

The Disposition Effect and Momentum *

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Abstract

The tendency of some investors to hold on to their losing stocks 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.

Kahneman and Tversky's (1979) theory of choice, "prospect theory," can accommodate many behaviors that are inconsistent with standard expected utility theory. The main element of prospect theory is an S-shaped value function that is concave in the domain of gains and convex in the domain of losses, both measured relative to a reference point. Subsequently, Thaler (1985) constructed a framework known as "mental accounting" which provides a foundation for the way that decision makers set reference prices for gambles. 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.

If the relevant accounts are profits in individual stocks, a direct implication of prospect theory and mental accounting 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 is perhaps the most well-documented empirical regularity in behavioral finance: 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.¹

This paper studies how equilibrium asset prices evolve over time in a model – motivated by prospect theory and mental accounting – where investors are subject to the disposition effect to differing degrees. The simplest version of this model, and the one we use to motivate our theoretical intuition, arises when some investors are perfectly rational (and thus not subject to the disposition effect) and the remaining investors have identical "disposition tendencies." (This version of the model also has the virtue of showing that rational agents do not undo the equilibrium effects of disposition investors.) The most basic and unambiguous prediction of our model is that stocks with aggregate unrealized capital gains tend to outperform stocks with aggregate unrealized capital losses. Since past returns are a noisy proxy for aggregate unrealized gains and losses, the disposition effect may account for the tendency of past winning stocks to subsequently outperform past losing stocks. We find strong empirical support for this hypothesis.

¹Weber and Camerer (1998) and Heilmann, Lager and Oehler (2000) find evidence for disposition behavior in experimental markets. Ferris, Haugen and Makhija (1988) argue that a disposition effect has to exist by studying the relationship between volume at a given point in time with historical volume at differential prices, controlling for seasonal effects to isolate tax motivated trading. Odean (1998) analyzes accounts at a large brokerage house. He finds that there was a greater tendency to sell stocks with paper capital gains than those with paper losses. Grinblatt and Keloharju (2001) find a similar effect among all types of investors in Finland, even after controlling for a variety of variables that may determine trading. Shapira and Venezia (2001) show that both professional and independent investors in Israel exhibit the disposition effect, although the effect is stronger for independent investors. Heath, Huddart and Lang (1999) uncover disposition behavior relative to a reference price of a prior high for the stock price by studying the option exercise behavior of over 50,000 employees at seven corporations. Locke and Mann (2000) document that professional futures traders hold losing trades longer than winning trades and average position sizes for losing trades are larger than for winners. The disposition effect also influences agents in the housing market (e.g., Case and Shiller, 1988, and Genesove and Mayer, 2001), IPO market (e.g., Kaustia, 2001), as well as some mutual fund managers (e.g., Wermers, 2003).

Investors subject to the disposition effect perturb otherwise rational demand functions for a stock they own because they have experienced unrealized capital gains or losses in the stock. Such investors have higher demand for losing stocks than for winning stocks, other things being equal. Thus, stocks that have been privy to good news in the past would have excess selling pressure relative to stocks that have been privy to adverse information. If demand for that same stock by rational investors is not perfectly elastic, then such a demand perturbation, induced by a disposition effect, 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 a disposition effect – and the market price of the stock. In equilibrium, past winners tend to be undervalued and past losers on average are overvalued.

This phenomenon, generated by the disposition effect, is sufficient to dampen certain price movements, but does not necessarily generate momentum in stock prices per se. For example, if all investors are identical and subject to the disposition effect, the representative buy and hold investor simply underreacts to news. If this underreaction is perpetual, there is no reason to think that it would generate stock return predictability. A dampened random process is still a random walk!² Our simple theoretical insight is that if investors are heterogeneous in the degree to which they are subject to the disposition effect, there will be trading. 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. It is this convergence that gives market price underreaction a mean reverting quality. Stocks with prices that exhibit the greatest degree of underreaction to past news have underreaction that reverts to a state of no underreaction at the fastest rate.

The tendency to revert to a state of no underreaction, driven by investor heterogeneity, generates what will empirically be perceived as momentum. Past winning stocks tend to have positive unrealized capital gains while past losers are more likely to have unrealized capital losses. The aggregate unrealized capital gain or loss proxies for the degree of underreaction to past news. Therefore, past winners tend to outperform past losers. Past returns, however, are noisy predictors for unrealized capital gains and losses. It is the pattern of past returns, combined with the pattern of past trading volume, that determines whether a stock has experienced an unrealized capital gain or a loss in the aggregate. Because of this, proxies for aggregate capital gains (losses) should be better than past returns as predictors of future returns. Moreover, our model predicts that there are certain (albeit rare) patterns for which returns are not persistent and that intermediate

²A 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 deviation of a fixed reference price from the market price will exhibit positive return autocorrelation. With a finite horizon, more and more news about the final liquidation payoff arrives over time. The assumed impact of the disposition effect thus decreases monotonically, and the stock price converges deterministically to the fundamental value.

return horizons will be the ones with the greatest perceived momentum.

The empirical implications of the 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 disposition effect is controlled for with a regressor that proxies for the aggregate capital gain.

It is important to emphasize that the disposition effect generally refers to an empirical phenomenon, which could be generated from a variety of sources, such as a belief in mean reversion that is not tied to the capital gain per se, portfolio rebalancing, or differential gain or loss on the stock. In the former case, the unrealized gain or loss on a stock would be a noisy predictor of future returns when compared to the gain measured relative to the price the stock reverts to. Moreover, Odean (1998) shows that subsequent portfolio performance is inconsistent with the rebalancing explanation and that the higher trading costs of selling losers cannot explain disposition behavior either.

The disposition effect we are analyzing here is a theoretical one, motivated by prospect theory and mental accounts for which the cost basis in a stock is the reference price. It is only this theoretically motivated disposition effect that would have precisely the empirical implications we document in this paper.³

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. Section 3 discusses the relation of our work to prior literature, both theoretical and empirical. Section 4 concludes the paper.

³Another key element of prospect theory, that the decline in utility for a loss (measured relative to a reference point) exceeds the increase in utility for an equal-sized gain (relative to the same reference point), is not needed to derive disposition behavior (a reluctance to *realize* a loss), but it has been studied in several papers. For example, Benarzi and Thaler (1995) find that the size of the equity premium is consistent with the previously estimated parameters of prospect theory if loss averse investors evaluate their portfolios annually. Shumway (1997) develops an equilibrium asset pricing model based on loss-averse investors and shows that it leads to higher risk premium in down market. Barberis, Huang and Santos (2001) model investor preferences to reflect a combination of loss aversion and the “house money effect” of Thaler and Johnson (1990). Variation in the risk aversion of the representative agent in their model leads to excess volatility, asset return predictability and profitability of contrarian strategies. Barberis and Huang (2001) use mental accounting and loss aversion to address cross-sectional expected return patterns, such as the value premium. They find individual stock mental accounting is more successful than portfolio level mental accounting in describing the data. Finally, some recent papers study portfolio choices and equilibrium prices under prospect theory type preference. See, for example, Ang, Bekaert, and Liu (2001), Berkelaar and Kouwenberg (2000), and Gomes (2000).

1 Conceptual Framework

1.1 Model

Focusing on two investor types is the simplest way to illustrate how disposition effect heterogeneity among investors induces stock return predictability. We assume that one of the types is not subject to the disposition effect at all. To obtain closed form solutions for the equilibrium, the disposition type exhibits a constant geometric perturbation of the rational type's demand function. This modeling device allows us 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. We refer to the latter price as the stock's fundamental value. The tractability gained with this approach generates simple and obvious solutions. Studying the marginal effect of disposition behavior on the time series properties of any equilibrium price path allows us to be agnostic about utility functions. More importantly, it allows us to present the model in a remarkably brief fashion and concentrate on the empirical results.

Let's begin by analyzing how the partial demand function of a single risky stock among possibly many assets has its equilibrium price path affected by the existence of such a disposition effect. The risky stock that we focus on is in fixed supply normalized to one unit. Public news about the fundamental value of the stock arrives at discrete dates $t = 0, 1, 2, \dots$ just prior to trading on those dates. By definition, the fundamental value F is the present value that a fully rational market places on the free cash flow stream of the stock conditional on all information currently available, adjusted for the risk premium.⁴ As a convenient benchmark, and consistent with an extensive literature in finance, we assume that the fundamental value follows a random walk:⁵

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

To assess how the disposition effect alters the stochastic process for equilibrium prices, we need to study how the demand function of disposition investors, a fixed fraction, μ , of aggregate market, deviates from that of otherwise identical rational agents (the rest of the market). The experimental and empirical evidence shows that disposition investors have a relatively greater propensity to sell stocks on which they have accumulated a gain, and a lower propensity to sell a stock with a paper loss.⁶ Therefore, their excess demand is lower for their winners and higher for their losers. As suggested above, parsimony

⁴The 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. We simply want to understand as clearly and analytically as possible how a perturbation of investors' demand for a single stock, due to the disposition effect, generates deviations from the fully rational equilibrium.

⁵With appropriate mental accounts, we obtain the same results for a random walk with drift (irrespective of dividend policy). We omit this elaboration of the model for the sake of brevity.

⁶See, for example, Odean (1998) and Grinblatt and Keloharju (2001).

and tractability are enormously enhanced if we assume that the demand deviation from rational behavior is of the form:

$$\begin{aligned} \text{rational demand: } D_t^r &= 1 + b_t(F_t - P_t) \\ \text{disposition demand: } D_t^d &= 1 + b_t[(F_t - P_t) + \lambda(R_t - P_t)] \end{aligned}$$

where P_t is the price of the stock, and R_t , known prior to date t trading, is a reference price relative to which disposition investors measure their gains or losses. λ is a positive constant that measures the relative importance of the disposition component of demand for disposition investors. With positive λ , the disposition agents' demand deviation specified above is motivated by prospect theory and mental accounting. b_t represents the slope of the rational component of the demand functions for the stock.⁷ Consistent with the limits to arbitrage argument, espoused by Shleifer and Vishny (1997), we assume that rational agents' demand functions for risky stocks are not perfectly elastic, or $b_t \neq 0$, although this assumption is consistent with every utility function and every numerical simulation we have explored.⁸

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

$$P_t = wF_t + (1 - w)R_t, \quad \text{where } w = \frac{1}{1 + \mu\lambda} \quad (2)$$

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 disposition investors, μ , and the relative intensity of the demand perturbation induced by the disposition effect, λ . The fewer the number of disposition investors, and the smaller the degree to which each perturbs demand, the closer the market price will be to its fundamental value.

An individual disposition 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

⁷We can think of b_t as being whatever solves for the optimal rational demand function given a utility function. It does not generally imply a 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. 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 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 proves that arbitrageurs never undo the disposition effect, even when they are aware of it.

⁸This assumption reflects the risk aversion in those utility functions, but it may also reflect liquidity, incomplete information, capital constraints, or other forces restraining unlimited trade by investors. 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.

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.

$$R_{t+1} = V_t P_t + (1 - V_t) R_t \quad (3)$$

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, but our theoretical results would generalize if another mechanism for reference price updating were equally plausible.

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

$$P_{t+1} - P_t = w(F_{t+1} - F_t) + (1 - w)(R_{t+1} - R_t) \quad (4)$$

Expected changes in F are zero (by definition), while equation (3) 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, such as a model with no trading, there is no expected price change. However, heterogeneity in the degree to which investors are subject to the disposition effect, of any variety, induces trades and revises the cost basis of the shares in an investor's portfolio. Hence, if the cost basis is the reference price, the market price, like the reference price, reverts to the fundamental value.

1.2 Implications

Let's assume that the cost basis is the reference price for a stock's mental account. Then, stocks for which the disposition investor-type has a paper gain will tend to have reference prices and market prices that increase over time and vice versa. Stocks with paper gains tend to be those that are past winners. Stocks with paper losses tend to be those that are past losers. This means that the momentum observed in stock returns may simply arise from past returns being a proxy for the paper gains and losses disposition investors experience in a stock.⁹

Equation (4) suggests that the expected speed of convergence of market prices is proportional to the expected speed of convergence of the reference price. This, in turn, depends on the size of the existing gain and fraction of shares trading hands during the instant of convergence. That is, from the last two equations,

⁹An analytic proof is available from the authors demonstrating that expected price change next period is positive (negative), conditional on a stock's price having increased (decreased) over a sufficient long period.

$$E_t[P_{t+1} - P_t] = (1 - w)V_t(P_t - R_t) \quad (5)$$

The 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 is very simple. If the portfolio formation horizon is very short, extreme winners and losers don't have much of a return gap and thus have very little difference in their capital gains and losses. The top and bottom decile past return performers have larger differences in returns the longer the past return horizon. At very long horizons, however, the capital gain and the return tend to diverge because of trading. The tendency of the gain to revert to zero is very strong at long horizons: 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 on the top and bottom decile past return performers over a long past return horizon.

Indeed, the model suggests that expected returns are path dependent. Stocks that are consistent winners, or stocks that are at their all-time highs, are more likely to have large unrealized gains than stocks that have the same past return, achieved through a handful of outstanding months in the distant path. Likewise, consistent losers or stocks that are at their all time lows tend to underperform other stocks with the same poor past return achieved with a different path.¹⁰ There are even historical price and turnover paths for a stock that generate negative gains, and hence negative expected returns, even when past prices have increased. Similar, anomalous paths exist for losing stocks.

The model has implications about trading volume as well as the relation between trading volume and price momentum. It implies that large price decreases (increases) will be associated with the greatest volume impact for stocks that have experienced major and consistent increases (decreases) in value. These findings, as we observe later, have been confirmed in other papers that test our model.

1.3 Lack of Impact of Arbitrageurs

In the model presented above, the critical variable determining the sign and magnitude of a stock's expected return is the difference between the stock's market price and its reference price. Despite having fully rational investors in the model, they 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.

First, rational investors cannot ascertain when reference prices, and hence market

¹⁰Grinblatt and Moskowitz (2002) find that momentum profits are stronger for consistent winners and losers. George and Hwang (2002) find that profits to a momentum strategy based on nearness to a 52-week high are superior to those that compare current price to the price that prevailed a fixed length of time in the past (e.g., 6 months ago).

prices, will converge to fundamental values. Market prices can diverge further from their fundamental values before they converge.¹¹ 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 disposition behavior on prices will be further reduced. For example, Liu and Longstaff (2000) 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 disposition factor.

2 Empirical Tests

This section explores the empirical relationship between aggregate capital gains and the cross-section of expected returns. Lacking information on who the disposition investors are, we simply estimate a proxy for the market's unrealized gain.

Our estimate is of this critical variable is

$$R_t = \sum_{n=1}^{\infty} \left(V_{t-n} \prod_{\tau=1}^{n-1} [1 - V_{t-n+\tau}] \right) P_{t-n} \quad (6)$$

where V_t is date t 's turnover ratio in the stock. Note that the term in parentheses 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 (3). 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 MiniCRSP

¹¹In our model, although the spread between market price and fundamental value tend to mean revert towards zero, it can become wider when a sufficiently big shock to the fundamental value that is of the same sign as the capital gain variable arrives.

database. The dataset includes all ordinary common shares traded on the NYSE and AMEX exchanges. NASDAQ firms are excluded because of multiple counting of dealer trades. 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.

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, three interaction terms, computed as the product of the former volume variable and returns over the three past return horizons). We then study the coefficient on g_{t-1}^j , a capital gains related proxy. Formally, we analyze the regression,

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 s + a_6 g \quad (7)$$

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

Recall that the theoretical model states that

$$E_{t-1} \left[\frac{P_t - P_{t-1}}{P_{t-1}} \right] = (1 - w) V_{t-1} \frac{P_{t-1} - R_{t-1}}{P_{t-1}}. \quad (8)$$

This equation suggests that a measurable variable that predicts expected returns is the percentage difference between the market price and the reference price at the beginning of week t . Our proxy for this variable, the capital gains overhang, 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 (6). 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 5-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 reference price.

2.2 Summary Statistics

Figure 1 plots the weekly time series of the 10th, 50th, and 90th percentile of the cross-section of the capital gains 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 gains 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 gains 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.¹² Controlling

¹²The 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.

for past returns, a low volume winner has a larger capital gain, while a high volume loser has a larger capital loss. 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 gains overhang. Past returns, which are correlated with the capital gains 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 gains 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 returns into 5 portfolios labeled as $R1$ (losers), \dots , $R5$ (winners). Within each past returns quintile, stocks are further sorted into 5 portfolios by their capital gains overhang from the lowest to the highest quintile $G1$, \dots , $G5$. Panel C reverses the sort order.

Table 2 Panel A reports the time series average of the cutoff values for the capital gains quintiles within each past one-year returns sort, and the cutoff values for the past one-year returns quintiles within each capital gains sort. The capital gains and past one-year returns 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 gains overhang quintile. Moreover, the differences between the returns of the highest and lowest capital gains quintiles within each of the past returns quintiles is generally significant, ranging from about 0.12% to 0.25% per week (about 6% to 13% per annum).¹³ Panel C indicates that the reverse is not true: the difference between extreme winner and loser quintile portfolios within a given capital gains quintile is generally not significant.

The portfolio returns during the January months are not consistent with a stable disposition parameter λ . Within Panel B's past returns quintile, the January returns of high capital gains stocks tend to be below those of the low capital gains stocks. This may reflect a January tax-loss selling effect, as we discuss later. It may also reflect a size effect,

¹³We classify a week as belonging to a particular calendar month if it ends in that month. If we exclude the 30 weeks that begin in January and ends in February, 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.

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 separately from February through November.

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

Table 3 presents the average coefficients and time-series t -statistics for the regression described by equation (7) 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.¹⁴ 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 $0.004 \times 60\% = 0.24\%$ per week, or 12.5% per year.

¹⁴We 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.

2.5 Explaining Seasonalities

The seasonalities observed in Table 3 are consistent with what other researchers have found.¹⁵ 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 off-set in December by the marginal impact tax-loss selling. If we generalize the demand function of the disposition investor,

$$D_t^d = 1 + b_t[(F_t - P_t) + \lambda_t(R_t - P_t)] \quad (9)$$

and assume that λ_t drifts downward in December for certain, and reverts to its normal positive value sometime in early January, 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 disposition demand, equation (9), the expected price change, formerly in equation (5), generalizes to

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

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 but is positive during the rest of the year. Viewed from the end of November, this would be like knowing that $w_{t+1} = 1$ and larger than w_t , thus generating a larger coefficient on the gain regressor in December than would be observed in months with $w_{t+1} = w_t$. Viewed from the end of December, $w_t = 1$ and larger than w_{t+1} . This makes the expected price change during January negatively related to the gain regressor.

¹⁵For 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).

2.6 Alternative Explanations

Could the strength of the capital gains variable as a predictor of returns be due to some alternative explanation? Table 4 investigates this issue with respect to two alternatives. First, Panels A and B examine whether there is some sort of interaction between a firm’s average historical turnover and future returns. For example, the results in Table 3 Panel C may have arisen because cross-sectional differences in liquidity imply that the reference prices of more liquid stocks place greater weight on more recent prices than the reference prices of less liquid stocks. By formulating a reference price using the average turnover over the past year in place of each week’s actual turnover, we assess whether it is only the cross-sectional difference in liquidity that is responsible for the predictive power of our original gain variable, or whether the information about a stock’s capital gain inherent in the time series of its historical weekly turnover also contributes to the predictive power of our findings in Table 3.

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 V s in equation (6). 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 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 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 actual capital gains 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 as a predictor of future returns is consistent with more precise estimates of the aggregate capital gain being better predictors of future returns.

A second concern about the significance of our capital gains proxy in Table 3 is that it represents some complicated interaction between volume and past returns. For example, Lee and Swaminathan (2000) find that high volume losers significantly underperform low volume losers.¹⁶ Hence, it is possible that our findings in Table 3 arise from the capital

¹⁶In an earlier version of the paper, we use the law of iterated expectation and equation (5), (6) to prove that momentum profits is higher for stocks with low past turnover and high current turnover. This explains why momentum profits are higher for high volume stocks. It also explains the finding of Lee and Swaminathan (2000) that most of the predictive power of trading volume is attributable to recent changes in the level of trading activity, rather than lagged volume.

gains overhang variable being correlated with some interaction between intermediate horizon past returns and volume. Panels C and D of Table 4 test this hypothesis by adding three turnover and past returns interaction terms.

Table 4 Panel C analyzes the impact of these regressors in the absence of a capital gains regressor. The volume-return interaction moderates the strong one-month return reversal, but the inclusion of these regressors does not subsume the intermediate horizon momentum effect. However, once the capital gains variable is added to the regression, as in Table 4 Panel D, the intermediate horizon past return becomes insignificant, while the capital gains coefficient is highly significant. Comparing Table 3 Panel C with Table 4 Panel D, the average regression coefficient for the capital gains variable and its t -statistic are almost unchanged in the presence of the three turnover and past return interaction terms.

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 gains regressor. Panel A and B of Table 5, which repeat Panel C of Table 4 for the two subperiods, confirm this hypothesis. There is only about a one standard error difference between the average coefficients on the capital gains 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 gains variable.¹⁷

We also conducted additional robustness checks based on data frequency. The results presented in Table 6 show that the significant predictive power of capital gains for future returns is not an artifact of the weekly frequency of the cross-sectional regressions. The regressions reported in the Panel C of Table 3, as well as Panels B and D of Table 4 are repeated for monthly Fama-MacBeth cross-sectional regressions with the return over the next month as the dependent variable. As can be seen from Panels A, B, and C of Table 6, the capital gains variable is still significantly positively related to next month's return. Moreover, once the capital gains overhang is controlled for, the past intermediate horizon return loses its predictive power. Again, this effect cannot be explained by either

¹⁷Although we do not report this formally in a table, the signs and significance of the capital gains overhang regressor are not drastically altered by restricting the sample to various size quintiles either.

cross-sectional liquidity differences or interactions between past returns and past turnover.

We also studied numerous alternative variables that might explain our results. The maximum 52-week stock price has also been suggested as a possible reference price (see, e.g., Heath, Huddart and Lang, 1999). Table 7 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 gains regressor calculated using the aggregate cost basis as the reference price as in equation (6) is added as a regressor, it turns out that both capital gains variables are significantly positive (see Table 7 Panel B). This is what we would expect if the model was correct and both variables are imperfect proxies for the theoretical variable.

In all of the regressions discussed so far, the intermediate horizon past returns is measured by the return between one year and one month ago. To accommodate the possibility that 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 A of Table 8 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.

Finally, equation (8) suggests that if a stock's turnover is independent of the degree to which it underreacts to news, an appropriate substitute regressor for the capital gains regressor, g , is the product of g and last period's turnover. Table 8 Panel B reports the analog of Table 3 Panel C using this variable as a regressor rather than the capital gain itself. The results support the implication of our model (8) that $V_{t-1} \frac{P_{t-2} - R_{t-1}}{P_{t-2}}$ is positively and significantly related to the next-period expected returns. Moreover, this variable renders the intermediate horizon past return insignificant in predicting future return, suggesting that the intermediate horizon past return is a noisier proxy for the impact of disposition behavior on returns.¹⁸ We obtain essentially the same results for other regressions reported above, when we use the product of the gain variable and turnover instead of the gain variable itself.

3 Related Research

Jegadeesh and Titman (1993) popularized the notion that strategies of buying stocks with high returns over the prior three to twelve months and selling stocks with poor returns over the same past horizon dominates a buy and hold strategy. This finding appears to be

¹⁸Based on our model (8), the estimated coefficient 0.4876 for $V_{t-1} \frac{P_{t-2} - R_{t-1}}{P_{t-2}}$ in Table 8 Panel B implies that on average, $1 - w = 0.4876$. By equation (2), this suggests that market price of a typical stock is about the average of its fundamental value and its aggregate cost basis.

fairly universal and robust to methodological tweaking. For example, Rouwenhorst (1997) finds that momentum strategies work in twelve European markets. Chui, Titman, and Wei (2000) document that with the exception of Japan and Korea, momentum profits can be earned in Asian markets. Jegadeesh and Titman (2001) document that momentum profits persisted throughout the 1990s. In contrast, other well known anomalies such as the small firm and book-to-market effects disappeared after being well-publicized. Given the persistence of this anomaly, and its economic magnitude, it is important to understand its cause.

Chan, Jegadeesh and Lakonishok (1996) show that intermediate horizon return continuation can be partially explained by underreaction to earnings news but that price momentum is not subsumed by earnings momentum. Jegadeesh and Titman (1993) and Fama and French (1996) find that risk adjustment tends to accentuate momentum profits. Conrad and Kaul (1998) argue that the profitability of momentum strategies could be due to cross-sectional variation in the unconditional expected returns rather than any predictable time-series variation in stock returns. This hypothesis implies that momentum profits should be the same in any post ranking period, which is inconsistent with the empirical results and convincing arguments of Jegadeesh and Titman (2001).¹⁹

Moskowitz and Grinblatt (1999) find that a significant component of momentum can be explained by industry effects. However, this does not mean that individual stock momentum does not exist. Moskowitz and Grinblatt (1999), Grundy and Martin (2001), and Chordia and Shrivakumar (2000) show that a component of individual stock momentum is distinct from industry momentum. The latter paper also argues that momentum profits are driven by time varying conditional expected returns that are related to the business cycle. Berk, Green and Naik (1999) provides a theoretical model which suggests that predictable changes in firms' assets and growth options as a consequence of optimal investment choices can lead to momentum. Johnson (2002) offers another rational explanation for momentum by allowing the expected dividend growth rate to change over time.

Another strand of the literature uses behavioral models to explain momentum profits. 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' conservatism 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,

¹⁹Jegadeesh and Titman (2002) argue that the Conrad and Kaul (1998) simulations are subject to a small sample replacement bias. Moskowitz and Grinblatt (1999) show that only a small portion of momentum profits is due to cross-sectional variation in unconditional expected returns.

but cause overreaction at long horizons in doing so.

None of these theories would make the predictions our model does about the overwhelming importance of the capital gain as the driver of intermediate horizon momentum. Our theory, unlike some of the others, above, does not predict that there would be reversals at other horizons. Moreover, our model makes unique predictions about trading volume and volatility, which has been tested in another paper. Goetzmann and Massa (2003) derive several additional implications of our model for volume, volatility as well as return, based on their sensitivities with respect to the proportion of disposition investors in the economy, i.e., the parameter μ in equation (2) which is kept constant throughout our paper. 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 are positive. Further, their results suggest that exposure to this disposition factor seems to be priced.

4 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 the market prices and the aggregate cost basis for stocks, which we call the capital gains overhang, are positively related to the expected future returns. On the other hand, past 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).

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 gains 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 capital gains overhang and future stock returns. 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 difference in liquidity or interaction of past returns and turnover.

Our results suggests that it is the correlation between past returns and behavioral variables related to the disposition effect that may be driving momentum in stock re-

turns. In addition, our results support the explanation for the disposition effect based on prospect theory and mental accounting rather than mistaken belief about stock price mean reversion.

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 $\log(\text{market capitalization})$ 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_{adj}^2 is the average of the weekly cross-sectional regression R^2 s adjusted for degrees of freedom.

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

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

	$r_{-4:-1}$	$r_{-52:-5}$	$r_{-156:-53}$	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_{adj}^2
0.5527 (73.0290)	0.4907 (51.7965)	0.1771 (37.5209)	-0.9159 (-7.6351)	-6.4051 (-45.0322)	-2.7843 (-27.8215)	0.0504 (55.9642)	0.5879

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), \dots , $R5$ (winners). Within each past return quintile, stocks are further sorted into 5 equally-weighted portfolios by their capital gains overhang: $G1$ (lowest), \dots , $G5$ (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 Percentile	Gain for cutoff percentile					Past 1-year return for cutoff 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 Return	January					February-December				
	R1	R2	R3	R4	R5	R1	R2	R3	R4	R5
G1	0.0280 (6.6595)	0.0221 (7.0545)	0.0200 (6.6434)	0.0190 (6.9072)	0.0185 (6.3635)	0.0007 (0.9502)	0.0010 (1.5026)	0.0009 (1.4741)	0.0017 (2.5651)	0.0015 (2.0121)
G2	0.0203 (5.8051)	0.0133 (5.2044)	0.0130 (6.0074)	0.0112 (4.9437)	0.0108 (4.4362)	0.0013 (1.8056)	0.0015 (2.5014)	0.0019 (3.3143)	0.0023 (3.8856)	0.0028 (3.8803)
G3	0.0158 (5.5196)	0.0110 (4.6749)	0.0097 (4.8941)	0.0091 (4.7914)	0.0088 (3.8287)	0.0010 (1.3886)	0.0021 (3.7149)	0.0023 (4.3071)	0.0026 (4.7599)	0.0034 (5.1018)
G4	0.0133 (4.9083)	0.0097 (4.3987)	0.0071 (3.8552)	0.0058 (3.2502)	0.0075 (3.6064)	0.0013 (1.9823)	0.0020 (3.7639)	0.0023 (4.4642)	0.0028 (5.2575)	0.0036 (5.4608)
G5	0.0104 (4.6832)	0.0065 (3.5666)	0.0057 (3.3550)	0.0035 (2.0306)	0.0062 (2.9009)	0.0015 (2.4505)	0.0020 (3.8347)	0.0026 (5.1891)	0.0030 (5.6310)	0.0041 (6.1472)
G5-G1	-0.0175 (-6.5141)	-0.0155 (-7.6702)	-0.0143 (-6.2049)	-0.0154 (-7.4544)	-0.0123 (-5.5134)	0.0008 (1.6146)	0.0010 (2.6852)	0.0017 (4.8102)	0.0012 (3.3838)	0.0026 (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 (5.5684)	0.0134 (5.0817)	0.0096 (4.5359)	0.0064 (3.5626)	0.0038 (2.3398)	0.0007 (0.8731)	0.0015 (2.2777)	0.0019 (3.3185)	0.0021 (4.1417)	0.0026 (5.2192)
R2	0.0219 (6.4120)	0.0130 (5.0721)	0.0099 (4.5740)	0.0074 (4.0176)	0.0036 (2.0662)	0.0012 (1.6494)	0.0016 (2.5961)	0.0022 (4.1083)	0.0023 (4.5382)	0.0028 (5.5472)
R3	0.0216 (6.7364)	0.0127 (5.1222)	0.0107 (5.2252)	0.0074 (4.1786)	0.0044 (2.5006)	0.0012 (1.7236)	0.0019 (3.1652)	0.0023 (4.3337)	0.0025 (4.8110)	0.0032 (5.7671)
R4	0.0221 (6.7250)	0.0150 (6.2859)	0.0109 (4.8773)	0.0086 (4.4152)	0.0059 (2.9039)	0.0009 (1.3786)	0.0017 (2.6789)	0.0021 (3.6634)	0.0028 (4.9085)	0.0033 (5.1949)
R5	0.0266 (7.9147)	0.0166 (6.3692)	0.0129 (5.4491)	0.0105 (4.2918)	0.0089 (3.5782)	0.0004 (0.5634)	0.0016 (2.2953)	0.0025 (3.5621)	0.0029 (4.0363)	0.0043 (5.6412)
R5-R1	0.0040 (1.5204)	0.0031 (1.9304)	0.0032 (2.2502)	0.0040 (2.4970)	0.0051 (2.9409)	-0.0003 (-0.6167)	0.0001 (0.2956)	0.0006 (1.4524)	0.0008 (1.8355)	0.0017 (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; $s = \log(\text{market capitalization})$ 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 (-35.6415)	0.0012 (2.9527)	-0.0005 (-3.0054)	-0.0004 (-4.2733)
Jan	-0.0700 (-9.6647)	-0.0087 (-4.5972)	-0.0068 (-6.6744)	-0.0040 (-10.9146)
Feb-Nov	-0.0459 (-34.0613)	0.0018 (4.3344)	-0.0001 (-0.6243)	-0.0001 (-1.4488)
Dec	-0.0491 (-9.9440)	0.0051 (3.8921)	0.0015 (2.8930)	0.0008 (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 (-37.2470)	0.0014 (3.5703)	-0.0005 (-2.6700)	-0.0540 (-2.5732)	-0.0004 (-4.4200)
Jan	-0.0706 (-9.7366)	-0.0086 (-4.5561)	-0.0069 (-6.5561)	0.0681 (0.9793)	-0.0042 (-11.2309)
Feb-Nov	-0.0465 (-36.0594)	0.0021 (5.1324)	-0.0000 (-0.1979)	-0.0729 (-3.1591)	-0.0001 (-1.5202)
Dec	-0.0489 (-10.2429)	0.0049 (3.7745)	0.0015 (2.8046)	0.0088 (0.1214)	0.0009 (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 (-35.9364)	-0.0002 (-0.6794)	-0.0007 (-5.0871)	-0.0188 (-0.9364)	-0.0004 (-5.2885)	0.0040 (7.7885)
Jan	-0.0520 (-10.9905)	-0.0001 (-0.0477)	-0.0025 (-3.8964)	-0.0620 (-0.9768)	-0.0026 (-8.4381)	-0.0117 (-4.9519)
Feb-Nov	-0.0407 (-32.6251)	-0.0000 (-0.0768)	-0.0006 (-3.6950)	-0.0291 (-1.3143)	-0.0002 (-2.8816)	0.0050 (9.4191)
Dec	-0.0498 (-10.8151)	-0.0022 (-1.8953)	-0.0005 (-1.3410)	0.1238 (1.7980)	0.0001 (0.2702)	0.0104 (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 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. Panels C and D investigate whether significance is generated by the capital gains variable being correlated with some interaction between past returns and volume over several horizons. Panels C and D add three turnover and past return interaction terms 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 (-35.3749)	-0.0003 (-0.9434)	-0.0008 (-5.6612)	-0.0160 (-0.8074)	-0.0003 (-4.3955)	0.0043 (8.0694)
Jan	-0.0511 (-10.8551)	-0.0004 (-0.3277)	-0.0026 (-4.0810)	-0.0553 (-0.8509)	-0.0030 (-9.4107)	-0.0097 (-3.9209)
Feb-Nov	-0.0403 (-32.0373)	-0.0001 (-0.3395)	-0.0007 (-4.2724)	-0.0266 (-1.2182)	-0.0002 (-1.8236)	0.0051 (9.2848)
Dec	-0.0488 (-10.7502)	-0.0019 (-1.7329)	-0.0005 (-1.3532)	0.1250 (1.8159)	0.0003 (1.2605)	0.0103 (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 (-34.7482)	-0.0003 (-1.0308)	-0.0008 (-5.1146)	-0.0133 (-0.6459)	-0.0003 (-3.8746)	0.0028 (2.4381)	0.0014 (1.2590)
Jan	-0.0524 (-10.9145)	-0.0010 (-0.7809)	-0.0029 (-4.2183)	-0.0193 (-0.2889)	-0.0022 (-7.7160)	-0.0238 (-4.0727)	0.0154 (2.5766)
Feb-Nov	-0.0405 (-31.3421)	-0.0001 (-0.2966)	-0.0006 (-3.6772)	-0.0260 (-1.1447)	-0.0001 (-1.8369)	0.0042 (3.6161)	0.0007 (0.5650)
Dec	-0.0513 (-10.7503)	-0.0020 (-1.6643)	-0.0004 (-0.9656)	0.1160 (1.5729)	0.0002 (0.9717)	0.0152 (4.5511)	-0.0048 (-1.4017)

Panel C

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

Period	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
All	-0.0601 (-39.0925)	0.0013 (2.7829)	-0.0007 (-2.9421)	-0.0805 (-3.1500)	1.2308 (13.2851)	0.0169 (0.8890)	0.0178 (1.8128)	-0.0004 (-4.4309)
Jan	-0.0863 (-10.3072)	-0.0115 (-4.7567)	-0.0086 (-6.3218)	-0.0261 (-0.3156)	1.6915 (4.8222)	0.2757 (2.8754)	0.1494 (3.0648)	-0.0041 (-11.3921)
Feb-Nov	-0.0569 (-36.9647)	0.0020 (4.3620)	-0.0002 (-0.8066)	-0.1055 (-3.7325)	1.1440 (11.3819)	0.0074 (0.3675)	0.0132 (1.2977)	-0.0001 (-1.5696)
Dec	-0.0647 (-12.7619)	0.0067 (4.6382)	0.0023 (3.5868)	0.1080 (1.2784)	1.6171 (5.1047)	-0.1455 (-3.2586)	-0.0672 (-2.1602)	0.0008 (3.1884)

Panel D

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 \bar{V} * r_{-4:-1} + a_6 \bar{V} * r_{-52:-5} + a_7 \bar{V} * r_{-156:-53} + a_8 s + a_9 g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
All	-0.0505 (-36.9999)	-0.0004 (-1.0135)	-0.0010 (-5.2744)	-0.0448 (-1.8042)	0.8291 (9.8004)	0.0172 (0.9803)	0.0203 (2.0141)	-0.0004 (-5.4115)	0.0041 (7.7062)
Jan	-0.0631 (-10.9625)	0.0004 (0.2253)	-0.0020 (-2.1356)	-0.0606 (-0.7509)	1.2519 (4.2349)	0.0256 (0.3194)	-0.0324 (-0.7282)	-0.0026 (-8.6123)	-0.0127 (-5.2671)
Feb-Nov	-0.0481 (-33.5092)	-0.0004 (-0.8019)	-0.0010 (-4.7637)	-0.0668 (-2.4386)	0.7449 (8.0398)	0.0230 (1.2122)	0.0295 (2.7375)	-0.0002 (-3.0289)	0.0052 (9.5347)
Dec	-0.0619 (-12.0063)	-0.0017 (-1.3278)	-0.0004 (-0.8323)	0.1836 (2.2080)	1.2275 (4.2620)	-0.0471 (-1.0533)	-0.0171 (-0.5460)	0.0001 (0.3912)	0.0102 (5.9292)

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, $s = \log(\text{market capitalization})$ 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 (-31.6943)	-0.0005 (-0.9578)	-0.0013 (-5.7743)	-0.0143 (-0.4054)	-0.0007 (-5.2407)	0.0046 (6.1793)
Jan	-0.0631 (-7.9314)	-0.0005 (-0.2847)	-0.0045 (-4.5862)	-0.1711 (-1.7864)	-0.0038 (-8.4704)	-0.0123 (-4.0505)
Feb-Nov	-0.0532 (-29.2124)	-0.0004 (-0.6562)	-0.0011 (-4.2579)	-0.0231 (-0.5866)	-0.0004 (-3.0217)	0.0058 (7.5394)
Dec	-0.0666 (-10.9771)	-0.0016 (-0.8759)	-0.0007 (-1.2674)	0.2267 (1.9665)	0.0001 (0.2758)	0.0102 (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 (-20.3628)	0.0000 (0.1063)	-0.0001 (-0.6985)	-0.0233 (-1.2045)	-0.0002 (-1.8569)	0.0035 (4.8216)
Jan	-0.0401 (-8.9945)	0.0004 (0.2767)	-0.0004 (-0.4923)	0.0540 (0.6699)	-0.0013 (-3.6897)	-0.0110 (-3.0077)
Feb-Nov	-0.0284 (-18.1436)	0.0003 (0.6909)	-0.0001 (-0.4204)	-0.0350 (-1.7047)	-0.0001 (-0.8256)	0.0042 (5.7574)
Dec	-0.0325 (-5.1506)	-0.0028 (-1.9620)	-0.0003 (-0.5609)	0.0177 (0.2447)	0.0000 (0.0839)	0.0106 (4.6193)

Table 6: Robustness Check: Monthly Fama-MacBeth Regressions

This table reports results for Fama-MacBeth (1973) cross-sectional regressions that are run monthly. There are 353 monthly cross-sectional regressions from July 1967 to December 1996. 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, $s = \log(\text{market capitalization})$ 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. Panel A is the monthly analog of Panel C of Table 3, where the regressors are past returns of three non-overlapping horizons, average turnover, size and the capital gains overhang. Panel B reports the monthly regression results of the horse race between our original capital gains variable and the alternative variable studied in Panel A and Panel B of Table 4. Panel C adds three turnover and past return interaction terms as regressors. The corresponding results using weekly regressions are reported in Panel D of Table 4. The parameter estimates and t -statistics (in parentheses) are obtained from the time series of the corresponding cross-sectional regression coefficients. There are 353 monthly cross-sectional regressions from July 1967 to December 1996. 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	-0.0674 (-16.6929)	0.0021 (1.4099)	-0.0017 (-2.5740)	-0.1708 (-2.2182)	-0.0010 (-2.6895)	0.0127 (5.4241)
Jan	-0.0910 (-4.1583)	0.0013 (0.2239)	-0.0089 (-2.5983)	-0.3477 (-1.4647)	-0.0090 (-5.5341)	-0.0345 (-4.1412)
Feb-Nov	-0.0632 (-15.2941)	0.0028 (1.7591)	-0.0011 (-1.4978)	-0.1923 (-2.2249)	-0.0004 (-1.0585)	0.0152 (6.3402)
Dec	-0.0864 (-7.0285)	-0.0043 (-0.7936)	-0.0014 (-0.9822)	0.2232 (1.0281)	0.0006 (0.5383)	0.0344 (4.6423)

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	0.0663 (-16.4249)	0.0022 (1.5292)	-0.0017 (-2.4368)	-0.1842 (-2.3954)	-0.0008 (-2.1869)	0.0147 (2.8357)	-0.0026 (-0.5287)
Jan	-0.0994 (-4.5957)	-0.0021 (-0.3766)	-0.0106 (-2.9741)	-0.2287 (-0.9752)	-0.0078 (-5.2280)	-0.0822 (-3.1302)	0.0563 (2.0931)
Feb-Nov	-0.0607 (-14.7234)	0.0029 (1.9076)	-0.0009 (-1.2143)	-0.2171 (-2.5230)	-0.0002 (-0.6833)	0.0209 (4.2018)	-0.0072 (-1.4773)
Dec	-0.0895 (-7.6957)	-0.0034 (-0.6660)	-0.0009 (-0.6986)	0.1957 (0.8515)	0.0009 (0.8631)	0.0486 (2.4798)	-0.0148 (-0.8021)

Panel C

$$r = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 \bar{V} + a_5 \bar{V} * r_{-4:-1} + a_6 \bar{V} * r_{-52:-5} + a_7 \bar{V} * r_{-156:-53} + a_8 s + a_9 g$$

Period	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
All	-0.0878 (-18.6299)	0.0012 (0.6509)	-0.0032 (-3.5577)	-0.2415 (-2.3550)	2.0525 (6.9778)	0.0399 (0.5638)	0.1018 (2.8245)	-0.0011 (-2.7897)	0.0135 (5.5374)
Jan	-0.1213 (-4.8185)	0.0034 (0.3828)	-0.0088 (-2.0636)	-0.2836 (-0.9137)	3.6621 (3.0771)	-0.0110 (-0.0376)	0.0373 (0.3218)	-0.0089 (-5.4854)	-0.0375 (-4.4065)
Feb-Nov	-0.0823 (-17.0113)	0.0015 (0.7401)	-0.0028 (-2.9493)	-0.2931 (-2.5423)	1.8306 (5.8166)	0.0609 (0.7761)	0.1221 (3.0517)	-0.0005 (-1.1967)	0.0165 (6.6516)
Dec	-0.1107 (-7.8830)	-0.0035 (-0.5624)	-0.0010 (-0.5064)	0.3245 (1.1450)	2.6926 (2.5487)	-0.1215 (-0.7954)	-0.0389 (-0.3332)	0.0007 (0.6218)	0.0332 (4.2588)

Table 7: 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 \bar{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 $s = \log(\text{market capitalization})$ 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

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

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

Panel B

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

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

Table 8: 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 Panel A, 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. In Panel B, the capital gains variable g is replaced by $V_{-1} * g$, where V_{-1} is the turnover over the last week. 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

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

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

Panel B

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

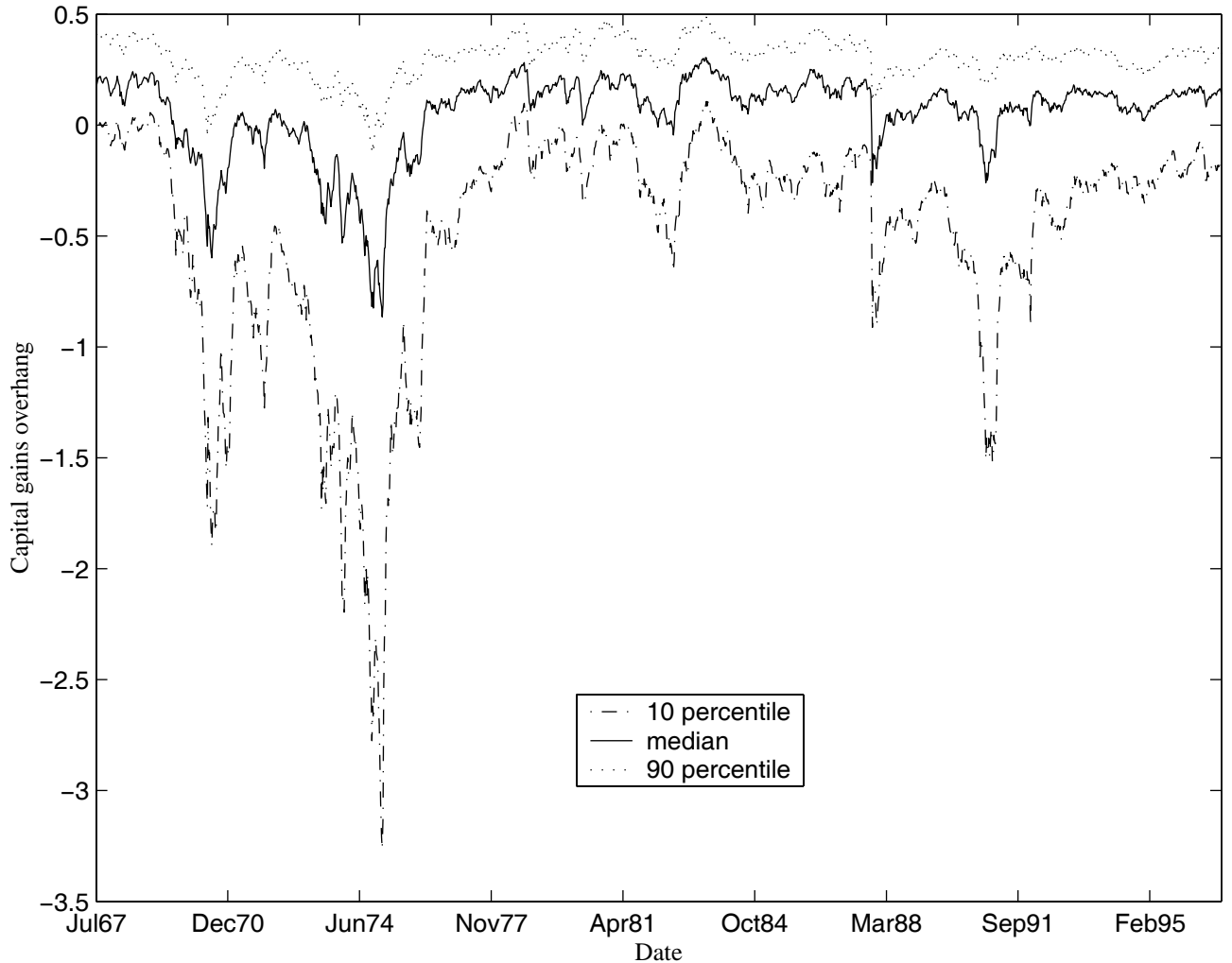
Period	a_1	a_2	a_3	a_4	a_5	a_6
All	-0.0494 (-40.9516)	-0.0000 (-0.0918)	-0.0006 (-4.1084)	-0.0671 (-3.2748)	-0.0004 (-4.4009)	0.4876 (15.6377)
Jan	-0.0661 (-13.0585)	-0.0051 (-3.6265)	-0.0046 (-6.2913)	-0.0535 (-0.8750)	-0.0036 (-10.7269)	-0.1685 (-1.2841)
Feb-Nov	-0.0472 (-36.7643)	0.0004 (1.0364)	-0.0004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

Figure 1: **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.



References

- [1] Ang, Andrew, Geert Bekaert, and Jun Liu, 2001, "Why stocks may disappoint," Working Paper, Columbia University and UCLA.
- [2] Barberis, Nicholas, Andrei Shleifer and Robert Vishny, 1998, "A model of investor sentiment," *Journal of Financial Economics* 49, 307-343
- [3] Barberis, Nicholas, Ming Huang and Tano Santos, 2001, "Prospect theory and asset prices," *Quarterly Journal of Economics*, February, 2001
- [4] Barberis, Nicholas, Ming Huang, 2001, "Mental accounting, loss aversion, and individual stock returns," *Journal of Finance* 56, 1247-1292
- [5] Benartzi, Shlomo, and Richard H. Thaler, 1995, "Myopic Loss Aversion and the Equity Premium Puzzle," *Quarterly Journal of Economics*, February 1995, 73-92
- [6] Berk, Jonathan, Richard Green and Vasant Naik, 1999, "Optimal Investment, Growth Options and Security Returns," *Journal of Finance* 54, 1153-1607
- [7] Berkelaar, Arjan, and Roy Kouwenberg, 2000, "Optimal portfolio choice under loss aversion," Econometric Institute Report 2000-08, Erasmus University Rotterdam, The Netherlands
- [8] Case, Karl, and Robert Shiller, 1988, "The behavior of home buyers in boom and post-boom markets," *New England Economic Review*, November/December, 29-46.
- [9] Chan, Louis K., Narasimhan Jegadeesh, and Josef Lakonishok, 1996, "Momentum strategies," *Journal of Finance* 51, 1681-1713.
- [10] Conrad, Jennifer S., and Gautam Kaul, 1998, "An anatomy of trading strategies," *Review of Financial Studies* 11, 489-519.
- [11] Constantinides, George, 1984, "Optimal stock trading with personal taxes: Implications for prices and the abnormal January returns," *Journal of Financial Economics* 13, 65-69
- [12] Daniel, Kent, David Hirshleifer and Avanidhar Subrahmanyam, 1998, "Investor psychology and security market under- and overreactions," *Journal of Finance* 53, 1839-1886
- [13] De Bondt, Werner, and Richard Thaler, 1985, "Does stock market overreact?," *Journal of Finance* 40, 793-808
- [14] DeLong, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert Waldmann, 1990, "Positive feedback investment strategies and destabilizing rational speculation," *Journal of Finance* 45, 379-395

- [15] Fama, Eugene F., and James MacBeth, 1973, "Risk, return, and equilibrium: empirical tests," *Journal of Political Economy* 81, 607-636
- [16] Fama, Eugene F., and Kenneth R. French, 1996, "Multifactor explanations of asset pricing anomalies," *Journal of Finance* 51, 55-84
- [17] Ferris, Stephen P., Robert A. Haugen and Anil K. Makhija, 1988, "Predicting contemporary volume with historic volume at differential price levels: evidence supporting the disposition effect," *Journal of Finance* 43, 677-697
- [18] Genesove, David, and Christopher Mayer, 2001, "Loss aversion and seller behavior: evidence from the housing market," NBER Working Paper No. W8143, March 2001
- [19] George, Thomas and Chuan-Yang Hwang, 2002, "52-Week High and Momentum Investing," Working Paper, Hong Kong University of Science and Technology. August, 2002
- [20] Gervais, Simon, Ron Kaniel and Dan H. Mingelgrin, 2001, "The high-volume return premium," *Journal of Finance* 56, 877-919
- [21] Goetzmann, William N., and Massimo Massa, 2003, "Disposition matters: Volume, volatility and price impact of a behavioral bias," Yale ICF Working Paper, No. 03-01, January, 2003
- [22] Gomes, Francisco, 2000, "Loss aversion and the demand for risky assets," job market paper, Harvard University, Jan 2000
- [23] Grinblatt, Mark, and Matti Keloharju, 2001, "What makes investor trade?," *Journal of Finance* 56, No. 2, 589-616
- [24] Grinblatt, Mark, and Tobias Moskowitz, 2002 "Predicting stock price movements from the pattern of past returns," forthcoming *Journal of Financial Economics*
- [25] Grundy, Bruce D., and Spencer J. Martin, 2001, "Understanding the nature of risks and source of rewards to momentum investing," *Review of Financial Studies*, Vol. 14, No. 1, 29 – 78
- [26] Heath, Chip, Steven Huddart, and Mark Lang, 1999, "Psychological factors and stock option exercise," *Quarterly Journal of Economics* 114, No.2, 601-628
- [27] Heilmann, Klaus, Volker Laeger, and Andreas Oehler, 2000, "Evidence about the investors aversion to realize losses: A contribution to behavioral finance through the use of experimental call markets," working paper, University of Bamberg
- [28] Hong, Harrison, and Jeremy Stein, 2000, "A unified theory of underreaction, momentum trading and overreaction in asset markets," *Journal of Finance* 54, 2143 – 2184

- [29] Jegadeesh, Narasimhan, and Sheridan Titman, 1993, "Returns to buying winners and selling losers: implications for stock market efficiency," *Journal of Finance* 48, 65 – 91
- [30] Jegadeesh, Narasimhan, and Sheridan Titman, 2001, "Profitability of momentum strategies: An evaluation of alternative explanations," *Journal of Finance* 56, 699-720
- [31] Jegadeesh, Narasimhan, and Sheridan Titman, 2002, "Cross-sectional and time-series determinants of momentum strategies," *Review of Financial Studies* 15, 143-157
- [32] Johnson, Timothy, 2002, "Rational momentum effects," *Journal of Finance* 57, 585-608
- [33] Kaustia, Markku, 2001, "Can loss aversion move the market? Evidence from IPO trading volume," Working Paper, Helsinki School of Economics and Business Administration, 2001
- [34] Kahneman, Daniel, and Amos Tversky, 1979, "Prospect theory: An analysis of decision under risk," *Econometrica* 47, 263-291
- [35] Lee, Charles M.C. and Bhaskaran Swaminathan, 2000, "Price momentum and trading volume," *Journal of Finance* 55, No.5, 2017-2069
- [36] Liu, Jun, and Francis Longstaff, "Losing Money on Arbitrages: Optimal Dynamic Portfolio Choice in Markets with Arbitrage Opportunities," forthcoming, *Review of Financial Studies*
- [37] Locke, Peter R., and Steven C. Mann, 2000, "Do Professional Traders Exhibit Loss Realization Aversion," manuscript, George Washington University and Texas Christian University, November 2000
- [38] Moskowitz, Tobias, and Mark Grinblatt 1999, "Do industries explain momentum?," *Journal of Finance* 54, No. 4, 1249-1290
- [39] Odean, Terrance, 1998, "Are Investors Reluctant to Realize Their Losses?," *Journal of Finance* 53, 1775-1798
- [40] Rouwenhorst, K. Geert, 1998, "International momentum strategies," *Journal of Finance* 53, 267-284
- [41] Shapira, Zur, and Itzhak Venezia, 2001, "Patterns of behavior of professionally managed and independent investors," *Journal of Banking and Finance*, 25 (2001), 1573-1587

- [42] Shleifer, Andrei, 2000, "Inefficient markets: an introduction to behavioral finance," *Clarendon Lectures in Economics*, Oxford University Press, 2000
- [43] Shleifer, Andrei, and Robert Vishny, 1997, "The limits to arbitrage," *Journal of Finance* vol 52, 35-55
- [44] Shefrin, Hersh, and Meir Statman, 1985, "The disposition to sell winners too early and ride losers too long: Theory and evidence," *Journal of Finance* 40 777-90
- [45] Shumway, Tyler, 1997, "Explaining returns with loss aversion," Working Paper, University of Michigan
- [46] Thaler, Richard, 1985, "Mental accounting and consumer choice," *Marketing Science* 4, 199-214
- [47] Thaler, Richard, and Eric Johnson, 1990, "Gambling with house money and trying to break even: the effects of prior outcomes on risky choice," *Management Science*, 36, 643-660
- [48] Thaler, Richard, 1999, "Mental accounting matters," *Journal of Behavioral Decision Making* 12, 183-206
- [49] Weber, Martin and Colin Camerer, 1998, "The disposition effect in securities trading: an experimental analysis," *J. Economic Behavior And Organization*, 33 (2) 167-184
- [50] Weber, Martin and Heiko Zuchel, 2001, "The Disposition Effect and Momentum," Working Paper, University of Mannheim, 01-26
- [51] Wermers, Russ, 2003, "Is Money Really "Smart"? New Evidence on the Relation Between Mutual Fund Flows, Manager Behavior, and Performance Persistence," Working Paper, University of Maryland, May 2003