A Synthesis on Stock Momentum

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Jegadeesh and Titman (1993) popularized the notion that the momentum strategy is profitable and dominates a buy and hold strategy. The momentum strategy is simple: it buys buys stocks with high returns over the prior three to twelve months and sells stocks with poor returns over the same past horizon. This article surveys the large and growing literature on stock momentum. We focus on interesting empirical facts about the momentum profits and various explanations for these findings.

1 Empirical Facts

1.1 Basic Results

Momentum strategy is also known as relative strength strategy. Note that the momentum strategy surveyed here is related but distinct from "momentum" in technical analysis, which measures the rate of the rise or fall in stock prices. In addition, the momentum strategy or relative strength strategy we talk about in this paper is based on cross-sectional comparison of stocks' past returns. It should be differentiated from the relative strength index, a frequently used technical indicator to time stock entry and exit, which is computed using time series data for the given stock.

Forming portfolios based on past three- to 12-month returns, Jegadeesh and Titman (1993) show that past winners on average continue to outperform past losers over the next three to 12 months. For example, a zero-cost portfolio that is long the past 6-month winners (stocks whose past 6-month returns rank in the top 10% in the cross-section) and short the past 6-month losers (those stocks whose past 6-month returns rank in the bottom 10%) generates an excess "return" (profit per dollar long) of about 12% per annum between 1965 to 1989. Similar results can be found in Asness (1995). These results lend support to earlier claims by Levy (1967) that a trading rule that buys stocks with current prices that are substantially higher than their average prices over the last 27 weeks realize significant abnormal returns. They also extend the finding of Jegadeesh (1990) that stocks that have done well (badly) over the previous few months continue to have high (low) returns over the next month. Finally, profitability of momentum strategy which sort stocks based on their intermediate

horizon past returns should be contrasted with evidences of stock return reversal over very short horizon (e.g., 1 week to 1 month as in Lehmann, 1990) as well as over long horizon (e.g., 3-5 year as in De Bondt and Thaler, 1985).

The original findings of Jegadeesh and Titman (1993) appear to be universal. For example, Rouwenhorst (1997) finds that momentum profits are also large in twelve European markets. Chui, Titman and Wei (2000) document that with the exception of Japan and Korea, momentum strategies work in Asian markets, although the profits are weaker. Griffin, Ji and Martin (2003?) find that momentum profits are generally economically and statistically important around the world. The average monthly momentum profit is 1.63%, 0.78%, 0.32% and 0.77% in Africa, Americas (excluding the U.S.), Asia, and Europe respectively.

Unlike other well known anomalies such as small firm effect and book-to-market effect that disappeared after being well-publicized, Jegadeesh and Titman (2000) document that momentum profits persisted throughout the 1990s. The results are also fairly robust to methodological tweaking. For example, Grundy and Martin (2001) show that a "hedged" momentum strategy that sorts stocks on the component of their returns not related to the realization of the Fama-French factors is even more profitable than the original momentum strategy that sorts on total returns.

1.2 Is Momentum Strategy an Arbitrage Opportunity?

The risk-adjusted returns associated with momentum investing do not imply an arbitrage opportunity. While notionally the momentum strategy requires zero investment, it is far from riskless. For example, Grundy and Martin (2001) show that over the 828 months between 1926 and 1995, the total return momentum strategy earns a negative return in 322 of 828 months, and the hedged total return momentum strategy lost money in 261 of 828 months. While momentum strategy is profitable on average over long periods of time, it can be money losing over some shorter horizon. For example, an investor who first entered the momentum strategy in January 1991 and continued the strategy over the 55 months through July 1995 would have lost 58 cents per dollar long.

Researchers also find that momentum strategy tends to do poorly in January.

For example, Jegadeesh and Titman (1993) point out that between 1965 to 1989, the momentum strategy loses about 7% on average in the Januarys, but generates positive return in each of the other months. Grundy and Martin (2001) find that only 15 of the 69 January returns between 1926 to 1995 are positive. The momentum strategy's mean January return is -5.85%, with an associated t-statistic of -4.93. In contrast, 491 of the 759 non-January returns are positive, with a mean of 1.01% and a t-statistic of 4.44. The total return momentum strategy is risky with a January seasonal in its losses.

1.3 When Are Momentum Profits Stronger?

Although momentum is a fairly universal phenomena, researchers have found many interesting variations in the momentum profits. Most of the results summarized below are motivated by various explanations for the profitability of momentum strategies (see section 2).

Most asset pricing anomalies are more severe among the small-cap stocks. Jegadeesh and Titman (1993) and many subsequent papers confirm that momentum results are most pronounced for small stocks. Hong, Lim and Stein (2000) show that momentum strategies work better among stocks with low analyst coverage, and the effect of residual analyst coverage on the momentum profits is almost entirely driven by the loser stocks. Ali and Trombley (2004) study the role of short sales constraints in preventing the arbitrage of momentum returns. They find that momentum profit is much stronger for stocks with high short sales constraints than for stocks with low short sales constraints, with the difference mostly driven by loser stocks.

Grinblatt and Moskowitz (2003) find that low institutional ownership enhances the profitability of momentum strategy for small-cap stocks. This effect is most evident in December and January. However, institutional ownership has negligible impact on the profitability of momentum strategy for large-cap stocks. Han and Wang (2004) find that a refined momentum strategy that is long the past winners that the institutions currently overweight and is short the past losers that institutions currently underweight generates significantly higher profit than the simple momentum strategy that invest in all winners and losers. By contrast, the momentum strategy does

not generate statistically significant profit when applied to winners that institutions underweight and losers they overweight. These results hold for both large-cap stocks and small-cap stocks.

Jegadeesh and Titman (1993) state that the abnormal performance of the zero-cost momentum portfolio is due to the buy side of the transaction rather than the sell side. They find that the portfolio of past winners achieve significant positive abnormal return when the value-weighted index is used as a benchmark, while the abnormal return of the portfolio of past losers is not statistically significant with this benchmark. In contrast, Hong, Lim and Stein (2000) and Lee and Swaminathan (2000) show that portfolios of losing stocks subsequently underperform a portfolio of average performing stocks to a greater degree than winning stocks outperform average stocks. In other words, these two papers indicate that losers momentum appears to be somewhat stronger than winners momentum. Grinblatt and Moskowitz (2003) show that the characteristics of average stocks differ dramatically from those of past winning and losing stocks. Thus, the returns of stocks with the past returns in the middle grouping are not an appropriate benchmark for either past winning or past losing stocks. Grinblatt and Moskowitz (2003) examine hedged returns which control for size, book-to-market and industry effect. Using this approach, the positive and negative abnormal returns of the winners and losers portfolio are both statistically significant, and there is no significant difference between winner and loser momentum.

Instead, Grinblatt and Moskowitz (2003) find that *consistency* in past return is as important as the *magnitude* of past return in predicting future returns. For example, between 1966 to 1995, the hedged returns of equal-weighted portfolio of consistent winners (defined to be firms with at least 8 positive monthly returns within the last 11 months) is 0.91% per month. The extremely consistent winning firms earned 0.99% per month. In contrast, firms in equal-weighted winner portfolio that are not consistent winners on average earn only 0.45% per month. Thus, the marginal impact of being a consistent winner is 0.46% per month.

Lee and Swaminathan (2000) document interesting interaction between stock turnover and momentum profits. Their key finding is that high volume losers significantly *underperform* low volume losers. The effect of volume for winner momentum is not strong and is insignificant. However, Scott, Stumpp and Xu (2003) argue that

this phenomenon is mostly a result of the underreaction of investors to earnings news-an effect that is most pronounced for high-growth companies. After earnings-related news and a stock's growth rate have been controlled for, the interaction between momentum and volume largely disappears. Connolly and Stivers (2003) document new patterns in the dynamics between stock returns and trading volume. They find substantial momentum in consecutive weekly returns when the latter week has unexpectedly high turnover.

Grinblatt and Han (2004) show that using simple past returns in forming momentum portfolio is inferior to sorting stocks on their capital gains overhang, or the difference between current market price and the average cost basis for each stock among its shareholders. Their proxy for the capital gain overhang for a given stock is obtained using the time series of past return and past turnover. They find that stocks with high capital gains overhang subsequently outperform significantly stocks for which most investors suffer large paper losses. The simple intermediate horizon past return loses its predictive power for future return once the capital gain is controlled for.

The Grinblatt and Han results are consistent with but not subsumed by the interaction between trading volume and price momentum. Their model also explains why consistency in return matter for momentum. Using the highest stock price during the past 52-week as investors' reference point for measuring paper gain or loss, their model would predict that stocks tend to continue to go higher (lower) after surpassing its 52-week high (low). George and Hwang (2004) confirm this. They find that profits to a portfolio formation strategy based on nearness to a 52-week high are superior to those based on past returns over a fixed horizon. Ranking by the 52-week high criterion subsumes and improves upon the forecasting power of past returns for future returns.

Cooper, Gutierrez, and Hameed (2003) show that momentum profits depend on the state of the market. From 1929 to 1995, the mean monthly momentum profit following positive market returns is 0.93% percent, whereas the mean profit following negative market returns is negative 0.37%. If good market return promotes more overconfidence, their results are consistent with overreaction theories of momentum profits (see section2.3).

Researchers have also examined the interaction of value and momentum strategies. For example, Asness (1997) find that measures of momentum and value are negatively correlated across stocks, yet each is univariately positively related to the cross-section of average stock returns. Value strategies work in general, but are strongest among low momentum (loser) stocks and weakest among high momentum (winner) stocks. The momentum strategy works in general, but is particularly strong among low value (expensive) stocks. Daniel and Titman (1999) argue that investor overconfidence can potentially generate stock return momentum and that this momentum effect is likely to be the strongest in those stocks whose valuation requires the interpretation of ambiguous information. Consistent with this, they find that momentum effects are stronger for growth stocks than value stocks.

Chan and Kot (2002) explore how the profits of momentum-sorted portfolios will be affected when they are formed at the early stage versus the late stage of the contrarain cycle. They find that an "early stage" momentum strategy (buy stocks that are of short-term winners but long-term losers and sell stocks that are of short-term losers but long-term winners) generates significantly positive. On the other hand, while returns while the return of the "late stage" momentum strategy (buy stocks that are of both short-term and long-term winners and sell stocks that are of both short-term and long-term losers) is not significantly different from zero.

Turning to the seasonality in momentum profits, besides the January seasonal effect (see section1.2), Jegadeesh and Titman (1993) as well as Grinblatt and Moskowitz (2003) show that momentum strategy tend to be most profitable in December. Grinblatt and Han (2004) explain both the January and December seasonal effect in momentum profits through the combination of disposition effect during February through November and tax-loss selling in December. Grinblatt and Moskowitz (2003) find that small, high turnover stocks with low institutional ownership exhibit more pronounced past return and seasonal effects. This supports the tax-loss selling explanation for the January seasonal effect. They also show that the seasonality in momentum profits are only present in high tax years.[1] Jegadeesh and Titman (1993) show that the momentum profits tend to be stronger in April and November as well.

[1]High tax years are defined as years or intervals of years at which the beginning year has a maximum short-term capital gains tax rate that is at least 20% higher than the average of the maximum rate in the two surrounding year (e.g., 1968-1969, 1972-1975, 1981, 1985-1986, 1988-1999).

1.4 Momentum Profits over Long Horizons

Jegadeesh and Titman (1993) first document that the momentum profits slowly dissipates over longer horizons. For example, the portfolio formed on the basis of returns realized in the past 6 months generates an average cumulative return of 9.5% over the next 12 months but loses more than half of this return in the following 24 months. find similar results. Lee and Swaminathan (2000) and Jedgadeesh and Titman (2001) confirm this long run reversal of momentum profits. However, Nagel (2001) argue that these long horizon reversals of momentum profits are a book-to-market effect. They disappear after adjusting returns for book-to-market and taking into account the predictable changes in book-to-market experienced by extreme performers following portfolio formation.

There are also variations in the long-run returns of the momentum portfolio. For example, Lee and Swaminathan (2000) find that the persistence of price momentum is a function of past trading volume. Conditional on past volume, Lee and Swaminathan (2000) create Jegadeesh and Titman-type momentum portfolios (winners minus losers) that either exhibit long-horizon return reversals or long-horizon return continuations. The momentum strategy that buys high volume winners and low volume losers immediately begins losing after the first year following portfolio formation. In contrast, the strategy that buys low volume winners and high volume losers earns significant positive returns for years 1, 2, and 3 before the effect dissipates. Chan and Kot (2002) find that the profits of early stage momentum strategy which buys stocks that are of short-term winners but long-term losers and sells stocks that are of short-term losers but long-term winners continues to increase in the 60-month holding period.

Stevenson (2002) find evidence of performance persistence in international real estate markets, but no statistically significant evidence of performance reversals over longer horizons. Cooper, Gutierrez, and Hameed (2003) find that only the momentum profits following positive market returns reverses in the long-run. George and Huang (2004) find that future returns forecasted using a 52-week high criteria do not reverse in the long run, suggesting that short-term momentum and long-term reversals are not likely to be components of the same phenomenon.

1.5 Additional Evidences on Momentum

Subsequent to the ground-breaking work of Jegadeesh and Titman (1993), researchers find that the momentum phenomenon exist not just for individual stocks, but also hold for various stock portfolios and in other financial markets. In addition to price momentum, there is also earnings momentum.

1.5.1 Industry and Momentum

Moskowitz and Grinblatt (1999) form industry portfolios of stocks based on 2-digit Standard Industry Classification (SIC) codes. They find that these industry portfolios exhibit significant momentum even after controlling for size, book-to-market equity (BE/ME), individual stock momentum, the cross-sectional dispersion in mean returns, and potential microstructure influences. Grundy and Martin (2001) show that the Moskowitz and Grinblatt results are most pronounced when the formation period is contiguous with the investment period-much of the observed pro.tability of an industry momentum strategy comes in the month immediately after the formation period. The industry momentum strategies seem not to exhibit the level of profit shown by the total return strategy. For example, Grundy and Martin (2001) find that the total return strategy earns 1.59% per month in the non-January months in the period 1962 to 1995, while the comparable numbers for the industry strategies are 0.55% (value-weighted) and 0.89% (equal-weighted). Moskowitz and Grinblatt (1999), and Chordia and Shivakumar (2000) also show that a component of individual stock momentum is distinct from industry momentum.

Menzly and Ozbas (2004) find evidence of cross-industry momentum. Industries related to each other through the supply chain (upstream or downstream) exhibit strong cross-momentum. A trading strategy that consists of buying (selling) industries with large positive (negative) returns to their upstream industries over the previous month yields an annual premium of more than 6% and a Sharpe ratio of 0.7.

Chui, Titman and Wei (2001) find evidences for intra-industry momentum using the real estate investment trusts data. Wang (2004) also provides empirical evidence of within industry momentum, i.e., the zero-cost strategy to long past winners and short past losers within an industry can generate profits. She also find that such

within-industry momentum varies significantly across industries. In particular, industries with higher concentration levels tend to generate higher momentum. Sonti (2000) illustrates an economic benefit to stratifying firms based on industry growth and relative company growth intra-industry in forming momentum portfolios. Individual stock momentum varies almost monotonically by industry growth. Firms in highest industry growth quintile have significantly higher momentum compared to those in the lowest growth quintile. Further, momentum profits of the highest industry growth quintile are always higher than those for for the universe of firms.

1.5.2 Momentum for Other Portfolios

Lewellen (2002) extends the results of Moskowitz and Grinblatt (1999) to size, book-to-market (B/M) ratio, and size and B/M double sorted portfolios. Momentum in these portfolios are strong and sometimes stronger than momentum in individual stocks or industry portfolios. For example, over the first 6 months, the cumulative profits from value-weighted size quintiles is 2.56%, from value-weighted B/M deciles is 2.14%, and from 25 value-weighted size-B/M portfolios is 3.23%. Equal-weighted portfolios produce larger profits. The Sharpe ratios of these portfolios are around 0.15 to 0.2.

Similarly, Chen (2003) shows that drifts in future returns over the next twelve months are predictable from equity style cycle information. Stocks with in-favor characteristics continuously outperform stocks with out-of-favor characteristics. Characteristics momentum, buying stocks with persistent in-favor characteristics and selling stocks with persistent out-of-favor characteristics, is profitable and has longer-lasting effects than price or industry momentum in predicting future returns.

Several studies examine momentum and reversals in international equity market indices. For example, Asness, Liew, and Stevens (1997) find momentum in country equity market indices during the first year after the portfolio formation date. Chan, Hameed and Tong (2000) show that the momentum profits for international equity market indices arise mainly from time-series predictability in stock market indices - very little profit comes from predictability in the currency markets. In addition, the profits for momentum portfolios are higher when implemented on markets with higher volume in the previous period. Bhojraj and Swaminathan (2004) also find

similar the predictability in country stock indices. Connolly and Stivers (2003) find that the autocorrelation in equity-index returns is increasing with the unexpected dispersion across the latter week's firm-level returns.

Nijman, Swinkels, and Verbeek (2004) examine the presence of country and industry momentum in Europe. They find that the positive expected excess returns of momentum strategies in European stock markets are primarily driven by individual stocks effects, while industry momentum plays a less important role and country momentum is even weaker. These results are robust to the inclusion of value and size effects.

1.5.3 Does Momentum Hold in Other Markets?

The profitability to momentum-based strategies holds for several other markets as well. For example, Okunev and White (2003) find that the long/short strategy of buying the most attractive currency and shorting the least attractive currency obtains average excess returns that are significantly positive. The profitability to momentum strategies in foreign exchange markets has been particularly strong during the latter half of the 1990s. Moreover, the correlations of the long/short momentum strategies using differing base currencies are very high - typically around 0.90. Stevenson (2002) find strong evidence of performance persistence in international REITs market over medium term horizons. Caginalpa, Porter and Smith (2000) show that the momentum model has predictive power for traders' behavior in experimental asset markets.

However, investment grade corporate bonds do not exhibit momentum at the three to twelve month horizons; rather there is evidence of reversals (e.g., Gebhardt, Hvidkjaer, and Swaminathan, 2004). Interestingly, there is significant evidence of a momentum spillover from equities to investment grade corporate bonds of the same firm. Specifically, firms earning high (low) equity returns over the previous year earn high (low) bond returns the following year. Bond ratings of firms with positive equity momentum continue to improve in the future. The spillover results are stronger among firms with lower-grade debt and higher equity trading volume.

1.5.4 Earnings Momentum

Bernard and Thomas (1989) and many other papers find that firms reporting unexpectedly high earnings outperform firms reporting unexpected low earnings. Hong, Lee, and Swaminathan (2003) examine the profitability of earnings momentum strategies based on analyst forecast revisions in eleven international equity markets. They find that in general, markets with high levels of corruption (low investor protection) exhibit weak momentum. They argue that the momentum phenomenon is related to information dissemination mechanisms within a country. Dische (2002) finds that an earnings momentum strategy is more profitable when applied to stocks with a low dispersion in analyst forecasts.

Price momentum and earnings momentum are closely related. Jegadeesh and Titman (1993) document that past winners realize consistently higher returns around their earnings announcements in the 7 months following the portfolio formation date than do past losers. However, in each of the following 13 months past losers realize higher returns than past winners around earnings announcements.

It is also possible that stock price momentum is due to the component of medium horizon returns that is related to earnings-related news. If this is the case, then momentum strategies will not be profitable after controlling for past innovations in earnings and earnings forecasts. Chan, Jegadeesh and Lakonishok (1996) show that intermediate horizon return continuation can be partially explained by underreaction to earnings news but the price momentum is not subsumed by earnings momentum. It seems that an earnings momentum strategy exploits market underreaction to information related to short term earnings surprises, while a price momentum strategy may benefit from market's slow response to information related to long term earnings.

Soffer and Walther (2000) find that the serial correlation of returns and the serial correlation of earnings surprises are related. Controlling for cross-sectional differences in firms' serial correlations in earnings surprises, they are able to eliminate the serial correlation in returns at 3-, 24-, 36-, and 48-month intervals, but still find some evidence of residual serial correlation in returns at 6-, 12-, and 60-month intervals. Chordia and Shivakumar (2001) also study the relation between price momentum and earnings momentum. They argue that price momentum is primarily attributable to a portfolio that is long in stocks that have had high earnings changes in the last

quarter and is short in stocks that have had low earnings changes in the last quarter.

1.6 Are Momentum Strategies Tradable?

All of the results summarized above ignore transaction cost. From a practical investment perspective, it is important to assess whether the momentum strategy remains profitable after accounting for transaction costs. Do momentum strategies represent a real opportunity for investors to earn abnormal returns?

An investor trying to exploit the strategies described above would need to account for trading costs in deciding whether to pursue these strategies. The investor would want to avoid or downweight stocks with low prices and small market capitalizations, and would be more interested in value- than equal-weighted portfolios. The investor also might avoid employing information from the past one-month return due to potential market-microstructure effects.

Pure momentum strategies tend to involve high turnover, but the turnover required is far from 100% per month because the formation periods corresponding to investment months t and $t+1$ will share five months in common (when sorting stocks on their past six-month returns). Stocks with extreme performance over a six-month formation period are likely to still qualify as winners/losers when the start of the formation period is shifted forward by one month. Grundy and Martin (2001) show that on average, only about 40% of the winners are sold at the end of the investment month, and only 36% of the short positions in the losers are closed out at the end of the month. For 1999, a particularly volatile year, Grinblatt and Moskowitz (2003) show that the turnover (dollar-buys plus dollar-sells per dollar invested) on the long side of the momentum strategy is 38.86% per month, while that on the short side is 63.75% per month. Trading costs of about 1% are approximately the break-even costs for the momentum strategy. Real world trading costs appear to be smaller than this.[2] Similarly, Grundy and Martin (2001) conclude that momentum strategy would be profitable for investors whose round-trip costs were less than 1.5%.

[2]Wayne Wagner, (www.plexusgroup.com) has estimated that for large cap stocks, a cost of about 0.32% reflects market impact and brokerage commission for trades, while 0.55% covers a smaller cap trade. With Internet and the introduction of decimalization, these costs may now be even lower.

Moreover, Grinblatt and Moskowitz (2003) point out that even if short-sales restrictions were costly, there are still substantial rents that can be earned from the long side of the momentum strategy which beats a similar book-to-market, size, and industry-matched benchmark. For example, the profits for the long side of the strategy net of benchmark portfolio returns are 66 basis points per month. This would only be wiped out by one-way transaction costs of at least 1.70%, which could be almost an order of magnitude too high for value-weighted portfolios. Further, Han and Wang (2004) find that past winners that have abnormally high institutional ownership continue to have very high future returns, even among the large-cap stocks. Such stocks are liquid and have very low transaction costs.

Whether momentum profits are robust to transaction costs is subject to some debates. Lesmond, Schill and Zhou (2004) analyze four direct or indirect measures of transaction costs for the extreme past winner stocks and loser stocks, and find little evidence that trading costs for the standard momentum strategy are below 1.5% per trade. Thus, they view that the profits are largely "illusive" for the standard momentum strategy. Korajczyk and Sadka (2004) also examine the impact of total trading costs including the price impact of trades. They assume convex price impact functions which may over-estimate the trading costs of large trades. But even with these conservative trading costs estimates, Korajczyk and Sadka (2004) find that after taking into account the price impact induced by trades, as much as 5 billion dollars (relative to December 1999 market capitalization) may be invested in some momentum-based strategies before the apparent profit opportunities vanish.

Finally, we want to point out that even if transactions costs may eliminate the profitability of momentum strategy, they do not explain the equilibrium underlying that anomaly. In the next section, we turn to various explanations for the momentum profits.

2 What Drives Momentum?

While the existence of momentum has been well documented, there is little agreement on the sources of profits of such strategies. In this section, we first look at two useful decompositions for the expected returns of momentum portfolios, which highlight the

different components that contribute to momentum profits. Then we review risk-based explanations as well as behavioral models for the momentum phenomenon.

2.1 Different Sources of Momentum Profits

The profitability of momentum strategy imply that stocks that generate higher than average returns in one period also generate higher than average returns in the period that follows. In other words,

$$\mathrm{E}[(r_{it} - r_{m,t})|r_{i,t-1} - r_{m,t-1} > 0] > 0$$

and

$$\mathrm{E}[(r_{it} - r_{m,t})|r_{i,t-1} - r_{m,t-1} < 0] < 0$$

where $r_{i,t-1}$ is the asset i's return in month $t-1$ and $r_{m,t-1}$ is the return on equal-weighted market index in month $t-1$. Thus

$$\mathrm{E}[r_{it} - r_{m,t})(r_{i,t-1} - r_{m,t-1})] > 0 \tag{1}$$

The left hand side of the above equation equals the expected profits from the portfolio strategy that weights stocks by their past returns less the past equally weighted market returns. It is closely related to the momentum profits. It is a cross-sectional auto-covariance of stocks' excess return. To better understand this term, let us assume the following one-factor model for the stock returns

$$\begin{aligned} r_{it} &= \mu_i + b_i f_t + e_{it} \\ \mathrm{Cov}(e_{it}, f_t) &= 0, \ \forall i \\ \mathrm{Cov}(e_{it}, e_{jt-1}) &= 0, \forall i \neq j \end{aligned}$$

where μ_i is the unconditional expected return on stock i, f_t is the unconditional unexpected return on a factor-mimicking portfolio, e_{it} is the firm-specific component of return at time t. Jegadeesh and Titman (1993) show that under this one-factor

model, the cross-sectional auto-covariance equation (1) can be rewritten as

$$\mathrm{E}[(r_{it} - r_{m,t})(r_{i,t-1} - r_{m,t-1})] = \sigma_u^2 + \sigma_b^2 \mathrm{Cov}(f_t, f_{t-1}) + \bar{\mathrm{Cov}}_i(e_{it}, e_{it-1}) \qquad (2)$$

where σ_{mu}^2 and σ_b^2 are the cross-sectional variances of the expected returns and factor sensitivities respectively, and $\bar{\mathrm{Cov}}_i(e_{it}, e_{it-1})$ denotes the cross-sectional average of the auto-covariances of the stock-specific component in returns.

The above decomposition suggests three potential sources for momentum profits. The first term in equation (2) measures the cross-sectional dispersion in expected returns. By nature, momentum strategies tend to buy stocks with high unconditional means: on average, stocks with the highest unconditional means also tend to have the highest realized returns. Note that momentum sometimes is loosely referred to as positive autocorrelation in stock return. However, we see that profits of momentum strategy can be positive even in the absence of time series return predictability.

Empirically, there have been some debates about the relative importance of time series v.s. cross-sectional return predictability in explaining the momentum profits. Conrad and Kaul (1998) argue that the profitability of momentum strategies can be entirely explained by the cross-sectional variation in mean returns of individual securities, rather than appealing to time-series predictability. Conrad and Kaul (1998) presents striking evidence suggesting that the momentum profits are attributable to cross-sectional differences in expected returns rather than to any time-series dependence in returns. However, Moskowitz and Grinblatt (1999) and Jegadeesh and Titiman (2002) show that the effect of such dispersion is not strong enough to fully explain observed momentum. Cross-sectional differences in expected returns explain very little, if any, of the momentum profits. Jegadeesh and Titman (2001) find that the cumulative return in months 13 to 60 after the formation of momentum portfolio is negative, which is inconsistent with the Conrad and Kaul hypothesis. Grundy and Martin's (2001) evidence also appears to contradict this hypothesis. They find that the risk-adjusted profitability of a total return momentum strategy is more than 1.3% per month and remarkably large and stable across subperiods, even after subtracting each stock's mean return from its return during the investment period.

Coming back to the decomposition of portfolio returns, we note that the second

term in equation (2) is related to the potential to time the common factor. Momentum profits can arise from a positive serial-correlation of the common factor driving stock returns. In this case, the momentum strategy will tend to pick stocks with high sensitivity to the factor when the factor return is high. In theory, it is possible that momentum profits are partly driven by predictability in common factor returns. However, there is little empirical support for the positive autocorrelation in common factors. For example, Jegadeesh and Titman (1993) find a slightly negative serial covariance for the 6-month returns of equal-weighted market index. Grundy and Martin (2001) find the Fama-French factors do not exhibit significant positive momentum either. Thus, serial covariance of factor portfolio returns is unlikely to be the source of momentum profits.

Momentum profits are usually attributed to persistence in firm-specific returns (the third term in equation (2)). For example, investors could underreact or overreact to firm specific news. But firm-specific returns can also be positively autocorrelated because stocks covary too strongly (lead-lag effect). To understand this point better, let us consider another decomposition of portfolio return (see, e.g., Lo and Mackinlay, 1990, and Lewellen, 2002).

The equal-weighted momentum portfolio in month t puts a weight on asset i (when there are N stocks)

$$w_{it} = \frac{1}{N}(r_{i,t-1} - r_{m,t-1})$$

Let r_t be a vector stacking the mean return of all N stocks and μ denotes the vector of uncondition mean stock returns μ_i, $i = 1, \cdots, N$. Let $\Omega = \mathrm{E}[(r_{t-1} - \mu)(r_t - \mu)]$ be their auto-covariance matrix. Then the profit to the momentum portfolio can be written as

$$\pi_t = \sum_i w_{i,t} r_{i,t} = \frac{1}{N} \sum_i (r_{i,t-1} - r_{m,t-1}) r_{i,t}$$

Thus the expected profit of the momentum portfolio is

$$\begin{aligned} \mathrm{E}[\pi_t] &= \frac{1}{N} \sum_i \mathrm{E}\left[\sum_i r_{i,t-1} r_{i,t}\right] - \frac{1}{N} \mathrm{E}\left[r_{m,t-1} \sum_i r_{i,t}\right] \\ &= \frac{1}{N} \sum_i (\rho_i^2 + \mu_i^2) - (\rho_m^2 + \mu_m^2) \end{aligned} \tag{3}$$

where ρ_i and ρ_m are the auto-covariances of asset i and the equal-weighted market index, respectively. Note that ρ_m critically depends on the cross serial-correlation or the lead-lag relations among stocks.

Equation (3) highlights that momentum might be caused by autocorrelation in returns, cross serial-correlation in returns, or cross-sectional dispersion in unconditional means. Intuitively, a stock that outperformed other stocks in the past continue to do so for three reasons: (1) the stock simply has a high unconditional mean relative to other stocks; (2) the stock return is positively autocorrelated, so its own past return predicts high future returns; (3) the stock return is negatively correlated with lagged returns on other stocks. A firm with high return today predicts that other firms will have low returns in the future. In this case, the stock does relatively well in the future only because other stocks do poorly.

Lewellen (2002) provides support for the last view above. He finds that industry, size, B/M portfolios are negatively auto- and cross-serially correlated, and argue that lead-lag relations among stocks play an important role in explaining the momentum profits. On the other hand, Pan, Liano and Huang (2004) find that the industry momentum effect is mainly driven by the own-autocorrelation in industry portfolio returns, not by return cross-autocorrelations or by cross-sectional differences in mean returns. Indeed, the industry momentum strategy generates statistically significant profits only when own-autocorrelations are positive and statistically significant.

2.2 Risk Explanations

There are two broad categories of explanations for momentum profits. One claims that they are compensation for some risks. The other argues that it is investors' systematic biases in their expectations that are responsible for the patterns in momentum portfolio returns.

For momentum profits to be rational, risk would have to increase after positive returns. This may appear counter-intuitive, but there are models that can generate this feature. In general, these models examine how economic risk factors affect firm investment life cycles and growth rates.

In the model of Berk, Green and Naik (1999), a firm's value depends on interest

rates as well as the number of and systematic risk of its existing projects. Slow turnover in the firm's project portfolio leads to persistence in both the firm's asset base and its systematic risk, all of which makes expected returns positively correlated with lagged expected returns. Simulations from the calibrated model produce momentum profits of roughly the magnitude observed in the U.S., but at slightly longer horizons than that observed in U.S. empirical data.

Sagi and Seasholes (2002) extend the analysis of Berk, Green and Naik (1999), and argue that the profitability of momentum strategies can be tied to the dynamics of firm-specific factors. They show that momentum can exist when the log market value of equity is increasing and convex (or decreasing and concave) with respect to the log price of the commodity produced by the firm. The addition of growth options will increase the convexity, and thus the profits from a momentum strategy.

In the model of Johnson (2002), momentum arises from a positive relation between expected returns and firm growth rates. In effect, a firm with an extreme realized return is experiencing a highly persistent shock to the dividend growth rate, which in turn changes future expected returns in the same direction. Calibration of this partial equilibrium model produces momentum profits which can decline rapidly (as observed empirically), but remain cumulatively positive at longer horizons.

Zhang (2004) also proposes a rational model with time varying risk premium to demonstrate that firm-specific risks can be priced in the equilibrium and can generate momentum. In general, business risks at both the market level and firm level can affect a firm's investment decisions, and a firm usually has certain ability to forecast firm-level risks, such as demand changes or technology innovations. When a firm dynamically adjusts its business according to forecasted firm-level risks, investors face a beta risk (which proxies for firm-level risks) in addition to the market risk. These two risks jointly create a nonlinear risk premium, which simultaneously explains momentum and the Fama-French (1993) three-factor model.

Next, we summarize results of some studies that examine whether risks can explain momentum profits. Jegadeesh and Titman (1993) show that momentum is not driven by market risk. Fama and French (1996) find that their *unconditional* three-factor model cannot explain momentum either. Both papers find that risk adjustment tends to accentuate momentum profits. Fama and French (1996) state that "the main

embarrassment of the three-factor model, (is) its failure to capture the continuation of short-term returns documented by Jegadeesh and Titman (1993) and Asness (1994)"

Other papers study whether accounting for time-varying factor exposure help explain the profitability of momentum strategies.[3] Grundy and Martin (2001) find that controlling for dynamic exposure to Fama-French three-factors only serves to deepen the momentum puzzle. Over the 1926 through 1995 period a momentum strategy would have earned an average monthly return of 0.44% (with an associated t-statistic of 1.83). Hedging out the strategy's dynamic exposure to size and market factors would have removed 78.6% of the monthly return variance, and would have increased the mean monthly return to 1.34% (with an associated t-statistic of 12.11). However, Wu (2002) claims that conditional Fama-French regression model seems misspecified. After relaxing linearity assumption and imposing some cross-sectional restrictions, he finds that incorporation of conditioning information into an asset-pricing model helps capture return momentum.

Researchers have also investigated risk-adjustments beyond the Fama-French factors. For example, Ahn, Conrad, and Dittmar (2003) utilize the stochastic discount factor methodology and non-parametric benchmark to study momentum trading strategies. Nonparametric risk adjustment explains roughly half of momentum strategy profits. They cannot rule out the possibility of residual mispricing. Karolyi and Kho (2004) use a new estimation-based bootstrap simulation procedure to test whether different returns-generating models can explain the profitability of momentum strategies. They find that accounting for time-varying expected returns with market-wide and macroeconomic instrumental variables can explain up to 75 to 80 percent of the momentum profits, but none of the models they consider are able to generate simulated profits as large as the actual profits.

Chordia and Shivakumar (2002) argue that the momentum profits are driven by time-varying conditional expected returns and are related to macroeconomic business cycle. They investigate the one step ahead forecasts obtained by projecting

[3]To understand the time varying factor exposure of a momentum strategy, consider the following example. If the stock market outperforms T-bills, winners will tend to be stocks with betas above one. Thus, following up-markets, a momentum strategy will tend to place a positive beta bet on the market; i.e., the strategy will go long in stocks with betas above one and short in stocks with betas below one. Conversely, following down-markets, a momentum strategy will tend to involve a negative beta bet on the market.

momentum profits onto lagged macroeconomic variables. They conclude that U.S. momentum profits are explainable using these forecasts.

However, Griffin, Ji and Martin (2003) document that the forecasting model proposed by Chordia and Shivakumar (2002) has very low explanatory power for momentum profits when taken to the international data. Internationally, momentum profits bear basically no statistically or economically significant relation to the Chen, Roll, and Ross (1986) macroeconomic factors. Performance of a forecasting model based on lagged macroeconomic variables also indicates that there is no measurable relation between macroeconomic risk and momentum either abroad or in the U.S. They also find significant momentum profits in both good and bad business cycle states, which is incompatible with momentum being a reward for priced business cycle risk.

2.3 Behavioral Explanations

Another strand of the literature uses "behavioral" models to explain momentum profits. These models generate new testable implications on momentum. The empirical tests of these models reveal many new facts about the profitability of momentum strategies (see results summarized in section 1.3) and enrich our understanding of the momentum phenomenon.

The behavioral models can be divided into two camps, depending on whether investor behavior generates overreaction or underreaction. The original conjecture of Jegadeesh and Titman (1993) was that the market systematically underreacts to firm-specific information regarding their short-term prospects. Alternatively, it is possible that transactions by investors who buy past winners and sell past losers temporarily move prices away from their long-run values, thereby causing prices to overreact.

In DeLong, Shleifer, Summers, and Waldmann (1990), such overreaction is caused by rational speculators who indulge in positive feedback trading. Prices initially overreact to news about fundamentals, and continue to overreact for a period of time. Daniel, Hirshleifer and Subrahmanyam (1998) present a model where investors are overconfident. This implies overeaction to private information and underreaction to public information arrival. The investors also suffer from a self-attribution bias. Their behavior generates delayed overreaction to the information which is eventually

reversed. Among other things, the fact that momentum profits are stronger for harder to value stocks (such as growth stocks) and stronger following good market returns support the overconfidence-delayed overreaction explanation for momentum profits, as overconfidence can be expected to be stronger in these cases.

In contrast, stock momentum arises because price underreacts to information in the models of Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), and Grinblatt and Han (2003). The Barberis, Shleifer and Vishny model uses two behavioral biases, motivated by Griffin and Tversky (1992).[4] One is the conservativism bias: Investors underweight new evidence and conservatively update their beliefs in the right direction, but by too little in magnitude with respect to more objective information. In other words, investors places more emphasis on the strength of information rather than statistical weight, relative to a rational Bayesian. At the same time, investors tend to extrapolate current earnings growth well into the future. This is the representative bias. The two biases combined together lead to underreactions to earnings changes and overreactions to long-term earnings trends. This explains both the short run continuation and long run reversal in stock prices.

In Hong and Stein (1999), agents can use only part of the information about the economy because of communication frictions. In their model, private information diffuses slowly through the population of investors, which causes underreaction in the short run. Momentum traders can profit by trend-chasing, but cause overreaction at long horizons in doing so. Using analyst coverage as a proxy for the speed of information diffusion, Hong, Lim, and Stein (2000) find that momentum strategies work better among stocks with low analyst coverage, which is consistent with the prediction of the model of Hong and Stein (1999).

In Grinblatt and Han (2003), price underreact to news even when there is no information asymmetry. Their model is based on the framework of prospect theory (e.g., Kahneman and Tversky, 1979) and mental accounting (e.g., Thaler, 1985). They show that both disposition effect and momentum can be explained by this frame-

[4]Griffin and Tversky argue people update their beliefs based on the "strength" and the "weight" of new evidence. "Strength" refers to the magnitude or significance of the evidence. It looks at the data itself. "Weight" in contrast refers to features such as relevant sample size, behavior of sample (presence of outliers). The key point of the framework is that people tend to concentrate on the strength of the evidence and tend to ignore its weight.

work. In their model, price underreaction arises from the so-called disposition effect: the tendency of investors to hold onto their losing stocks to a greater extent than they hold onto their winners. A stock that has been privy to prior good news has excess selling pressure relative to a stock that has been privy to adverse information. If demand for a stock by rational investors is not perfectly elastic, then such a demand perturbation tends to generate price underreaction to public information. In equilibrium, past winners tend to be undervalued and past losers tend to be overvalued. As the mispricings get corrected, momentum arises.

Grinblatt and Han (2004), and George and Huang (2004) find evidence supporting the predictions of the Grinblatt and Han (2003) model for stock momentum. The Grinblatt and Han (2003) model has other interesting implications for volume, volatility, and stock return pattern around other information settings such as earning announcements. Some of these predictions have been verified by Goetzmann and Massa (2003) and Frazzini (2004).

3 Conclusions

Momentum refers to the persistence in the returns of stocks over horizons between three months and one year. Jegadeesh and Titman (1993) found that past winning stocks, as measured by returns over the prior six months tended to subsequently outperform past losing stocks by about twelve percent per year. Hundreds of papers have been published on momentum during the last decade. Our survey covers all aspects of this large and growing literature.

Although momentum remains one of the most puzzling anomalies in finance, our understanding of financial market and asset pricing in particular no doubt have been enriched by all the studies on momentum. We now understand better than ten years ago about how time varying risks and biases in investor beliefs affect time series and cross-sectional properties of stock returns. Momentum is also intimately related to investors' trading behavior (e.g., Grinblatt, Titman and Wermers, 1995, Wermers, 1999, Badrinath and Wahal, 2002). Finally, momentum plays an important role in understanding other phenomenon in the financial market such as the persistence of mutual fund performance (e.g., Wermers 2003) and the "smart money" effect (e.g.,

Sapp and Tiwari, 2004).

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