Mean Reversion of Size-Sorted Portfolios and Parametric Contrarian Strategies*

by *Jeffrey Gropp*, Department of Economics and Management, DePauw University, Greencastle, Indiana

Abstract

Evidence of mean reversion in U.S. stock prices during the post-World War II era is mixed. I find that using the standard portfolio formation method to construct size-sorted portfolios is inadequate for detecting mean reversion. Using alternative portfolio formation methods and additional cross-sectional power gained from size-sorted portfolios during the period 1963 to 1998, I find strong evidence of mean reversion in portfolio prices. My findings imply a significantly positive speed of reversion with a half-life of approximately three and a half years. Parametric contrarian investment strategies that exploit mean reversion outperform buy-and-hold and standard contrarian strategies.

JEL Classification: G10; G14;

Keywords: Mean Reversion; Market Efficiency; Investment Strategies; Panel Estimation; Portfolio Formation

1. Introduction

Findings of reversion in stock prices towards some fundamental value have been present in the finance literature for over a decade.[1] Fama and French (1988) employ a time series approach to detect the presence of a transitory component in stock prices. Specifically, they regress monthly stock returns on lagged multi-year returns. Using industry and size-sorted portfolio (based on total market capitalization) data, Fama and French find that 25-45 percent of the variation of 3- to 5-year stock returns is predictable from past returns. More recently however, support for such mean reversion has been strongly criticized. Jegadeesh (1991), Gangopadhyay (1996), and Gangopadhyay and Reinganum (1996) find that seasonal effects influenced previous conclusions in support of mean reversion.[2] Jegadeesh also finds that there is little evidence of mean reversion in the post-World War II period. Similarly, Kim, Nelson, and Startz (1991) and McQueen (1992) confirm this result, and suggest that relying on standard econometric techniques, i.e., OLS, places an inordinate level of importance on the relatively high volatility during the pre-war era and thus exaggerates the overall level of mean reversion.[3] Such difficulties only stress the problems associated with detecting a mean reverting component in asset prices.

This paper examines the difficulties associated with using size-sorted portfolios to detect the presence of mean reversion. Many of the studies discussed above have evaluated mean reversion using size-ranked portfolios and have failed to detect the presence of mean reversion.[4] The motivation for the use of portfolios is to reduce measurement error and other noise, as well as, maintaining enough dispersion in returns to increase the power of tests for mean reversion. As Cochrane (2001, p. 530) argues, sorting by market capitalization is as good as sorting by beta or any other criterion as long as the above two conditions are met. Using a panel model developed by Balvers, Wu, and Gilliland (2000), I find significant evidence of mean reversion in portfolio prices while showing that the method of sorting stocks on the basis of market capitalization used in past studies is inadequate when testing for the existence of mean reversion. If stock prices return to some fundamental level after experiencing a temporary shock, i.e., mean reversion exists, then it should be possible for investors to increase their expected return by shorting those stocks with the highest return in the previous period and purchasing those stocks with the lowest returns in the previous period. I explore the economic importance of the mean reversion results by examining various investment strategies.

The remainder of this paper is organized as follows. The following section describes the methodology and discusses the inherent problems associated with analyzing mean reversion. Section 3 presents the empirical results. Section 4 provides confirmation of earlier findings by examining the effectiveness of 'parametric contrarian investment strategies'. The paper ends with a brief summary of conclusions.

2. Methodology: Model

Following Balvers, Wu, and Gilliland (2000), the hypothesis of mean reversion in stock prices can be motivated with the following model:[5]

$$R^i_{t+1} - R^b_{t+1} = \alpha^i - \lambda\left(P^i_t - P^b_t\right) + \sum_{j=1}^{k} \phi^i \left(R^i_{t+1-j} - R^b_{t+1-j}\right) + \omega^i_{t+1}. \tag{1}$$

Equation (1) is similar to the standard augmented Dickey-Fuller (ADF) test for a unit root (Dickey and Fuller, 1981). Specifically, it allows us to test for a unit root in the difference of the price series $P^i_t - P^b_t$, where P^i_t represents the natural log of the price for portfolio i, P^b_t indicates the log of some unspecified benchmark portfolio price, $R^i_{t+1} = P^i_{t+1} - P^i_t$ is equivalent to the continuously compounded return for portfolio i, received by investors at time t+1, α^i is a constant, and ω^i_{t+1} is a stationary shock term with an unconditional mean of zero. It is possible that the error term, ω^i_{t+1}, is serially correlated. As a result, higher order lags of the return differential may be necessary to remove the serial correlation, $\sum_{j=1}^{k} \phi^i \left(R^i_{t+1-j} - R^b_{t+1-j}\right)$. λ measures the *speed of reversion,* which is assumed equal across portfolios.[6] Specifically, if $0 < \lambda < 1$, deviations in price from its fundamental value are transitory and will be reversed over time. Traditional tests of mean reversion test the hypothesis that $\lambda = 0$. Acceptance of the null implies that the price of portfolio i is an integrated process of order one, I(1). If $\lambda^i = 1$ then deviations in price are fully reversed in the subsequent period.

The rationale behind this panel framework is simple. As many researchers have noted in the past, the fundamental values of share prices are unobserved and therefore difficult to define, requiring researchers to derive proxies for the fundamental value, i.e., earnings and dividend-to-price ratios.[7] The use of such proxies is inherently flawed and creates a potential loss of information that could assist in distinguishing between temporary and permanent components of asset prices. For example, expected deviations in earnings or dividends per share will likely influence the fundamental value during the period in which expectations change; however, the proxy will only reflect such changes in later periods. As a result of such latency problems, estimates of λ would be inconsistent and possess a downward bias. The use of the panel approach discussed above enables one to examine mean reversion in portfolios relative to a benchmark index under the assumption that differences in portfolio prices are stationary.

Selecting the benchmark index could lead to possible data-snooping biases. In an effort to avoid such problems, I select the most obvious index to represent the benchmark index. Specifically, since the primary data used in this analysis comes from the New York and American stock exchanges, I select the equal-weighted NYSE/AMEX index. I assign the optimal lag length, k, in accordance with the Akaike information criterion (1973) and Schwartz-Bayesian criterion (1978), hereafter referred to as AIC and SBC, respectively.

2.1 Power and Test Statistics

Additional reasons for using the panel approach discussed above include the following: First, as Cochrane (1991) and DeJong, Nankervis, Savin, and Whiteman (1992) have shown, standard unit root tests possess low power in small samples. As a result, many researchers have recommended the use of panel data over single equation alternatives in order to gain statistical power. For example, Levin and Lin (1993) argue that, even for relatively small samples (i.e., 10 cross-sections and 25 observations), "the panel framework can provide dramatic improvements in power compared to performing a standard unit root test for each individual time series" (p. 26).[8] Such conclusions are directly applicable to this analysis since conducting tests for mean reversion over non-overlapping return intervals leads to a limited number of observations. Using a simulation approach, Creel and Farrell (1996) maintain that Zellner's (1962) seemingly unrelated regression (SUR) method may be substantially more efficient than ordinary least squares (OLS) estimation. Accordingly, I use the SUR approach in order to account for heteroskedasticity and contemporaneous correlation across size-ranked portfolios.

The test statistics used to evaluate the null hypothesis of no mean reversion, $\lambda = 0$, are $t = \hat{\lambda} / se(\hat{\lambda})$ and $z_{\lambda} = T\hat{\lambda}$, where T is the sample size, $\hat{\lambda}$ is the estimate of λ, and $se(\hat{\lambda})$ is the standard error of $\hat{\lambda}$. The above test statistics are not characterized by conventional distributions. For this reason, the appropriate critical values are determined using Monte Carlo simulations in an attempt to avoid reliance upon asymptotic distributions (see Balvers et al., for details).

2.2 Data

The basic data were obtained from the Center for the Research in Security Prices (CRSP) and consist of the monthly returns for all stocks traded on the New York and American stock exchanges. After portfolios are constructed, monthly portfolio returns are calculated by equally weighting the individual security returns. Monthly portfolio returns are then transformed into continuously compounded non-overlapping returns with return horizons of 1 and 2 years.

The sample period used in estimation is the 1963 to 1998 period (except for *PFM 3*). 1963 is the first full year of data that CRSP provides for both the NYSE and AMEX exchanges. Thus, beginning the sample period in 1963 incorporates all available data on the American stock exchange. Coincidentally, using 1963 as the starting point maximizes the total number of observable data, i.e., the total number of available time-series multiplied by the total number of available cross-sections.

The fact that stocks delist during the sample period used in the above portfolio formation methods is unavoidable. Although commonly practiced in the finance literature, simply dropping firms from their respective portfolios once they delist does not accurately reflect the true returns that accrue to investors. In accordance with Shumway (1997), I attempt to account for such survivorship issues (see Appendix for details).[9]

2.3 Portfolio Formation Methods

Standard methods of portfolio formation require that securities be placed into ten (decile) portfolios after ranking them at the end of the previous year based upon their total market capitalization, where market capitalization is defined by multiplying the number of shares outstanding by the price per share. Thus, portfolios are rebalanced on an annual basis. The concept of updating portfolios on a yearly basis is not inconsequential.

Fama and French (1988) suggest, but do not explore, the possibility that temporary price swings and their subsequent reversals may be missed when using portfolios that are rebalanced on a year-to-year basis. The problem with this method of portfolio formation, with respect to tests for mean reversion, is that those stocks that are most likely to exhibit a mean reverting price component are precisely those stocks that are most likely to move between deciles, thus decreasing the likelihood of detecting mean reversion. Hence, periodically updating portfolios based on end-of-period firm specific factors, such as market capitalization, may impart a tendency to underestimate, or reject outright, the existence of mean reversion.

To test this conjecture, I use the following portfolio formation methods (*PFM*) (summarized in Table 1). *PFM 1*: for comparison purposes I use the standard approach to portfolio formation described above. Stocks are placed into their respective deciles after ranking them at the end of the previous year based upon their total market capitalization. *PFM 2*: stocks are ranked on the basis of their August through December 1962 total market capitalization level and assigned this ranking *for all subsequent periods*, i.e., stocks are ranked on the basis of their average market capitalization level through this period. Hence, stocks are required to be actively traded during the August to December 1962 period in order to be included in their respective portfolios. For comparability, *PFM 1* also consists of stocks that are actively traded during this period. Of the available stocks, 1,981 stocks qualify for this selection process. Hence, *PFM 1* is directly comparable to *PFM 2* since both methods consist of the same 'pool' of available stocks. By implication, the period used in estimation is 1963 to 1998.

It is important to note that the above portfolio selection method is not the only portfolio selection method that is available. Any portfolio formation method that does not require updating is a suitable candidate. For completeness, I adopt additional portfolio formation methods. *PFM 3*: stocks are ranked on the basis of their 1963 through 1967 total market capitalization level and assigned this ranking for all subsequent periods (1,526 stocks qualify for portfolio selection).[10] Accordingly, the sample period used in estimation is reduced to 1968 through 1998. *PFM 4*: using stocks that continually trade over the 1963 to 1998 period allows us to rank firms based on the *average* of their year-end market capitalization ranking. Of the available stocks, 358 qualify for this selection process. *PFM 4* resembles both types of portfolio formation methods mentioned above. That is, stocks are ranked in a similar manner to that used in *PFM 1* but are then assigned one ranking for the whole period based on the *average* of their yearly ranking. Hence, as in *PFM 2* and *3*, portfolios are not updated on a periodic basis.

3. Empirical Results

The results from the various portfolio formation methods are presented in Table 2. What is striking about the results is the difference in the point estimates of λ for the alternative portfolio formation methods. Many of these differences are quite substantial. For example, *Portfolio Formation Method 2* (*PFM 2*) yields point estimates of 0.194 and 0.516 for the 12- and 24-month non-overlapping return horizons, respectively, while the corresponding results for *PFM 1* indicate point estimates of λ only 0.072 and 0.141. Using portfolios that are not updated on a yearly basis provides point estimates of λ that are as much as two hundred and fifty percent greater than those for portfolios that are updated periodically. While unable to detect mean reversion during this period using portfolios that are updated yearly (*PFM 1*), the results using portfolios that are not updated provide conclusive evidence of mean reversion in portfolio prices.

It is well known that λ is biased upwards in small samples. Accordingly, I correct for the small-sample bias under the alternative using Monte Carlo simulations (see Balvers *et al.,(2000)*). Even after correcting for the upward bias in the estimate of λ, the median-unbiased estimates provide strong confirmation of mean reversion in asset prices. The median-unbiased estimates of λ are quite large and thus economically important. Using *PFM 2* and a return horizon of 24 months, the implied half-life, the amount of time required for an asset's price to revert half-way toward its fundamental value after a one-time shock, of the median-unbiased estimate is three and a half years.[11] Similarly, using *PFM 3* and a return horizon of 24 months, the implied half-life is just over three years.

The results presented in Table 2 confirm the idea that using size-sorted portfolios that are updated periodically could potentially bias attempts to detect mean reversion and suggests that past researchers (for example, Jegadeesh (1991), Gangopadhyay (1996), and Gangopadhyay and Reinganum (1996)) have incorrectly concluded that mean reversion does not exist. What makes these results particularly interesting is that the period under analysis is the post-World War II era. That is, Jegadeesh (1991) and others argue that mean reversion is exclusively a pre-World War II phenomenon. Using only post-war period data, I am able to detect the presence of mean reversion in portfolio prices. In addition to the alternative portfolio formation methods used, possible explanations for this incongruity include the increased power associated with using a panel framework and the increased information from avoiding the necessarily incorrect derivation of a proxy for the fundamental value.

4. Economic Significance

In the preceding sections I show that size-sorted portfolios possess a mean reverting price component. Accordingly, in an attempt to increase expected returns, it should be possible to construct investment strategies that exploit this information. In this section I explore the economic importance of the mean reversion results by examining various portfolio switching strategies.

4.1 Rolling Regression – Parametric Contrarian Investment Strategy

In order to evaluate the mean reversion results discussed earlier, I use the following portfolio switching strategy. Initially, I estimate equation (1) from the beginning of the sample up to a point t_0. After estimating the system, I use the parameter estimates and observations up to time t_0 to calculate the expected return for each portfolio at time $t_0 + 1$. The portfolio with the highest expected return is then purchased and held during the following period. The system is again estimated, however, the sample period is updated by one additional observation. Therefore, the system is estimated from the beginning of the sample period up to a point $t_0 + 1$. Again, the parameter estimates are used to calculate the expected return for each portfolio at time $t_0 + 2$. The portfolio is then switched to the decile with the highest expected return over this period. This process (*Rolling Regression*) is repeated until there are no more observations remaining. Completing this process creates a portfolio with the highest expected return (hereafter referred to as the "Max" portfolio).

Similarly, I create a "Min" portfolio that consists of deciles with the lowest expected return. Returns from a strategy that involves purchasing the "Max" portfolio and shorting the "Min" portfolio represent excess returns from the zero net investment per dollar received in shorting the "Min" portfolio. This zero net portfolio will be referred to as the "Max-Min" portfolio. Balvers, Wu, and Gilliland (2000) suggest that this strategy is the equivalent of the "parametric version of the contrarian strategy devised by DeBondt and Thaler (1985)" (p. 761), and refer to it as the 'parametric contrarian' investment strategy.

I use the portfolio switching strategy discussed above for the various formation methods used in the previous section (*PFM 1-4*). Hence, I am able to analyze whether the economic significance of the mean reversion results, and any excess returns that may result, are sensitive to using portfolios that are updated on a periodic basis (*PFM 1*). One would expect *PFM 2 – 4* to outperform *PFM 1* given that the null hypothesis of no mean reversion could not be rejected using the latter method.

In order to provide a sufficient number of observations to ensure that the covariance matrix is positive definite, and thus invertible, the return horizon selected for this analysis is twelve months. To ensure that there are enough observations to estimate the first set of parameters t_0 is set at 1/3 the sample for each of the portfolio methods explored. Hence, all forecasts begin in 1975.

4.2 Alternative Investment Strategies

For purposes of comparison, I implement a *Buy-and-Hold* strategy. I calculate the geometric average buy-and-hold returns from holding the equal-weighted index, as well as an equal-weighted portfolio that consists of each of the ten available deciles. This allows us to compare the findings from the "parametric contrarian" strategy to commonly used benchmarks.

If prices do not possess a mean reverting component then it follows that a strategy that simply selects those portfolios that have performed well in the past should outperform the portfolio switching strategy outlined above. This implies that prices follow a random-walk-with-drift. In order to determine the validity of such a conjecture, I adapt the rolling regression technique described above by restricting $\lambda = 0$. I refer to this new strategy as the *Random Walk* (with drift) strategy. Hence, if the *Rolling Regression* strategy outperforms the *Random Walk* strategy then we can conclude that prices do possess a mean reverting component.

For further comparison, I implement the standard *Contrarian* strategy developed by DeBondt and Thaler. Specifically, portfolios are ranked on the basis of their average three-year return. The portfolio with the lowest return indicates a 'loser' portfolio, while the portfolio with the highest return designates a 'winner' portfolio. Following DeBondt and Thaler, 'losers' are expected to yield the highest returns in the following three years after portfolio formation, while the opposite is true for 'winner' portfolios. Hence, the "Max" portfolio for this strategy represents the portfolio with the highest expected returns ('losers') and the "Min" portfolio represents the portfolio with the lowest expected returns ("winners").

4.3 Results

The results for the various investment strategies are presented in Table 3. The *Rolling Regression* investment strategy uniformly outperforms all other investment strategies. For example, using *PFM 4*, the *Rolling Regression* strategy provides an average annual return of 19.3%, while the *Buy-and-Hold* strategy for the equal-weighted index only provides an annual return of 15.5%. Evidence against mean reversion implies that the mean return using the *Rolling Regression* method is less than or equal to the mean return of buying and holding the equal-weighted index, i.e., $\bar{R}_{\max} \leq \bar{R}_{ew}$. Testing this hypothesis yields a t-statistic of 2.36, which is significant at the 5% level. Even more convincing is the fact that the *Rolling Regression* strategy produces a higher return than the, *ex post*, highest return for any decile over this period.[12] Furthermore, the zero-net investment strategy yields significant excess returns of 9.1% (*p*-value 0.000). Similar results are found using *PFM's 2* and *3*. Further evidence of mean reversion exists when we compare the results from the *Rolling Regression* and *Random Walk* strategies. Again, the "Max-Min" portfolio from the *Rolling Regression* strategy outperforms the alternative investment strategy.

What is surprising about the results is the lack of positive excess returns when using the *Contrarian* investment strategy. DeBondt and Thaler maintain that significant return reversals exist for 'loser' and 'winner' portfolios and attribute such reversals to the irrational behavior of investors. Therefore, portfolio returns are believed to revert to some fundamental level over time. When applying a similar methodology to that used by DeBondt and Thaler, the results appear to indicate otherwise. For example, using *PFM 2* yields *negative* returns for the zero-net investment strategy. In fact, the "Max" portfolio never outperforms its counterpart portfolio when the "parametric contrarian" investment strategy is implemented.

A likely reason for the lack of performance by the *Contrarian* investment strategy is the inherent differences in the portfolios used in this analysis and those used by DeBondt and Thaler. The methodology used by DeBondt and Thaler require that *extreme* 'winners' and 'losers' be selected for portfolio formation. Specifically, they require that 'winner' and 'loser' portfolios consist of the top 35 stocks (as measured by excess returns relative to the equal-weighted index) in their respective category. At the time of portfolio formation, there exist enormous differences in portfolio returns. Using the methodology that I have outlined is unlikely to produce such a large difference in returns between 'winner' and 'loser' portfolios, since stocks are not initially ranked on the basis of returns.

Thus, it is unlikely that the results for the Contrarian investment strategy would mirror DeBondt and Thaler's results, since we are not dealing with extremes. Accordingly, it becomes increasingly more difficult to distinguish between the true 'winners' and 'losers' using standard contrarian investment strategies. It is this fact that makes the results for the *Rolling Regression* strategy all the more interesting. Taking advantage of cross-sectional information and forecasting returns using a parametric version of the contrarian strategy appears to more efficiently predict future returns, even when the relative differences between overall portfolio returns are small.

In contrast to the results for *PFM 2*, *3*, and *4*, using *PFM 1* provides little support for the existence of mean reversion in portfolio prices. While the "Max" portfolio does outperform the "Min" portfolio, the zero-net investment strategy produces excess returns of only 0.019. The hypothesis that the mean returns of the respective portfolios are equal cannot be rejected (*p-value* 0.660), thus confirming the proposition that temporary price swings and their subsequent reversals may be missed when using portfolios that are rebalanced on a year-to-year basis.

4.4 Possible Explanations

The results clearly indicate that using a "parametric contrarian" investment strategy that capitalizes on the existence of mean reversion yields returns that compare quite favorably to alternative investment strategies. One question that does arise is whether the results are achievable. The portfolios used in this analysis consist of a large number of stocks. From an individual investor's perspective, the results of the portfolio switching strategy outlined above are likely not easily obtained. Nevertheless, it may be possible to obtain similar excess returns by using portfolios with characteristics that mirror those used in this study. The portfolios that I have constructed are essentially generalizations of popular mutual funds, i.e., micro-, small-, mid-, and large-cap mutual funds and thus, to some extent, realistically portray actual portfolio choices. Assessing the impact of applying "parametric contrarian" investment strategies to such realistic alternatives remains an empirical question and is beyond the scope of this paper.

Even if the returns associated with the portfolio switching strategy used above are achievable, it is possible that there are rational explanations for their existence. For example, portfolio switching is likely to incur greater transaction costs than simply buying and then holding one of the available indexes. Even if we consider the zero-net investment strategy, in which one takes a long position on the "Max" portfolio and a short position on the "Min" portfolio, there are no more than two 'switches' a year. The average number of switches for the zero-net investment strategy is approximately one per year. Even with an assumed transactions cost of 2% the "Max-Min" portfolio returns are quite sizeable.

Another possible explanation for the returns associated with the portfolio switching strategy is relative risk factors. It is possible that the high returns are simply a trade-off for incurring greater levels of systematic risk. While I will not develop the notion of risk versus return in detail, I provide a quick look at the relative risk factors associated with each portfolio by calculating simple Sharpe-Lintner betas. Betas for each of the various investment strategies were calculated using the one-month Treasury-bill rate from Ibbotson and Associates as the risk-free rate and the equal-weighted NYSE/AMEX index as the market return.

The results are presented in Table 3. Broadly speaking, the betas presented in Table 3 appear to indicate that the returns from the “parametric contrarian” strategy underestimate the true returns from pursuing this strategy. Relative to the equal-weighted index, the risk-adjusted returns are actually greater than the calculated returns. In as far as the CAPM provides an appropriate method of measuring risk, the results presented earlier are not driven by relative risk factors of the “Max” and “Min” portfolios.

5. Conclusions

The findings presented above provide the following contributions to the existing literature on mean reversion in stock prices. Primarily, by employing a model developed for the study of international markets to the study of domestic markets, I have shown that mean reversion in stock prices does exist.

I have shown that analyzing the existence of mean reversion using size-sorted portfolios using the standard portfolio formation method is inadequate at detecting a long-term anomaly such as mean reversion and has lead past researchers (for example, Jegadeesh (1991), Gangopadhyay (1996), and Gangopadhyay and Reinganum (1996)) to incorrectly conclude that mean reversion does not exist. I have provided an alternative method of analyzing mean reversion using size-sorted portfolios that better accounts for the loss of information that occurs using the standard portfolio formation method and have found an overwhelming rejection of the random walk hypothesis for stocks that trade on the New York and American stock exchanges. Further, I find speeds of reversion between three to three and a half years. Contrary to the findings of Jegadeesh (1991) and others, rejection of the random walk hypothesis occurs despite the use of post-World War II data. A contributing factor to such findings is the use of panel estimations that capitalize on cross-sectional variation.

The results indicate that using a parametric version of DeBondt and Thaler’s (1985) non-parametric contrarian strategy allows investors to earn substantial excess returns by exploiting information in asset prices that revert to some fundamental trend value. By using information in stock price variation more efficiently, vis-à-vis reparameterizing forecasts based on a series of rolling regressions, the parametric contrarian strategy outperforms strategies based on standard contrarian strategies. Such significant excess returns are not easily explained by simple beta risk differences between “Max” and “Min” portfolios.

Appendix: Delisting Returns and Survivorship

If a firm liquidates, equity holders are often left holding shares with an effective price of zero. The corresponding return in the following period is –1. However, this return would not be reported in the monthly returns data provided by CRSP. Rather than simply dropping a stock from a portfolio once it is delisted, I assign the delisting return as provided by the CRSP data files. Delisting returns represent the last available return to investors and should be included in calculating a particular stock's overall return. Therefore, where present, delisting returns will be assigned to the relevant stock. The qualifier "where present" is significant.

An important issue regarding the delisting data provided by CRSP was noted in Shumway (1997). Shumway found that when stocks are delisted unexpectedly due to performance reasons there is evidence of omitted delisting returns on the average of about –30 percent. That is, stocks that delist for performance reasons (i.e., delisted for the following reasons: insufficient number of market makers, shareholders, price below acceptable level, insufficient capital, surplus, and/or equity, bankruptcy, etc….) are often coded as 'dropped' (missing data) in the CRSP delisting returns data. As a result, Shumway suggests that stocks should be assigned a delisting return of –0.30 if stocks have missing delisting returns and delist due to performance reasons. However, CRSP has taken extensive measures to correct this bias in the 1998 CRSP data files by researching over 800 stocks that were coded as 'dropped' in previous versions of the CRSP data files, including those used by Shumway and Vincent (CRSP, 1999). It is my understanding that the research conducted by CRSP in this particular area was in direct response to the findings in Shumway (1997). In any event, those stocks selected for research by CRSP were precisely those stocks in which Shumway found fault. Specifically, CRSP required a stock to meet the following three guidelines prior to being researched: a) dropped from the New York or American stock exchanges after 1962, b) assigned a delisting code between 500 and 588 (delisted for reasons of performance), c) possessed a missing delisting return. While unable to provide new delisting returns for all of the stocks researched, CRSP was able to assign new delisting returns for many of these stocks. Thus, the number of stocks that should be given the corrected delisting return (–30 percent), as suggested by Shumway, should be greatly diminished. Nevertheless, I assign the remaining stocks that delist due to poor performance and possess missing delisting returns a return of –30 percent. Furthermore, a stock that liquidates and is missing its delisting return is assigned a delisting return of –1. Whether a stock delists due to liquidation, poor performance, merger, or acquisition is determined by the delisting code that accompany all stocks covered in the CRSP database. Delisting codes are three digit codes that range from 100 to 802. Generally, stocks fall into one of four categories: stocks that are actively trading, delist due to merger, delist due to liquidation, or delist due to other performance reasons ('dropped'). I adopt Shumway's definition for stocks that delist due to performance reasons as those stocks with delisting codes of 500, and 505 through 588.

Acknowledgments

I would like to thank Ronald Balvers and Yangru Wu and anonymous reviewers for helpful comments and suggestions that have led to substantial improvements in the quality of this paper. Appreciation is also warranted for Nick Rupp and seminar participants at the SEA conference. I would also like to thank Adam Duston from the Center for Research in Securities Prices for data assistance. The usual disclaimer applies.

*Contact information: Jeffrey Gropp, Department of Economics and Management, DePauw University, Greencastle, IN 46135, phone: 765-658-6561, email: jgropp@depauw.edu

Endnotes

1. For a more complete discussion of literature on mean reversion see Forbes (1996).

2. Moreover, a significant portion of the mean reverting component in asset prices is concentrated in the month of January, while very little mean reversion exists in the remaining months. Possible explanations for this finding have included a December sell-off of poorly performing securities for tax purposes to time-variations in the market risk premium.

3. In fact, McQueen, using additional data from the Cowles Commission, fails to reject the null hypothesis of a random walk in the period prior to 1926 (1871-1925) as well as after 1946 (1947-1987).

4. Among those that analyze the time series properties of asset prices within the context of market capitalization levels are Fama and French (1988), Jegadeesh (1991), Gangopadhyay (1996), and Gangopadhyay and Reinganum (1996).

5. This model can be derived directly from the Fama and French (1988) temporary and permanent components model.

6. This assumption does not imply that mean reversion across asset prices is synchronized.

7. For example, Chiang, Liu, and Okunev (1995), relying on Marsh and Merton's (1987) claim that a firm's fundamental value can be expressed as a simple linear function of earnings and dividends, use earnings and dividends per share as a proxy for the fundamental. Also, Cutler, Poterba, and Summers (1991) use the logarithm of the dividend-to-price ratio as a proxy for the fundamental value.

8. Similarly, in an international context, other researchers (Wu and Zhang (1997), Wu and Zhang (1996), and Oh (1996)) have provided evidence of the increased power attributable to the use of panel frameworks when testing for unit roots.

9. While I have attempted to estimate the most realistic returns that are received by investors, it is important to clarify that the results are not sensitive to the alterations mentioned above. In many cases the results are even more convincing in favor of mean reversion when stocks are simply dropped from their respective portfolios. In any event, the differences are minute.

10. A reduction in the total number of stocks takes place due to the increased time horizon that stocks must be actively traded.

11. The half-life is calculated as (ln(0.5)/ln(1-))Y, where is the median-unbiased estimate of the speed of reversion and Y is the number of years used for the return horizon.

12. Holding Decile 2 over this period yields a return of 16.2%.

References

Balvers, Ronald, Yangru Wu, and Erik Gilliland (2000), "Mean Reversion Across National Stock Markets and Parametric Contrarian Investment Strategies," *Journal of Finance*, 55, 745-772.

Center for the Research in Securities Prices (1999), 1998 CRSP Data Definitions and Coding Schemes Guide.

Chiang, Raymond, Peter Liu, John Okunev (1995), "Modelling Mean Reversion of Asset Prices Towards Their Fundamental Value," *Journal of Banking and Finance*, 19, 1327-1340.

Cochrane, John (2001), *Asset Pricing,* Princeton and Oxford: Princeton University Press.

Cochrane, John (1991), "A Critique of the Application of Unit Root Tests," *Journal of Economic Dynamics and Control*, 15, 275-284.

Creel, Michael, and Montserrat Farrell (1996), "SUR Estimation of Multiple Time-Series Models with Heteroscedasticity and Serial Correlation of Unknown Form," *Economic Letters*, 53, 239-245.

Cutler, David, James Poterba, and Lawrence Summers (1991), "Speculative Dynamics," *Review of Economic Studies*, 58, 529-546.

DeBondt, Werner, and Richard Thaler (1985), "Does the Stock Market Overreact?," *Journal of Finance*, 40, 793-805.

DeJong, David, J. Nankervis, N. Savin, and C. Whiteman (1992), "The Power Problems of Unit Root Tests in Time Series with Autoregressive Errors," *Journal of Econometrics*, 53, 323-343.

Dickey, David, and Wayne Fuller (1981), "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root," *Econometrica*, 49, 1057-1072.

Fama, Eugene, and Kenneth French (1988), "Permanent and Temporary Components of Stock Prices," *Journal of Political Economy*, 96, 246-273.

Forbes, William (1996), "Picking Winners? A Survey of the Mean Reversion and Overreaction of Stock Prices Literature," *Journal of Economic Survey*, 10, 123-158

Gangopadhyay, Partha (1996), "Macroeconomic Variables and Seasonal Mean Reversion in Stock Returns," *Journal of Financial Research*, 19, 395-416.

Gangopadhyay, Partha and Marc Reinganum (1996), "Interpreting Mean Reversion in Stock Returns," *Quarterly Review of Economics and Finance*, 36, 377-394.

Jegadeesh, Narasimhan (1991), "Seasonality in Stock Price Mean Reversion: Evidence from the U.S. and the U.K.," *Journal of Finance*, 46, 1427-1444.

Kim, Myung, Charles Nelson, and Richard Startz (1991), "Mean Reversion in Stock Prices? A Reappraisal of the Empirical Evidence," *Review of Economic Studies*, 58, 515-528.

Levin, Andrew, and Chien-Fu Lin (1993), "Unit Root Tests in Panel Data: New Results," University of California, San Diego Department of Economics Working Paper: 93-56.

Marsh, Terry, and Robert Merton (1987), "Dividend Behavior for the Aggregate Stock Market," *Journal of Business*, 60, 1-40.

McQueen, Grant (1992), "Long-Horizon Mean-Reverting Stock Prices Revisited," *Journal of Financial and Quantitative Analysis*, 27, 1-18.

Oh, Keu-Yeob (1996), "Purchasing Power Parity and Unit Root Tests Using Panel Data," *Journal of International Money and Finance*, 15, 405-418.

Shumway, Tyler (1997), "The Delisting Bias in CRSP Data," *Journal of Finance*, 52, 327-340.

Shumway, Tyler, and Warther, Vincent (1999), "The Delisting Bias in CRSP's Nasdaq Data and Its Implications for the Size Effect," *Journal of Finance*, 54, 2361-79.

Wu, Yangru, and Hua Zhang (1997), "Do Interest Rates Follow Unit-Root Processes? Evidence from Cross-Maturity Treasury Bill Yields," *Review of Quantitative Finance and Accounting*, 8, 69-81.

Wu, Yangru, and Hua Zhang (1996), "Mean Reversion in Interest Rates: New Evidence from a Panel of OECD Countries," *Journal of Money, Credit, and Banking*, 28, 604-621.

Zellner, Arnold (1962), "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests of Aggregation Bias," *Journal of the American Statistical Association*, 57, 348–368.

Table 1
Summary of Portfolio Formation Methods

Portfolio Formation Method	Number of times stocks are ranked	Period in which stocks must trade to be considered for analysis	Number of stocks that qualify for analysis	Stocks are ranked on the following basis of	Period used for estimation purposes
PFM 1 (Standard)	Annually	August – December 1962	1981	Year-End Market Capitalization (MC)	1963 – 1998
PFM 2	Once	August – December 1962	1981	Average MC from Aug – Dec 1962	1963 – 1998
PFM 3	Once	Jan 1963 – Dec 1967	1526	Average MC from Jan 1963 – Dec 1967	1968 – 1998
PFM 4	Once	Jan 1963 – Dec 1998	358	Average Year-End MC Ranking from 1962 – 1997	1963 – 1998

Table 2
Panel Tests for Mean Reversion: Analysis of Portfolio Formation Methods

The table below reports the SUR estimation results for stock prices relative to a benchmark. The following restricted model is used to test for the presence of mean reversion:

$$R^i_{t+1} - R^b_{t+1} = \alpha^i - \lambda\left(P^i_t - P^b_t\right) + \sum_{j=1}^{k}\phi^i\left(R^i_{t+1-j} - R^b_{t+1-j}\right) + \omega^i_{t+1}.$$

The null hypothesis of H_o: $\lambda = 0$ is tested against the alternative hypothesis, H_1: $\lambda > 0$. The test statistic is defined as $t_\lambda = \hat{\lambda} / se(\hat{\lambda})$, where $se(\hat{\lambda})$ is the standard error of the parameter estimate, $\hat{\lambda}$. Portfolio Formation Methods are defined as follows. *Method 1*- portfolios consist of stocks that trade in August 1962 through December 1962, stocks are ranked on the basis of their year-end total market capitalization level and thus are updated on a yearly basis (sample used in estimation: 1963-1998). *Method 2*- portfolios consist of stocks that trade in August 1962 through December 1962, stocks are ranked on the basis of their total market capitalization level through December 1962. *Method 3*-portfolios consist of stocks that continuously trade over the period 1963-1967, stocks are ranked on the basis of total market capitalization through this period (sample used in estimation: 1968-1998). *Method 4*-portfolios consist of stocks that continuously trade over the period 1963-1998, stocks are ranked on the basis of their average year-end total market capitalization ranking. The implied half-life is calculated as (ln(0.5)/ln(1-λ))Y, where λ is the median-unbiased estimate of λ and Y is the number of years used for the return horizon.

	Portfolio Formation Method							
Nonoverlapping	*Method 1*		*Method 2*		*Method 3*		*Method 4*	
Return Horizon	12-months	24-months	12-months	24-months	12-months	24-months	12-months	24-months
Equal-Weighted Index								
Point Estimate of	0.072	0.141	0.194	0.516	0.192	0.532	0.179	0.546
t_λ	4.377	3.125	6.749	9.112	6.635	9.300	7.002	11.242
p-value	0.684	0.931	0.031	0.050	0.060	0.090	0.031	0.019
z_λ	2.511	2.403	6.776	8.764	5.753	7.973	6.275	9.283
p-value	0.813	0.792	0.010	0.001	0.049	0.004	0.047	0.004
Median-Unbiased Estimate	-0.008	-0.030	0.110	0.330	0.121	0.338	0.085	0.368
90% Confidence Interval	[-0.04, 0.02]	[-0.08, 0.03]	[0.04, 0.17]	[0.17, 0.48]	[0.04, 0.17]	[0.16, 0.46]	[0.02, 0.16]	[0.20, 0.51]
Implied Half-Life	—	—	5.950	3.460	5.370	3.360	7.800	3.010

Table 3
Economic Significance: Portfolio Switching Strategies

The table below presents the mean annual return, $\overline{R}$, and Sharpe-Lintner betas, β, for each of the various investment strategies. Sharpe-Lintner betas are calculated using the one-month Treasury-bill rate from Ibbotson and Associates as the risk-free rate and the equal-weighted NYSE/AMEX index as the market return. Sample periods vary by strategy. Strategies: *Buy-and-Hold*-represents the average returns from holding the equal-weighted index (EW-Index) and the equal-weighted portfolio of all deciles (Portfolios); *Rolling Regression*-represents a series of regressions (equation 1) from which forecasts are made. Forecasts are based upon the updated parameters in each succeeding time period; *Random Walk*-equivalent to the rolling regression strategy except that stock prices are assumed to follow a random walk (λ=0) with drift; *Contrarian*-is based on the contrarian investment strategy developed by DeBondt and Thaler (1985). Portfolios are ranked on the basis of their average three-year return. The portfolio with the lowest return indicates a 'loser' portfolio, while the portfolio with the highest return designates a 'winner' portfolio. Following DeBondt and Thaler, 'losers' are expected to yield the highest returns in the following three years, while the opposite is true for 'winner' portfolios. Hence, "Max" represents the portfolio with the highest expected returns ('losers') and "Min" represents the portfolio with the lowest expected returns ("winners"). Significance is only determined for "Max-Min" portfolios. Portfolio Formation Methods: *PFM 1*- portfolios consist of stocks that trade in August 1962 through December 1962. Stocks are ranked on the basis of their year-end total market capitalization level and thus are updated on a yearly basis. *PFM 2*-portfolios consist of stocks that trade in Aug.-Dec. 1962. Stocks are ranked on the basis of their total market capitalization level through December 1962. *PFM 3*-portfolios consist of stocks that continuously trade over the period 1963-1967, stocks are ranked on the basis of total market capitalization through this period. *PFM 4*- portfolios consist of stocks that continuously trade over the period 1963-1998, stocks are ranked on the basis of their average year-end total market capitalization ranking. All forecasts are made using a return horizon of twelve months.

		PFM 1		*PFM 2*		*PFM 3*		*PFM 4*	
Strategy	Type	$\overline{R}$	β	$\overline{R}$	β	$\overline{R}$	β	$\overline{R}$	β
Buy-and-Hold	EW-Index	0.155	1.000	0.155	1.000	0.154	1.000	0.155	1.000
	Portfolios	0.172	0.986	0.158	0.903	0.157	0.886	0.157	0.741
Rolling	Max	0.177	0.780	0.198	0.917	0.201	0.803	0.193	0.742
Regression	Min	0.158	0.845	0.128	0.857	0.116	0.790	0.103	0.873
	Max-Min	0.019	0.007	**0.070****	0.131	0.085**	0.103	**0.091****	-0.051
Random	Max	0.132	0.553	0.158	0.886	0.135	0.637	0.126	0.841
Walk (λ = 0)	Min	0.146	0.592	0.149	0.588	0.139	0.932	0.153	0.465
	Max-Min	-0.014	0.033	0.009	0.370	-0.004	-0.293	-0.027	0.457
Contrarian	Max	0.146	0.985	0.165	0.939	0.130	0.702	0.148	0.761
(DeBondt-Thaler)	Min	0.164	0.843	0.179	0.672	0.138	0.796	0.134	0.545
	Max-Min	-0.018	0.241	-0.014	0.338	-0.008	-0.005	0.014	0.297

Note: *, **, represent statistical significance at the five and one percent levels, respectively (only assigned to the "Max-Min" portfolios).