Prospect Theory, Mental Accounting, and Momentum *

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Abstract

The tendency of some investors to hold on to their losing stocks, driven by prospect theory and mental accounting, creates a spread between a stock's fundamental value and its equilibrium price, as well as price underreaction to information. Spread convergence, arising from the random evolution of fundamental values and updating of reference prices, generates predictable equilibrium prices that will be interpreted as possessing momentum. Cross-sectional empirical tests are consistent with the model. A variable proxying for aggregate unrealized capital gains appears to be the key variable that generates the profitability of a momentum strategy. Past returns have no predictability for the cross-section of returns once this variable is controlled for.

One of the most well-documented regularities in the financial markets is that investors tend to hold on to their losing stocks too long and sell their winners too soon. Shefrin and Statman (1985) labelled this the "disposition effect." It has been observed in both experimental markets and financial markets (e.g., stock, futures, options, and real estate), and appears to influence investor behavior in many countries.

Kahneman and Tversky's (1979) theory of choice, "prospect theory," combined with Thaler's (1983) "mental accounting" framework, is perhaps the leading explanation for the disposition effect. The main element of prospect theory is an S-shaped value function that is concave (risk-averse) in the domain of gains and convex (risk-loving) in the domain of losses, both measured relative to a reference point. Mental accounting provides a foundation for the way that decision makers set reference points for the accounts that determine gains and losses. The main idea is that decision makers tend to segregate different types of gambles into separate accounts, and then apply prospect theory to each account by ignoring possible interactions.

It is fairly easy to see that if the relevant accounts are profits in individual stocks, prospect theory and mental accounting (PT/MA) generates a disposition effect. The reason is that PT/MA investors are risk averse over gambles for some stocks and risk loving in gambles for others. The distinction between risk attitudes towards these two classes of stocks is driven entirely by whether the stock has generated a paper capital gain or a paper capital loss.

Consider Figure 1, which plots the S-shaped value function of a PT/MA investor for outcomes in a particular stock. Let us analyze how this S-shape alters traditional investment behavior. The curve above the point labelled "reference point" has the shape of power utility. For true power utility, the fraction of wealth invested in the stock is increasing in the stock's expected return, but is unaffected by the (initial wealth) starting point. How is this demand function shifted by the substitution of a convex utility function to the left of the inflection point? Comparing a starting position at Point D with Point C in Figure 1, one can infer that demand is increased more at Point C. If we start from Point D, gambles rarely end up in the convex portion of the curve. Indeed, for any given positive mean return, demand increases as the starting position moves left of point D because gambles experience an increasing likelihood of outcomes in the convex portion of the value function. This pattern of larger demand (for a given mean) as the starting position moves left continues as our starting position crosses the inflection point and moves into the convex region. Clearly, the critical determinant of demand is the starting position in the value function.

When the relevant mental accounts employ the cost basis in a stock as the reference point, the starting positions are dictated by the unrealized capital gain or loss in the stock. Stocks that are extreme winners start the investor at Point D. Stocks that are extreme losers start the investor at Point A, and so forth. It follows that a PT/MA demand function differs from that of a standard utility investor not just because winners are less desirable than losers, other things equal. One also concludes that there is a greater appetite for large losers (point A) than for small losers (point B). Moreover, there is a lesser desire to shun small winners (point C) than large winners (point D) because of the greater degree to which realizations in the convex region enter the expected value calculation.

This paper considers a model of equilibrium prices in which a group of investors is subject to PT/MA behavior. These investors have demand distortions that are inversely related to the unrealized profit they have experienced on a stock. Their demand functions distort equilibrium prices relative to those predicted by standard utility theory. The price distortion will depend on the degree to which the marginal investor experiences the stock as a winner or a loser. A stock that has been privy to prior good news has excess selling pressure relative to a stock that has been privy to adverse information. If demand for a stock by rational investors is not perfectly elastic, then such a demand perturbation, induced by PT/MA, tends to generate price underreaction to public information. This produces a spread between the fundamental value of the stock – its equilibrium price in the absence of PT/MA investors – and the market price of the stock. In equilibrium, past winners tend to be undervalued and past losers tend to be overvalued.

The model's price distortions translate into return distortions. To obtain forecastibility in the cross-section of "risk-adjusted" stock returns, there needs to be a mechanism for undervaluation or overvaluation to diminish over time. Investor heterogeneity is the mechanism the model uses to achieve this. (There are other, more artificial mechanisms that can generate a tendency towards a rational model's valuation over time. A liquidation at a finite horizon is one such alternative mechanism, but we doubt that the effects from such an alternative approach are quantitatively detectable. Dividend streams, a partial liquidation, are subject to the same criticism.) Investor heterogeneity with respect to PT/MA behavior leads to differing demand functions and hence trades of a type consistent with the disposition effect. As this disposition effect trading occurs, the cost bases across investors change as does an appropriate aggregation of the cost basis for the economy as a whole. On average, the dynamics of this process tend to reduce the absolute spread between the aggregate cost basis and the market price. Once this reduction in spread occurs, the market price in the next trading round reverts towards its fundamental value.

One implication is that we expect to see momentum in stock returns. The model predicts that any variable which captures the unrealized capital gain experienced by the marginal PT/MA investor will also be a predictor of the cross-section of expected returns. Stocks with high past returns tend to have positive unrealized capital gains for most investors while low past return stocks are more likely to have generated unrealized capital losses.

The model distinguishes itself from others that explain momentum in predicting that (one-period) lagged capital gains are sufficient statistics for forecasting the cross-section of returns. Any other metric of a winner or loser effect will be a noisy proxy for the true capital gain metric. For example, momentum (as well as the disposition effect) can simply be generated by a belief that stock prices revert to a particular value, like the stock price observed one year ago. In such an alternative model, demand pushes the equilibrium price of 1-year winners downward, relative to fundamentals, etc. Here, mean reversion is inferred solely from the 1-year past return, without reference to the capital gains or losses of investors in each stock. If such an alternative were true, a capital gain-based variable will not be the best predictor of the cross-section of stock returns. Instead, a variable representing the gap between the current price and the reversion price would dominate as a forecasting variable.

It is the pattern of past returns, combined with pattern of past trading volume, that determines whether the stock has experienced an aggregate unrealized capital gain or a loss. Because of this, proxies for aggregate capital gains (losses) should be better than past returns as predictors of future returns. Thus, one way to test our model and the importance of PT/MA is to run a horse races between capital gains and past return variables as predictors of future stock returns.

The empirical implications of our model, outlined above, are verified with cross-sectional "Fama-MacBeth" regressions. Motivated by mental accounting, an estimate of the aggregate cost basis for a given stock is used as a proxy for its aggregate reference price. In all of our regression specifications, the capital gains variable thus defined predicts future returns, even after controlling for the effect of past returns, but the reverse is rarely true. Indeed, the return-based momentum effect disappears once the PT/MA disposition effect is controlled for with a regressor that proxies for the aggregate capital gain.

The rest of this paper is organized as follows. In Section 1, we discuss a model that captures the intuition discussed above and explore its testable implications. Section 2 presents empirical data and provides numerous tests illustrating that our findings are not due to omitted variables that others have used in the literature to analyze momentum. Our main finding here is that the capital gains overhang is a critical variable in any study of the relation between past returns and future returns, as the theory predicts. It also discusses additional implications of the model that have been tested by others. Section 3 concludes the paper.

1 The Model

This section analyzes how PT/MA-inspired demand functions alters the equilibrium price path of a single risky stock (in an economy with many assets). We assume

- The risky stock is in fixed supply, normalized to one unit.
- Public news about the date t fundamental value of the stock, F_t, arrives just prior

to the date t round of trading. The fundamental value is the fully rational price that would prevail if there was no PT/MA behavior in the economy.

- The fundamental value follows a random walk:

$$F_{t+1} = F_t + \epsilon_{t+1}.$$

  This equation generates a convenient benchmark for analyzing the PT/MA-induced alteration of the price path. With appropriate mental accounts for drift, or if the drift is paid out as a dividend, any other benchmark for fully rational price dynamics would generate identical findings about the price path alteration induced by PT/MA behavior.

The economy has two investor types: one is not subject to the PT/MA demand at all. This is a simple way of representing the investor heterogeneity needed for reference price updating. It also has the virtue of demonstrating that rational investors cannot undo the equilibrium. The PT/MA investors, a fixed fraction μ of all investors, have relatively greater (lesser) demand for stocks on which they have experienced losses (gains). The assumed demand functions are

$$\begin{array}{rrcl} \text{PT/MA demand:} & \mathrm{D}_t^{PT/MA} & = & 1 + b_t[(F_t - P_t) + \lambda(R_t - P_t)] \\ \text{rational demand:} & \mathrm{D}_t^{rational} & = & 1 + b_t(F_t - P_t), \end{array}$$

where P_t is the price of the stock; R_t, known prior to date t trading, is a reference price relative to which PT/MA investors measure their gains or losses; λ is a positive constant that measures the relative importance of the capital gain component of demand for PT/MA investors, and b_t represents the slope of the rational component of the demand functions for the stock.

To obtain closed-form solutions for the equilibrium, the PT/MA investor-type exhibits a constant geometric perturbation of the rational type's demand function. This modeling device allows us to avoid solving for the rational demand function. Instead, we obtain a closed form solution for the deviation of a stock's market price from the equilibrium price that would prevail if everyone is rational. This is fully appropriate if we only wish to study the marginal effect of PT/MA behavior on the time-series properties of any equilibrium price path. The process by which the market arrives at a fundamental value in an intertemporal multi-asset economy can be quite complicated, but that is not our concern.

In this regard, it is useful to think of b_t as being whatever solves for the optimal rational demand function given a utility function. It does not generally imply linear demand because b_t can be a complex function, depending for example on how the return properties of all investments affect utility. The solution to rational investor demand may affect the fundamental value; beyond this, however, it is not relevant to the model.[1] Consistent with the limits to arbitrage argument, we assume b_t is finite. (The assumption that rational agents' demands are not perfectly elastic is consistent with every utility function and every numerical simulation we have explored. This assumption generally arises from the risk aversion in utility functions, but it may also reflect liquidity, incomplete information, capital constraints, or other forces restraining unlimited trade by investors. See Shleifer and Vishny (1997) for a thorough discussion of this issue. Among others, Harris and Gurel (1986), Shleifer (1986), Loderer, Cooney and Van Drunen (1991), Kaul, Mehrotra and Morck (1999) and Wurgler and Zhuravskaya (2000) all provide empirical support for finite price elasticity (1997).)

By aggregating investors' demand functions and clearing the market, we find that the equilibrium market price is a weighted average of the fundamental value and the reference price:

$$P_t = wF_t + (1-w)R_t, \quad \text{where } w = \frac{1}{1+\mu\lambda}.$$

Since $0 < w < 1$, the market price underreacts to public information about the fundamental value, holding the reference price constant. The degree of underreaction, measured by w, depends on the proportion of PT/MA investors, μ, and the relative intensity of the demand perturbation induced by PT/MA, λ. The fewer the number of PT/MA investors, and the smaller the degree to which each perturbs demand, the closer the market price will be to its fundamental value.

Each PT/MA investor is assumed to use a mental account that is separate for each stock. If the relevant reference price is the cost basis for the shares he acquired of that stock, that reference price gets updated as shares are exchanged between the investor-types each period. New reference prices are thus weighted averages of old reference prices and the prices at which new shares trade.

$$R_{t+1} = V_t P_t + (1-V_t)R_t. \tag{1}$$

This means that the reference price has a tendency to revert to the current market price. Since the latter is a weighted average of the fundamental value and the reference price, it is ultimately the fundamental value to which the reference price is reverting to. We believe that the updating weight, V_t, should be related to the stock's turnover ratio, since the cost basis is the reference price that motivates the mental account. However, our theoretical results would generalize if another mechanism for reference price updating were equally plausible.

[1]The irrelevance of b_t to all but the fundamental value allows one to alternatively define b_t as the solution to the equilibrium demand of rational investors who have full knowledge of the existence of PT/MA disposition investors. An example in which we explicitly solve for such b_t in a multiperiod exponential utility model for a single asset market is available from the authors. The existence of an equilibrium here illustrates that arbitrageurs do not fully counter the effect PT/MA behavior on the equilibrium, even when they are aware of it.

With w a constant, the dynamics of the market price can be expressed as

$$P_{t+1} - P_t = w(F_{t+1} - F_t) + (1 - w)(R_{t+1} - R_t) \tag{2}$$

Expected changes in F are zero (by definition), while equation (1) implies that expected changes in R are of the same sign as the gain – the difference between the market price and the reference price. In the absence of a mechanism for the reference price to change, there is no expected price change. However, heterogeneity in the degree to which investors are subject to PT/MA, of any variety, induces trades and revises the cost basis of the shares in an investor's portfolio.[2] This process of trading redefines the unrealized gains and losses of investors who trade in the stock. When we aggregate across investors, we find that news, on average, tends to make the market's effective reference price for a stock's aggregate capital gain converge to the stock's market price. The reference price updating also leads both the market price and the reference price to revert to the fundamental value.

Equation (2) suggests that the expected change in the stock's price from t to $t+1$ is proportional to the change in the reference price that has been generated by trading at date t. This, in turn, depends on the size of the unrealized capital gain and the fraction of shares that just changed hands. That is, from equations (1) and (2),

$$\mathrm{E}_t[P_{t+1} - P_t] = (1 - w)V_t(P_t - R_t)$$

which is equivalent to

$$E_t\left[\frac{P_{t+1} - P_t}{P_t}\right] = (1 - w)V_t\ \frac{P_t - R_t}{P_t}. \tag{3}$$

This equation suggests that a stock's expected return is monotonically increasing in the marginal investor's (percentage) unrealized capital gain, $(P_t - R_t)/P_t$. Also, for a fixed sized gain or loss, high current turnover implies that the forecasted absolute return is larger. This is because with high current turnover, next period's unrealized gain or loss is likely to be smaller, shifting next-period's aggregate demand function closer to the rational benchmark. This abrupt shift in demand generates an end-of-period equilibrium price that is closer to the fundamental value, giving rise to a large forecasted absolute return.

Equation (3) also has implications for momentum in stock returns. Since a stock's capital gain is likely to be correlated with its past return, the past return is a noisy proxy

[2]A contemporaneous theoretical paper by Weber and Zuchel (2001) argues that a single asset market with a representative investor possessing demand that is linear in mean/variance as well as the deviation of a fixed reference price from the market price will exhibit positive return autocorrelation. With a finite horizon, information about the final liquidation payoff gets more precise over time. The assumed impact of the PT/MA behavior thus decreases monotonically, and the stock price converges deterministically to the fundamental value.

for the unrealized aggregate capital gain that PT/MA investors are experiencing in a stock. With reasonable parameters, our model can generate the empirically observed momentum profit.[3] The model also suggests that the portfolio formation horizon over which momentum is likely to be strongest is an intermediate one. We have confirmed the hump shape of the intensity of the momentum effect as a function of horizon with numerical simulations of the model. However, the intuition for the horizon effect is very simple. If the portfolio formation horizon is very short, extreme decile portfolios, constructed from stocks with extreme returns, can only have small differences in their capital gains and losses. The flow of information over short horizons is often too small to generate large differences in capital gains (or returns) across stocks. The top and bottom decile past return performers have larger differences in past returns the longer the past return horizon. However, the spreads for capital gains within these same extreme return decile portfolios do not exhibit the same monotonicity with respect to horizon length. The tendency for the gain, $P_t - R_t$, to revert to zero is quite strong at long horizons: Positions in large losers get replenished with additional shares at more recent market prices and winners tend to be sold. Hence, there is very little dispersion in the paper gain or loss in the top and bottom decile past return performers over a long past return horizon.

2 Empirical Analysis

We test the theoretical model's price dynamics, expressed in equation (3), by analyzing the relationship between aggregate capital gains and the cross-section of expected returns.[4] Lacking information on who the PT/MA investors are, we simply estimate a proxy for the market's unrealized gain in a stock and assume it is the relevant reference price for the mental account.

Our estimate of this critical variable is

$$R_t = \sum_{n=1}^{\infty} \left(V_{t-n} \prod_{\tau=1}^{n-1} [1 - V_{t-n+\tau}] \right) P_{t-n} \tag{4}$$

where V_t is date t's turnover ratio in the stock. Note that the term in parentheses

[3] An earlier draft of this paper demonstrates this. That draft also contains a (non-trivial) analytic proof that momentum in stock returns will arise in our model. The proof uses the law of iterated expectation and recursively applies equation (1) and equation (2).

[4] The model also suggests multiplying the gain by one-period lagged turnover. The observed empirical relationship between this product and the cross section of returns is essentially the same as those presented here without the gain alone. We largely opt for the more parsimonious representation for both theoretical and empirical reasons. First, the literature has already documented an acceleration of momentum effects for high volume. Our results need to be distinguished from these volume effects. Second, there may be a cross-sectional relation between a firm's typical turnover V and w, which we cannot estimate. We do, however, report some results with this variable later in this section.

multiplying P_{t-n} is a weight and that all the weights sum up to one. The weight on P_{t-n} is just the probability that a share was last purchased at date $t-n$ and has not been traded since then. Note that we obtain the same equation by iteratively applying equation (1). The cost basis for the market used in empirical work is thus consistent with the reference price dynamics expressed in the model.

Our empirical work utilizes weekly returns, turnover (weekly trading volume divided by the number of outstanding shares), and market capitalization data from the Mini-CRSP database. The dataset includes all ordinary common shares traded on the NYSE and AMEX exchanges. NASDAQ firms are not available. The sample period, from July 1962 to December 1996, consists of 1799 weeks, which is the extent of the weekly data sample. Our choice of weekly data arises from the need to have a reasonable proxy for a critical variable, the capital gains overhang. This requires higher frequency data than monthly data provide and transaction prices that are less influenced by market microstructure than daily data provide. Moreover, the volume numbers on the weekly MiniCRSP data set have been revised to make them more reliable (see Lim, Adamek, Lo, and Wang 2003).

2.1 Regression Description

We analyze the average slope coefficients of weekly cross-sectional regressions and their time series t-statistics, as in Fama and MacBeth (1973). The week t return of stock j, $r_t^j = \frac{P_t^j - P_{t-1}^j}{P_{t-1}^j}$, is the dependent variable. Denote $r_{t-t_2:t-t_1}^j$ as stock j's cumulative return from weeks $t-t_2$ to $t-t_1$. The prior cumulative returns over short, intermediate, and long horizons are used as control regressors for the return effects described in Jegadeesh (1990), Jegadeesh and Titman (1993), and De Bondt and Thaler (1985). Regressor s_{t-1}^j, the logarithm of firm j's market capitalization at the end of week $t-1$, controls for the return premium effect of firm size. We also control for the possible effects of volume, including those described in Lee and Swaminathan (2000) and Gervais, Kaniel, and Minelgrin (2001), by including $\bar{V}_{t-52:t-1}^j$, stock j's average weekly turnover over the 52 weeks prior to week t as a regressor (and in later regressions, interaction terms, computed as the product of the former volume variable and extreme quintile return rank dummies). We then study the coefficient on g_{t-1}^j, a capital gains related proxy. Formally, we analyze the regression,

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 g \tag{5}$$

and variants of it, where, for brevity, we have dropped j superscripts and t subscripts.

Our proxy for the capital gains overhang at the beginning of week t, is

$$g_{t-1} = \frac{P_{t-2} - R_{t-1}}{P_{t-2}}.$$

Theory says that this key regressor should employ P_{t-1} instead of P_{t-2}. We lag the market price by one week to avoid confounding market microstructure effects, such as bid-ask bounce.

We estimate the aggregate reference price, R_t, based on equation (4). Obviously, it is not practical to use an infinite sum. Recognizing that distant market prices have little influence on the reference price, we truncate the estimation at five years and rescale the weights to sum to one. This allows us to estimate the reference price in a consistent manner across the sample period. The five-year cutoff, while arbitrary, admits a reasonable portion of our sample period: July 1967 on. Stocks that lack at least five years of historical return and turnover data at a particular week are excluded from the cross-sectional regression for that week. We verified that our regression results remain about the same when return and turnover data over three or seven prior years are used to calculate the aggregate reference price.

2.2 Summary Statistics

Figure 2 plots the weekly time series of the 10th, 50th, and 90th percentile of the cross-section of the capital gain overhang of stocks traded on NYSE and AMEX. It indicates that there is wide cross-sectional dispersion in this regressor and a fair amount of time series variation as well. The time series average (median) of the difference between the 90th percentile and 10th percentile of the cross-section of the capital gain variable between July 1967 and December 1996 is 76% (60%). For most firms, the time series of this variable exhibits significant comovements with the past returns of the S&P 500 index. The correlations of the above three percentiles with the past one-year percentage change in the S&P 500 index are respectively 0.50, 0.60, and 0.62.

Table 1 Panel A reports summary statistics on each of the variables used in the regression described above. These include time series means and standard deviations of the cross-sectional averages of the dependent and independent variables, along with time series means of their 10th, 50th and 90th percentiles. We obtain further insight into what determines the critical capital gains regressor by regressing it (cross-sectionally) on stock j's cumulative return and average weekly turnover for three past periods: very short term (defined as the last four weeks), intermediate horizon (between one month and one year ago) and long horizon (between one and three years ago). Size is also included as a control regressor.

Panel B of Table 1 reports that, on average, about 59% of the cross-sectional variation in the capital gain variable can be explained by differences in past returns, past turnover, and firm size. As we explained in section 1, the reference price is always trying to catch up to the market price that deviates from the reference price for large return realizations. Moreover, the higher the turnover, the faster the reference price converges to the market price. Consistent with these facts, Panel B shows that our capital gains variable is positively related to past returns and negatively related to past turnover.[5] Controlling for past returns, a low volume winner has a larger capital gain. Also, consistent with our explanation of why intermediate horizons are most important, we find that the effect of intermediate horizon turnover on the capital gains variable is much stronger than the effect of turnover from the other two horizons. Finally, the size coefficient in this regression is significantly positive, perhaps reflecting that large firms have grown in the past at horizons not captured by our past return variables and thus tend to have experienced larger capital gains.

2.3 Double Sorts

Recall that in our model, the risk-adjusted expected return of a stock is determined only by its capital gain overhang. Past returns, which are correlated with the capital gain variable, also predict risk-adjusted returns, but should be noisier predictors. As an initial test of this implication, we study the average returns of portfolios obtained by double sorting both on past 1-year returns and the capital gain overhang variable. The double sort is done in two ways. In Panel B of Table 2, stocks are first sorted by their past 1-year return into five portfolios labeled as $R1$ (losers), ..., $R5$ (winners). Within each past return quintile, stocks are further sorted into five portfolios by their capital gains overhang from the lowest to the highest quintile $G1$, ..., $G5$. Panel C reverses the sort order.

Table 2 Panel A reports the time series average of the cutoff values for the capital gain quintiles within each past 1-year return sort, and the cutoff values for the past 1-year return quintiles within each capital gain sort. The capital gain and past 1-year return are positively correlated, but there is substantial independent variation.

Panels B and C of Table 2 report the average returns of 25 equally-weighted portfolios formed on the two double sorts. Januarys are reported separately from non-January months. Consistent with our model's prediction, Panel B shows that during non-January months, for each given past return quintile, the average returns of portfolios increase monotonically with their capital gain overhang quintile. Moreover, the differences between the returns of the highest and lowest capital gain quintiles within each of the past return quintiles is generally significant, ranging from about 0.12% to 0.25% per week (about 6% to 13% per annum).[6] Panel C indicates that the reverse is not true: the difference between extreme winner and loser quintile portfolios within a given capital

[5]The time series mean, median and standard deviation of the cross-sectional correlation between a firm's capital gains overhang and past 1-year return are 0.5482, 0.5529 and 0.1250, respectively.

[6]We classify a week as belonging to a particular calendar month if it ends in that month. If we exclude the 30 weeks during our sample that begin in January and end in February from the calculation of average portfolio return during February to December, the lone insignificant $t-$statistic (for the mean return of the portfolio of high minus low capital gains stocks among the loser quintile) also becomes significant.

gain quintile is generally not significant.

The portfolio returns during the January months are not consistent with a stable PT/MA parameter λ. Within Panel B's past returns quintile, the January returns of high capital gain stocks tend to be below those of the low capital gain stocks. This may reflect a December tax-loss selling effect, as we discuss later. It may also reflect a size effect, since the capital gains variable loads positively on the size of the firm. Double sorting cannot explicitly control for other variables that influence the expected return and it is impractical to sort on three or more variables. To control for these alternative hypotheses, we further test our model with regression analysis and analyze December and January separately from February through November.

2.4 Expected Returns, Past Returns, and the Capital Gain Overhang

Table 3 presents the average coefficients and time-series t-statistics for the regression described by equation (5) and variations of it that omit certain regressors. Each panel reports average coefficients and test statistics for all months in the sample, for January only, for February-November only, and for December only.[7] All panels include the firm size regressor. Panel A adds only the three past return regressors. Panel B adds volume as a regressor to the four regressors from Panel A. Panel C adds the capital gains overhang to the regressors from Panel B.

Panels A and B contain no surprises. As can be seen, when the capital gains overhang variable is excluded from the regression, there is a reversal of returns at both the very short and long horizons, but continuations in returns over the intermediate horizon. Panel B indicates that there is a volume effect, albeit one that is hard to interpret, but it does not seem to alter the conclusion about the horizons for profitable momentum and contrarian strategies.

Panel C is rather astounding, however. When the capital gains overhang regressor is included in the regression, there is no longer an intermediate horizon momentum effect. The coefficient, a_2, is insignificant, both overall and from February through November. However, except for January, there is a remarkably strong cross-sectional relation between the capital gains overhang variable and future returns, with a sign predicted by the model. The estimated average coefficient (0.004) for the capital gain variable from weekly cross-sectional regressions is also consistent with the finding of Jegadeesh and Titman (1993) that momentum strategies generate profits of about 1% per month. Given that the median difference between the 90th and 10th percentile of capital gains is about 60%, it implies that winners outperform losers by about 0.004*60%=0.24% per

[7] We verified that none of the subsequent results change materially if we exclude 89 ambiguous weeks: (i) begin in December and end in January, (ii) begin in January and end in February, and (iii) begin in November and end in December.

week, or 12.5% per year.

2.5 Explaining Seasonalities

The seasonalities observed in Table 3 are consistent with what other researchers have found.[8] Table 3 suggests that they are not due to a calendar-based size effect per se. They are fairly easy to explain, however, within the context of our theoretical model if we accept that there is an additional perturbation in demand arising from tax-loss selling.

Odean (1998), and Grinblatt and Keloharju (2001), for example, found that the disposition effect is weakened or even offset in December by the marginal impact of tax-loss selling. A generalized demand function for the PT/MA investor,

$$\mathrm{D}_t^{PT/MA} = 1 + b_t[(F_t - P_t) + \lambda_t(R_t - P_t)] \tag{6}$$

could plausibly have λ_t drift downward in December and revert to its normal positive value in early January. In this case, we would find that the equilibrium effects of this seasonal demand perturbation would be consistent with our empirical findings. The downward drift in λ in December implies that market prices move closer to fundamental values. For stocks with capital losses, implying that the fundamental value is below the market price, convergence towards the fundamental value from the decline in λ represents an added force that makes the market price decline even further than it would were λ to remain constant. Similarly, the increase in λ in early January would make the prices of these same stocks with capital losses deviate again from their fair values, leading to a January reversal.

To understand this more formally, note that with the generalized PT/MA demand, equation (6), the expected return, formerly in equation (3), generalizes to

$$\mathrm{E}_t\left[\frac{P_{t+1} - P_t}{P_t}\right] = \left((1 - w_t)V_t + \frac{(w_{t+1} - w_t)(1 - w_t V_t)}{w_t}\right)\left(\frac{P_t - R_t}{P_t}\right).$$

where $w_t = \frac{1}{1+\mu\lambda_t}$. Hence, if we know that λ_{t+1} is going to be lower than λ_t, which makes $w_{t+1} - w_t$ positive, the expected return between dates t and $t+1$ is going to be larger. The evidence in Grinblatt and Keloharju (2001) suggests that over the course of December, λ declines to zero (implying $w_t = 1$) but is positive during the rest of the year. Viewed from the end of November, this would be like knowing that w_{t+1} is one and larger than w_t, thus generating a larger coefficient on the gain regressor in December

[8] For example, momentum strategies that form portfolios from past returns over intermediate horizons appear to be most effective in December, and there is a strong January reversal in when portfolio formation uses past returns over any horizon. See, for example, Jegadeesh and Titman (1993), Grundy and Martin (2001) and Grinblatt and Moskowitz (2002).

than would be observed in prior months with $w_{t+1} = w_t < 1$. Viewed from the end of December, w_t is one and larger than w_{t+1}. This makes the expected price change during January negatively related to the gain regressor.

2.6 The Capital Gain Variable and Volume

Could the strength of the capital gains variable as a predictor of returns be due to some alternative explanation? Our gain variable is a volume weighting of past returns and many researchers have documented a connection between volume, past returns, and future returns. Our model's predictions are very specific, however. The largest gain (loss) occurs when there is a lot of volume in the distant past and a large runup (decline) in the stock price with no volume. Because volume is generally quite persistent, it is generally the stocks with low volume that have the most extreme gains for a given past return. If the enhanced precision of the gain proxy from the time series pattern of volume in a stock improves the gain variable's forecasting power, that would be striking evidence in favor of our theory. On the other hand, if the magnitude of the gain coefficient in Table 3 Panel C arises entirely from cross-sectional differences in turnover, there could be some alternative explanation for our results. For example, it may be that the most effective trading strategies for momentum involve portfolio formation from past horizons that are more distant for less liquid stocks. This would be picked up by our gain variable, but it would also be picked up by a gain variable constructed from a reference price that ignores the time series pattern of volume for each stock.

To investigate this issue, we formulate a reference price using the average turnover over the past year in place of each week's actual turnover. In Panels A and B of Table 4, we compute an alternative week t reference price using $\bar{V}_t^j$, firm j's average weekly turnover from weeks $t-52$ to $t-1$, for all of the 260 Vs in equation (4). Panel A replicates Panel C of Table 3, except that in place of the original gain variable, we compute an alternative gain variable using the alternative reference price. As Panel A indicates, using a firm's average turnover for the reference price computation instead of the actual weekly turnover generates a significant coefficient on the gain variable. The results are similar to those of Table 3 Panel C, in that intermediate horizon past returns have no predictive power. Moreover, the coefficients and t-statistics on the alternative gain variable are similar to those in Table 3 Panel C.

Table 4 Panel B runs a horse race between the two gain variables. It is identical to Table 4 Panel A, except that our original proxy for firm j's capital gain as used in Table 3 Panel C is added as a regressor. The inclusion of this variable eliminates the significance of the alternative gain variable, and its coefficient is about the same size as that in Table 3 Panel C in non-January months. While our original gain variable is based on an imperfect model of the a stock's actual capital gain overhang in the market, it is probably a more precise estimate of aggregate capital gains than the alternative capital gains proxy constructed from average historical turnover. The fact that it "knocks out" the alternative gain variable as a predictor of future returns is consistent with more precise estimates of the aggregate capital gain being better predictors of future returns.

The literature has also documented that complicated interactions between volume and past returns improve forecasting. For example, Lee and Swaminathan (2000) find that high volume losers significantly underperform low volume losers. This result is actually consistent with our model, for which volume is a "double-edged sword." High volume in the cross-section tends to reduce the gain. However, this observation ignores the impact of the time series. Our return prediction, found in equation (3), multiplies the gain by last period's volume. Hence, the largest absolute predicted return occurs if there is low volume in the distant past and then high volume again just before trading takes place. The recent updating of the reference prices of PT/MA investors, through trading, shifts their demand functions closer to the rational benchmark in the subsequent round of trading. It is this convergence to the rational benchmark that drives stock return predictability. We did not use this variable in our earlier regressions largely out of concern that it could be reinventing the Lee and Swaminathan variable in another form. However, if it were used in Table 3 Panel C in place of the gain variable it approximately doubles the t-statistic, as indicated in Table 4 Panel C. Again, it knocks out the intermediate horizon past return as a predictor of future returns.

Our model's prediction that recent volume, as a multiplicative interaction term, exacerbates the predictive power of capital gains in the cross-section, is consistent with other empirical findings of Lee and Swaminathan (2000). They find that most of the predictive power of variables that interact trading volume with past returns is attributable to recent changes in the level of trading activity. To assess their variable against ours, Panels D, E, and F of Table 4 add a proxy for the critical Lee and Swaminathan variable to the mix of regressors: the product of a dummy variable for being in the lowest quintile of past one-year returns and the average past one-year turnover.

Table 4 Panel D analyzes the impact of the Lee and Swaminathan regressor in the absence of a capital gain regressor. Consistent with Lee and Swaminathan (2000), the volume-loser quintile interaction variable is significantly negative. However, once the capital gain variable is added to the regression, as in Table 4 Panel E, the Lee and Swaminathan variable becomes insignificant, while the capital gain coefficient is still highly significant. In Panel F, our capital gain-volume interaction variable replaces the capital gain variable. Again, the Lee and Swaminathan variable is insignificant.

2.7 Robustness Checks

To most observers, the first and second half of our sample period present different portraits of the stock market. From July 1967 to March 1982, average returns were low, liquidity was low, and trading costs including commissions were high. The second half of our sample period, April 1982 to December 1996 corresponds to a sea change in the stock market. Beginning in August 1982, average returns and trading volume appeared to explode and trading costs rapidly declined. These subperiods also demarcate an important turning point in the strength of the firm size effect. In the second half of our sample period, size was far less important as a determinant of return premia. Despite these differences, if our theory is part of the core foundation of equilibrium pricing, there should be little difference in the coefficient on our capital gain regressor. Panels A and B of Table 5, which repeat equation (5) for the two subperiods, confirm this hypothesis. There is only about a one standard error difference between the average coefficients on the capital gain regressor in the two subperiods. In both subperiods, the average coefficient is highly significant and positive, while the average coefficient for the intermediate horizon past return is never significant in the presence of the capital gain variable.[9]

We have studied numerous alternative variables that might explain our results. For example, the maximum 52-week stock price has also been suggested as a possible reference price (see, e.g., Heath, Huddart and Lang, 1999). Table 6 Panel A shows that a capital gains proxy constructed using this reference price in the cross-sectional regressions is significantly positive, and it knocks out intermediate horizon past returns as a predictor of future returns. When our original capital gain regressor calculated using the aggregate cost basis for the reference price, as in equation (4), is added as a regressor, it turns out that both capital gains variables are significantly positive (see Table 6 Panel B). This is what we would expect if the model was correct and both variables are imperfect proxies for the theoretical variable.

The significant predictive power of capital gains for future returns is not an artifact of the weekly frequency of the cross-sectional regressions. In Table 7 Panel A, the dependent return variable in the Fama-MacBeth cross-sectional regression is the monthly return (in lieu of the weekly return). As can be seen from Panel A of Table 7, which corresponds to the specification in Panel C of Table 3, the capital gains variable is still significantly positively related to next month's return. Moreover, once the capital gain is controlled for, the past intermediate horizon return loses its predictive power.

In all of the regressions discussed so far, the intermediate horizon past return is measured by the return between one year and one month ago. To accommodate the possibility that the past return effect is more complex, we replace this variable by three distinct past return variables: between 3 months and 1 month ago, between 6 months and 3 months ago, and between 12 and 6 months ago. Panel B of Table 7 shows that none of these intermediate past returns variables have significant predictive power for future returns once the capital gains overhang is controlled for. The seasonal pattern stays the same as in Panel C of Table 3. The same results hold when the intermediate past return regressor is replaced by twelve past returns, each over a four-week period.

[9] Although we do not report this formally in a table, the signs and significance of the capital gain overhang regressor are not drastically altered by restricting the sample to various size quintiles either.

2.8 Additional Implications

Several papers have produced empirical results since the earliest drafts of this paper. These results are extraordinarily consistent with our model.

Our model suggests that expected returns are path dependent. While momentum in stock returns may be an artifact of the PT/MA behavior because past returns are correlated with variables like aggregate capital gains, our model implies that for a given past return, some types of paths will generate higher expected returns than others. Holding past returns constant, the capital gains overhang (or the difference between current price and the aggregate cost basis) is higher in magnitude for consistent winners and consistent losers. Stocks that are consistent winners, or stocks that are at their all-time highs, are more likely to have larger unrealized gains than stocks that have the same past return, achieved through a handful of outstanding months in the distant past. Grinblatt and Moskowitz (2002) find that momentum profits are stronger for consistent winners. George and Hwang (2004) find that profits to a portfolio formation strategy based on nearness to a 52-week high are superior to those based on past returns over a fixed horizon.

Moreover, our model makes unique predictions about trading volume and volatility. Goetzmann and Massa (2003) derive several additional implications of our model for volume and volatility, as well as returns. They find strong empirical support for these implications. For example, in a period of rising prices on average, there is a significant negative correlation between the prevalence of disposition investor trades and turnover or volatility. Consistent with our model's implication, Goetzmann and Massa (2003) find that a behavioral factor capturing the stochastic change in the percentage of disposition investors is significantly negatively related to returns when the capital gains overhang is positive. Further, their results suggest that exposure to this disposition factor seems to be priced.

In our model, stocks with large unrealized capital gains under-react to positive news while stocks with large unrealized capital losses under-react to negative news. When past stock return is used as a proxy for news, our model explains the stock price momentum pattern. Our model also applies to situations when firm-specific information is released such as earnings announcements and analysts' recommendation. Frazzini (2004) examines these cases and find additional support for our model.

For example, consistent with one proposition of our model contained in an earlier draft of this paper, Frazzini (2004) show that post-earnings-announcement drift is significantly higher when the news and the capital gains overhang have the same sign. The magnitude of the post-event drift is directly related to the amount of unrealized capital gains (losses) experienced by the stock holders prior to the event date. Similarly, stocks with large unrealized capital gains display the most severe drift following analysts' recommendation changes.

Frazzini (2004) also confirms that our proxy for the aggregate cost basis as given by equation (4) works very well. First, he documents strong evidence of disposition effect among the mutual fund managers. Then he constructs a measure of reference prices for individual stocks using mutual funds holdings. The alternative capital gain thus obtained produces similar results as the one we use in this paper. In both cases, just as our theory predicts, high capital gain overhang stocks under-react most to earnings news while no-overhang stocks do not display significant post-event drift.

3 Conclusion

Our paper has developed a model of equilibrium asset prices motivated by prospect theory and mental accounting, and consistent with the empirical evidence on the disposition effect. In our model, the differences between a stock's market price and its aggregate cost basis is positively related to the stock's expected future return. On the other hand, past 1-year returns are poorer predictors of future returns. Moreover, momentum strategies are profitable but the profits are path dependent. Our model also explains the link between momentum and turnover as documented in Lee and Swaminathan (2000).

The empirical tests of our model strongly support its main implications. Using double sorts, we find that holding past returns constant, the average returns of portfolios increase monotonically with their capital gain overhang quintile. On the other hand, there is generally no significant difference between the average returns of portfolios sorted on past returns within each capital gains overhang quintile. Using Fama-MacBeth regressions, we find a significantly positive cross-sectional relation between a stock's capital gain overhang and its future stock return. The predictive power of the intermediate horizon past return becomes insignificant once the capital gain is controlled for. In other words, the Jegadeesh and Titman (1993) momentum effect largely disappears. Our results are robust, and cannot be explained by cross-sectional differences in liquidity or the interaction of past returns and turnover.

In the model developed here, fully rational arbitrageurs cannot eliminate the impact of the capital gain on equilibrium prices. Although prices always underreact to news, trying to arbitrage away this underreaction is risky. There are several reasons for this. First, rational investors cannot ascertain when reference prices, and hence market prices, will converge to fundamental values. Market prices can diverge further from their fundamental values before they converge. Second, the fundamental values are unpredictable. Thus, risk averse rational agents will not take infinite positions to get rid of the mispricing. Third, if rational agents have limited capital or a short horizon, their ability to eliminate the impact of PT/MA behavior on prices will be further reduced. For example, Liu and Longstaff (2004) show that arbitrageurs optimally underinvest or even walk away from an arbitrage opportunity when faced with margin requirements. Moreover, DeLong et al (1990) show that when there are positive feedback traders in the economy, rational arbitrageurs who anticipate their impact on demand can front-run the positive feedback investors and may even destabilize prices, rather than help to bring market prices in line with fundamental values.

The high risk associated with the strategy of buying stocks with low reference prices and shorting stocks with high reference prices (relative to market prices) applies even when there are many assets. Within a linear factor model, for example, this naive attempt at arbitrage is not accounting for the fact that the sensitivities to priced and unpriced factors are correlated with reference price discounts/premia. Hence, a portfolio constructed solely on the basis of reference price discounts/premia necessarily has large factor exposure. In empirical work, it will appear as if there is a PT/MA factor.

We have mostly focused on the momentum anomaly here. Clearly, there are other behavioral models that seem to address this issue in interesting ways as well. Daniel, Hirshleifer and Subrahmanyam (1998) present a model where investors are overconfident and also suffer from a self-attribution bias. Their behavior generates delayed overreaction to information which is eventually reversed. Barberis, Shleifer and Vishny (1998) argue that the representative heuristic may lead investors to extrapolate current earnings growth well into the future. At the same time, investors' conservativism bias leads to underreaction to public information. In Hong and Stein (2000), agents can use only part of the information about the economy because of communication frictions. In their model, private information diffuses slowly through the population of investors, which causes underreaction in the short run. Momentum traders can profit by trend-chasing, but cause overreaction at long horizons in doing so.

None of these models have the extraordinary set of predictions found in this model, most of which have been verified. None suggest that aggregate capital gains is the critical variable in forecasting the cross section. None explain why the intermediate past return horizon generates the strongest momentum. Only this simple model is consistent with the work of Goetzmann and Massa (2003), George and Hwang (2004), and Frazzini (2004). Only this model explains the Lee and Swaminathan (2000) results. In addition, none of the previous theories is able to explain the seasonality in the momentum profits, but our model can. Finally, none of these theories predict a disposition effect. Our PT/MA investors are responsible both for momentum and disposition behavior, which is perhaps the most well-documented empirical regularity.[10]

Perhaps the most promising avenue for further research is the implications this model has for volume. Most equilibrium models have no trade in them. Our behavioral model is an exception. We have not explored the volume implications empirically, but they are interesting. Volume turns out to be a path dependent function of movements in the fundamental value. The greatest volume is found when there is a sudden price drop

[10]See, for example, Shefrin and Statman (1985), Case and Shiller (1988), Ferris, Haugen, and Makhija (1988), Odean (1998), Weber and Camerer (1998), Heath, Huddart, and Lang (1999), Grinblatt and Keloharju (2001), Genesove and Mayer (2001), Shapira and Venezia (2001), Kaustia (2001), Wermers (2003) and Frazzini (2004).

after a large and long-lasting price run-up. Although some researchers have begun to study the volume implications of the model, the volume implication discussed above is one of a number of volume implications that are yet to be explored.

Table 1: Summary Statistics

This table reports summary statistics of weekly data on NYSE and AMEX securities from July 1967 to December 1996, obtained from mini-CRSP. Panel A provides time series averages of the cross-sectional mean, median, standard deviation, and 10th, 50th, and 90th percentiles of each of the variables used in the regression

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + +a_5 s + a_6 g$$

where r is the week t return, $r_{-t_1:-t_2}$ is the cumulative return from week $t - t_1$ through $t - t_2$; $\bar{V}$ is the average weekly turnover ratio over the prior 52 weeks, the ratio of the week's share volume to the number of outstanding shares; s is log(market capitalization) measured at the beginning of week t; g is the capital gains regressor, computed as one less the ratio of the beginning of week $t-1$ reference price to the end of week $t-2$ price, where the week $t-1$ reference price is the average cost basis calculated from the formula

$$R_{t-1} = \frac{1}{k} \sum_{n=1}^{260} \left(V_{t-1-n} \prod_{\tau=1}^{n-1} [1 - V_{t-1-n+\tau}] \right) P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one. Panel B presents more detailed data on the association between the capital gains regressor and other variables. It contains the time-series average of the coefficients and their associated time series t-statistics for 1539 weekly Fama-MacBeth type cross-sectional regressions of the form

$$g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{-4:-1} + a_5 V_{-52:-5} + a_6 V_{-156:-53} + a_7 s$$

where $V_{-t_1:-t_2}$ is the average weekly turnover from $t - t_1$ through $t - t_2$. R^2_{adj} is the average of the weekly cross-sectional regression R^2s adjusted for degrees of freedom.

Panel A: Time series average of summary statics of the regressors in the regression

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 g$$

	$r_{-4:-1}$	$r_{-52:-5}$	$r_{-156:-53}$	$\bar{V}$	s	g
Mean	0.0119	0.1493	0.3487	0.0092	18.7207	0.0560
Median	0.0045	0.0940	0.2098	0.0072	18.7251	0.1062
Std	0.1073	0.4192	0.7585	0.0079	1.9441	0.2508
10 percentile	-0.0959	-0.2538	-0.3227	0.0025	16.1399	-0.2810
90 percentile	0.1223	0.5816	1.1097	0.0181	21.2322	0.3122

Panel B: Average coefficients and t-statistics (in parentheses) for the regression
$$g = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{-4:-1} + a_5 V_{-52:-5} + a_6 V_{-156:-53} + a_7 s$$

a_1	a_2	a_3	a_4	a_5	a_6	a_7	R^2_{adj}
0.5527	0.4907	0.1771	-0.9159	-6.4051	-2.7843	0.0504	0.5879
(73.0290)	(51.7965)	(37.5209)	(-7.6351)	(-45.0322)	(-27.8215)	(55.9642)	

Table 2: Average Returns of Portfolios Sorted on Past Returns and Capital Gains

This table reports the average weekly return of portfolios sorted on both past one-year return and the capital gains overhang variable. Panel A reports summary statistics that describe the distribution of 50 portfolio generated by the double-sort criteria. The left half reports the average gain associated with the cutoff gain percentile after first sorting into quintiles based on the past 1-year return; the right half reports the past return associated with 4 cutoff return percentiles after first sorting into quintiles based on the capital gain. Each week, all stocks traded on NYSE and AMEX with 5 years of prior data are double sorted in two ways. In Panel B, stocks are first sorted into quintiles based on their past 1-year return: $R1$(losers), ..., $R5$(winners). Within each past return quintile, stocks are further sorted into 5 equally-weighted portfolios by their capital gains overhang: $G1$ (lowest), ..., $G5$ (highest). Panel C reverses the sort order. The sample period is from July 1967 to December 1996. $t-$statistics are reported in parentheses.

Panel A: Time Series Average of Gain/Past Return for Cutoff-Percentiles of Double Sorts

Cutoff	Gain for cutoff percentile					Past 1-year return for cutoff percentile				
Percentile	R1	R2	R3	R4	R5	G1	G2	G3	G4	G5
20%	-0.6352	-0.2553	-0.0907	0.0132	0.0948	-0.3082	-0.1414	-0.0273	0.0804	0.2298
40%	-0.4011	-0.1023	0.0334	0.1216	0.2020	-0.2038	-0.0516	0.0630	0.1765	0.3638
60%	-0.2423	-0.0056	0.1103	0.1897	0.2753	-0.1059	0.0375	0.1553	0.2795	0.5220
80%	-0.1014	0.0834	0.1803	0.2556	0.3525	0.0320	0.1718	0.3019	0.4466	0.7859

Panel B: Mean Portfolio Return: First Sort on Past 1-year Return

Average	January					February-December				
Return	R1	R2	R3	R4	R5	R1	R2	R3	R4	R5
G1	0.0280	0.0221	0.0200	0.0190	0.0185	0.0007	0.0010	0.0009	0.0017	0.0015
	(6.6595)	(7.0545)	(6.6434)	(6.9072)	(6.3635)	(0.9502)	(1.5026)	(1.4741)	(2.5651)	(2.0121)
G2	0.0203	0.0133	0.0130	0.0112	0.0108	0.0013	0.0015	0.0019	0.0023	0.0028
	(5.8051)	(5.2044)	(6.0074)	(4.9437)	(4.4362)	(1.8056)	(2.5014)	(3.3143)	(3.8856)	(3.8803)
G3	0.0158	0.0110	0.0097	0.0091	0.0088	0.0010	0.0021	0.0023	0.0026	0.0034
	(5.5196)	(4.6749)	(4.8941)	(4.7914)	(3.8287)	(1.3886)	(3.7149)	(4.3071)	(4.7599)	(5.1018)
G4	0.0133	0.0097	0.0071	0.0058	0.0075	0.0013	0.0020	0.0023	0.0028	0.0036
	(4.9083)	(4.3987)	(3.8552)	(3.2502)	(3.6064)	(1.9823)	(3.7639)	(4.4642)	(5.2575)	(5.4608)
G5	0.0104	0.0065	0.0057	0.0035	0.0062	0.0015	0.0020	0.0026	0.0030	0.0041
	(4.6832)	(3.5666)	(3.3550)	(2.0306)	(2.9009)	(2.4505)	(3.8347)	(5.1891)	(5.6310)	(6.1472)
G5-G1	-0.0175	-0.0155	-0.0143	-0.0154	-0.0123	0.0008	0.0010	0.0017	0.0012	0.0026
	(-6.5141)	(-7.6702)	(-6.2049)	(-7.4544)	(-5.5134)	(1.6146)	(2.6852)	(4.8102)	(3.3838)	(6.7453)

Panel C: Mean Portfolio Return: First Sort on Capital Gains

Average Return	January					February-December				
	G1	G2	G3	G4	G5	G1	G2	G3	G4	G5
R1	0.0225	0.0134	0.0096	0.0064	0.0038	0.0007	0.0015	0.0019	0.0021	0.0026
	(5.5684)	(5.0817)	(4.5359)	(3.5626)	(2.3398)	(0.8731)	(2.2777)	(3.3185)	(4.1417)	(5.2192)
R2	0.0219	0.0130	0.0099	0.0074	0.0036	0.0012	0.0016	0.0022	0.0023	0.0028
	(6.4120)	(5.0721)	(4.5740)	(4.0176)	(2.0662)	(1.6494)	(2.5961)	(4.1083)	(4.5382)	(5.5472)
R3	0.0216	0.0127	0.0107	0.0074	0.0044	0.0012	0.0019	0.0023	0.0025	0.0032
	(6.7364)	(5.1222)	(5.2252)	(4.1786)	(2.5006)	(1.7236)	(3.1652)	(4.3337)	(4.8110)	(5.7671)
R4	0.0221	0.0150	0.0109	0.0086	0.0059	0.0009	0.0017	0.0021	0.0028	0.0033
	(6.7250)	(6.2859)	(4.8773)	(4.4152)	(2.9039)	(1.3786)	(2.6789)	(3.6634)	(4.9085)	(5.1949)
R5	0.0266	0.0166	0.0129	0.0105	0.0089	0.0004	0.0016	0.0025	0.0029	0.0043
	(7.9147)	(6.3692)	(5.4491)	(4.2918)	(3.5782)	(0.5634)	(2.2953)	(3.5621)	(4.0363)	(5.6412)
R5-R1	0.0040	0.0031	0.0032	0.0040	0.0051	-0.0003	0.0001	0.0006	0.0008	0.0017
	(1.5204)	(1.9304)	(2.2502)	(2.4970)	(2.9409)	(-0.6167)	(0.2956)	(1.4524)	(1.8355)	(3.6596)

Table 3: Cross-sectional Regression Estimates

This table presents the results of Fama-MacBeth (1973) cross-sectional regressions run each week on NYSE and AMEX securities from July 1967 to December 1996. The weekly cross-sectional regressions include all stocks that have at least five years of historical trading data on mini-CRSP. The cross section of stock returns in week t, denoted r, are regressed on a constant and some or all of the following variables: $r_{-t_1:-t_2}$ = the cumulative return from week $t-t_1$ through $t-t_2$, computed over three past return horizons; $\bar{V}$ = the average weekly turnover ratio over the prior 52 weeks, with turnover being the ratio of the week's share volume to the number of outstanding shares; s = log(market capitalization) measured at the beginning of week t; and g = the capital gains regressor, computed as one less the ratio of the beginning of week $t-1$ reference price to the end of week $t-2$ price, where the week $t-1$ reference price is the average cost basis calculated from the formula

$$R_{t-1} = \frac{1}{k} \sum_{n=1}^{260} \left(V_{t-1-n} \prod_{\tau=1}^{n-1} [1 - V_{t-1-n+\tau}] \right) P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one. There are a total of 1539 weekly regressions. The parameter estimates and t-statistics (in parentheses) are obtained from the time series of the corresponding cross-sectional regression coefficients. We report the results of regressions over all months, for January only, February through November only, and December only. Panel A omits the capital gains and turnover variables. Panel B omits the capital gains variable. Panel C contains the full set of regressors.

Panel A

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V}$$

Period	a_1	a_2	a_3	a_4
All	-0.0482	0.0012	-0.0005	-0.0004
	(-35.6415)	(2.9527)	(-3.0054)	(-4.2733)
Jan	-0.0700	-0.0087	-0.0068	-0.0040
	(-9.6647)	(-4.5972)	(-6.6744)	(-10.9146)
Feb-Nov	-0.0459	0.0018	-0.0001	-0.0001
	(-34.0613)	(4.3344)	(-0.6243)	(-1.4488)
Dec	-0.0491	0.0051	0.0015	0.0008
	(-9.9440)	(3.8921)	(2.8930)	(3.0164)

Panel B

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s$$

Period	a_1	a_2	a_3	a_4	a_5
All	-0.0488	0.0014	-0.0005	-0.0540	-0.0004
	(-37.2470)	(3.5703)	(-2.6700)	(-2.5732)	(-4.4200)
Jan	-0.0706	-0.0086	-0.0069	0.0681	-0.0042
	(-9.7366)	(-4.5561)	(-6.5561)	(0.9793)	(-11.2309)
Feb-Nov	-0.0465	0.0021	-0.0000	-0.0729	-0.0001
	(-36.0594)	(5.1324)	(-0.1979)	(-3.1591)	(-1.5202)
Dec	-0.0489	0.0049	0.0015	0.0088	0.0009
	(-10.2429)	(3.7745)	(2.8046)	(0.1214)	(3.1917)

Panel C

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0425	-0.0002	-0.0007	-0.0188	-0.0004	0.0040
	(-35.9364)	(-0.6794)	(-5.0871)	(-0.9364)	(-5.2885)	(7.7885)
Jan	-0.0520	-0.0001	-0.0025	-0.0620	-0.0026	-0.0117
	(-10.9905)	(-0.0477)	(-3.8964)	(-0.9768)	(-8.4381)	(-4.9519)
Feb-Nov	-0.0407	-0.0000	-0.0006	-0.0291	-0.0002	0.0050
	(-32.6251)	(-0.0768)	(-3.6950)	(-1.3143)	(-2.8816)	(9.4191)
Dec	-0.0498	-0.0022	-0.0005	0.1238	0.0001	0.0104
	(-10.8151)	(-1.8953)	(-1.3410)	(1.7980)	(0.2702)	(6.2673)

Table 4: Alternative Explanations

This table investigates alternative explanations for the significance of the coefficient on the capital gains regressor. For Panels A and B, $\bar{g}$ is calculated from a reference price using $\bar{V_t^j}$, firm j's average weekly turnover from weeks $t-52$ to $t-1$ in the formula for the gain variable used in week t's cross-sectional regression. Panel A replicates Panel C of Table 3, replacing our original capital gains variable by $\bar{g}$. In Panel B, the relative significance of the two gain variables are compared by including both as regressors. In Panel C, we use the product of the gain variable g with last week's turnover as a regressor, rather than the gain variable itself. Panels D and E investigate whether significance is generated by the capital gains variable being correlated with some interaction between past returns and past turnover. Panel D and Panel add the interaction of average turnover over past 1 year and a dummy for the losers over past 1 year as a regressor, without and with our original capital gains variable, respectively. The parameter estimates and t-statistics (in parentheses) are obtained from the time series of the corresponding cross-sectional regression coefficients. There are a total of 1539 weekly regressions.

Panel A

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 \bar{g}$$

Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0419	-0.0003	-0.0008	-0.0160	-0.0003	0.0043
	(-35.3749)	(-0.9434)	(-5.6612)	(-0.8074)	(-4.3955)	(8.0694)
Jan	-0.0511	-0.0004	-0.0026	-0.0553	-0.0030	-0.0097
	(-10.8551)	(-0.3277)	(-4.0810)	(-0.8509)	(-9.4107)	(-3.9209)
Feb-Nov	-0.0403	-0.0001	-0.0007	-0.0266	-0.0002	0.0051
	(-32.0373)	(-0.3395)	(-4.2724)	(-1.2182)	(-1.8236)	(9.2848)
Dec	-0.0488	-0.0019	-0.0005	0.1250	0.0003	0.0103
	(-10.7502)	(-1.7329)	(-1.3532)	(1.8159)	(1.2605)	(6.0802)

Panel B

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 g + a_7 \bar{g}$$

Period	a_1	a_2	a_3	a_4	a_5	a_6	a_7
All	-0.0424	-0.0003	-0.0008	-0.0133	-0.0003	0.0028	0.0014
	(-34.7482)	(-1.0308)	(-5.1146)	(-0.6459)	(-3.8746)	(2.4381)	(1.2590)
Jan	-0.0524	-0.0010	-0.0029	-0.0193	-0.0022	-0.0238	0.0154
	(-10.9145)	(-0.7809)	(-4.2183)	(-0.2889)	(-7.7160)	(-4.0727)	(2.5766)
Feb-Nov	-0.0405	-0.0001	-0.0006	-0.0260	-0.0001	0.0042	0.0007
	(-31.3421)	(-0.2966)	(-3.6772)	(-1.1447)	(-1.8369)	(3.6161)	(0.5650)
Dec	-0.0513	-0.0020	-0.0004	0.1160	0.0002	0.0152	-0.0048
	(-10.7503)	(-1.6643)	(-0.9656)	(1.5729)	(0.9717)	(4.5511)	(-1.4017)

Panel C

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 V_{-1} * g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0494	-0.0000	-0.0006	-0.0671	-0.0004	0.4876
	(-40.9516)	(-0.0918)	(-4.1084)	(-3.2748)	(-4.4009)	(15.6377)
Jan	-0.0661	-0.0051	-0.0046	-0.0535	-0.0036	-0.1685
	(-13.0585)	(-3.6265)	(-6.2913)	(-0.8750)	(-10.7269)	(-1.2841)
Feb-Nov	-0.0472	0.0004	-0.0004	-0.0815	-0.0002	0.5271
	(-36.7643)	(1.0364)	(-2.4415)	(-3.5783)	(-1.7896)	(16.2106)
Dec	-0.0545	0.0013	0.0010	0.0582	0.0007	0.7522
	(-13.3977)	(1.2904)	(2.3554)	(0.8299)	(2.7569)	(6.6208)

Panel D

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 \bar{V} * D_{loser} + a_6 s$$

Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0394	0.0013	-0.0003	-0.0445	-0.0447	-0.0003
	(-32.6763)	(3.8855)	(-1.8161)	(-2.1892)	(-2.9342)	(-3.3180)
Jan	-0.0575	-0.0054	-0.0054	0.0137	0.1415	-0.0034
	(-10.7987)	(-3.4640)	(-5.7927)	(0.2254)	(1.8017)	(-9.9059)
Feb-Nov	-0.0374	0.0019	0.0001	-0.0586	-0.0587	-0.0001
	(-29.8235)	(5.1123)	(0.4711)	(-2.5979)	(-3.7923)	(-0.6463)
Dec	-0.0417	0.0031	0.0010	0.0350	-0.0924	0.0007
	(-9.0601)	(2.6911)	(2.2312)	(0.5031)	(-1.7119)	(2.7178)

Panel E

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 \bar{V} * D_{loser} + a_6 s + a_7 g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6	a_7
All	-0.0426	-0.0003	-0.0007	-0.0140	-0.0126	-0.0004	0.0040
	(-35.9361)	(-0.8690)	(-4.9930)	(-0.6927)	(-0.8761)	(-5.3449)	(7.8140)
Jan	-0.0521	-0.0003	-0.0025	-0.0575	-0.0315	-0.0026	-0.0119
	(-10.9755	(-0.2333)	(-3.8984)	(-0.9318)	(-0.4486)	(-8.5155)	(-5.0607)
Feb-Nov	-0.0409	-0.0001	-0.0005	-0.0231	-0.0156	-0.0002	0.0050
	(-32.6142)	(-0.2740)	(-3.5798)	(-1.0314)	(-1.0337)	(-2.9252)	(9.4495)
Dec	-0.0500	-0.0020	-0.0006	0.1171	0.0345	0.0001	0.0106
	(-10.8500)	(-1.7670)	(-1.4337)	(1.7137)	(0.7322)	(0.2477)	(6.4041)

Panel F

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 \bar{V} * D_{loser} + a_6 s + a_7 V_{-1} * g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6	a_7
All	-0.0495	-0.0001	-0.0006	-0.0645	-0.0113	-0.0004	0.4882
	(-40.9412)	(-0.2311)	(-4.0264)	(-3.1323)	(-0.7334)	(-4.4434)	(15.7044)
Jan	-0.0664	-0.0051	-0.0046	-0.0533	0.0321	-0.0036	-0.1567
	(-13.0559)	(-3.6300)	(-6.2585)	(-0.8886)	(0.4736)	(-10.7410)	(-1.1920)
Feb-Nov	-0.0473	0.0003	-0.0004	-0.0786	-0.0136	-0.0002	0.5276
	(-36.7611)	(0.8679)	(-2.3864)	(-3.4329)	(-0.8206)	(-1.8328)	(16.2763)
Dec	-0.0546	0.0013	0.0010	0.0610	-0.0326	0.0007	0.7425
	(-13.3992)	(1.3174)	(2.3335)	(0.8625)	(-0.6477)	(2.7592)	(6.5686)

Table 5: Robustness Check: Subsamples

This table presents the subsample results of Fama-MacBeth (1973) cross-sectional regressions that study the relation between capital gains and expected returns. Corresponding results using the whole sample (July 1967 to December 1996) can be found in Panel C of Table 3. Panel A reports results using weekly data from July 1967 to the end of March 1982. Panel B reports results using the second half of the sample from April 1982 to the end of December 1996. The cross-sectional regressions are run weekly on NYSE and AMEX securities that have five years of historical trading data on mini-CRSP (used to calculate the aggregate cost basis and capital gains). The dependent variable is week t's stock return. Regressors include $r_{-t_1:-t_2}$ = the cumulative return from week $t-t_1$ through $t-t_2$, computed over three past return horizons; $\bar{V}$ = the average weekly turnover ratio over the prior 52 weeks, s = log(market capitalization) measured at the beginning of week t; and g = the capital gains regressor, computed as $(P_{t-2} - R_{t-1})/P_{t-2}$, where

$$R_{t-1} = \frac{1}{k} \sum_{n=1}^{260} \left(V_{t-1-n} \prod_{\tau=1}^{n-1} [1 - V_{t-1-n+\tau}] \right) P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one. The parameter estimates and t-statistics (in parentheses) are obtained from the time series of the corresponding cross-sectional regression coefficients. We report the results of regressions over all months, for January only, February through November only, and December only.

Panel A: July 1967 to March 1982

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0552	-0.0005	-0.0013	-0.0143	-0.0007	0.0046
	(-31.6943)	(-0.9578)	(-5.7743)	(-0.4054)	(-5.2407)	(6.1793)
Jan	-0.0631	-0.0005	-0.0045	-0.1711	-0.0038	-0.0123
	(-7.9314)	(-0.2847)	(-4.5862)	(-1.7864)	(-8.4704)	(-4.0505)
Feb-Nov	-0.0532	-0.0004	-0.0011	-0.0231	-0.0004	0.0058
	(-29.2124)	(-0.6562)	(-4.2579)	(-0.5866)	(-3.0217)	(7.5394)
Dec	-0.0666	-0.0016	-0.0007	0.2267	0.0001	0.0102
	(-10.9771)	(-0.8759)	(-1.2674)	(1.9665)	(0.2758)	(4.2340)

Panel B: April 1982 to December 1996

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0297	0.0000	-0.0001	-0.0233	-0.0002	0.0035
	(-20.3628)	(0.1063)	(-0.6985)	(-1.2045)	(-1.8569)	(4.8216)
Jan	-0.0401	0.0004	-0.0004	0.0540	-0.0013	-0.0110
	(-8.9945)	(0.2767)	(-0.4923)	(0.6699)	(-3.6897)	(-3.0077)
Feb-Nov	-0.0284	0.0003	-0.0001	-0.0350	-0.0001	0.0042
	(-18.1436)	(0.6909)	(-0.4204)	(-1.7047)	(-0.8256)	(5.7574)
Dec	-0.0325	-0.0028	-0.0003	0.0177	0.0000	0.0106
	(-5.1506)	(-1.9620)	(-0.5609)	(0.2447)	(0.0839)	(4.6193)

Table 6: Robustness Check: Using Past One-Year High as Reference Price

This table reports results of Fama-MacBeth (1973) cross-sectional regressions run each week on NYSE and AMEX securities from July 1967 to December 1996, similar to Table 3. The only difference is that here each stock's reference price is taken to be its past 52 week high in computing an alternative capital gains regressor $g*$. We continue to denote by g the original capital gains overhang computed as $(P_{t-2} - R_{t-1})/P_{t-2}$, where

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1 - V_{t-1-n+\tau}]\right)P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one. Panel A studies the predictive power of the alternative gains variable $\bar{g}$ for expected returns, controlling for $r_{-t_1:-t_2}$ = the cumulative return from week $t-t_1$ through $t-t_2$, computed over three past return horizons; $\bar{V}$ = the average weekly turnover ratio over the prior 52 weeks, and s = log(market capitalization) measured at the beginning of week t. Panel B compares the two gains variable by including them simultaneously as regressors. There are a total of 1539 weekly regressions. The parameter estimates and t-statistics (in parentheses) are obtained from the time series of the corresponding cross-sectional regression coefficients. We report the results of regressions over all months, for January only, February through November only, and December only.

Panel A

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4\bar{V} + a_5 s + a_6 g^*$$

Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0426	0.0003	-0.0003	-0.0198	-0.0004	0.0043
	(-36.8035)	(0.9040)	(-1.6889)	(-1.0619)	(-4.8157)	(8.9118)
Jan	-0.0538	-0.0034	-0.0050	-0.0664	-0.0031	-0.0052
	(-11.4558)	(-2.7598)	(-5.9271)	(-1.1459)	(-9.6145)	(-2.4838)
Feb-Nov	-0.0411	0.0006	0.0001	-0.0257	-0.0002	0.0052
	(-33.5797)	(1.8163)	(0.4991)	(-1.2414)	(-2.4379)	(10.2560)
Dec	-0.0454	0.0009	0.0011	0.0834	0.0005	0.0048
	(-10.3698)	(0.7818)	(2.6272)	(1.3520)	(1.9373)	(3.0944)

Panel B

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4\bar{V} + a_5 s + a_6 g + a_7 g^*$$

Period	a_1	a_2	a_3	a_4	a_5	a_6	a_7
All	-0.0437	-0.0005	-0.0005	-0.0030	-0.0004	0.0026	0.0032
	(-37.6869)	(-1.6377)	(-3.4039)	(-0.1583)	(-5.6575)	(4.8956)	(6.6383)
Jan	-0.0528	-0.0003	-0.0023	-0.0690	-0.0026	-0.0130	0.0028
	(-11.5159)	(-0.2813)	(-3.4364)	(-1.1577)	(-8.6337)	(-5.9260)	(1.5015)
Feb-Nov	-0.0422	-0.0003	-0.0003	-0.0085	-0.0003	0.0033	0.0037
	(-34.2590)	(-1.0275)	(-1.8000)	(-0.4012)	(-3.3040)	(5.9960)	(7.1028)
Dec	-0.0492	-0.0023	-0.0008	0.1149	0.0001	0.0114	-0.0013
	(-11.1069)	(-1.9592)	(-1.8100)	(1.8163)	(0.3849)	(6.4287)	(-0.7723)

Table 7: Additional Robustness Check

This table provides further robustness check on the results of Fama-MacBeth cross-sectional regressions reported in Panel C of Table 3. In Table 3, the dependent variable is weekly return and the cross-sectional regressions are run eaach week. Panel A of this table reports the average coefficient estimates and t-statistics (in parentheses) obtained from cross-sectional regressions that are run once a month. Let t be the beginning of a month. In month t's cross-sectional regression, the dependent variable is simple return over month t. Regressors $r_{-t_1:-t_2}$ = the cumulative return from week $t-t_1$ through $t-t_2$, computed over three past return horizons; $\bar{V}$ = the average weekly turnover ratio over the prior 52 weeks, s = log(market capitalization) measured at the beginning of week t; and g = the capital gains regressor, computed as $(P_{t-2} - R_{t-1})/P_{t-2}$, where

$$R_{t-1} = \frac{1}{k}\sum_{n=1}^{260}\left(V_{t-1-n}\prod_{\tau=1}^{n-1}[1-V_{t-1-n+\tau}]\right)P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one. There are a total of 353 monthly cross-sectional regressions from July 1967 to December 1996. Panel B of this table differs from Panel C of Table 3 only in that the past return between 1 year and 1 month ago is being replaced by 3 non-overlapping returns over intermediate past horizons: months -1 to -3, -4 to -6, and -7 to -12. We report the results of regressions over all months, for January only, February through November only, and December only.

Panel A: Monthly Regressions

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4\bar{V} + a_5 s + a_6 g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0674	0.0021	-0.0017	-0.1708	-0.0010	0.0127
	(-16.6929)	(1.4099)	(-2.5740)	(-2.2182)	(-2.6895)	(5.4241)
Jan	-0.0910	0.0013	-0.0089	-0.3477	-0.0090	-0.0345
	(-4.1583)	(0.2239)	(-2.5983)	(-1.4647)	(-5.5341)	(-4.1412)
Feb-Nov	-0.0632	0.0028	-0.0011	-0.1923	-0.0004	0.0152
	(-15.2941)	(1.7591)	(-1.4978)	(-2.2249)	(-1.0585)	(6.3402)
Dec	-0.0864	-0.0043	-0.0014	0.2232	0.0006	0.0344
	(-7.0285)	(-0.7936)	(-0.9822)	(1.0281)	(0.5383)	(4.6423)

Panel B: More Refined Intermediate Horizon Past Returns

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-13:-5} + a_3 r_{-26:-14} + a_4 r_{-52:-27} + a_5 r_{-156:-53} + a_6\bar{V} + a_7 s + a_8 g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
All	-0.0437	-0.0040	-0.0004	0.0004	-0.0008	-0.0211	-0.0004	0.0047
	(-35.9816)	(-5.5374)	(-0.6773)	(1.1588)	(-5.5893)	(-1.1094)	(-5.5158)	(8.8904)
Jan	-0.0530	-0.0027	0.0032	0.0015	-0.0024	-0.0905	-0.0025	-0.0123
	(-10.3896)	(-0.8353)	(0.9277)	(1.2120)	(-3.7591)	(-1.5476)	(-8.0866)	(-5.2322)
Feb-Nov	-0.0419	-0.0037	-0.0005	0.0005	-0.0006	-0.0272	-0.0003	0.0058
	(-32.9948)	(-4.9480)	(-0.9261)	(1.2087)	(-4.2594)	(-1.2835)	(-3.2591)	(10.6286)
Dec	-0.0518	-0.0083	-0.0025	-0.0011	-0.0006	0.1056	0.0001	0.0112
	(-10.7456)	(-2.7814)	(-1.3900)	(-0.7937)	(-1.5469)	(1.6812)	(0.2205)	(6.5430)

Figure 1: **Prospect Theory Value Function**

This figure plots an example of the S-shaped prospect theory value function, generated by the following:

$$\begin{aligned} U(W) &= \frac{(W-R)^{1-\gamma}}{1-\gamma}, \qquad \text{if } W \geq R; \\ U(W) &= -\lambda \frac{(R-W)^{1-\gamma}}{1-\gamma}, \quad \text{if } W < R \end{aligned}$$

where R is a reference level, $\gamma = 0.5$ and $\lambda = 2.25$.

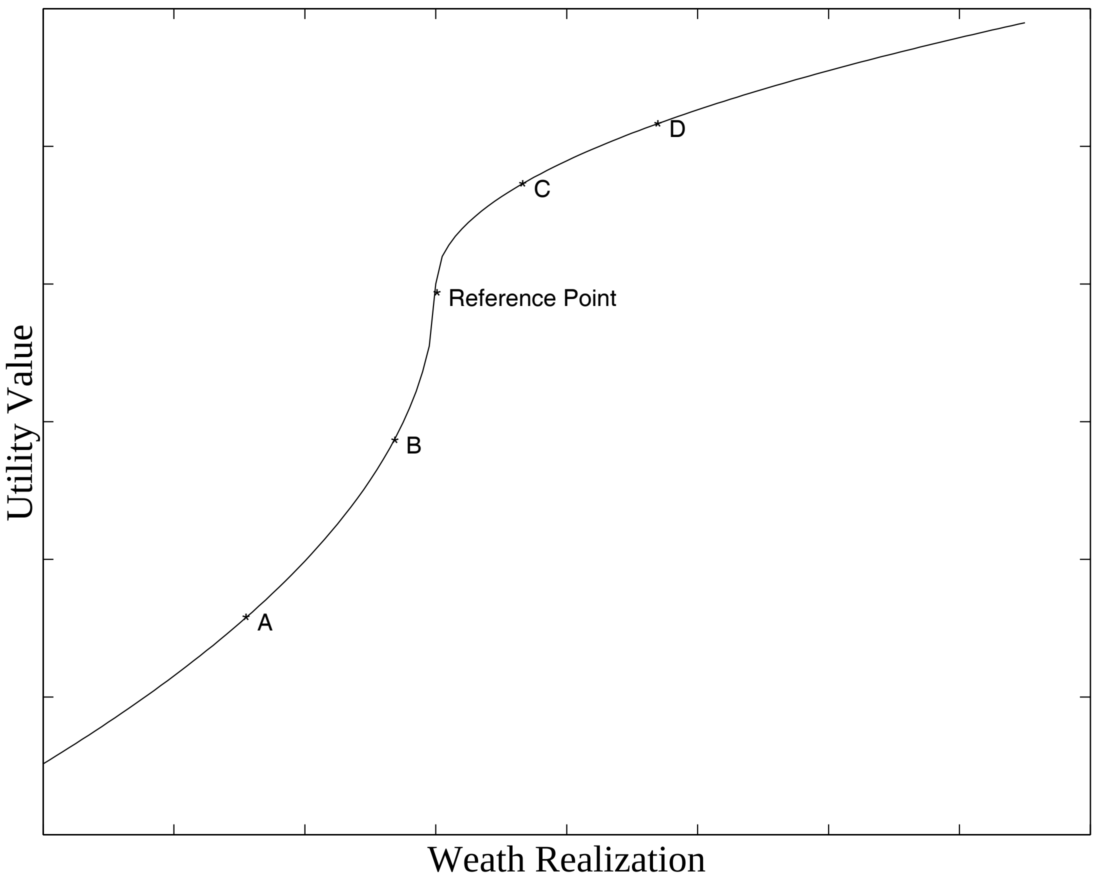
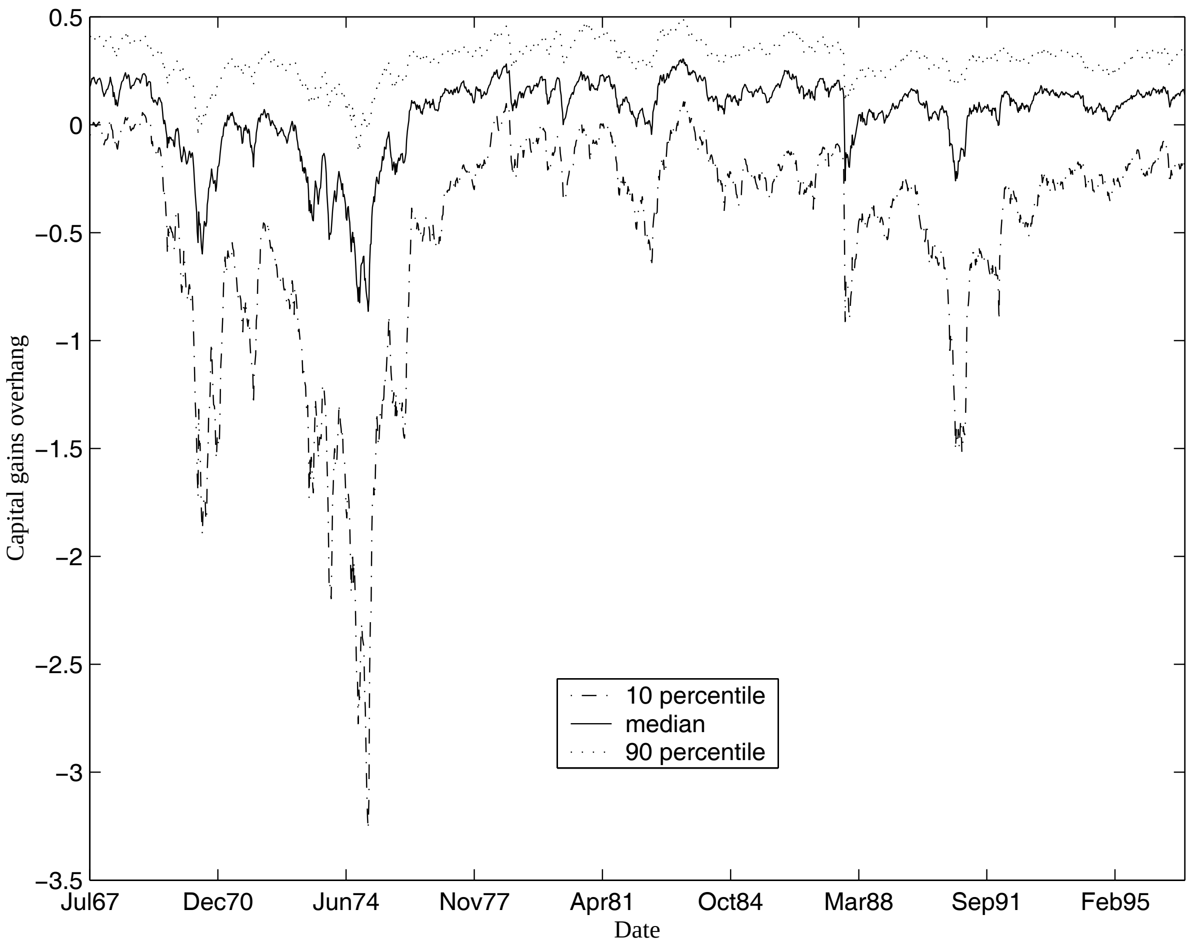


Figure 2: **Time Series of Cross-Sectional Percentiles of the Capital Gains Regressor**

This figure plots the time series of the empirical 10th, 50th and 90th percentiles of the cross-sectional distribution of the capital gains regressor. The sample period is from July 1967 to December 1996, for a total of 1539 weeks. Each week, we include all stocks (with sharecode 10 or 11) listed on the NYSE and AMEX that have at least five years of historical trading data from mini-CRSP. The previous five years of return and turnover data are used to calculate the capital gains variable as one less the ratio of the beginning of week $t-1$ reference price to the end of week $t-2$ price, where the week $t-1$ reference price is the average cost basis obtained from the formula

$$R_{t-1} = \frac{1}{k} \sum_{n=1}^{260} \left(V_{t-1-n} \prod_{\tau=1}^{n-1} [1 - V_{t-1-n+\tau}] \right) P_{t-1-n}$$

with k a constant that makes the weights on past prices sum to one.



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