IBA Institute of Business Administration Karachi
Leadership and Ideas for Tomorrow

Business Review

Article 2

Volume 14 Issue 1
January-June 2019

1-1-2019

The reversal strategy: A test case for an emerging market

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https://ir.iba.edu.pk/businessreview/vol14/iss1/2
DOI: https://doi.org/10.54784/1990-6587.1022

Business Review: (2019) 14(1):12-27
Original Paper

The reversal strategy: A test case for an emerging market

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Abstract The reversal strategy in the Pakistan Stock Market has shown significant profits for the time period January 1993 - September 2017. The available asset pricing models are unable to link these returns with the risk premium. This paper explores an alternative channel of predicting risk premium. It suggests that reversal profits can be considered as compensation for providing liquidity to the market during times of high volatility. Results reveal that reversal is stronger for illiquid and volatile stocks. Furthermore, firms that show reversal, are cash constrained, have lower return on asset (ROA) and equity (ROE), lesser operating profitability (OP), investment (INV) and net income (NI).

Keywords Reversal strategy · Risk premium · Market volatility · Liquidity provision.

1 Introduction

Short-term reversal has been documented for the US market in the study of Jegadeesh (1990) and Lehmann (1990). In essence, this tendency of the stocks to exhibit reversal, can be used to generate a zero cost investment strategy. By going long in recent losers and short in recent winners one may earn profits where these losers/winners are the stocks that have performed the worst/best in any given month/week t. By iterating this investment strategy for the given sample, studies such as Jegadeesh (1990) reported 2.5% monthly profits for the US market for the time period 1934-1987,[1] whereas Lehmann (1990) reported 1.7% weekly profits for the reversal strategy for the time period 1962-1986.

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[1] Recently, for the time period 1963-2012, Bali et al (2016) reported reversal profits to be 2.69% for the US markets. This indicates that reversal profits are quite stable over time.

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DOI: https://doi.org/10.54784/1990-6587.1022

The existence of reversal profits also encompasses other stock markets. Griffin et al (2010) reported that on average 8.7% annual profits exist in developed markets and 11.4% in emerging markets. Similarly, Cakici and Topyan (2014) have shown that for 5 Asian emerging markets out of 8, the reversal effect is economically meaningful and statistically reliable.

Arguably, the existence of the reversal effect is the negation of the weak-form hypothesis of market efficiency. The information on the recent losers and winners is available in the history of the prices of the stocks and can easily be implemented as an investment strategy. However, once the market recognizes this, the reversal profits should evaporate as per the dictates of the efficient market hypothesis. But empirical findings suggest otherwise.

Fama and French (1993) argued that if higher returns are linked to higher risk premiums, then one may not infer the breach of market efficiency, as these higher returns are expected from these strategies that are exposed to market based risks. Interestingly, Bali et al (2016) have shown that reversal profits for the US market do not reconcile with their factor loading as proposed in, CAPM of Sharpe (1964); Lintner (1965); Mossin (1966), 3-factor model of Fama and French (1993) and 4-factor model (Carhart 1997). Thus these strategies leave significant and predictable risk adjusted alphas. Lehmann (1990) also tested the same argument that either the reversal profits are expected predictable returns or the manifestation of market inefficiency.

Lehmann (1990), proposed that the existence of short-term reversal indicates market inefficiency and relates it with the lack of liquidity for the stocks that have experienced large price changes recently. Avramov et al (2006) largely concur with the findings of Lehmann (1990), that reversal profits are due to stresses in market liquidity. However, they cast doubt about the overall profitability of the reversal strategies in excess of their transaction cost and rationalized the results within the efficient market hypothesis.[2]

The study by Cheng et al (2017) also shows that the lack of provision of liquidity gives impetus to reversal profits. They proxy the lack of provision of liquidity by the exit of active and institutional investors in those stocks which perform poorly for the previous quarter. More importantly, Nagel (2012) explicitly linked the reversal profits with the returns earned by the liquidity providers[3] at the time when liquidity evaporates and market distress is higher. There are also studies with alternative explanations of the reversal profits that link it with the microstructure issues that induce the negative autocorrelation in the stock returns.[4]

One common denominator of all these studies is that reversal profits are stronger in smaller, illiquid and highly volatile firms and associated with the increase in market illiquidity and volatility (Avramov et al 2006; Huang et al

[2] Avramov et al (2006) do not negate the idea that reversal profits are the compensation for the liquidity providers to accommodate the price pressures created by non-information based immediacy to trade.

[3] Nagel (2012) never restricted definition of the liquidity providers to just market makers, even the individual investors provide liquidity to the market (Kaniel, Saar, and Titman (2008)).

[4] Lo and MacKinlay (1990) provide an account of studies that induce negative serial correlation between stock returns, such as bid-ask bounce, transaction cost and other factors.

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2009; Nagel 2012). All of these settings are ideal for conducting the reversal related study for the Pakistan Stock Market (PSX). For instance, we find that the reversal profits in the PSX for the time period January 1993-September 2017 (1993-2017 onwards) are 55.32% on an annual basis. These returns are far superior than returns available on the overall market. Further, reversal profits unlike momentum strategy (Barroso and Santa-Clara (2015) and Daniel & Moskowitz (2016)) do not show large downturns that result in negative skewness. In fact, the reversal strategy is positively skewed to an extent of 45.19.

Figure 1, conveniently illustrates the wealth index with an initial investment of Rs.1 in reversal strategy (R1-R5), in market index (MKT), in the risk free rate (RF) in recent loser (R1) and in recent winner (R5). The total horizon related return for rolling over investment for the given sample for the reversal strategy (R1-R5) is Rs. 25,501. It is far greater than both the return on market index and on risk free rate.

This exceptional performance of the reversal strategy in PSX requires detailed introspection within the context of the existing literature. There are three dimensions in which the reversal returns are studied. Firstly, a strong and predictable reversal effect is due to predictability of the risk premium. Therefore, if we find that the factor loadings on the market based risk commensurate well with the reversal profits than these profits are not the breach of market efficiency. For that we tested three different asset pricing models CAPM of Sharpe (1964); Lintner (1965); Mossin (1966), 3-factor model of Fama and French (1993) and 4-factor model (Carhart 1997). Results indicate that all models leave economically significant and statistically reliable alphas. Resultantly, the excess returns on the reversal strategy do not have any risk related explanation.

Secondly, we test whether the reversal profits are compensation for providing liquidity for those stocks that recently witness pronounced changes in their prices. As in Nagel (2012), it is shown for the US market that the reversal profits are higher in adverse times when market volatility is higher. We also find that when market volatility is higher than its median point then the reversal profits are almost 3 times higher. Further, lagged market volatility is strongly associated with future reversal returns. Resultantly, we can infer that the reversal profits compensate market participants who provide liquidity for the stocks in which reversal effect is vindicated. Therefore, it is not surprising that the reversal profits are stronger for more illiquid and volatile stocks in the PSX.

Thirdly, we test that if these reversal related returns are due to microstructure issues, such as bid-ask bounce that also generate negative auto-correlation in stock returns.[5] This negative correlation imbued by microstructure issues could be a probable source of reversal profits. This point is fostered more concisely by Asparouhova et al (2010), they argue that microstructure issues may inflate the premium upwards and suggested the simple methodology for correction. They suggest that each observed return in any stock may be weighted by its previous gross return to adjust the upward bias in returns induced by microstructure issues. Once this methodology is implemented for the reversal

[5] Studies such as Keim (1989), Hasbrouck (1991); Conrad et al (1997) and others pointed out the relationship between the microstructure issues and negative serial autocorrelation between stock returns.

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profits in the PSX, we find that the annual returns are decreased from 55.32% to 52.73%. These results indicate that reversal profits are not exclusively generated by microstructure issues.

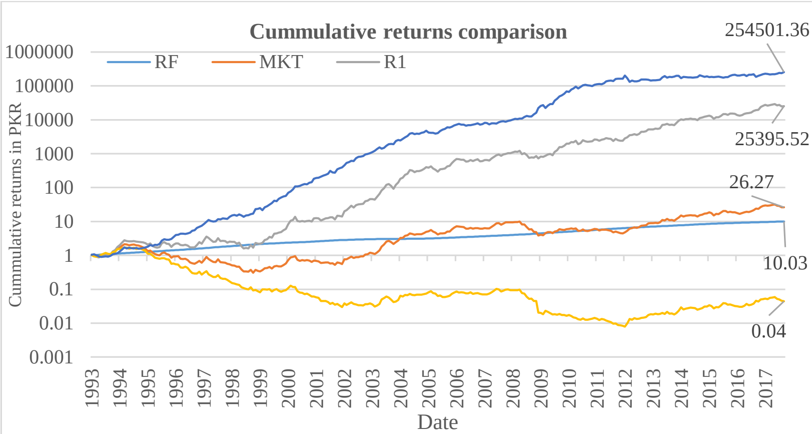

Fig. 1: Cumulative returns comparison
This figure shows the comparison between reversal strategies, market excess returns and the risk-free rate for the period from January 1993 through September 2017. The initial investment amount is assumed to be equal to one Pakistani Rupee. In addition, it is also assumed that no part of the investment is withdrawn during the investment period. RF is the risk-free rate of return, MKT is the market excess returns, R1 is the excess return in the month t + 1 on the stocks which are among 20% of the worst performing stocks in the month t. Likewise R5 is the excess return in the month $t + 1$ on the stocks which are among 20% of the best performing stocks in the month t. Finally, R1-R5 is the zero-cost investment strategy in which R1 is the long side and R5 is the short side. Based on the excess returns on these strategies, the cumulative log excess returns for the horizon of 1993-2017 is calculated.

The paper is organized such that section II discusses in detail the construction of the reversal strategy, its time series properties and the fundamentals associated with the firms with higher reversal returns. In section III we elaborate upon the main possible explanation of these reversal returns in the context of the PSX. Then we discuss the asset pricing models, such as CAPM of Sharpe (1964); Lintner (1965); Mossin (1966), 3-factor model of Fama and French (1993) and 4-factor model (Carhart 1997). In section IV we incorporate other explanations of the reversal profits which relate the reversal premium with the compensation that the liquidity provider demands. In section V we conclude the whole discussion.

2 The characteristics of reversal profits in the PSX

To construct the reversal strategy and to discuss the firms related characteristics, the data is downloaded using the DataStream (DS). Our sample contains both the listed and delisted (active/dead) companies of the PSX to control for

Published by iRepository, December 2020

https://ir.iba.edu.pk/businessreview/vol14/iss1/2
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the survival ship bias. The data covers a period of 23 years starting from January 1993 until September 2017. It the comprehensive data set coverage in the context of PSX as it tracks the historical performance of the market over the time.

As suggested in the literature (Ince and Porter 2006) that some precautions are required to be exercised while using the data of DS. Accordingly, we adopted all the static and dynamic screens suggested in the study of Ince and Porter (2006), which has become a norm for conducting asset pricing related studies. Following these screening criteria the investable universe contains 418 stocks.[6]

In order to construct the reversal portfolios we partitioned the returns of all stock in 5 quintiles in any month t in ascending order. The recent loser/winner indicated as R1/R5 is composed of those 20% of stocks which performed the worst/best in the recent months. The reversal strategy goes long in losers R1 and short in winners R5 by the start of each month t+1, then these positions are reversed by the end of t+1, and the returns are noted as R1-R5. As is indicated in table A1, this reversal strategy iterated each month from January 1993 till September 2017, earns a monthly profit of 4.61%. The arithmetic average of reversal profits is quite similar to its counterpart geometric mean of 4.28% on monthly basis. This results in horizon related returns of Rs. 254,501 for 297 months with an initial investment of Rs. 1 in the reversal strategy. It is not just that the reversal strategy offers a better long term prospect in comparison to the market, it is also less risky in the short run as well.

The probability of shortfall for the investment of the total period of 1993-2017, comprising of 297 months for reversal strategy is negligible and for the market portfolio it is 1.63%. Even at a shorter investment horizon of one month these probabilities are 33.34% and 45.07% respectively. The attractiveness of the reversal strategy is also shown in table A1, through positive skewness, such that the larger positive returns are more probable than negative returns. Resultantly, the maximum return in any month is as high as 38.89%, whereas the minimum return is 22.15%. Further, the median value is 3.96% and it indicates that 50% times the reversal profits (roughly 148 months) are higher than 3.96% on a monthly basis. Similarly, 5% of total observations are having profits lower than -7.64% and higher than 18.86%. These results give the impression that there is lesser downturn risk associated with the reversal profits in the PSX.

2.1 Characteristics of reversal related stocks

Most of the studies on reversal strategies have generally ignored the fundamental characteristics of the stocks that witness profound price changes. It is generally assumed that reversal profits do not reflect the firms related fundamentals (Bali et al 2016). Nevertheless, in most of the asset pricing models such as Fama and French (1993, 2015) and Hou, Xue and Zhang (2015) it is suggested the firms related fundamentals are priced at market level. These fundamentals are size,

[6] The detailed procedures adopted to refine the PSX data are discussed in Mohsin and Butt (2017).

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value, investments, profitability and others. On the other hand, studies such as Amihud (2002) and Avramov et al (2006) have proposed that firms that are illiquid and have higher idiosyncratic volatility have higher expected returns.

In table 2, we have given a detailed coverage of various fundamental characteristics of the stocks that are falling in some specific quintile. These quintiles are based on the performance of the stocks in the current month and are shown as REV. Our main focus is to understand how different are the firms that fall in the quintile R1 (recent losers) and R5 (recent winners) with the firms that are in R2, R3 and R4 (neutral firms). For instance, the firms belonging to extreme quintiles are overall, smaller sized firms and have higher book-to-market ratios in comparison to the firms which belong to the intermediary quintiles. Recent losers are slightly lesser capitalized and have higher book-to-market ratios in comparison to the recent winners.[7] This could be due to the recent price depression which is pronounced for the firms in R1.

In addition to size and value factors, in recent studies of Fama and French (2015) and Hou, Xue and Zhang (2015) the investment and operating profitability are shown to have some important pricing implications for the stocks. It can be noted that investment and profitability are quite low for both the R1 and R5 quintiles, and these quintiles in the next month witness the highest reversals. In a nutshell, reversal profits are present in those firms which have lower investment and lesser profitability. The former aspect reconciles with Hou, Xue and Zhang (2015) reasoning that the low investment firms give higher returns, but not the later one, as here we see that less profitable firms are giving higher returns.

To gauge the liquidity and idiosyncratic volatility we have estimated three variables LES, AMI and IV. The LES[8] indicates the average zero returns of the firms and AMI[9] average price impact to its traded volume. IV is the average volatility of any firm for the last three months. As per LES and AMI, firms which are the candidates for the reversal strategy (R1 and R5) are more illiquid than the firms in R2, R3 and R4. This is quite obvious using the AMI measure. Similarly, the reversal prone stocks are also highly volatile. Resultantly, the reversal profits are higher for illiquid and volatile stocks. Same results are also reported in Avramov et al (2006) for the US market. Further, the reversal is stronger among cash constrained firms shown as CF, especially the firms with the most depressed returns have significant negative cash flows. The dividend yield on the other hand is not the defining characteristics of the reversal stocks.

The current assets CA, current liabilities CL and long term debs LTD are also shown in table A2, for each quintile. Here the reversal related stocks have lower asset base and their current and long term liabilities are also less. The return on asset (ROA) and on equity (ROE) is especially less for the most de-

[7] This can be seen under the column R1-R5.

[8] The LES is estimated as per Bekaert et al (2007) and Lee (2011), the main premise of this measure is as per Lesmond et al. (1999) that the firms which are traded less and have more zero returns in any month are more illiquid.

[9] This measure is estimated as per Amihud (2002) and it gauges an impact of the traded volume in any day upon the absolute returns of that day. This daily impact is average across all number of the days when the firm is traded. If this ratio is higher then it indicates that the firm is illiquid.

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pressed stocks. The earnings before interest and taxes EBIT, the net income NI and revenue of the firms REVN are generally lower for both R1 and R5, but these are specifically lower for R1. The main impression that emerges from table A2 is that reversal inclined stocks have lower capitalization, cash flows, investment, profitability and income. On the other hand these stocks have higher book-to-market ratio, illiquidity and volatility. This indicates that higher risks are involved in profiting through reversal effect in the PSX. In the next section we analyze if the higher reversal profits can be explained through existing asset pricing models.

3 Reversal profits and asset pricing models

The reversal strategy in the PSX has shown significant profits for the time period 1993-2017. These returns are inconsistent within the parameters of the weak form of market efficiency. The past history of the prices is available to everyone, therefore it cannot enable an investor to earn on average a monthly return of 4.61%. Fama and French (1993) suggested that higher returns are not the manifestation of market inefficiency, instead these returns are very much expected if risk premium attached with some investment strategy is higher. To test this we tested three different kinds of asset pricing models as under.

$$REV_{it} = \alpha_i + \beta_i(Fac_t) + \epsilon_t \tag{1}$$

here REV_{it} is the time series of returns on the reversal strategy, and Fac_t is the set of all explanatory variable such as $[Fac_t = Mkt_t, SMB_t, HML_t, MOM_t]$ [10] that have been used in the models such as, as CAPM of Sharpe (1964); Lintner (1965); Mossin (1966), 3-factor model of (Fama and French 1993) and 4-factor model (Carhart 1997).

Table A3 describes the output of the estimation of equation (1) for three different types of the models. First we see that CAPM based market risk is not reconciled with the returns on extreme quintiles R1 and R5. This is obvious by looking into model based alphas, generally termed as risk-adjusted returns. If the model is capturing the inherent risk associated with the returns on R1 and R5 then the alpha must be economically small and statistically unreliable. But it is economically large and statistically significant for recent losers and winners with opposite signs such that R1 is too underpriced and R5 is too overpriced. Resultantly, the risk adjusted profit on the reversal strategy is 4.30%, and this is equivalent to its observed counterpart average of 4.61%. To sum up this discussion, the performance of other models such as FF3 and CF4 with different pricing factors is even more dismal. They leave even higher alphas, because the factor loadings of these models are not sufficiently high as the returns are on the reversal strategy. In fact, sometimes these factor loadings have the opposite signs.

There is an alternative explanation of the above results by Lakonishok,

[10] The detailed construction of these variables is not mentioned to conserve space. Although the procedure is very much standard, the procedure along with the code to generate these strategies can be shared with the interested readers upon request.

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Shleifer and Vishney (1994, 1995), as they suggest that market participants make systematic errors[11] in pricing those stocks which have underperformed/over performed recently. Investors become too pessimistic for recent losers and too optimistic for recent winners, and this predictable erroneous behavior can be exploited by using the simple reversal strategy. The reversal strategy invests more in underpriced losers and underinvests in overpriced winners,[12] and hence, it earns the profits. There is also another way to see why the performance of the models is not that commendable. As we have already seen in table A2, the reversal is stronger for the stocks in R1 and R5 that cannot be distinguished on the basis of their size, value, investment and profitability. The model based factors are in essence the excess returns generated by the zero investment strategies at market level using the stocks that differ in term of their size, value, investment and profitability. Resultantly, we see that reversal strategy does not bear high factor loading on these factors. Although in this paper we have not tested for the Fama and French (2015) 5-factor model,[13] or the model proposed by Hou, Xue and Zhang (2015), we doubt that their performance will be better than the models tested, as it is already noted that R1 and R5 do not differ much on the basis of investment and operating profitability.

In table 4, we explore this point further and incorporate the studies such as, Avramov et al (2006) and Huang et al (2009) that suggest that reversal is stronger for illiquid and volatile stocks. In addition to that we have also tested the relationship between the reversal profits and size, liquidity, volatility, value, momentum and cash flows. In panel A, as a procedure we have portioned the firms using the medium value of size, illiquidity[14] and volatility.[15] As expected the reversal profits are at least three times higher for lesser capitalized firms, firms that are more illiquid and volatile. Especially, the link of reversal profits with the idiosyncratic volatility of any stock is very pronounced. We find for the first time that 50% of the firms which are less volatile do not have significant risk adjusted returns. We further find that the reversal is independent of the factors such as value, momentum and cash flows as is indicated in table 4, panel B. Reversal profits are overall less, but not different across the firms that are different in terms of their book to market ratio or cash flows.

[11] That is markets are inefficient.

[12] Studies such as De Bondt and Thaler (1985), Haugen (1994) and La Porta (1996) have discussed that underpricing and overpricing is linked with investors behavior who become either too pessimistic or over optimistic for the stocks that performed too bad or too good historically.

[13] These models require multiple sorting procedures and generally the information on investment and profitability is not that ubiquitous to generate the kind of market factor which is the most diversified as we do not have that sufficient number of stocks.

[14] Illiquidity is captured by the average zero returns of any firm.

[15] Volatility of any stock is estimated as suggested in Fama and French website, such that the volatility is gauged from the volatility in the daily returns of any stocks for the last three months. Only those stocks are included that are at least traded for 20 days for the last three months.

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4 Reversal profits and market volatility

Nagel (2012) argues that the cost of liquidity provision increases under market distress. Further, the liquidity provision is not just restricted to designated market makers. The individual investors also act as liquidity provider as is suggested in Kaniel, Saar, and Titman (2008). This is especially relevant in the context of PSX where there are no officially designated market makers. Further, Nagel (2012) hypothesis that reversal profits may be considered as the proxy for the compensation for providing liquidity to the markets. Therefore, there should be some discernable patterns in the reversal related returns. These returns are higher when market liquidity is tight and supply of liquidity is expensive. Brunnermeier and Pederson (2009) suggest that funding constraints are higher when volatility is higher. This higher volatility can be proxy through VIX[16] and studies such as Adrian and Shin (2010) suggest, that at times when VIX is higher, the risk taking appetite of market participants decreases.

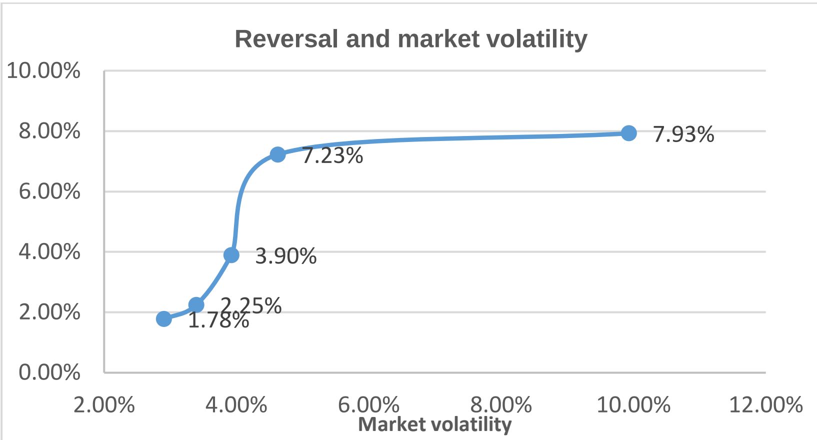

Fig. 2: Market volatility based quintiles and reversal profits
The series of market volatility is partitioned in five quintiles and then the reversal profits are averaged in these quintiles. The dotted points show the average returns as per y-axis and market volatility quintile as per x-axis.

Therefore, it is interesting to analyze how the reversal returns in the PSX behave when market volatility is higher. Unfortunately, at the PSX, the index based options are not yet traded to construct VIX sort of proxy of market volatility. However, we construct alternative proxy of market volatility that incorporate both the time-series and cross-sectional aspects of the volatility of the stocks traded in the PSX. For each stock the monthly volatility is calculated by averaging the volatility of the daily returns for last three months. To construct the market volatility, the volatility of each stock is averaged across all stocks in any month.

[16] VIX is the measure of the implied volatilities of S&P-500 index of options.

Published by iRepository, December 2020

https://ir.iba.edu.pk/businessreview/vol14/iss1/2
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Once the measure of market volatility is constructed, then to observe the relationship between the reversal strategy and the changes in the market volatility, we demarcated the quintile points for the time series of market volatility. Then the reversal returns falling into market volatility related quintile are averaged. Figure 2 shows the relationship between market volatility and reversal profits. Reversal profits are linked with market volatility and they increase as market volatility increases. This evidence gives the credence to the explanation of Nagel (2012), that the reversal premium is akin with the cost of providing market liquidity. This cost increases as the funding constraints are tightened when market volatility increases. In figure 3 this point is further illustrated once we run the following model:

$$REV_{it} = \alpha_i + \beta_i(Mkt_{Vol_{t-1}}) + \epsilon_t \tag{2}$$

as when the REV_{it} is regressed on the market volatility of the previous month ($Mkt_{Vol_{t-1}}$), the regression coefficient as shown in figure 3 is 2.645 with the t-stat of 6.573. This indicates the when the market volatility increases by 1% the reversal profits increase by 2.645%. Further, for the predictive regression the R^2 of 12.89% is quite higher. It is interesting to note that the autocorrelation coefficient on the market volatility is 0.858. This indicates that volatility is predictable and higher episodes of market volatility will be followed by higher volatility. Resultantly, the predictable reversal profits are related with the premium attached to market volatility. Overall, the analysis suggest the reversal profits are higher when market volatility is higher and at these times the provision of liquidity is expensive. Resultantly these higher profits can be construed as a cost of providing liquidity.

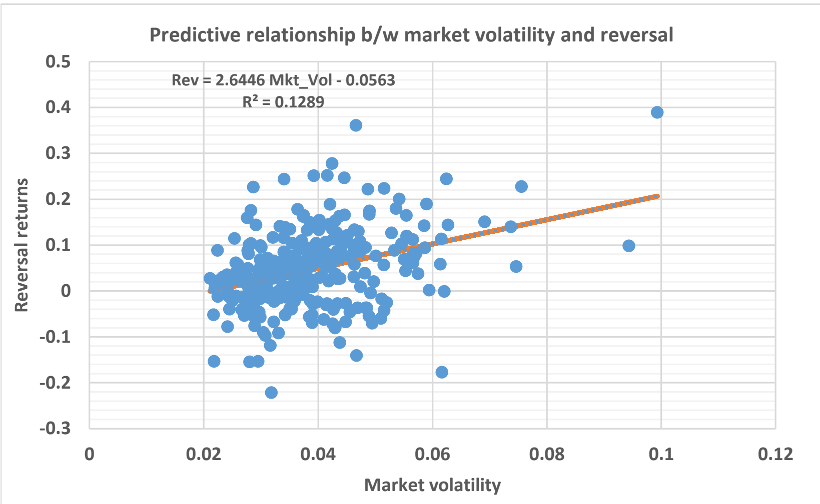

Fig. 3: Regression of reversal profits on lagged market volatility
The reversal profits are regressed on the market volatility of the previous month. The regression out-put, R^2 and the performance of the model is shown.

There are some other explanations of the reversal profits. These profits can-

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not be exploited as they are a mere outcome of market microstructure. In the study by Ball, Kothari, and Wasley (1995) and Conrad et al (1997) the reversal profits for the US are shown to be within the bound of bid-ask spread. The study of Asparouhova et al (2010) discusses the presence of inflated premiums due to microstructure issues and also suggests the simple methodology for correction. Their suggestion incorporates the view of Blume and Stambaugh (1983) that each observed return in any stock may be weighted by its previous gross return to adjust the upward bias in returns induced by the microstructure. Once this methodology is implemented for the reversal profits in the PSX we find that the annual returns are decreased from 55.32% to 52.73%. These results indicate that reversal profits are not exclusively generated due to microstructure issues.

5 Conclusion and Policy Recommendations

The reversal strategy which one may easily replicate using the historical data of previous months can earn annual profits of 55.32% in the PSX. This strategy results in a holding period return of Rs. 254,501/- for an investor who invests one rupee at the start of January 1993 and rolls over the investment till September 2017. The presence of such huge returns is more puzzling than the obvious negation of the efficient market hypothesis in its weak form. Furthermore, asset pricing models cannot explain the reversal profits for obvious reasons that recent loser and winner are not very different in terms of fundamental characteristics of the firms except for cash flows.

However, most of the models have not yet incorporated the cash flows as the market risk based explanation. The key characteristic that is associated with the reversal profits is the idiosyncratic volatility of the reversal prone stocks. We find the reversal exists only in those 50% of the stocks which are more volatile than half of the market. Furthermore, the explanation given in Nagel (2012) seems relevant in the context of the PSX. Reversal profits are large when market conditions are too depressed and investors demand higher premium for providing liquidity in the stocks whose prices have fluctuated the most recently. This study highlights that the reversal profits in other markets may also be analyzed on the lines suggested in this paper to reconcile such profits within the ambit of the efficient market hypothesis.

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Appendix

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DOI: https://doi.org/10.54784/1990-6587.1022

Table A1: Summary statistics of reversal portfolios

	Mean	T-Stats	SD	Skew	Kurt	Min	5%	25%	Median	75%	95%	Max	N
R1	4.90	7.30	11.54	47.01	47.94	-23.88	-12.10	-2.42	4.25	10.72	26.81	45.26	296
R5	0.27	0.46	10.16	4.69	309.62	-53.33	-14.43	-6.12	-0.28	5.72	16.41	37.00	296
R1-R5	4.61	9.49	8.37	45.19	155.58	-22.15	-7.64	-0.96	3.96	9.25	18.86	38.89	296

This table presents the summary statistics of the reversal strategies from January 1993 until September 2017. Reversal strategies are constructed based on the previous month's returns. R1 is the return for the month of t+1 on the portfolio comprising 20% of those stocks which perform the worst in the month t. R5 is the return for the month of t+1 on the portfolio comprising 20% of those stocks which perform the best in the month t. R1-R5 is the zero-cost investment strategy that is long in R1 portfolio and short in R5 portfolio. For this reversal strategy, average (Mean), t-stats (T-Stats), standard deviation (SD), skewness (Skew), Kurtosis (Kurt), minimum (Min), 5th percentile (5%), 25th percentile (25th), median (Median), 75th percentile (75%) and maximum (Max) values are calculated. N represents the total number of months in the sample. All values are reported in percentage terms.

Published by iRepository, December 2020

https://ir.iba.edu.pk/businessreview/vol14/iss1/2
DOI: https://doi.org/10.54784/1990-6587.1022

Table A2: Reversal portfolios characteristics

Portfolios	R1	R2	R3	R4	R5	R1-R5
REV	-0.154	-0.052	0.004	0.069	0.264	-0.416
SIZE	8.203	11.990	14.075	14.199	9.576	-1.368
BTPV	0.963	0.818	0.786	0.747	0.682	0.280
MOM	0.010	0.012	0.016	0.022	0.037	-0.027
LES	0.300	0.247	0.237	0.240	0.260	0.040
AMI	0.012	0.004	0.002	0.003	0.010	0.002
INV	22.910	35.673	42.160	39.878	23.496	-0.584
OP	1.027	1.841	2.284	2.272	1.363	-0.335
IV	0.049	0.034	0.032	0.033	0.047	0.002
EPS	5.498	6.904	7.281	7.658	6.800	-1.297
DY	4.341	4.528	4.623	4.341	3.475	0.863
VO	0.020	0.027	0.030	0.041	0.038	-0.018
CA	3.979	5.909	6.251	6.282	4.188	-0.208
CF	-451.675	18.387	21.409	-70.866	-77.971	-372.437
CL	3.717	5.206	5.254	5.112	3.780	-0.062
LTD	1.902	2.652	2.903	2.593	1.970	-0.068
ROA	2.973	4.949	5.582	5.861	4.845	-1.866
ROE	1.003	5.727	9.221	8.438	7.675	-6.649
EBIT	0.619	1.182	1.510	1.516	0.885	-0.266
NI	1.112	1.910	2.331	2.305	1.492	-0.378
REVN	10.100	16.090	17.803	17.004	11.575	-1.470
No of firms	28	29	29	29	28	-

This table shows the characteristics of the reversal portfolios in the month t. In total 6 portfolios are constructed. R1 contains 20% of the stocks which have the lowest returns in the month t. Similarly, R5 consists of the stocks which have the highest returns in the same month. R1-R5 is the difference in returns in the 20% of the stocks which performed the best and the worst in the month t. Different firm characteristics are reported to assess the relationship between reversal portfolios and these characteristics. These characteristics include REV which is the average of last month's returns for each reversal portfolio, size is the market capitalization, BTPV is the ratio of book to price value of firm, MOM is the 11-months (t-12 to t-2) average returns, LSE is the Lesmond (1999) zero-measure of liquidity, AMI is the Amihud (2002) liquidity measure, INV is the total investment of firm, OP is the operating profitability of firm, IV is the volatility of previous three months, EPS denotes the earnings per share, DY is the dividends yields, VO is the volume, CA is the current assets, CF is the cash flows to sales ratio, CL is the current liabilities, LTD is the long term debt, ROA is the return on assets, ROE is the returns on equity, EBIT is the earnings before interest and taxes, NI is the net income and REVN it the revenue of a firm. The last row shows the average number of firms in each portfolio. The sample period is from January 1993 to September 2017.

Published by iRepository, December 2020

https://ir.iba.edu.pk/businessreview/vol14/iss1/2
DOI: https://doi.org/10.54784/1990-6587.1022

Table A3: Risk based explanations of univariate sorted reversal portfolios

Models	R1	R2	R3	R4	R5	R1-R5
			CAPM			
Alpha	0.028	0.008	0.003	0.001	-0.01	0.043
	(9.50)	(3.83)	(1.36)	(0.75)	(-4.95)	(8.86)
MKT	1.10	0.938	0.846	0.933	0.937	0.156
	(35.39)	(43.03)	(34.97)	(46.33)	(30.86)	(3.08)
R^2	0.81	0.86	0.81	0.88	0.76	0.03
			FF			
Alpha	0.029	0.009	0.003	0.001	-0.015	0.045
	(9.58)	(4.64)	(1.42)	(0.61)	(-5.14)	(9.11)
MKT	1.107	0.971	0.842	0.916	0.923	0.184
	(31.72)	(40.51)	(30.92)	(40.56)	(26.90)	(3.22)
SMB	-0.122	-0.181	-0.0682	-0.0500	0.108	-0.243
	(-1.96)	(-4.41)	(-1.41)	(-1.30)	(1.79)	(-2.42)
HML	-0.003	-0.058	0.024	0.062	0.021	-0.036
	(-0.06)	(-1.91)	(0.66)	(2.15)	(0.47)	(-0.48)
R^2	0.81	0.87	0.81	0.88	0.77	0.05
			FFC			
Alpha	0.029	0.010	0.004	0.002	-0.015	0.045
	(9.18)	(4.57)	(1.80)	(0.76)	(-4.93)	(8.68)
MKT	1.107	0.972	0.845	0.917	0.923	0.183
	(31.57)	(40.36)	(31.02)	(40.43)	(26.77)	(3.20)
SMB	-0.122	-0.181	-0.070	-0.051	0.108	-0.243
	(-1.96)	(-4.41)	(-1.45)	(-1.31)	(1.79)	(-2.41)
HML	-0.003	'-0.066	-0.008	0.051	0.023	-0.034
	(-0.06)	(-1.86)	(-0.20)	(1.54)	(0.43)	(-0.40)
WML	-0.001	-0.016	-0.070	-0.023	0.003	0.003
	(-0.01)	(-0.41)	(-1.55)	(-0.63)	(0.06)	(0.03)
R^2	0.81	0.87	0.81	0.88	0.77	0.05
N	296	295	296	294	296	297

This table reports the results of future returns and univariate sorted portfolios from January 1993 until September 2017. Five reversal portfolios (i.e. R1, R2, R3 R4 and R5) are constructed based on the sorted returns in the previous months. The portfolios breakpoints are the 20th, 40th, 60th and 80th percentiles. The last column (R1-R5) shows the values of zero-cost long/short reversal strategy. Three versions of asset pricing models (Capital Asset Pricing Model (CAPM), Fama French Three Factor Model (FF3) and Carhart Four Factor Model (CF4)) are used to rationalize the excess returns on reversal portfolios. Abnormal returns are denoted as Alphas, MKT is coefficient of market factor, SMB, HML and WML are the coefficients of size, value and momentum factors. R^2 reports the percentage of variations explained by each model. N represents the total number of months. Alphas are reported monthly. All corresponding T-statistics are shown in the parentheses.

Published by iRepository, December 2020

https://ir.iba.edu.pk/businessreview/vol14/iss1/2
DOI: https://doi.org/10.54784/1990-6587.1022

Table A4: Bivariate sorted portfolios and risk based explanations

Panel A

Portfolios	Size		Liquidity		Volatility	
	S1	S2	L1	L2	V1	V2
R1	6.46	2.81	2.65	6.69	2.90	5.76
R2	3.68	1.81	2.24	3.27	2.06	3.71
R3	2.23	1.58	1.68	1.88	1.85	1.72
R4	2.42	1.68	1.94	2.23	2.02	1.87
R5	0.34	0.55	0.87	-0.21	1.87	-0.31
R1 - R5	6.08	2.25	1.77	6.85	1.01	6.02
	(9.95)	(4.87)	(3.18)	(10.97)	(1.95)	(10.29)
R1 - R5 CAPM α	0.057	0.020	0.017	0.062	0.006	0.057
	(9.37)	(4.25)	(2.91)	(10.29)	(1.14)	(9.69)
R1 - R5 FF α	0.059	0.022	0.019	0.063	0.006	0.058
	(9.43)	(4.6)	(3.24)	(10.22)	(1.14)	(9.84)
R1 - R5 FFC α	0.059	0.022	0.020	0.063	0.008	0.059
	(9.06)	(4.56)	(3.30)	(9.89)	(1.38)	(9.50)

Panel B

Portfolios	Value		MOM		Cash Flows	
	B1	B2	M1	M2	CF1	CF2
R1	2.044	3.507	3.492	3.810	3.22	3.69
R2	1.375	3.403	2.182	2.760	2.08	2.90
R3	1.778	2.415	1.286	2.387	1.50	2.59
R4	1.530	1.825	1.730	1.966	1.81	2.34
R5	0.658	2.218	-0.125	0.672	1.32	2.05
R1 - R5	1.360	1.30	3.610	3.10	1.91	1.64
	(2.72)	(2.29)	(6.14)	(6.00)	(3.21)	(2.93)
R1 - R5 CAPM α	0.0125	0.0121	0.0363	0.0280	0.02	0.01
	(2.45)	(2.09)	(6.07)	(5.40)	(2.88)	(2.56)
R1 - R5 FF α	0.0140	0.0168	0.0388	0.0289	0.02	0.02
	(2.70)	(2.94)	(6.46)	(5.47)	(3.70)	(2.80)
R1 - R5 FFC α	0.0150	0.0206	0.0399	0.0302	0.03	0.02
	(2.75)	(3.47)	(6.33)	(5.44)	(4.00)	(3.14)

This table shows the results of reversal portfolios constructed based on dual sorting criteria. First, five portfolios (R1, R2, R3, R4, R5) are constructed by sorting stocks based on reversal (previous months returns) then, each portfolio is further divided into median based on certain firm characteristics such as size (market capitalization), liquidity (zero returns in a month), volatility (previous three months standard deviation), Value (book to market ratio), mom (average returns of t-12 to 1-2) and cash flows (cash flows to sales ratio). In addition, zero-cost portfolios are also constructed. Panel A reports the results of bivariate sorted portfolios in which reversal is present while Panel B, shows results of portfolios in which reversal in weak. Further, to rationalize the excess returns of each portfolio, different versions of asset pricing models are used (Capital Asset Pricing Model (CAPM), Fama French Three Factor Model (FF3) and Carhart Four Factor Model (CF4)). The abnormal returns are reported only for the zero-cost investment portfolios. S1 (S2) is the average returns of portfolios having market capitalization below (above) the median. L1 (L2) is the average returns of illiquid (liquid) portfolios, V1 (V2) represents the low (high) volatility averaged portfolios returns. B1 (B2) is the average returns of low (high) book to market ratio, M1 (M2) are the average returns of losers (winners) portfolios and CF1 (CF2) are the returns on low (high) cash flows to sales ratio. All the portfolio returns are reported monthly. The t-statistics for the zero-cost portfolios and alphas are shown in parentheses. The same starts from January 1993 to September 2017.

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