Stock Return Momentum and Reversal

A comprehensive study.

Ilya Figelman

A fundamental question in finance is how a firm's past stock performance affects future stock returns. For well over a decade stock return momentum and reversal have been known to both practitioners and academicians. The intermediate-term momentum effect was noted first by Jegadeesh and Titman [1993]. Two stock return reversal effects are also well known: short-term (one-month) reversal, first analyzed by Jegadeesh [1990], and long-term reversal, first analyzed by De Bondt and Thaler [1985].

I further investigate these three stock return momentum and reversal effects, and document two new very strong momentum effects. This work adds to the literature in four ways. First, it comprehensively analyzes the three known return momentum and reversal effects on stocks in the S&P 500. Other authors have provided perceptive insights into stock momentum and reversal, but none of them has comprehensively and consistently analyzed all three effects simultaneously.[1]

Second, I document two new stock momentum effects, long-term yearly periodicity and intermediate-term quarterly periodicity, that are even stronger than the three known effects. In the long term, stock returns tend to exhibit a pattern every 12 months; thus a stock's relative return in June is positively related to its relative returns in June of previous years.[2] In the intermediate term, stock returns tend to exhibit a pattern every three months; thus a stock's relative return in June is positively related to its relative returns in the previous March, December, September, and June.

Third, I dissect the five momentum and reversal effects in various ways in order to understand them better. All the effects are driven generally by both stock-specific and

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industry dynamics, except for short-term reversal, which is purely a stock-specific phenomenon. This observation complements the work of Moskowitz and Grinblatt [1999], Grundy and Martin [2001], and Chordia and Shivakumar [2002].

It is shown that the five momentum and reversal effects are prevalent in most calendar months. In January months, however, there is a strong reversal even for the intermediate term, which exhibits momentum in most other months. All these effects, except for quarterly periodicity, are enhanced in months of earnings announcements.

Finally, I include implementation considerations for stock return momentum and reversal strategies.

DATA AND METHODOLOGY FOR UNIVARIATE ANALYSIS

The momentum and reversal study is performed on all stocks in the S&P 500 universe. Monthly stock returns are obtained from the Center for Research in Security Prices for January 1970 through December 2004. Most academic articles use much broader stock universes, such as all stocks listed on the New York Stock Exchange and the American Stock Exchange, which are dominated by small- and micro-cap stocks. It is much more accurate in measurement of the profitability of a return-based investment strategy to use large-cap stocks. Large-cap stocks are more liquid, and their quoted prices are much closer to their executable prices, especially for portfolios of any significant size.

Historically, the stocks in the S&P 500 have represented between 55% and 75% of the total U.S. market capitalization, but less than 10% of the total number of securities. Thus, it is especially important to use large-cap stocks in studies such as this because the simulated investment strategies involve portfolios of equally weighted stocks. Otherwise the results would be dominated by illiquid small- and micro-cap stocks.

This work mainly analyzes the effect of a stock's past return on its future return. A quintile-based historical analysis is performed to measure the effect of various combinations of past stock returns on future stock returns. Transaction costs are not considered in this analysis (but will be discussed later). The forward return spread between the first and fifth quintiles is a proxy for the potential profit from various momentum and reversal strategies.

The historical univariate quintile methodology has four steps. All my exhibits present information based on this methodology.

Step 1

The momentum, reversal, or related variable to be tested is chosen. The variable is either:

1. The cumulative return for a previous period (e.g., past months 1-12).
2. Or the return of a particular previous month (e.g., past month 12).
3. Or a given combination of previous months' returns (e.g., past months 3, 6, 9, and 12).

Step 2

For each month, all the stocks in the S&P 500 are ranked by the given variable defined in Step 1 and then grouped into quintiles on the basis of this ranking.

The return variables could be computed either relative to the market (the S&P 500) or relative to an equally weighted industry benchmark return. (Ranking past stock returns relative to the S&P 500 return yields the same results as ranking by absolute past returns. This is not the case when one is ranking past stock returns relative to an industry benchmark.)

Ranking stocks relative to their industry controls for the industry effect and isolates the stock-specific effect of the momentum or reversal variable. Stocks are placed into one of 38 industries using a proprietary methodology that is based on SIC codes and Morgan Stanley's Global Industry Classification Standards (GICS).

If a stock is relatively new and does not have enough past return history, a market or industry return is assigned to the missing months for that stock. (Eliminating observations with not enough historical returns has no significant effect on the results.)

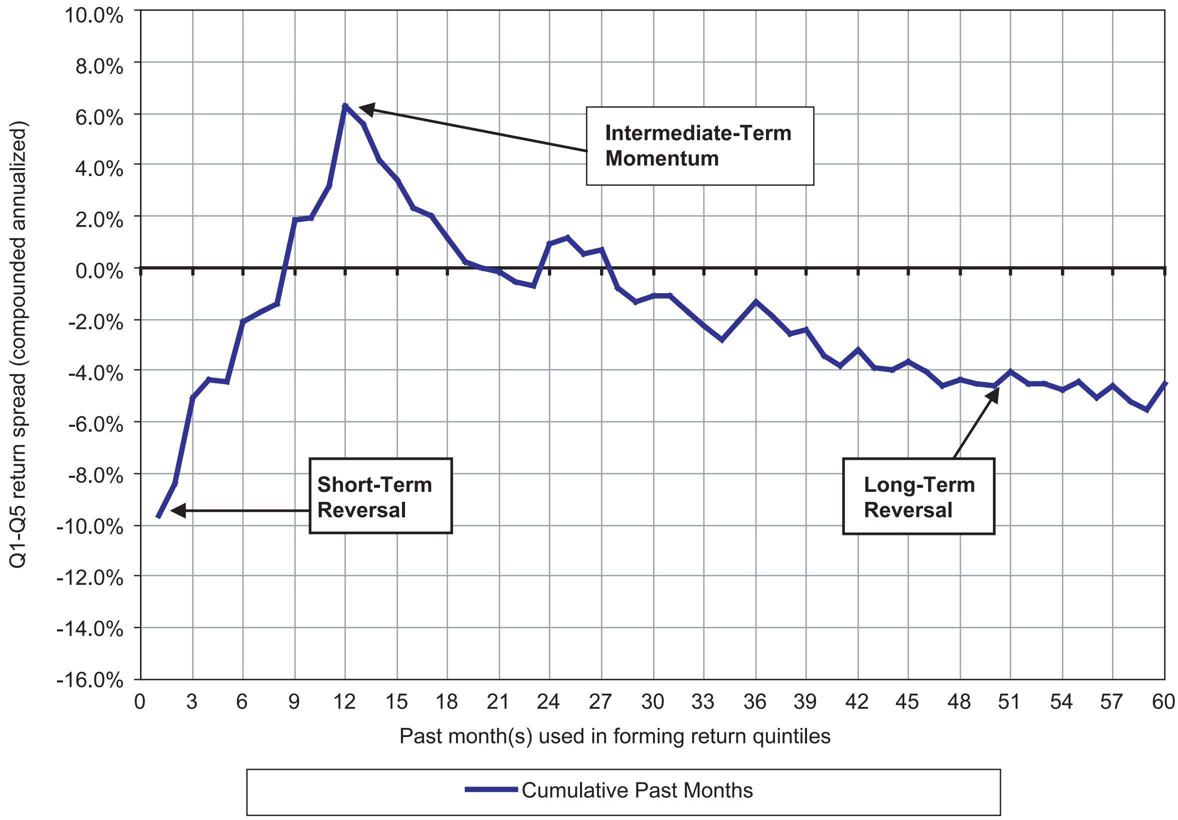
Step 3

In each month, two equally weighted portfolios are created—one that buys all stocks in the first quintile (Q1), and another that buys all stocks in the fifth quintile (Q5). It is usually assumed that both these portfolios are held for one month and then completely rebalanced. Longer holding (rebalancing) periods of one quarter, one half-year, and one year are also considered. Since these portfolios are formed every month, there is an overlap in the return profits for longer holding periods.

To avoid bias, a stock's forward return is captured even if it disappears from the S&P 500 during that month

EXHIBIT 1

Historical Simulation of Return Momentum and Reversal



Annualized Q1 – Q5 return spread for one-month holding period.
Quintiles ranked by previous cumulative returns. Equally weighted quintiles formed each month by past returns relative to total market. Universe: S&P 500. Time period: Jan 1970-Dec 2004 (overlapping). No transaction costs.

(quarter, half-year, or year). If a stock has a missing return in any forward month, the market return is assigned to that stock for that month.

Step 4

The difference between the compounded annualized historical returns of the Q1 and Q5 portfolios is computed. This difference is referred to as the Q1 – Q5 return spread. The corresponding annualized standard deviation, information ratio, and t-statistic are sometimes calculated as well. Transaction costs are not included in this analysis.

The historical annualized return of each quintile relative to the market return is also sometimes shown. For this calculation, the forward market return is an equally weighted S&P 500 return, even if in Step 2 stocks are ranked by past returns relative to the industry benchmark.

EMPIRICAL RESULTS

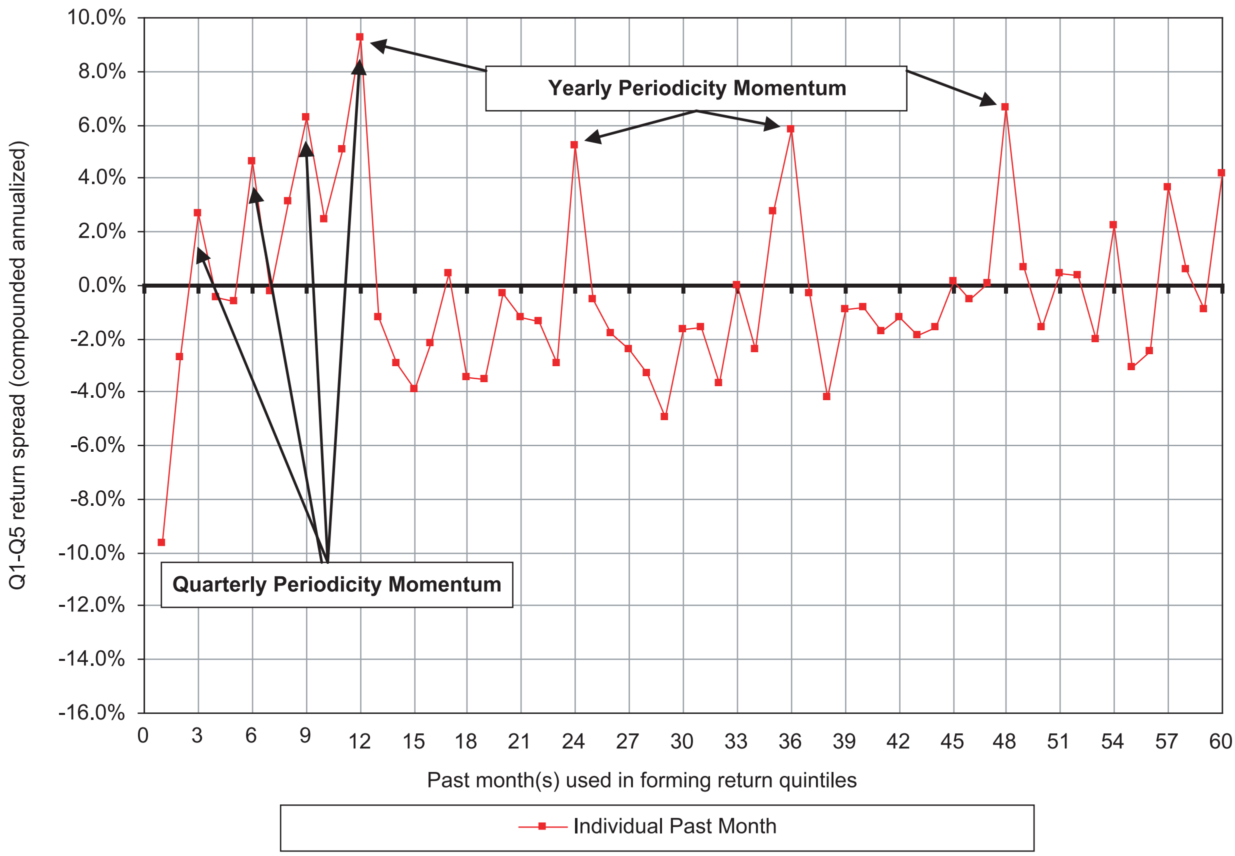
Exhibit 1 shows the annualized return spread between quintile 1 (Q1) and quintile 5 (Q5) for a one-month holding (rebalancing) period. The quintiles are ranked by the previous cumulative months' return (on the X-axis). The plot shows the one momentum and two reversal concepts: short-term reversal, intermediate-term momentum, and long-term reversal.

Exhibit 2 shows the same Q1 – Q5 spread, except that the quintiles are ranked by a past individual month's return. This plot demonstrates the two new momentum effects, yearly and quarterly periodicity.

Exhibit 3 shows the Q1 – Q5 return spread for longer holding periods; the quintiles are ranked by previous cumulative returns. This chart demonstrates the sustainability of momentum and reversal effects (discussed later).

EXHIBIT 2

Historical Simulation of Return Momentum and Reversal



Annualized Q1 – Q5 return spread for one-month holding period.
Quintiles ranked by previous individual months' returns. Equally weighted quintiles formed each month by past returns relative to total market. Universe: S&P 500. Time period: Jan 1970-Dec 2004 (overlapping). No transaction costs.

Exhibits 4 and 5 examine whether these momentum and reversal effects are driven by stock-specific or industry dynamics. Quintiles are constructed by ranking the previous stock returns relative to an equally weighted industry benchmark. For comparison purposes, Exhibits 4 and 5 also show the return spread when quintiles are ranked by returns relative to the whole market as in Exhibits 1, 2, and 3. Ranking by the previous stock returns relative to industry controls for the industry momentum or reversal effect and isolates the stock-specific momentum or reversal effect. Ranking by the previous stock returns relative to the whole market combines the industry and stock-specific momentum or reversal effects.

Exhibit 4 ranks the previous cumulative returns and considers one- and six-month holding periods. Exhibit 5 ranks by the previous individual returns and considers only a one-month holding period.

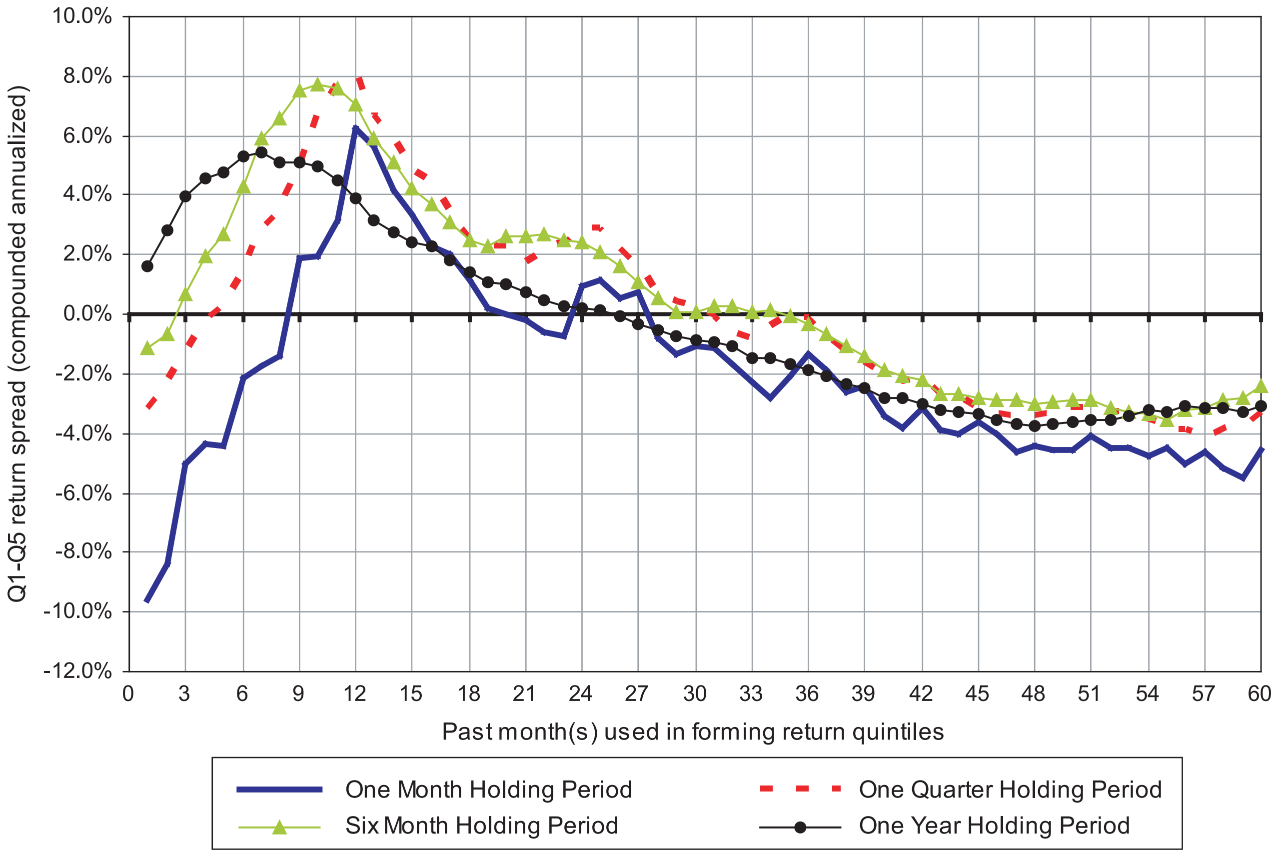
Exhibits 6 and 7 present the results of a historical quintile-based simulation for the five momentum and reversal variables. The methodology used in these tables is very similar to the one used to create the graphs in Exhibits 4 and 5.

Exhibit 6 ranks the stock return momentum and reversal variables relative to the total market, and Exhibit 7 ranks them relative to an equally weighted industry benchmark. The holding (rebalancing) period is one month. The annualized return spread between the first and the fifth quintiles is shown along with the corresponding standard deviations, information ratios, and t-statistics.

It is important to recognize that the statistical significance of the results in this study is dependent on the strategy chosen, an equally weighted Q1 – Q5 return spread. Thus, the t-statistics provide only a guide to the statistical significance of the effect of past returns on future returns.

EXHIBIT 3

Historical Quintile Simulation of Return Momentum and Reversal



Annualized Q1 – Q5 spread for various holding periods.
Quintiles ranked by previous cumulative returns. Equally weighted quintiles formed each month by past returns relative to total market. Universe: S&P 500. Time period: Jan 1970-Dec 2004 (overlapping). No transaction costs.

Each quintile's annualized return is also presented relative to the market. The market return is always an equally weighted S&P 500 return, even in Exhibit 7, which ranks the momentum variables relative to the industry benchmark. (The average of the relative returns of the five quintiles is not necessarily zero because of compounding.)

The past month's return is used to measure the short-term reversal effect. Intermediate-term momentum is measured in two ways: by ranking returns for previous months 1 through 12 and previous months 2 through 12. The first measure is more intuitive economically, and the second eliminates the short-term reversal effect. Similarly, long-term reversal is also measured in two ways: by ranking returns for previous months 1 through 48 and previous months 13 through 48. Long-term yearly periodicity is measured by ranking the total returns for previous individual months 12, 24, 36, and 48, and intermediate-term quarterly periodicity is measured by previous months 3, 6, 9, and 12.

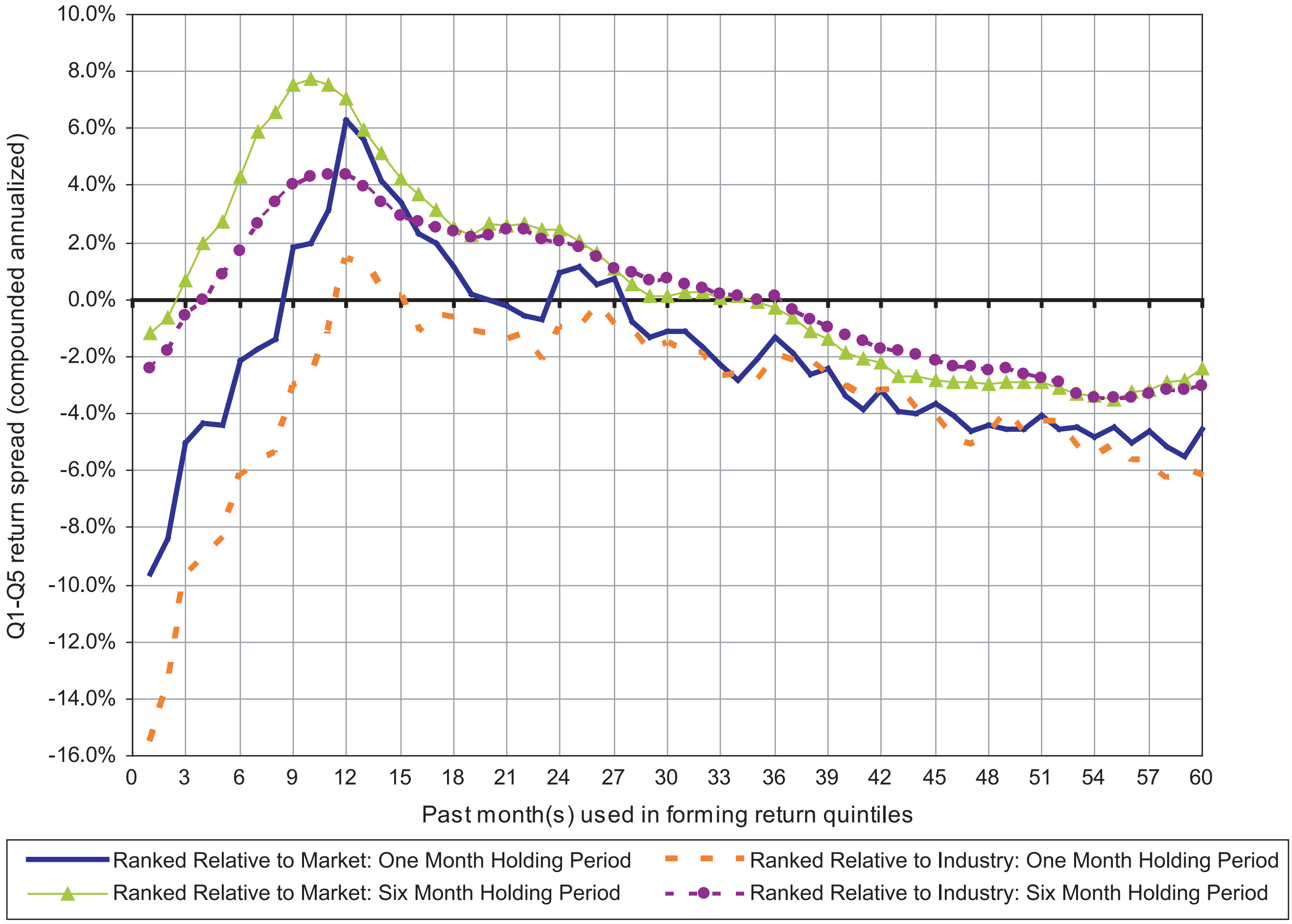
Short-Term (1-Month) Reversal

Exhibit 1 shows a strong negative relation between a stock's previous month's return and its next month's return. Jegadeesh [1990] presents very similar results. Exhibits 6 and 7 show that this short-term reversal is stronger when stocks are ranked by previous returns relative to their industry (annualized Q1 – Q5 return spread of –15.51%, with t-statistic of –9.27) than relative to the whole market (annualized Q1 – Q5 return spread of –9.59%, with t-statistic of –3.82). Exhibits 4 and 5 also show the same results.

This implies that short-term reversal is mainly a company-specific effect. In fact, Moskowitz and

Exhibit 4

Historical Quintile Simulation of Return Momentum and Reversal



Annualized Q1 – Q5 spread for one- and six-month holding periods.
Quintiles ranked by previous cumulative returns relative to specific industry as well as total market. Equally weighted quintiles formed each month by past returns relative to total market/industry. Universe: S&P 500. Time period: Jan 1970-Dec 2004 (overlapping). No transaction costs.

Grinblatt [1999] find that industries themselves exhibit one-month momentum, not reversal.

Exhibits 3 and 4 show that the short-term reversal effect is not sustainable and is significantly weaker for longer holding periods. This occurs because, for longer holding periods, this effect is not purely short-term any longer; intermediate-term momentum dynamics weaken the measure for longer holding periods. Remember that the returns in the exhibits do not include transaction costs. This would significantly affect the profitability of this strategy as it requires very high turnover.

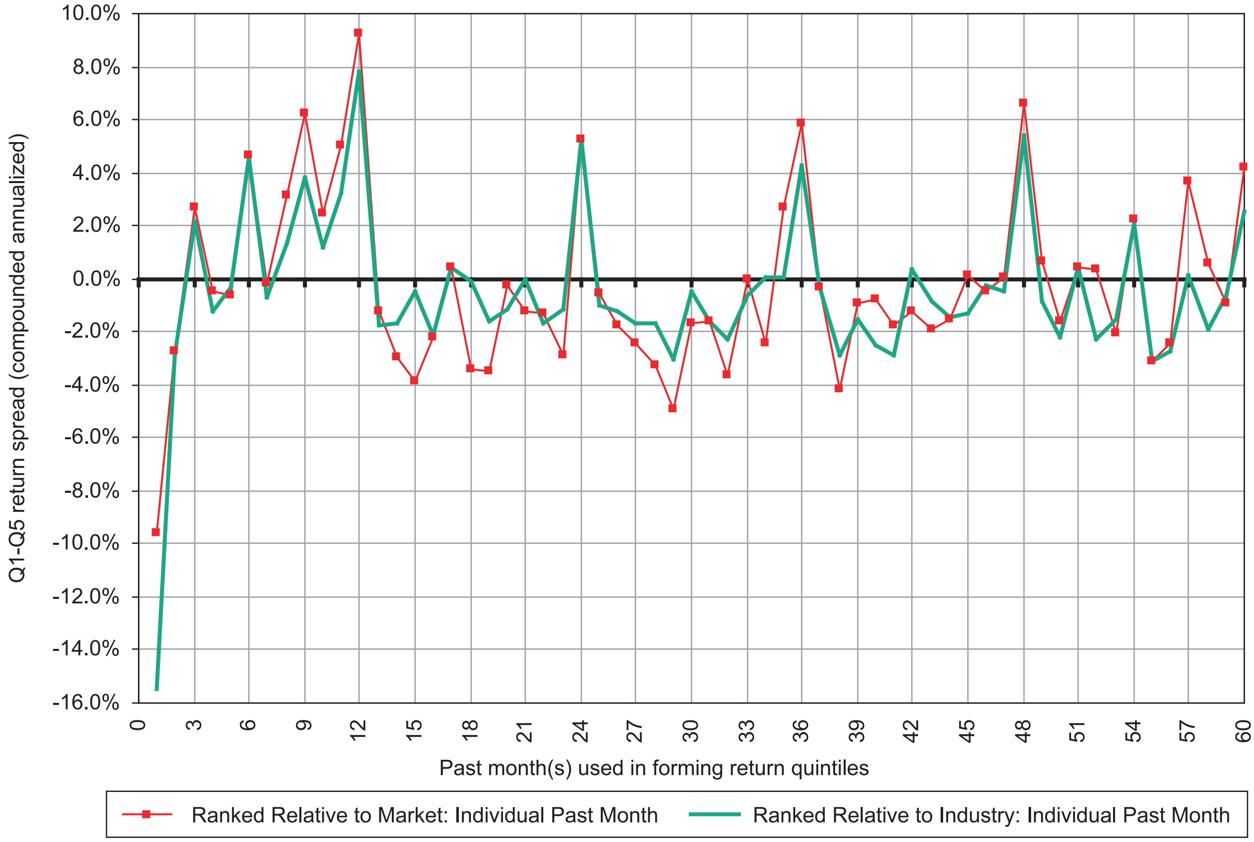
I believe that the most plausible explanation for short-term reversal is that a combination of market microstructure dynamics and transaction costs prevents it from being fully arbitraged away. Jegadeesh and Titman [1995] claim that market microstructures contribute to the appearance of short-term reversal, although this is probably not the only cause. Mech [1993] argues that transaction costs prevent the arbitrage of the short-term reversal effect.

Intermediate-Term (12-Month) Momentum

The intermediate-term return momentum effect was first analyzed by Jegadeesh and Titman [1993]. Exhibit 3 shows that the past cumulative 12-month return has a strong positive influence on future returns. Exhibit 2 also shows that within the previous 12 months, the individual

EXHIBIT 5

Historical Quintile Simulation of Return Momentum and Reversal



Annualized Q1 – Q5 spread for various holding periods.
Quintiles ranked by previous individual months' returns relative to specific industry as well as total market. Equally weighted quintiles formed each month by past returns relative to total market/industry. Universe: S&P 500. Time period: Jan 1970-Dec 2004 (overlapping). No transaction costs.

months that are farther in the past actually have a stronger effect on future returns.[3]

Exhibit 3 also shows that intermediate-term momentum is sustainable and persists for longer holding periods. In fact, it is even a bit stronger for the three- and six-month holding periods than for a one-month holding period. This occurs because the negative influence (reversal) associated with the previous month's return (which is part of the previous cumulative 12-month return) is stronger for shorter holding periods.

Two observations are worth noting for a one-year holding period with a previous 12-month ranking period. First, its effect is weaker than shorter holding periods. Second, the previous cumulative return with the strongest influence is somewhere between 6 and 9 months (less than the 12 months for shorter holding periods). In the case of a one-year holding period, the measured effect is not purely intermediate-term; some long-term dynamics are captured as well. There is a reversal effect in the long term, which explains these two observations.

A superficial examination of Exhibit 4 might prompt a conclusion that the intermediate-term momentum effect, is overwhelmingly driven by stock specific dynamics. In fact, Exhibit 6 shows that when previous returns are ranked relative to the whole market, the annualized Q1 – Q5 return spread is 6.25% with a t-statistic of 1.76. Exhibit 7 shows that when previous returns are ranked relative to the specific industry, the Q1 – Q5 spread is only 1.28% with a t-statistic of 0.55.

In fact, the past cumulative 12-month return is not the best measure to use as an intermediate-term momentum variable since it is muddied by the most recent past month's return. As I have noted, there is a strong stock-specific one-month return reversal. Moskowitz and

EXHIBIT 6
Historical Quintile Simulation of Return Momentum and Reversal (annualized)

Momentum/Reversal Variables	Previous Months	Sign	Annualized Quintile Avg Minus Equally Weighted Market Avg High Previous Returns Q1	Q2	Q3	Q4	Low Previous Returns Q5	Q1-Q5 Spread Average	Std. Dev.	I.R.
Short-Term Past Return	1	-	-5.03%	-1.81%	0.55%	1.65%	4.56%	-9.59%	14.65%	-0.65
(t-statistic)			*(-4.19)*	*(-2.45)*	*(0.89)*	*(2.60)*	*(3.12)*	*(-3.82)*		
Intermediate-Term Past Return	1-12	+	3.06%	0.21%	-0.46%	-0.46%	-3.19%	6.25%	20.36%	0.31
(t-statistic)			*(1.85)*	*(0.23)*	*(-0.70)*	*(-0.56)*	*(-1.62)*	*(1.76)*		
Long-Term Past Return	1-48	-	-2.72%	-1.56%	-0.13%	2.16%	1.65%	-4.38%	18.14%	-0.24
(t-statistic)			*(-1.60)*	*(-1.77)*	*(-0.17)*	*(2.62)*	*(0.93)*	*(-1.32)*		
Yearly Periodicity Past Return	12, 24, 36, 48	+	6.98%	0.93%	0.28%	-1.81%	-5.98%	12.96%	10.07%	1.29
(t-statistic)			*(6.22)*	*(1.46)*	*(0.48)*	*(-2.65)*	*(-5.75)*	*(7.05)*		
Quarterly Periodicity Past Return	3, 6, 9, 12	+	5.28%	2.48%	-0.43%	-1.35%	-5.93%	11.21%	12.96%	0.87
(t-statistic)			*(4.52)*	*(3.60)*	*(-0.71)*	*(-1.90)*	*(-4.35)*	*(4.97)*		
Alternative Variables										
Intermediate-Term Past Return	2-12	+	4.35%	1.23%	-0.38%	-0.52%	-5.28%	9.63%	19.52%	0.49
(t-statistic)			(2.69)	(1.45)	(-0.60)	(-0.66)	(-2.83)	(2.84)		
Long-Term Past Return	13-48	-	-4.25%	-0.68%	0.42%	1.19%	3.01%	-7.25%	15.50%	-0.47
(t-statistic)			(-2.52)	(-0.90)	(0.60)	(1.51)	(2.11)	(-2.56)		
Long-Term Past Return w/o January	13-48	-	-2.02%	1.65%	2.86%	2.95%	1.51%	-3.54%	13.00%	-0.27
(t-statistic)			(-0.45)	(0.43)	(0.76)	(0.77)	(0.36)	(-1.49)		

Quintiles ranked relative to total market.
One-month holding period. Equally weighted quintiles formed each month by past returns relative to the total market. Universe: S&P 500. Time period: Jan 1970-Dec 2004 (overlapping). No transaction costs.

Grinblatt [1999] find there to be a one-month industry return momentum (not reversal). Thus, not including the most recent past month's return enhances the strength of intermediate-term momentum. The return for a one-month holding period is enhanced the most, although the returns for longer holding periods are enhanced as well.

Therefore, the intermediate-term momentum effect would be better measured by the return for previous months 2 through 12. Exhibits 1 and 2 provide the profitability from the 2 to 12 month return momentum variable. The annualized Q1 – Q5 return spread when this momentum variable is ranked relative to the market is 6.03%, which is significant but lower than the Q1 – Q5 spread, 9.63%, when it is ranked relative to the industry, although the former has a lower standard deviation (12.30% versus 19.52%), which makes the t-statistics of the two similar, 2.69 and 2.84. This implies that it is very likely that there is both industry and stock-specific momentum.

Moskowitz and Grinblatt [1999] directly compare industry momentum to stock-specific momentum. They conclude that intermediate-term industry momentum is strong and stock-specific momentum is insignificant. Their first conclusion seems to agree with my findings, and their second conclusion seems to disagree with them. Grundy and Martin [2001] as well as Chordia and Shivakumar [2002] reaffirm that intermediate-term stock-specific momentum is significant and distinct from industry momentum. Ahn, Conrad, and Dittmar [2003] indirectly show that approximately 50% of profit from stock momentum is attributable to industry factors.

Scowcroft and Sefton [2005] show that, for global large-cap market-weighted portfolios, momentum profit is driven by industry and country dynamics. For global small-cap equally weighted portfolios, momentum profit is driven by stock-specific dynamics. The S&P 500 portfolio I use is large-cap, but equally weighted, so my conclusion that momentum is driven by both industry and stock-specific dynamics is consistent with the results of Scowcroft and Sefton [2005].

Gutierrez and Pirinsky [2004] and Zlotnikov et al. [2005] show that eliminating the capital asset pricing model beta from stock returns does not change the profitability of intermediate-term momentum. Fama and French [1996] also show that their market-based

EXHIBIT 7

Historical Quintile Simulation of Return Momentum and Reversal (annualized)

			Annualized Quintile Avg Minus Equally Weighted Market Avg					Q1-Q5 Spread		
	Previous		*High Previous Returns*				*Low Previous Returns*			
Momentum/Reversal Variables	**Months**	**Sign**	Q1	Q2	Q3	Q4	Q5	Average	Std. Dev.	I.R.
Short-Term Reversal	1	-	-7.45%	-3.86%	-0.20%	4.11%	8.06%	-15.51%	9.76%	-1.59
(t-statistic)			*(-9.22)*	*(-6.13)*	*(-0.33)*	*(7.47)*	*(7.24)*	*(-9.27)*		
Intermediate-Term Momentum	1-12	+	1.12%	-1.22%	-0.81%	0.89%	-0.16%	1.28%	13.24%	0.10
(t-statistic)			*(0.94)*	*(-1.74)*	*(-1.38)*	*(1.32)*	*(-0.12)*	*(0.55)*		
Long-Term Reversal	1-48	-	-2.28%	-0.82%	-0.49%	1.17%	2.36%	-4.64%	11.66%	-0.40
(t-statistic)			*(-1.61)*	*(-1.15)*	*(-0.61)*	*(1.56)*	*(2.07)*	*(-2.18)*		
Yearly Periodicity Momentum	12, 24, 36, 48	+	5.58%	1.76%	-0.74%	-1.72%	-4.35%	9.93%	6.46%	1.54
(t-statistic)			*(6.83)*	*(3.18)*	*(-1.20)*	*(-2.75)*	*(-5.37)*	*(8.42)*		
Quarterly Periodicity Momentum	3, 6, 9, 12	+	4.86%	1.20%	0.09%	-1.70%	-4.12%	8.97%	7.89%	1.14
(t-statistic)			*(6.34)*	*(2.01)*	*(0.16)*	*(-3.03)*	*(-4.18)*	*(6.53)*		
Alternative Variables										
Intermediate-Term Momentum	2-12	+	3.39%	-0.09%	-0.45%	-0.25%	-2.64%	6.03%	12.30%	0.49
(t-statistic)			(2.96)	(-0.13)	(-0.70)	(-0.36)	(-1.97)	(2.69)		
Long-Term Reversal	13-48	-	-3.13%	0.27%	-0.07%	1.07%	1.92%	-5.05%	9.71%	-0.52
(t-statistic)			(-2.30)	(0.40)	(-0.10)	(1.46)	(2.07)	(-2.85)		

Quintiles ranked relative to specific industry.
One-month holding period. Equally weighted quintiles formed each month by past returns relative to specific industry. Universe: S&P 500. Time period: Jan 1970-Dec 2004 (overlapping). No transaction costs.

return factors cannot explain stock-specific or industry intermediate-term momentum

Harvey and Siddique [2000], by the way, show that the intermediate-term momentum strategy has exposure to negative skewness. Therefore, the standard deviations presented in Exhibits 1 and 2 do not fully reflect the true risk of the strategy, although it is not clear to what degree they do not.

Although I concentrate on stocks in the U.S., Rouwenhorst [1998 and 1999] and Griffin, Ji, and Martin [2003 and 2005] find intermediate-term stock return momentum in most other countries. In addition, Chan, Hameed, and Tong [2000] and Scowcroft and Sefton [2005] show that global stock market indexes also exhibit relative momentum effects. Scowcroft and Sefton [2005] find that momentum exists for global industries.

I believe that the most plausible explanation for intermediate-term momentum is related to the slow dissemination or interpretation of news (both stock-specific and industry) in the market. This implies that the market underreaction to new information causes intermediate-term momentum.

Barberis, Shleifer, and Vishny [1998] and Hong and Stein [1999] provide theoretical models of investor behavior, while Chan, Jegadeesh, and Lakonishok [1996 and 1999], Hong, Lim, and Stein [2000] and Scott, Stumpp, and Xu [2003] provide empirical analysis that supports this explanation of intermediate-term momentum. In Figelman [2007], I argue that managers' manipulation of earnings combined with slow dissemination and interpretation of news enhances intermediate-term momentum.

Window dressing by mutual and hedge fund managers may contribute to momentum as well. Basically, fund managers are inclined to buy past outperformers and sell past underperformers at the end of each quarter to convey the impression to clients in quarter-end holdings reports that they have been selecting good stocks.

Long-Term (48-Month) Reversal

Exhibit 3 shows a negative relation between long-term past stock returns and future stock returns. This effect is strongest somewhere between the past three and five years, so I choose four years for analysis. Exhibit 3 also shows that this effect is strongest for a one-month holding period, although it is sustainable for longer holding periods.

The long-term reversal effect is best measured by the past return of months 13-48, since this time period eliminates the effects of intermediate-term momentum and short-term reversal. Similar to intermediate-term momentum, long-term reversal appears to be both a stock-specific and an industry effect.

Exhibit 6 shows that when past returns are ranked relative to the market, the annualized Q1 − Q5 return spread is −7.25% which is stronger than the Q1 − Q5 spread of −5.05% when stock past returns are ranked relative to the specific industry, as shown in Exhibit 7. The former has a higher standard deviation, however (15.50% versus 9.71%), which makes the t-statistics of the two similar, −2.56 and −2.85. This implies it is very likely that there are both industry and stock-specific long-term reversals.

De Bondt and Thaler [1985 and 1987] first documented long-term stock return reversal. In their study, the future return period is three years, which is much longer than ours (although the conclusions are similar). De Bondt and Thaler [1985] and Chopra, Lakonishok, and Ritter [1992] as well as Grinblatt and Moskowitz [2004] find that a significant portion of the return spread from the long-term reversal strategy occurs in January months. Thus, it is unclear whether the significance of the long-term reversal effect is robust. (I will examine this later in the article.) Richards [1997] finds also that there is relative long-term return reversal in stock market country indexes.

I believe that the long-term reversal effect is driven by a variety of dynamics. For a weak company (in terms of management or product), a relatively short period of poor stock returns will bring it closer to failure. Thus, companies that have survived a long period of underperformance tend to be stronger companies that end up bouncing back in the future. Conversely, companies that have had a long period of outperformance tend to be overpriced. Therefore, there is a reversion to the mean. This is very much related to the fact that value stocks tend to outperform growth stocks on average.

My explanation is also consistent with Fama and French's [1996] finding that the long-term reversal effect can be explained by the Fama and French [1993] three-factor model.

Long-Term Yearly Periodicity Momentum and Intermediate-Term Quarterly Periodicity Momentum

Exhibit 2 shows that there is a strong positive relation between this month's return and previous individual months' returns whose lag is a multiple of 12 (months 12, 24, 36, 48, and 60). I call this effect *long-term yearly return periodicity momentum*, and define a variable that is the cumulative return of only these past months. Heston and Sadka [2007] find a similar effect for all stocks in CRSP.

Exhibits 6 and 7 show that long-term yearly periodicity is mostly company-specific, although there is some industry effect as well. The annualized Q1 − Q5 return spread when this variable is ranked relative to the market is 12.96% (t-statistic of 7.05). When ranked relative to the industry, this variable yields a Q1 − Q5 spread of 9.93% (t-statistic of 8.42). Exhibit 5 also shows similar results.

It appears that long-term yearly periodicity has the strongest effect on future returns for a one-month holding period of any of the variables discussed here (except for short-term reversal when the past return is ranked relative to the industry). In a regression analysis, Jegadeesh [1990] shows that the returns of lagged past months 12, 24, and 36 are positively related to this month's return, which complements my quintile-based analysis.

Exhibit 2 also shows a positive relation between this month's return and previous individual months' returns whose lags are a multiple of three (months 3, 6, 9, and 12). I call this effect *intermediate-term quarterly periodicity momentum,* and define a variable that is the cumulative return of only these past months. (Obviously, this variable includes 4 of the 12 months in the intermediate-term momentum variable.)

As with long-term yearly periodicity, intermediate-term quarterly periodicity seems to be mostly a company-specific effect, with some industry effects. Exhibit 6 shows that the annualized Q1 − Q5 return spread is 11.21% (t-statistic of 4.97) when this variable is ranked relative to the market. When ranked relative to industry, this variable yields a Q1 − Q5 spread of 8.97% (t-statistic of 6.53).

Exhibit 5 shows similar results. Exhibits 2 and 5 show that intermediate-term quarterly periodicity significantly weakens after month 12, although it is not clear whether it completely disappears when past returns are ranked relative to industries.

Similar to short-term reversal, both yearly and quarterly periodicity strategies would require high turnover, and transaction costs would significantly reduce their profits.

I do not have a clear explanation of either of these effects, but I have tested various hypotheses. Exhibit 8 shows that these effects are prevalent in most calendar months. Even though they are stronger in some months than in others, there does not appear to be a consistent

EXHIBIT 8
Seasonality Analysis

Months	Short-Term Reversal 1	Intermediate-Term Momentum 1-12	Intermediate-Term Momentum 2-12	Long-Term Reversal 1-48	Long-Term Reversal 13-48	Yearly Periodicity 12,24,36,48	Quarterly Periodicity 3,6,9,12
January	-2.85%	**-2.79%**	**-2.33%**	-3.98%	-3.17%	2.08%	-0.81%
February	-0.35%	1.22%	1.31%	-0.68%	-1.56%	0.49%	1.38%
March	-1.47%	-0.18%	0.26%	-1.30%	-0.95%	1.41%	0.22%
April	-0.91%	-0.90%	-0.71%	-0.49%	-0.14%	0.27%	-0.25%
May	-0.32%	-0.06%	0.13%	-0.77%	-0.79%	0.91%	0.45%
June	-0.63%	2.07%	2.45%	1.32%	0.27%	0.55%	1.91%
July	-0.60%	1.11%	1.50%	0.66%	-0.15%	0.26%	0.74%
August	-0.48%	-0.02%	0.05%	-0.39%	-0.42%	0.18%	0.71%
September	-0.09%	2.21%	2.38%	0.92%	-0.52%	1.52%	1.75%
October	-0.99%	0.50%	0.79%	1.25%	1.77%	2.44%	1.16%
November	0.32%	-0.37%	-0.21%	-0.58%	0.14%	0.39%	0.17%
December	-0.94%	1.43%	1.84%	-0.19%	-0.83%	0.90%	1.99%
Average Monthly Return	-0.77%	0.35%	0.62%	-0.35%	-0.53%	0.95%	0.79%
Average Monthly Return w/o Jan	-0.59%	0.64%	0.89%	-0.02%	-0.29%	0.85%	0.93%
Simply Annualized Return	-9.29%	4.22%	7.46%	-4.23%	-6.36%	11.42%	9.43%
Percent of Return in Jan	30.6%	-66.1%	-31.3%	**94.1%**	**49.9%**	18.2%	-8.5%

Historical quintile simulation of return momentum and reversal. Q1 − Q5 return spread by calendar month (not annualized).
One-Month holding period. Equally weighted quintiles formed each month by past returns relative to the total market. Universe: S&P 500. Time period: Jan 1970-Dec 2004 (overlapping). No transaction costs.

pattern. In addition, the yearly and quarterly periodicity effects are not always strong in the same calendar month, which implies that they are somewhat different phenomena.

Exhibit 9 also shows that in months companies announce earnings, yearly periodicity is only slightly enhanced, and quarterly periodicity is unaffected. This is a somewhat surprising result, especially relating to quarterly periodicity; one would think that both effects would be significantly magnified in months of earnings announcements.

In untabulated results, I find that both of these effects are unaffected by dividend payments and that most industries exhibit yearly and quarterly periodicity momentum. I leave the economic explanation of these effects to further research.

Seasonality, January Reversal, and Earnings Announcement Dates

What months contribute to the profitability of momentum and reversal strategies? I address this question in two ways. First, I decompose the profitability of these effects by calendar month. Second, I test whether these momentum and reversal effects are stronger during the months companies announce earnings.

Seasonality and January Reversal. Exhibit 8 shows the profitability, by calendar month, of all momentum and reversal quintile-based strategies. Simple average monthly Q1 − Q5 return spreads are shown rather than the compounded annualized Q1 − Q5 return spreads shown so far. A one-month holding (rebalancing) period is considered, and past returns are ranked relative to the total market.

There appears to be a strong inverse relation between returns in January months and past cumulative returns for the short, intermediate, and long horizons. Particularly interesting is that, for the intermediate-term horizon, where there is a strong momentum effect in total, there is a strong reversal effect in January.

Exhibit 8 shows that when previous months 2–12 (1–12) are used as the past return variable, the Q1 − Q5 return spread is −2.33% (−2.79%) for January months and 0.62% (0.35%) for all other months. Grundy and Martin [2001] show similar results. Gutierrez and Pirinsky [2004], however, find intermediate-term momentum, not reversal, in January months for CAPM beta-adjusted stock-specific momentum.

When past long-term returns are ranked by the past months 1–48, almost all of the profits from the quintile-based strategy occur in January months. (Since this is a reversal strategy, "profits" occur when there is a negative Q1 − Q5 spread.) Exhibit 8 shows that the simple annu-

EXHIBIT 9
Effect of Earnings Announcement Months

Panel A: Short-Term Reversal *(Previous Month)*

	Q1	Q2	Q3	Q4	Q5	Q1-Q5 Spread
Earnings Anouncement Months	-0.03%	0.33%	0.46%	0.58%	0.92%	-0.95%
(t-statistic)	*(-0.16)*	*(2.16)*	*(3.62)*	*(3.84)*	*(4.83)*	*(-3.34)*
Other Months	-0.50%	-0.31%	-0.21%	-0.04%	0.00%	-0.49%
(t-statistic)	*(-4.23)*	*(-3.92)*	*(-2.73)*	*(-0.47)*	*(-0.02)*	*(-2.17)*

Panel B: Intermediate-Term Momentum *(Previous Months 2-12)*

	Q1	Q2	Q3	Q4	Q5	Q1-Q5 Spread
Earnings Anouncement Months	0.84%	0.48%	0.40%	0.40%	0.14%	0.70%
(t-statistic)	*(4.07)*	*(3.30)*	*(2.62)*	*(2.91)*	*(0.63)*	*(1.92)*
Other Months	0.02%	-0.20%	-0.21%	-0.23%	-0.45%	0.47%
(t-statistic)	*(0.12)*	*(-2.36)*	*(-2.75)*	*(-2.71)*	*(-2.49)*	*(1.56)*

Panel C: Long-Term Reversal *(Previous Months 13-48)*

	Q1	Q2	Q3	Q4	Q5	Q1-Q5 Spread
Earnings Anouncement Months	0.03%	0.30%	0.62%	0.64%	0.75%	-0.71%
(t-statistic)	*(0.17)*	*(2.19)*	*(4.06)*	*(3.58)*	*(3.82)*	*(-2.32)*
Other Months	-0.40%	-0.29%	-0.19%	-0.15%	-0.04%	-0.35%
(t-statistic)	*(-2.57)*	*(-3.55)*	*(-2.49)*	*(-1.71)*	*(-0.31)*	*(-1.48)*

Panel D: Yearly Periodicity Momentum *(Previous Months 12, 24, 36, 48)*

	Q1	Q2	Q3	Q4	Q5	Q1-Q5 Spread
Earnings Anouncement Months	1.01%	0.54%	0.15%	0.14%	-0.13%	1.14%
(t-statistic)	*(7.29)*	*(4.12)*	*(0.95)*	*(0.87)*	*(-0.80)*	*(4.98)*
Other Months	0.21%	-0.17%	-0.12%	-0.36%	-0.60%	0.82%
(t-statistic)	*(1.70)*	*(-2.30)*	*(-1.70)*	*(-4.12)*	*(-5.59)*	*(4.27)*

Panel E: Quarterly Periodicity Momentum *(Previous Months 3, 6, 9, 12)*

	Q1	Q2	Q3	Q4	Q5	Q1-Q5 Spread
Earnings Anouncement Months	0.86%	0.55%	0.03%	0.16%	0.23%	0.63%
(t-statistic)	*(5.64)*	*(3.80)*	*(0.19)*	*(1.09)*	*(1.24)*	*(2.37)*
Other Months	0.08%	-0.09%	-0.18%	-0.23%	-0.62%	0.70%
(t-statistic)	*(0.57)*	*(-1.09)*	*(-2.66)*	*(-2.78)*	*(-4.57)*	*(3.11)*

Historical quintile simulation of return momentum and reversal. Average relative quintile returns and Q1 – Q5 return spread (not annualized). One-month holding period. Two sets of equally weighted quintiles formed each month: one set for stocks with earnings announcements and one set for stocks without earnings announcements A given month must have at least 5 stocks Q1 and Q5 to be included Universe: S&P 500. Time period: Jan 1975-Dec 2004 (overlapping).

alized Q1 – Q5 return spread is –4.23%, and –3.98% of it occurs in January months.

To disaggregate the intermediate-term momentum effect, it is more accurate to measure long-term reversal by the past returns for months 13-48. With this measure, approximately half (–3.17% of –6.36%) of the profits from the quintile-based strategy occur in January months. De Bondt and Thaler [1985], Chopra, Lakonishok, and Ritter [1992], Jegadeesh and Titman [2001], and Grinblatt and Moskowitz [2004] provide similar results.

Exhibit 6 shows that non-January months still exhibit long-term reversal (annualized Q1 − Q5 return spread of −3.54%), although their profits are not statistically significant (t-statistic of -1.49). Exhibit 6 also shows that the long-term reversal effect is statistically significant when all months are included (annualized Q1 − Q5 spread of −7.25%, with a t-statistic of −2.56). These results leave the significance of the long-term reversal effect ambiguous.

It is not surprising that the yearly periodicity, unlike the other four effects, does not show a reversal effect in January (Q1 − Q5 return spread is a positive 2.08%). Yearly periodicity just measures the effect of the returns of the previous four Januaries on this January's return, so there is no interaction with other months.

One possible driver of January return reversal is that tax-aware investors tend to sell stocks in December that have previously performed poorly in order to realize a capital loss as late as possible. This artificially deflates the price of past poorly performing stocks, and they tend to rebound in January. Thus, a part of January reversal is driven by past underperformers (Q5).

Another possible driver of January reversal is that tax-aware investors will tend to sell stocks in January that have previously performed well in order to realize a capital gain as early as possible. This causes the price of past well-performing stocks to decline in January. Thus, another part of January reversal is driven by past outperformers (Q1).

Grinblatt and Moskowitz [2004] and Hvidkjaer [2002] show that the January effect is driven by small traders or individuals rather than by large traders or institutions. Grinblatt and Moskowitz [2004] also provide a lengthy discussion of the effect of taxes on January return reversal.

Exhibit 8 also shows that the strongest momentum months are June, September, and December. This somewhat supports the window dressing explanation of momentum—that fund managers are inclined to buy past outperformers and sell past underperformers at the end of each quarter. They want clients to think they have been selecting good stocks. Yet March exhibits only marginal momentum, which is not completely consistent with the window dressing explanation.

Earnings Announcement Dates. Are the five momentum and reversal effects stronger in months companies announce earnings?[4] Quarterly earnings announcement dates are obtained from Compustat, and this field becomes available for stocks in the S&P 500 at the beginning of 1975. In each month, two sets of quintiles are formed, one set for stocks that announce earnings that month and another set for stocks that do not. For both earnings announcement and non-earnings announcement months, the historical average return of each quintile is computed relative to an equally weighted S&P 500, along with the Q1 − Q5 spread. For a month to be counted (for either earnings or non-earnings announcement groups), it must include at least five stocks in both Q1 and Q5.

Exhibit 9 shows that the average monthly return for all quintiles is significantly higher in earnings announcement months; this is true for all five strategies. Basically, stocks tend to outperform the market in months their firms announce earnings.

One explanation for this finding is that stocks tend to outperform the market after a positive earnings surprise, and most earnings announcements tend to provide positive earnings surprises. (My results do not distinguish between a stock's return prior to its earnings announcement and after its earnings announcement in a given month.)

Exhibit 9 also shows that all effects except for quarterly periodicity are enhanced in months of earnings announcements. Actually, all these effects seem to pertain in other months as well, so it does not appear that earnings announcements completely explain any of these effects.

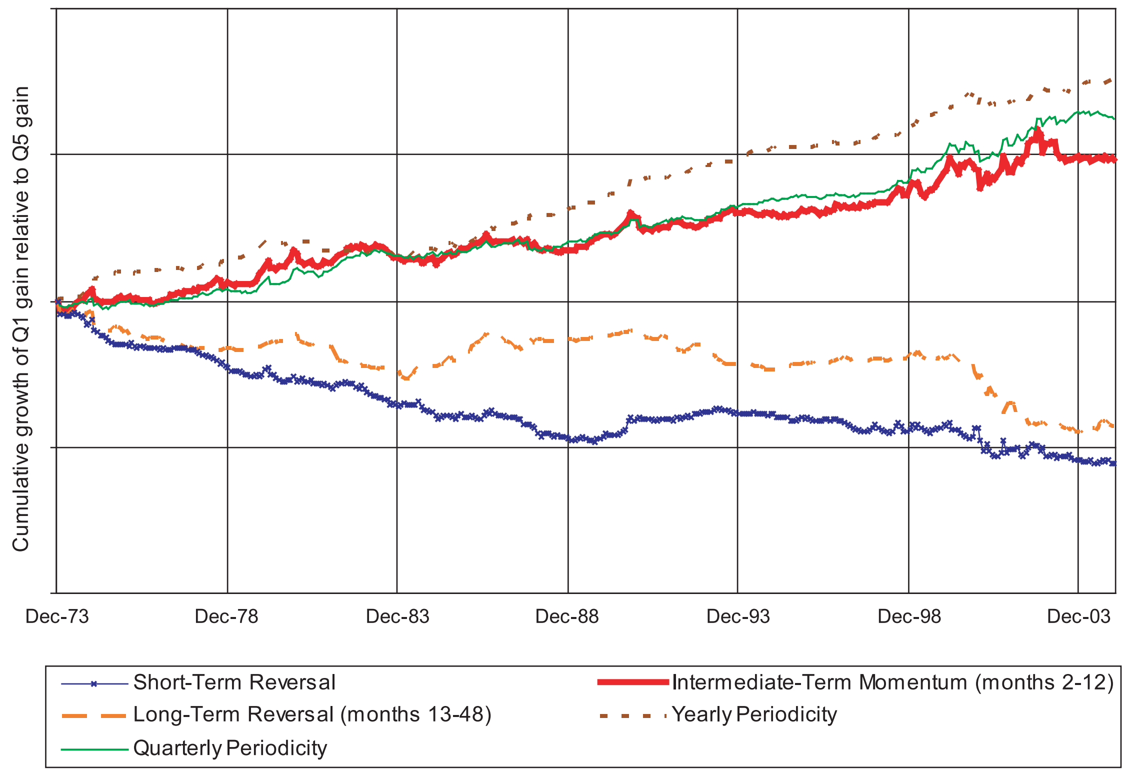
The average Q1 − Q5 spreads in earnings announcement months are: −0.95% (t-statistic of −3.34) for short-term reversal; 0.70% (t-statistic of 1.92) for intermediate-term momentum; −0.71% (t-statistic of −2.32) for long-term reversal; 1.14% (t-statistic of 4.98) for yearly periodicity; and 0.63% (t-statistic of 2.37) for quarterly periodicity. The spreads for all other months are: −0.49% (t-statistic of −2.17) for short-term reversal; 0.47% (t-statistic of 1.56) for intermediate-term momentum; −0.35% (t-statistic of −1.48) for long-term reversal; 0.82% (t-statistic of 4.27) for yearly periodicity; and 0.70% (t-statistic of 3.11) for quarterly periodicity.

It is somewhat surprising that quarterly periodicity is the only effect that is not enhanced during earnings announcement months, and I leave this to further research. Results on the effects of only annual earnings announcements turn out to be very similar to results for quarterly earnings announcements.

Momentum and Reversal Historical Trends

Exhibit 10 shows the trend throughout history of all momentum and reversal variables. For each effect, the chart shows the growth of $1 from the Q1 portfolio

EXHIBIT 10
Historical Simulation of Return Momentum and Reversal



Cumulative trend of Q1 relative to Q5 for all five effects.
Equally weighted quintiles formed each month by past returns relative to total market. Universe: S&P 500. Time period: Jan 1974-Dec 2004 (overlapping). No transaction costs. Log scale.

relative to the Q5 portfolio. The quintiles are constructed every month, and profits are calculated for a one-month holding period. The chart uses a log scale to present gains and losses symmetrically. Previous months 2–12 are used for intermediate-term momentum quintiles, and previous months 13–48 are used for long-term reversal quintiles.

Exhibit 10 shows that intermediate-term momentum has not been working for the past few years of this study—2002–2004. (More recent data suggest that momentum worked well in 2005 and the first half of 2006.) Before then, intermediate-term momentum had been fairly steady, although there were periods of a few years in the early 1980s when it did not work.

Short-term reversal was fairly steady from the mid-1970s until the end of the 1980s, fairly flat throughout the 1990s, and then picked up again around 2000. Long-term reversal was pretty much flat from the late 1970s until the end of the 1990s, but it has been persistent after 2000 and was in the mid-1970s.

Yearly periodicity has been very persistent throughout history except for a few years of flat performance in the early 1980s. Not surprisingly, quarterly periodicity shows a similar trend to intermediate-term momentum. Yet it has been working in the past few years, even though intermediate-term momentum has not been.

RETURN MOMENTUM AND REVERSAL SUSTAINABILITY AND IMPLEMENTATION CONSIDERATIONS

I have shown several interesting return momentum and reversal effects. These effects need to be sustainable in order for them to be useful in the construction of real-world portfolios. Even though many practitioners tend to build expected return models on monthly data and refresh them every month, the sustainability of expected return signals is still very important because there are significant transaction costs for frequently rebalancing a portfolio.

Therefore, a signal that changes every month would be difficult to incorporate into expected return models.

Exhibit 3 shows that the intermediate-term momentum variable is sustainable for at least six months. Sadka [2002], Hanna and Ready [2003], and Korajczyk and Sadka [2004], however, show that momentum profits significantly diminish when trading costs are accounted for. Korajczyk and Sadka [2004] also show that equally weighted portfolios exhibit stronger pre-transaction cost momentum profits and weaker after-transaction cost profits than market value weighted portfolios.

Lesmond, Schill, and Zhou [2004] make a strong argument that intermediate-term momentum profits completely disappear when transaction costs are included. They show stocks that exhibit strong momentum are the ones with high transaction costs.

While all the research cited here uses a very broad universe of stocks, including micro-cap securities, the results are still relevant to large-cap stocks. Note that in a multivariate model trading costs are related to the total expected return signal. As momentum is usually just one of several variables in expected return models, its effect on trading costs is mitigated by the other variables.

My results suggest that the momentum variable is stronger when the last month's return is not included. This may not be the case when transaction costs are taken into account. Let's consider a portfolio that uses two expected return signals, value (book-to-price) and momentum (without the last month's return). Let's assume that a given stock has a very large negative return in the last month and modest returns for past months 2-12. Thus, for this month, it will have a strong positive value signal (because its book-to-price would have dropped) and a neutral momentum signal, prompting its purchase for the portfolio.

Let's assume this stock is purchased and it experiences a modest reversal (positive return) this month. Now, for the next month, it would have a very strong negative momentum signal, possibly prompting its sale. It is not clear whether this modest return reversal covers the transaction costs associated with buying the stock one month and selling it the next month. More research in this area would be interesting.

Unfortunately, three of the five momentum and reversal variables (short-term reversal and both periodicity momentum variables) are not sustainable for more than one month. Their signals are driven by individual-month returns that are not adjacent. Therefore, the current month's signal for each of these variables would be generally unrelated to the previous months. Even though these three variables are quite interesting, it would be a challenge to incorporate them into an investment process, given the transaction costs associated with high-turnover portfolios.

It is important to be aware of these effects. It might be worth considering delaying a sale of an established position if some of these variables showed a strong positive signal.

SUMMARY AND CONCLUDING REMARKS

I have shown the presence of short-term reversal, intermediate-term momentum, and long-term reversal in S&P 500 stock returns. The historical quintile analysis reaffirms the original work of De Bondt and Thaler [1985], Jegadeesh [1990], and Jegadeesh and Titman [1993]. For all three time horizons (even the intermediate term), there is a much stronger return reversal in Januarys than in other months. In fact, a significant portion of the profit from the long-term reversal strategy is gained in January months. In addition, two other strong momentum effects have been documented: long-term yearly periodicity, and intermediate-term quarterly periodicity.

I also show that short-term reversal, intermediate-term momentum, long-term reversal, and yearly periodicity are somewhat enhanced in months a firm announces earnings. Quarterly periodicity is not affected by earnings announcements, which is somewhat surprising. Further research into the two periodicity effects would be very interesting.

There is considerable debate in the literature as to the potential sources of short-term reversal, intermediate-term momentum, and long-term reversal. I have analyzed whether these effects are stock-specific or driven by industries. The evidence suggests that short-term reversal is a stock-specific phenomenon.

Intermediate-term momentum appears to be driven by both common factor and stock-specific dynamics; it has both an industry and a stock-specific component. I believe intermediate-term momentum is caused by the slow dissemination or interpretation of news (both stock-specific and industry) in the market. Window dressing by fund managers may also contribute to intermediate-term momentum.

Long-term reversal is weaker than the other two effects, and it is not clear whether it is statistically significant. Like intermediate-term momentum, long-term reversal also appears to be driven by both common factors and stock-specific dynamics, although the evidence for a stock-specific dynamic component is much weaker. It has an industry component as well as a stock-specific component. I believe there is a relation between the long-term reversal effect and the outperformance of value stocks over growth stocks.

Because of transaction costs associated with portfolios of any meaningful size, variables in expected return models need to be sustainable for several months. Intermediate-term momentum, which is sustainable, is currently an important variable in many practitioner models. Short-term reversal, long-term yearly periodicity, and intermediate-term quarterly periodicity are not sustainable for more than one month. While it is important to be aware of these effects, one must recognize it would be difficult to directly incorporate them in expected return models.

ENDNOTES

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[1]Most authors analyze much broader stock universes dominated by highly illiquid small- or micro-cap securities. Analyzing large-cap stocks of the S&P 500 captures the economic significance of return momentum and reversal much better because these stocks are more liquid.

[2]Heston and Sadka [2007] find a similar effect for all stocks in the Center for Research in Security Prices database.

[3]Jegadeesh and Titman [1993] find that the past cumulative 12-month return has the strongest relation with the next quarter's return, which is consistent with Exhibit 3. They also find the past cumulative 6-month return a more consistent indicator among different future time periods. Exhibit 3 shows that the past cumulative 12-month return generally dominates the past cumulative 6-month return. This small discrepancy is probably due to the different data samples—Jegadeesh and Titman [1993] include large-, small-, and micro-cap stocks in their universe, and I use only stocks in the S&P 500.

[4]In a different type of analysis, Chan, Jegadeesh, and Lakonishok [1996 and 1999] show that momentum persists through several quarters of earnings announcements.

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Appendix

Market Microstructure Explanation for Short-Term Reversal

Jegadeesh and Titman [1995] offer a market illiquidity-based explanation for short-term reversal. They argue that risk-averse market makers set prices above stocks' intrinsic values in the event of increased demand to buy the stock and below intrinsic values in the event of increased demand to sell. Because prices are positively related to demand, stocks that have experienced recent high returns tend to have prices above their intrinsic values (and the converse). Therefore, prices tend to reverse to their intrinsic value in the short term.

Another market microstructure explanation provided by Roll [1984] is that the last traded price that the Center for Research in Security Prices uses to calculate returns is more likely to be the ask price for stocks that have recently experienced positive returns and the bid price for stocks experiencing negative returns. Boudoukh, Richardson, and Whitelaw [1994] also argue that short-term return reversal is due to market frictions.

Conversely, Mech [1993] argues that short-term return reversal is not due to market maker trading strategies. He points out that short-term return reversal cannot be arbitraged away due to transaction costs.

Behavioral Explanations for Intermediate-Term Momentum and Long-Term Reversal

Several theoretical models cite investor behavior as explaining the intermediate-term momentum and long-term reversal phenomena. In the model of Daniel, Hirshleifer, and Subrahmanyan [1998], homogeneous investors tend to be overconfident about private information. Their beliefs, based on their private information, are irrationally reaffirmed by returns (public information), so overreaction causes intermediate-term return momentum. When enough public information is disseminated, investors correct their initial errors, causing long-term return reversal.

In a somewhat opposite approach, Barberis, Shleifer, and Vishny [1998] model the reactions of homogeneous investors to earnings. The crux of their model is that investors believe the earnings pattern is either trending or in mean-reversion; earnings, however, actually follow a random walk. This dynamic causes investors to underreact to intermediate-term earnings patterns, and overreact to long-term earnings patterns, causing intermediate-term return momentum and long-term return reversal, respectively.

Hong and Stein [1999] provide a model of two types of investors: news watchers and momentum traders. News watchers invest solely on the basis of private information, and momentum traders invest solely on the basis of past returns. Hong and Stein [1999] assume that information is disseminated slowly; thus, news watchers invest gradually, which causes stock returns to underreact, prompting intermediate-term momentum. Momentum traders continue the trend in returns initially created by news watchers, which causes the returns to overreact, prompting long-term reversal.

Holden and Subrahmanyan [2002] provide a framework based on the interaction of three types of traders: informed, uninformed, and liquidity. An uninformed trader can choose to become informed by acquiring private information for a price. Intermediate-term momentum is based on these dynamics.

It is very difficult to evaluate behavioral models, as it is impossible to directly test them empirically, but several articles give indirect empirical evidence in support of some of these models. Hong, Lim, and Stein [2000] show that firms with little analyst coverage (adjusted for size) tend to have stronger intermediate-term momentum effects. They also find that low analyst coverage has a stronger effect on stocks with poor past returns than stocks with good past returns. They believe that, for low-coverage stocks, company management dominates the dissemination of information. As managers tend to disseminate bad news much more slowly than good news, this causes a stronger prolonged downward momentum for firms with unhealthy information. This analysis supports the slow dissemination theory of Hong and Stein [1999].

Chan, Jegadeesh, and Lakonishok [1996, 1999] find that intermediate-term momentum persists through several quarters of earnings announcements. Scott, Stumpp, and Xu [2003] show that momentum is stronger in growth stocks, which they argue are more sensitive to news than value stocks. In Figelman [2007], I show that intermediate-term momentum is enhanced by company management's manipulation of earnings.

All these authors claim their analysis provides evidence of the gradual diffusion of information that is consistent with models of Hong and Stein [1999] and Barberis, Shleifer, and Vishny [1998].

De Bondt and Thaler [1987] show that past long-term stock returns are inversely related to future earnings, which they claim is evidence of market overreaction, causing long-term reversal. This is also consistent with models of Hong and Stein [1999] and Barberis, Shleifer, and Vishny [1998].

Cooper, Gutierrez, and Hameed [2004] find that intermediate-term momentum is persistent only after up markets. They claim that investors are more overconfident and less risk-averse after up markets. Such an overconfidence claim supports the model of Daniel, Hirshleifer, and Subrahmanyan [1998]. A risk-aversion claim supports the model of Hong and Stein [1999] who show that, in their model, less risk aversion causes greater intermediate-term momentum. (I believe, however, that the results of Cooper, Gutierrez, and Hameed [2004] can be attributed to stock betas, not overconfident investors.)

Table C2, Panel B, of Appendix C in Lee and Swamanithan [2000] show that high-volume stocks exhibit stronger momentum than low-volume stocks. This is consistent with the theory of Daniel, Hirshleifer, and Subrahmanyan [1998], as it is reasonable for overconfidence to drive volume. Yet this finding is not consistent with the theory of Hong and Stein [1999] because it is reasonable to assume that the lower the volume, the slower the information diffusion.

Lee and Swamanithan [2000] also provide an interesting explanation for the role of volume as the link between intermediate-term momentum and long-term reversal, which they call the momentum life cycle hypothesis.

Other articles give explanations for intermediate-term momentum and long-term reversal based on actual investor behavior. Gutierrez and Pirinsky [2004] claim that institutions overreact to total return momentum and underreact to stock-specific momentum. They argue that money managers chase total stock returns because cash flows into their funds, which need to be invested, are related to their past performance. They also suggest that managers tend to underreact to stock-specific momentum due to the reputation or compensation risk of underperforming their benchmark.

Grinblatt and Moskowitz [2004] and Hvidkjaer [2002] argue that intermediate-term momentum is driven by individuals or small traders rather than by institutions or large traders. Badrinath and Wahal [2002] show at the same time that institutions do follow certain momentum strategies. They find institutions are intermediate-term momentum traders when taking new positions and intermediate-term reversal traders when exiting or adjusting current positions. Grinblatt, Titman, and Wermers [1995] also show that mutual fund managers follow a momentum strategy.

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