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Riding the Wave of Sentiment: An Analysis of Return Consistency as a Predictor of Future Returns

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This article analyzes the degree to which return consistency in the past predicts future returns. I show that consistency is a strong predictive measure for future stock returns. In a portfolio context, positively consistent stocks exhibit positive future risk-adjusted returns, and negatively consistent stocks exhibit negative future risk-adjusted returns. The results are economically and statistically significant over multiple subperiods. Also, odd return behavior persists for nearly two years after portfolio formation. Stocks that have been consistently positive (negative) for longer time horizons have higher (lower) risk-adjusted returns during the following month than those that have been consistent for shorter time periods. Finally, high consistency enhances momentum when the two factors are allowed to interact. Thus, there appears to be strong path dependence in the momentum effect, and consistency in stock returns appears to be an important component of return predictability.

Background and Extended Literature Review

Understanding return predictability from risk-based and behavioral perspectives has gained importance in the field of finance. Jegadeesh and Titman [1993] document medium-term predictability in stock returns. By forming portfolios based on deciles of prior mean returns, they determine that excess profits can be earned by purchasing stocks in the highest return decile, and selling those in the lowest return decile. They show that the profits cannot be explained by the unconditional CAPM or by delayed price reaction to common factors. Generally speaking, no asset pricing model has been able to explain this momentum effect.

Jegadeesh and Titman [1999], Lee and Swaminathan [2000], and others show that returns tend to reverse over long horizons, leading to the argument that investors overreact to past returns. These results represent a potential violation of market efficiency, and lead to the question of which cues lead investors to overreact.

The overreaction might be expected if past returns are factored into the investor's model for predicting future stock returns. Lee and Swaminathan [2000] argue that trading volume is one of the conditioning variables researchers might use to understand how past returns are factored into the expected return calculation. Additional variables are overconfidence (Daniel, Hirshleifer, and Subrahmanyam [1998]) and earnings momentum (Chan, Jegadeesh, and Lakonishok [1996]).

This paper analyzes the importance of *consistency* as a predictor of future stock returns, controlling for momentum effects and other variables that might lead to return predictability. We define consistency as the relative frequency of positive or negative returns over a given period. More specifically, consistency is initially measured by dummy variables that account for whether the stock has had a run of positive or negative returns during the prior six months. We also include a weaker consistency measure, in which firms are considered positively (negatively) consistent if four of the last six returns are positive (negative).

The consistency question is logical, given that return momentum without considering the consistency of those returns is incomplete. If one analyzes the technical side of the momentum phenomenon, it might be meaningful to determine whether investors react to the magnitude of past returns, or to the consistency with which those returns are realized. Does a high-return stock with six continuous months of consistent returns receive preferential treatment over a stock with the same gains that had only one very strong return, skewing its return distribution for the pre-investment period? This is the question that we attempt to answer.

An analysis of consistency might also provide clues as to whether there is a risk-based explanation for the momentum effect. If there is, then uncovering path dependence in the process leaves more to be explained. Path dependence is a technical phenomenon, and is not as easily linked to fundamentals. However, discovery of these relationships does not preclude the possibility of a risk-based explanation. We must keep in mind that investor sentiment can be considered a macroeconomic risk factor as well, and path dependence in the momen-

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tum effect may imply that sentiment changes through time depending on the consistency of a stock's recent performance.

Path dependence is illustrated in the graphs of stocks A, B, and C in Figure 1. Which of these stocks truly exhibits momentum? Some might not consider stock A to be a high-momentum stock, even though its return for the past six months is the same as the others. Some might even consider stock C to be a negative momentum stock. Stock B appears to have the most consistent improvement in price, given that its price each month exceeds the price from the prior month. Understanding whether the market treats each of these securities differently may provide clues as to why the market prices momentum, and why it might make sense for investors to place a higher value on high-momentum stocks than low-momentum ones.

The predictability of consistency may be driven by the herding behavior of momentum traders. It may also be related to some form of "slow information leakage," where good news is followed by more good news, or positive information is incorporated more readily than negative information (perhaps due to short-selling constraints). A high-momentum stock with strong consistency is more likely to fit with theories of under- and overreaction to information. Therefore, we might expect that price consistency, in and of itself, contains information about future returns *above and beyond* what we can obtain by simply analyzing the mean. Whether this information relates to fundamental changes in value or predictable time variation in noise trader sentiment is another question, however.

To our knowledge, Grinblatt and Moskowitz [2002] is the only paper that has analyzed return consistency and its interaction with momentum. The authors used securities from 1963 through 1999, and find a consistent winner effect over medium-term horizons. They also found that the sign of past returns matters when predicting future returns.

This paper takes the additional steps of analyzing security returns in subperiods from 1927 through 1999. I find a strong and robust loser consistency effect that maintains itself over the following two years.

Finally, I determine that future excess returns are increasing (decreasing) over the length of time the stock has been positively (negatively) consistent. These results support the theoretical predictions of Grinblatt and Han [2001] and Shefrin and Statman [1985]. They argue that a "disposition effect," in which investors are less likely to sell securities that have amassed capital losses, leads to path dependence in the momentum effect. The presence of a strong consistent winner and loser effect may point to a behavioral explanation for momentum.

The second section describes the data and variables used here. The third section revisits the Jegadeesh and Titman [1993] study. The fourth section presents results from empirical tests, and the fifth section analyzes varying measures of consistency. The sixth section analyzes additional interactive effects between consistency and momentum. And the paper concludes with the seventh section.

The Data and Variable Descriptions

Stock returns were gathered from the Center for Research in Securities Prices (CRSP) database for the period of January 1927 through December 1999. Securities with less than twenty-four months of returns history are eliminated from the sample. Securities must also have data available on each of the variables for the test in which it is included.

The first and primary measure of return consistency involves analyzing securities with six months of consecutive price increases or decreases. For this initial measure, a security is considered positively (negatively) consistent if its returns are positive (negative) during every month of the entire pre-investment period. Weaker measures are considered in the next section. Six months is chosen here for the pre-investment period because it is long enough to draw some inference, but not so long that there are no stocks that meet the criterion. Other horizons are considered later.

Equations (1) and (2) present these definitions in equation form:

$$\text{Positive dummy(t)} = 1_k \text{ where } 1_K = \begin{cases} 1 & \text{if } r_{t-1}, \ldots, r_{t-K} > 0 \\ 0 & \text{else} \end{cases} \quad (1)$$

$$\text{Positive dummy(t)} = 1_k \text{ where } 1_K = \begin{cases} 1 & \text{if } r_{t-1}, \ldots, r_{t-K} < 0 \\ 0 & \text{else} \end{cases} \quad (2)$$

r_j refers to the return during period j, where j is the (t-j)th realization in the return-generating process. Positive dummy (negative dummy) is a dummy variable with the value of 1 if all returns during the prior K periods are positive (negative), and 0 otherwise. These variables are formulated for every month of the time series and for every stock in the cross-section.

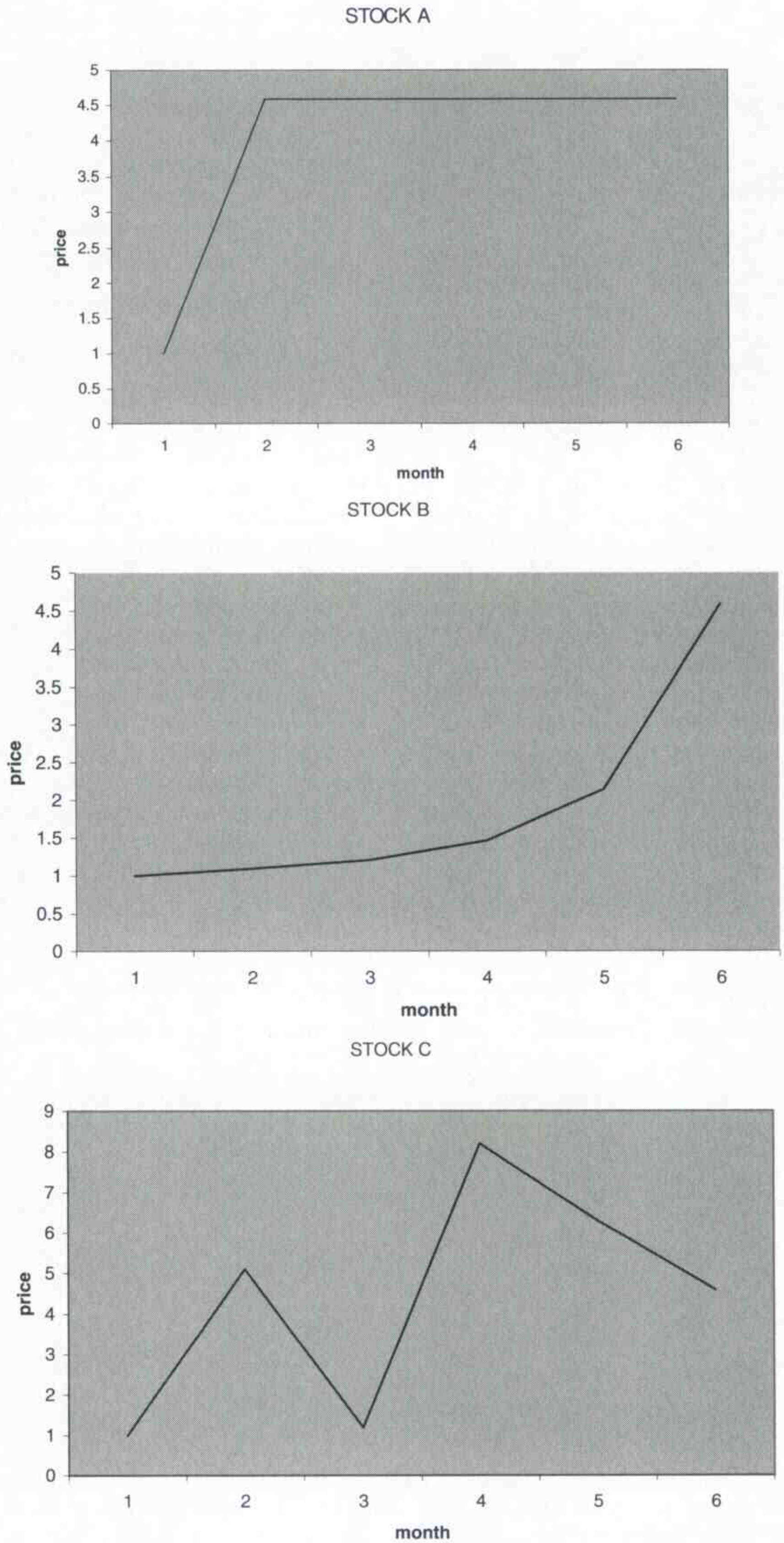
Weak consistency dummies are also calculated for use later in the paper. Weak consistency dummies have a value of 1 if the firm has had positive returns for four of the past six months. Equivalent measures for twelve, twenty-four, and thirty-six months are also calculated. To see this in equation form, consider the following. If we let:

$$\lambda_j = \begin{cases} 1 & \forall\ r_j > 0,\ j = t\text{-}1, \ldots, t\text{-}6 \\ 0 & else \end{cases} \quad (3)$$

we can then define:

$$\theta(t) = \sum_{j=t-1}^{t-6} \lambda_j \quad (4)$$

FIGURE 1
The Price Series of Three Stocks Over a Given Six-Month Period



Note: On the x-axis lies the given month after investment; on the y-axis lies the price of the stock.

Finally, we have a weak positive consistency dummy variable that can be defined as:

$$W^{t}{}_{j} = \begin{cases} 1 \ \forall \ \theta(t) > 4 \\ 0 \ \ else \end{cases} \quad (5)$$

This equation is specific to the six-month pre-investment evaluation period, but could easily be generalized to other evaluation periods. In all cases, a security is defined as weakly consistent if two-thirds of its returns are either all positive or all negative.

Table 1 shows that roughly 1%-1.5% of all securities during a given month have had six consecutive months of positive returns. The breakdown by decade shows that the percentage is relatively stable, with the maximum occurring during 1980-1989, when 1.75% of all firms met the criterion. The minimum is the 1927-1939 time period, when only 0.86% of all firms reached the standard.

Negative runs have roughly the same likelihood as positive ones. The overall average is only slightly lower (1.32% versus 1.12%), so the aggregate positive and negative consistency measures have a surprisingly strong negative autocorrelation through time. The maximum average (not surprisingly) occurs during the Depression, and the minimum occurs during the 1980s, the same time period that the maximum occurs for the positives. The number of firms meeting the standard is low. Even during the decades with the greatest number of publicly traded securities, less than forty stocks per year are included in either strong consistency group.

Note that the weak consistency dummies capture a greater proportion of the cross-section than the strong consistency dummies. The mean proportion of firms with weak positive consistency is only slightly higher than that for negative firms (roughly 31% versus 28%). Across decades, we see that the minimum for the weak positive consistency measure is during the Depression, and the maximum is during the 1950s. For the weak negative consistency measure, the minimum occurs during the 1980s, and the maximum occurs during the Depression. So there is a connection between the consistency variables and economic activity. There is also a strong negative correlation between the positive and negative consistency measures, i.e., the low points for one usually occur at the high points for the other.

Results from Empirical Tests

Strong Consistency Tests

The initial tests in this research begin with strong consistency measures. For now, we consider stocks to be highly consistent if they have six months of consecutive positive or negative returns. This is obviously restrictive, and weaker measures are considered later. I calculate hedge portfolio returns each month by subtracting the equal-weighted mean return for all stocks that are not highly consistent from the equal-weighted mean return for those that are highly consistent. Also, a final hedge portfolio is calculated by subtracting the returns of the negative consistency portfolio from the returns of the positive consistency portfolio.

Table 2 shows the results from these portfolios, with buy-and-hold returns for up to two years broken into six-month intervals. This dissection of time periods allows us to determine if and when the rewards to consistency show themselves. A rudimentary analysis on this level is enough to determine if further study into consistency is warranted.

Table 1. *The Percentage of Stocks With Six Months of Consecutive Positive or Negative Returns*

Variable	1927–1939	1940–1949	1950–1959	1960–1969	1970–1979	1980–1989	1990–1999	Overall
Mean								
N	669.98	818.05	994.62	1297.50	1922.23	2019.85	2680.66	1486.13
Six month positive dummy	0.86%	1.10%	1.72%	1.29%	1.12%	1.75%	1.38%	1.32%
Six month negative dummy	1.33%	0.96%	0.87%	1.35%	1.59%	0.70%	1.02%	1.12%
Four of six months positive dummy	23.66%	31.27%	35.79%	30.59%	26.90%	34.98%	31.95%	30.73%
Four of six months negative dummy	33.39%	28.20%	24.72%	30.17%	32.26%	24.62%	25.51%	28.41%
Standard Deviation								
Six month positive dummy	0.06	0.07	0.10	0.09	0.08	0.11	0.10	0.09
Six month negative dummy	0.09	0.07	0.07	0.09	0.09	0.07	0.09	0.08
Four of six months positive dummy	0.36	0.39	0.44	0.42	0.40	0.45	0.45	0.41
Four of six months negative dummy	0.39	0.38	0.39	0.42	0.42	0.40	0.41	0.40
Skewness								
Six month positive dummy	14.39	14.33	13.27	14.87	17.80	11.96	11.74	14.05
Six month negative dummy	12.45	16.09	16.55	13.84	15.86	17.13	12.55	14.92
Four of six months positive dummy	2.27	1.44	0.80	1.22	1.58	0.77	0.89	1.28
Four of six months negative dummy	1.01	1.88	1.68	1.12	1.09	1.47	1.30	1.36

Note: All stocks in the CRSP universe from January 1927 through December 1999 were analyzed for every month during this time frame. The percentage of stocks with six months of consecutive positive or negative returns were calculated and averaged across decades (see below). A weaker dummy variable was also calculated as the percentage of stocks with four of the past six months having positive or negative returns. The time series mean of the cross-sectional mean, standard deviation, skewness, and sample size are shown below. The results are presented for the entire time period and by decade.

Table 2. *For Every Month From January 1927 Through December 1999 Stocks are Sorted Into Groups Based on Whether They Have Had Six Consecutive Months of Positive Returns*[a]

Horizon	Hedge	T-stat	Positive	T-stat	Non-positive	T-stat
Positive consistency dummy						
Months 1–6	3.34	6.74	7.43	10.20	3.40	5.45
Months 7–12	0.53	1.16	3.76	5.43	3.49	5.57
Months 13–18	–0.74	–1.86	2.62	3.54	3.51	5.58
Months 19–24	0.52	1.20	3.67	4.77	3.51	5.57
Negative consistency dummy						
Months 1–6	–4.94	–9.97	–2.09	–2.49	3.48	5.58
Months 7–12	–3.23	–6.92	–0.04	–0.05	3.53	5.64
Months 13–18	–0.83	–1.75	2.54	3.15	3.51	5.57
Months 19–24	–0.89	–1.72	2.63	2.93	3.51	5.57
Positive minus negative						
Months 1–6	9.57	12.50	7.43	10.20	–2.09	–2.49
Months 7–12	3.75	4.92	3.76	5.43	–0.04	–0.05
Months 13–18	–0.08	–0.11	2.62	3.54	2.54	3.15
Months 19–24	1.65	2.02	3.67	4.77	2.63	2.93

Note: The mean return for these stocks is then analyzed during months t + 1 through t + 6, t + 7 through t + 12, t + 13 through t + 18, and t + 18 through t + 24. Each return is then compared to the buy-and-hold return for the same time period for those securities without six consecutive months of positive returns. The hedge portfolio buy-and-hold returns are shown below. This process is then repeated for those securities with six consecutive months of negative returns (negative consistency dummies). Finally, the mean return each month for stocks with six months of negative returns is subtracted from the mean return for those with six months of positive returns, creating the "positive minus negative" portfolio. This is shown in the third panel.

[a] All coefficients are multiplied by 100.

To summarize Table 2, there are three hedge portfolios formed (one for each panel of the table). The first panel compares the stocks that have high positive consistency with those that do not; the second panel compares for high negative consistency; and the third panel compares those that have positive consistency with those that have negative consistency.

The buy-and-hold returns for each hedge portfolio are calculated during months t + 1 through t + 6, t + 7 through t + 12, t + 13 through t + 18, and t + 19 through t + 24. The returns are orthogonalized, meaning there is no overlap in the investment horizons or return calculations.

For example, the returns for months 7-12 do not include investment months before t + 7 or after t + 12. This allows us to see the return for a given portfolio during each investment period. Risk adjustments are not quite reasonable when analyzing semiannual returns for portfolios formed during the past, so these results are calculated for raw hedge portfolio returns only. If the magnitude of return differences is strong, it is nearly impossible to determine whether the difference in risk between the high- and low-consistency portfolios drives the entire return difference. We address risk adjustments with more tests later.

The positive consistency hedge portfolios show strong gains during the first six months after formation. The mean return for positively consistent stocks during the first six months is roughly 13.5% per year, giving a hedge portfolio return of 6.68% per year. During the first six months, the returns on positively consistent stocks are nearly double that of other stocks in the cross-section. The return difference between positively consistent stocks and all others is only about 1% per year for months 7-12, and it is actually lower than other stocks during months 13-18. The return differential is not significant during months 19-24. It is clear that returns to the positive consistency strategy are very strong for the first six months after portfolio formation and appear to show some type of reversal over longer horizons. Returns are not analyzed for periods of longer than two years.

The results on negative consistency tell a different story. The returns are strongly negative for the first year, and there is no sign of reversal during the first two years, when returns to these stocks are always lower than those of other securities in the cross-section. The most negative hedge portfolio returns occur during the first six months, averaging –9.88% per year, when negatively consistent stocks have average returns of –4.18% per year. The negative performance of these firms continues during months t + 7 through t + 12, when hedge portfolio returns are –6.46% per year. The returns to negatively consistent stocks themselves are roughly zero at this time, so they level off. But they still severely underperform other stocks in the market.

During months t + 13 through t + 24, there is a less than 2% per year difference between the negatively consistent stocks and other stocks in the cross-section. But no reversal is apparent during the time period analyzed. Thus, there appears to be a consistency effect for losers as well, and evidence that the consistent loser effect is due to underreaction. It is also possible that these stocks are experiencing long-horizon corrections to previous overreactions, however. Finally, there is the possibility that reversals take place after year 2.

The positive minus negative hedge portfolio is analyzed in the final panel of Table 3. The difference between the returns on consistent winners and losers is extremely strong early, averaging over 19% per year during the first six months. The difference continues during months 7-12, at roughly 7.5% per year. The fact that these are zero investment hedge portfolios makes the result that much more significant.

The difference between the returns of each group is insignificant during months t + 13 through t + 18. This is when both groups of stocks underperform other stocks in the market. Finally, the difference is positive again during months t + 19 through t + 24, when winners slightly outperform the rest of the market and losers underperform.

Analysis with raw returns over various horizons gives some idea of the big picture of consistency and whether there may be a consistency effect. Obviously, we must question whether consistency is simply capturing momentum, and whether this phenomenon applies to the broader cross-section of securities. We must also address risk adjustment. We answer some of these questions in the next section, and address them in other ways later.

Table 3. *For Every month From January 1927 Through December 1999, All CRSP Stocks Are Sorted Based on the Number of Positive/Negative Returns During the Prior Six, Twelve, And Twenty-Four months*

Period/Horizon	Intercept	T-stat	SMB	T-stat	HML	T-stat	MKT	T-stat	MOM	T-stat	January	T-stat
Pre 1965												
6 month positive	0.42%	5.13	–0.16	–4.77	–0.06	–2.37	–0.06	–3.48	0.30	17.40	–0.01	–3.33
12 month positive	0.65%	5.60	–0.20	–4.38	–0.19	–5.04	–0.08	–3.51	0.26	10.56	–0.01	–1.27
24 month positive	0.57%	3.84	–0.38	–6.37	–0.49	–10.26	–0.05	–1.71	0.18	5.74	–0.01	–1.76
6 month negative	–0.29%	–3.66	0.00	–0.13	–0.04	–1.43	0.00	–0.02	–0.25	–15.11	0.01	3.51
12 month negative	–0.60%	–4.72	0.01	0.27	0.03	0.83	–0.02	–0.74	–0.14	–5.22	0.02	4.20
24 month negative	–0.54%	–2.86	0.06	0.82	0.06	1.06	–0.10	–2.73	–0.11	–2.71	0.04	5.29
6 months	0.50%	5.01	–0.10	–2.46	–0.01	–0.23	–0.05	–2.39	0.41	19.16	–0.01	–3.81
12 months	1.11%	6.17	–0.19	–2.61	–0.19	–3.26	–0.06	–1.73	0.35	9.26	–0.02	–3.21
24 months	1.06%	4.27	–0.42	–4.27	–0.53	–6.66	0.05	0.97	0.29	5.48	–0.04	–4.79
1965–1969												
6 month positive	–0.06%	–1.06	–0.07	–3.88	–0.05	–2.61	0.02	1.82	0.54	34.50	0.00	–1.55
12 month positive	0.18%	1.97	–0.11	–3.67	–0.16	–4.55	0.04	2.01	0.57	21.11	0.00	–0.76
24 month positive	0.05%	0.38	–0.22	–4.93	–0.38	–7.12	0.06	1.96	0.53	13.06	0.00	–0.37
6 month negative	–0.08%	–1.31	–0.02	–1.23	–0.02	–0.83	–0.02	–1.49	–0.49	–27.47	0.00	–0.92
12 month negative	–0.47%	–4.69	–0.02	–0.64	0.02	0.48	–0.05	–2.02	–0.52	–17.04	0.01	1.93
24 month negative	–0.90%	–4.71	0.11	1.66	0.19	2.59	0.02	0.57	–0.49	–8.56	0.02	2.65
6 months	0.02%	0.31	–0.04	–1.60	–0.03	–1.29	0.03	1.85	0.74	36.42	0.00	–0.02
12 months	0.59%	4.28	–0.07	–1.61	–0.15	–2.83	0.07	2.37	0.92	22.37	–0.01	–1.62
24 months	0.93%	3.87	–0.31	–3.79	–0.55	–5.74	0.03	0.63	0.96	13.20	–0.02	–2.20
1990–1999												
6 month positive	0.02%	0.32	–0.04	–1.52	–0.06	–2.27	0.01	0.47	0.50	19.02	–0.01	–1.98
12 month positive	0.40%	4.10	–0.06	–1.78	–0.16	–4.11	–0.01	–0.54	0.45	12.90	0.00	–1.07
24 month positive	0.47%	3.72	–0.19	–4.25	–0.24	–4.91	0.01	0.32	0.35	7.66	–0.01	–2.40
6 month negative	–0.12%	–1.53	0.02	0.83	–0.04	–1.37	0.07	3.37	–0.58	–20.26	0.00	–0.63
12 month negative	–0.99%	–6.35	0.15	2.82	–0.04	–0.59	0.13	3.15	–0.76	–13.40	0.01	1.02
24 month negative	–1.44%	–4.13	0.32	2.63	0.01	0.11	0.14	1.48	–0.98	–7.79	0.03	2.49
6 months	0.11%	1.23	–0.05	–1.64	0.00	–0.10	–0.04	–1.72	0.77	24.29	0.00	–0.78
12 months	1.22%	6.69	–0.18	–2.78	–0.08	–1.11	–0.13	–2.56	1.04	15.76	–0.01	–1.19
24 months	1.85%	4.92	–0.48	–3.66	–0.24	–1.59	–0.12	–1.22	1.28	9.41	–0.04	–3.01
Overall												
6 month positive	0.24%	5.07	–0.09	–5.40	–0.09	–5.51	–0.02	–1.90	0.37	31.22	–0.01	–4.44
12 month positive	0.51%	7.25	–0.13	–5.22	–0.21	–9.36	–0.03	–2.19	0.35	20.13	–0.01	–2.09
24 month positive	0.44%	4.82	–0.28	–8.45	–0.46	–15.53	–0.02	–0.92	0.28	12.35	–0.01	–2.46
6 month negative	–0.24%	–4.88	–0.01	–0.60	–0.04	–2.82	–0.01	–1.11	–0.32	–26.92	0.01	3.53
12 month negative	–0.70%	–8.48	0.02	0.81	–0.01	–0.31	–0.03	–1.82	–0.26	–12.88	0.02	5.58
24 month negative	–0.90%	–6.76	0.13	2.64	0.01	0.15	–0.07	–2.63	–0.24	–7.27	0.03	7.32
6 months	0.34%	5.64	–0.06	–2.66	–0.03	–1.29	–0.01	–0.68	0.51	33.78	–0.01	–4.35
12 months	1.06%	9.50	–0.13	–3.29	–0.17	–4.77	–0.01	–0.27	0.53	19.09	–0.02	–4.56
24 months	1.29%	7.72	–0.39	–6.41	–0.45	–8.29	0.05	1.46	0.50	12.17	–0.04	–6.80

Note: A stock is defined as positively (negatively) consistent if two-thirds of its returns during the given pre-investment period are positive (negative). A time series of hedge portfolio returns is calculated as the difference between the return on positively (negatively) consistent securities and other stocks in the cross-section. The return series of these portfolios are then regressed on the size, book-to-market, and market factors of the Fama-French three-factor model, a momentum factor, and a January dummy. Period refers to the subperiod of study from which the regression coefficients are calculated. Horizon refers to the length of the pre-investment horizon.

Less Restrictive Consistency Measures

Table 3 analyzes consistency effects using broader measures to allow for more flexibility. Rather than define positive (negative) consistency as six consecutive months of positive (negative) returns, we now define it as having positive (negative) returns for two-thirds of the pre-investment horizon. For example, if the pre-investment period is six months, a stock is positively consistent if four of those months are positive. This includes a much larger proportion of the cross-section of securities, with more than half falling into one consistency group or the other.

Raw portfolio returns (in excess of the mean return for all securities that are not in the high consistency group) are adjusted for risk in a more generalized factor model consisting of all known risk factors in the cross-section of securities: size, book-to-market, return on the market, momentum, and a January dummy. The size, book-to-market, and market factors are derived from the Fama-French three-factor model, and the momentum factor is formed by subtracting the returns of low-momentum NYSE stocks from the returns of high-momentum NYSE stocks. High and low momentum are defined as being in the top and bottom third, respectively.

Once again, three different portfolios are analyzed, one for positive consistency, one for negative consistency, and one for positive minus negative consistency. In the first case, the hedge portfolio returns are calculated by subtracting the equal-weighted mean return of all stocks not in the high positive consistency group from the stocks that are in the group. In the second case, the returns for all securities not in the high negative consistency group are subtracted from those that are in the group. In the final case, the positive consistency and negative consistency stocks are compared. The holding periods are one month for each portfolio.

If consistency has an effect in these regressions, we would expect the intercepts in a time series regression of hedge portfolio returns on the risk factors to be positive for the positive consistency portfolios and negative for the negative consistency portfolios. Also, the intercepts from the high minus low hedge portfolio should be positive. The results are analyzed for three separate time periods for robustness (pre-1965, 1965-1989, and 1990-1999). We also analyze three pre-investment consistency periods of six, twelve, and twenty-four months. Again, a stock is defined as consistently positive (negative) if two-thirds of the returns during the given pre-investment period are positive (negative).

We begin with a discussion of positive consistency alphas, which are positive for every pre-investment horizon and nearly every subperiod studied. The only exceptions are the alphas from the six-month positive consistency hedge portfolio measured during 1965-1989, where the alpha is negative and insignificant. The alphas from the six-month pre-investment horizon are not typically as strong as those from the twelve- and twenty-four-month horizons. However, they tend to be positive, with average annualized excess returns of 2.88%, 6.12%, and 5.28%, respectively, for the six-, twelve-, and twenty-four-month consistency measures.

The alphas for negative consistency show an even stronger trend. For every pre-investment horizon and subperiod, the alphas are significantly negative for the negative consistency portfolios. The average annualized excess returns for all negative consistency hedge portfolios are –2.88%, –8.4%, and –10.8%, respectively, for six, twelve, and twenty-four months. Once again, consistency over longer time horizons has a greater impact on stock returns in both the positive and negative directions. The 1990s show the strongest predictability for negative consistency. During this decade, the mean returns for these securities are –12% and –17.28%, respectively, for the twelve- and twenty-four-month consistency measures.

The positive minus negative hedge portfolio excess returns are positive for every pre-investment period and for every subperiod. The consistency returns are increasing over the amount of time the security has displayed its consistency. The risk-adjusted returns to the hedge portfolios are 4.08%, 12.72%, and 15.48%, respectively, for the six-, twelve-, and twenty-four-month consistencies. One notable period is the 1990s, where twenty-four-month consistency hedge portfolios earned 22.2% after all risk adjustments were taken into account.

The factor loadings are indicative of the characteristics of securities that help form the portfolios. The positive consistency factors tend to be large glamour stocks at the time of portfolio formation, given that they load negatively on the size and book-to-market factors. The magnitudes of the loadings are monotonic in the length of the pre-investment horizon. The loadings on the January dummy are negative for positive consistency portfolios. As expected, the positive consistency portfolios load positively on the momentum factor.

The size and book-to-market loadings for the negative consistency portfolios do not differ significantly from the rest of the market (remember these are zero investment hedge portfolios, so the coefficient in this regression is the difference between the coefficient on the long portfolio and that on the short one). Their betas are less than 1 on average, and they load negatively on momentum. They tend to have positive loadings on the January dummy. Overall, the positive minus negative hedge portfolios tend to have negative loadings on the size and book-to-market factors, positive loadings on momentum, and a negative loading on the January dummy.

Cross-Sectional Tests

The tests in the prior section seem to argue that consistency has an independent impact on returns, as well as an interactive effect with momentum. To provide further confirmation, we perform cross-sectional tests, which allow us to lengthen the investment horizon and determine how long the effects of consistency impact future stock returns.

The regressions are designed as follows:

$$r_i^t = \beta_1(pos_i^t) + \beta_2(neg_i^t) + \beta_3(size_i^t) + \sum_{k=4}^{6} \beta_k(omom(k)_i^t) + \beta_7(lagret_i^t) + \beta_8(turnover_i^t) + \varepsilon_i^t \quad (6)$$

r_i^t is the return on security i at time t. The left-hand side variable is changed to account for longer investment horizons. Returns are analyzed for one-, six-, twelve-, twenty-four-, and thirty-six-month investment horizons. pos_i^t and neg_i^t are dummy variables representing positive or negative consistency during the past six months, not including the current month. If a security has had positive returns in four of the last six months, the positive consistency dummy has a value of 1. If it has had negative returns over the same period, the negative consistency dummy has a value of 1. The intercept is removed because the structure of these variables creates near multicollinearity in the regression model in the presence of an intercept.

Size is the log of firm size during the given month. Omom(k) represents the three momentum measures used here. The momentum measures jointly represent the buy-and-hold returns during the past six, twelve, and twenty-four months. They are orthogonalized, in that the six-month factor [Omom(4)] is measured as the buy-and-hold return for the past six months, and the twelve-month factor [Omom(5)] captures the buy-and-hold return for months 7-12. Similarly, the returns to the twenty-four-month momentum measure include only months 13-24. The momentum measures must be structured this way to prevent overlapping.

Turnover is the share turnover for the firm during the given month. Turnover is defined as shares traded divided by shares outstanding. This measure is included because turnover captures the glamour or value status of the security (see Lee and Swaminathan [2000]). This is a better measure to use in cross-sectional tests than book-to-market because it does not require all stocks to have data on Compustat, thus allowing us to use a larger data set. Lagret is the raw security return from the previous month.

The regressions are run cross-sectionally for every month from January 1927 through December 1999. The coefficient estimates for every month are then averaged and checked for significance. For robustness, coefficient estimates are averaged for the pre-1965 period, 1965-1989, and 1990-1999. Regressions for return horizons exceeding one month should be "taken with a grain of salt," because the right-hand side variables do not adjust for certain risk factors for longer-horizon stock returns. In other words, the inclusion of size from month t does not account for the fact that size in month t + k also plays a role in returns for a given firm in month t + k.

These regressions allow us to determine whether consistency affects future returns independently of momentum, and how consistency during month t affects returns during future months. In effect, the cross-sectional tests here support the joint portfolio sorting procedures of the prior section. Our focus here is only on the sign of the consistency coefficients, not the magnitude. A positive sign for the positive consistency dummy and a negative sign for the negative consistency dummy would serve as additional evidence that consistency should be studied in future research.

Table 4 shows the coefficients on the positive and negative consistency dummies along with the t-statistics. We don't present the other coefficients for the sake of space. Overall, the consistency dummy variables have the predicted sign. For nearly every investment horizon, the positive consistency dummies have positive coefficients, and the negative consistency dummies have negative coefficients. This result holds across nearly all subperiods. Positive consistency begins to weaken during the twenty-four- to thirty-six-month investment horizon, however, where the positive consistency dummy has an insignificantly negative coefficient. This could be evidence of long-term reversals. The positive consistency dummies maintain their significance for investment horizons of up to twelve months.

Nearly all the coefficients on the negative consistency dummy are significant. The exceptions tend to occur in the pre-1965 time period, when stock returns were quite volatile. The generally negative tone of the negative consistency coefficients tends to confirm the results of prior sections. We can conclude that positive consistency tends to reverse, and negative consistency tends to persist. Figure 2 shows the path of the positive and negative consistency dummies as the investment horizon increases.

The regressions appear to argue that consistency has an unconditional impact on stock returns, and that this impact persists through long horizons. Of course, additional testing would be necessary to fully understand long-horizon implications of this phenomenon. In all, the cross-sectional regressions appear to confirm the sign of the consistency effect found in other sections. This makes consistency relevant in the return distribution for a given security.

Potential Explanations

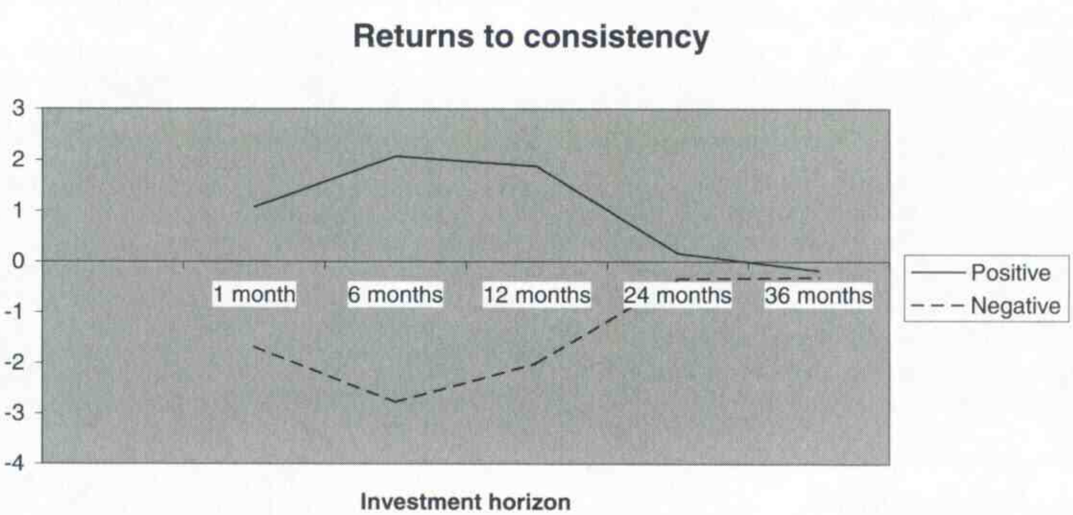
There could be many explanations for the consistency effects uncovered. Three possible theories involve earnings consistency, characteristic effects, and negative skewness. It has been argued that managers tend to smooth earnings (Kirschenheiter and Melumad [2002], Dye [1988], Chaney and Lewis [1995]), which may lead

Table 4. *Results of the cross-sectional regression model*

Horizon/Period	6 Month Positive	T-Stat	6 Month Negative	T-Stat
1 month				
Pre 1965	–0.04	–0.23	–0.12	–0.83
1965–1989	0.07	1.19	–0.13	–2.23
1990–present	0.24	2.76	–0.17	–1.60
Overall	0.09	2.02	–0.14	–2.82
6 months				
Pre 1965	0.32	0.88	–0.28	–1.04
1965–1989	1.00	6.46	–1.39	–9.00
1990–present	1.49	6.64	–1.78	–6.63
Overall	1.04	8.42	–1.39	–10.92
12 months				
Pre 1965	0.02	0.04	0.23	0.68
1965–1989	0.78	4.69	–1.06	–7.34
1990–present	1.87	7.33	–1.22	–4.54
Overall	0.94	6.93	–1.00	–8.20
24 months				
Pre 1965	0.10	0.27	0.23	0.59
1965–1989	0.17	1.22	–0.37	–2.70
1990–present	0.23	0.97	–0.41	–1.88
Overall	0.17	1.54	–0.34	–2.97
36 months				
Pre 1965	0.00	0.00	–0.34	–0.79
1965–1989	–0.14	–0.98	–0.55	–3.62
1990–present	–0.37	–1.58	0.53	1.73
Overall	–0.18	–1.41	–0.31	–2.40

Note: Results of the cross-sectional regression model $r_i^t = \beta^1(pos_i^t) + \beta^2(neg_i^t) + \beta^3(size_i^t) + \sum_{k=4}^{6}\beta^k(omom(k)_i^t) + \beta^7(lagret_i^t) + \beta^8(turnover_i^t) + \varepsilon_i^t$ where the future return of the security over various horizons is regressed on the six-month positive consistency dummy (pos), the six-month negative consistency dummy (neg), the log of firm size during the given month (size), four momentum factors (omom), the return during the given month (lagret), and share turnover (turnover). The positive (negative) consistency dummy equals the value of 1 if four of the firm's last six returns are positive (negative). The momentum factors are defined as: Omom(4) is the buy-and-hold return for months t - 6 through t – 1. Omom(5) is the buy-and-hold return for months t - 12 through t – 7. Omom(6) is the buy-and-hold return for months t – 24 through t – 12. Lagret is the return for month t – 1. Turnover is the number of shares traded divided by the number of shares outstanding for the given firm. The regression is run every month from August 1927 through December 1999. The coefficients are then averaged and checked for significance. To save space, only the coefficients for the positive and negative consistency dummies are shown here. Also, the coefficient estimates are presented for various subperiods: pre 1965, 1965–1989, and 1990–1999.

FIGURE 2
Annualized Coefficients From the Cross-Sectional Regressions in Table 6



Note: The horizontal axis captures the length of the investment horizon. Horizons are orthogonalized, implying that no horizon overlaps with any other. The Y-axis shows the annualized coefficient on the positive or negative consistency dummy variable. The solid line represents the coefficients on the positive consistency dummy, and the dotted line represents the coefficients on the negative consistency dummy.

to consistency effects in stock returns. If the market rewards earnings consistency (or considers consistent earnings to be a signal of reduced risk), this would lead to higher firm valuations in subsequent periods. The fact that return momentum and earnings momentum appear related increases the likelihood of this relationship (Chan, Jegadeesh, and Lakonishok [1996]).

A second possibility is a characteristics-based reaction to consistency. Investors (institutional or otherwise) who believe in market efficiency may believe that their ability to predict future returns is limited. However, a stock with consistently negative returns may be perceived as an "unlucky" draw from the returns distribution. This approach may be naïve, but not all price setters are sophisticated enough to correctly assess future stock returns. An investor who witnesses such autocorrelation in a stock's return distribution may believe that returns for a given firm are no longer a random walk. Given that other players in the market may or may not be rational, it would not be completely illogical to use the price trend for additional inference.

A third possibility involves risk induced by the path of prior stock returns. According to Chen, Hong, and Stein [2001], the manner in which information is incorporated into stock returns tends to lead to a series of positive price movements, introducing negative skewness into the returns distribution. Quasi-rational investors would recognize these effects and require additional return to compensate for the skewness risk, even if it is induced by behavioral factors. But answers to these questions are ultimately for future research.

Conclusion

We analyze return continuation and its impact on future stock returns. We find a clear and strong consistency effect in the returns distribution. This effect is stronger in the negative direction than the positive, and continues to persist for the following two years. Consistent winners strongly outperform all other stocks and consistent losers. This effect appears to be robust through time and various risk adjustments.

There is some reversal for winners over the next two years, however, but no reversal for losers. The fact that consistent winners (losers) have stronger returns than inconsistent winners (losers) seems to point to a potential explanation for the momentum effect. However, the fact that consistency has an impact independent of momentum argues that it may be a return predictor in itself.

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