

Double Then Nothing: Why Stock Investments Relying on Simple Heuristics May Disappoint

by

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Current Version: September 20, 2011

FORTHCOMING IN REVIEW OF BEHAVIORAL FINANCE

ABSTRACT

Behavioral researchers argue that while individuals often rely on heuristics or rules of thumb that reduce the complexity involved in predicting values, such heuristics can lead to severe and systematic errors. I test this argument in an investment context by focusing on a simple heuristic whereby momentum traders are attracted to buying stocks that have recently doubled in price in anticipation of further gains. I show that such a strategy can lead to predictable disappointment for these investors and severe underperformance relative to the market (-28% over a four-year period), whereas investors who avoid relying on this simple heuristic are likely to perform as expected, on average similar to the overall market. I also find that underperformance is more severe for stocks that have doubled faster. The “doubling” variable is a significant predictor of future price reversals in addition to past performance per se, as uncovered by DeBondt and Thaler (1985).

JEL Codes: G11, G12, G14

Keywords: behavioral finance, overreaction, predictability, valuation, stock investments, survivorship bias

*Foerster, PhD, CFA, is a Professor of Finance at the Ivey Business School. This paper was previously titled “Double Then Nothing: Why Individual Stock Investments Disappoint.” I wish to thank an anonymous referee, George Athanassakos, Werner DeBondt, Steven Jones, Alessandro Previtero and Stephen Sapp, and seminar participants at the Academy of Behavioral Finance & Economics Conference, Laval University, the Toronto CFA Society, and York University for useful comments. Please address correspondence to Steve Foerster: Richard Ivey School of Business, The University of Western Ontario, London, Ontario, Canada, N6A 3K7; Phone: 1-519-661-3726; Fax: 1-519-661-3485; E-mail: sfoerster@ivey.ca.

INTRODUCTION

This paper tests the argument by behavioral researchers Tversky and Kahneman (1974) in their seminal work, that individuals often rely on heuristics or rules of thumb that reduce the complexity involved in predicting values, but such heuristics can lead to severe and systematic errors. I test their argument in the context of investments by focusing on a simple heuristic whereby investors may be attracted to buying stocks that have recently doubled in price in anticipation of further gains, however may end up investing near the stock's peak price. Such a study is important because relying on such simple heuristics may destroy investors' wealth. I show that a strategy of buying stocks that have recently doubled in price can lead to predictable disappointment for these investors and severe underperformance relative to the market (-28% over a four-year period), whereas investors who avoid relying on this simple heuristic are likely to perform as expected, on average similar to the overall market. I find that underperformance is more severe for stocks that have doubled faster. This "doubling" variable is a significant predictor of future price reversals in addition to past performance per se, as uncovered by DeBontd and Thaler (1985) in their well-known overreaction study. Thus based on this study investors can become aware of the dangers of relying on simple heuristics and can avoid disappointment in investment returns.

This paper's research focus on stocks that have doubled in price is motivated by axioms highlighted in previous research, investment books, and the popular press due to its simplicity, since any investor can readily relate to and strive for such doubling performance. For example, Reinganum (1988) identifies "winner" stocks as those that have doubled within a calendar year, with his sample firms drawn primarily from William O'Neil's publication, *The Greatest Stock Market Winners: 1970-1983*. BusinessWeek writer Stevermann (2008) surveys investment experts for strategies related to identifying stocks that are expected to double in price. One of the surveyed investment expert focuses on stock price movement rather than the value of the stock per se. Andreassen (1987) argues that the media can play a role in price continuations by providing explanations that essentially rationalize recent price increases, thereby leading

to further price increases in a stock. Sheimo (1999) examines a wide variety of investment axioms, one of which focuses on the likelihood of stocks doubling in price. He claims that both low-priced and high priced stocks can double in price given a variety of factors including revenue and earnings growth potential, using Apple Computer and Lowe's as examples. Investment strategists such as Boik (2007) also focus on price trends. He defines "monster stocks" as those "that have at least doubled in a short time frame" usually within the last 18 months. He claims such stocks possess similar characteristics in terms of trends and "history has proven that repeatable patterns have occurred many times in the stock market." His idea is that investors only need to have invested in a few of these monster stocks that will continue to perform well in order to have a major positive impact on their overall wealth.

Previous studies suggest that investors may be influenced by perceived price trends. DeBondt (1993) argues that, besides fundamental explanations, there are two other possible explanations as to why stock prices fluctuate, both of which are related to individual investor psychology and systematic misperceptions of value. First, investors put too much emphasis on the latest information and not enough on base-rate information, an application of Tversky and Kahneman's (1974) representativeness heuristic. Second, investors tend to discover trends in past prices and expect such trends to continue. DeBondt (1993) experiments by giving subjects 48 months of past prices for a variety of series and asks them to predict prices 7 and 13 months in the future. Based on 38,000 forecasts of stock prices and exchange rates he finds that non-expert individual investors expect a continuation of apparent past trends in prices.¹ More recently, He and Shen (2010) estimate expected returns directly from stock prices and financial information and show that investor expectations are overoptimistic for stocks that recently experienced high returns.

¹ In other experiments, Andreassen and Kraus (1990) find that subjects are more likely to buy as prices rise when the change in price is high; Baltussen (2009) notes that investors can be persistent in their beliefs and once they are convinced a particular stock will increase in price they will underweight any evidence suggesting otherwise.

While difficult to prove that investors rely on a particular heuristic to make investment decisions based on empirical data (aside from a controlled experiment environment), anecdotal evidence suggests some investors do pay attention to recent stock performance as at least one criteria for making investment decisions. Many Internet investment sites highlight recent winner and loser stocks and some provide filters to screen for stocks based on recent price performance. My conjecture is that uninformed investors (such as individual investors who rely on the popular press as well as an naïve examination of recent price trends) may react to news stories about favorable stock performance causing them to enter the market when a stock may be overvalued (and hence when informed investors may be ready to sell). This conjecture is also consistent with results present in Barber and Odean (2008) who show that individual investors tend to be net buyers of attention-grabbing stocks. As an example, consider a Dow Jones News story that appeared on June 8, 2003 indicating that online advertising firm DoubleClick had seen its stock price double in value since the beginning of the year. First, I conjecture that such news would translate into further attention for the stock and consequently the trading volume would increase. Second, I conjecture that if in the short-term there was more buying-initiated trading by uninformed investors, then the stock price would increase *in the short-term*. Third, I conjecture that *longer-term* the stock price would decline as informed investors sell, consistent with the over-reaction literature discussed below. Consistent with these three conjectures, I find that the trading volume doubles in the month after the article appears compared to the previous month, accompanied by a 20% price increase. However, only six months after the article, the stock price is about 10% below the price at the time of the article. While this evidence is clearly anecdotal, it provides a story consistent with the notion that uninformed investors may rely on heuristics such as being attracted to stocks that have doubled in value, in the hopes and expectation of further gains, only to be disappointed.

This study attempts to replicate the data-gathering behavior and performance of some such uninformed positive feedback² or momentum traders who follow a simple price-trend heuristic to make investment decisions. I begin with a sample universe that contains

² See De Long et al. (1990) for a discussion of positive feedback traders.

two types of stocks that I refer to as “stellar” and “non-stellar” based strictly on recent price performance. I arbitrarily define stellar stocks as those that have doubled in price within the last four years (for motivation, I refer to DeBondt (1993) who presents subjects with four years of historical data).³ If a stock has doubled in price within that time period, then it should appeal to positive feedback traders and is immediately placed in the investment universe (e.g., if a stock doubles in price after 18 months then no more history is required). Momentum stocks would typically fall under the stellar stock category so long as the stock has doubled reasonably quickly.

The other performance-based category, non-stellar stocks, is those that do not double in price but yet still have a complete four-year track record. Such stocks might form the universe for all other investors, whom I refer to as the fundamentalists. Value stocks would typically fall under this category. Note that any stock with a shorter track record (e.g., because it has gone bankrupt or has no longer met the listing requirements of the exchange) is not included in either investment universe, and thus a “backward-looking” survivorship bias is induced in the screening period. However, as I discuss below, there is no survivorship bias in the testing period.

In this study, by happenstance I find an almost even split of the stocks in this survivorship-biased screening period sample that have at least doubled in price versus those that have not, with a total sample (i.e., stellar and non-stellar stocks) median annual return of 20.1% or a median excess-of-market return of 10.1%. It is not surprising to find this strong performance in the screening period since about half of the sample stocks were included because they recently doubled in value. However, in a subsequent four-year (survivorship-bias-free) investment or test period, only about a quarter of the total sample stock prices doubled (or more), with a total sample median annual return of a disappointing 6.6% (excess-of-market return of -3.6%). Returns in the test period are much more volatile for stocks that had previously doubled compared to those that did not.

³ Identifying that a stock has recently doubled in price is a simple reference point for an individual investor, much simpler, say, than identifying a stock as being in the lowest decile of returns within a particular dataset over a particular sample period (as is common in many studies) – in the former case, all that is required is the recent price history of that one stock while in the latter case one needs to make a relative comparison over a much larger sample.

Those that doubled in the screening period are less likely to double subsequently than those that had not doubled previously, invariably leading to disappointment for the positive feedback trader group. The cumulative excess return after four years for those stocks is -28.0%. In contrast, fundamentalists who invest in stocks that did not double during the screening period experience near-zero cumulative excess returns after four years (-0.2%).

I then investigate the extent to which stock returns for this sample are predictable and thus whereby contrarian investors can improve their chances of investment success. Much of the cross-sectional variation in investment period returns can be explained not only by past stock performance (a negative relationship as expected based on the overreaction literature) and test period market returns (a positive relationship as expected), but *also* whether the stock has recently doubled in price (a negative relationship), past earnings, and various valuation-related metrics measured at the start of the investment period. A probit model identifies *ex ante* variables that are able to predict whether or not a stock will at least double in value over the investment period. A contrarian investment strategy based on the predicted probability of a stock doubling offers large potential rewards. I also show that those stocks that have doubled quicker in the screening period tend to have more severe underperformance in the test period.

While this study is related in particular to the overreaction or contrarian profits literature and papers such as DeBondt and Thaler (1985, 1987), it is nonetheless distinct in a number of ways. First, instead of focusing on categorizing stocks in portfolios based on historical “winner” or “loser” returns *relative to one another*, it relies on one simple heuristic readily available to any investor with a recent history of past stocks prices – identifying whether a stock has doubled in price within the past four years. Second, this study relies on a much more extensive sample of firm-observations, including over 5,000 cases of firms that have doubled during the screening period. In contrast, DeBondt and Thaler (1985) focus on portfolios that average only between 35 and 50 stocks for their three and five year periods, respectively. Third, as I show in a hypothetical example of price patterns in **Figure 1**, it is not necessarily the case that the firms that I categorize as

“stellar” (and thus have doubled in price over the screening period) coincide with DeBondt and Thaler “winners.” As I show in the figure, it is possible that my sample of “doubling” stocks might actually include stocks that would have been categorized by DeBondt and Thaler and others as either winners, losers, or in neither such category. In this example, all three stocks have an end-of-screening period price of \$20, and all have doubled in price in the previous 12 months, thus being categorized as the stellar “doubling” stocks in my sample. However, over the entire 48-month period, three different patterns emerge with the “loser” stock dropping from an original price of \$40, the “winner” stock increasing from an initial price of \$5, and the “neutral” stock fluctuating around \$20. Thus while some of my results are consistent with some of the findings of previous studies, I argue that the phenomenon of the doubling stocks is an example of a simple heuristic and may be distinct from the winners/losers phenomenon in a similar way that Hwang and George (2004) find a 52-week high phenomenon that is related to but distinct from other momentum studies.⁴

The rest of the paper is organized as follows. The ‘Behavioral Finance and Stock Return Predictability Review’ section provides a review of the literature and motivates the paper. The ‘Data and Methodology’ section describes the data sources and discusses the methodologies used. The ‘Results’ section presents results related to why positive feedback traders may be disappointed and presents evidence related to the predictability of stock returns based on knowing whether a stock has doubled during the screening period. I also investigate the importance of how fast a stock doubles in terms of subsequent performance. Robustness checks are also presented. The ‘Summary and Conclusions’ section concludes the paper.

⁴ Below I report analysis whereby I replicate the DeBondt and Thaler (1985) results. In additional unreported analysis I confirm that the “doubling” portfolio (made up of stocks that have recently doubled in price the fastest) contains a sample of stocks in each of 16 distinct 3-year sample periods that is approximately two-thirds different from the corresponding DeBondt and Thaler “winner” portfolio, and yet the reversal effect is just as strong.

BEHAVIORAL FINANCE AND STOCK RETURN PREDICTABILITY REVIEW

A growing literature has focused on the investments of individual investor trading and stock returns and has generally concluded that such investors tend to underperform the market, although the results have been mixed.⁵ Individual investors often have a concentrated investment portfolio and tend not to diversify to the extent portfolio theory suggests they should.⁶ Many studies that focus on individual investors are closely tied to the growing behavioral finance literature that attempts to account for the emotional or psychological side of investment decisions in order to explain the seemingly irrational actions of many investors, countering the notion of rational behavior and market efficiency.⁷

Existing behavioral finance studies provide evidence as to why positive feedback traders might be attracted to recently doubled-in-price stocks and what irrational decision might follow that would lead to their disappointment. In their survey papers, Barberis and Thaler (2003) and Rabin (1998) review various beliefs and preferences that are consistent with a number of forms of irrationality.⁸ Individuals tend to be *overconfident* in their judgments, implying positive feedback traders may confidently predict that stocks that have done well in the past will continue to do so.⁹ They cite studies indicating that most people have *excess optimism* and unrealistically rosy views of their abilities and prospects. In the *hindsight bias*, people tend to believe, after an event has occurred, that it was predictable – in the present context, this could be observing that they “knew” a stock was going to double in price. People disproportionately weight salient or memorable evidence even if they have better sources of information. Evidence of *anchoring* suggests people start with some initial estimate and then adjust away from it – for example, expecting that a stock that has recently doubled will double again. *Belief perseverance*

⁵ See Odean (1998, 1999), Barber and Odean (2000, 2001, 2008), Grinblatt and Keloharju (2000, 2001), Griffin, Harris, and Topaloglu (2003), Coval, Hirshleifer, and Sumway (2005), Barber, Odean, and Zhu (2006), Barber, Lee, Liu and Odean (2006), San (2007), and Kaniel, Saar and Titman (2008).

⁶ See Blume and Friend (1975) and, more recently, Barber and Odean (2000), Polkovnichenko (2005), Ivkovic, Sialm and Weisbenner (2008) and Goetzmann and Kumar (2007).

⁷ See Samuelson (1965), Fama (1970) and others.

⁸ In an investments context, see also studies by Shefrin and Statman (1984, 1985), and Lakonishok et al. (1994).

⁹ Cited evidence suggests those with more experience and expertise, such as financial analysts, may actually exhibit even more overconfidence.

shows that once people have formed an opinion, they hold on to it for too long, implying why positive feedback traders may not sell a stock that has doubled in value in the recent past but is not doing well now. According to the bias referred to as *the law of small numbers*, people exaggerate how closely a small sample resembles the overall population. In the present context, if positive feedback traders are presented with a sample of, say, a dozen stocks that recently doubled, they may infer that most stocks double in a short period of time.

Researchers have also examined the impact of what happens when stock prices diverge from their true or intrinsic value, particularly when a stock becomes overvalued. Overvaluation is an important issue because as Jensen (2005) notes, it can lead to substantial value destruction. More importantly, as Jensen (p. 17) notes, overvaluation can and does occur not only in market-wide¹⁰ or industry-wide waves that happen from time to time, but at a specific firm-level: “Although it is probably true that an event like the recent simultaneous overvaluation of many firms will occur only occasionally we can expect there to be problems with a few substantially overvalued firms on an annual basis.” While it is often difficult to determine whether a stock, or a market for that matter, is overvalued until after-the-fact, one can at least measure proxies for overvaluation, such as the speed of dramatic price changes (e.g., doubling in price).

While it is generally accepted that overvaluation (and under-valuation) does occur, then to what extent is overvaluation predictable? An important branch of research in the finance literature expands on the notion of both under- and overvaluation to focus on the apparent predictability of stock returns based solely on the movement of past prices or returns.¹¹ One implication of overreaction studies such as DeBondt and Thaler (1985, 1987) is that contrarian investors that buy “losers” (i.e., a portfolio of stocks whose prices have declined or performed poorly over the past) and sell “winners” stand to gain. Other

¹⁰ See Chancellor (1999) and Kindelberger and Aliber (2005) for examples of market-wide “bubbles.”

¹¹ See Poterba and Summers (1988), Lehman (1990), Jegadeesh (1990), and Jegadeesh and Titman (1993) for shorter horizons and DeBondt and Thaler (1985, 1987), Poertba and Summers (1988), Fama and French (1988), and Jegadeesh and Titman (2001) for longer horizons.

research in the area has tried to further document and explain these various phenomena.¹² Despite much progress in terms of new models and possible explanations, many questions remain. Thus a study that examines stock investment decisions in the context of a possible overvaluation environment is of interest to investors who stand to profit or lose from stock price changes, to managers who make decisions that impact on stock prices, to directors who owe a fiduciary duty to shareholders to maximize value, and to policy-makers who are concerned with possible social implications from overvaluation.

This study makes two important contributions. First, it highlights the importance that psychological factors might have on investment decisions and outcomes of positive feedback traders, particularly when those decisions are based on survivorship biased data that investors face when comparing past performance and setting expectations for future returns. While the notion of a survivorship bias is well-known in the literature,¹³ I show that depending on the framing, it may have been understated in the present context. Second, this study uncovers the predictability of stock returns based on a simple yet unique heuristic not employed in previous studies. I show that a simple variable that indicates whether a stock has recently doubled in price can be an incremental predictor of future stock performance in addition to past performance per se as uncovered in previous studies.

DATA AND METHODOLOGY

The underlying premise of this study is that the frame of reference used by some naïve (uninformed) positive feedback traders to screen stocks based on past performance leads to a biased sample of generally well-performing stocks and hence can lead to inevitable disappointment of future stock performance. It is also conjectured that stocks that have

¹² See Chan (1988), Lo and MacKinlay (1990), Chopara, Lakonishok and Ritter (1992), Jones (1993), and Jegadeesh and Titman (1995). See also studies related to overreaction or momentum by Ball et al. (1995), Fama and French (1996), Richards (1997), Veronesi (1999) Hong et al. (2000), Lee and Swaminathan (2000), Korajczyk and Sadka (2004), and George and Hwang (2004), and behavioral model explanations by Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999).

¹³ For example see Brown et al. (1992) and Liang (2000).

doubled in price during the screening period are more likely to experience negative or moderate returns during the test period, and such performance has a predictable element.

An important design innovation of this study is to remove the somewhat rigid constraint of many previous studies that examined price changes over fixed periods such as one, three, or five years, but rather this study uses a more flexible screening period that takes into account the *degree* of a rapid price changes (such as a doubling of the price level) that may occur over a particular period. This design is meant to capture a more realistic investing approach that replicates much of the emotional side of investing: if an investor knows a stock has recently doubled in value it is more likely to get his/her attention. Another element is to distinguish between past stellar stocks (as measured over a particular time period) that subsequently become non-stellar versus those that continue to be stellar.

In terms of data, prices, dividends, earnings, shares outstanding, book value of equity, industry type, and related information on U.S. firms as well as the S&P 500 index are derived from the Compustat North America Price, Dividends & Earnings monthly file, January 1962 to May 2007. Data for prices, dividends, earnings, shares outstanding, and book value of equity must be available, however if earnings or shares outstanding data are not available (since there are sometimes small gaps of missing data for only a few months in the Compustat file), such data from the past (up to 12 months) are used in order to avoid discarding data. To avoid any “penny stocks” a minimum stock price of \$5.00 is required at the beginning of the screening period.

Firm-observations are created in a relatively unique manner and thus for further clarity an example is provided in **Figure 2**. Monthly data for each firm are read from the beginning of the sample of available data for that firm (e.g., January 1988). If the stock’s initial price is below \$5.00 (note that this is the stock’s actual price on that day, not adjusted subsequently for any splits, etc.) then the algorithm proceeds to the next month to check for the minimum initial \$5.00 price. If the price meets the minimum \$5.00 screen, then the stock’s price is tracked for up to 48 subsequent months, or less if it at least doubles in

price, at which point the first screening period is complete (e.g., no later than December 1991 in this example) and firm and market data (described below) are captured. The firm's performance is then tracked over a test (or investment) period of 48 months – or less if there are no more available data (e.g., by the end of the sample in May 2007). The process up to this point allows for the creation of one firm-observation and at this point the same process is used to identify another observation for this same firm, if sufficient data are available. Thus there may be several firm-observations for one firm. The data generates 11,264 firm-observations, distributed as follows based on the screening date: pre-1970 – 36 observations (0.3% of the sample), 1970-1979 – 800 (7.1%), 1980-1989 – 1,606 (14.3%), 1990-1999 – 4,001 (35.5%), and post-2000 – 4,821 (42.8%).

I categorize stock performance over the initial screening period. Stocks are placed in one of two categories: “stellar” firms that have shown a substantial increase (i.e., doubling) in their stock price within a four-year period and are assumed to be attractive to positive feedback traders, and “non-stellar” firms that have a four-year track record but have not doubled in price and thus form the sample set for the fundamentalists. For those firms in the former category, this implies an annualized return of at least 19% but perhaps much greater depending on the time it takes for the stock price to double. At this point, a number of firm-specific and market-wide attributes are measured, including: the dollar value of annualized earnings per share, *Earn*; the firm's earnings-to-price ratio divided by the S&P 500 earnings-to-price ratio as a relative measure, *RelEP*; the firm's book-to-market ratio divided by the S&P 500 book-to-market ratio as a relative measure, *RelBM*; the annualized dividend per share divided by the price per share, *DivYld*; the natural log of the market value of equity in millions of dollars, *Size*; the firm's average monthly return during the screening period *SceenRet*; as well as the corresponding average monthly S&P 500 (or market) return during the screening period, *ScreenMktRet*. Returns are measured excluding dividends in order to focus on price changes. These variables are used to predict subsequent four-year test period performance. Both the firm's average monthly return during the test period, *TestRet*, as well as the corresponding average monthly S&P 500 return during the test period, *TestMktRet*, are measured.

Both Ordinary Least Squares (OLS) regressions and probit analysis are performed. Newey and West (1987) standard errors are estimated in order to account for possible heteroskedasticity or autocorrelation. For the OLS regressions, the dependent variable is the test period return, *TestRet*, and for the probit analysis the dependent variable is a dummy variable equal to 1 if the firm's stock price doubles in the test period (or if the test period has fewer than 48 monthly observations then if the average monthly compound return, *TestRet*, is greater than or equal to a rate that implies doubling over 48 months) and zero otherwise, *TestDouble*. Independent variables include the firm's average monthly return during the screening period, *ScreenRet*; a dummy variable equal to 1 if the firm's stock price doubled (or more) during the screening period and zero otherwise, *ScreenDouble*; a dummy variable equal to 1 if the firm's end-of-screening-period earnings were negative and zero otherwise, *DEearn*; the average monthly S&P 500 return during the test period, *TestMktRet*; the firm's end-of-screening-period earnings-to-price ratio divided by the corresponding S&P 500 earnings-to-price ratio, *RelEP*; the firm's end-of-screening-period book-to-market ratio divided by the corresponding S&P 500 book-to-market ratio, *RelBM*; the firm's end-of-screening-period annualized dividend per share divided by the price per share, *DivYld*; the firm's end-of-screening-period natural log of the market value of equity in millions of dollars, *Size*; and *Sic1* through *Sic9* are dummy variables equal to 1 corresponding to the nine industries organized by SIC codes (SIC<1000 is Agricultural, Forestry/Fishing, 1000-1499 is Mining, 1500-1799 is Construction, 2000-3999 is Manufacturing, 4000-4999 is Transportation, 5000-5199 is Wholesale/Distributors, 5200-5999 is Retail, 6000-6799 is Finance, Insurance/Real Estate, 7000-8999 is Services), and zero otherwise.

RESULTS

Why Positive Feedback Traders May Be Disappointed

The first part of this study examines why positive feedback traders may have high expectations for stock investments and then be disappointed by future results. I begin by examining the summary statistics of the key variables, presented in **Table 1**. The sample consists of 11,264 firm-observations. Firms have average or mean (median) earnings per

share of \$1.21 (\$0.47), yet 19.1% of firms have negative earnings. Given the negative skewness, the mean E/P ratio (not reported in the table) is negative while the median ratio is 0.047, corresponding to a price-earnings ratio of 21.3 times. The mean (median) book-to-market ratio (not reported) is 0.55 (0.42), corresponding to a price-to-book ratio of 1.81 (2.38) times. The median relative earnings-price ratio and book-to-market ratio are 91% and 108%, respectively, close to the 100% one would expect. The mean (median) dividend yield is 1.6% (0.2%). Consistent with results from other studies, over one-quarter of firm-observations had zero dividend yields. The mean (median) firm size is \$614 million (\$573 million), corresponding to the natural log values in the table. The mean (median) monthly screening period return is 2.87% (1.05%), which corresponds with an average annualized return of 40.37% (13.34%), or 27.01% (3.35%) in excess of the S&P 500 market return. This high average return is not surprising given the screening methodology and as discussed below almost half the sample includes stocks that have recently doubled in price.

An examination of the test period results reveal the source of potential positive feedback trader disappointment. The mean (median) monthly test period return is 0.45% (0.57%), which corresponds with an average annualized return of 5.59% (7.00%), or 3.02% (3.13%) *less than* that of the S&P 500 market return. Thus these test period returns reveal disappointing results relative to both the market and in particular relative to the returns earned during the screening period.

Table 2 presents additional analysis contrasting the screening period and test period results. 45.8% of the firms at least doubled in value during the screening period. The disappointment factor is highlighted by the much smaller 28.5% of firms that subsequently double during the test period (recall that the test period is survivorship-bias-free). A further disappointment is experienced by positive feedback traders who concentrated their investments among the screening sample of stocks that doubled as only 25.8% of those stocks doubled again during the test period versus 30.8% of stocks that did not double during the screening period (the fundamentalist investor sample).

Panel B presents difference in means tests between those stocks that did double during the screening period (ScreenDouble=1, the stocks attractive to positive feedback traders sample) and those that did not (ScreenDouble=0, the fundamentalist sample) for the key variables. Note that the variables are measured as of the end of the screening period (which is also the start of the testing period). There is no significant difference in the average earnings per share. Firms that doubled during the screening period had lower relative book-to-market ratios which tend to be associated with growth stocks. Somewhat surprisingly larger firms tended to double more frequently. One possible explanation is that many of the low priced and thus small market capitalization stocks have been eliminated from this sample. Thus given the biased screening technique, it appears that it is larger growth stocks that have done better in the past, in contrast to the well-known results of Fama and French (1992, 1993) and provides another possible explanation as to why positive feedback traders are disappointed: they have a tendency to choose attractive-looking growth and large cap stocks whereas value and small cap stocks tend to do better over the long-term.¹⁴ Consistent with the overreaction literature, stocks that did not double during the screening period have (by design) lower screening period returns than those that did double, but then higher test period returns. Note that these results are not being driven by market returns as the test period corresponding market returns are virtually the same for both the sample of stocks that doubled in the screening period and those that did not.¹⁵

The Predictability of Future Performance of Individual Stocks

The second part of this study examines the predictability of stock returns for this particular screening period sample and subsequent four-year horizon test period. The dependent variable is the firm's average monthly return during the test period, *TestRet*. Univariate regression analysis results are presented in **Table 3**. The independent variables are Winsorized by capping the extreme observations at the 1% and 99% cutoffs in Table 1.

¹⁴ See Doukas and Li (2009) for a discussion of how value stocks tend to have a slower price adjustment than growth stocks.

¹⁵ I also examine test period versus screening period returns by industry (see Moskowitz and Grinblatt (1999)). In all cases returns are significantly different between these two periods, consistent with the overall results.

Testing period returns are significantly and negatively related to screening period returns, *ScreenRet*, consistent with mean-reversion and the overreaction literature. As well, firms that doubled in the screening period as indicated by the dummy variable *ScreenDouble*, are more likely to experience lower testing period returns. Firms that experienced negative earnings during the screening period as indicated by the dummy variable *DEarn*, are also more likely to experience lower testing period returns. Not surprisingly, testing period returns are positively related to the testing period market return, *TestMktRet*, and the explanatory power as measured by the adjusted R-square is a similar order of magnitude to that of the screening period returns. Testing period returns are positively related to the relative book-to-market variable, *RelBM*, and the relative price-to-earnings variable, *RelEP*, but the coefficients are not significant. Testing period returns are positively related to the dividend yield, *DivYld*, consistent with the value effect. Finally, the size variable, *Size*, is positively related to future returns but the coefficient estimate is quite small and the regression intercept is negative.

Multivariate regression results are presented in **Table 4**.¹⁶ Regressions 1 and 2 are ex ante models based strictly on information available at the start of the test period while regressions 3 and 4 include the test period market return variable, *TestMktRet*. In all regressions, the screening period return coefficient, *ScreenRet*, is negative and significant, consistent with the univariate regression and consistent with the overreaction literature. However, the main focus of this study is the double-in-screening-period dummy variable coefficient, *ScreenDouble*, which is also negative and significant, which suggests that simply knowing whether a stock has recently doubled in value provides important incremental information in terms of predicting future stock returns.

The negative earnings dummy variable coefficient, *DEarn*, is negative and significant in this and all regressions, consistent with the univariate regressions. The relative earnings-price and book-to-market coefficients, *RelEP* and *RelBM* respectively, are not significant.

¹⁶ The multivariate regressions effectively provide risk-adjusted results since they include similar factors as Fama and French (1992, 1993): a market factor, a size factor, and a book-to-market factor.

Unlike the univariate regression, the dividend yield coefficient, *DivYld*, is consistently negative and significant across all regressions, suggesting higher priced stocks (and hence lower dividend yield stocks) tend to do better in the test period, although the interpretation is more complex given the preponderance of stocks that don't pay any dividends. Consistent with the univariate analysis, the size coefficient, *Size*, is positive and significant across regressions. Regressions 2 and 4 control for any industry differences. Only the Mining Industry dummy coefficient, *Sic2*, is significant across the various industries, while the other variable coefficients are of similar sign, size, and significance. Regressions 3 and 4 add a test period market return variable, *TestMktRet*, which is positive and significant as expected. The significance is similar to that of the screening period return, *ScreenRet*.

To summarize, much of the variability of the test period returns can be explained by variables available at the beginning of the test period, indicating that returns have a predictable component. The double-in-screening-period dummy is a new variable with incremental predictive power that has not been uncovered in past studies. Unlike other studies, it is simple to estimate based on price information for each particular stock and does not require any relative comparisons across firms (e.g., forming winner and loser portfolios based on an entire sample).

Probit analysis results are presented in **Table 5**. The dependent variable is a dummy variable equal to 1 if the firm's stock price doubles in the test period (or if the test period has fewer than 48 monthly observations then if the average monthly compound return, *TestRet*, is greater than or equal to a rate that implies doubling over 48 months) and zero otherwise, *TestDouble*. The independent variables include the variables in Table 4 excluding the test period market return (since it is a contemporaneous variable) and the industry dummies (since they are generally not significant): the screening period return, *ScreenRet*; *ScreenDouble*, which is a dummy variable equal to 1 if the firm's stock price doubled (or more) during the screening period and zero otherwise; *DEarn* which is a dummy variable equal to 1 if the firm's end-of-screening-period earnings were negative and zero otherwise; the relative book-to-market ratio, *RelBM*; the relative earnings-price

ratio, *RelEP*; the dividend yield, *DivYld*; and firm size, *Size*; Note that all of the independent variables are measured as of the end of the screening period (i.e., as of the start of the testing period). As described above, since I use individual stocks (as opposed to the more common portfolio approach that reduces “noise”), the independent variables are Winsorized based on the 1% and 99% cutoffs in Table 1.

The probability of doubling during the test period is significantly and negatively related to the screening period return, but consistent with the regression analysis the double-in-screening-period dummy is also significant and negative, suggesting that this latter variable has incremental predictive power to predict whether a stock will double in the subsequent four-year period. This analysis presents further results to suggest why positive feedback traders who invest in stocks that have recently doubled in price may be disappointed by future returns which fall short of past return performance.

The relative earnings-price ratio and the dividend yield are negatively related to the probability a stock’s price will double in the subsequent four-year period, while the relative book-to-market ratio and firm size variables have a positive relationship. Thus the ex ante predictability of the doubling of a firm’s stock price is significant, consistent with the regression analysis of the predictability of returns in Table 4, and the double-in-screening-period dummy has incremental predictive power.

I repeat the analysis above using an additional screen: beginning-of-test period prices are required to be a minimum of \$5.00 (in addition to the beginning-of-screening period minimum \$5.00 price). The resulting sample size is reduced by about 10% to 10,157. Such a decrease in sample size with this additional constraint is not surprising and simply indicates that with an existing sample of firms with initial prices above \$5.00, after 48 months approximately 10% will have dropped below that threshold. With the second sample I find a subtle but important additional survivorship bias that tends to make past performance of the remaining firms even more attractive. I repeat the analyses above and the results are qualitatively the same.

Next, I examine the extent to which the speed of doubling in the screening period impacts on subsequent test period returns. The conjecture is that stocks that have doubled faster are more likely to be featured in the media. Based on results in Barber and Odean (2008), given the limited attention span that many investors have while choosing stocks, they may be more likely to utilize a doubling heuristic when such stocks gain more visibility faster through the media. However, such excess hype may result in pushing prices farther from their intrinsic value and consequently lead to even more severe underperformance. Monthly test period returns are gathered for the 10,157 firm-observations (i.e., the sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price) for each of the 48 months. For each firm-observation, returns (i.e., log normal stock price changes) are calculated and compared to S&P 500 returns in order to calculate firm-observation excess or abnormal returns. For each of the 48 months, average returns are calculated and then cumulated.

Figure 3 presents the results graphically and analysis is presented in **Table 6**. In general, consistent with the conjecture, the quicker the doubling, the greater the test period underperformance. For example, for firms that double within 12 months the 48-month cumulative excess return is -50.2%; for firms that doubled in 13 to 24 months: -20.8%; for firms that doubled in 25 to 36 months: -13.6%; and for firms that doubled in 37 to 48 months: -17.2%. All of the cumulative excess returns are statistically negatively significant by month 13, and by month 5 for the sample that doubled within a year. T-tests across adjacent series show that the underperformance is statistically lower for the sample that doubled in 12 months or less compared with the sample that doubled in 13 to 24 months; significantly lower at the 10% confidence level between the sample that doubled in 13 to 24 months versus the sample that doubled in 25 to 36 months; and not statistically different between the sample that doubled in 25 to 36 months and the sample that doubled in 37 to 48 months. Thus these results reinforce the earlier conclusion that stock returns contain a predictable component and reliance on the simple piece of information related to whether or not a stock has at least doubled in price in the past four years (or less) may be quite valuable.

Robustness Checks

A further analysis of the probit results is presented in **Table 7**, which examines the average returns available to investors who make their decisions based on the probability of doubling. Test period return analysis is based on the probability of doubling in price from a probit analysis similar to that in Table 6 but based on the sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price. Average monthly and annualized returns are presented for individual firm-observations (“stock”) as well as the corresponding S&P 500 return (“market”) and the difference between the two (“excess”). Five sets of results are presented for 1%, 5%, 10%, 25%, and 50% sample thresholds based on a sort of the probabilities. For example, after the 10,157 “probability of doubling in the test period” prediction results are sorted from lowest to highest, the 1,016 “low 10%” and the 1,016 “high 10%” average test period returns are compared.

For the 1% threshold, the most likely to double stocks experience an average annualized return of 20.9%, 13.6% in excess of the corresponding market return. In contrast, the least likely to double stocks experience an average annualized return of -1.2% or -6.9% excess returns. The excess return difference between the high 1% and low 1% groups is 20.4%. With the less stringent screen comparing the top and bottom 5%, the excess return difference is 19.1%. With a 10% screen the difference is 18.3%, with a 25% screen the difference is 15.3%, and with a 50% screen the difference is still a large 10.6%. Thus these results suggest that screening stocks on the basis of their doubling probability may lead to profitable investment outcomes.

A final set of robustness checks are performed to investigate the extent to which the results depend on the test holding period, the relationship with past “winners” and “losers”, the probability of doubling, and various sub-period results. For each firm-observation, returns are calculated and compared to S&P 500 returns in order to calculate firm-observation excess returns. For each of the 48 months, average returns are calculated and then cumulated. Results are presented in **Figure 4**. Consistent with momentum studies (e.g., Jegadeesh and Titman (1993 and 1995)), for the first two months the sample

outperforms the market by a small margin (cumulative 0.41% after two months). However, subsequently monthly excess returns are negative in every month from 3 to 35 and again in months 37 and 38 before showing modest gains for the remainder of the test period. Cumulative excess returns are as low as -17%. Thus the results do not appear to be sensitive to the duration of the test period.

Figure 4 also segregates the sample into those that doubled during the screening period (recall from Table 2, 50.8% of the sample) and those that did not (49.2% of the sample). The non-doubling sample shows little deviation from zero excess returns, with a 48-month cumulative excess return of -0.2%. In contrast, the doubling sample shows substantial under-performance, with a cumulative excess return as low as -30.9% by month 38, before ending with a 48-month cumulative excess return of -28.0%.

Figure 5 compares samples based on a simple sorting of screening-period returns, creating a type of “winners” and “losers” in the spirit of DeBondt and Thaler (1985, 1987), for the top and bottom decile and the top and bottom quartile. The Past Losers samples underperform slightly for about 18 months but by the end of 48 months, the lowest quintile sample has a cumulative excess return of 4.8% and the lowest decile has a cumulative excess return of 8.5%. In contrast, the Past Winners samples substantially underperform. The highest quintile portfolio has cumulative positive excess returns for only two months and by the end of 48 months has a cumulative excess return of -37.5%. The highest decile portfolio has negative cumulative positive excess returns immediately and by the end of 48 months has a cumulative excess return of -56.6%. Thus the top and bottom decile sample differential is 65.1%, much greater than in other winner/loser studies.

Figure 6 compares samples based on the probability of doubling for the top and bottom decile and the top and bottom quartile. Probabilities are derived from the probit analysis results described above with all of the independent variables available as of the start of the test period. Consistent with Table 7 results, the low probability sample underperforms as expected, with the lowest quintile sample experiencing a cumulative excess return of -

43.5% and the lowest decile -55.0%. In contrast, the high probability samples substantially outperform. The highest quintile portfolio has cumulative positive excess return of 16.7%. The highest decile portfolio has a cumulative excess return of 29.2%. Thus the top and bottom decile sample differential is 84.2%.

Figure 7 compares the screening-period doubling versus non-doubling samples based on three arbitrary (but roughly equal) sub-periods: pre-1995 (3,524 observations), 1996-2002 (3,376 observations) and post-2002 (3,258 observations). While the patterns differ in magnitude they consistently show a substantial spread between the non-doubling sample and doubling sample 48-month cumulative excess returns. In the first sub-period the spread is 14.9% (-4.9% for the non-doubling sample versus -19.8% for the doubling sample), in the second sub-period the spread is 50.1% (2.1% versus -48.0%), and in the third sub-period the spread is 10.4% (3.8% versus -6.7%). The second sub-period contains much of the technology “bubble” period and thus it may not be surprising to find the greatest differential in this sample. Part of the results for the third sub-period may be impacted by a less than 48-month testing period for the post-2003 portion of the sample (recall that in cases when there are less than 48 observations, in order to avoid any survivorship bias by discarding such observations, available data are extrapolated, i.e. a firm is deemed to have doubled if its price has increased at a rate consistent with doubling over 48 months).

For the final robustness check, I compare my results more directly to DeBondt and Thaler (1985). I begin by replicating their main findings as reported in their Figure 1 and Table 1 (row 2), presented here in **Figure 8**. I then form an alternative portfolio to their Winner portfolio that includes a portfolio of 35 stocks that have doubled in price in the fewest number of months, which I refer to as the “Fastest Doubling” portfolio. I then compare the replicated Loser-Winner differences with the new Loser-Fastest Doubling differences. Consistent with the hypothetical price patterns presented in Figure 1, in 9 of the 16 non-overlapping periods (1933 to 1980), at least one stock in the Loser portfolio is actually a stock that doubled in price, and in the second formation period 8 of the 35 Loser stocks

had recently doubled in value. The Loser-Fastest Doubling results are similar to but actually slightly stronger than the DeBondt and Thaler Loser-Winner results.

SUMMARY AND CONCLUSIONS

Tversky and Kahneman (1974) argue that relying on simple heuristics to predict values can lead to severe and systematic errors. This paper examines one such simple heuristic whereby investors are attracted to buying stocks that have recently doubled in price in anticipation of further gains. This research shows why such naïve positive feedback traders may often be disappointed by investments in stocks with attractive track records, and also uncovers a new variable that adds incremental value to the predictability of stock returns in addition to previously uncovered in other studies. The research design is a departure from much of the literature that focuses on portfolios of stocks and that requires a fixed screening period.

I highlight the contrast between a backward looking survivorship-biased screening period sample and a survivorship-bias-free forward looking sample. Even including a mix of stellar and non-stellar stocks, over half (50.8%) of the stocks in this survivorship-biased sample have at least doubled in price, with an attractive total sample median annual return of 20.1%, outperforming the market by 10.1%. However, in a subsequent four-year (survivorship-bias-free) test period, only 27.1% of sample stock prices doubled (or more), with a total sample median annual return of 6.6%, under-performing the market by 3.6%. In addition, those that doubled in the screening period are less likely to double subsequently than those that had not doubled previously. Positive feedback traders experience significant cumulative excess return losses – -28% over four years – while fundamentalists experience near-zero excess returns. I also find that underperformance is more severe for stocks that have doubled faster.

Much of the cross-sectional variation in investment period returns can be explained not only by investment period market returns (a positive relationship) but also past stock performance (negative), whether the stock has recently doubled in price (negative), past

earnings (positive), and various valuation-related metrics measured at the start of the investment period. A probit model identifies ex ante variables that are able to predict whether or not a stock will at least double in value over the investment period. Investing in stocks with a high (ex ante) probability of doubling leads to annualized excess returns of 11%-20% greater than investing in stocks with a low probability of doubling.

This research contributes to the behavioral finance literature and also offers a possible explanation of why some investors may have a tendency to choose attractive-looking growth and large cap stocks, which have performed well in the survivorship-biased screening period, whereas value and small cap stocks tend to do better over the long-term. This research also shows that stock return predictability may be based on some very simple information readily available to most investors.

While the results are consistent with the overreaction literature, as pioneered by DeBondt and Thaler, I show that while the “doubling” phenomenon is related to the classic Losers-Winners, there are some unique elements similar to the way the 52-week high phenomenon is distinct from the momentum phenomenon. Given the simplicity of the measurement technique for individual investors who can readily measure when a stock has doubled in price (compared with the formation of portfolios based on rank-orders of returns), and given the close intuitive ties to many behavioral phenomenon, the doubling phenomenon provides one explanation why many investors may be disappointed with stock investments based on simple heuristics and also provides a simple screen by which investors can avoid future disappointment.

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Table 1
Summary Statistics

Mean (Mean), standard deviation (Std Dev), 1% quantile cutoff (1% Q), median (Median), and 99% cutoff (99% Q), firm/screening-period observations for all U.S. stocks available on Compustat. The screening period and corresponding test period for a particular firm are up to 48 months each depending on whether a stock price has doubled in the screening period (in which case the screening period ends; otherwise the screening period is 48 months) and how much data are available in a test period (48 months unless there are no more observations); thus a firm may have multiple observations as re-sampling occurs at the end of each test period. The variables, measured as of the end of the screening period, represent: the dollar value of annualized earnings per share (Earn), the firm's earnings-to-price ratio divided by the S&P 500 earnings-to-price ratio (RelEP), the firm's book-to-market ratio divided by the S&P 500 book-to-market ratio (RelBM), the annualized dividend per share divided by the price per share (DivYld), the natural log of the market value of equity in millions of dollars (Size), the firm's average monthly return during the screening period (ScreenRet), the firm's average monthly return during the test period (TestRet), the corresponding average monthly S&P 500 return during the screening period (ScreenMktRet), and the corresponding average monthly S&P 500 return during the test period (TestMktRet). Returns are measured excluding dividends. Results are based on 11,264 observations.

| Variable | Mean | Std Dev | 1% Q | Median | 99% Q |
|-----------------|-------------|----------------|-------------|---------------|--------------|
| Earn | 1.219 | 62.825 | -6.400 | 0.470 | 6.750 |
| RelEP | -2.278 | 107.089 | -25.178 | 0.907 | 5.387 |
| RelBM | 1.491 | 23.712 | -94.848 | 1.076 | 8.424 |
| DivYld | 0.016 | 0.029 | 0.000 | 0.002 | 0.113 |
| Size | 6.420 | 2.264 | 1.190 | 6.351 | 11.741 |
| ScreenRet | 0.029 | 0.089 | -0.056 | 0.010 | 0.399 |
| TestRet | 0.005 | 0.030 | -0.068 | 0.006 | 0.067 |
| ScreenMktRet | 0.011 | 0.057 | -0.014 | 0.008 | 0.060 |
| TestMktRet | 0.007 | 0.008 | -0.008 | 0.008 | 0.029 |

Table 2**Comparison of Firms that Did/Didn't Double in Price During Screening Period**

Panel A describes the screening period and test period samples including the sample size, N, and the percentage of observations, % (see Table 1 for further descriptions of each sample). Panel B presents the means, differences, and difference-of-means t-test p-values for the variables described in Table 1 based on Welch- Satterthwaite t-tests assuming unequal variances.

Panel A: Screening and Test Period Samples

| <u>Category</u> | <u>N</u> | <u>%</u> |
|--|----------|----------|
| Screening Period Sample: | 11264 | |
| Firms that did not double during screening period (ScreenDouble=0) | 6108 | 54.23% |
| Firms that doubled during screening period (ScreenDouble=1): | 5156 | 45.77% |
| Test Period Sample Overall: | 11264 | |
| Firms that did not double during test period (TestDouble=0): | 8050 | 71.47% |
| Firms that doubled during test period (TestDouble=1): | 3214 | 28.53% |
| Test Period Sub-Sample 1 -- ScreenDouble=0: | 6108 | |
| Firms that did not double during test period: | 4225 | 69.17% |
| Firms that doubled during test period: | 1883 | 30.83% |
| Test Period Sub-Sample 2 -- ScreenDouble=1: | 5156 | |
| Firms that did not double during test period: | 3825 | 74.19% |
| Firms that doubled during test period: | 1331 | 25.81% |

Panel B: Difference in Means Tests (ScreenDouble=0 and ScreenDouble=1 samples)

| Variable | Screen Double=0 | Screen Double=1 | Diff | p-value |
|-----------------|----------------------------|----------------------------|-------------|----------------|
| Earn | 1.216 | 1.223 | -0.007 | 0.995 |
| RelEP | -4.852 | 0.770 | -5.622 | 0.003 |
| RelBM | 1.987 | 0.902 | 1.085 | 0.009 |
| DivYld | 0.022 | 0.008 | 0.014 | <0.001 |
| Size | 6.070 | 6.839 | -0.769 | <0.001 |
| ScreenRet | -0.007 | 0.070 | -0.077 | <0.001 |
| TestRet | 0.007 | 0.002 | 0.005 | <0.001 |
| ScreenMktRet | 0.006 | 0.016 | -0.010 | <0.001 |
| TestMktRet | 0.007 | 0.007 | -0.001 | <0.001 |

Table 3
Univariate Regressions

Univariate regression analysis. The dependent variable is the firm's average monthly return during the test period (TestRet). The independent variables (Indep Var) are described in Table 1 except for ScreenDouble, which is a dummy variable equal to 1 if the firm's stock price doubled (or more) during the screening period and zero otherwise; and DEarn which is a dummy variable equal to 1 if the firm's end-of-screening-period earnings were negative and zero otherwise. The independent variables are winsorized based on the 1% and 99% cutoffs in Panel A of Table 1. The intercept (Int), coefficients (Coeff), t-statistics (t-stat) based on Newey and West (1987) standard errors and adjusted R-squares (Adj-R²) are presented. Results are based on 11,264 observations.

| Indep Var | Int | (t-stat) | Coeff | (t-stat) | Adj-R ² |
|---------------------|---------------|----------------|----------------|----------------|--------------------|
| ScreenRet | 0.0065 | (21.13) | -0.0765 | (-15.04) | 0.0251 |
| ScreenDouble | 0.0070 | (20.10) | -0.0053 | (-9.09) | 0.0075 |
| DEarn | 0.0060 | (24.07) | -0.0075 | (-6.84) | 0.0093 |
| TestMktRet | 0.0001 | (0.19) | 0.6432 | (11.37) | 0.0236 |
| RelEP | 0.0045 | (13.92) | 0.0001 | (0.48) | 0.0001 |
| RelBM | 0.0039 | (5.44) | 0.0005 | (1.00) | 0.0022 |
| DivYld | 0.0038 | (9.57) | 0.0093 | (5.31) | 0.0014 |
| Size | -0.0018 | (-1.91) | 0.0010 | (7.82) | 0.0051 |

Table 4
Multivariate Regressions

Multivariate regression analysis. The dependent variable is the firm's average monthly return during the test period (TestRet). The independent variables are described in Table 1 except for ScreenDouble, which is a dummy variable equal to 1 if the firm's stock price doubled (or more) during the screening period and zero otherwise; DEarn which is a dummy variable equal to 1 if the firm's end-of-screening-period earnings were negative and zero otherwise; and Sic1 through Sic9 which are dummy variables equal to 1 corresponding to the nine industries described in the text and zero otherwise. The independent variables are winsorized based on the 1% and 99% cutoffs in Table 1. The intercept (int), t-statistics (in brackets below the coefficient estimates) based on Newey and West (1987) standard errors and adjusted R-squares (Adj-R²) are presented. Results are based on 11,264 observations.

| | 1 | 2 | 3 | 4 |
|---------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
| int | 0.002 (1.33) | 0.001 (0.21) | -0.002 (-1.34) | -0.003 (-1.03) |
| ScreenRet | -0.0714 (-12.37) | -0.070 (-12.20) | -0.065 (-11.35) | -0.064 (-11.23) |
| ScreenDouble | -0.002 (-2.34) | -0.002 (-2.47) | -0.002 (-3.21) | -0.002 (-3.29) |
| DEarn | -0.009 (-6.46) | -0.009 (-6.38) | -0.008 (-5.98) | -0.008 (-5.92) |
| TestMktRet | | | 0.605 (10.27) | 0.602 (10.25) |
| RelEP | -0.000 (-1.48) | -0.000 (-1.51) | -0.000 (-1.39) | -0.000 (-1.41) |
| RelBM | 0.000 (0.83) | 0.000 (0.82) | 0.001 (1.03) | 0.001 (1.02) |
| DivYld | -0.037 (-4.08) | -0.037 (-3.73) | -0.035 (-3.94) | -0.034 (-3.51) |
| Size | 0.001 (6.97) | 0.001 (7.01) | 0.001 (7.16) | 0.001 (7.17) |
| Sic1 | | -0.001 (-0.11) | | -0.001 (-0.24) |
| Sic2 | | 0.006 (1.93) | | 0.006 (1.89) |
| Sic3 | | 0.003 (0.74) | | 0.003 (0.85) |
| Sic4 | | 0.001 (0.38) | | 0.001 (0.31) |
| Sic5 | | 0.000 (0.03) | | 0.000 (0.02) |
| Sic6 | | 0.002 (0.60) | | 0.002 (0.63) |
| Sic7 | | 0.001 (0.35) | | 0.001 (0.37) |
| Sic8 | | 0.002 (0.68) | | 0.002 (0.57) |
| Sic9 | | 0.000 (0.12) | | 0.000 (0.13) |
| Adj-R ² | 0.0426 | 0.0431 | 0.0631 | 0.0635 |

Table 5
Probit Analysis

In this probit analysis the dependent variable is a dummy variable equal to 1 if the firm's stock price doubles in the test period (or if the test period has fewer than 48 monthly observations then if the average monthly compound return, testRet, is greater than or equal to a rate that implies doubling over 48 months) and zero otherwise (TestDouble). The independent variables are described in Table 1 except for ScreenDouble, which is a dummy variable equal to 1 if the firm's stock price doubled (or more) during the screening period and zero otherwise; and DEarn which is a dummy variable equal to 1 if the firm's end-of-screening-period earnings were negative and zero otherwise. The independent variables are winsorized based on the 1% and 99% cutoffs in Table 1. The intercept (int), t-statistics (in brackets below the coefficient estimates) and Pseudo R-squares (Pseudo R²) are presented. Pseudo R-square is defined as 1 minus the ratio of the log likelihood for the estimated model divided by the log-likelihood for a model with only an intercept as an independent variable. Results are based on 11,264 observations.

| | |
|-----------------------|---------------------------------|
| int | -0.620 (-13.44) |
| ScreenRet | -2.128 (-7.41) |
| ScreenDouble | -0.116 (-3.50) |
| DEarn | -0.125 (-3.00) |
| RelEP | -0.018 (-4.11) |
| RelBM | 0.015 (2.84) |
| DivYld | -7.546 (-11.95) |
| Size | 0.043 (6.96) |
| Pseudo R ² | 0.023 |

Table 6
Speed of Doubling Analysis

Test period return analysis based on 48 monthly averages of log normal stock price changes in excess of log normal S&P 500 price changes. Cumulative excess or abnormal returns are indicated as CAR with accompanying t-statistics (t-stat). Based on 10,157 firm-observations (sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price) for the entire sample. The sample that doubled in price during the screening period are presented based on the time required to double: <=12 months (1,249 observations); 13-24 months (1,509 observations); 25-36 months (1,375 observations); and 37-48 months (936 observations). Difference-of-means t-test p-values based on Welch- Satterthwaite t-tests assuming unequal variances are presented for adjacent series (i.e., <=12 months versus 13-24 months, 13-24 months versus 25-36 months, and 25-36 months versus 37-48 months).

| Month | <=12 months | | 13-24 months | | 25-36 months | | 37-48 months | |
|--|-------------|--------|--------------|--------|--------------|--------|--------------|--------|
| | CAR | t-stat | CAR | t-stat | CAR | t-stat | CAR | t-stat |
| 1 | -0.003 | -0.51 | 0.009 | 2.36 | 0.009 | 2.41 | -0.007 | -1.56 |
| 2 | -0.003 | -0.33 | 0.009 | 1.67 | 0.012 | 2.32 | -0.004 | -0.65 |
| 3 | -0.015 | -1.41 | 0.008 | 1.23 | 0.005 | 0.81 | 0.002 | 0.30 |
| 4 | -0.021 | -1.90 | 0.002 | 0.25 | 0.003 | 0.38 | 0.005 | 0.60 |
| 5 | -0.043 | -3.36 | -0.003 | -0.41 | 0.007 | 0.98 | 0.002 | 0.21 |
| 6 | -0.035 | -2.62 | -0.008 | -0.89 | 0.004 | 0.47 | 0.002 | 0.19 |
| 7 | -0.047 | -3.13 | -0.007 | -0.74 | 0.004 | 0.47 | 0.003 | 0.28 |
| 8 | -0.064 | -4.00 | -0.009 | -0.86 | 0.006 | 0.61 | 0.003 | 0.26 |
| 9 | -0.088 | -5.00 | -0.012 | -1.10 | 0.001 | 0.09 | -0.009 | -0.64 |
| 10 | -0.111 | -5.91 | -0.019 | -1.61 | -0.003 | -0.31 | -0.018 | -1.25 |
| 11 | -0.129 | -6.61 | -0.032 | -2.63 | -0.011 | -1.00 | -0.017 | -1.18 |
| 12 | -0.155 | -7.40 | -0.037 | -2.91 | -0.015 | -1.30 | -0.036 | -2.36 |
| 13 | -0.177 | -8.19 | -0.047 | -3.56 | -0.029 | -2.32 | -0.046 | -2.89 |
| 14 | -0.204 | -9.11 | -0.052 | -3.74 | -0.044 | -3.40 | -0.050 | -3.00 |
| 15 | -0.225 | -9.68 | -0.066 | -4.58 | -0.048 | -3.69 | -0.062 | -3.40 |
| 16 | -0.241 | -10.08 | -0.072 | -4.87 | -0.052 | -3.82 | -0.072 | -3.85 |
| 17 | -0.257 | -10.39 | -0.079 | -5.14 | -0.058 | -4.20 | -0.079 | -4.08 |
| 18 | -0.278 | -11.06 | -0.088 | -5.54 | -0.064 | -4.48 | -0.087 | -4.41 |
| 24 | -0.361 | -12.66 | -0.118 | -6.59 | -0.104 | -6.26 | -0.112 | -5.25 |
| 36 | -0.508 | -14.96 | -0.191 | -9.06 | -0.161 | -7.89 | -0.215 | -8.23 |
| 48 | -0.502 | -14.50 | -0.208 | -8.98 | -0.136 | -6.50 | -0.172 | -6.52 |
| t-test p-value across adjacent series | | | 0.000 | | 0.064 | | 0.284 | |

Table 7**High versus Low Probability-of-Doubling Return Analysis**

Test period return analysis based on the probability of doubling in price from the probit analysis (10,157 observations; based on the sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price). Average monthly and annualized returns are presented for individual firm-observations (stock) as well as the corresponding S&P 500 return (market) and the difference between the two (excess). The number of observations (N) and the probit minimum cutoff for the high and maximum cutoff for the low (prob) are presented for 1%, 5%, 10%, 25%, and 50% sample thresholds based on a sort of the probabilities.

| | N | Prob | Monthly | | | Annualized | | |
|-------------------|------|--------|---------|--------|--------|------------|--------|---------|
| | | | Stock | Market | Excess | Stock | Market | Excess |
| high 1% | 102 | 51.90% | 1.59% | 0.52% | 1.07% | 20.88% | 6.48% | 13.60% |
| low 1% | 102 | 6.23% | -0.10% | 0.49% | -0.59% | -1.19% | 6.04% | -6.85% |
| difference | | | 1.69% | 0.03% | 1.66% | 22.07% | 0.44% | 20.44% |
| high 5% | 508 | 41.11% | 1.26% | 0.64% | 0.62% | 16.19% | 7.99% | 7.65% |
| low 5% | 508 | 12.47% | -0.45% | 0.56% | -1.01% | -5.28% | 6.93% | -11.48% |
| difference | | | 1.71% | 0.08% | 1.63% | 21.48% | 1.06% | 19.13% |
| high 10% | 1016 | 37.33% | 1.19% | 0.70% | 0.49% | 15.21% | 8.71% | 6.02% |
| low 10% | 1016 | 16.32% | -0.47% | 0.61% | -1.08% | -5.47% | 7.62% | -12.23% |
| difference | | | 1.65% | 0.08% | 1.57% | 20.67% | 1.09% | 18.25% |
| high 25% | 2539 | 32.31% | 1.04% | 0.72% | 0.31% | 13.16% | 9.02% | 3.83% |
| low 25% | 2539 | 21.60% | -0.36% | 0.65% | -1.01% | -4.29% | 8.06% | -11.50% |
| difference | | | 1.40% | 0.07% | 1.33% | 17.45% | 0.96% | 15.33% |
| high 50% | 5079 | 27.05% | 0.87% | 0.72% | 0.16% | 10.98% | 8.95% | 1.88% |
| low 50% | 5078 | 27.05% | -0.07% | 0.68% | -0.75% | -0.83% | 8.53% | -8.68% |
| difference | | | 0.94% | 0.03% | 0.91% | 11.81% | 0.42% | 10.56% |

Figure 1 Hypothetical Price Patterns

Hypothetical price patterns for three different stocks relative to the end-of-screening period at month 0. All three stocks have an end-of-screening price at month t 0 of \$20 and a t-12 month price of \$10. The “loser” stock has a price of \$40 at t-48, the “neutral” stock has a price of \$20 at t-48, and the “winner” stock has a price of \$5 at t-48. All three stocks would have been categorized in this study as having doubled in price depending on the beginning of screen date.

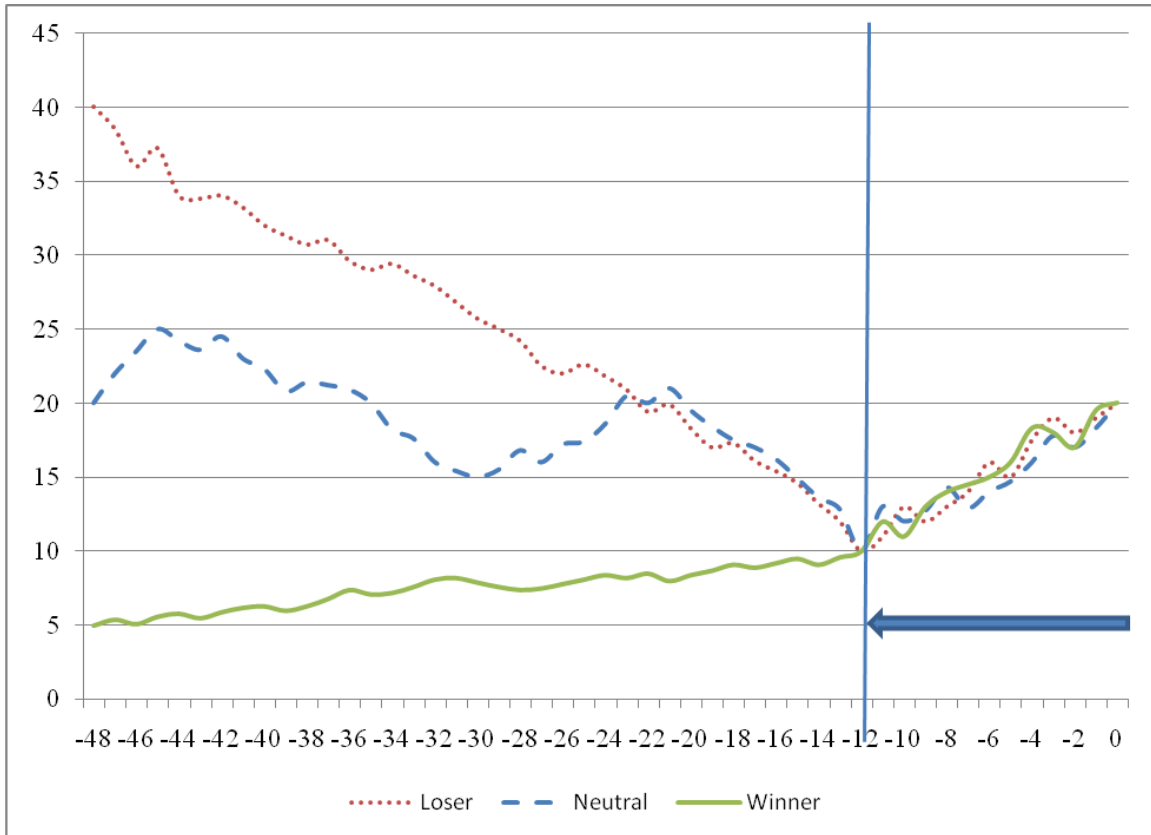


Figure 2
Example of Firm-Observation Data Generation Process

Example of data generation for a particular firm with available data from January 1988 to May 2007. An observation is a combination of a screening period and a corresponding test period. For each firm there may be several firm-observations depending on the amount of available data. In this example there are three firm-observations. Each screening period is the lesser of 48 months or the time it takes the stock price to double. Each test period is 48 months or less if there are no more available data, such as at the end of the sample period in May 2007.

| Firm 1 | | | |
|------------|---------|------------|----------|
| Data Point | Date | Price (\$) | Period |
| 1 | 01/1988 | 6.00 | Screen 1 |
| 2 | 02/1988 | 5.75 | Screen 1 |
| 3 | 03/1988 | 7.25 | Screen 1 |
| ... | | | |
| 19 | 07/1989 | 10.75 | Screen 1 |
| 20 | 08/1989 | 11.25 | Screen 1 |
| 21 | 09/1989 | 12.50 | Screen 1 |
| 22 | 10/1989 | 11.75 | Test 1 |
| 23 | 11/1989 | 11.63 | Test 1 |
| ... | ... | | |
| 68 | 08/1993 | 9.50 | Test 1 |
| 69 | 09/1993 | 9.25 | Test 1 |
| 70 | 10/1993 | 9.00 | Screen 2 |
| 71 | 11/1993 | 8.75 | Screen 2 |
| ... | ... | | |
| 116 | 08/1997 | 12.00 | Screen 2 |
| 117 | 09/1997 | 12.63 | Screen 2 |
| 118 | 10/1997 | 12.75 | Test 2 |
| 119 | 11/1997 | 12.13 | Test 2 |
| ... | ... | | |
| 164 | 08/2001 | 13.13 | Test 2 |
| 165 | 09/2001 | 13.50 | Test 2 |
| 166 | 10/2001 | 13.25 | Screen 3 |
| 167 | 11/2001 | 14.38 | Screen 3 |
| ... | ... | | |
| 212 | 08/2005 | 15.50 | Screen 3 |
| 213 | 09/2005 | 16.25 | Screen 3 |
| 214 | 10/2005 | 17.12 | Test 3 |
| 215 | 11/2005 | 16.75 | Test 3 |
| ... | ... | | |
| 232 | 04/2007 | 17.88 | Test 3 |
| 233 | 05/2007 | 15.12 | Test 3 |

Firm-Observation #1

Firm-Observation #2

Firm-Observation #3

Price doubles after 21 months;
21 month screening period #1

48 month test period #1

No price doubling;
48 month screening period #2

48 month test period #2

No price doubling;
48 month screening period #3

End of available data after 20 months;
20 month test period #3

Figure 3

Test Period Cumulative Excess Return: Past Double, Speed of Doubling

Test period return analysis based on 48 monthly averages of log normal stock price changes in excess of log normal S&P 500 price changes. Month 0 is the start of the test period with zero excess returns. Based on 10,157 firm-observations (sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price) for the entire sample. The sample that doubled in price during the screening period, “Double” are presented separately based on the time required to double: 12 months or less (1,249 observations), 13-24 months (1,509 observations), 25-36 months (1,375 observations), and 37-48 months (936 observations).

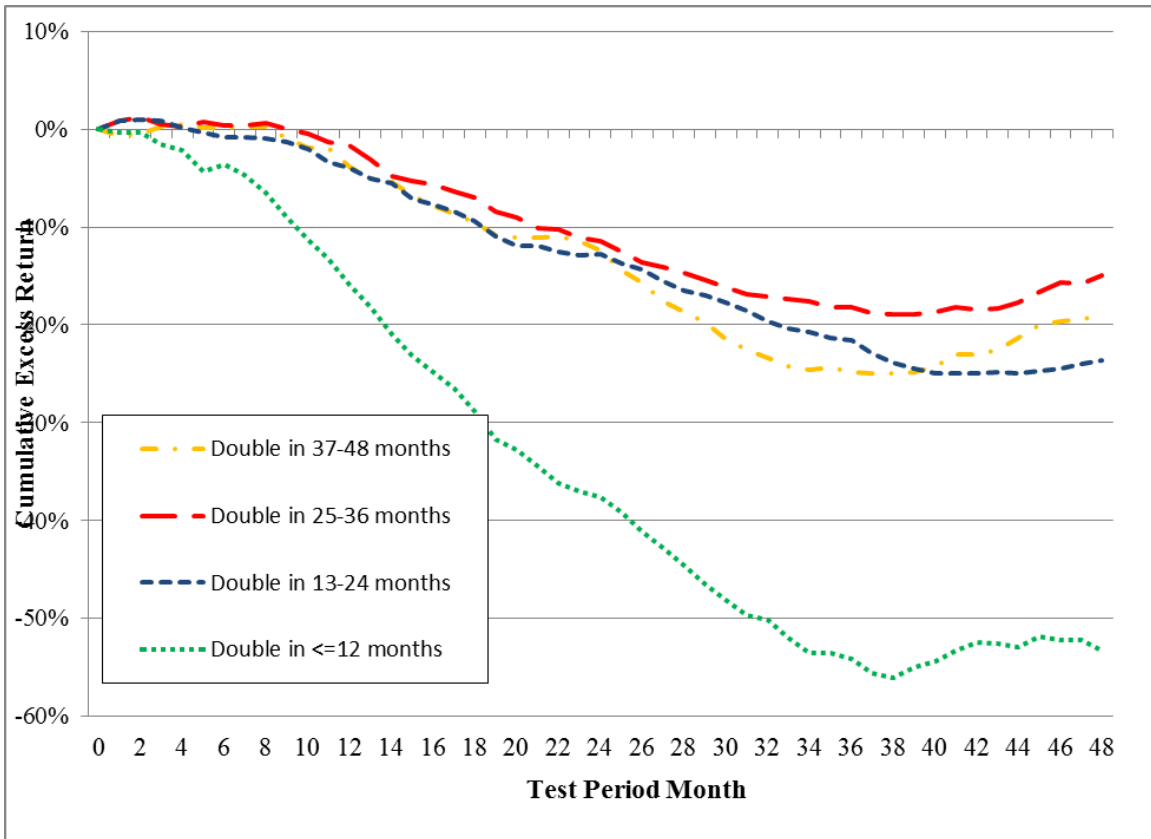


Figure 4

Test Period Cumulative Excess Return: Past Double versus Non-Double

Test period return analysis based on 48 monthly averages of log normal stock price changes in excess of log normal S&P 500 price changes. Month 0 is the start of the test period with zero excess returns. Based on 10,157 firm-observations (sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price) for the entire sample 5,002 firm-observations for the sample that did not double in price during the screening period, "Past Non-Double"; and 5,155 firm-observations for the sample that did double in price during the screening period, "Past Double."

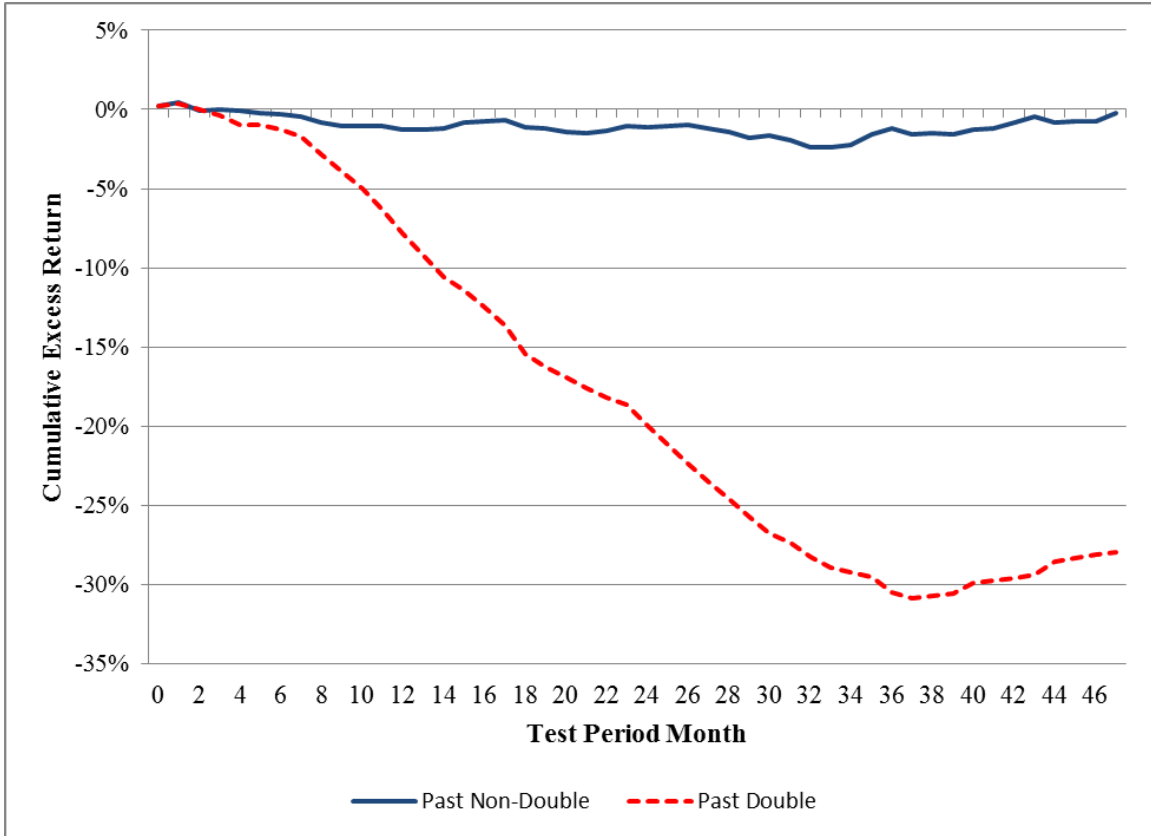


Figure 5

Test Period Cumulative Excess Return: Past Winners/Losers

Test period return analysis based on 48 monthly averages of log normal stock price changes in excess of log normal S&P 500 price changes. Month 0 is the start of the test period with zero excess returns. Based on 10,157 firm-observations (sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price). Firms are sorted based on screening-period returns. The highest 10% and 25% are indicated as “Past Winners” and the lowest 10% and 25% are indicated as “Past Losers.”

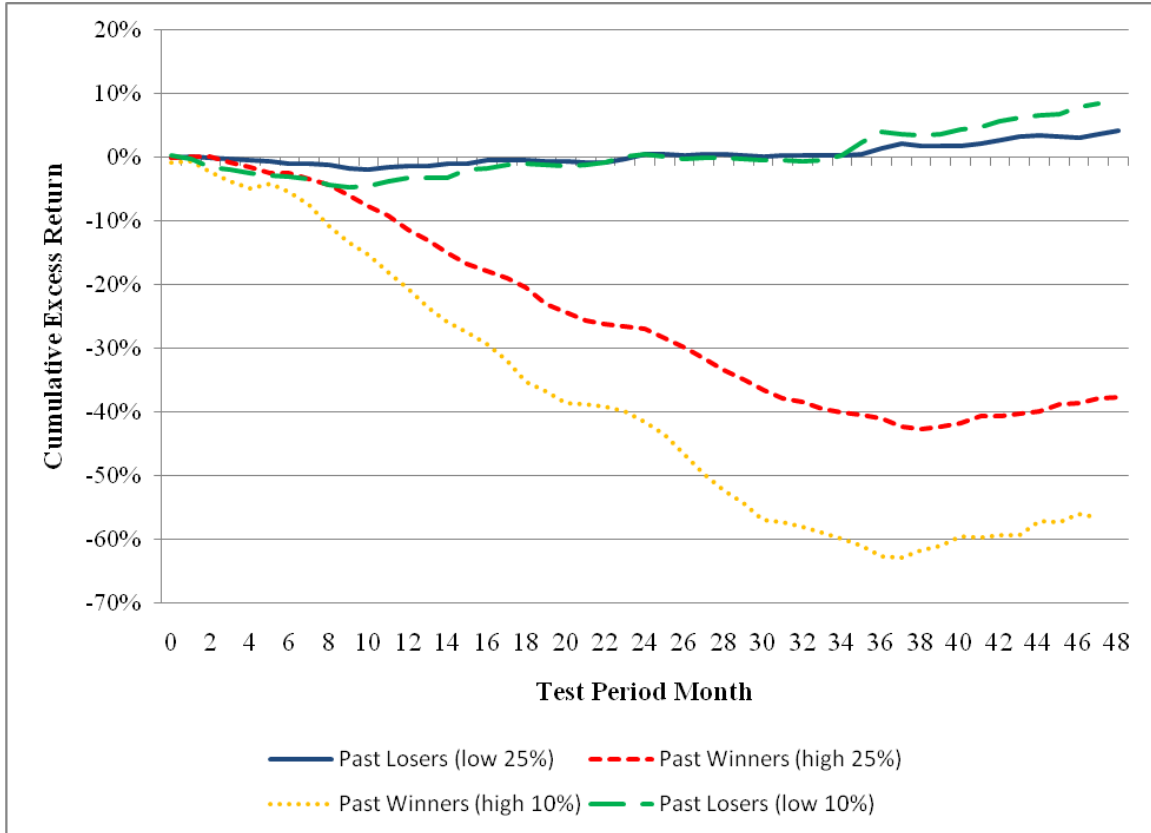


Figure 6

Test Period Cumulative Excess Return: Low/High Probability of Doubling

Test period return analysis based on 48 monthly averages of log normal stock price changes in excess of log normal S&P 500 price changes. Month 0 is the start of the test period with zero excess returns. Based on 10,157 firm-observations (sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price). Firms are sorted based on probit model probability of doubling in the test period. The highest 10% and 25% are indicated as “High Double Prob” and the lowest 10% and 25% are indicated as “Low Double Prob.”

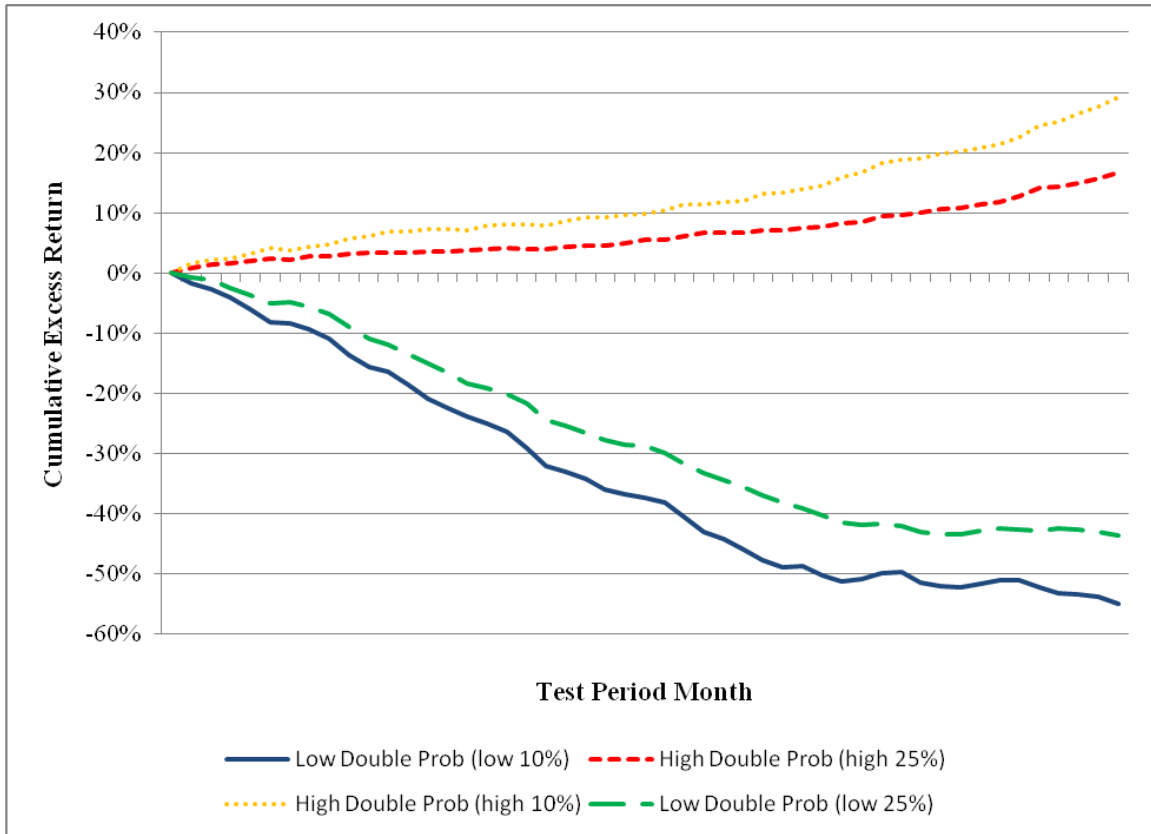


Figure 7

Test Period Cumulative Excess Return: Past Double/Non-Double Sub-period Results

Test period return analysis based on 48 monthly averages of log normal stock price changes in excess of log normal S&P 500 price changes. Month 0 is the start of the test period with zero excess returns. Based on 10,157 firm-observations (sample that includes the additional restriction of a minimum \$5.00 end-of-screen-period share price) for the entire sample. The sample that did not double in price during the screening period, "Past Non-Double"; and the sample that did double in price during the screening period, "Past Double" are presented separately for three sub-periods (based on the end-of-screen date): pre-1995 (3,524 observations), 1996-2002 (3,376 observations), and post-2002 (3,258 observations).

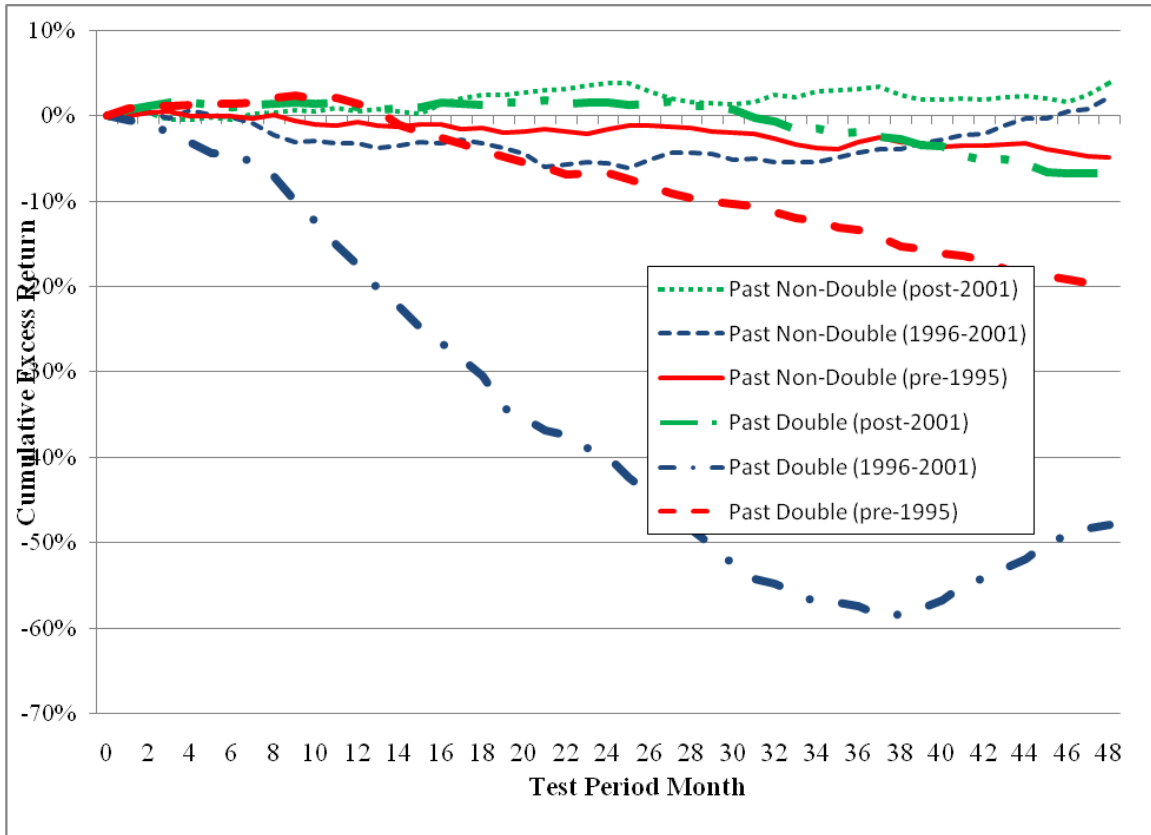


Figure 8

Comparison of “Fastest Doubling” Portfolio with DeBondt and Thaler “Winner” Portfolio

Replication of DeBondt and Thaler’s (1985) Figure 1: cumulative average residuals (CAR) for Winner and Loser portfolios of 35 stocks (indicated as D-T Winner Portfolio and D-T Loser Portfolio, respectively); 1-36 months into the test period with a three-year formation period; average of 16 three-year test periods between January 1933 and December 1980. The Winner portfolio is compared to a portfolio of up to 35 stocks that have doubled in price the quickest as of the end of the formation period (Fastest Doubling Portfolio).

