Cross-sectional Return Dispersion and the Payoffs of Momentum, Longer-run Contrarian, and Book-to-Market Strategies[1]

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Abstract

We document a striking new regularity in the payoffs of momentum, longer-run contrarian, and book-to-market (B/M) stock strategies. Over our 1962 to 2005 sample, we find that the several month trend in the stock market's cross-sectional return dispersion (RD) is substantially related: (1) negatively, to the subsequent change in 6-month momentum payoffs, (2) positively, to the subsequent change in 36-month contrarian payoffs; and (3) positively, to the subsequent change in both 6-month and 36-month high-minus-low B/M strategies. When decomposing each payoff-change into the forward-looking payoff and the lagged reference payoff, we find that the RD-trend is generally reliably related to both the forward-looking payoff (in the same direction as for the respective payoff-change) and the lagged reference payoff (in the opposite direction as for the respective payoff-change). We offer an interpretation which suggests that RD is a leading indicator of market-state changes and that market-state transitions are important for understanding the payoffs of momentum, contrarian, and book-to-market strategies.

JEL Classification: G12, G14

Keywords: Momentum, Contrarian, Book-to-Market Equity Ratio, Return Dispersion

1. Introduction

Cross-sectional variation in mean stock returns tied to past relative-return strength and to book-to-market (B/M) equity ratios has an important role in both current financial practice and theory. The reliability, magnitude, and nature of momentum payoffs and high-minus-low B/M payoffs has lead to these spreads being proposed as factor-mimicking portfolios in asset pricing models. However, while it is generally agreed that these spreads' payoffs are at odds with the classic CAPM, there is an ongoing debate as to whether these prominent spreads represent risk factors or anomalies. Further, longer-run contrarian strategies tend to have positive average returns, which seems at odds with medium-run momentum.[1]

In this paper, we document a striking relation between the trend in the market's cross-sectional return dispersion (RD) and the payoffs of 6-month momentum, 36-month contrarian, and book-to-market strategies at both the 6-month and 36-month horizon.[2] We examine 6-month strategies because this horizon is prominent in the momentum literature with performance that survives standard risk adjustments. We examine 36-month strategies because this horizon is in the spirit of economic cycles and follows from the longer-run contrarian results in DeBondt and Thaler (1985). With these horizons, we also hope to further our understanding of how medium-run momentum and longer-run contrarian strategies interrelate.

A priori, why might the market's RD trend be related to changes in the subsequent payoffs of momentum, contrarian, and book-to-market strategies? We focus on one possibility that appeals to the intuition of market and industry cycles. The market's RD is one measure of the cross-sectional divergence in realized stock returns. Going back to the Dow Theory that originated in the early

[1]By momentum (contrarian) strategies, we mean the return spread between a portfolio of past relative winners (losers) and a portfolio of past relative losers (winners). By HML strategies, we mean the return spread between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks. For background, see the following (to list just a few): DeBondt and Thaler (1985), Lo and MacKinlay (1990), Jegadeesh and Titman (1993) and (2002), Fama and French (1993), (1996), (1998) and (2008), Carhart (1997), Daniel and Titman (1997), Conrad and Kaul (1998), Moskowitz and Grinblatt (1999), Grundy and Martin (2001), Chordia and Shivakumar (2002), Griffin, Ji, and Martin (2003), Conrad, Cooper, and Kaul (2003), Cooper, Gutierrez, and Hameed (2004), Zhang (2005), Petkova and Zhang (2005), Avramov, Chordia, Jostova, and Philipov (2007), and Bulkley and Nawosah (2007).

[2]In our paper, the stock market's monthly RD is defined as the cross-sectional standard deviation of monthly individual stock returns or disaggregate portfolio returns, depending upon the particular RD metric.

1900's, Wall Street practitioners have promoted the notion that increasing cross-sectional return divergence can indicate higher market uncertainty and foreshadow a transition in market states. For example, in his Wall Street Journal editorial on May 24, 1924, William Peter Hamilton, one of the founders of the Dow Theory, observes that "it seems that a clear inference, in a movement where the averages do not confirm each other, that uncertainty still continues as concerns the business outlook ...", where 'averages' refers to different sector stock indices.[3]

Our motivating framework considers that the market's RD may trend up during market-state transitions; and, if so, this may generate a relation between the RD-trend and momentum, contrarian, and book-to-market payoffs.[4] As the market-state transitions, the relative return performance of different sectors and firm-types is likely to change due to shocks in expected future cash flows (in the sense of Veronesi (1999) and Pastor and Veronesi (2008)), changes in risk premia (in the sense of Fama and French (1989) or Pastor and Veronesi (2008)), changes in evolving technology (in the sense of Pastor and Veronesi (2008)), and/or change in investor sentiment (in the sense of Baker and Wurgler (2006)). These changes are likely to result in shifts in the relative return performance of different industry sectors and different firm-types; and, possibly, an increasing RD trend.

For example, consider a transition toward a weak economic state where investors do not know the true state in real time. With the shift to the weak state, the more cyclical stocks (that were the relative winners in the prior good state) may transition to underperformance (relative to less cyclical stocks) and the winners over the past ranking period could suddenly become the current relative losers. Under this possibility, then momentum payoffs should decrease and contrarian payoffs increase during/following market-state transitions. Similarly, if the changes in market state are also associated with changes in the relative performance of growth versus value stocks, then

[3]See Brown, Goetzmann, and Kumar (1998) for evidence that supports the performance of the Dow Theory. A recent example of significant return divergence occurred as the so-called technology bubble peaked in 2000. In the early months of 2000, there was a clear divergence between the DJIA and the NASDAQ, when the DJIA stalled but the NASDAQ continues its final bull market run to historical new highs. This divergence between the two indexes was followed by a severe bear market that lasted for about three years. During the subsequent bear market, NASDAQ (which is heavily represented by growth stocks) had a much weaker performance than the DJIA (which consists more of stable and value-oriented stocks).

[4]By market-state transitions, we refer to a broad interpretation that includes: (1) transitions from economic expansions to recessions, (2) transitions from relatively calm growth periods to volatile downturn periods, or (3) transitions tied to technological revolutions in the sense of Pastor and Veronesi (2008).

the RD-trend may also be related to changes in the payoffs of B/M strategies.

Thus, if the market's RD tends to trend up during market-state transitions, a 'market-state transition' hypothesis suggests: (1) a negative intertemporal relation between the RD-trend and the subsequent change in medium-run momentum payoffs, and (2) a positive intertemporal relation between the RD-trend and the subsequent change in longer-run contrarian payoffs (assuming market-states of sizable duration). Further, under this hypothesis, one might observe a positive (negative) intertemporal relation between the RD-trend and subsequent change in B/M payoffs, if the RD tends to increase more during transitions to a state where value-stocks (growth-stocks) perform relatively better than growth-stocks (value-stocks).

Given the empirical implications of the 'market-state transition' hypothesis, our paper's empirical focus is on the relation between the RD-trend and the subsequent change in the payoffs of momentum, longer-run contrarian, and book-to-market strategies. In contrast, related time-series studies such as Chordia and Shivakumar (2002) and Cooper et al (2004) focus on variation in the simple payoff level and they focus exclusively or primarily on momentum. In our paper, we also examine variation in the simple payoff levels of the different strategies, but in a secondary role.

For our 'change in payoff' variables, we focus on the difference between the forward-looking realized payoff over holding-months t to $t+5$ (t to $t+35$) and a lagged realized payoff over holding-months $t-9$ to $t-4$ ($t-39$ to $t-4$) for the 6-month (36-month) strategies. This timing is relative to our primary RD-trend measure that features the RD moving-average over months $t-1$ to $t-3$. Thus, the key 3-month RD moving-average comes before the forward-looking payoff and after the lagged reference payoff. We stress that our results are robust to alternate timing variations that are similar in concept for the payoff-change and RD-trend variables.

Our primary RD-trend term is defined as the difference between the 3-month RD moving-average over months $t-1$ to $t-3$ and an earlier 12-month RD moving-average. We investigate both the market's simple monthly RD and a monthly market-adjusted 'relative RD' (or RRD), which is constructed to be orthogonal to the concurrent absolute market return.[5]

Over our 1962 to 2005 sample, we document new empirical regularities that describe the time-

[5]Since a month's simple RD should vary with the absolute monthly market return due to dispersion in firm's market-betas (Stivers (2003)), we construct the RRD to isolate better the dispersion effects. We investigate four alternate RD metrics: a broad-market RD in individual stocks, the RD in large-firm stocks, the RD across 48 industries, and the RD across 100 book-to-market and size double-sorted portfolios.

series of payoffs to momentum, contrarian, and book-to-market strategies. First, we find that the market's RD-trend is negatively and substantially related to the subsequent change in 6-month momentum payoffs.[6] For example, when the lagged RRD-trend is in its top quartile, the subsequent 6-month momentum-payoff decreases 73.2% of the time with an average payoff *decrease* of 10.5% from the earlier reference payoff (where 'decrease' refers to the numeric difference in payoff levels, not the percentage change from the earlier payoff). Conversely, when the lagged RRD-trend is in its bottom quartile, the subsequent momentum-payoff decreases only 32.3% of the time with an average payoff *increase* of 6.8%.

Next, and even stronger, we find that the market's RD-trend is positively and substantially related to the subsequent change in 36-month contrarian payoffs. Here, when the lagged RRD-trend is in its top quartile, the subsequent 36-month contrarian-payoff increases 82.1% of the time with an average payoff *increase* of 48.9%. Conversely, when the lagged RRD-trend is in its bottom quartile, the subsequent contrarian-payoff increases only 25.9% of the time with an average payoff *decrease* of 48.7%.

Next, we find that the market's RD trend is positively related to the subsequent change in HML B/M strategies, at both the 6-month and 36-month horizon. Here, when the lagged RRD-trend is in its top quartile, the subsequent HML-payoff increases 67.7% (76.8%) of the time, with an average payoff *increase* of 5.4% (28.0%) for the 6-month (36-month) horizon. However, when the lagged RRD-trend is in its bottom quartile, the subsequent HML-payoff increases only 27.6% (16.1%) of the time with an average payoff *decrease* of 5.6% (26.6%) for the 6-month (36-month) horizon.[7]

The partial relations between RD and the subsequent payoff-changes remain virtually unchanged while controlling for macroeconomic variables suggested by the literature, and the macroeconomic variables add little explanatory power in our setting. Further, our RD-trend findings are robust to: (1) alternate RD metrics; (2) sample subperiods; (3) strategies implemented on industry-level

[6]Our symmetric momentum strategies go long (short) stocks whose returns were above (below) a percentile threshold over the 6-month ranking period (deciles for the firm-level strategies and quartiles for the industry-level strategies) and hold this portfolio for a 6-month holding period. Conversely, our symmetric contrarian strategies go short (long) stocks whose returns were above (below) a percentile threshold over the 36-month ranking period (deciles for the firm-level strategies and quartiles for the industry-level strategies) and hold this portfolio for a 36-month holding period.

[7]Here, HML refers to the difference between the average return for the two highest decile-portfolios and the two lowest decile-portfolios from sorting stocks on their book-to-market equity ratio, from the K. French data library.

portfolio returns (rather than individual stocks), (4) large-firm only strategies, and (5) strategies that omit extreme winner and loser stocks or omit extreme B/M stocks.

We also decompose the payoff-change terms into the forward-looking payoff and the lagged reference payoff, and then investigate each component separately. For all three strategies, we find that the RD-trend is generally related to both the forward-looking payoff (in the same direction as for the respective payoff-change term) and the lagged reference payoff (in the opposite direction as for the respective payoff-change term). Thus, consistent with our 'market-state transition' hypothesis, the RD-trend is consistently related to each component of the payoff-change term, but the RD-trend is more strongly related to the payoff-change term.

We also present additional evidence to help interpret our RD findings. We estimate a two-state, bivariate regime-switching model on industry stock returns and show that a higher RD-trend is associated with market-state transitions, especially good-to-bad state transitions. We also document that NBER recessionary months tend to be preceded by relatively high RD values.

To sum up, we document a sizable and pervasive relation between the market's RD trend and the payoffs to momentum, contrarian, and book-to-market strategies. Our collective evidence suggests a common market condition where the subsequent payoffs to all three different strategies tend to change appreciably. We offer a 'market-state transition' perspective to frame and interpret our empirical investigation; where the RD-trend is a leading indicator of market-state changes and where market and industry cyclicality is important in understanding momentum, contrarian, and book-to-market strategies.

However, we acknowledge that our findings do not flow from a formal theoretical model and that readers are likely to propose alternate explanations. Our evidence may prove theoretically useful in understanding these spreads; since theories, either rational or behavioral, should attempt to understand these spreads' time-series regularities as well as their average payoffs. Regardless of the theoretical underpinnings, our findings may have a practical importance for investors who vary their loadings on these spread strategies in the sense of Avramov and Chordia (2006).

Section 2 discusses related literature and hypothesis development. Section 3 presents our data and variable construction. Section 4 investigates momentum and contrarian payoffs, and Section 5 investigates payoffs to book-to-market strategies. Section 6 presents robustness evidence and Section 7 provides additional evidence to assist in interpretation. Section 8 concludes.

2. Additional Background and Hypothesis Development

2.1. Other Related Literature and Background

The performance of relative-strength strategies remain an ongoing puzzle in financial economics, with medium-run momentum (in the 3 to 12 month range) exhibiting reliable profits but with longer-run relative-strength payoffs tending to be negative (or, equivalently, longer-run contrarian payoffs that tend to be positive). The literature on relative-strength strategies is vast, so we only discuss recent related studies here. Chordia and Shivakumar (2002) find evidence that momentum profits can be linked to business cycles and predicted by lagged macroeconomic variables.[8] Cooper, Gutierrez, and Hameed (2004) present evidence that momentum profits are only reliably positive following positive long-run market returns. They conclude that "models of asset pricing, both rational and behavioral, need to incorporate (or predict) such regime switches." Avramov and Chordia (2006) show that an optimizing investor who conditions on business-cycle variables can successfully vary their momentum exposure during different economic times.

Return spreads based on book-to-market equity ratios have also been widely documented and debated in the finance literature. Value-versus-growth refers to the observed phenomenon where stocks with a high book-to-market ratio tend to have higher average returns than stocks with a low book-to-market ratio. See, e.g., Fama and French (1993), (1996) and (1998), Daniel and Titman (1997), Conrad, Cooper, and Kaul (2003), Cohen, Polk, and Vuolteenaho (2003), Zhang (2005), and Petkova and Zhang (2005) for perspective and recent evidence on HML spreads.

Our empirical investigation considers that the market's RD may trend higher during market-state transitions. Prior studies find evidence consistent with this notion. Stivers (2003) notes that RD is higher during economic recessions and finds that RD has incremental information about subsequent market volatility. Loungani, Rush, and Tave (1990) find that RD tends to lead unemployment, which suggests a link between RD and economic reallocation across firms.[9]

[8] However, Cooper, Gutierrez, and Hameed (2004) find that the results in Chordia and Shivakumar (2002) are not robust to methodological adjustments that guard against market frictions and penny stocks driving the results. Griffin, Ji, and Martin (2003) find that the results in Chordia and Shivakumar (2002) tend to not hold in other countries.

[9] See Bekaert and Harvey (1997), (2000), and Chang, Cheng, and Khorana (2000) for examples of other uses of RD in the literature.

2.2. The 'Market-state Transition' Hypothesis

In this section, we offer a simple two-state, return-generating process to provide a conceptual framework and intuition for our 'market-state transition' hypothesis. We first provide an illustrative example of a simple stock market with three categories of stocks, each with different cyclicality. Second, we provide a formal analytical framework to show how the payoffs of relative-strength strategies can be influenced by market cyclicality. We stress that this framework is not intended to be rich enough to capture actual market behavior, but rather is intended to represent market and sector cyclicality.

To begin with, consider a two-state stock market where the good-regime is the predominant regime with an expected duration of 64 months. The bad-regime has an expected duration of 24 months and is presumably associated with recessions or other financial crises. The true market state is unknown, in real time, but investors can learn about the state in the sense of Lewellen and Shanken (2002). Next, assume three different stock types; Stock A (representing highly cyclical stocks), Stock B (representing stocks of average cyclicality), and Stock C (representing less cyclical stocks), which have unconditional one-month expected returns of 1.2%, 1%, and 0.8%, respectively. Further, assume that Stocks A, B, and C have one-month mean returns of 1.70%, 1.30%, and 0.60% in the good-regime and -0.13%, 0.20%, and 1.33% in the bad-regime, respectively.

Such differences in regime-specific mean returns could be attributed to at least two factors. First, times that were classified as a bad-regime (good-regime), *ex post*, are likely to have experienced negative (positive) earnings surprises in real time, especially for highly cyclical stocks. Second, Fama and French (1989) argue that market-wide risk-premia are higher when economic conditions are weak. If so, then stock prices should tend to fall during transitions to the bad-regime as the market-wide risk-premium increases (and vice versa). These two effects could translate to variation in "realized mean returns" across regimes. Thus, the regime-specific means are interpreted as "realized subset means associated with an economic outcome", rather than conditional risk premia.[10]

The differences in regime-specific means affect the payoffs of relative-strength strategies in two opposing ways. First, the cross-sectional variance in regime-specific means is greater than the cross-

[10]Consistently, over our 1962 to 2005 sample, the mean return of the CRSP value-weighted stock index is 0.40% per month during recessionary months and 0.98% per month during expansionary months.

sectional variance in unconditional means. Thus, relative-strength strategies for 'within regime' outcomes will be greater than the payoffs implied solely by the unconditional mean returns.[11] However, 'across-regime' outcomes should be associated with negative payoffs to momentum strategies (or positive payoffs to contrarian strategies), because stocks that perform relatively well in one regime tend to perform relatively poorly in the other regime. The net impact of regime switching to momentum and contrarian performance is unclear and will vary with the strategy's horizon.

We calculate the payoffs to symmetric 6-month momentum and 36-month contrarian strategies in this market. The momentum (contrarian) strategy buys the relative winner (loser) and shorts the relative loser (winner) over the ranking period. First, the average 6-month momentum-payoff is over twice that suggested by the cross-sectional variation in unconditional mean returns (+0.90% versus +0.40% per month), with about 14% of the realized payoffs being negative. Next, the average 36-month contrarian payoff is positive and appreciably higher than that suggested by the cross-sectional variation in unconditional mean returns (+0.36% versus -0.40% per month), with about 34% of the realized 36-month contrarian-payoffs being negative.

We also calculate the change in payoffs across state transitions, defined as the difference between: (1) the payoff during a state-transition where the holding period begins in the first month of a new market-state, and (2) an earlier strategy payoff that precedes the transition. Here, the average *decrease* in the 6-month momentum payoffs is -2.67% per month; and the average *increase* for the 36-month contrarian payoffs is +1.78% per month, when using the same timing for the payoff-change terms as specified in our introduction.

Thus, in this simple two-state framework, changes in the market state should be associated with sizable decreases in the subsequent 6-month momentum payoff and sizable increases in the subsequent 36-month contrarian payoff. Further, consistent with the stylized facts, the unconditional average payoffs of both 6-month momentum and 36-month contrarian are appreciably greater than that suggested solely by the cross-sectional variation in unconditional mean returns.

When stepping away from the simple 3-stock market example, the cross-sectional RD may trend higher during state-transitions because of sizable cross-sectional variation in equity re-valuations due to: (1) changes in expected cash flows with economic sector reallocations (sector rotation)

[11]By 'within regime' ('across regime'), we mean outcomes for the relative-strength strategy where the ranking period and the holding period are within the same uninterrupted regime (across different regimes). By outcome, we mean the profit from a single 'ranking-period/holding-period' event.

as the relative performance of 'more cyclical' versus 'less cyclical' stocks shifts with the market state (or the relative performance of value versus growth stocks), (2) changing risk premia with the changing market state, and/or (3) shifts in investor sentiment in the sense of Baker and Wurgler (2006). If so, then the two-state framework in this subsection clearly suggests: (1) a negative relation between the realized RD-trend and the subsequent change in momentum payoffs, and (2) a positive relation between the realized RD-trend and the subsequent change in contrarian payoffs.

The relative return performance of value stocks versus growth stocks are also commonly thought of as running in cycles; see, e.g. Gulen, Xing, and Zhang (2008) . For example, over the growth 1996 to 1999, the average HML B/M payoff in our data was negative at -0.9% per month. Conversely, over the downturn in 2000 to 2002, the average monthly HML B/M payoff in our data was positive at 1.1% per month. Thus, this two-state framework also suggests the possibility of a positive (negative) intertemporal relation between the realized RD trend and subsequent changes in HML payoffs, if the realized RD tends to be higher during transitions to a state where value (growth) does relatively better than growth (value).

We also offer a formal analytical two-state framework to analyze how regime-switching can influence the payoffs of relative-strength strategies. Our analytical framework starts from the decomposition of the 'weighted related strength' momentum strategy in Lo and MacKinlay (1990) and Conrad and Kaul (1998). We then incorporate the autocovariance function with regime-switching from Timmermann (2000). Concerning the payoffs of relative-strength strategies, this analytical work generates the same empirical implications as does our simple example above. For brevity, details are in Appendix A.

3. Data and Variable Construction

3.1. Data Sources

Our empirical work features stock return data from two sources. For U.S. individual stocks, we examine monthly NYSE and AMEX stock returns from CRSP. We also use the following monthly, value-weighted portfolio returns from the Kenneth French data library: (1) 48 industry portfolios, (2) decile portfolios based on stocks' book-to-market equity ratios, (3) 100 book-to-market and size-based portfolios, formed using a double-sort (10 x 10) of a stock's book-to-market equity ratio and market capitalization, (4) size-based, decile portfolios based on stock's market capitalization, and (5) the 'market return less the risk-free return' factor. Following Jegadeesh and Titman (1993) and Conrad and Kaul (1998), we focus on the period from January 1962. Our sample extends through December 2005.

Our study also uses the following: (1) business cycle data from the National Bureau of Economic Research (NBER), (2) the yield of Moody's BAA bonds, Moody's AAA rated bonds, 10-year T-notes, and 3-month T-bills from the Federal Reserve Statistical Release H.15, and (3) the aggregate dividend payout data from CRSP.

3.2. Measuring Momentum, Contrarian, and B/M Strategy Payoffs

Our work features symmetric percentile-based momentum and contrarian strategies. These strategies form zero-cost portfolios by starting with an equally-sized long and short position, based on the relative performance of stock returns over the lagged ranking period. For the ranking periods, we use the standard skip-a-month case (where the ranking period is gapped by one month from the holding period).

More specifically, for our firm-level decile momentum strategy, we rank NYSE and AMEX stocks into deciles based on their 6-month ranking-period return (months $t-7$ through $t-2$ with the the skip-a-month). Equally-weighted, decile-portfolios are formed based on this ranking-period sort. Our firm-level momentum payoff is the return of the top decile portfolio (the winners) less the return of the bottom decile portfolio (the losers). The positions are held for the subsequent 6-month period (months t to $t+5$). We exclude stocks priced less than five dollars at the beginning of each holding period to minimize microstructure issues related to illiquid and low-priced stocks. For our primary firm-level momentum series, we also require a stock to be in the top 80^{th} percentile by market capitalization in the last month of the ranking period. This choice ensures the smallest micro-cap stocks are not driving our results.

For our 36-month contrarian strategy, our portfolio goes long the relative losers (lowest decile) and goes short the relative winners (highest decile) over a ranking period over months $t-37$ to $t-2$. The holding period spans months t to $t+35$. The stock selection and screening process is the same as for the momentum strategy.

Alternately, we also examine a large-firm only momentum and contrarian series. For our large-firm series, a stock's market capitalization must be in the top 20^{th} percentile in the last month of the ranking period in order for it to be selected for the winner or loser grouping.

For our industry-level momentum and contrarian strategies, we perform a similar procedure on the 48 industry returns, except with a quartile threshold so the winner and loser groupings contain a sizable number of 12 industries. Quartiles are close to the 30-percentile threshold in Moskowitz and Grinblatt (1999).

In our time-series empirical work, we use the following timing convention. The payoff for month t, Mom_t for the momentum series or Ctr_t for the contrarian series, refers to the return payoff for the entire holding period, over months t to $t+5$ for the momentum series and months t to $t+35$ for the contrarian series.

Thus, an important difference between our approach and previous time-series work in Jegadeesh and Titman (1993), Chordia and Shivakumar (2002), and Griffin, Ji, and Martin (2003), is that their momentum profits for a given month use an averaging across the last n investment portfolios and thus reflect n different ranking periods, where n is the number of months for the ranking and holding period (typically 6). In contrast, in our work, each month's payoff corresponds to the outcome from a single 'ranking period/holding period' event. Our timing convention is more appropriate for our work because the outcome for month t corresponds directly to the explanatory variables up through month $t-1$.

For our 6-month and 36-month HML payoffs based on B/M, we use the same timing convention as for the momentum and contrarian strategies (but, of course, the ranking period is not applicable for the HML payoffs). HML_t^j denotes the payoff for month t for either the 6-month or 36-month horizon (j denotes the horizon, either 6 or 36 months); where the month's payoff refers to the aggregate payoff over months t to $t+5$ for the 6-month horizon and months t to $t+35$ for the 36-month horizon. Our primary monthly HML spread is the difference between the average return of the two highest decile portfolios and the two lowest decile portfolios, using the book-to-market decile-portfolios from the French data library.

Our sample period is chosen so that the first monthly spread observation for both horizons commences in August 1962, which follows from the 6-month horizon's ranking period over January to June 1962 with July 1962 as the skip-a-month. The final month of return data is December 2005. Thus, the 6-month overlapping spread series commence in August 1962 (with the first holding period over August 1962 to January 1963); and conclude in July 2005 (with the final holding period over July 2005 to December 2005). For the 36-month overlapping spread series, the first holding period is over August 1962 to July 1965 and the final holding period is over January 2003 to December 2005.

Table 1 reports descriptive statistics for the momentum, contrarian, and B/M return payoffs. Note that: (1) the average 6-month momentum payoff is reliably positive for both the firm-level and industry-level spreads, consistent with the momentum literature; (2) the average 36-month contrarian payoff is positive, consistent with the longer-run contrarian literature; and (3) the averages of the HML payoffs are reliably positive, consistent with the value-versus-growth literature, and (4) all of the strategies have an appreciable proportion of negative outcomes.

3.3. The Stock Market's Realized Cross-sectional Return Dispersion

Our work features the stock market's cross-sectional RD over a calendar month. We evaluate four alternate measures of the dispersion in disaggregate returns. A month's RD is simply the cross-sectional standard deviation of the monthly disaggregate returns, as follows:

$$RD_t = \sqrt{\left[\frac{1}{n-1}\sum_{i=1}^{n}(R_{i,t} - R_{\mu,t})^2\right]} \tag{1}$$

where n is the number of individual stocks (or disaggregate portfolios) that is used for the particular RD metric, $R_{i,t}$ is the return of individual stock i (or disaggregate portfolio i) in month t, and $R_{\mu,t}$ is the equally-weighted portfolio return of the individual stocks (or disaggregate portfolios) included in the RD metric for month t.

First, we construct and evaluate a large-firm RD that is comprised of the largest 10% of NYSE/AMEX stocks by market capitalization, excluding stocks priced less than one dollar, with the size ranking repeated each month. We examine a large-firm RD because large firms may be more indicative of the economic environment, since small firms may add noise through non-synchronous trading or high idiosyncratic volatility. Evidence in Connolly and Stivers (2003) supports this notion. Second, we construct and evaluate a broad-market RD that uses all individual NYSE/AMEX stocks, except those in the smallest size quintile and those stocks priced less than one dollar. Third, we construct and evaluate an RD from the monthly returns of the 100 disaggregate book-to-market/size portfolios. Finally, we construct and evaluate an industry-based RD using the 48 industry returns.

Our work features both the simple realized RD from equation (1) and a market-adjusted relative return dispersion (or RRD). As Stivers (2003) shows, a month's RD should vary with the month's absolute market return, due to dispersion in market betas. Since we are interested in whether the RD is relatively high or low beyond the variation tied to the realized market return, we construct a monthly RRD that is orthogonal to the month's simple market return and absolute market return. The RRD is defined as the estimated residual, ϵ_t, from the following regression:

$$RD_t = \lambda_0 + \lambda_1 \left|R_{M,t}\right| + \lambda_2 D_t^- \left|R_{M,t}\right| + \epsilon_t \tag{2}$$

Where RD_t is the month's simple RD from equation (1), $|R_{M,t}|$ is the absolute market-level stock return, D_t^- is a dummy variable that equals one when the market return is negative, and the λs are coefficients to be estimated. The CRSP value-weighted market index is used as the market return.

When estimating (2) with our large-firm RD over 1962 to 2005, we find that λ_1 is reliably positive (λ_1=0.328, t-statistic=7.30) and λ_2 is reliably negative (λ_2=-0.097, t-statistic=-2.37). For the same estimation with the book-to-market/size RD, we find that λ_1 is reliably positive (λ_1=0.154, t-statistic=6.80) and λ_2 is essentially zero (λ_2=-0.01, t-statistic=-0.00). The estimations indicate that RD varies positively with the absolute market return, as expected, but firm returns are less disperse for negative market returns (consistent with the asymmetric correlations in Ang and Chen (2002)). The R-squared values are 16.3% for the large-firm RD and 11.5% for the book-to-market/size RD, which indicates that much of the RD variability is not directly tied to the market return.

Table 2, Panel A, reports descriptive statistics for the alternate RD measures featured in this paper. Note that each RD series is substantially autocorrelated, which indicates persistence in the market's RD environment.

4. The RD-trend and Momentum and Contrarian Payoffs

This section investigates the relation between the market's RD-trend and the payoffs of 6-month momentum and 36-month contrarian strategies. We separately evaluate the payoff-change terms and the two components of the payoff-change terms (the forward-looking component and the lagged reference component). Section 4.1 specifies our empirical models. Section 4.2 reviews the empirical predictions of the 'market-state transition' hypothesis. Section 4.3 provides our main empirical results.

4.1. Empirical Models

For the change in 6-month momentum payoffs, we estimate the following two models:

$$\Delta Mom_{t,t-9} = \beta_0 + \beta_1\, RD_{1-3,8-19} + \beta_2\, StR_{1-36} + \epsilon_t \tag{3}$$

$$\Delta Mom_{t,t-9} = \beta_0 + \beta_3\, RRD_{1-3,8-19} + \epsilon_t \tag{4}$$

where $\Delta Mom_{t,t-9}$ is the difference between Mom_t (the 6-month momentum payoff over holding months t to $t+5$) and Mom_{t-9} (the 6-month momentum payoff over holding months $t-9$ to $t-4$); $RD_{1-3,8-19}$ is the RD-trend variable that is equal to 'the 3-month RD moving average over months $t-1$ through $t-3$' minus 'the 12-month RD moving average over months $t-8$ through $t-19$'; $RRD_{1-3,8-19}$ is the same as $RD_{1-3,8-19}$ except the 'market-adjusted relative RD' replaces the simple RD; StR_{1-36} is the 36-month aggregate stock market return over months $t-1$ to $t-36$; and the β's are coefficients to be estimated. We estimate the models for both the firm-level and industry-level momentum strategies, as defined in Section 3.2. For our ΔMom term, we feel that this 3-month gap between the forward-looking payoff and the lagged payoff is reasonable because three months seems a reasonable horizon to consider changes in market conditions.

For the RD-trend models in this section and Section 5, we include the lagged 36-month market return as a control for the market-return state, as suggested by results in Cooper, Gutierrez, and Hameed (2004). We estimate the coefficients by ordinary least squares, but we report t-statistics with heteroskedastic- and autocorrelation-consistent standard errors. The number of correlated residual lags are set to equal the number of months in the strategy's horizon, since our estimation has overlapping monthly observations. We stress that our results are robust to alternate variations for the gap in the payoff-change term and for the timing used for the RD-trend and RRD-trend (see Section 6.3).

Thus, our primary RD-trend, $RD_{1-3,8-19}$, is equal to the difference between the recent 3-month RD moving average over months $t-1$ to $t-3$ and an older, 12-month RD moving average. Our primary RD-trend has this differencing; because, with longer-term trends in volatility (see, e.g., French, Schwert, and Stambaugh (1987) and Campbell, Lettau, Malkiel, and Xu (2001)), a 3-month moving average by itself may not adequately measure whether the RD is economically high, relative to the recent RD environment. We choose the recent 3-month moving average, denoted as RD_{1-3}, because: (1) we feel that 3 months is a reasonable compromise that is responsive to changing market conditions but also removes some of the noise in month to month variations, and (2) there is only a small overlap with the ranking period of the forward-looking momentum and contrarian payoffs, so the RD-trend may indicate market conditions that have changed from the overall ranking period. Recall that the $t-1$ to $t-3$ timing is before the forward-looking payoff of the payoff-change term and after the lagged reference payoff of the payoff-change term.

For the older RD moving average in the RD-trend term, we use a 12-month moving average that just predates the ranking period for month t's momentum payoff, because: (1) we feel that a 12-month RD moving average is long enough to be informative about whether the most recent 3-month RD moving average is relatively high or relatively low, as compared to the recent RD environment, and (2) with the $t-8$ to $t-19$ timing, the older RD moving average is not coincident with any return used in the ranking-period or holding-period for the forward-looking momentum payoff.

As discussed in Section 3.3, we also desire to examine an RD-trend that features a monthly RD that is orthogonal to the month's realized market return. Thus, we also construct and evaluate a comparable RRD-trend, $RRD_{1-3,8-19}$, but with the market-adjusted RRD replacing the simple RD. In our view, the simple RD-trend is attractive because it can be constructed in real time with no estimated parameters. The RRD-trend is attractive because it uses a monthly market-adjusted RD that is orthogonal to the month's absolute and simple market return.

Table 2, Panel B, reports the correlations across the different 3-month RD moving-averages and the RD-trend terms evaluated in this study, when using the four different monthly raw RD series detailed in Section 3.3. Note that all of the alternate series are highly positively correlated.

We also evaluate each component of the momentum payoff-change term separately. We use the same right-hand side of the models given by equations (3) and (4), but with either the forward-looking payoff, Mom_t, or the lagged reference payoff, Mom_{t-9}, replacing the $\Delta Mom_{t,t-9}$ term.

For the change in 36-month contrarian payoffs, we estimate the following two models:

$$\Delta Ctr_{t,t-39} = \beta_0 + \beta_1 \, RD_{1-3,38-49} + \beta_2 \, StR_{1-36} + \epsilon_t \tag{5}$$

$$\Delta Ctr_{t,t-39} = \beta_0 + \beta_3 \, RRD_{1-3,38-49} + \epsilon_t \tag{6}$$

where $\Delta Ctr_{t,t-39}$ is the difference between Ctr_t (the 36-month contrarian payoff over holding months t to $t+35$) and Ctr_{t-39} (the 36-month contrarian payoff over holding months $t-39$

to $t-4$); $RD_{1-3,38-49}$ is the RD-trend variable that is equal to 'the 3-month RD moving average over months $t-1$ through $t-3$' minus 'the 12-month RD moving average over months $t-38$ through $t-49$'; $RRD_{1-3,38-49}$ is the same as $RD_{1-3,38-49}$ except the 'market-adjusted relative RD' replaces the simple RD; and the other terms are as defined for equations (3) and (4). Again, we estimate the models for both the firm-level and industry-level contrarian strategies. As for the 6-month momentum case, note that the older 12-month RD moving average from the RD-trend term just predates the ranking period for the forward-looking payoff, Ctr_t.

We also evaluate each component of the contrarian payoff-change term separately. We use the same right-hand side of the models given by equations (5) and (6), but with either the forward-looking payoff, Ctr_t, or the lagged reference payoff, Ctr_{t-39}, replacing the $\Delta Ctr_{t,t-39}$ term.

For the market's monthly RD metric in models (3) through (6), we estimate variations of the model for all four of our alternate RD measures. See Section 3.3.

4.2. Empirical Predictions

Recall that our framework in Section 2.2 suggests that relative-strength strategies should have: (1) relatively high payoffs for outcomes where the ranking period and holding period fall in the same market state, and (2) relatively low payoffs for outcomes where the ranking period and holding period fall in different states.

If the market's RD-trend ($RD_{1-3,8-19}$ and/or $RRD_{1-3,8-19}$) tends to be higher during market-state transitions, then we would expect: (1) that the forward-looking momentum payoff (Mom_t) would tend to be relatively low following higher RD-trend observations, because the payoff's holding period and ranking period are more likely to be an 'across-regime' event; (2) that the lagged, reference momentum payoff (Mom_{t-9}) would tend to be relatively high preceding higher RD-trend obsrvations, because the payoff's holding period and ranking period are more likely to be a 'within-regime' event. Combining these two implications, we would expect that the momentum payoff-change term ($\Delta Mom_{t,t-9}$) would be strongly negatively related to the RD-trend term because the payoff-change term combines the expected negative relation for the forward-looking payoff and the expected positive relation for the lagged reference payoff.

Thus, from the context of equations (3) and (4) for the 6-month momentum strategy, our 'market-state transition' hypothesis suggests that the estimated β_1 and β_3 coefficients are likely to be: (1) negative, when explaining the momentum payoff-change, $\Delta Mom_{t,t-9}$; (2) negative, when explaining the forward-looking momentum payoff, Mom_t; (3) positive, when explaining the lagged, reference momentum payoff, Mom_{t-9}; and (4) stronger, when explaining the momentum payoff-change than for either the forward-looking or lagged reference payoff separately.

For the contrarian payoffs and the RD-trend ($RD_{1-3,38-49}$ and/or $RRD_{1-3,38-49}$), we would expect the opposite implications to those for the momentum payoffs (since the contrarian strategy is the opposite of the momentum strategy, but at a longer horizon). This argument assumes that the market-states are of sufficient duration to influence these longer-run payoffs.

Thus, from the context of equations (5) and (6) for the 36-month contrarian strategy, our 'market-state transition' hypothesis suggests that the estimated β_1 and β_3 coefficients are likely to be: (1) positive, when explaining the contrarian payoff-change, $\Delta Ctr_{t,t-39}$; (2) positive, when explaining the forward-looking contrarian payoff, Ctr_t; (3) negative, when explaining the lagged, reference contrarian payoff, Ctr_{t-39}; and (4) stronger, when explaining the contrarian payoff-change than for either the forward-looking or lagged reference payoff separately.

4.3. Empirical Results

4.3.1. The RD-trend and Variation in 6-month Momentum Payoffs

Table 3 reports on how the RD-trend is related to the 6-month momentum payoffs, using the models given by equations (3) and (4). The table reports separately on strategies implemented on individual stocks and on industry portfolio returns. Here, we report results using the large-firm RD, but the results are qualitatively consistent with our other three alternate RD measures.

To begin with, Table 3, Panel A, indicates that the RD-trend is reliably related to the subsequent change in the 6-month momentum payoffs. For both the firm-level and industry-level strategies, the estimated β_1 coefficients on the RD-trend and the β_3 coefficients on the RRD-trend are reliably negative with a 0.1% p-value. The RRD-trend, by itself, explains around 14% of the variation for both the firm-level and industry-level ΔMom variables. Subperiod results are qualitatively consistent in all cases with reliably negative β_1 and β_3 coefficients.

Next, Table 3, Panel B, indicates that the RD-trend is reliably related to the subsequent level of the 6-month momentum payoffs, Mom_t (rather than the change). For both the firm-level and industry-level strategies, the estimated β_1 coefficients on the RD-trend and the β_3 coefficients on the RRD-trend are reliably negative with a 1% p-value, or better. Subperiod results are consistent with estimates of β_1 and β_3 being negative for both one-half subperiods, although the estimated coefficients are not statistically significant in the first-half period for the firm-level strategy.

Finally, Table 3, Panel C, indicates that the RD-trend is also reliably related to the lagged reference-payoff (Mom_{t-9}) of the momentum payoff-change. For both the firm-level and industry-level strategies, the estimated β_1 coefficients on the RD-trend and the β_3 coefficients on the RRD-trend are reliably positive with a 0.1% p-value. Subperiod results are consistent, with the estimates of β_1 and β_3 being positive and statistically significant for both one-half subperiods and for both the firm-level and industry-level strategies.

4.3.2. The RD-trend and Variation in 36-month Contrarian Payoffs

Next, Table 4 reports on how the RD-trend is related to the 36-month contrarian payoffs, using the models given by equations (5) through (6). Again, we report results using the large-firm RD, but the results are qualitatively consistent with our other three alternate RD measures.

To begin with, Table 4, Panel A, indicates that the RD-trend is reliably related to the subsequent change in the 36-month contrarian payoffs. For both the firm-level and industry-level strategies, the estimated β_1 coefficients on the RD-trend and the β_3 coefficients on the RRD-trend are reliably positive with a 0.1% p-value. The RRD-trend, by itself, explains around 40% of the variation for both the firm-level and industry-level ΔCtr variables. Subperiod results are qualitatively consistent in all cases with reliably positive β_1 and β_3 coefficients.

Next, Table 4, Panel B, indicates that the RD-trend is reliably related to the subsequent level of the 36-month contrarian payoffs, Ctr_t (rather than the change). For both the firm-level and industry-level strategies, the estimated β_1 coefficients on the RD-trend and the β_3 coefficients on the RRD-trend are reliably positive with a 0.1% p-value, or better. Subperiod results are consistent with estimates of β_1 and β_3 being reliably positive for both one-half subperiods.

Finally, Table 4, Panel C, indicates that the RD-trend is also reliably related to the lagged reference-payoff (Ctr_{t-39}) of the contrarian payoff-change term. For both the firm-level and industry-level strategies, the estimated β_1 coefficients on the RD-trend and the β_3 coefficients on the RRD-trend are reliably negative with a 5% p-value, or better. Subperiod results are consistent with estimates of β_1 and β_3 being negative in all cases. However, the relation is not statistically significant for the firm-level strategy in the second-half subperiod.

4.3.3. Discussion of Results

All of our results in this section are consistent with our 'market-state transition' hypothesis. The RD-trend is negatively related to the momentum payoff-change and positively related to the contrarian payoff-change. Further, in terms of the two components of the payoff-change terms, the relations between the RD-trend and the payoff-changes occur because: (1) following high RD-trends, the performance of relative-strength portfolios is lower than average, and (2) preceding high RD-trends, the performance of relative-strength portfolios is greater than average. Thus, as predicted for both the momentum and contrarian strategies, the RD-trend relation is stronger for the payoff-change terms than for either the forward-looking payoff or the lagged reference payoff separately.

Another way to examine the relation between the RD-trend and the momentum and contrarian payoffs is to sort the payoff observations into groupings based on the lagged RRD-trend's percentile. This method re-evaluates the RD relations using a simple intuitive method that clearly depicts the payoff variation tied solely to the RRD-trend.

First, we sort both the momentum and contrarian payoff-change observations on the respective lagged RRD-trend series, where the payoff-change terms and RRD-trend terms are as defined in Tables 3 and 4 for Panel A. Figure 1 reports the results from this sorting exercise.[12] The figure depicts sizable variations with the lagged RRD-trend. For example, when the lagged RRD-trend is in its top decile, then: (1) the momentum-payoff decreases by -2.74% per month, on average, and the momentum-payoff decreases 78.42% of the time, and (2) the contrarian payoff increases by 2.13% per month, on average, and the contrarian-payoff increases 100% of the time. These numbers compare to an overall result where the payoffs decrease roughly 50% of the time, with an average payoff-change of near zero (see Table 1).

Next, we sort the forward-looking payoffs of both the momentum and contrarian strategies on the respective lagged RRD-trend series, where the payoffs and RRD-trend terms are as defined in Tables 3 and 4 for Panel B. Figure 2 reports the results from this sorting exercise. The figure

[12]For the two figures discussed in this subsection and the figure discussed in Section 5.3.2, we report a standardized monthly mean that equals the cumulative holding-period mean for each strategy divided by the number of months in the strategy's holding period.

depicts sizable variations with the lagged RRD-trend. For example, when the lagged RRD-trend is in its top decile, the subsequent momentum-payoff has an average value of only 0.22% per month and the payoff is negative for 45.1% of the time. This compares to an overall monthly momentum mean of 1.21% with negative observations for only 24.4% of the time. When the lagged RRD-trend is in its top decile, the subsequent contrarian-payoff has an average value of 1.56% per month and the observations are always positive. By comparison, the overall mean for the contrarian payoffs is 0.30% per month with 41.8% of the observations being negative.

5. RD-Trend and the Payoffs of HML B/M Strategies

This section provides our primary empirical results regarding the relation between the market's RD-trend and the payoffs of HML B/M strategies, at both the 6-month and 36-month horizon. We separately evaluate the payoff-change terms and the two components of the payoff-change terms. Section 5.1 specifies our empirical models. Section 5.2 reviews the empirical predictions of the 'market-state transition' hypothesis. Section 5.3 provides our main empirical results.

5.1. Empirical Models

We begin by estimating the following two models for the 6-month HML payoffs:

$$\Delta HML^{6}_{t,t-9} = \beta_0 + \beta_1\, RD_{1-3,8-19} + \beta_2\, StR_{1-36} + \epsilon_t \tag{7}$$

$$\Delta HML^{6}_{t,t-9} = \beta_0 + \beta_3\, RRD_{1-3,8-19} + \epsilon_t \tag{8}$$

where $\Delta HML^{6}_{t,t-9}$ is the difference between the 6-month HML payoffs over months t to $t+5$ and months $t-9$ to $t-4$; and the other terms are as defined for equations (3) and (4). The coefficients of interest are β_1 and β_3.

Similarly, for the 36-month HML payoffs, we estimate the following two models:

$$\Delta HML^{36}_{t,t-39} = \beta_0 + \beta_1\, RD_{1-3,38-49} + \beta_2\, StR_{1-36} + \epsilon_t \tag{9}$$

$$\Delta HML^{36}_{t,t-39} = \beta_0 + \beta_3\, RRD_{1-3,38-49} + \epsilon_t \tag{10}$$

where $\Delta HML^{36}_{t,t-39}$ is the difference between the 36-month HML payoffs over months t to $t+35$ and months $t-39$ to $t-4$; and the other terms are as defined for equations (5) and (6). The coefficients of interest are β_1 and β_3.

We also evaluate each component of the HML payoff-change terms separately. For the 6-month HML payoffs, we use the same right-hand side of equations (7) and (8), but with either the forward-looking payoff, HML_t^6, or the lagged reference payoff, HML_{t-9}^6, replacing the $\Delta HML_{t,t-9}^6$ term. For the 36-month HML payoffs, we use the same right-hand side of equations (9) and (10), but with either the forward-looking payoff, HML_t^{36}, or the lagged reference payoff, HML_{t-39}^{36}, replacing the $\Delta HML_{t,t-39}^{36}$ term.

5.2. Empirical Predictions

Our results in Section 4 indicate that a higher RD-trend is associated with subsequent decreases in the payoffs of relative-strength strategies. Given our strong empirical results, it seems plausible that the RD-trend may also be associated with variations in the relative return performance of value versus growth stocks, based on book-to-market equity ratios.

However, under our 'market-state transition' hypothesis, any of the following three outcomes are plausible for the relation between the RD-trend and subsequent HML payoff-changes: (1) no relation, if the RD trends high similarly for both transitions to a value-over-growth state and transitions to a growth-over-value state; (2) a possible positive relation, if the RD trends relatively higher for transitions to a stronger value-over-growth state; or (3) a possible negative relation, if the RD trends relatively higher for transitions to a growth-over-value state (or to a weaker value-over-growth state).

To foreshadow later findings, in Section 7 we present results that suggest the RD tends to trend relatively higher during transitions from a stronger market state to a weaker market state. This notion fits with the example in our introduction (see our footnote 3), where high cross-sectional return divergence was observed as the technology boom peaked in 2000 and then there was a multi-year down market when value stocks substantially outperformed growth stocks.

Thus, if the RD trends relatively higher for transitions to a stronger value-over growth state, we would expect to observe the following empirical relations. In terms of our models (7) through (10), the estimated β_1 and β_3 coefficients would likely be: (1) positive, when explaining the HML payoff-changes, $\Delta HML_{t,t-9}^6$ and $\Delta HML_{t,t-39}^{36}$; (2) positive, when explaining the forward-looking HML payoffs, HML_t^6 and HML_t^{36}; (3) negative, when explaining the lagged, reference HML payoff, HML_{t-9}^6 and HML_{t-39}^{36}; and (4) stronger, when explaining the HML payoff-change terms than for either the forward-looking payoff or lagged reference payoff separately.

5.3. Empirical Results

5.3.1. Main Empirical Results

Table 5, Panel A, reports on whether the RD-trend is related to the subsequent change in HML spreads at the 6-month and 36-month spread horizons. Here, we report results using the RD from the book-to-market/size portfolios, but the results are qualitatively consistent for our three alternate RD measures.

To begin with, we find that the RD-trend contains reliable information about the subsequent change in the 6-month HML spread. For the overall sample, the estimated β_1 coefficient on the RD-trend and the β_3 coefficient on the RRD-trend are reliably positive with a 0.1% p-value. Subperiod results are consistent. The R-squared values seem sizable at 12.7%, 9.6%, and 16.9% with the RRD-trend only; for the overall period, first-half, and second-half, respectively.

Next, and even stronger, we find that the RD-trend contains reliable information about the subsequent change in the 36-month HML spread. For the overall sample, the estimated β_1 coefficient on the RD-trend and the β_3 coefficient on the RRD-trend are reliably positive with a 0.1% p-value. Subperiod results are consistent with highly reliable RD-trend coefficients. The R-squared values are sizable at 25.1%, 17.9%, and 39.4% with the RRD-trend only; for the overall period, first-half, and second-half, respectively.

We next examine the two components of the HML payoff-change terms. Results in Table 5, Panel B, indicate that the RD-trend is positively and reliably related to the subsequent level of the 36-month HML payoffs (rather than the change). For the 6-month horizon, the estimated β_1 and β_3 coefficients are also positive, but statistically insignificant and near zero.

Finally, results in Table 5, Panel C, indicate that the RD-trend is negatively and highly reliably related to the lagged reference payoffs from the HML payoff-change terms (HML^{6}_{t-9} and HML^{36}_{t-39}), for both the 6-month and 36-month horizons. Subperiod results are consistent. This result indicates that growth stocks tends to perform exceptionally well, relative to value stocks, prior to market periods with high cross-sectional return dispersion.

5.3.2. Discussion of Results

We find that the the payoff to HML B/M strategies tends to increase substantially following periods when the market's cross-sectional return dispersion trends higher. This pattern is evident with both 6-month and 36-month HML holding periods. In terms of the two components of the payoff-change terms, the relation between the RD-trend and the 36-month HML payoff-changes occurs because: (1) following high RD-trends, one observes a relatively strong value-over-growth performance, (2) preceding high RD-trends, there is a relatively strong growth-over-value performance. However, for the 6-month horizon, the payoff-change result is primarily about the strong relative performance of growth stocks prior to the high RD trend.

Another way to consider the relation between the RD-trend and changes in HML payoffs is to sort the HML payoff-changes into groupings based on the lagged RRD-trend percentile. We perform this exercise and report results in Figure 3, where the payoff-change terms and RRD-trend terms are as defined in Table 5, Panel A. We find sizable variations with the lagged RRD-trend. For example, when the lagged RRD-trend is in its top decile, the 6-month HML payoffs increase about 1.30% per month, on average, and the payoffs increase 76.5% of the time (as compared to the overall mean payoff-change of about zero, see Table 1).

6. Robustness and Other Supplementary Evidence

6.1. Controlling for Macroeconomic Variables

Chordia and Shivakumar (2002) and Avramov and Chordia (2006) find that macroeconomic variables are informative about time-variation in momentum payoffs. Cooper et al (2004) find that the market-return state is informative about time-variation in momentum payoffs. We next investigate whether the relations between the RD-trend and subsequent payoff-changes, as depicted in Tables 3 through 5, remain evident when including the macroeconomic and market explanatory variables suggested in these papers.

We estimate the following models:

$$\Delta Mom_{t,t-9} = \theta_0 + \theta_1 RRD_{1-3,8-19} + \theta_2 StR_{1,36} + \theta_3 dy_{t-1} + \theta_4 div_{t-1} + \theta_5 trm_{t-1} + \theta_6 yd3_{t-1} + \epsilon_t \quad (11)$$

$$\Delta Ctr_{t,t-39} = \theta_0 + \theta_1 RRD_{1-3,38-49} + \theta_2 StR_{1,36} + \theta_3 dy_{t-1} + \theta_4 div_{t-1} + \theta_5 trm_{t-1} + \theta_6 yd3_{t-1} + \epsilon_t \quad (12)$$

$$\Delta HML^6_{t,t-9} = \theta_0 + \theta_1 RRD_{1-3,8-19} + \theta_2 StR_{1,36} + \theta_3 dy_{t-1} + \theta_4 div_{t-1} + \theta_5 trm_{t-1} + \theta_6 yd3_{t-1} + \epsilon_t \quad (13)$$

$$\Delta HML^{36}_{t,t-39} = \theta_0 + \theta_1 RRD_{1-3,38-49} + \theta_2 StR_{1,36} + \theta_3 dy_{t-1} + \theta_4 div_{t-1} + \theta_5 trm_{t-1} + \theta_6 yd3_{t-1} + \epsilon_t \quad (14)$$

where dy_{t-1} is the lagged default yield spread, equal to the yield difference between Moodys BAA and AAA bonds, div_{t-1} is the stock market's lagged aggregate dividend yield, trm_{t-1} is the lagged difference between the yield of 10-year T-bonds and 3-month T-bills, $yd3_{t-1}$ is the lagged 3-month T-bill yield, the θ's are coefficients to estimated, and the other terms are as defined in equations (4), (6), (8), and (10).

Table 6 reports the results from estimating equations (11) through (14). For all four equations, we find that the estimated θ_1 coefficients on the RRD-trend term are sizable and highly statistically significant (p-values $< 0.1\%$). The five other explanatory variables generally add very little explanatory power. Only the coefficient on the default yield spread is statistically significant and only for the two 36-month strategies. Collectively, when controlling for the RRD-trend term, the macroeconomic variables are not reliably related to the payoff-change term for the momentum, contrarian, or 6-month HML strategy (as reported by the F-statistic in column eight of the table). We conclude that our findings are substantially distinct from earlier time-series findings in Chordia and Shivakumar (2002), Cooper et al (2004), and Avramov and Chordia (2006).

6.2. One-Quarter Subperiod Analysis

We extend our subperiod analysis by evaluating one-quarter subperiods for both the 6-month momentum and 6-month HML spread strategies. We re-estimate our primary models separately for one-quarter subperiods of 11-years duration each, again using our primary models given by equations (3), (4), (7), and (8).[13] The results are reported in Table 7. For both the firm-level and industry-level momentum strategies, we find that the RD-trend and RRD-trend are negatively and reliably related to the subsequent change in the momentum payoff for each of the one-quarter subperiods, with p-values of 0.02 or less. For the 6-month HML spreads, we find that the estimated relations for the RD-trend and RRD-trend are positive for each one-quarter subperiod, and the estimated relation is statistically significant for the second, third, and fourth one-quarter subperiods. Overall, we conclude that our primary RD-trend results are evident in one-quarter subperiods.

[13]We do not evaluate one-quarter subperiods for the 36-month strategies, because the subperiods seem too short to meaningfully evaluate the longer horizon.

6.3. Other Robustness Evidence

In this subsection, we report a series of additional evidence that bears on robustness and interpretation for the relation between the RD-trend and subsequent changes in the payoffs of momentum, contrarian, and B/M strategies. For brevity in our main text, we only summarize results here.[14]

First, we re-estimate our primary models, given by equations (3) through (10), but with the simple 3-month moving average of the large-firm RD (over months $t-1$ to $t-3$) replacing the RD-trend. Our primary results are still reliably evident, but generally weaker, with this simpler RD-trend measure.

Second, we re-estimate our primary models, given by equations (3) through (10), for the RD-trend using all four of our alternate RD metrics (the large-firm RD, the broad firm-level RD, the industry-level RD, and the portfolio-level RD using 100 book-to-market/size portfolios). While the large-firm RD tends to be the best performer for the momentum and contrarian strategies and the book-to-market/size RD tends to be the best performer for the HML B/M strategies, our primary results are reliably evident for all four RD measures.

Third, we are interested in whether our momentum and contrarian findings are substantially driven by small-cap firms. We examine alternate series that include only stocks that are in the top 20^{th} percentile of NYSE/AMEX firms by market capitalization (see Section 3.2). For the large-firm series, the average momentum profits are 4.6% per six months (t-stat=4.4) and the average contrarian profits are 16.3% per 36 months (t-stat=2.5). For the large-firm series, we find that the relations between the RD-trend and the payoff-change terms are also highly reliable and as depicted in Tables 3 and 4.

Fourth, we are also interested in whether our momentum and contrarian findings are substantially driven by stocks that have extreme returns in the ranking period. We examine 'Decile-9 versus Decile-2' spreads, where the momentum (contrarian) spreads are long (short) the decile-9 winners and short (long) the decile-2 losers over the respective ranking period. Thus, these series omit the extreme 10% of winners and 10% of losers from the strategy. Again consistent with our primary findings in Tables 3 and 4, we find that the relations between the RD-trend and the payoff-change terms are also sizable and highly reliable for the 'Decile-9 versus Decile-2' spreads.

Fifth, we are also interested in whether our RD-HML findings are substantially driven by

[14] Tabular results are available from the authors by request in a supplementary appendix.

stocks that have extreme book-to-market equity ratios. We examine 'Decile-9 minus Decile-2' HML spreads, that are long the decile-9 book-to-market stocks and short the decile-2 book-to-market stocks. Consistent with our primary findings in Table 5, we find that the relations between the RD-trend and the ΔHML terms are also positive, sizable, and highly reliable for the 'Decile-9 minus Decile-2' HML spreads.

Sixth, we also investigate alternate variations for the RD-trend terms and payoff-change terms that are similar in concept to our primary measures in Tables 3 through 5. We evaluate variations for: (1) the gap between payoffs for the payoff-change term, (2) the lengths of the two RD moving averages in the the RD-trend term, (3) the gap between the two RD moving averages in the RD-trend term, and (4) the lagged reference payoff in the payoff-change terms, by using a 3-month moving average for the lagged reference payoff instead of a single realized payoff. Our results remain reliably evident with minor variations in all these terms.

Seventh, a month's RD is a measure of cross-sectional volatility that is substantially positively skewed (as volatility measures are, by their nature). Accordingly, we form alternate RRD-trend measures that use the log transformation of a month's RD to reduce the skewness, in place of the raw RD. We then re-estimate our RRD-trend models using the log version of the RRD-trend. We find nearly identical results to those reported in Tables 3 through 5.

To conclude, the robustness findings in Sections 6.1 through 6.3 indicate that our results are: (1) reliable across subperiods; (2) distinct from macroeconomic variables suggested by prior literature; and (3) evident across variations in the models, RD measures, and strategies. These pervasive results suggest a broad systematic viewpoint for our findings, rather than one tied to an isolated event or a small subset of fringe stocks.

7. Towards Interpreting the RD Trend

In Sections 4 and 5, we find that the market's trend in cross-sectional return dispersion is negatively related to the subsequent change in the payoffs of relative-strength strategies and positively related to the subsequent change in the payoffs of value-minus-growth strategies. Our collective findings fit the empirical predictions of our 'market-state transition' hypothesis and suggest a broad systematic view for understanding our results. A pervasive viewpoint is consistent with recent evidence in Fama and French (2008), who show that momentum is evident in micro-cap, small-cap, and large-cap stocks; and Dittmar, Kaul, and Lei (2007), who argue that momentum is not an anomaly.

In a nutshell, our evidence suggests that RD is a leading indicator of market-state changes and that market and industry cyclicality is important in understanding the behavior of momentum, contrarian, and book-to-market strategies. If so, we would expect to find other evidence that supports this interpretation of RD. In this section, we offer additional evidence that bears on the 'market-state transition' hypothesis.

7.1. Empirical Estimation of Regime-Switching in the Stock Market

We first report on an empirical estimation of two-state regime-switching in the stock market. Here, we are primarily interested in whether our lagged RD-trend measures are associated with a higher probability of regime change. Secondarily, we are interested in whether the regime-specific mean returns and regime durations are consistent with the premise of the two-state framework suggested in Section 2.2 and Appendix A. Our estimation here features the monthly returns of the 48 value-weighted industry returns from the French data library. We use industry portfolios because differences in cyclicality across industries are widely accepted and each industry has monthly return observations over the entire sample.

Our bivariate regime-switching model features a more-cyclical and a less-cyclical portfolio of industry returns, where each portfolio contains six industries (of the 48 in our sample). The more-cyclical (less-cyclical) portfolio contains the six industries with the highest (lowest) market beta, with the market betas estimated over the entire sample. We choose a bivariate, two-state model as a parsimonious approach that appeals to the intuition of a two-state cyclical market.

Our model allows for the probability of shifting regimes to vary with the lagged RD-trend. More specifically, we estimate the following two-state, bivariate regime-switching model on the monthly returns of two different portfolios of industries, a more-cyclical portfolio (denoted MC) and a less-cyclical portfolio (denoted LC):

$$r_{mc,t} = \mu_{mc}^{s} + \sigma_{mc}^{s} \eta_{mc,t} \tag{15}$$

$$r_{lc,t} = \mu_{lc}^{s} + \sigma_{lc}^{s} \eta_{lc,t} \tag{16}$$

Where $r_{mc,t}$ and $r_{lc,t}$ are the monthly returns of our MC portfolio (mc subscript) and our LC portfolio (lc subscript), μ_{mc}^{s} and μ_{lc}^{s} are regime-specific mean returns for each respective series,

σ^s_{mc} and σ^s_{lc} are regime-specific standard deviations for each respective series, $\eta_{mc,t}$ and $\eta_{lc,t}$ are bivariate, standard, normally-distributed random variables, and s is the state variable where s either equals one for the good regime or two for the bad regime.

The s state variable is modeled with time-varying transition probabilities $(p_{jj(t)})$, as follows:

$$p_{jj(t)} = \frac{e^{c_j + d_j RD_{1-3,8-19}}}{1 + e^{c_j + d_j RD_{1-3,8-19}}} \tag{17}$$

where j = 1 (the good regime) or j = 2 (the bad regime); $p_{jj(t)}$ equals the probability that $s_t = j$ (the second subscript), given that $s_{t-1} = j$ (the first subscript); and $RD_{1-3,8-19}$ is our large-firm RD-trend as defined for equation (4). The μ^ss, σ^ss, c_js, d_js, and correlations between the η_ts are regime-specific parameters to be estimated. We estimate the model by maximizing the log-likelihood function for the bivariate normal density while allowing for regime-switching. This specification for the transition probabilities follows from Diebold, Lee, and Weinbach (1994). We acknowledge that our simple framework here is clearly not rich enough to capture actual market return behavior, but we feel it meets the hurdle of usefulness.

Our results are as follows. First, the market-beta of our MC portfolio (LC portfolio) is 1.33 (0.70). Next, we feel the time-series behavior of the estimated regimes seems plausible. The estimation suggests average durations of about 29 months for the good regime and about 12 months for the bad regime. For the CRSP value-weighted index returns, the mean and standard deviation of returns over the good-regime months (bad-regime months) are 1.10% and 3.35% (0.38% and 6.59%) per month, respectively. Every NBER recessionary period is approximately associated with episodes of the bad regime. These observations fit with the intuition of a predominant good regime with lower volatility and a less common bad regime with higher volatility.

The 'market-state transition' hypothesis suggests that the d_j coefficients will be negative, which would indicate that the probability of shifting regimes increases with the RD-trend. Table 8 reports the estimated parameters. Note that the estimated d_1 and d_2 coefficients are both negative and that the estimated d_1 is reliably negative with a 0.1% p-value (for d_2, the p-value is 0.154). This indicates that the transition probability of shifting regimes increases with the lagged RD-trend, especially for the good-to-bad transition.

Next, note the substantial contrast in the differences in regime-specific means when comparing the MC and LC portfolios. For the MC portfolio, the estimated good-regime mean is 1.53%/month and the bad-regime mean is 0.18%/month, so the difference in regime-specific means is about

1.35%/month. For the LC portfolio, the estimated good-regime mean is 1.14%/month and the bad-state mean is 0.84%/month, so the difference in regime-specific means is about 0.30%/month. To sum up, the estimated negative d_j coefficients, the regime durations, and the differences in regime-specific means are all consistent with the premise of the 'market-state transition' hypothesis.

7.2. Relating RD to Economic Contractions

We also explore the relation between RD and economic recessions per the NBER. Recessions are uncommon (only 12.3% of our sample's months) and are associated with transition in the stock market.

We examine whether the 3-month RD moving average (which is featured in our RD-trend variables) is different when the subsequent month t is in an economic recession. For our large-firm RD, when month t is a recessionary month (expansionary month), then the mean of the 3-month RD moving average over months $t-1$ to $t-3$ is 8.04% (6.67%). This difference of 1.37% is statistically significant with a 0.1% p-value. For the book-to-market/size RD, when month t is a recessionary month (expansionary month), then the mean of the 3-month RD moving average over months $t-1$ to $t-3$ is 3.43% (2.97%). This difference of 0.46% is statistically significant with a 1.8% p-value. Thus, recessionary months tends to be preceded by a high RD environment.

7.3. Clustering in High RD-trend Realizations

If the RD-trend tends to be higher during market-state transitions, we would expect to see substantial clustering in the relatively high observations of our RD-trend terms during times that seem plausibly associated with market transitions. We evaluate the lagged RRD-trend realizations that are in the top 10 percentile of their respective distributions. We analyze all four RRD-trend series that are featured and defined in Tables 3 through 5.

Over 1966 to 2005, the RRD-trend realizations that fall in the top 10 percentile are concentrated in ten of the 44 calendar years. Specifically, 83.8% of these extremely high lagged RRD-trend realizations occur in 1966, 1974-75, 1980-81, 1992, or 1998-2001 with 1981, 1999, and 2000 being the three most frequent years. This timing seems consistent with the notion that a high RD-trend tends to be associated with market-state transitions.[15] Further, the high RRD-trend values in the

[15]We begin this analysis in 1966 because, with our payoff-change timing, the 36-month RRD-trend terms are not used until November 1965.

early 1980's and 1999-2000 suggest that the relation between market-state changes and the RRD could also be tied to technological revolutions in the sense of Pastor and Veronesi (2008). They analyze technological revolutions and stock price patterns and specifically mention the "Internet craze" of the late 1990's and the "biotech revolution" of the early 1980's. We also note that 16 different calendar years have no RRD-trend realizations that fall in the top 10 percentile.

7.4. The RD-Trend and Changes in Size Spreads and the Market Factor

Given the reliability and magnitude of our primary RD-trend results in Sections 4 and 5, a natural question is whether the RD-trend is also related to subsequent changes in size-based spreads or the excess market return (following from the other two terms in Carhart's four-factor asset pricing model). We investigate this question by re-estimating our primary models from Tables 3 through 5, but with a size-based spread or the market-factor replacing the other payoff-change terms.

As reported in Table 9, we find mixed results.[16] First, we find that a higher RRD-trend tends to be associated with subsequent decreases in the market's excess return. This observation is consistent with the notion that the RRD-trend is more associated with transitions to a weaker market state. However, the relation is only consistently reliable for the 36-month horizon. For the size-based spreads, there is little evidence of a relation with the RRD-trend (except for the isolated result of the 36-month horizon in the second-half subperiod). Overall, the RRD-trend relations for the size spread and market-return terms tend to be appreciably weaker than for the comparable RRD-trend relations for the momentum, contrarian, and HML spreads, both in terms of the reliability of the estimated coefficients and the R-squared values.

7.5. Risk Adjustments

Normally, in an empirical study such as ours, one would also investigate whether the RD-trend relations are still evident after risk-adjusting the strategy payoffs. However, in our case, a risk adjustment is problematic because the momentum and HML spreads are conceptually tied to two of the four factors in the Carhart four-factor asset pricing model. So, in our view, trying to

[16] Our size-based spread is equal to the average of the smallest two size-based decile-portfolio returns less the average of the largest two size-based decile-portfolio returns; using value-weighted, size-based portfolio returns from the K. French data library. The market factor is the 'market less the risk-free return' factor from the K. French data library.

risk adjust with the four-factor model would not make sense and we can think of no compelling alternatives. How does one risk-adjust a risk factor?

We do perform a simple CAPM-adjustment. First, we regress the excess returns of the strategies' payoffs against the market excess return, and retain the residuals. We then use the payoff's residuals in place of the raw payoffs when forming the 'change in payoff' terms. For all three strategies, we find very similar results with these CAPM-adjusted residuals as we do for the raw payoffs.

8. Conclusions

Payoffs from medium-run momentum, longer-run contrarian, and book-to-market strategies have a prominent place in current financial practice and theory. In this paper, we show that the payoffs of these ubiquitous strategies can be tied to variation in the market's cross-sectional return dispersion. Specifically, we find that the stock market's RD trend is negatively related to the subsequent change in 6-month momentum payoffs and positively related to the subsequent change in 36-month contrarian payoffs, in 6-month HML B/M payoffs, and in 36-month HML B/M payoffs.

By 'subsequent change in payoffs', we refer to the difference between the forward-looking payoff and a lagged reference payoff, relative to a several month RD-trend that occurs before the forward-looking payoff but after the lagged reference payoff. Over our 1962 to 2005 sample, these empirical regularities are robust in subperiods, to different RD metrics, to variations in RD-trend timing, to variations in timing for the payoff-change variables, and for alternate momentum, contrarian, and book-to-market strategies.

We offer a 'market-state transition' perspective to frame and interpret our results, which suggests that RD is a leading indicator of market-state changes and that market cyclicality is important in understanding medium-run momentum, longer-run contrarian, and HML B/M payoffs. Consistent with this interpretation, we show that RD is informative about the likelihood of market-state changes in a regime-switching estimation on industry stock returns and that a high RD tends to lead recessionary months.

When decomposing the payoff-change terms into the forward-looking payoff and the lagged reference payoff, we find that the market's RD-trend is consistently related to both the forward-looking payoff (in the same direction as for the respective payoff-change term) and the lagged reference payoff (in the opposite direction as for the respective payoff-change term). Thus, the

RD relation for the payoff-change terms are stronger than the results for either the individual forward-looking payoffs or the individual lagged reference payoffs, which fits with our 'market-state transition' explanation.

We also show that a two-state return-generating framework suggests that average medium-run momentum payoffs and average longer-run contrarian payoffs should both be higher than suggested solely by the cross-sectional variation in unconditional mean returns. This aspect of our analytical framework is attractive because it is consistent with the stylized facts on how the average payoffs of relative-strength strategies vary with the strategy's horizon.

Our findings extend earlier studies that indicate momentum payoffs vary with the market state, such as Chordia and Shivakumar (2002) and Cooper et al (2004). In contrast to these earlier related papers, we also examine longer-run contrarian strategies and book-to-market strategies and we focus on the change in the strategies' payoffs, rather than the simple payoff level. We also stress that the macroeconomic variables from these earlier studies have relatively little explanatory power in our payoff-change setting, and that controlling for their lagged macroeconomic variables has almost no effect on the partial relation between the RD-trend and the subsequent payoff changes.

To conclude, we document a robust and sizable new regularity in the payoffs of medium-run momentum, longer-run contrarian, and book-to-market strategies. These regularities bear on theoretically understanding these strategy's payoffs. While we feel that our 'market-state transition' perspective contributes towards understanding our results, theorists are likely to refine this idea or propose new ideas that might explain the empirical regularities and generate additional empirical implications. In practice, our findings may prove important for investors who try to vary their loadings on spread-type strategies.

Finally, Cochrane (2005) emphasizes that potential state variables should tell us something about forward-looking changes in the investment opportunity set. In this sense, our results suggest that the market's RD-trend may serve as a market state variable. If so, our results support the idea that the market's cross-sectional return divergence is a harbinger of market-state changes, a notion which goes back to at least the Dow Theory that originated in the early 1900's.

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Table 1: Summary Statistics for the Payoffs of the Momentum, Contrarian, and B/M Strategies

This table reports the means, standard deviations, minimum, maximum, and the percentage of negative observations for the return payoffs of our primary momentum, contrarian, and HML B/M series in this study. All return statistics are in percentage units corresponding to the cumulative holding period. Mom_t is the 6-month momentum payoff, where the holding period is over t to $t+5$ and the ranking period is over $t-7$ through $t-2$. $\Delta Mom_{t,t-9}$ is the difference between the 6-month momentum payoff over holding months t to $t+5$ and the 6-month momentum payoff over holding months $t-9$ to $t-4$. Ctr_t is the 36-month contrarian payoff, where the holding period is over t to $t+35$ and the ranking period is over $t-37$ through $t-2$. $\Delta Ctr_{t,t-39}$ is the difference between the 36-month contrarian payoff over holding months t to $t+35$ and the 36-month contrarian payoff over holding months $t-39$ to $t-4$. Statistics are reported for both the firm-level and industry-level momentum and contrarian strategies, as defined in Section 3.2. HML_t^j is the j-month high-minus-low book-to-market spread over months t to $t+(j-1)$, as defined in Section 3.2, where j equals either 6 or 36 months for the two horizons. $\Delta HML_{t,t-(j+3)}^j$ is the difference between the j-month HML spread over holding months t to $t+(j-1)$ and the j-month HML spread over holding months $t-(j+3)$ to $t-4$. For the means of the average payoff levels, a t-statistic is in parentheses which indicates whether the mean is reliably different than zero, calculated with heteroskedastic- and autocorrelation-consistent standard errors. The sample period is 1962 through 2005.

	Mean	Std. Dev.	Minim.	Maxim.	% Negative Observ.
Firm-level Mom_t	7.26 (7.48)	11.78	-45.22	49.23	24.4
Firm-level Ctr_t	10.76 (1.38)	40.33	-112.10	136.91	41.8
Firm-level $\Delta Mom_{t,t-9}$	0.03	18.07	-59.22	61.91	49.5
Firm-level $\Delta Ctr_{t,t-39}$	-2.09	64.31	-220.17	149.28	53.5
Industry-level Mom_t	3.30 (4.59)	8.74	-34.70	34.83	34.7
Industry-level Ctr_t	3.62 (0.51)	36.40	-107.30	88.76	49.0
Industry-level $\Delta Mom_{t,t-9}$	-0.02	13.15	-49.82	43.76	49.7
Industry-level $\Delta Ctr_{t,t-39}$	-2.60	56.83	-147.54	173.94	57.9
HML_t^6	2.83 (3.13)	9.57	-20.69	39.47	42.2
HML_t^{36}	16.72 (2.97)	25.81	-35.25	88.20	26.7
$\Delta HML_{t,t-9}^6$	-0.04	13.23	-37.94	41.61	53.5
$\Delta HML_{t,t-39}^{36}$	0.24	40.55	-87.57	88.11	55.3

Table 2: Descriptive Statistics for the Stock Market's Cross-sectional Return Dispersion

This table reports the means, standard deviations, autocorrelations, and cross-correlations for five alternate RD measures. The five alternate RD measures are as follows: (1) RD_{Large} is the RD formed from the largest decile of NYSE/AMEX stocks, by market capitalization; (2) RD_{Broad} is the RD formed from all NYSE/AMEX stocks except for those in the smallest quintile, by market capitalization; (3) $RD_{Industry}$ is the RD formed from the 48 value-weighted industry returns from the French data library; (4) $RD_{BM\&Sz}$ is the RD formed from 100 book-to-market/size portfolio returns from the French data library, where the portfolios are formed from a 10x10 double-sort on size and book-to-market; and (5) RRD_{Large} is the market-adjusted, relative return dispersion of the largest decile of NYSE/AMEX stocks, as defined in Section 3.3. Panel A reports univariate statistics for the monthly values of each alternate RD. Panel B reports the cross-correlations for the 3-month moving RD average, RD_{1-3}, (on the upper diagonal) and for the RD-trend, $RD_{1-3,8-19}$, (on the lower diagonal), constructed for each each alternate measure. RD_{1-3} is the RD moving average over months $t-1$ through $t-3$ and $RD_{1-3,8-19}$ is the RD-trend variable that is equal to 'the RD moving average over months $t-1$ through $t-3$' minus 'the RD moving average over months $t-8$ through $t-19$'. The sample period is 1962 through 2005.

Panel A: Univariate Monthly RD Statistics, in %					
	RD_{Large}	RD_{Broad}	$RD_{Industry}$	$RD_{BM\&Sz}$	RRD_{Large}
Mean	6.84	9.94	4.22	3.02	0.00
Std. Deviation	2.09	2.23	1.45	1.29	1.91
Autocorrelation(1)	0.679	0.603	0.559	0.588	0.624
Autocorrelation(2)	0.621	0.491	0.518	0.536	0.579
Autocorrelation(3)	0.665	0.513	0.532	0.520	0.630

Panel B: Cross-Correlations of RD_{1-3} (upper diagonal) and $RD_{1-3,8-19}$ (lower diagonal)					
	RD_{Large}	RD_{Broad}	$RD_{Industry}$	$RD_{BM\&Sz}$	RRD_{Large}
RD_{Large}	1	0.850	0.854	0.772	0.964
RD_{Broad}	0.773	1	0.812	0.755	0.782
$RD_{Industry}$	0.801	0.785	1	0.793	0.809
$RD_{BM\&Sz}$	0.747	0.686	0.626	1	0.756
RRD_{Large}	0.924	0.635	0.675	0.717	1

Table 3: The RD-Trend and Payoffs to 6-month Momentum Strategies

This table reports how the realized RD-trend is related to momentum payoffs for a symmetric 6-month strategy. We estimate variations of the following three models:

$$\text{Model 1}: \quad \Delta Mom_{t,t-9} = \beta_0 + \beta_1\, RD_{1-3,8-19} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,8-19} + \epsilon_t$$

$$\text{Model 2}: \quad Mom_t = \beta_0 + \beta_1\, RD_{1-3,8-19} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,8-19} + \epsilon_t$$

$$\text{Model 3}: \quad Mom_{t-9} = \beta_0 + \beta_1\, RD_{1-3,8-19} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,8-19} + \epsilon_t$$

where $\Delta Mom_{t,t-9}$ is the difference between Mom_t (the 6-month momentum payoff over holding months t to $t+5$)and Mom_{t-9} (the 6-month momentum payoff over holding months $t-9$ to $t-4$); $RD_{1-3,8-19}$ is the large-firm RD-trend variable that is equal to 'the RD moving average over $t-1$ through $t-3$' minus 'the RD moving average over $t-8$ through $t-19$'; $RRD_{1-3,8-19}$ is the same as $RD_{1-3,8-19}$ except the 'market-adjusted relative RD' replaces the simple RD; StR_{1-36} is the 36-month aggregate stock market return over months $t-1$ to $t-36$; and the β's are coefficients to be estimated. Panel A reports on Model 1 with the payoff-change terms. Panel B reports on Model 2 with the forward-looking payoffs. Panel C reports on Model 3 with the lagged reference payoffs from the payoff-change term. The table reports on both a firm-level momentum strategy and an industry-level momentum strategy, as defined in Section 3.2. The sample period is 1962 to 2005. T-statistics are in parentheses, based on heteroskedastic- and autocorrelation-consistent standard errors. For each panel, columns 3 through 5 report on the model with β_3 restricted to zero, and Columns 6 through 7 report on the model with β_1 and β_2 restricted to zero.

Panel A: Change in Momentum Payoffs - Model 1

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
		Panel A.1: Results for Individual Stock Strategy				
Full	1962-	-5.75	0.083	18.4%	-5.47	14.5%
	2005	(-5.81)	(1.89)		(-4.90)	
1st half	1962-	-5.04	-0.017	13.2%	-6.55	15.2%
	1983	(-3.46)	(-0.19)		(-4.01)	
2nd Half	1984-	-7.27	0.176	27.6%	-4.90	14.4%
	2005	(-4.96)	(3.53)		(-3.35)	
		Panel A.2: Results for Industry-level Strategy				
Full	1962-	-4.15	0.074	18.1%	-3.83	13.5%
	2005	(-5.97)	(2.41)		(-4.66)	
1st half	1962-	-4.05	0.061	15.5%	-4.50	12.7%
	1983	(-3.89)	(1.12)		(-3.62)	
2nd Half	1984-	-4.51	0.097	21.3%	-3.48	14.5%
	2005	(-4.23)	(2.04)		(-3.11)	

Table 3: (Continued)

Panel B: Forward-looking Momentum Payoffs - Model 2

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
		Panel B.1: Results for Individual Stock Strategy				
Full	1962-	-2.37	0.088	9.2%	-1.83	3.8%
	2005	(-3.22)	(2.69)		(-2.61)	
1st half	1962-	-1.54	0.108	6.7%	-1.98	2.9%
	1983	(-1.24)	(1.62)		(-1.37)	
2nd Half	1984-	-3.50	0.126	18.8%	-1.82	5.2%
	2005	(-4.69)	(3.38)		(-2.51)	
		Panel B.2: Results for Industry-level Strategy				
Full	1962-	-1.83	0.071	10.2%	-1.44	4.2%
	2005	(-3.62)	(2.92)		(-2.68)	
1st half	1962-	-1.39	0.075	7.0%	-1.48	2.9%
	1983	(-1.65)	(1.54)		(-1.56)	
2nd Half	1984-	-2.23	0.079	14.2%	-1.37	5.6%
	2005	(-4.15)	(2.80)		(-2.09)	

Panel C: Lagged, Reference Momentum Payoffs - Model 3

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
		Panel C.1: Results for Individual Stock Strategy				
Full	1962-	3.39	0.005	17.0%	3.64	14.9%
	2005	(5.55)	(0.17)		(5.06)	
1st half	1962-	3.50	0.125	21.7%	4.56	15.8%
	1983	(4.71)	(2.95)		(4.48)	
2nd Half	1984-	3.77	-0.050	20.2%	3.07	14.4%
	2005	(4.02)	(-1.52)		(3.19)	
		Panel C.2: Results for Industry-level Strategy				
Full	1962-	2.31	-0.004	13.8%	2.40	11.8%
	2005	(4.43)	(-0.20)		(3.69)	
1st half	1962-	2.67	0.013	14.0%	3.02	12.1%
	1983	(4.22)	(0.40)		(3.82)	
2nd Half	1984-	2.28	-0.018	15.1%	2.11	12.6%
	2005	(2.93)	(-0.60)		(2.42)	

Table 4: The RD-Trend and Payoffs to 36-month Contrarian Strategies

This table reports how the realized RD-trend is related to contrarian payoffs for a symmetric 36-month strategy. We estimate variations of the following three models:

$$\text{Model 1}: \quad \Delta Ctr_{t,t-39} = \beta_0 + \beta_1\, RD_{1-3,38-49} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,38-49} + \epsilon_t$$

$$\text{Model 2}: \quad Ctr_t = \beta_0 + \beta_1\, RD_{1-3,38-49} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,38-49} + \epsilon_t$$

$$\text{Model 3}: \quad Ctr_{t-39} = \beta_0 + \beta_1\, RD_{1-3,38-49} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,38-49} + \epsilon_t$$

where $\Delta Ctr_{t,t-39}$ is the difference between Ctr_t (the contrarian payoff over holding months t to $t+35$) and Ctr_{t-39} (the contrarian payoff over holding months $t-39$ to $t-4$); $RD_{1-3,38-49}$ is the large-firm RD-trend variable that is equal to 'the RD moving average over $t-1$ through $t-3$' minus 'the RD moving average over $t-38$ through $t-49$'; $RRD_{1-3,38-49}$ is the same as $RD_{1-3,38-49}$ except the 'market-adjusted relative RD' replaces the simple RD; StR_{1-36} is the 36-month aggregate stock market return over months $t-1$ to $t-36$; and the β's are coefficients to be estimated. Panel A reports on Model 1 with the payoff-change terms. Panel B reports on Model 2 with the forward-looking payoffs. Panel C reports on Model 3 with the lagged reference payoffs from the payoff-change term. The table reports both on the firm-level and industry-level contrarian strategies, as defined in Section 3.2. The sample period is 1962 to 2005. T-statistics are in parentheses, based on heteroskedastic- and autocorrelation-consistent standard errors. For each panel, columns 3 through 5 report on the model with β_3 restricted to zero, and Columns 6 through 7 report on the model with β_1 and β_2 restricted to zero.

Panel A: Change in Contrarian Payoffs - Model 1

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
Panel A.1: Results for Individual Stock Strategy						
Full	1962-	19.39	-0.100	42.5%	20.91	39.9%
	2005	(4.76)	(-0.42)		(4.31)	
1st half	1962 -	28.3	-0.295	67.8%	32.92	66.7%
	1983	(10.59)	(-1.03)		(10.40)	
2nd Half	1984 -	12.66	-0.004	25.9%	13.22	23.6%
	2005	(3.50)	(0.02)		(3.97)	
Panel A.2: Results for Industry-level Strategy						
Full	1962-	16.21	0.065	39.7%	19.57	44.7%
	2005	(7.31)	(0.30)		(9.88)	
1st half	1962 -	15.70	-0.091	43.4%	19.81	50.8%
	1983	(8.03)	(-0.30)		(7.74)	
2nd Half	1984 -	16.69	0.065	38.3%	19.51	42.0%
	2005	(6.03)	(0.26)		(8.24)	

Table 4: (Continued)

Panel B: Forward-looking Contrarian Payoffs - Model 2

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
Panel B.1: Results for Individual Stock Strategy						
Full	1962-	12.74	-0.407	53.3%	13.21	43.0%
	2005	(9.00)	(-3.76)		(5.82)	
1st half	1962-	13.65	-0.441	63.9%	17.79	54.0%
	1983	(13.66)	(-2.26)		(9.98)	
2nd Half	1984-	9.87	-0.259	40.2%	10.06	39.0%
	2005	(7.50)	(-3.57)		(7.58)	
Panel B.2: Results for Industry-level Strategy						
Full	1962-	9.14	-0.183	32.8%	10.71	36.1%
	2005	(7.31)	(-1.32)		(8.84)	
1st half	1962-	9.10	-0.059	40.1%	11.39	46.0%
	1983	(6.48)	(-0.31)		(6.59)	
2nd Half	1984-	8.71	-0.116	27.0%	10.07	32.9%
	2005	(4.22)	(-0.79)		(6.20)	

Panel C: Lagged, Reference Contrarian Payoffs - Model 3

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
Panel C.1: Results for Individual Stock Strategy						
Full	1962-	-6.65	-0.307	21.6%	-7.69	13.7%
	2005	(-2.28)	(-1.71)		(-2.37)	
1st half	1962-	-12.59	-0.146	42.1%	-15.13	43.9%
	1983	(-5.73)	(-0.82)		(-4.58)	
2nd Half	1984-	-2.80	-0.255	10.8%	-3.16	3.4%
	2005	(-1.10)	(-1.33)		(-1.39)	
Panel C.2: Results for Industry-level Strategy						
Full	1962-	-7.07	-0.248	27.0%	-8.86	23.5%
	2005	(-3.80)	(-2.04)		(-4.48)	
1st half	1962-	-6.60	0.031	18.3%	-8.42	21.9%
	1983	(-3.40)	(0.18)		(-3.88)	
2nd Half	1984-	-7.97	-0.181	35.7%	-9.44	32.0%
	2005	(-4.40)	(-1.20)		(-6.06)	

Table 5: The RD-trend and Payoffs to High-minus-Low B/M Strategies

This table reports how the realized RD-trend is related to the payoffs of high-minus-low (HML) strategies based on book-to-market equity ratios. We report on both the 6-month and 36-month HML horizon.

$$\text{Model 1}: \quad \Delta HML^j_{t,t-(j+3)} = \beta_0 + \beta_1\, RD_{1-3,(j+2)-(j+13)} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,(j+2)-(j+13)} + \epsilon_t$$

$$\text{Model 2}: \quad HML^j_t = \beta_0 + \beta_1\, RD_{1-3,(j+2)-(j+13)} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,(j+2)-(j+13)} + \epsilon_t$$

$$\text{Model 3}: \quad HML^j_{t-(j+3)} = \beta_0 + \beta_1\, RD_{1-3,(j+2)-(j+13)} + \beta_2\, StR_{1-36} + \beta_3\, RRD_{1-3,(j+2)-(j+13)} + \epsilon_t$$

where $\Delta HML^j_{t,t-(j+3)}$ is the difference between HML^j_t (the j-month HML payoff over months t to $t+(j-1)$) and $HML^j_{t-(j+3)}$ (the j-month payoff over months $t-(j+3)$ to $t-4$), where j equals either 6 or 36-month for the two HML horizons. The RD-trend, RRD-trend, and StR terms are as defined for Tables 3 and 4. The monthly RD metric here is the $RD_{BM\&Sz}$, as defined in Section 3.3, and the β's are coefficients to be estimated. Panel A reports on Model 1 with the payoff-change terms. Panel B reports on Model 2 with the forward-looking payoffs. Panel C reports on Model 3 with the lagged reference payoffs from the payoff-change term. For each panel, columns 3 through 5 report on the model with β_3 restricted to zero, and Columns 6 through 7 report on the model with β_1 and β_2 restricted to zero. The monthly HML payoff is defined in Section 3.2. The sample period is 1962 to 2005.

Panel A: Change in HML Payoffs, 6-month and 36-month Horizon - Model 1

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
		Panel A.1: 6-month HML Horizon				
Full	1962-	4.56	-0.002	12.1%	4.89	12.7%
	2005	(4.65)	(-0.06)		(4.63)	
1st Half	1962-	4.35	0.084	8.6%	6.89	9.6%
	1983	(1.76)	(1.21)		(2.48)	
2nd Half	1984-	4.99	-0.047	19.6%	4.31	16.9%
	2005	(4.57)	(-1.16)		(4.31)	
		Panel A.2: 36-month HML Horizon				
Full	1962-	17.31	-0.182	27.4%	17.76	25.1%
	2005	(4.65)	(-1.06)		(4.19)	
1st Half	1962-	21.24	-0.235	19.3%	25.07	17.9%
	1983	(2.48)	(-0.72)		(2.53)	
2nd Half	1984-	16.53	-0.052	39.7%	17.19	39.4%
	2005	(5.07)	(-0.56)		(4.93)	

Table 5: (Continued)

Panel B: Forward-looking HML Payoffs, 6-month and 36-month Horizon - Model 2

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
		Panel B.1: 6-month HML Horizon				
Full	1962-	0.18	-0.018	0.3%	0.25	0.1%
	2005	(0.28)	(-0.79)		(0.39)	
1st Half	1962-	0.17	0.042	1.4%	1.74	1.3%
	1983	(0.09)	(0.98)		(0.87)	
2nd Half	1984-	0.24	-0.034	1.3%	-0.13	0.0%
	2005	(0.32)	(-1.07)		(-0.16)	
		Panel B.2: 36-month HML Horizon				
Full	1962-	4.85	-0.288	14.3%	4.49	3.7%
	2005	(3.29)	(-0.29)		(2.36)	
1st Half	1962-	5.23	-0.166	5.1%	6.11	2.7%
	1983	(1.23)	(-0.52)		(1.30)	
2nd Half	1984-	5.80	-0.180	18.9%	6.28	15.5%
	2005	(4.57)	(-2.13)		(4.84)	

Panel C: Lagged, Reference Payoffs, 6-month and 36-month Horizon - Model 3

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
		Panel C.1: 6-month HML Horizon				
Full	1962-	-4.38	-0.016	23.1%	-4.64	21.6%
	2005	(-4.62)	(-0.60)		(-4.61)	
1st Half	1962-	-4.17	-0.042	12.8%	-5.15	11.9%
	1983	(-2.81)	(-0.93)		(-3.17)	
2nd Half	1984-	-4.74	0.013	32.5%	-4.54	29.8%
	2005	(-3.61)	(0.40)		(-3.68)	
		Panel C.2: 36-month HML Horizon				
Full	1962-	-12.46	-0.106	36.6%	-13.27	32.6%
	2005	(-3.92)	(-1.31)		(-4.03)	
1st Half	1962-	-16.00	0.069	27.8%	-18.95	28.1%
	1983	(-2.83)	(0.71)		(-2.85)	
2nd Half	1984-	-10.72	-0.128	43.8%	-10.92	36.9%
	2005	(-3.52)	(-1.55)		(-3.90)	

Table 6: The RD-trend, Strategy Payoffs, and Macroeconomic Variables

This table examines whether well-known macroeconomic variables are also important explanatory variables for the change-in-payoff terms for the momentum, contrarian, and HML B/M strategies, while controlling for the RRD-trend. We estimate the following regressions:

$$\Delta Mom_{t,t-9} = \theta_0 + \theta_1 RRD_{1-3,8-19} + \theta_2 StR_{1,36} + \theta_3 dy_{t-1} + \theta_4 div_{t-1} + \theta_5 trm_{t-1} + \theta_6 yd3_{t-1} + \epsilon_t$$

$$\Delta Ctr_{t,t-39} = \theta_0 + \theta_1 RRD_{1-3,38-49} + \theta_2 StR_{1,36} + \theta_3 dy_{t-1} + \theta_4 div_{t-1} + \theta_5 trm_{t-1} + \theta_6 yd3_{t-1} + \epsilon_t$$

$$\Delta HML^{6}_{t,t-9} = \theta_0 + \theta_1 RRD_{1-3,8-19} + \theta_2 StR_{1,36} + \theta_3 dy_{t-1} + \theta_4 div_{t-1} + \theta_5 trm_{t-1} + \theta_6 yd3_{t-1} + \epsilon_t$$

$$\Delta HML^{36}_{t,t-39} = \theta_0 + \theta_1 RRD_{1-3,38-49} + \theta_2 StR_{1,36} + \theta_3 dy_{t-1} + \theta_4 div_{t-1} + \theta_5 trm_{t-1} + \theta_6 yd3_{t-1} + \epsilon_t$$

where dy_{t-1}, div_{t-1}, trm_{t-1}, $yd3_{t-1}$ are the lagged macroeconomic explanatory variables; the θ's are coefficients to estimated; and the other terms are as defined for Tables 3 through 5. dy is the default yield spread, div is the stock market's aggregate dividend yield, trm is the difference between the yield of 10-year T-bonds and 3-month T-bills, and $yd3$ is the 3-month T-bill yield. T-statistics are in parentheses, based on heteroskedastic- and autocorrelation-consistent standard errors. The column labeled 'F-stat' reports the F-statistic for a joint test that θ_2 through θ_6 are all equal to zero, with the p-value in brackets. The sample period is 1962 through 2005.

Strategy	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6	F-stat (θ_2 to θ_6=0)	R^2
6-month	-6.60	0.068	-0.070	0.095	0.028	0.0075	1.71	18.2%
Momentum	(-5.50)	(1.47)	(-1.62)	(0.04)	(0.19)	(0.83)	[0.128]	
36-month	17.55	-0.034	0.49	-7.96	-0.074	-0.013	1.59	45.0%
Contrarian	(4.57)	(-0.12)	(2.16)	(-0.84)	(-0.73)	(-0.20)	[0.159]	
6-month	4.80	-0.0069	0.051	-1.79	-0.0080	-0.0002	0.58	14.7%
HML B/M	(3.88)	(-0.18)	(1.47)	(-1.06)	(-0.75)	(-0.04)	[0.714]	
36-month	14.93	-0.183	0.415	-9.95	-0.044	-0.0066	3.23	37.3%
HML B/M	(3.33)	(-0.99)	(3.43)	(-1.32)	(-0.79)	(-0.28)	[0.006]	

Table 7: RD-trend and the Payoffs of the 6-month Strategies: One Quarter Subperiods

This table reports how the RD-trend is related to the subsequent change in the 6-month momentum payoffs and the 6-month HML B/M payoffs. Here, we report on one-quarter subperiod analysis. The terms and models are identical to those in Table 3, Panel A, for the payoff-changes with the 6-month momentum strategy and to those in Table 5, Panel A, for the payoff-changes with the 6-month HML strategy. Columns 3 through 5 report on the respective Variation 1 of the model, using the simple RD-trend term with the β_1 coefficient. Columns 6 through 7 report on the respective Variation 2 of the model, using the RRD-trend term with the β_3 coefficient. Panel A reports on the 6-month firm-level momentum payoffs, Panel B on the 6-month industry-level momentum payoffs, and Panel C on the 6-month HML payoffs.

		Variation 1: ($\beta_3 = 0$)			Variation 2: ($\beta_1, \beta_2 = 0$)	
Sample	Dates	β_1	β_2	R^2	β_3	R^2
	Panel A: Change in 6-month Momentum Payoffs, Firm-level Strategy					
1st Qtr	1962-	-9.21	0.167	22.0%	-10.03	25.2%
	1972	(-3.06)	(1.57)		(-3.76)	
2nd Qtr	1973-	-4.01	-0.073	13.6%	-5.12	11.2%
	1983	(-2.30)	(-0.68)		(-2.66)	
3rd Qtr	1984-	-9.98	0.058	25.7%	-10.78	20.6%
	1994	(-4.42)	(0.69)		(-3.30)	
4th Qtr	1995-	-7.07	0.208	34.7%	-3.96	15.0%
	2005	(-3.61)	(2.97)		(-2.52)	
	Panel B: Change in 6-month Momentum Payoffs, Industry-level Strategy					
1st Qtr	1962-	-6.83	0.191	25.3%	-6.91	21.5%
	1972	(-4.00)	(2.60)		(-3.93)	
2nd Qtr	1973-	-3.37	0.023	14.2%	-3.52	9.4%
	1983	(-2.81)	(0.35)		(-2.32)	
3rd Qtr	1984-	-4.91	-0.009	19.1%	-4.93	12.9%
	1994	(-3.93)	(-0.18)		(-3.00)	
4th Qtr	1995-	-4.86	0.135	25.8%	-3.24	15.8%
	2005	(-3.49)	(2.31)		(-2.52)	
	Panel C: Change in 6-month HML Payoffs					
1st Qtr	1962-	4.76	0.071	6.7%	4.84	4.6%
	1972	(1.20)	(0.69)		(1.02)	
2nd Qtr	1973-	3.97	0.087	9.6%	8.18	14.0%
	1983	(1.34)	(1.11)		(2.66)	
3rd Qtr	1984-	6.80	0.074	12.6%	6.73	8.7%
	1994	(2.51)	(1.10)		(2.34)	
4th Qtr	1995-	5.07	-0.074	30.1%	4.13	24.8%
	2005	(3.92)	(-1.67)		(3.61)	

Table 8: A Bivariate Regime-Switching Model for Stock Returns and the RD-Trend

This table reports on estimating the following two-state, bivariate regime-switching model for the monthly returns of a more-cyclical and less-cyclical industry-based portfolio:

$$r_{mc,t} = \mu^s_{mc} + \sigma^s_{mc}\eta_{mc,t}$$

$$r_{lc,t} = \mu^s_{lc} + \sigma^s_{lc}\eta_{lc,t}$$

Where $r_{mc,t}$ and $r_{lc,t}$ are the monthly returns of our more-cyclical portfolio of industries and our less-cyclical portfolio of industries, respectively, where the more-cyclical (less-cyclical) portfolio contains the 6 industries with the highest (lowest) market beta of the 48 industries in our sample; μ^s_{mc} and μ^s_{lc} are regime-specific mean returns for the respective series; σ^s_{mc} and σ^s_{lc} are regime-specific standard deviations for each respective series; and $\eta_{mc,t}$ and $\eta_{lc,t}$ are bivariate, standard, normally-distributed, random variables. The superscript s refers to the regime, either regime-one (the good regime) or regime-two (the bad regime). The s state variable is modeled with time-varying transition probabilities ($p_{jj(t)}$):

$$p_{jj(t)} = \frac{e^{c_j + d_j RD_{1-3,8-19}}}{1 + e^{c_j + d_j RD_{1-3,8-19}}},$$

where j = 1 (regime-one) or j = 2 (regime-two); $p_{jj(t)}$ equals the probability that $s_t = j$(the second subscript), given that $s_{t-1} = j$ (the first subscript); $RD_{1-3,8-19}$ is our large-firm RD-trend variable used in Table 3. The μ^ss, σ^ss, c_js, d_js, and correlations between the η_ts are parameters to be estimated. We estimate the model by maximizing the log-likelihood function for the bivariate normal density with regime-switching between the two states. The sample period is 1962 to 2005. The coefficient estimates are reported below, with standard errors in parentheses. The return parameters are given in percentage units. [1], [2], [3], and [4], indicate 0.1%, 1%, 5%, and 10% p-values for whether the regime-specific means, and the estimated c_j and d_j coefficients are statistically significantly different than zero.

	Good Regime ($s = 1, j = 1$)		Bad Regime ($s = 2, j = 2$)	
Coeff.	Estimated Parameters		Estimated Parameters	
μ^s_{mc}	1.53[1]	(0.271)	0.180	(0.745)
μ^s_{lc}	1.14[1]	(0.164)	0.844[4]	(0.447)
σ^s_{mc}	4.85	(0.227)	9.16	(0.545)
σ^s_{lc}	2.94	(0.170)	5.58	(0.324)
ρ	0.672	(0.033)	0.646	(0.044)
c_j	2.91[1]	(0.343)	1.98[1]	(0.353)
d_j	-0.876[1]	(0.253)	-0.283	(0.198)

Table 9: The RD-Trend and Payoff Changes for Size and the Market-return Spreads

This table examine whether the RRD-trend terms are related to the subsequent change in both Small-minus-Big and Market-minus-RiskFree return spreads. We estimate the following two models for the 6-month and 36-month horizons:

$$\text{Model 2}: \quad \Delta MktRf^{j}_{t,t-(j+3)} = \beta_0 + \beta_1\, RRD_{1-3,(j+2)-(j+13)} + \epsilon_t$$

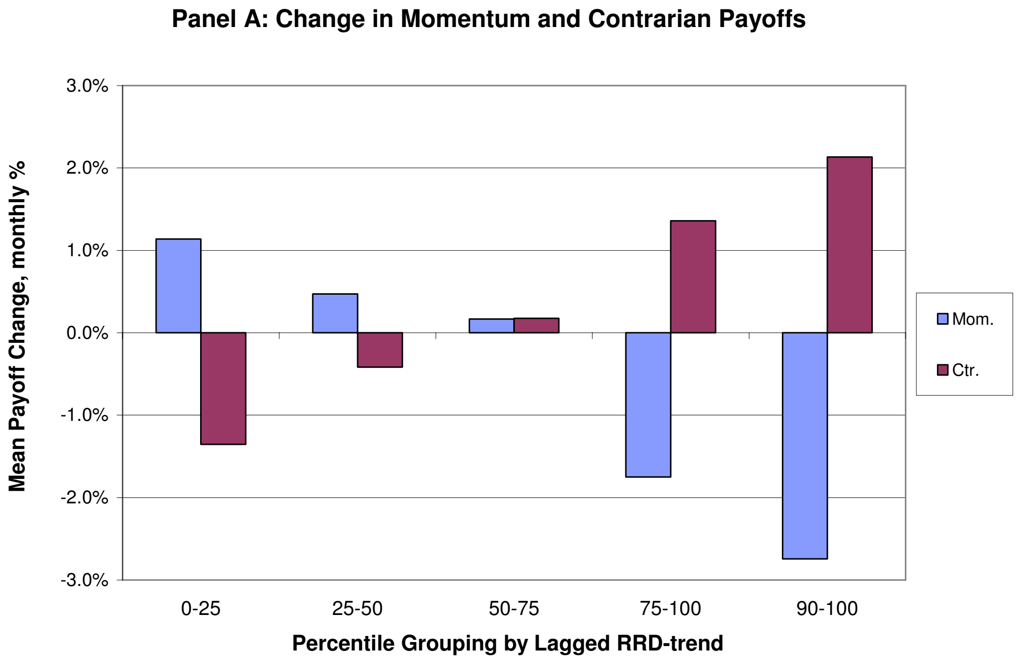
$$\text{Model 1}: \quad \Delta SMB^{j}_{t,t-(j+3)} = \beta_0 + \beta_1\, RRD_{1-3,(j+2)-(j+13)} + \epsilon_t$$

where $\Delta MKTRF^{j}_{t,t-(j+3)}$ ($\Delta SMB^{j}_{t,t-(j+3)}$) is the change in $Mkt - Rf$ (SMB) payoff for the j-month horizon with j equal to either 6 or 36 months, with the same timing convention as in Table 5 for the 'change in HML spreads'. The market factor is the 'market less the risk-free return' factor from the K. French data library. The size-based spread is equal to the average of the smallest two size-based decile-portfolio returns less the average of the largest two size-based decile-portfolio returns; using value-weighted, size-based portfolio returns from the K. French data library. The timing for the RRD-trend is as used in Table 5 for each respective horizon, and we estimate the models with both our large-firm RD and the size&book-to-market RD. T-statistics are in parentheses, based on heteroskedastic- and autocorrelation-consistent standard errors. The sample period is 1962 through 2005.

		1. Large-firm RD for RRD-trend term		2. Size&Book-to-Market RD for RRD-trend term	
Strategy	Period	β_1	R^2	β_1	R^2
6-month $\Delta MktRf$	1962-2005	-0.98 (-0.99)	0.6%	-2.54 (-2.56)	2.3%
6-month $\Delta MktRf$	1962-1983	-0.52 (-0.24)	0.1%	-4.29 (-1.07)	2.1%
6-month $\Delta MktRf$	1984-2005	-1.20 (-1.22)	1.4%	-2.12 (-2.79)	3.3%
36-month $\Delta MktRf$	1962-2005	-9.02 (-2.65)	19.3%	-14.93 (-5.13)	18.3%
36-month $\Delta MktRf$	1962-1983	-0.74 (-0.34)	0.2%	-10.64 (-2.96)	6.7%
36-month $\Delta MktRf$	1984-2005	-14.49 (-6.30)	41.0%	-16.16 (-5.01)	22.8%
6-month ΔSMB	1962-2005	0.44 (0.39)	0.1%	-0.97 (-0.58)	0.4%
6-month ΔSMB	1962-1983	0.28 (0.21)	0.1%	2.53 (0.78)	0.9%
6-month ΔSMB	1984-2005	0.55 (0.35)	0.1%	-1.78 (-1.13)	2.2%
36-month ΔSMB	1962-2005	11.70 (3.11)	13.7%	15.21 (3.65)	8.0%
36-month ΔSMB	1962-1983	5.97 (1.05)	2.1%	-7.84 (-0.71)	0.6%
36-month ΔSMB	1984-2005	15.71 (9.67)	51.2%	19.34 (5.95)	34.8%

Figure 1: The Changes in Momentum and Contrarian Payoffs, when Sorted by the RRD-Trend

This figure reports on subset means and the percentage of negative observations for the payoff-changes for 6-month momentum and 36-month contrarian payoffs, when sorted into percentile grouping on the lagged RRD-Trend. We report on our primary firm-level strategies and the lagged RRD-trend variables, as in Tables 3 and 4, Panel A. The means are standardized to a month, by dividing the holding-period mean by the number of months in the holding period.



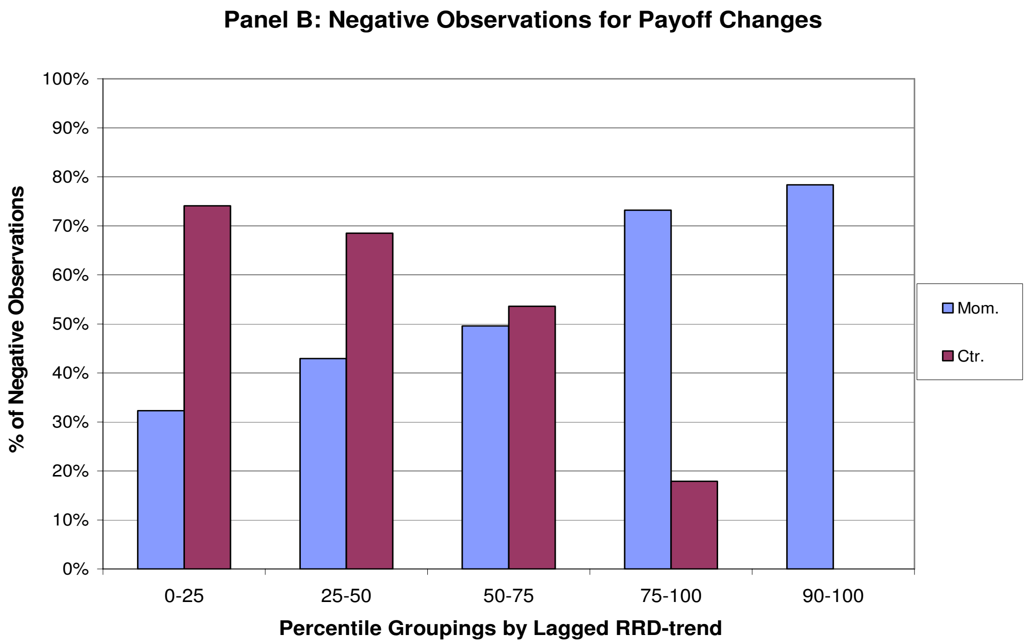
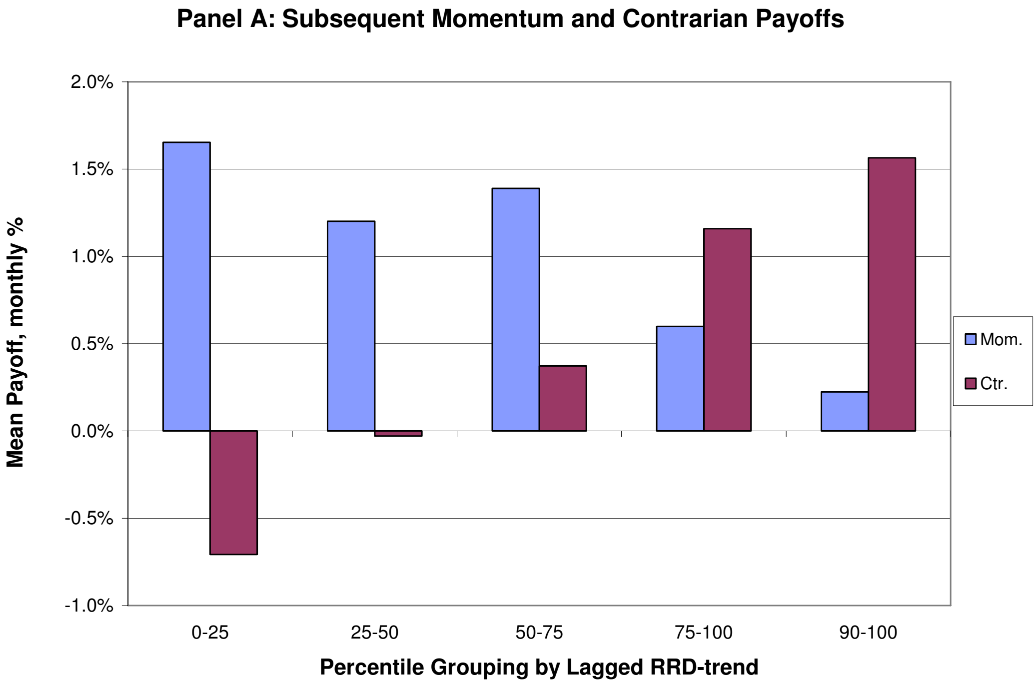


Figure 2: Subsequent Momentum and Contrarian Payoff Levels, when Sorted by the RRD-Trend

This figure reports on subset means and the percentage of negative observations for the subsequent momentum and contrarian payoffs, when sorted into percentile grouping on the lagged RRD-Trend. We report on our primary firm-level strategies and the lagged RRD-trend variables, as in Tables 3 and 4, Panel B. The means are standardized to a month, by dividing the holding-period mean by the number of months in the holding period.



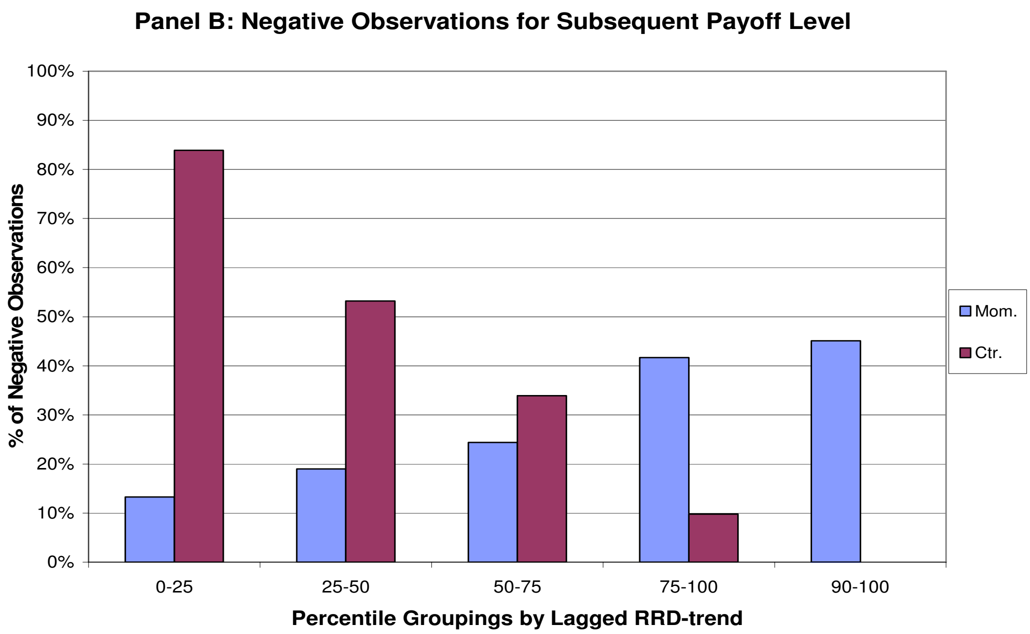
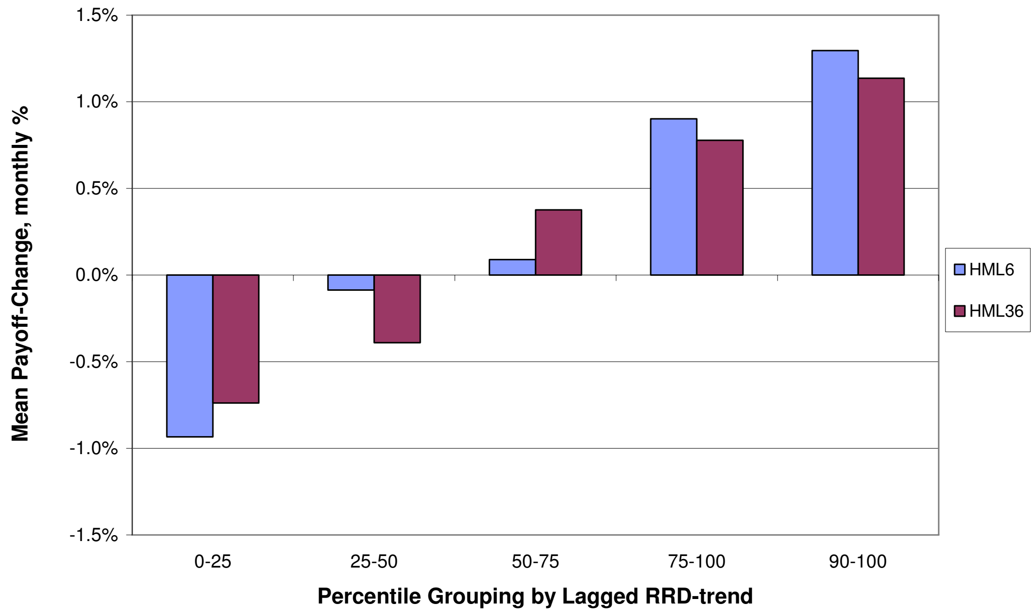


Figure 3: The Changes in HML Payoffs, when Sorted by the RRD-Trend

This figure reports on subset means and the percentage of negative observations for the payoff-changes of 6-month and 36-month HML B/M payoffs, when sorted into percentile grouping on the lagged RRD-Trend. We report on the HML payoffs and lagged RRD-trend variables as in Table 5, Panel A. The means are standardized to a month, by dividing the holding-period mean by the number of months in the holding period.

Panel A: Change in 6-month and 36-month HML Payoffs



Panel B: Negative Observations for Payoff Changes

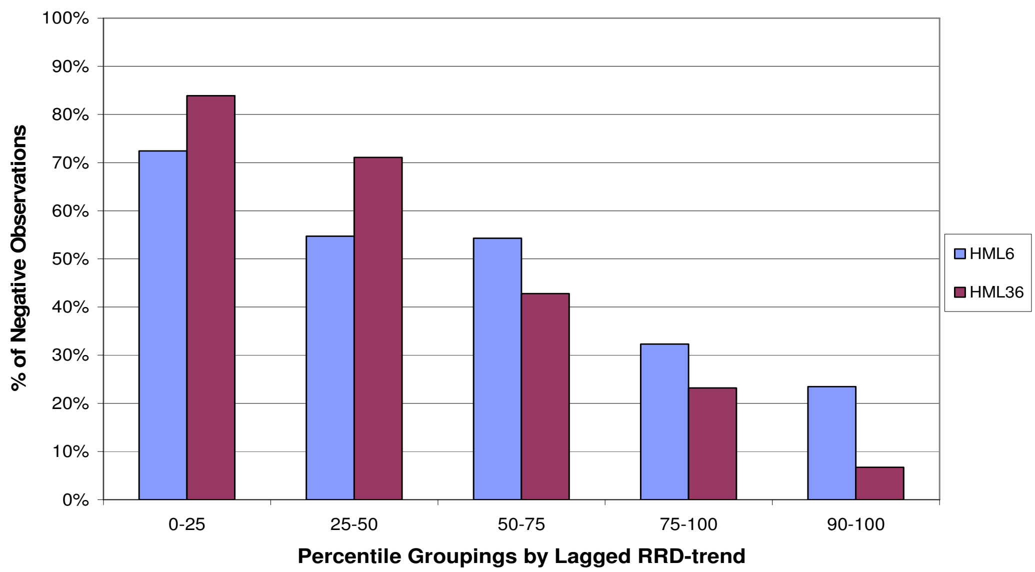
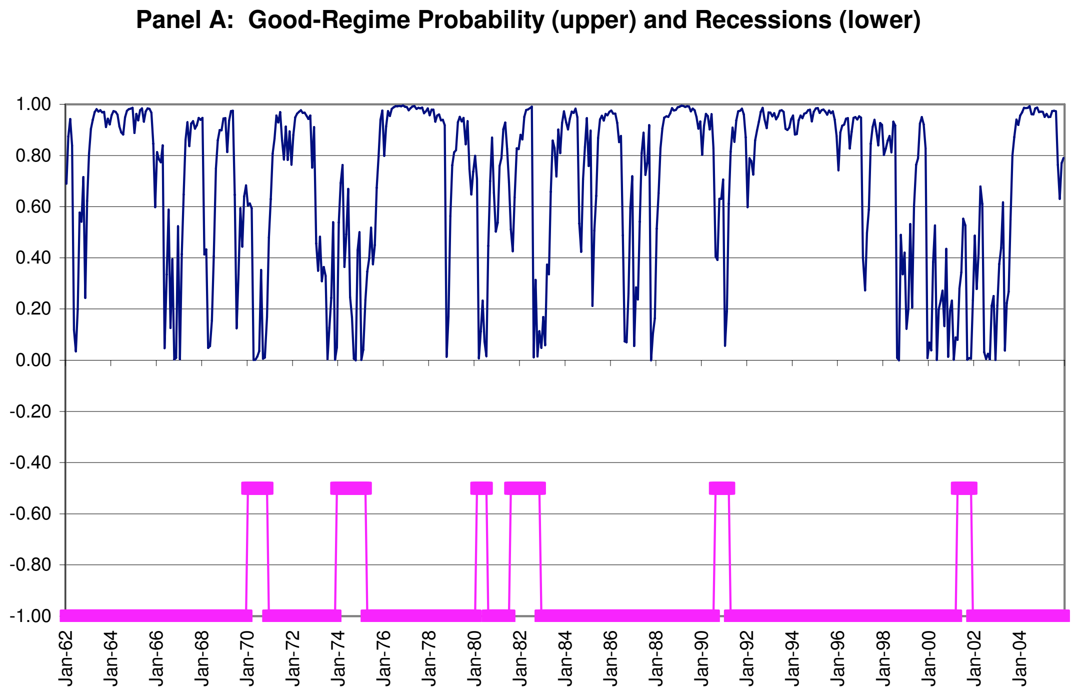
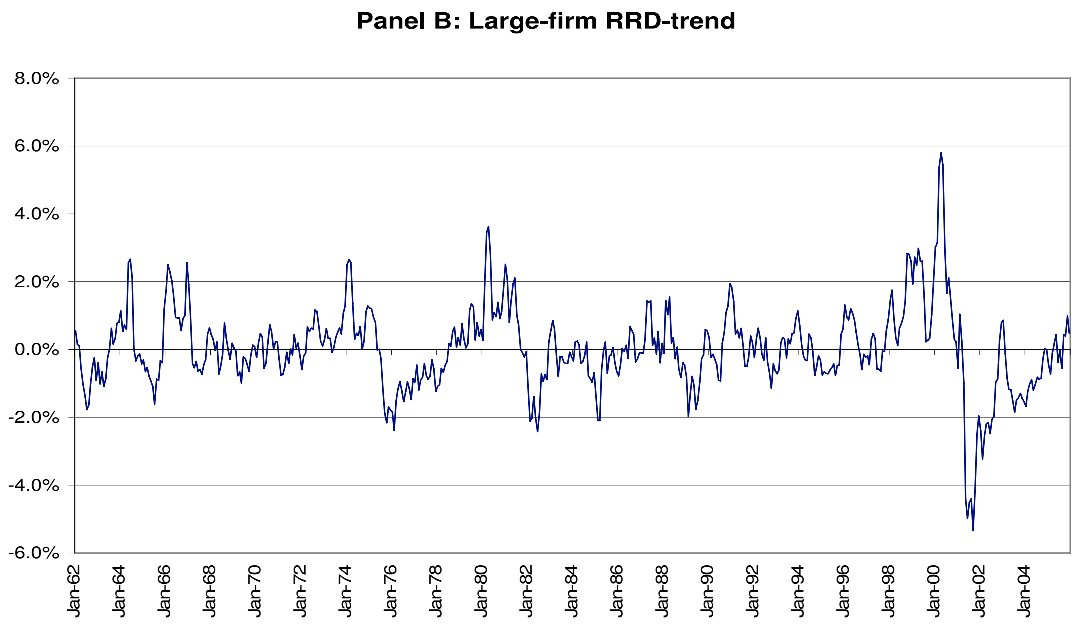


Figure 4: Regime-Switching and the RRD-Trend

Panel A plots the filtered probability of being in the good regime over time for the bivariate regime switching model from Table 8 for the upper series. For comparison, the lower series in Panel A indicates the contractionary economic periods from the NBER business cycle data, with a value of -0.5 indicating a contractionary month and a value of -1 indicating an expansionary month. Panel B plots the time-series of our large-firm RRD series, denoted $RRD_{1-3,8-19}$, as featured in Table 3. The sample period is 1962 through 2005.





Appendix A

An Analytical Framework for Momentum Profits with Regime Switching

Here, we offer a formal analytical framework to analyze how two-state regime-switching can influence momentum payoffs. The intuition follows from our simple example in Section 2.2. Our framework starts from the decomposition of the weighted relative strength strategy (WRSS) in Lo and MacKinlay (1990) and Conrad and Kaul (1998).

Lo and MacKinlay (1990) propose a momentum strategy termed the weighted relative strength strategy (WRSS), which has also been widely used in the literature; see, e.g. Conrad and Kaul (1998), Jegadeesh and Titman (2002), and Lewellen (2002). Jegadeesh and Titman (1993) find that returns from the WRSS and the decile-based strategy have a correlation of 0.95 in their sample. Here, we use the WRSS because it is analytically convenient to decompose the WML profits.

Under the WRSS, investors buy or short stocks in proportion to how the individual stock return over the ranking period differs from the average stock return over the ranking period. Specifically, the investment weight assigned to stock i at time t is given by:

$$w_{it} = \frac{1}{N}(r_{it-1} - \bar{r}_{t-1}) \tag{18}$$

where r_{it-1} equals the return of stock i over period $t-1$ and $\bar{r}_{t-1}$ is the return on an equally-weighted portfolio of all N stocks in the sample. The weights sum to zero. The profits over period t from this strategy can be expressed as

$$\pi_t = \frac{1}{N}\sum_{i=1}^{N} r_{it}(r_{it-1} - \bar{r}_{t-1}) \tag{19}$$

Lo and MacKinlay (1990) and Conrad and Kaul (1998) show that expected profits from the WRSS can be decomposed into three distinct sources.

$$E(\pi_t) = -Cov(\bar{r}_t, \bar{r}_{t-1}) + \frac{1}{N}\sum_{i=1}^{N} Cov(r_{it}, r_{it-1}) + \sigma^2(\mu) \tag{20}$$

where the first term is the negative of the autocovariance of the market, the second term is the cross-sectional average of the autocovariances of individual stocks, and $\sigma^2(\mu)$ is the cross-sectional variance in the unconditional expected returns.

Next, we consider the influence of regime-switching on momentum payoffs.[17] Our focus is on the analytical relation between momentum payoffs and the parameters of the regime-switching process. The framework only requires that certain stocks have relatively higher realized means in good market states and other stocks have relatively higher realized means in poor market states. More formally, we assume the return-generating process for a stock i can be written as:

$$r_{it} = \mu_i^s + \sigma_i^s \eta_{it} \tag{21}$$

[17] See Turner, Startz, and Nelson (1989), Veronesi (1999), and Ang and Bekaert (2002) for examples of regime-switching applications in finance.

where s denotes the unobserved regime indicator (1 or 2) and η is a zero-mean random variable that is identically and independently distributed. Conceptually, for our purposes as argued in Sections 2.2 and 7.1, we consider the regime-specific means to be "realized subset means" associated with a market cycle or economic outcome, rather than to indicate a conditional risk premia that reflects the risk-return tradeoff ex ante. Following Hamilton (1989), we assume that s follows a two-state, first-order Markov process with the following transition probability matrix

$$P = \begin{pmatrix} p_{11} & 1-p_{11} \\ 1-p_{22} & p_{22} \end{pmatrix} \tag{22}$$

where $p_{11} = \text{prob}(s_t = 1|s_{t-1} = 1)$ and $p_{22} = \text{prob}(s_t = 2|s_{t-1} = 2)$. In this specification, the transition probabilities dictate the persistence of the regimes, where the expected duration of regime i in periods, D_i, is defined as $D_i = \frac{1}{1-p_{ii}}$. To contribute to WML spreads, the process only requires regime shifts in the mean return. However, volatility is also likely to change with the regime, so equation (21) also allows for the volatility to switch.

Denote λ_1 as the unconditional probability that the process is in regime 1 ($\lambda_1 = \frac{1-p_{22}}{2-p_{11}-p_{22}}$). Timmermann (2000) shows that the autocovariance function for this two-state regime-switching model can be written as follows:

$$Cov(r_t, r_{t-n}) = \lambda_1(1-\lambda_1)(\mu^1 - \mu^2)^2 vec(P^n)' v_1 \tag{23}$$

where $v_1 = ((1-\lambda_1), -(1-\lambda_1), -\lambda_1, \lambda_1)'$. Then, the first-order autocovariance is given by

$$Cov(r_t, r_{t-1}) = \lambda_1(1-\lambda_1)(\mu^1 - \mu^2)^2 (p_{11} + p_{22} - 1). \tag{24}$$

From equation (24), first note that the larger the magnitude of the regime-mean difference $(\mu^1 - \mu^2)$, the higher the autocorrelation, other things being equal. Second, note that the first-order autocovariance will be positive if $(p_{11}+p_{22}) > 1$. Numerical results in Timmermann (2000) suggest that this basic regime-switching model can easily generate monthly autocorrelations comparable to that in the data.

Proposition 1 shows how a regime-switching process can contribute to determining the average momentum profit, beyond the profit suggested by $\sigma^2(\mu)$. This proposition gives the expected momentum profit per period, where a period is the length of the strategy's symmetric ranking and holding horizon.

Proposition 1 *Under the regime-switching process for stock returns as described in equations (21) and (22), the expected WRSS profit, $E[\pi_t]$, is given by:*

$$E[\pi_t] = A\sigma^2(d) + \sigma^2(\mu), \tag{25}$$

where $A = \lambda_1(1-\lambda_1)(p_{11} + p_{22} - 1)$, $\sigma^2(d)$ is the cross-sectional variance of regime-mean differences, and $\sigma^2(\mu)$ is the cross-sectional variance of unconditional expected returns. The regime-mean difference for a stock is the difference between its mean return in one state and the other state.

To prove Proposition 1, we substitute equation (24) into equation (20). Then, we denote the regime mean for the equally-weighted market index as $\bar{\mu}^s$ for regime s, where:

$$\bar{\mu}^s = \frac{1}{N}\sum_{i=1}^{N}\mu_i^s \tag{26}$$

Next, define $d_i \equiv \mu_i^1 - \mu_i^2$ as the regime-mean difference for stock i. The expected WRSS profit becomes:

$$E[\pi_t] = \lambda_1(1-\lambda_1)(p_{11}+p_{22}-1)\left[\frac{1}{N}\sum_{i=1}^{N}(\mu_i^1-\mu_i^2)^2 - (\bar{\mu}^1-\bar{\mu}^2)^2\right] + \sigma^2(\mu) \tag{27}$$

$$= \lambda_1(1-\lambda_1)(p_{11}+p_{22}-1)\left[\frac{1}{N}\sum_{i=1}^{N}(d_i-\bar{d})^2\right] + \sigma^2(\mu) \tag{28}$$

$$= \lambda_1(1-\lambda_1)(p_{11}+p_{22}-1)\sigma^2(d) + \sigma^2(\mu) \tag{29}$$

Hence, in this framework, expected average WRSS profits can be attributed to three sources: the cross-sectional variance of regime-mean differences ($\sigma^2(d)$), the cross-sectional variance of unconditional expected returns ($\sigma^2(\mu)$), and the transition probabilities. As long as $(p_{11}+p_{22}-1) > 0$, A will be positive, which is strongly suggested by the data for the 6-month horizon. Therefore, average medium-run momentum profits will be positive and will also be greater than suggested by the cross-sectional variation in unconditional expected returns. It is important to note that this proposition is defined in terms of one-base period and the framework does not allow for regime-switching at a smaller horizon than this defined base period.

Conceptually, as the strategy's horizon increases to near the expected duration of the less persistent regime, the transition probability p_{22} will approach zero. As p_{22} shrinks, $(p_{11}+p_{22})$ will become less than one and the first term in equation (25) will become negative and act to reduce the expected WRSS profits (as compared to the profits implied solely by $\sigma^2(\mu)$). Therefore, for longer horizon spreads where the strategy's horizon approaches the duration of the shorter regime, average WRSS profits will be less than suggested by the cross-sectional variation in unconditional mean returns, and the expected WRSS profit could be negative.

For example, assume regime-one has an expected duration of 48 months and regime-two has an expected duration of 24 months. When 6 months is the base period in (25), the implied p_{11} and p_{22} are 0.875 and 0.75, respectively (with durations of eight and four 6-month periods for the two regimes, respectively). Thus, for a 6-month WRSS horizon, the 'A' value is positive at 0.14 and WRSS profits would be greater than implied solely by the cross-sectional variation in unconditional mean returns. Alternately, assume that 24-months is the base period in (25). Now, the implied p_{11} and p_{22} are 0.5 and 0, respectively (with durations of two and one 24-month period for the two regimes, respectively). Thus, for a 24-month WRSS, the 'A' value is negative at -0.11 and WRSS profits would be less than implied solely by the cross-sectional variation in unconditional mean returns.