineering other implementation aspects.

Rebalancing Frequency and Methodology

We examine each factor portfolio over three rebalancing frequencies. Specifically, we let all three implementation portfolios track the same signal portfolio by rebalancing daily, monthly, and biannually. When rebalanced daily, the implementation portfolio captures the changing distribution of factor score strengths on a daily basis and is effectively the same as the signal portfolio;[8] we refer to this implementation portfolio as Portfolio-D. We refer to the implementation portfolios rebalanced monthly and biannually as Portfolio-M and Portfolio-B, respectively, hereafter.

Because all factor investing is active—in the sense that the manager assumes and maintains a deliberate active risk against the market-cap-weighted benchmark—closer tracking of the signal portfolio will tend to occur at the expense of a greater amount of turnover. Many in the literature have been concerned as to whether factor premiums—often obtained with monthly rebalancing—would survive the potential impact of transaction costs as factor portfolios either grow in size or have signals that change fast, such as momentum.[9] These concerns are particularly relevant for our study because, instead of dismissing the idea outright as impractical, we are exploring whether a daily rebalanced factor portfolio may be viable, or even preferred, vis-à-vis the more conventional monthly and biannual rebalancing. To ensure that we

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[6] To ensure that our findings are not driven by illiquid stocks with a limited capacity, we impose the following liquidity requirements on all stocks in the portfolio: (1) 20-day average trading volume within the top 2,600 names and (2) market capitalization of at least $100 million. These requirements effectively leave out illiquid and micro-cap stocks.

[7] In Axioma, *medium-term momentum* is defined as the stock's cumulative return over the past year, largely excluding the past month's return. *Value* is defined as the ratio of the most recent common equity to the 30-day moving average of market capitalization. *Quality*—labeled "profitability" in Axioma—is defined as the average of the following six metrics: return on equity, return on assets, cash flow to assets, cash flow to income, gross margin, and sales to assets. All definitions are broadly consistent with the general treatment in the literature.

[8] A notable difference is that the daily rebalanced portfolio incurs transaction costs on a daily basis.

[9] See, for example, Korajczyk and Sadka (2004); Frazzini, Israel, and Moskowitz (2015); and Novy-Marx and Velikov (2016).

capture realistic transaction costs, we assume 30 bps per transaction volume for all trading; in addition, for extended periods with elevated volatility—notably around the dot-com bust (1999–2004) and the great financial crisis (2008–2009)—we double the trading cost assumption to 60 bps per transaction volume.[10]

We conclude this section with a description of the rebalancing approaches used in our study. For all three approaches, rebalancing is self-financed in the sense that all buy orders are fully financed by the proceeds from the sell orders. That said, the rest of the rebalancing approach for Portfolio-D is different from that of Portfolios-M and -B. For Portfolio-D, the implementation portfolio is rebalanced at the close of each trading day to fully mimic the signal portfolio; this requirement leads to the maximal possible turnover because even a small discrepancy in active weight is offset daily. On the other hand, for Portfolios-M and -B, we incorporate elements of realism in how they are rebalanced. First, on a rebalance day when we compare the implementation and signal portfolios, we transact only on securities that are in one but not in both portfolios; put differently, we do not trade on securities that are already held in the implementation portfolio from a prior rebalance and continue to be recommended by the signal portfolio on the current rebalance date. This particular rebalancing approach contains a great dose of realism because, all else equal, most managers prefer closing the gap with the signal portfolio while keeping turnover at a low level.[11] By conserving the portfolio turnover, holding all else equal, Portfolios-M and -B have lower transaction costs. This contrasts with Portfolio-D which runs an unconstrained turnover budget and incurs significantly higher transaction costs.[12]

RESULTS COMPARING DAILY VERSUS SLOWLY REBALANCED PORTFOLIOS

Return Distributions of the Three Implementation Portfolios

We begin our investigation with Exhibit 1, which summarizes the distributional properties of monthly (arithmetic) returns of the three portfolios targeting the momentum factor.[13] For the 356-month period from January 1990 to August 2019, Exhibit 1 reports the first four central moments—average, standard deviation, skewness, and excess kurtosis—of the monthly excess return (over Russell 3000) distribution for the three implementation portfolios (first three columns from the left), Portfolio-D's return in excess of Portfolio-M and Portfolio-B (next two columns), and the Russell 3000 index (rightmost column). All returns, except for those of the Russell 3000 index, are net of transaction costs as discussed in the previous section. Both average return and return standard deviation—the first two rows—are annualized.

[10] There may be some disagreement about what constitutes realistic transaction costs because they depend on the size of the funds. Our choice is informed by the market microstructure literature on equities. For example, Corwin and Schultz (2012) reported that the average bid–ask spread is 50 bps for large-cap US companies, which implies 25 bps for a small enough one-way trade with no market impact. With 30 bps during normal times and 60 bps during periods of heightened volatility, we assume a realistic set of transaction costs for an investor who can demand liquidity of small enough quantities on the margin. See the Appendix for other transaction cost assumptions.

[11] This rebalancing approach is also similar in spirit to the sS rebalancing approach explored by Novy-Marx and Velikov (2016).

[12] See Exhibit A1 in the Appendix, which plots the entire—two-way—turnover volume incurred by running the three portfolios for all four factors. Generally, Portfolio-M's turnover is more than twice Portfolio-B's, and Portfolio-D's trading is more than three times Portfolio-M's.

[13] We aggregate fund returns to the monthly level because it makes the results easier to interpret.

EXHIBIT 1

Return Distributions of Momentum Portfolios

Momentum Portfolios	Excess Return (Portfolio-D)	Excess Return (Portfolio-M)	Excess Return (Portfolio-B)	Excess Return (Port. D - M)	Excess Return (Port. D - B)	Russell 3000
Mean Return (ann., %)	8%	6%	4%	2%	3%	9%
Standard Deviation (ann., %)	15%	16%	16%	4%	8%	14%
Skewness	1.5	1.0	0.7	1.2	2.5	–0.7
Excess Kurtosis	18.6	14.4	11.7	20.2	38.3	4.4

Starting with the average returns in the first row, and consistent with numerous studies in the literature, we note that all three momentum portfolios provide a premium over the Russell 3000 index in excess of 4% per year.[14] That said, note that Portfolio-D outperforms the other two implementation portfolios by noteworthy margins of 2% and 3%. Furthermore, this outperformance is realized despite Portfolio-D having a volatility of 15%, slightly lower than the volatilities of Portfolio-M and Portfolio-B.

Inspecting the skewness and kurtosis of each distribution, we surmise that Portfolio-D's outperformance is driven by the notable right tail of its return distribution, when the target factor itself delivers an outsized positive return. To see this, observe that all three momentum portfolios deliver positive factor premiums thanks to the positive skewness. In long-only factor investing, positive skewness means that earning outsized returns when the targeted factor itself is in vogue is central to achieving the expected factor premium.[15] With this insight, note that Portfolio-D has the greatest skewness of 1.5 and the greatest kurtosis of 18.6 in its excess return distribution. Economically, this means that when the momentum factor itself goes through a return environment that belongs to the right tail of the distribution—because momentum is in vogue—Portfolio-D enjoys a return that is even greater than the already outsized returns Portfolio-M and Portfolio-B experience. This effect on the right tail is large enough that Portfolio-D's excess returns over the other two portfolios have economically large positive skewness and kurtosis.

These findings are not specific to the three momentum portfolios considered. As Exhibit 2 shows, virtually all factors we examine in this article show similar patterns of return distributions among the three implementation portfolios. This is generally driven by a more positive skewness—significant right-tail return outcomes—in the return distribution of Portfolio-D vis-à-vis the other two portfolios. Taken together, these comparisons of unconditional return distributions suggest that Portfolio-D outperforms the two slowly rebalanced portfolios largely owing to the significant difference in the right tails of the distributions.

When Daily Rebalancing Outperforms Monthly Rebalancing

When can investors expect positive outsized returns from factor investing? Historically, these types of returns were observed in transition periods when either the business cycle or market cycle—market leadership—moved from one phase to another.[16] Our analysis also indicates that, indeed, the outsized divergence in cumulative returns among the three implementation portfolios is concentrated in a

[14] These results are based on the transaction cost assumptions discussed above. See Exhibits A2 and A3 for other transaction cost assumptions.

[15] The minimum or low volatility factor—with a negative skewness in the excess return distribution—is a notable exception to this pattern.

[16] See Hodges et al. (2017).

EXHIBIT 2

Return Distributions of Value, Quality, and Multifactor Portfolios

	Excess Return (Portfolio-D)	Excess Return (Portfolio-M)	Excess Return (Portfolio-B)	Excess Return (Port. D - M)	Excess Return (Port. D - B)	Russell 3000
Value Portfolios						
Mean Return (ann., %)	5%	3%	2%	2%	3%	9%
Standard Deviation (ann., %)	11%	10%	9%	3%	5%	14%
Skewness	0.9	0.5	0.6	1.0	1.1	–0.7
Excess Kurtosis	8.1	6.1	6.0	8.3	10.3	4.4
Quality Portfolios						
Mean Return (ann., %)	5%	4%	4%	1%	1%	9%
Standard Deviation (ann., %)	8%	9%	9%	6%	6%	14%
Skewness	1.3	0.6	0.5	1.6	1.5	–0.7
Excess Kurtosis	9.8	7.5	6.3	18.8	13.9	4.4
Multifactor Portfolios						
Mean Return (ann., %)	8%	6%	4%	2%	4%	9%
Standard Deviation (ann., %)	10%	12%	11%	4%	5%	14%
Skewness	0.8	1.0	0.7	1.0	2.6	–0.7
Excess Kurtosis	7.8	10.5	8.3	18.8	26.8	4.4

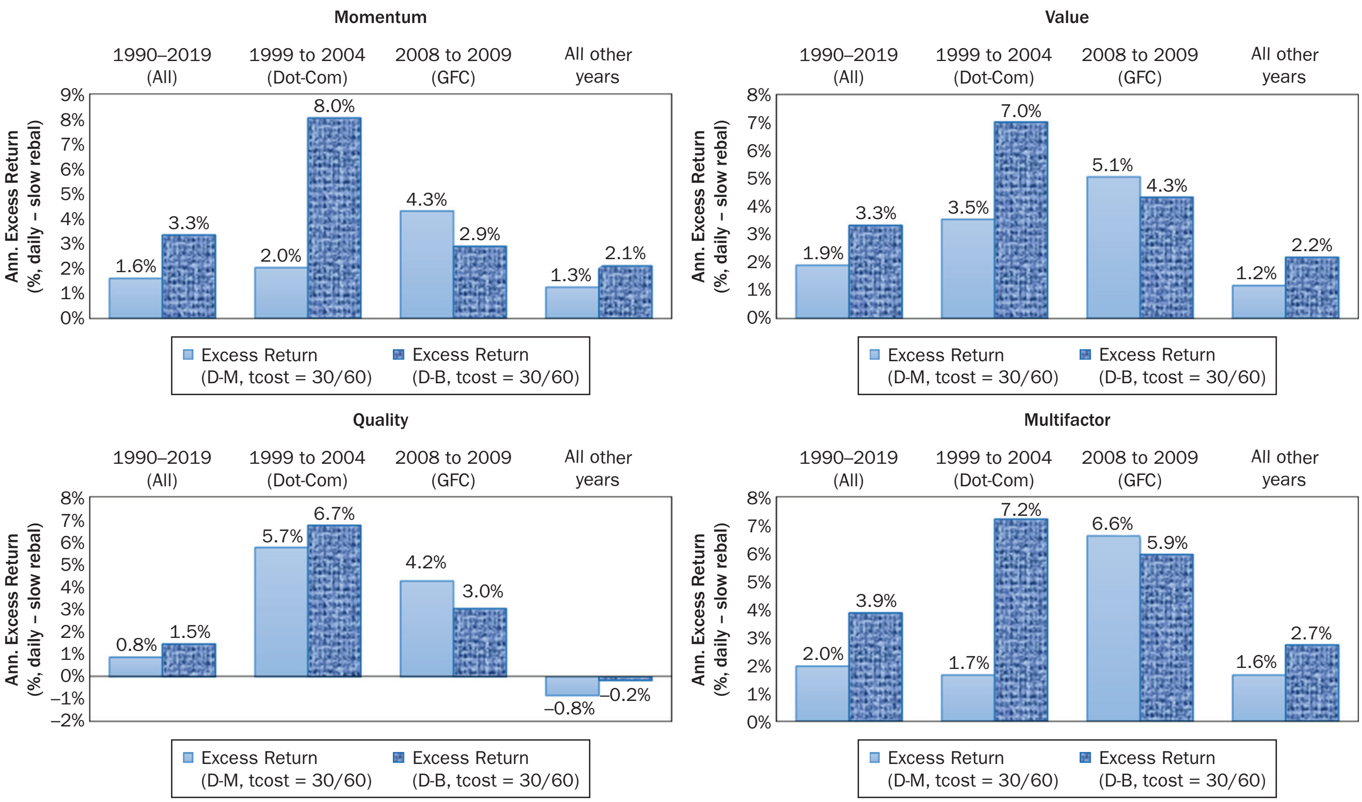
small number of periods, all coinciding with either business cycle transitions (e.g., from expansion to recession) or market cycle transitions (from bull market to bear market). In Exhibit 3, for each factor, we compute the relative (annualized) returns of Portfolio-D vis-à-vis Portfolio-M and Portfolio-B and report them under four different periods from 1990 to 2019. From left to right, the four periods are (1) 1990–2019, representing the entire period of the unconditional distribution; (2) 1999–2004, the dot-com bubble and bust period; (3) 2008–2009, the great financial crisis; and (4) the 1990–2019 period outside of the dot-com and great financial crisis periods.

For all four factors considered, we note that there is a clear, common pattern among the three portfolios' return differentials in these periods. Taking the quality factor as an example, the 0.8% (1.5%) outperformance of Portfolio-D vis-à-vis Portfolio-M (Portfolio-B) in the unconditional distribution is driven entirely by the 5.7% (6.7%) outperformance in the 1999–2004 period and 4.2% (3%) outperformance in the 2008–2009 period. Furthermore, for the quality factor, the relative performance in all periods outside of these two notable market cycle transitions is mildly negative; that is, the two slowly rebalanced portfolios slightly outperformed Portfolio-D most of the time between 1990 and 2019, aside from 1999–2004 and 2008–2009. We remind the reader that the results in Exhibit 3 are based on our baseline transaction cost assumption of 30 bps during normal times and 60 bps during the two major market cycle transitions in 1999–2004 and 2008–2009. In Exhibits A2 and A3, we show how these results change with more or less conservative transaction cost assumptions. Although greater transaction costs certainly reduce the magnitude of outperformance, it is equally apparent in Exhibits A2 and A3 that the findings documented survive even a highly conservative transaction cost assumption of 90 bps during the two market cycle transitions. Similar to quality, the other three factors lead to a qualitatively similar conclusion about when Portfolio-D's outperformance is concentrated—around market cycle transitions in 1999–2004 and 2008–2009.

To be clear, 1999–2004 and 2008–2009 are not the only periods over the last 30 years when Portfolio-D outperforms Portfolio-M and Portfolio-B. In Exhibits A4 and A5, we show rolling 12-month excess returns of Portfolio-D for each of the four factors under two transaction cost assumptions. Note that quality is the only

EXHIBIT 3

Performance of Daily Rebalanced Portfolio Relative to Monthly and Biannually Rebalanced Portfolios



factor to which we can apply the 1999–2004 and 2008–2009 periods and cleanly isolate the times when Portfolio-D clearly outperforms. For all other factors, there are other periods when Portfolio-D outperforms the other two portfolios.[17] Our conjecture is that the changing composition of market leadership, and how this interacts with the factors considered in this article, constitutes a likely driver of this phenomenon. That is, as market outlook changes significantly, so does the makeup of the market leadership; against this backdrop, different factors embodying the investment theme that is in vogue tend to accelerate. Extending this logic, the two major market cycle transitions of 1999–2004 and 2008–2009 provide a natural setting in which market leadership undergoes most dynamic changes, and all factors play prominent roles in various segments within the 1999–2004 and 2008–2009 periods. We believe that this is what we capture by focusing on the 1999–2004 and 2008–2009 periods.

Based on the three momentum portfolios, we further shed light on when the divergence in the three portfolios takes place in Exhibit 4. In the exhibit, we plot how the three implementation portfolios grow over time, compounding an initial dollar investment in the beginning of the period by the portfolio's return in excess of Russell 3000.[18] Indeed, as the dot-com bust unfolds in 2000 and 2001, Portfolio-D pulls ahead of the other two portfolios, primarily by not declining as dramatically in late 2001, and then increasing more rapidly—note that Portfolio-D's growth is steeper

[17] By the same token, Portfolio-D does underperform for some parts of the 1999–2004 and 2008–2009 periods for all factors, although on the whole it outperforms far more than it underperforms, making the average excess sufficiently greater than zero.

[18] These represent growing an investment by the factor premium net of market return.

EXHIBIT 4

Performance Divergences of Momentum Portfolios

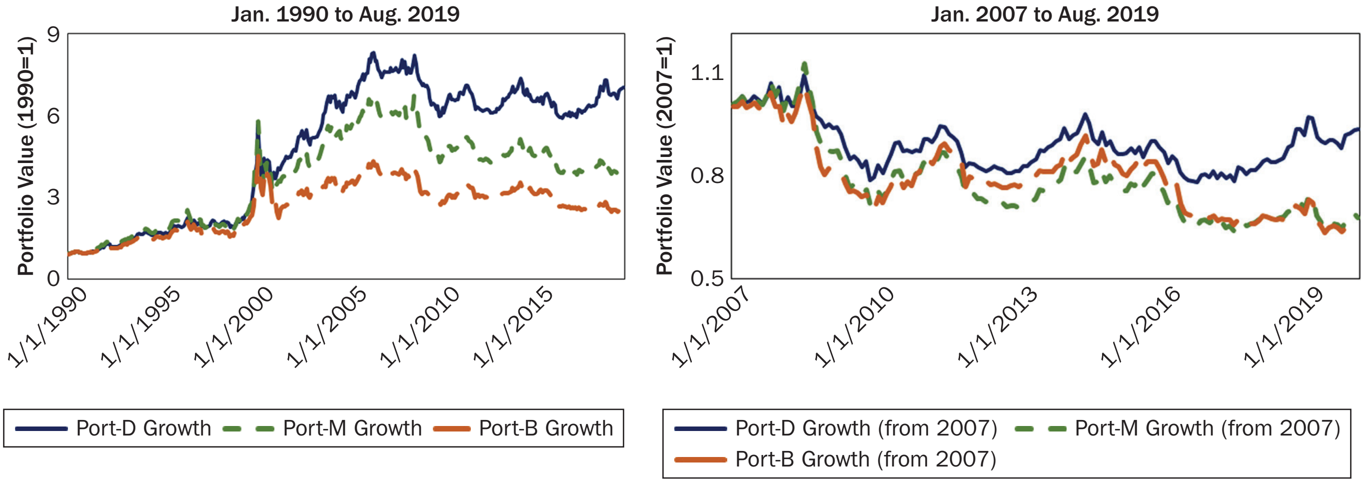
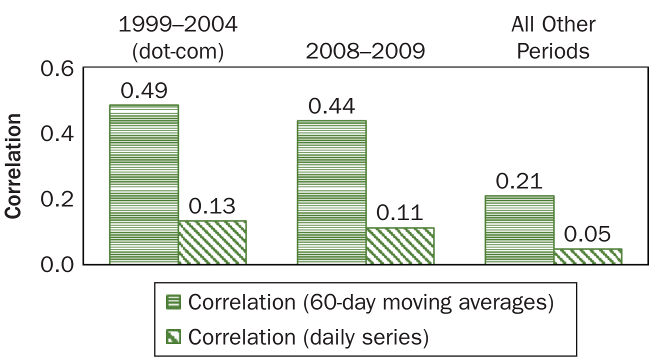


EXHIBIT 5

Correlation between Signal Capture and Excess Return of Value Portfolio



than the other two portfolio's—into the 2002 market. Similarly, during the 2008–2009 crisis, Portfolio-D outperforms the other two portfolios, chiefly by not declining as much in 2008 and 2009 when the factor itself comes under significant duress.

Mechanism behind the Outperformance of Portfolio-D

Why is Portfolio-D's outperformance over its slowly rebalanced counterparts concentrated in notable market cycle transitions, when both market and factor volatilities tend to be significantly higher than their historical averages? Put differently, what would be the mechanism behind the seeming superiority of rebalancing daily over monthly and biannually in these times? Exhibit 5 examines the value portfolios and offers a first indication that it is likely because the signal portfolio changes more rapidly in these times.

In Exhibit 5, we report the correlation between the signal capture of Portfolio-M[19]—the extent to which the monthly rebalanced portfolio captures the signal portfolio—at the close of the day (on date t) and Portfolio-M's excess return vis-à-vis Portfolio-D from the next day (on date $t + 1$). Commonly known as the information coefficient in the industry, this correlation shows how much predictive power the signal capture on date t has over the excess return of the next day, $t + 1$. A positive correlation—a higher (lower) signal capture leading to a higher (lower) excess return—indicates that, on average, there is useful information in the signal portfolio that leads to a positive excess return. At 0.05, the information coefficient in "all other periods"

[19]Numerically, it is defined as the ratio of the value-weighted factor score—Z-score in Axioma—of the portfolio to its signal portfolio counterpart. Higher signal capture means the implementation portfolio is closer to the signal portfolio.

matches the level of skill by top decile active managers,[20] which explains the growing popularity behind factor investing. Of more interest to us in this article, note that the information coefficient jumps to 0.11 and 0.13, respectively, during the two market cycle transitions. With these large information coefficients, the hit rates also inch toward 0.6 during these periods, a level that is considered exceptional. It appears that during the two market cycle transitions, the signal portfolio contains information that is both unusually profitable and changing very rapidly on a daily basis. The two slowly rebalanced portfolios tend to miss out on the fast-changing, highly predictive information content of the signal portfolio, and this appears to be the main driver behind Portfolio-D's notable outperformance during these periods.

TWO CASE STUDIES ON REBALANCING FACTOR PORTFOLIOS DAILY

Having shown the efficacy of rebalancing daily during market cycle transitions, we now turn our attention to understanding what managing daily rebalanced factor portfolios might entail. Specifically, we explore this topic with the help of two case studies involving value and momentum factors.

Case 1: Value Factor Portfolio in 1999–2004

In Exhibit 6, using Portfolio-M for the value factor as an example, we juxtapose this portfolio's signal capture and tracking error with the signal portfolio between 1999 and 2004; both series are smoothed as 60-day moving averages. Throughout various phases of the dot-com market bubble and bust, the signal capture of this portfolio fluctuates quite substantially.[21] In addition, monthly rebalancing of the value portfolio runs active risk of over 2% against the signal portfolio most of the time—a level that may be considered too high for some investors who believe in tracking the target factor closely. The two series—signal capture and tracking error—show a negative correlation of –0.75, a greater magnitude than in normal market environments. Visually, this pattern is quite easy to spot in Exhibit 6, where a decay in signal capture tends to be accompanied by a rise in tracking error. To point out a few such periods, note that the pace of decay accelerated in the second halves of 2000, 2001, and 2002, and tracking error invariably increased during these times.

Having explored the context, in Exhibit 7 we show when Portfolio-M's underperformance vis-à-vis Portfolio-D arises in 1999–2004. In the three circled areas—previously noted as the second halves of years 2000, 2001, and 2002—periods of rapid decay in signal capture either coincided with or preceded a large underperformance in the range of –5% to –10%. Indeed, out of the 40% performance gap (–15% in January 1999 to –55% in December 2004) Portfolio-M runs against Portfolio-D during this period, roughly 25% is concentrated in these three circled periods. These months represent the tail events in the return distribution (see Exhibits 1 and 2) when the monthly rebalancing schedule—embedded into the portfolio design and construction process—proved too slow to prevent the precipitous decay in signal capture from taking place or to keep the tracking error from rising to an unusual level. In the process, of course, Portfolio-M left outsized returns on the table.

[20] See chapter 6 by Grinold and Kahn (2000). Of course, the caveat here is that factor returns are considered somewhat systematic rather than truly idiosyncratic.

[21] Most of the time, value factor's signal tends to be very stable over time and Portfolio-M's signal capture is typically above 90% even on the day before a scheduled rebalance date.

EXHIBIT 6

Signal Capture and Ex-Ante Tracking Error of Value Portfolio: 1999–2004

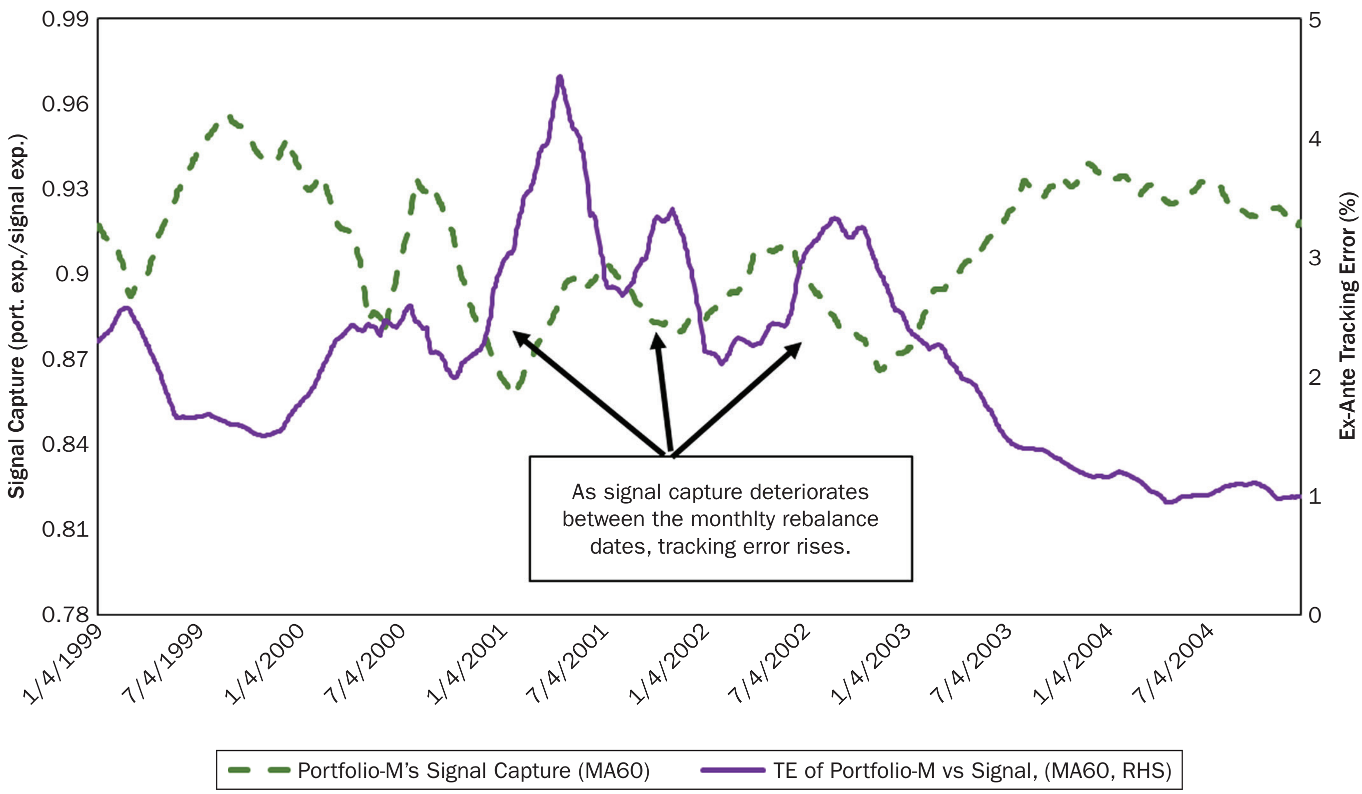


EXHIBIT 7

Signal Capture and Excess Return of Value Portfolio: 1999–2004

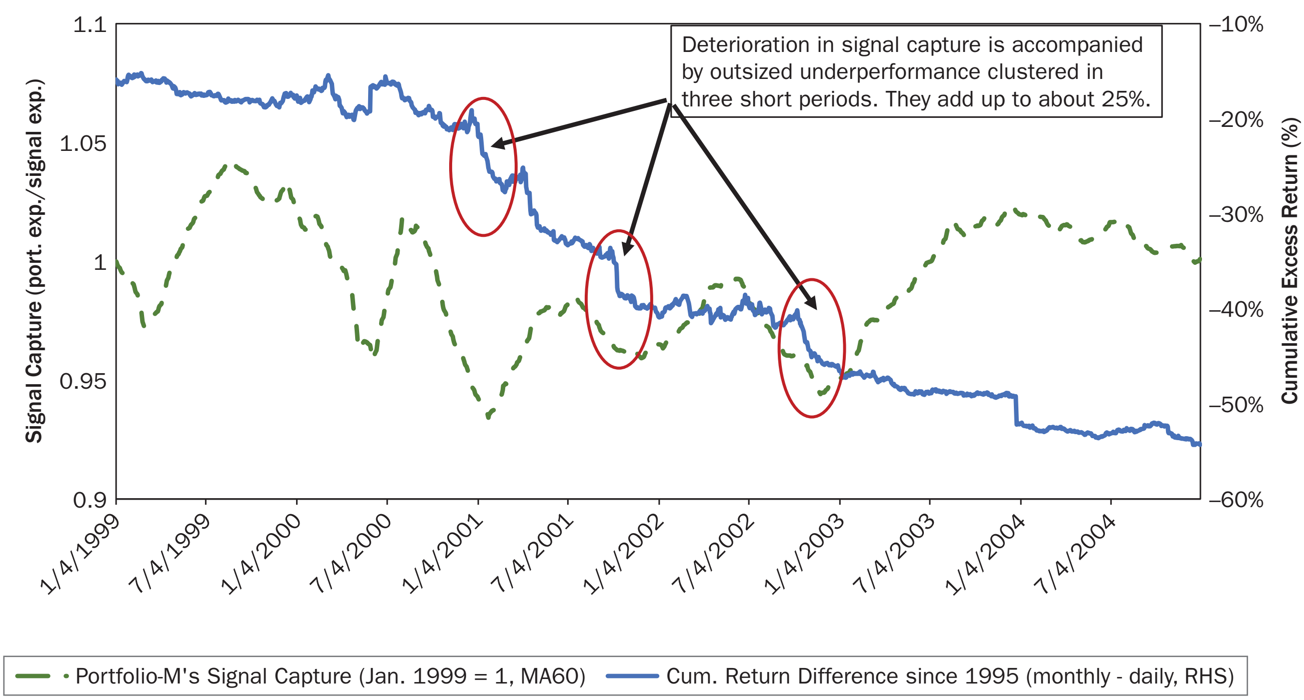
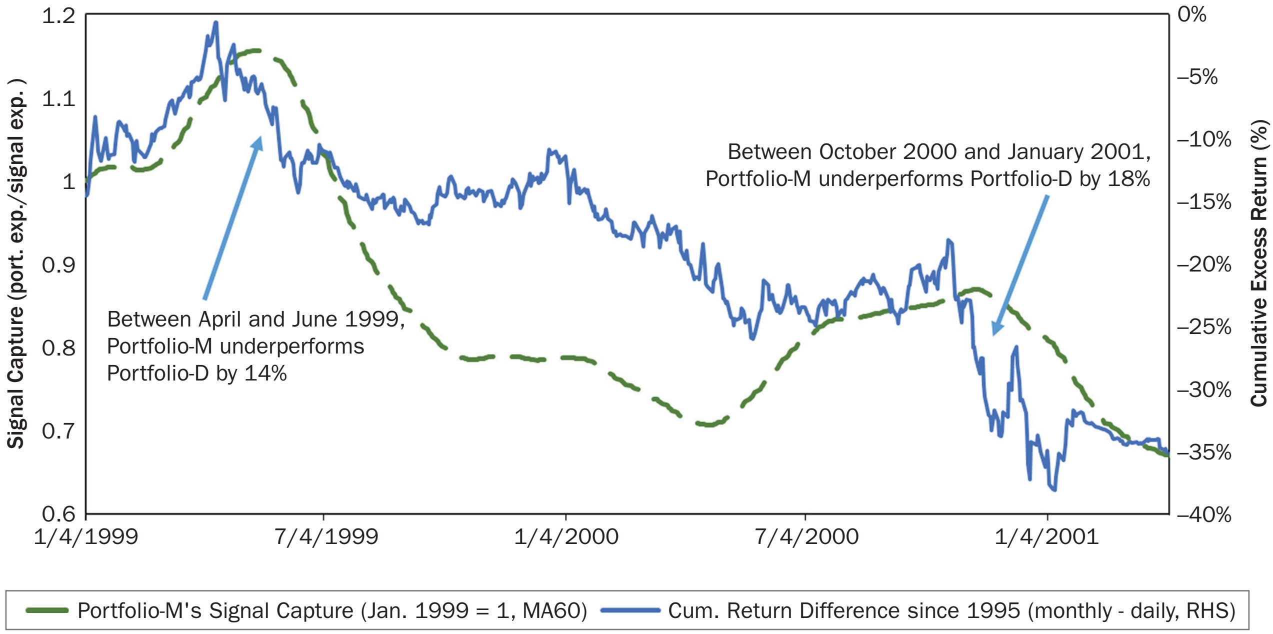


EXHIBIT 8

Signal Capture and Excess Return of Momentum Portfolio: 1999–2001



Case 2: Momentum Factor Portfolio in 1999–2004 and 2008–2009

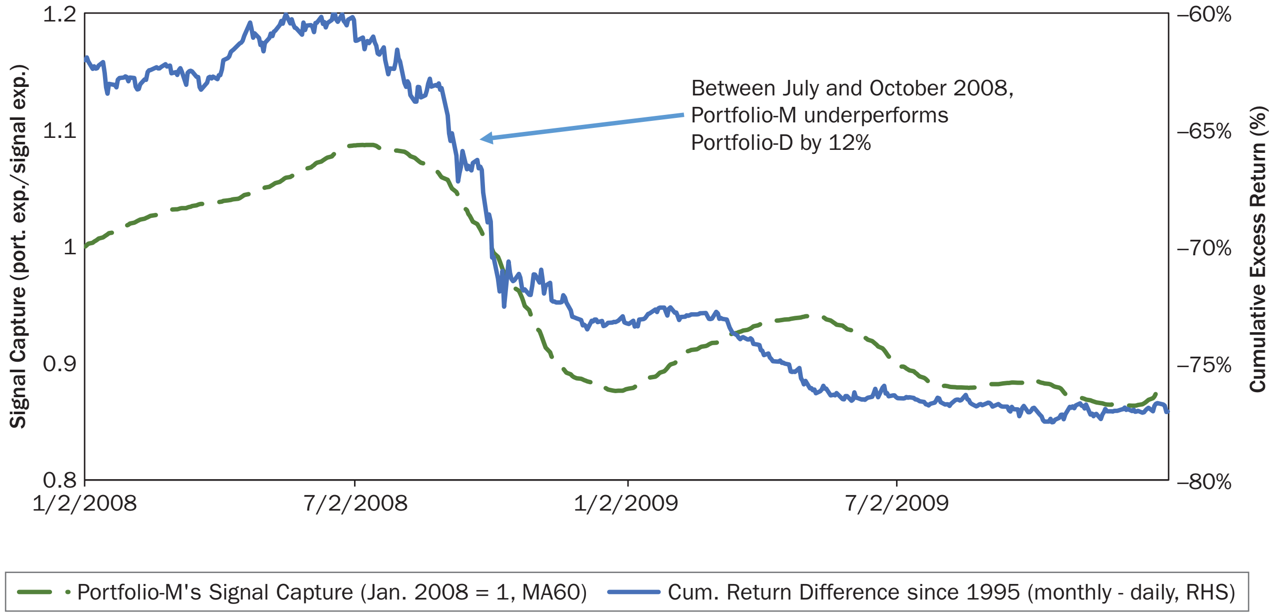
We now validate the reasoning developed earlier by applying it to the momentum portfolios in 1999–2001 and 2008–2009. In Exhibit 8, comparing Portfolio-M to Portfolio-D as before, we track how signal capture and cumulative return difference evolved over the run-up to the peak of the dot-com bubble and the bust afterward. Similar to our previous observations about the value portfolio, relative underperformance of Portfolio-M co-moves strongly with the decay in signal capture. In particular, more than half of the cumulative underperformance between 1999 and 2001 (a 24% gap from –11% in January 1999 to –35% in December 2001) stems from the two-month period from April to June 1999, when the performance gap widened by 14%. This was part of the last phase of frenzy of the dot-com bubble. The rest of underperformance came from late in 2000, when market leadership changed rapidly after the bubble burst throughout the year. Common to both periods' steep declines in the relative performance of Portfolio-M is that they were accompanied by a general decay in signal capture, similar to the signal decay of value Portfolio-M from the first case.

In Exhibit 9, we observe a pattern that looks familiar now. Between 2008 and 2009, effectively all underperformance of –15% comes from fall of 2008 around the Lehman default; specifically, between July 1, 2008 and October 10, 2009, Portfolio-M underperformed Portfolio-D by 12%. With the benefit of hindsight, this took place because Portfolio-M—given the rigidity of its monthly rebalancing schedule—held onto the winners before the default of Lehman Brothers for too long, without incorporating momentum scores that were changing rapidly by the day because the default news changed the investor outlooks fundamentally.

Based on the findings of this article, we make the following observations about managing long-only factor portfolios. First, the distribution of factor returns in general indicates the importance of right-tail returns in achieving its historically observed factor premium. That is, without the benefit of the outsized right-tail returns, it may be sensible to lower the return expectation from factors. Second, when factors are in

EXHIBIT 9

Signal Capture and Excess Return of Momentum Portfolio: 2008–2009



action and delivering outsized returns, rebalancing to the signal portfolio proactively—as frequently as on a daily basis—appears to deliver a factor premium significantly greater than the more slowly rebalanced alternatives. Third, in the rare moments when market cycle transitions take place, there may be signs that indicate the timing is right to dial up rebalancing intensity for factor fund managers that pay attention to these. An ability to increase the odds of seizing these moments may be a skill worth looking for in factor fund portfolio managers. Although a full characterization of a framework that would increase the odds of getting these moments right is beyond the scope of this article, it is a topic we hope to expand on in a future contribution.[22]

CONCLUSIONS

In this article, we examined the optimality of various rebalancing approaches to managing long-only factor funds. Although the indexed nature of many factor funds in the marketplace tends to create an impression that factor investing is a passive endeavor, we have shown that such a characterization cannot be further from the truth. Long-only factor returns are best characterized as having a long and fat right tail, being dormant much of the time, and showing up in outsized increments in a concentrated fashion around major market cycle transitions. Seize the moment when the target factor shows up, and the investor will be delighted for years to come. Miss the moment, and the investor may have missed a once-in-a-decade opportunity to earn a sizeable factor premium.

Successful factor investing appears to require not only patience—to wait until the factor is in action—but also well-timed agility to follow the signal aggressively when the right-tail return environment does present itself. Reflecting on these attributes and the apparent tension between the two, we return to the analogy of surfing and

[22] The key elements will include monitoring changes in active risk, deteriorations in signal capture, and factor return momentum (e.g., Ehsani and Linnainmaa 2019 and Gupta and Kelly 2019).

conjure an image that aptly captures an ideal approach toward factor investing: the image of a master surfer who waits for the big wave. Clearly lacking the ability to create waves, the surfer has no other option but to wait patiently for the big wave to appear. However, if and when the big wave does appear, how this surfer has prepared for this once-in-a-decade opportunity will be fully on display. A well-prepared master surfer will ride the wave from start to finish, whereas others may wait on the side line for too long and catch only the tail end of the wave, a wave that may not return for another decade.

APPENDIX

EXHIBIT A1

Two-Way Turnover of Factor Portfolios: Three Implementations

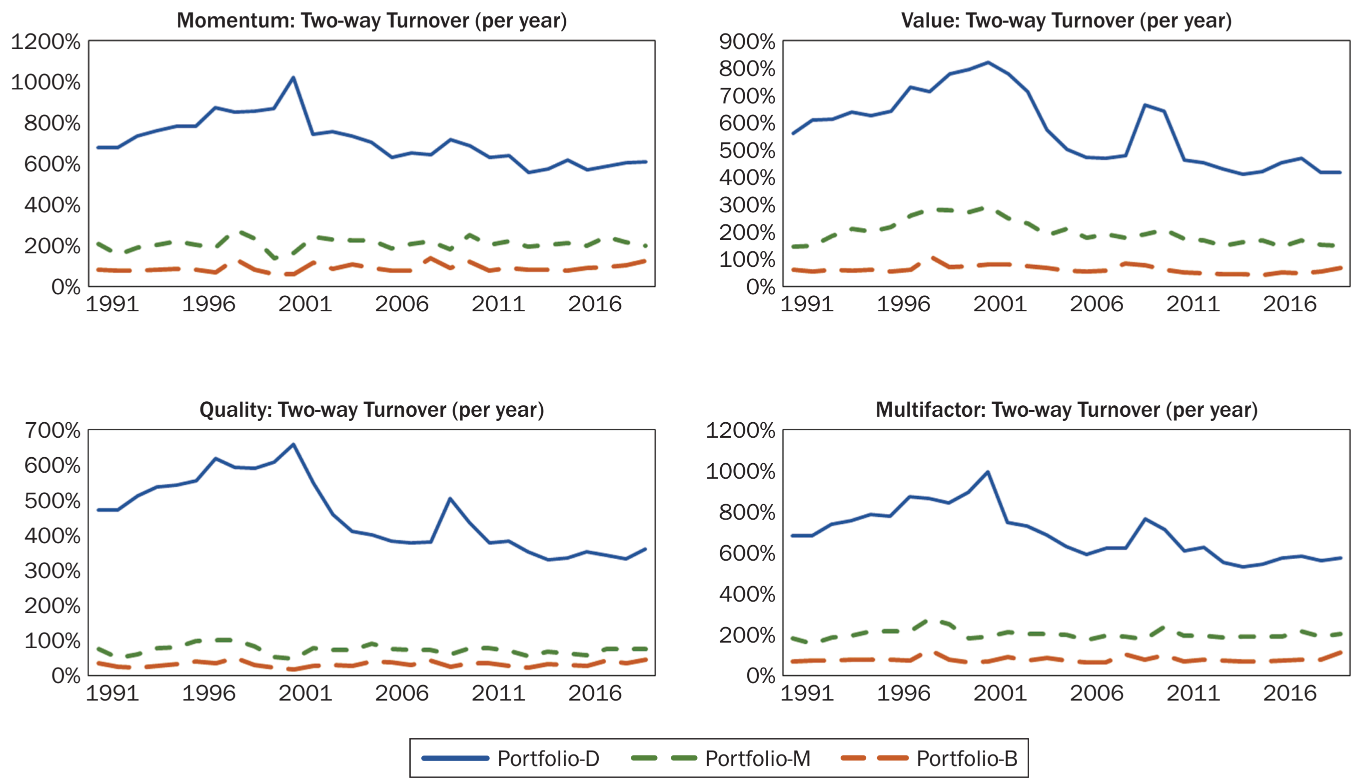
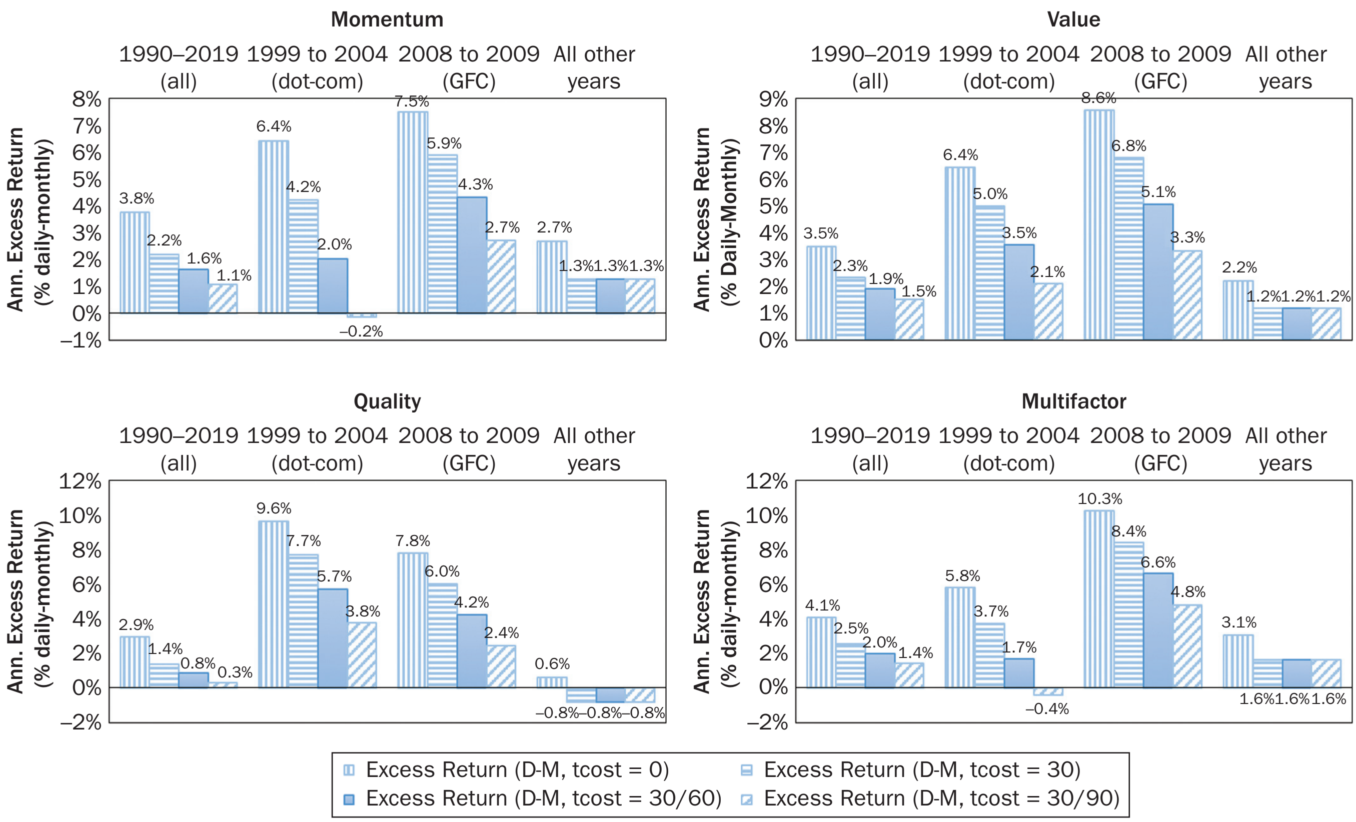


EXHIBIT A2

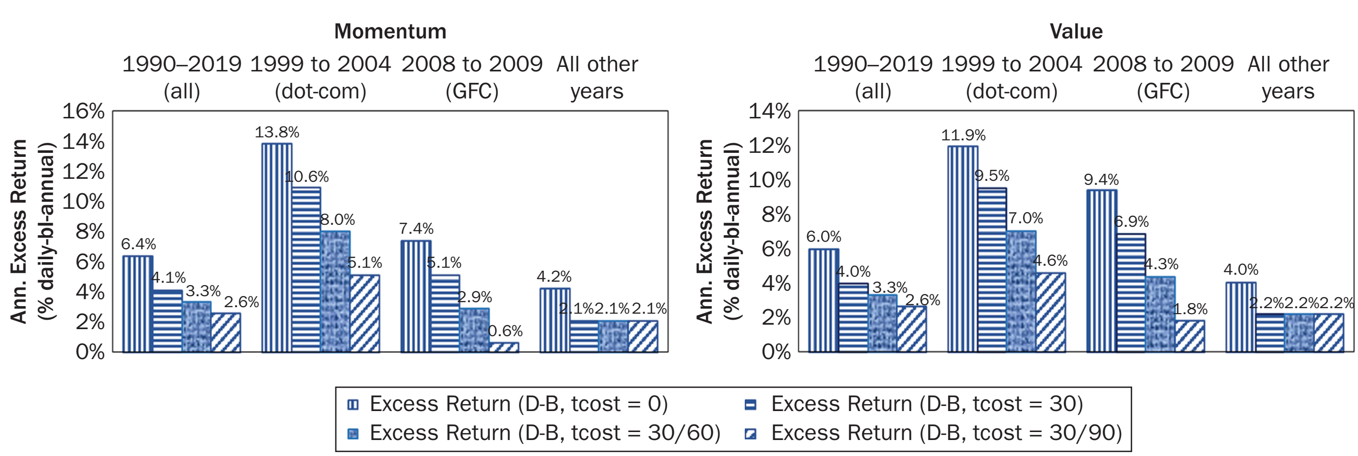
Excess Return of Portfolio-D over Portfolio-M under Various Transaction Cost Assumptions



NOTES: Each bar represents the annualized excess return of Portfolio-D over Portfolio-M under the four periods as defined in the article and in Exhibit 3. There are four trading cost assumptions: (1) zero transaction cost, (2) a one-way transaction cost of 30 bps per trading volume, constant throughout the whole 30-year period, (3) a one-way transaction cost of 30 bps per trading volume in normal times and 60 bps in the two market cycle transitions of 1999–2004 and 2008–2009, and (4) a one-way transaction cost of 30 bps per trading volume in normal times and 90 bps in the two market cycle transitions of 1999–2004 and 2008–2009.

EXHIBIT A3

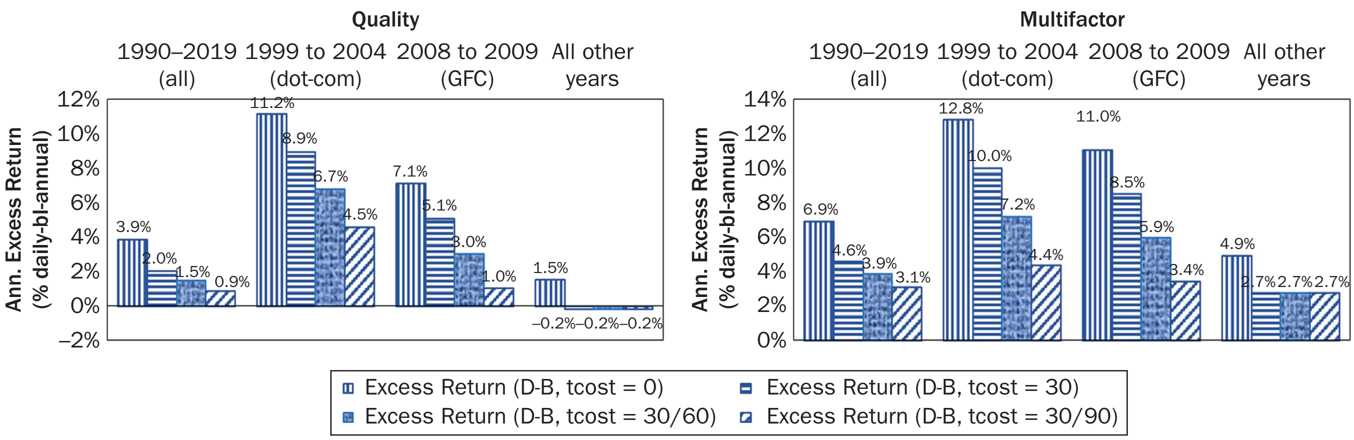
Excess Return of Portfolio-D over Portfolio-B under Transaction Cost Assumptions



(continued)

EXHIBIT A3 *(continued)*

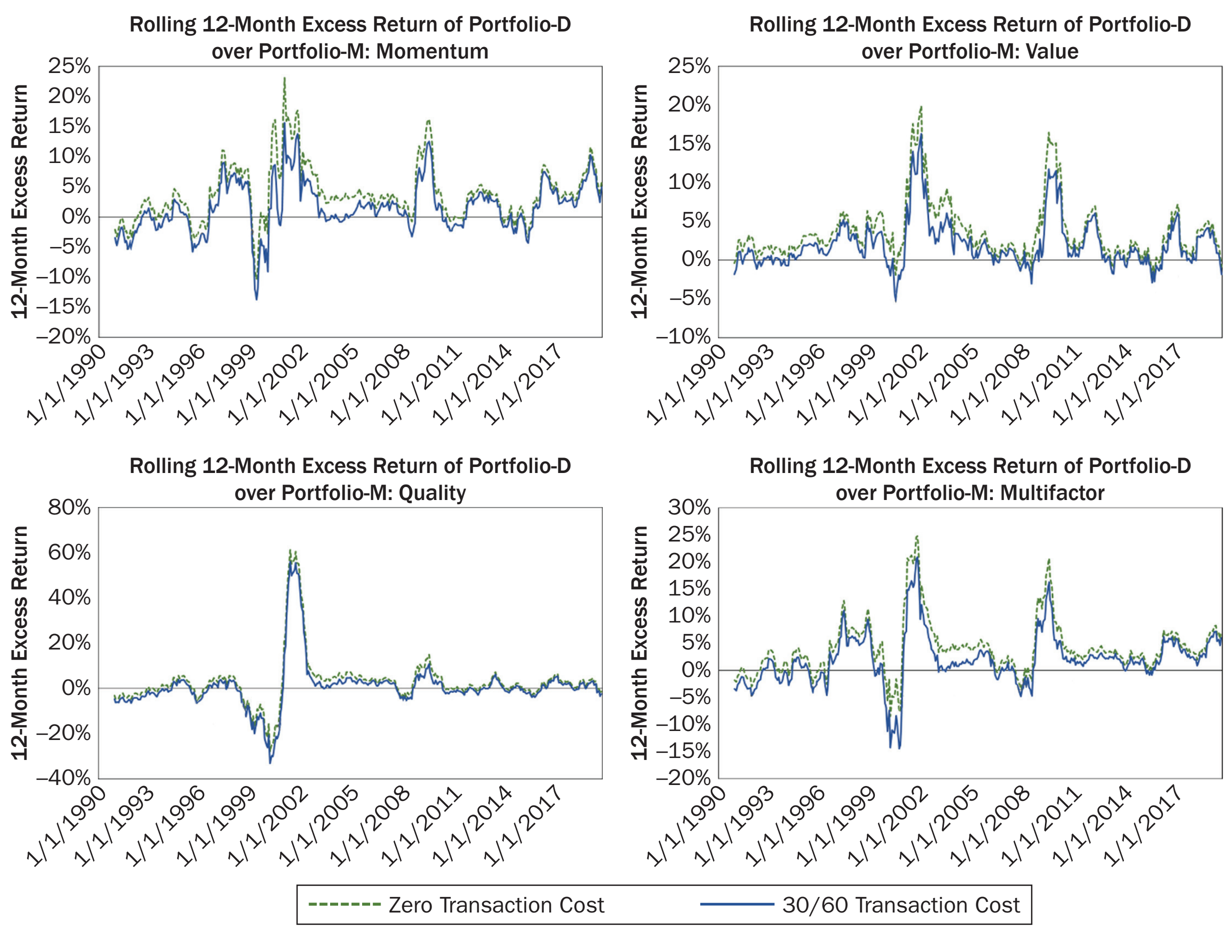
Excess Return of Portfolio-D over Portfolio-B under Transaction Cost Assumptions



NOTES: Each bar represents the annualized excess return of Portfolio-D over Portfolio-B under the four periods as defined in the article and in Exhibit 3 and trading cost assumptions described under Exhibit A2.

EXHIBIT A4

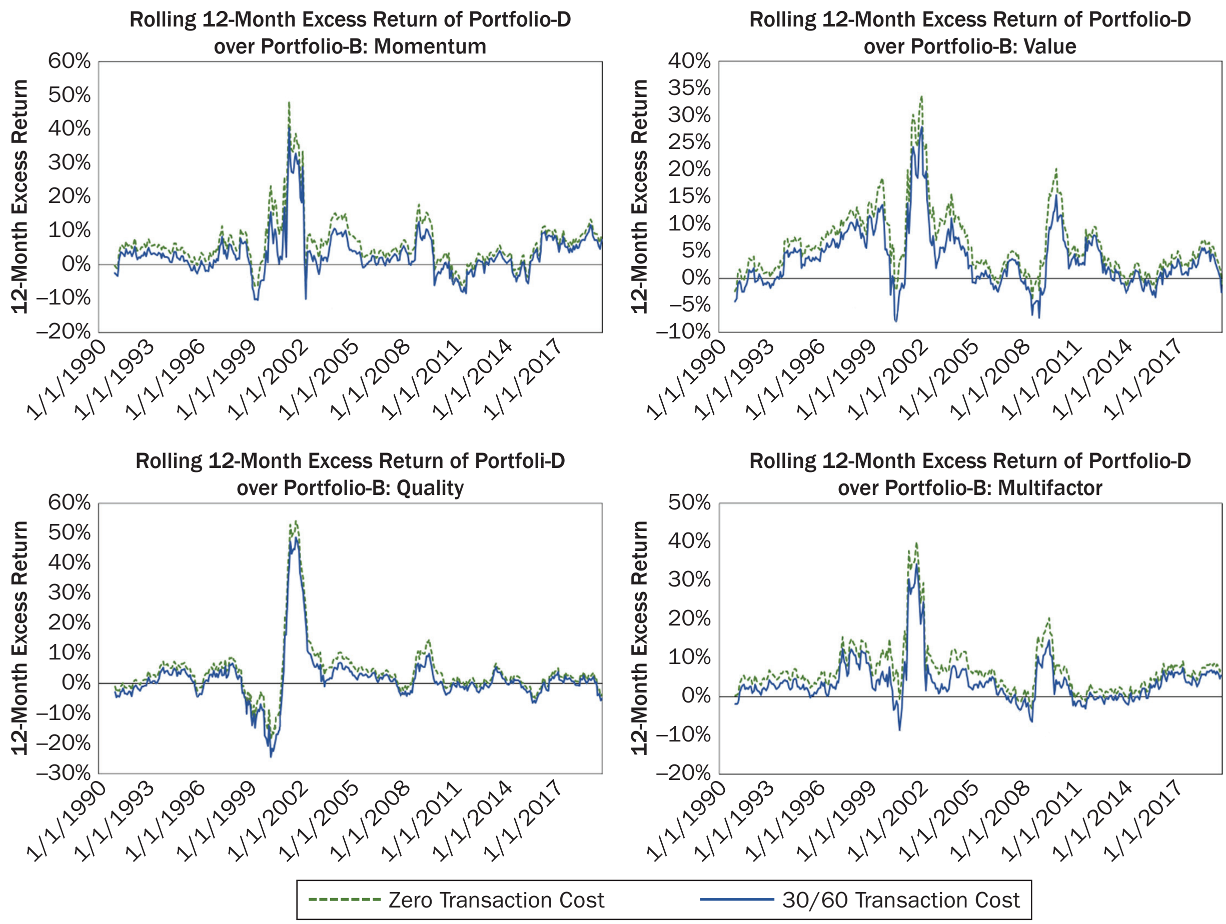
Excess Return of Portfolio-D vis-à-vis Portfolio-M over Time, January 1990 to August 2019



NOTES*:* Each chart shows rolling 12-month excess returns under two transaction cost assumptions: (1) zero transaction cost and (2) a one-way transaction cost of 30 bps per trading volume in normal times and 60 bps in the two market cycle transitions of 1999–2004 and 2008–2009.

EXHIBIT A5

Excess Return of Portfolio-D vis-à-vis Portfolio-B over Time, January 1990 to August 2019



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