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The death of the overreaction anomaly? A multifactor explanation of contrarian returns

Abstract

Are the returns accruing to De Bondt and Thaler's (1985) (DT) much celebrated overreaction anomaly pervasive? Using the CRSP data set used by DT for the period of 1926 through 1982, and additional two decades of data (1983 through 2003), we provide preliminary support for the original work of DT, reporting that the overreaction anomaly has not only persisted over the past twenty years but has increased when risk is unaccounted for. However, using the three-factor model of Fama and French (1993) (FF), we find no statistically significant alpha can be garnered via the overreaction anomaly, with contrarian returns seeming driven by the factors of size and value, not the hypothesized behavioral biases of investors. It is our conjecture that the anomaly is not robust under the FF framework, with 'contrarian' investors following such a scheme simply compensated for the inherent portfolio risk held.

Keywords: overreaction, anomaly, multifactor asset pricing model.
JEL Classification: G11, G12, G14.

Introduction

The debate surrounding investor overreaction and contrarian investing is one of the most extensive and controversial areas of research in finance. Despite the fact that there is a general agreement on the evidence of price reversal, there is no consensus about what is driving these reversals. From an investment management perspective, the concern regarding contrarian strategies relates to issues of portfolio risk and the ability of the anomaly to generate alpha. In the spirit of recent work scrutinizing or 'dissecting' anomalies (see Fama and French, 2006), we revisit the overreaction anomaly reported by De Bondt and Thaler (1985), updating the initial study with a further two decades of data. Using a multifactor asset pricing framework, we find that contrarian returns, particularly past 'losers', consistently weight towards size and the value factors at economically meaningful levels (with past 'winners' predominantly showing characteristics consistent with the value factor). It is our conjecture that investors following such a scheme are simply compensated for the inherent portfolio risk held.

1. The overreaction controversy

The overreaction anomaly, evidenced by long-term reversals in stock returns, was first identified by De Bondt and Thaler (1985), who showed that stocks which perform poorly in the past three to five years demonstrate superior performance over the next three to five years compared to stocks that have performed well in the past. The original study performed by De Bondt and Thaler (1985), hereafter DT, entitled "Does the stockmarket overreact?", provided evidence that abnormal excess returns could be gained by employing a strategy of buying past losers and selling short past winners, or the 'contrarian' strategy. Using an array of data for different time periods and in different markets, support for the findings of DT has been provided by, among others, Howe (1986), Fama and French (1988), Poterba and Summers (1988), Chopra, Lakonishok and Ritter (1992) and Campbell and Limmack (1997).

Soon after the publication of DT, Chan (1988) argued that the work lacked appropriate risk adjustment, and demonstrated that the single-factor CAPM had some explanatory power for the returns generated by DT. As asset pricing models developed, Fama and French (1993, 1995, and 1996) showed the relevance of size and value factors in explaining the cross-section of stock returns, however, to this day overreaction studies continue to ignore this work in their methodological approach to the anomaly. This appears to be a vital concern, and one which this work seeks to rectify. Further consideration of the literature following DT reveals that overreaction studies are subject to a number of criticisms. First, there is a lack of risk adjustment in the original study (Chan, 1988; Ball and Kothari, 1989). Second, the impact of the January effect on returns is not adequately dealt with (Zarowin, 1990). Finally, there is an ongoing discussion around the role of measurement biases in the sorting and testing periods (Conrad & Kaul, 1993). Our paper directly considers the impact of each of these issues for the U.S. setting from 1926 through 2003 (a further two

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decades of data following DT's observation window), finding that, on risk-adjusted basis, no statistically significant alpha can be garnered through the various approaches that attempt to exploit the overreaction anomaly.

To analyze the evidence for long-term reversals, we use the monthly return data from the Centre for Research in Security Prices (CRSP), the same data set used in the original DT study, for the period of January 1926 through December 2003 and build portfolios every period of the best (winner) and worst (loser) performing stocks in the previous *n* months. The equally-weighted CRSP market index is used as our market proxy (a description of the sorting approach is provided in Figure 1 of the Appendix). We then record the cumulative average monthly return to these self-financing portfolios over our sample period.

2. Decomposing contrarian returns

2.1. Out-of-sample test of De Bondt and Thaler (1985). The results from the recent sub-period (1983-2003) provide corroborating evidence of the overreaction hypothesis, and, interestingly, demonstrate that the magnitude of the anomaly, on a risk-unadjusted basis, has actually increased through time. During the period of January 1983 to December 2003, the loser portfolios outperform the market, on average, by 53.7%, 36 months after formation. The winner portfolios underperform the market by, on average, 4.03%. These results are displayed in Figure 2.

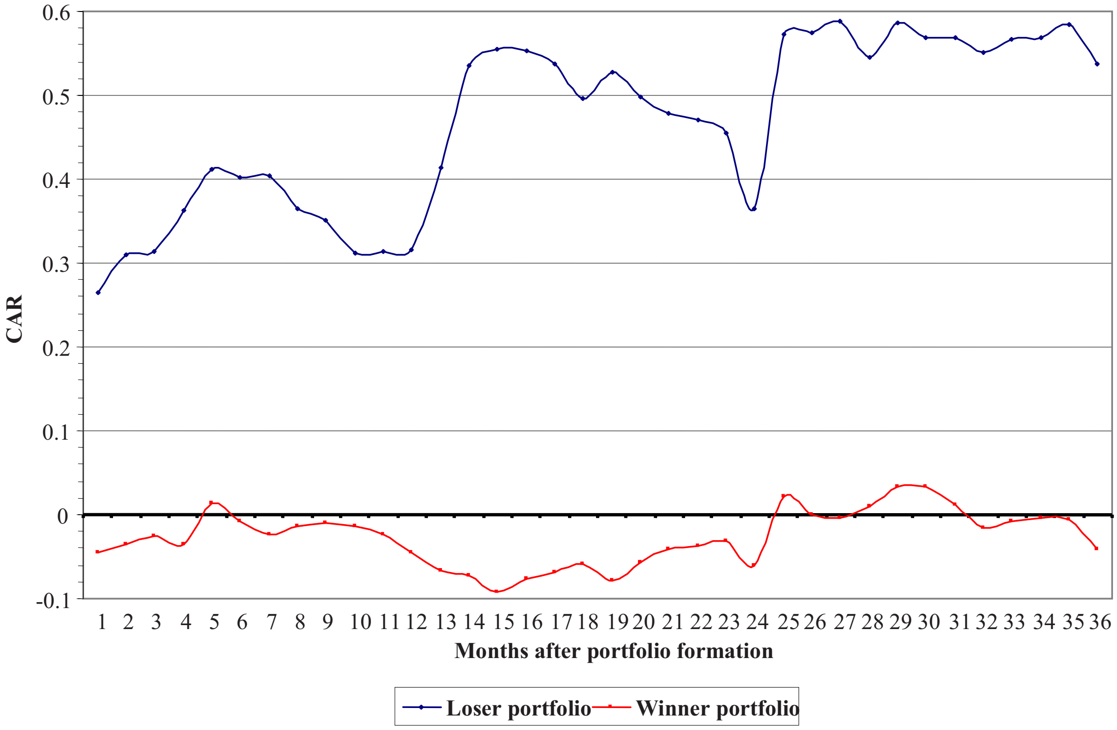

Fig. 2. Average CAR of portfolios formed for three-year sort and test periods for recent sub-period of January 1983 to December 2003

Examining the full dataset from 1926 to 2003 shows amplification of the anomaly on a risk-unadjusted basis, and reveals that if DT were to present the results of their study today, they would report a difference in the ACAR's of the winner and loser portfolios of 42.5%, over 50% larger than that reported in 1985! This amplification of the overreaction anomaly suggests that the overreaction anomaly is, perhaps, 'alive and well'.

2.2. Evidence in favor of risk adjustment. Understandably, DT have been extensively criticized for focusing on market-adjusted returns. By any metric, portfolio managers are constantly focusing on the risk-adjusted return of their investments. Hence, the core of our study applies various techniques to adjust for risk using four techniques: first, by appraising a suitable asset pricing model; second, through modeling time-varying risk coefficients in the data to investigate the appropriateness of beta estimates; third, by allowing for the well accepted return premium to small companies; and, finally, considering the results in light of the January effect[1].

In examining overreaction, Chan (1988) proposes that the risks of winner and loser stocks do not re-

[1] A summary of the size effect is provided by Schwert (1983), with further detail in Banz (1981), Reginganum (1981). Keim (1983), Reginganum (1983) and Haug and Hirschey (2006) provide a discussion of the January effect.

main constant over the combined time period of sorting and testing[1]. This line of argument suggests that striking changes in the risks of the portfolios, which are not accounted for in the DT study, assist in explaining the returns from the strategy. Research by Chan (1988), Brown, Harlow and Tinic (1988) and Ball and Kothari (1989) shows that when beta is estimated on the appropriate test period, rather than the sorting period, the strategy earns economically insignificant abnormal returns.

In order to overcome the perceived problem modelling changes in the beta during the rank period, Chan (1988) proposes a regression to test whether the betas change significantly from the rank period to the test period:

$$\lfloor R_{m,t} - R_{f,t} \rfloor = a_{1,i}(1-D_t) + a_{2,1}D_t + \beta_{1,i}\lfloor R_{m,t} - R_{f,t} \rfloor \cdot (1-D_t) + \beta_{2,i}\lfloor R_{m,t} - R_{f,t} \rfloor D_t + \varepsilon_{i,t}\,, \tag{1}$$

where the dummy variable D_t assumes the value of 0 for the sort period and 1 for the test period. $\alpha_{1,i}$ and $\alpha_{2,i}$ represent the excess returns for the sort and test periods respectively. $\beta_{1,i}$ and $\beta_{2,i}$ represent the beta coefficients for the sort and test periods respectively.

Using this method, two separate regressions are run to test if there are time-varying risk coefficients in the data, with the results presented in Table 1. The point of interest is if β changes from the sorting periods to the testing periods.

Table 1. Risk-change test for a 35 stock portfolio against an index constructed from the CRSP dataset for the period of 1926-2003

Sort period	Test period	Losers				
		α	α_i	β_i	β_{iD}	Adj R^2
3	3	-0.038** (-5.324)	0.002 (-0.026)	1.028** (10.377)	0.417* (2.505)	0.753
4	4	-0.032** (-5.209)	0.004 (0.344)	1.044** (12.260)	0.307* (2.060)	0.731
5	5	-0.024** (-3.710)	0.005 (0.409)	1.088** (10.379)	0.305 (1.730)	0.667
Sort period	Test period	Winners				
		α	α_i	β_i	β_{iD}	Adj R^2
3	3	0.045** (6.025)	-0.003 (-0.422)	1.707** (15.285)	-0.473* (-2.047)	0.806
4	4	0.036** (5.928)	-0.004 (-0.791)	1.632** (17.392)	-0.389* (-2.161)	0.810
5	5	0.033** (4.817)	-0.003 (-0.623)	1.395** (13.044)	-0.170 (-0.875)	0.699

Notes: Tests for abnormal returns under the assumption that the sort period and test period betas are not equal to Intercept estimates with t-statistics from the Chan (1988) model:

$(R_{i,t} - Rf_t) = \alpha_{1,i}(1-D)+\alpha_{2,i}D_t + \beta_{1,i}(Rm_t - Rf_t)(1-D)+\beta_{2,i}(Rm_t - Rf_tD_t)D_t + \varepsilon_{it}$.

T-statistics are in parentheses. Statistical significance is denoted at: 1% - **; 5% - *; 10% - #.

The results in Table 1 show clearly that risk for both the winner and loser portfolios changes from the sort period to the test period. The estimated sort period betas, given by β_i, are smaller for losers than winners. The estimated test period betas, given by β_{iD}, are larger for losers than winners. As Chan (1988) elucidates, the large changes in betas from the sort period to the test period are consistent with the risk explanation of the overreaction anomaly.

Our results corroborate the findings of earlier work, for all time periods examined, and hence the asset pricing tests for our study are run with the coefficients estimated from the test period.

[1] The premises of the criticisms in Chan's (1988) paper are that if beta is estimated in the sort period and there is no attempt to model changes in risk, the estimated beta will be a biased estimate of the beta in the test period. Since the risk of the loser portfolio increases in the sort period, the sort period beta underestimates the test period beta. The sort period is the time period which is used for the portfolios based on past returns. The test period is the period in which the future performance of these portfolios is measured. A full description of this methodology is contained in Appendix A.

2.3. Evidence in favor of the three-factor model. The work of Fama and French (1993, 1996) has demonstrated the relevance of size and value factors when pricing risky assets. Investment managers are justly mystified as to why researchers over the last decade continue to ignore this in their methodological approach to the anomaly[1]. This study implements the three-factor model developed by Fama and French (1993) (hereafter FF) on the original dataset used by DT, both in-sample and out-of-sample. We consider performance with the following equation:

$$\left\lfloor R_{i,t} - R_{f,t} \right\rfloor = \alpha_i + \beta_i \left\lfloor R_{m,t} - R_{f,t} \right\rfloor + \\ + \sigma_i \left\lfloor SMB_t \right\rfloor + \eta_i \left\lfloor HML_t \right\rfloor + \varepsilon_{i,t}, \qquad (2)$$

where α_i – risk adjusted abnormal returns from the three-factor model; β_i – measure of sensitivity of return on the portfolios to the market; $R_{i,t}$ – return on portfolio *i* in month *t*; $SMB_{i,t}$ – the time series of differences in average returns from the smallest and largest capitalization stocks (or small cap minus big cap); HML_{it} – the time series of differences in average returns from the highest to the lowest book to market ratios (or high book to price minus low book to price); $R_{f,t}$ – the one-month US Treasury bill rate (from Ibbotson Associates); $R_{m,t}$ – the equally-weighted return on all NYSE, AMEX and NASDAQ stocks; $\varepsilon_{i,t}$ – random error term.

The error term, $\varepsilon_{i,t}$, has an expected value of zero.

Ibbotson, Kaplan and Peterson (1997) believe that small firms, as measured by market value, will have their beta underestimated by the standard estimation procedure. They claim that a more relevant beta estimate is the sum of the regression coefficients of the stock's return regressed on market return for the same period, and on the market return lagged one period. Their explanation for this is that information for smaller firms takes longer to reflect in their stock prices. Their results demonstrate that the sum of the two regression coefficients (called "sum beta") rises as firm size falls. These findings suggest that size risk premium is not fully captured by beta and that the "sum beta" measure may partially explain the small firm effect.

However, Malkiel and Xu (1997) show that small firms also have higher idiosyncratic volatility of returns (measured by the return variance unexplained by overall market movements). It is therefore difficult to empirically show whether the higher return on small firms compensates for small size or the idiosyncratic volatility. In either case, it appears that the traditional beta alone does not fully capture the risk of smaller firms.

Table 2, below, shows that the three-factor model does an admirable job of explaining the return behavior of the contrarian portfolios. For the loser portfolios, we obtained uniformly positive, statistically significant weightings on both the size and value factors. For the winner portfolios, the size and value coefficients are, on the whole, statistically significant and negative. These findings suggest that long-term past losers tend to be small, distressed stocks and that the winner portfolios comprise larger, growth stocks and therefore the three-factor model predicts that the long-term past winners will necessarily not produce higher average returns[2].

Importantly for our study, the FF model is doing a better job than the CAPM (results not shown) in explaining the future returns generated by a contrarian strategy[3]. The average R^2 for the loser portfolios is 0.769 for the three-factor model, up from 0.648 in our single-factor results. Similarly, for the winner portfolios the average R^2 increases from 0.831 in the CAPM model to 0.882 in the three-factor model.

Table 2. Three-factor regressions of performance for a 50 stock portfolio against a geometric average index, 1926-2003

Sort period	Test period	Losers				
		α	β_i	σ_{SMB}	η_{HML}	Adj R^2
3	3	0.002 (-0.132)	1.173** (7.954)	0.695# (1.677)	0.648* (2.328)	0.784
3	4	0.005 (0.334)	0.954** (8.386)	1.546** (6.381)	0.870** (3.481)	0.744

[1] A view held by Bowman and Iverson (1998), Bauman et al. (1999), Schiereck et al. (1999), Gaunt (2000), Kang et al. (2002), Forner and Marhuenda (2003), Hirschey (2003), Lai et al. (2003) and Ma et al. (2005).

[2] Analysis of the two sub-periods presents similar results to those detailed for the full study.

[3] These results are available on request.

Table 2 (cont.). Three-factor regressions of performance for a 50 stock portfolio against a geometric average index, 1926-2003

Sort period	Test period	Losers				
		α	β_i	σ_{SMB}	η_{HML}	Adj R^2
3	5	0.002 (0.026)	0.993** (8.654)	1.644** (7.736)	0.944** (4.752)	0.733
4	5	0.001 (0.011)	1.216** (9.925)	0.558* (2.333)	0.643** (2.978)	0.783
5	5	0.002 (0.226)	1.142** (9.392)	0.504* (1.977)	0.595** (2.869)	0.773
Sort period	Test period	Winners				
		α	β_i	σ_{SMB}	η_{HML}	Adj R^2
3	3	-0.002 (-0.474)	1.112** (12.329)	-0.103 (-0.952)	-0.338* (-1.965)	0.857
3	4	-0.003 (-0.835)	1.201** (14.496)	0.809** (5.564)	0.092 (1.110)	0.874
3	5	-0.002 (-0.559)	1.159** (18.338)	0.679** (6.227)	0.080 (1.359)	0.888
4	5	-0.002 (-0.677)	1.153** (18.398)	-0.310** (-2.636)	-0.295* (-2.564)	0.893
5	5	-0.002 (-0.761)	1.171** 17.628	-0.293* (-2.270)	-0.296* (-2.350)	0.889

Notes: Fama-French 3-factor regressions for monthly excess returns on equal-weighted CRSP portfolios of 50 stocks formed on the basis of past returns: Non-overlapping portfolios for the period of January 1926 to December 2003. Intercept estimates with *t* statistics (the regression coefficient divided by its standard error) from the Fama-French 3-factor model:

$(R_{it} - Rf_t) = \alpha_i + \beta_i(Rm_t - Rf_t) + \sigma SMB_t + \eta HML_t + \varepsilon_{i,t}$.

The regression R^2's are adjusted for the degrees of freedom. T-statistics are in parentheses. Statistical significance is denoted at: 1% - **; 5% - *; 10% - #.

2.4. Evidence of the January effect. The findings of the original overreaction study were also challenged on the basis of the well-known January effect. The critique by Zarowin (1990) includes substantial discussion of seasonality in the overreaction phenomenon. This explanation is supported by Pettengill and Jordan (1990), who show that almost half of the average cumulative abnormal return for the year in their 90-stock loser portfolio is generated in January[1].

Similarly, Chopra, Lakonishok and Ritter (1992) demonstrate that the overreaction effect was "disproportionately concentrated in January [p. 249]." In order to study the consequences of the January effect in combination with the three-factor pricing model, and to ensure the robustness of the tests of persistence of the overreaction anomaly, our models were adjusted to allow for a January coefficient. The three-factor model with the January coefficient is specified:

$$\left[R_{i,t} - R_{f,t}\right] = \alpha_i + \beta_i\left[R_{m,t} - R_{f,t}\right] + \sigma_i\left[SMB_t\right] + \eta_i\left[HML_t\right] + \gamma_i\left[\theta_i\right] + \varepsilon_{i,t}\,. \quad (3)$$

The additional variable θ_i is a dummy variable, which is set to 1 for January and 0 for all other months. This enables separate testing of the results for the January effect.

Results from these tests are presented in Table 3, and show that the loser stocks are still small, distressed stocks and the January effect only has a marginal influence on some of the portfolios. Interestingly, for the winner portfolios, the market beta coefficients appear to be capturing the majority of the returns from these portfolios, and the January effect is not statistically significant in any portfolios. The explanatory power of the models increases only marginally with the addition of January, in the loser portfolios by 3.4% and in the winner portfolios by only 0.3%.

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[1] De Bondt and Thaler (1987) concede that they have no satisfactory explanation for the January effects.

Table 3. Three-factor regressions of performance for a 50 stock portfolio against a geometric average index, with January coefficient, for the full study period

Sort period	Test period	Losers					
		α	β_i	σ_{SMB}	η_{HML}	γ_{JAN}	Adj R^2
3	3	-0.002 (-0.586)	1.086** (7.698)	0.618 (1.505)	0.501# (1.732)	0.068# (1.834)	0.809
3	4	0.004 (0.231)	0.913** (8.397)	1.507** (6.354)	0.750** (3.252)	0.097 (1.556)	0.775
3	5	0.000 (-0.296)	0.962** (8.946)	1.543** (7.483)	0.806** (4.272)	0.096* (2.489)	0.770
4	5	0.000 (-0.102)	1.178** (10.189)	0.461* (2.063)	0.520** (2.590)	0.094* (2.069)	0.822
5	5	-0.001 (-0.086)	1.069** (9.030)	0.485^ (1.936)	0.536* (2.488)	0.049 (1.417)	0.797
Sort period	Test period	Winners					
		α	β_i	σ_{SMB}	η_{HML}	γ_{JAN}	Adj R^2
3	3	-0.001 (-0.222)	1.136** (12.16)	-0.082 (-0.746)	-0.289 (-1.533)	-0.016 (-1.030)	0.861
3	4	-0.003 (-0.82)	1.193** (14.549)	0.816** (5.570)	0.105 (1.312)	-0.008 (-0.574)	0.877
3	5	-0.001 (-0.418)	1.154** (18.157)	0.701** (6.320)	0.091 (1.474)	-0.012 (-0.958)	0.888
4	5	-0.002 (-0.581)	1.153** (18.433)	-0.280* (-2.407)	-0.276* (-2.345)	-0.024 (-1.283)	0.895
5	5	-0.001 (-0.353)	1.191** (17.743)	-0.271* (-2.066)	-0.250# (-1.869)	-0.017 (-1.625)	0.896

Notes: Fama-French 3-factor regressions for monthly excess returns on equal-weighted CRSP portfolios of 50 stocks formed on the basis of past returns: Non-overlapping portfolios for the period of January 1933 to December 2003. Intercept estimates with *t* statistics (the regression coefficient divided by its standard error) from the Fama-French 3-factor model:

$$(R_{i,t} - Rf_t) = \alpha_i + \beta_i(Rm_t - Rf_t) + \sigma SMB_t + \eta HML_t + \gamma_i(\theta_i) + \varepsilon_{i,t},$$

where the dummy variable θ is set to 1 for January and 0 for all other months. The regression R^2's are adjusted for the degrees of freedom. T-statistics are in parentheses. Statistical significance is denoted at: 1% - **; 5% - *; 10% - #.

2.5. Robustness tests. The focus of our study so far, has been on the DT non-overlapping portfolios. Portfolio managers are able to more effectively operationalize the contrarian strategy by forming portfolios on the basis of overlapping or rolling windows. Additionally, it is recognized that properly specified tests of time series data can achieve greater efficiency by the use of overlapping data[1].

In order to account for the problem of autocorrelation that overlapping observations induce, all results are appropriately modified via the heteroskedasticity and autocovariance consistent estimator of Newey and West (1987) in order to obtain asymptotically valid hypothesis tests. Table 4 reports the average results for the three-factor model rolling windows tests carried out on all the portfolio combinations previously discussed[2].

[1] In his work on testing the efficient market hypothesis, Gilbert (1986) recognized the importance of using a full sample of overlapping data, along with the inherent problems of heteroskedasticity.

[2] That is, an average of the 20, 35, and 50 stock portfolios. A full presentation of these tests would be too voluminous for this paper; however, the results presented in this section are representative of those obtained from the implementation of the individual tests of robustness.

Table 4. Rolling window tests of robustness for the three-factor model

Sort period	Test period	Losers				
		α	βι	σ_{SMB}	η_{HML}	Adj R^2
3	3	0.002 (-0.093)	1.289** (6.406)	0.799 (1.547)	0.861* (2.026)	0.727
3	4	0.003 (-0.019)	0.961** (6.803)	0.870* (1.929)	1.013** (3.296)	0.699
3	5	0.002 (-0.057)	0.994** (8.032)	0.787* (1.662)	0.985** (3.676)	0.708
4	5	0.001 (-0.027)	1.204** (8.786)	0.662^ (1.835)	0.693* (2.478)	0.738
5	5	0.002 (0.011)	1.087** (8.447)	0.689* (1.983)	0.735** (2.586)	0.706
Sort period	Test period	Winners				
		α	βι	σ_{SMB}	η_{HML}	Adj R^2
3	3	-0.003 (-0.572)	1.181** (10.729)	-0.120 (-0.630)	-0.357^ (-1.760)	0.845
3	4	-0.002 (-0.664)	1.175** (12.746)	-0.863 (-0.922)	-0.216^ (-1.743)	0.848
3	5	-0.002 (-0.750)	1.166** (14.32)	-0.856 (-0.958)	-0.365^ (-1.879)	0.846
4	5	-0.002 (-0.683)	1.174** (14.307)	-0.167 (-1.062)	-0.299* (-2.047)	0.855
5	5	-0.001 (-0.603)	1.121** (14.198)	-0.187 (-1.337)	-0.258^ (-1.934)	0.826

Notes: Fama French 3-factor regressions for monthly excess returns on equal-weighted CRSP portfolios averaged across 20, 35 and 50 stocks formed on the basis of past returns: Rolling Window Portfolios for the period of January 1933 to December 2003. Intercept estimates with *t* statistics (the regression coefficient divided by its standard error) from the Fama-French 3-factor model:

$(R_{i,t} - Rf_t) = \alpha_i + \beta_i(Rm_t - Rf_t) + \sigma SMB_t + \eta HML_t + \varepsilon_{i,t}.$

The standard errors are appropriately modified via the heteroskedasticity and autocovariance consistent estimator of Newey and West (1987) in order to obtain asymptotically valid hypothesis tests on the overlapping data. The regression R^2's are adjusted for the degrees of freedom. T-statistics are in parentheses. Statistical significance is denoted at: 1% - **; 5% - *; 10% - #. These results show that an investor employing a contrarian investment strategy using rolling windows will only earn returns to compensate for the market risk of the portfolios, combined with the risks of small, value companies, as captured by the SMB and HML coefficients[1].

Conclusion

In revisiting the overreaction anomaly we have shown that implementing a contrarian strategy for U.S. stocks does not produce alpha. The analysis suggests that the factors of size and value play a central role in explaining the future returns generated by a strategy of forming portfolios based on past returns. Perhaps the most interesting finding is that past losers consistently show a tendency towards both the size and value factors at statistically significant levels, and at levels consistently higher than their winner counterparts. Moreover, for past winners, this weighting is primarily towards the value factor. The long-term past winners either show a negative relationship on the value factor at statistically significant levels, or produce no relationship other than on the market factor, confirming previous research that categorizes overreaction as a 'loser-effect' rather than a 'loser-and-winner-effect'. These conclusions remain robust, even after adjusting for the January effect. Our study shows that portfolio managers could earn returns above the market by constructing portfolios based on the contrarian investment strategy; however, this additional return would come simply at the expense of increased risk – a win for the proponents of standard finance theory.

[1] Such findings are corroborated by using the FF model, incorporating the impact of the January effect, which, again for reasons of space, are not shown here, but are available on request.

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Appendix. Constructing contrarian portfolios

At the first stage of our study we follow an approach almost identical to that of DT, who demonstrate that most reversal evidence is contained in portfolios constructed for a 3-year time frame. We use data on stock returns from January 1927 through December 2003 for all stocks listed on the CRSP tapes. We follow the steps:

1. At every month-end, we rank all stocks according to their return above the market over the previous *m* months (period t-m + 1 to t) where t is on months.

2. Winner and loser portfolios are formed conditional upon past excess returns, with the top 35 stocks (those with the greatest cumulative excess returns) forming the winner portfolio, and the bottom 35 stocks (those with the smallest cumulative excess returns) forming the loser portfolio.

3. We then measure the return to each of these portfolios in every month for the next n months (period t + 1 to n + 1). Over an n-year period, the cumulative abnormal (monthly) return (CAR) for each stock is calculated as:

$$CAR_i = \sum_{n=1}^{36} AR_{i,n} \,, \tag{4}$$

where $AR_{i,t}$ is measured by $\alpha_{1,i}$.

4. This step is repeated for all following non-coincident n-month periods. Variations to the DT strategy that we use include non-equal values for m and n.

5. The cumulative average residual returns of all securities in the portfolios are calculated for the following n months. Following this, the average cumulative abnormal returns (ACAR) are calculated for months t-m + 1 to t. T-statistics are then calculated to determine if these ACARs are statistically significant. In summary, Figure 1 provides a 'snapshot' of the methodological approach central to the study[1].

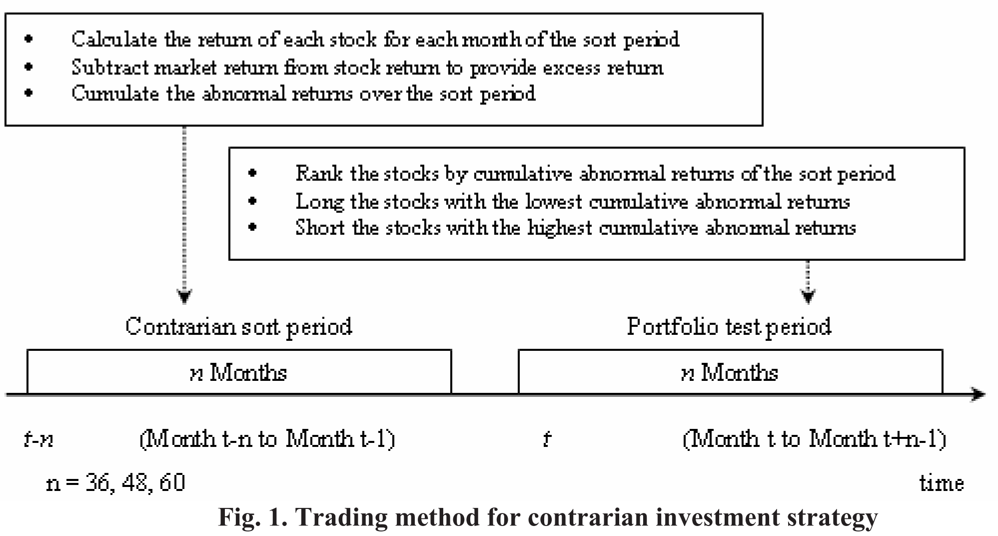

Fig. 1. Trading method for contrarian investment strategy

[1] See De Bondt and Thaler (1985) for a more detailed description of the portfolio formation technique.

In this study, we also examined the contrarian investment strategy with the following variations to Step 2:

2a Portfolios were formed containing 20 stocks and 50 stocks.

Additionally, our methodology acknowledges the numerous papers that have replicated, examined, extended and critiqued the original overreaction study by also conducting tests on many alternate portfolio compositions[1]. These alternatives are not so much areas of criticism, rather a sensible procedure for providing more robust results[2]. To overcome the perceived measurement shortcomings in the earlier work our methodology includes:

- portfolios that were examined on the basis of 20, 35 and 50 stocks;
- portfolios that were formed for both symmetrical windows (e.g., 3 year sort; 3 year test), and non-symmetrical windows (e.g., 3 year sort; 4, and 5 year test); and
- testing undertaken for the DT time period (1926-1982), the recent period (1983-2003) and the full sample (1926-2003).

[1] For example, Pettingill and Jordan (1990) examine 90 stock portfolios, Chopra, Lakonishok and Ritter (1992) use 20 stocks, many studies use decile portfolios, Levis and Liodakis (2001) examine top and bottom one-third, De Bondt and Thaler (1987) use 50 stocks and Schiereck, De Bondt and Weber (1999) use portfolios ranging from 10 to 40 stocks. For sort and test periods, Kryzanowski and Zhang (1992) who use periods ranging from 1 to five years, Campbell and Limmack (1997) who maintain a three year sort period but test over 1 to 5 years, and Schiereck, De Bondt and Weber (1999) who use much smaller sort periods of 1, 3, 6 and 12 months.

[2] In fact Schiereck, De Bondt and Weber (1999) concede the points made in Ball, Kothari & Shaken (1995) and, when referring to the original DT study, state that "profits may be illusory, a product of methodological and measurement problems [p. 104]".