Momentum Crashes:
The Impact of Market Conditions on Momentum in Japan

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Bachelor Thesis
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June 30 2023

Abstract:
Momentum is one of the main market anomalies across most global equities, however, academic research has found limited evidence for its presence in Japan. This paper focuses on evaluating the performance of momentum strategies in the Japanese equity markets in different states: bull, bear and recovery between 1974 and 2023. More notably, the paper finds evidence of periods of sustained negative returns known as momentum crashes that occur in panic states. The low ex ante expected returns in panic periods resemble options like payoffs of the momentum strategy. The study also uncovers a ‘shorting’ effect on ex ante volatility similar to written options. The analysis was conducted using OLS along with Fama MacBeth regressions.

Keywords: Momentum, Momentum Crashes, Asset pricing, Japan

1. Introduction

Momentum is a market phenomenon that describes the movement of a security's past returns, referring to the tendency of asset prices to continue moving in the same direction. The momentum effect first introduced by Jegadeesh and Titman (1993) is one of most recurring market anomalies in the financial literature. Generally, the momentum strategy describes a portfolio that takes long positions in firms with the highest past returns (winners) and short sales on the firms with the lowest returns (losers) in the chosen time period.

Daniel and Moskowitz (2016), find that although momentum strategies show strong positive average returns and sharpe ratios, they are exposed to occasional but significant crashes. Researchers have demonstrated the existence of momentum and its crashes across different equity markets both small and large and across different asset classes (Asness, Moskowitz and Pedersen, 2011) and different time periods (Goetzmann, 2018). Yet, one seemingly persistent exception seems to be the Japanese equity markets in which traditional momentum strategies have failed to generate abnormal returns. This begs the question whether Japan is the exception to the rule or if momentum's success elsewhere is the result of data mining, Asness (2012).

This paper sets out to examine the empirical validity of momentum in Japanese equity markets and inquires. It seeks to answer the research question:

What evidence of momentum crashes are there in the Japanese stock market and how would a momentum strategy perform overtime?

Momentum portfolios from the Asness, Moskowitz, and Pedersen (2013) AQR dataset are used to create 5 portfolios; Losers, Middle, Winners, Winners-Minus-Losers and a combination portfolio using value and momentum. With the help of ordinary least squares (OLS) and Fama MacBeth regressions, we run different conditional capital asset pricing models (CAPM) to examine performance in different market states. We focus on the bull, bear and recovery market states. Additionally, we investigate the impact of momentum crashes which have proven to be a robust feature of momentum strategies.

Our Fama MacBeth results show that the momentum strategy returns fall when the ex ante measures of market returns have been negative, consistent with Cooper, Gutierrez and Hameed (2004). We also demonstrate that the momentum premium is low when the market volatility is high in bear markets, which is in line with the findings of Stivers and Sun (2010). Considering these findings, we establish that momentum strategies exhibit a written call option-like payoff which is guided by the loser portfolio and confirms the findings of Daniel and Moskowitz (2016).

We find evidence of momentum crashes and identify that they occur during "panic periods", when the market has fallen and ex ante measures of volatility are high which also supports Daniel and

Moskowitz's findings. Moreover, the conclusions we find show that the effects of momentum crashes are not driven by changes in the strategy's market beta. This contradicts the conclusions of Kothari and Shanken (1992) who state that past- return sorted portfolios have significant time-varying exposure to systemic factors.

This paper is academically relevant as it can guide investment managers' strategies in Japanese equity markets in terms of risk management relating to momentum crashes, volatility effects and option-like payoffs that we uncovered. Furthermore, the drivers of momentum remain fairly enigmatic and although its existence is certain according to academia, new puzzles arise from its presence. As *The Economist* (2011) highlights, "The momentum effect drives a juggernaut through one of the tenets of finance theory, the efficient market hypothesis". This emphasizes the need for research such as this one to identify the main factors affecting momentum returns and causing them to crash. Consequently, this has implications for investment managers' portfolio construction.

The paper will be structured as follows; Section 2 first outlines the economic conditions of the Japanese equity market which is crucial given that Japan is an outlier in the data and also reviews relevant literature concerning momentum trading strategies. Section 3 explains the data, models and methodology used in the paper. Section 4 presents the regression results. Section 5 evaluates the conclusions and highlights limitations of the paper. Finally, Section 6 concludes the paper and proposes extension to the research. Any additional contents and extensions relevant to the study will be situated in the Appendix.

2. Literature Review

2.1 The Japanese Stock Market

Before commencing our analysis, we study the economic environment of the Japanese stock market, namely its institutional and regulatory features. Historically, Japan's financial markets reforms have evolved at a slower pace than other industrialized countries like the US (Hoshi and Kashyap 2001).

Within our studied time-frame, several market reforms took place in Japan. In December 1980, the Japanese government amended foreign trade law which facilitated foreign investment and became the first of many reforms to improve Japan's financial system. During the 1990s, Japan's share of global equity markets started shrinking and experienced prolonged domestic recession. In the first 9 months of 1990 the Nikkei, the main Japanese stock exchange, lost nearly half of its value and prices stagnated until around 2003. In an attempt to promote transparency and be internationally competitive, the government decided to implement major financial reforms referred to as the "Big Bang".

Notable changes from this reform include freely determined fees for all transactions as opposed to an ad valorem brokerage commissions system. Derivatives and options on individual stocks were allowed to be traded over the counter and household investors were allowed to trade equity mutual funds from banks. Moreover, the rule that required pension fund managers to hold a maximum of 30% of stock holdings was abolished. Finally, banks were allowed to engage in the trade of all securities through their own subsidiaries. As a consequence, the Japanese equity market saw large capital inflows following this period.

The *Big Bang* reforms were particularly successful; in 2001, overseas investors made up over 50% of annual turnover compared to 13% in 1989. Additionally, the share of ownership of foreign equity went from 4% in 1989 to 19% in 2001. Overall, with increased exposure and integration to foreign markets and investors, Japanese equity markets should have become more efficient. However that is not exactly the case.

Starting from the 1991 asset price bubble, Japan experienced a long sustained period of price deflation and economic stagnation. As a measure to counter deflation, Japanese interest rates were drastically lowered even to negative levels and they have continued to remain at these levels up to the time of this paper's publication (Koichi Hamada, Anil K Kashyap, David E. Weinstein, 2011). Low interest rates may have some implications for momentum trading strategies due to increased risk-taking from investors who seek a higher return than fixed income investments. A surge of new investors in the equity market would theoretically increase the volatility of the market. As we found in our results, volatility has an inverse relationship with the momentum premium, so periods of low interest rates would be unfavorable for momentum trading.

Jun Nagazusu (2003) underlines several factors that could explain the Japanese equity market's divergence from the efficient market hypothesis and the behavior of other OECD countries' equity markets. First he highlights the restrictions on short selling known as *kara-uri*. Dating back from 1947, short selling was not commonly available although the rules were revised in March 2002. The revision allows certain types of short sales including futures trading along with arbitrage and hedging strategies within equity futures and options. These restrictions could decrease the liquidity of block trades and deny institutional investors the ability to hedge large equity positions. Therefore, it should be noted that there would be difficulty in implementing a WML strategy pre early 2000s outside of an academic simulation, however there would be no issue to set one up nowadays. Additionally, practitioners could also implement long-only strategies which would be viable even given the short sale restriction.

The next factor that affects the Japanese equity market's efficiency are cross-shareholdings amongst Japanese corporations. Traditionally in the interest of good business relations, banks and non-financial corporations held significant shares of stocks of each other, "artificially" strengthening stock prices. Although it should be noted that across the 1990s this so-called cross shareholding had declined in proportion to the total Japanese market capitalization (Miyajima and Kuroki 2006)

The last factor is the government's Price Keeping Operations (PKO) implemented in 1992. These were monetary policies consisting of governmental equity purchases in order to combat the price decline of the 1990s recession. Assuming that the purchases are not based on market conditions, Nagazusu concludes the PKO likely eroded market pricing and counteracted the EMH.

Overall, the implementation of the "Big Bang" reforms creates two periods with entirely different conditions. The Japanese equity markets post-1997 can be characterized as much more efficient compared to pre-1997 in line with the market deregulation, liberalization and the influx of foreign capital. This has implications for momentum strategies because in an efficient market, any information that could be used to generate an abnormal return is already priced in. Therefore, in perfectly efficient markets, momentum should not exist. Although this paper finds evidence of momentum premium and crashes in both periods, the results pre-1997 are more significant and show stronger evidence.

Ziemba and Schwartz (1991) find that between 1949 and 1990, the Japanese equity market experienced on average a correction around every 2 years of around -23.4% and lasting 6 months. This has significant ramifications for the existence of momentum crashes in the Japanese market. To understand how it would affect a momentum trading strategy, one must investigate the stocks responsible for the market recovery after such corrections. If it is the "loser" (low momentum) stocks, that is indication that momentum crashes may well occur in this market. If the "winner" stocks are the ones driving the reversal then this could potentially discredit the occurrence of momentum crashes.

2.2 Momentum Trading

Momentum strategies have been an extensive topic of discussion in the academic literature. Introduced in 1993 by Jagadeesh and Titman, the two researchers constructed the first "winners minus losers" (WML) portfolio and generated positive abnormal returns. This study set the precedent for portfolio construction that omits the last month of returns. This is done to account for market reversals as they noted that the portfolio performed poorly in these periods. Later, in 1997 Carhart built on the Fama French 3 factor model and added the momentum factor as a means of explaining stock market returns. However, when applied to a Japanese context, the Carhart 4 factor model has a low explanatory power compared to the Fama French 3 factor model (Lai et al. 2009). The authors attribute this to Japanese corporate governance, financial practices, the political and cultural climate and economic performance .

Grundy and Martin (2001) highlight a fundamental limitation to momentum strategies. Because portfolio construction is based on past returns, if the market has fallen significantly during the formation period, it is likely that the firms selected as winners are low beta firms and the losers are high beta firms that fell in tandem with the market. As a result, during bear markets, momentum strategies can have a conditionally large negative beta. Although this analysis was consistent with our OLS regressions, when tested using Fama MacBeth regressions, we found positive bear market betas in the cross section of momentum.

In 2016, Daniel and Moskowitz expanded on the poor momentum performance during market reversals and highlighted a written call option like behavior from the WML portfolio. They find that the beta asymmetry between bear and bull market states is mostly driven by the past losers due to the losers' large negative market beta in bear markets, which leads to losses. The WML portfolio stands to generate low positive returns when the market rises and high negative returns when the market falls. In line with written call options, they also find that the momentum premium in bear markets is correlated with the strategy's time-varying exposure to volatility risk. The results of our conditional CAPM highlights this relationship across our entire sample and sub samples.

Derived from this option-like behavior, Daniel and Moskowitz coined the term "momentum crashes" to describe persistent negative returns of the momentum strategy. The existence of these crashes comes from the nature of the portfolio construction. In these so-called momentum crashes, the losers experience sudden large positive returns much larger than the winners. Since the strategy shorts the loser firms, their rapid upswing leads to the portfolio's large losses. Our data identifies similar patterns, we find in our Japanese equity samples that in the months of March to August 2009, the past losers portfolio rose by 53% whereas the winners lost about -5%. The conclusion of their findings is that momentum crashes are characterized by periods of market stress; when the market has fallen, ex-ante measures of volatility are high and the current market returns abruptly rise. The results of this paper confirm Daniel and Moskowitz's conclusions, although our model does not hold for the post-1997 sample.

In light of this finding, a dynamic portfolio was developed that performs well given the momentum crashes. This is achieved by weighing each asset based on their ex ante conditional volatility. Although this dynamic portfolio shows significant results in most equity markets, it remains relatively unsuccessful in the Japanese markets. Albeit this paper does not use a dynamic portfolio, we also find especially poor performance of our momentum strategy between 1974 and 2021, in fact it realizes a loss of -1.8%.

As it stands, finding a successful momentum trading strategy in Japan is challenging due to its particular market environment. However, Denis Chaves (2012) finds a momentum strategy that generates statistically significant abnormal returns in Japanese markets albeit with minimal improvement in performance. This is achieved by ranking securities on idiosyncratic momentum (the cumulative idiosyncratic returns) instead of the usual momentum (raw cumulative returns) during portfolio construction. This idiosyncratic momentum strategy has the benefit of limiting the portfolio exposure to the market beta and consequently, to systematic risk such as momentum crashes.

Overall, the results of this paper substantiate the results of the Daniel and Moskowitz "Momentum Crashes" paper which has laid the framework for our models. We find statistical evidence of option-like payoffs and momentum crashes in a Japanese context. We expand on previous research by running Fama Macbeth regressions in order to account for the heteroskedastic nature of time series data and conducting robustness tests by investigating the existence of momentum crashes in 2 sub-samples: before and after the Big Bang reforms of 1997.

3. Data & Methodology

3.1 Data

In order to construct the analysis, the Nikkei 225 will be used to represent the Japanese stock market. The Nikkei is a price weighted index composed of the largest 225 publicly traded Japanese companies and covers 64% of the total Tokyo Stock Exchange market cap (Nikkei Inc., 2014) sourced from the factset data library. The risk free rate used for this analysis will be the Japanese 1 year treasury bill from the Japanese Ministry of Finance data library. The 1 year treasury bill is used because it is one of the only Japanese risk free rates with reliable data going back far enough.

This paper will use portfolios sourced from Assness, Moskowitz and Pederson (2013). These portfolios are constructed using Japanese firms containing at least 12 months of past returns data between March 1974 and February 2023. In order to limit the securities to the most liquid, accessible ones, only the top cumulative 90% of market capitalization of the Japanese stock market is utilized. This represents around 26% of the largest firms. Assness et al then sort the remaining firms into 3 momentum groups. The momentum classification is determined by using the 12 month cumulative returns of the securities omitting the most recent month of data.

This creates 3 different momentum portfolios containing a loser portfolio (lower third), a neutral portfolio (middle third) and a winners portfolio (top third). A 4th portfolio "winners-minus-losers" is created by going long on the winners' portfolio and short on the losers. The losers, middle and winners portfolio will be referred to as sub-portfolios in the remainder of this study since the WML is constructed from them.

Finally, a similar winners minus losers portfolio is created by Assness et al for a value factor. This refers to firms ranked based on Book value to market value ratios. The lowest third of B/M firms will be shorted and the highest third will be bought. Combining the value and momentum portfolios, weighted 50-50% in each factor, generates the Val-Mom portfolio.

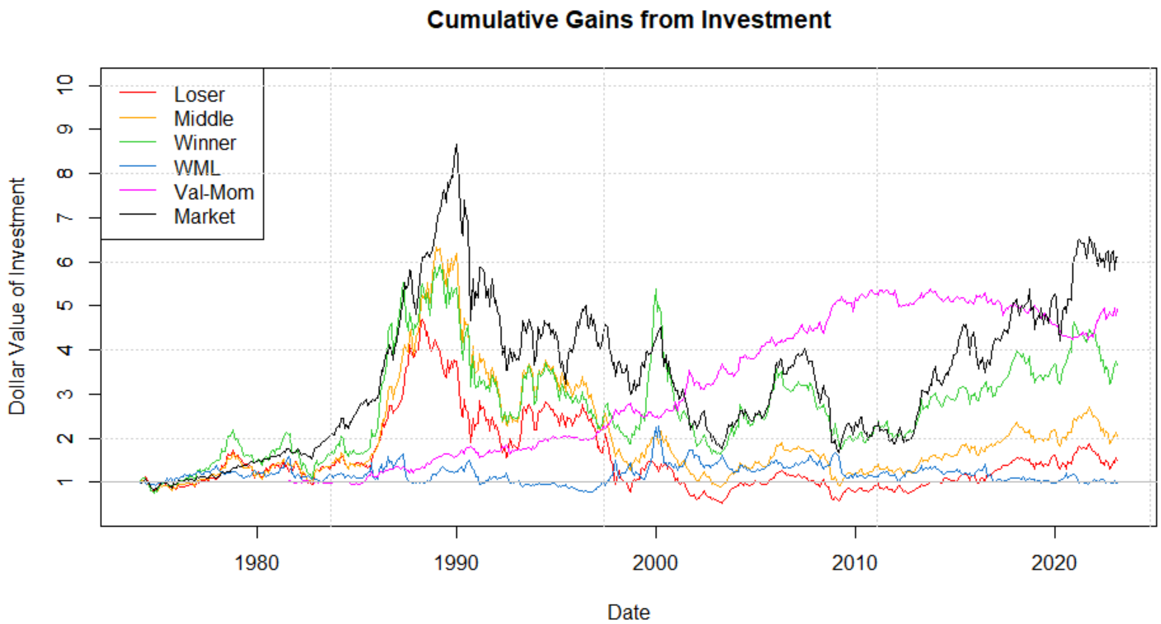
Table 1: *Summary statistics for all portfolios and the market. All values are displayed in percentages. The statistics were calculated using the R programming language. The Sharpe ratio is calculated as: Average Excess Returns / Standard Deviation.*

Summary Statistics for all Portfolios & The Market						
	Losers	Neutral	Winners	WML	Val-Mom	Market
Average Excess Returns	0.28	0.27	0.41	0.13	0.34	0.46
Standard Deviation	6.56	5.56	6.16	5.09	2.25	5.39
Sharpe Ratio	0.04	0.05	0.07	0.03	0.15	0.09
Median	-0.02	0.35	0.63	0.41	0.28	0.77
Minimum	-20.16	-17.58	-22.48	-22.88	-9.45	-23.83
Maximum	29.52	22.50	22.90	22.48	9.36	20.07
Skewness	0.52	0.10	0.16	-0.34	0.10	-0.32

Table 1 outlines the performance of the WML portfolio. First it displays the lowest average excess returns of any portfolio while maintaining a relatively similar volatility. This gives the WML portfolio the lowest sharpe ratio. Another observation is the WML portfolio's negative skewness, although similar to the skewness of the market, it is the only negative one out of the momentum portfolios. A negative skewness of the distribution of returns indicates that the security will generate frequent small gains and a few large losses. While this may demonstrate evidence of the WML returns crashing, because the average WML returns are already the lowest of all portfolios, there is arguably no favorable performance to crash from.

Additionally, the Val-Mom portfolio has the highest sharpe ratio of all portfolios, we conclude that Val-Mom performs very well relative to the other momentum portfolios, this improved performance should come from the value factor. The Val-Mom portfolio's sharpe ratio is derived from its low volatility that is almost half of the other portfolios and its strong returns relative to other momentum portfolios.

Figure 1: *The cumulative returns on each portfolio: (1) The Losers portfolio, (2) The Neutral Portfolio, (3) The Winners portfolio, (4) The WML portfolio, (5) The Val-Mom Portfolio, (6) The Japanese market index portfolio Nikkei 225*



From Figure 1, the first notable observation is that the winner minus losers portfolio is the worst performer in the Japanese markets across our chosen period (March 1974 - March 2023), This confirms the analysis from Table 1. In fact, the cumulative gains from a dollar invested during that period equal to 0.982, so the portfolio generates a loss. Similar to other momentum studies like Moskowitz (2018) the winners portfolio performed the best compared to the other momentum portfolios, followed by the neutral portfolio and finally the losers. Out of all artificial portfolios, the Val-Mom portfolio performed the best, which calls for the preliminary hypothesis that value performs better than momentum as a factor in Japanese markets. The market is the best performer out of all assets. Figure 1 also highlights the huge market growth in the 1980s and the extended recession in the 1990s.

In the data, there is no occurrence of 3 consecutive months where the loser portfolio outperforms the winner portfolio. This means that momentum crashes in Japan, if they occur, are short-lived. We however identify the 10 worst performing months of the WML portfolio, the results can be found in Appendix 1. The main poorly performing periods are; 31/05/1985 - 30/06/1987, the economic bubble leading up to the Japanese asset price bubble. 28/02/1991 - 31/08/1992, the Japanese asset price bubble and beginning of the lost decade. 31/01/1998 - 31/05/2000, corresponding to the dot-com bubble. Academic literature finds that periods of poor momentum performance are accompanied with a negative lagged 2 year market return and a positive contemporaneous market return. Our results from Appendix 1 do not find the same pattern, instead, most of the months with poor momentum performance show a positive 2 year lagged market return. The only occurrences of negative lagged market returns during poor WML performance is post 1991.

3.2 Methodology

Daniel and Moskowitz (2016) introduce 2 dummy variables in their momentum crash research paper, the 2 will be used in the analysis.

1. I_B is a simple ex-ante bear market indicator which equals 1 if the past 24 months of cumulative returns are negative and 0 otherwise.
2. I_U is an ex-post up-market indicator which equals 1 if the market excess returns (r_M - r_f) at time t are positive and 0 otherwise.

Furthermore, the Momentum Crashes paper implements a conditioning variable which they call a panic period indicator. I_P is formed by interacting the bear market indicator (I_B) with the variance of daily market excess returns over the past 126 trading days and a constant corresponding to the inverse of the full sample mean of variance of daily market excess returns for all months where I_B = 1. The reasoning behind the panic period indicator is that:

$$\Sigma_{I_B=1} I_P = 1$$

Thus, the coefficients of I_P and of any variables interacted with it explain the weighted average change in the corresponding coefficient during a bear market. In which, the weight on each observation is proportional to the ex-ante market variance leading up to that month.

Assessing the existence and magnitude of momentum crashes in the Japanese markets will be achieved through 6 different regressions. First a CAPM model is set up; albeit imprecise, CAPM is a widely recognised pricing model which will serve as the foundation of this paper's regressions. The equation is as follows:

$$R_{i,t} = \alpha_0 + \beta_0 R_{E,t} + \varepsilon_t \qquad (1)$$

Where R_i (= r_P - r_f) is the excess returns on the individual portfolio, R_E (= r_M - r_f) is the excess returns of the market, α_0 is the OLS estimate of the Jensen's alpha of the relevant portfolio and β_0 is the OLS estimation of the market beta of the portfolio.

The next regression performed is a conditional CAPM implementing the bear market indicator I_B. The regression is as follows:

$$R_{i,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + \beta_B I_{B,t-1}) R_{E,t} + \varepsilon_t \qquad (2)$$

This regression should capture the excess returns and the market beta changes during a bear market. It includes α_B which is the OLS estimate for the average change in portfolio abnormal returns during a bear market. β_B is the OLS estimation of the interaction term between the bear market indicator and the market excess returns, it represents the change in beta during bear markets.

The third regression builds on the last and analyzes how much the market betas differ in up- and down- market states (positive market excess returns or not):

$$R_{i,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + I_{B,t-1}(\beta_B + \beta_U I_{U,t}) R_{E,t} + \varepsilon_t \qquad (3)$$

In this regression, the coefficient β_U explains the market beta change in a bear market following positive market excess returns. This will determine the behavior of the returns of the portfolio and confirm whether they resemble option payoffs in bear markets.

Next to analyze the portfolios' reaction to market variance and volatility effects, we add in regression 4 a conditioning variable representing the variance of daily market excess returns over the preceding 126 trading days. the regression takes the form of:

$$R_{i,t} = (\alpha_0 + \alpha_B I_{B,t-1} + \alpha_V \sigma^2_{M,t-1}) + (\beta_0 + \beta_B I_{B,t-1} + \beta_V \sigma^2_{M,t-1}) R_{E,t} + \varepsilon_t \qquad (4)$$

In regression 4, α_V is the OLS estimate of the effect of daily market variance on the portfolio. β_V shows the effect of 6 month ex-ante market variance on the portfolio's market beta.

The last regression includes the panic indicator which is designed to capture periods where the market has fallen and volatility is high.

$$R_i = (\alpha_0 + \alpha_P I_{P,t}) + (\beta_P I_{P,t} + \beta_B I_{B,t-1} + \beta_V \sigma^2_{M,t-1}) R_{E,t} + \varepsilon_t \qquad (5)$$

In regression 5, α_P corresponds to the impact of a "panic state" on portfolio returns. β_P outlines the effect of the panic states on the market betas.

4. Results

4.1 Regression Results

Table 2 reports the basic CAPM, Regression 1, for each portfolio in the Japanese equity market from March 1974 - March 2023. The market beta for the losers portfolio is the highest at 0.658 and it decreases across momentum sub-portfolios. The middle one has a beta of 0.571 and the winners portfolio has a market beta of 0.564.

Next we observe that the WML portfolio has a negative market beta of -0.093 and it equals $\beta_{Winners}$ - β_{Losers} due to the nature of the construction of the portfolio. Finally, the value and momentum Val-Mom portfolio also has a negative beta of -0.073.

The Jensen's alpha of the sub portfolios are all positive and significant indicating that these portfolios outperform their expectations in this simplistic CAPM. Moreover, the WML has a negative and insignificant Jensen's alpha of -0.066, this shows that the WML returns are only explained by the market beta but it still performs poorly compared to the market benchmark. For the Val-Mom portfolio, the abnormal returns are positive and significant although at a much lower magnitude than the sub-portfolios.

It should be noted that the Adjusted R^2 are acceptable for the sub-portfolios but are extremely small for the WML and Val-Mom portfolio. As a preliminary conclusion, this standard CAPM does not explain the portfolio returns very well.

Table 2: *Simple CAPM, Regression 1 for each portfolio. The table reports the estimated coefficients and t-statistics in parentheses of a zero-investment equity momentum strategy in Japanese markets. The significance of each estimate is shown by the amount of asterisks behind the value.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
β_0	R_E	0.658***	0.571***	0.564***	−0.093***	−0.073***
		(19.4)	(20.3)	(16.9)	(-2.8)	(-4.6)
1	Constant	1.708***	1.523***	1.641***	−0.066	0.242**
		(7.6)	(8.1)	(7.4)	(-0.3)	(2.4)
Observations		583	583	583	583	500
R^2		0.394	0.415	0.329	0.013	0.041
Adjusted R^2		0.393	0.414	0.328	0.011	0.039

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3 explores the conditional CAPM that introduces the bear market indicator. Starting with the WML portfolio, only one coefficient is significant, β_B at -0.327 which indicates the change in beta during a bear market. Therefore, during a bull market, the WML market beta β_0 = 0.056 and during a bear market it is $\beta_0 + \beta_B$ = -0.271. Because the beta is positive in bull markets and negative in bear markets, this regression paints the WML portfolio as a strategy that reacts well to market changes and remains profitable in the long run in either market states. Yet, the beta in bull markets is not significant. The abnormal returns for the WML strategy are not statistically significant either.

For the sub-portfolios, the bull market beta is lowest for the losers portfolio β_0 = 0.514 and highest for the winners β_0 = 0.569 and the pattern inverses in bear markets. The losers portfolio has a bear market beta of $\beta_0 + \beta_B$ = 0.886 and for the winners it is 0.614. This regression reflects that the loser portfolio is indeed a poor performer as it is less correlated with the market in times of positive market returns and more correlated with the market in times of negative market returns. The pattern is reversed for the winner portfolio. The positive alphas in either market states for all sub-portfolios highlight a relatively successful performance relative to the benchmark but they are only significant for the middle and winner portfolios.

For the Val-Mom portfolio, the market beta remains relatively minimal and negative in all market phases with a β_0 = -0.028 in bull markets and $\beta_0 + \beta_B$ = -0.118 in bear markets. The negative bear market beta for the portfolio indicates that in the long run, the Val-Mom portfolio generates better returns in bear markets. Lastly, the relatively low absolute value of the beta indicates the relatively low exposure of the portfolio to systematic risk. The abnormal returns for the Val-Mom portfolio remains positive in all market states but only significant in bull markets.

Table 3: *Conditional CAPM, Regression 2 investigating alphas and betas in bear markets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	-0.192	-0.847^{**}	-0.773^{*}	-0.581	-0.186
		(-0.414)	(-2.2)	(-1.7)	(-1.2)	(-0.9)
β_0	R_E	0.514^{***}	0.517^{***}	0.569^{***}	0.056	-0.028
		(11.0)	(13.3)	(12.1)	(1.2)	(-1.3)
β_B	$I_B \cdot R_E$	0.372^{***}	0.176^{***}	0.045	-0.327^{***}	-0.090^{***}
		(5.4)	(3.1)	(0.645)	(-4.7)	(-2.8)
1	Constant	1.497^{***}	1.623^{***}	1.766^{***}	0.269	0.331^{***}
		(5.5)	(7.1)	(6.4)	(1.0)	(2.6)
Observations		563	563	563	563	500
R^2		0.434	0.444	0.343	0.050	0.056
Adjusted R^2		0.431	0.441	0.340	0.045	0.051

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4 reviews regression 3 results highlighting the portfolios' optionality in bear markets. For the WML portfolio, the market recovery beta is β_U = -0.464. It is the only statistically significant coefficient, and indicates that the portfolio performs badly when the market rebounds after a bear market, hinting at the existence of momentum crashes. In bull markets, the portfolio beta is β_0 = 0.056. In bear markets the portfolio beta is $\beta_0 + \beta_B$ = -0.097 and when the market rebounds, the beta is $\beta_0 + \beta_B + \beta_U$= -0.561. This demonstrates the written call optionality behavior of the WML portfolio; returns are low but positive in bull markets, slightly negative in bear markets and especially negative in bear markets when the contemporaneous market return is positive. Although the conditional betas exhibit the written call option behavior, only the coefficient β_U is significant and there is not enough statistical evidence to completely validate this conclusion.

The sub-portfolios do not demonstrate the same behavior, for all portfolios, the conditional beta remains positive throughout all market phases. The conditional beta in market rebounds for the winner portfolio is the only negative beta coefficient of all sub-portfolios, β_U= -0.085 and shows that the winners perform worse in market rebounds. Conversely, the losers portfolio, has a β_U= 0.379. This result of regression 3 is in line with the momentum crash hypothesis. During a market recovery, so the market rises, the losers portfolio performs very well, it has a conditional beta of $\beta_0 + \beta_B + \beta_U$= 1.122 and the winner portfolio has a beta of $\beta_0 + \beta_B + \beta_U$= 0.561. Because the losers portfolio is shorted, its high returns are in fact losses within the WML portfolio. Lastly, all the sub-portfolios have a positive, statistically significant abnormal return except for the winner portfolio in bear markets.

Finally, the Val-Mom portfolio maintains a negative beta throughout all market phases. In bull markets the beta is β_0 = -0.028, in bear market it is $\beta_0 + \beta_B$ = -0.107 and in recovery states the beta is $\beta_0 + \beta_B + \beta_U$= -0.125. So the Val-Mom portfolio will perform poorly in both bull and recovery states of the market but will generate positive returns in bear markets. This confirms the results from Table 3. Because our data sample contains prolonged periods of recession in the 1990s, it is coherent that the Val-Mom portfolio performs well. The abnormal returns of this portfolio also remain positive throughout. For the Val-Mom portfolio regression 3, only the bear market beta and the abnormal returns in a bull market are significant.

Table 4: *Conditional CAPM, Regression 3 investigating optionality in bear markets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	-1.225^{*}	-1.021^{*}	-0.542	0.684	-0.112
		(-1.9)	(-1.8)	(-0.8)	(1.0)	(-0.4)
β_0	R_E	0.514^{***}	0.517^{***}	0.569^{***}	0.056	-0.028
		(11.1)	(13.2)	(12.1)	(1.2)	(-1.3)
β_B	$I_B \cdot R_E$	0.229^{**}	0.152^{*}	0.077	-0.153	-0.079^{*}
		(2.4)	(1.9)	(0.8)	(-1.6)	(-1.9)
β_U	$I_B \cdot I_U \cdot R_E$	0.379^{**}	0.064	-0.085	-0.464^{***}	-0.027
		(2.2)	(0.4)	(-0.5)	(-2.6)	(-0.4)
1	Constant	1.497^{***}	1.623^{***}	1.766^{***}	0.269	0.331^{***}
		(5.5)	(7.0)	(6.4)	(1.0)	(2.6)
Observations		563	563	563	563	500
R^2		0.439	0.444	0.344	0.062	0.057
Adjusted R^2		0.435	0.440	0.339	0.055	0.049

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5 analyzes Regression 4 which adds as a conditioning variable the realized daily market variance in the last 126 trading days (6 months). The results of the WML portfolio show that a higher ex-ante market variance is associated with a lower market beta. Precisely, it falls by -0.052 per percent of ex-ante daily variance, this coefficient is statistically significant. Moreover, a higher market variance is also linked with substantially lower future abnormal returns to momentum with respect to the market return, this result is also statistically significant. This demonstrates that market variance does not stimulate performance for the WML portfolio, it decreases the excess returns of the portfolio. In line with our written call behavior assumption, an increase in volatility decreases the price of a written call option, which is comparable to the decrease in returns of the WML portfolio.

The loser and middle portfolio show a market beta increase during periods of increased volatility. However only the former is statistically significant. The winner portfolio experiences a decrease in market beta when volatility rises. Interestingly, the abnormal returns of the winner portfolio decreases the most of all sub-portfolios during volatile periods. Indicating that it might be susceptible to poor performance in times of market stress or agitation.

Finally, the Val-Mom portfolio results show that this strategy is resistant to volatility changes. The market beta falls by -0.009 per percent of volatility and abnormal returns fall by -0.062. Only the bear market beta and abnormal returns are significant. Table 5 shows that the main driver of the Val-Mom portfolio excess returns is its bull market beta. It drops by -0.074 when the market returns are negative.

Table 5: *Conditional CAPM, Regression 4 investigating market-variance effects.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	-0.232	-0.406	-0.016	0.216	-0.097
		(-0.4)	(-0.9)	(0.0)	(0.4)	(-0.4)
α_V	σ_M^2	0.056	-0.253^{**}	-0.471^{***}	-0.527^{***}	-0.062
		(0.4)	(-2.1)	(-3.2)	(-3.6)	(-0.9)
β_0	R_E	0.459^{***}	0.499^{***}	0.602^{***}	0.142^{***}	-0.013
		(8.7)	(11.3)	(11.3)	(2.7)	(-0.5)
β_B	$I_B \cdot R_E$	0.290^{***}	0.122^{*}	0.049	-0.240^{***}	-0.074^{**}
		(3.7)	(1.9)	(0.6)	(-3.1)	(-2.1)
β_V	$\sigma_M^2 \cdot R_E$	0.040^{**}	0.020	-0.012	-0.052^{***}	-0.009
		(2.2)	(1.3)	(-0.7)	(-2.9)	(-1.1)
1	Constant	1.373^{***}	1.905^{***}	2.361^{***}	0.988^{***}	0.421^{***}
		(4.1)	(6.9)	(7.1)	(3.0)	(2.7)
Observations		563	563	563	563	500
R^2		0.439	0.451	0.355	0.079	0.060
Adjusted R^2		0.434	0.446	0.349	0.071	0.050

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6 displays the results from Regression 5 which introduces the panic indicator from section 3.2. It is designed to capture periods where the market has fallen and volatility is high. Furthermore, the time variation in market beta is instrumentalised by adding the components of the panic indicator as interaction terms (see Regression 5). We first note that for the WML, both the stand alone panic indicator and its interaction are significant. This is an indication that market panic states have statistical effects on the WML portfolio. During a market panic state, the WML market beta will decrease by -0.025% and the abnormal returns will drop by -0.151%. This points to the conclusion that momentum crashes exist in Japanese markets. Nevertheless, the coefficients of I_P and its interaction terms are economically quite small, and arguably may not have a substantial impact on WML portfolio returns.

On the other hand, the sub portfolios all have negative β_p coefficients and all are statistically significant. We note that the winners have the most negative beta in panic periods (-0.118) and the losers have the least (-0.093). All sub portfolios have similar market variance effects on their market betas, an increase of around 0.250 per percentage volatility. In line with previous regressions, the loser portfolio has the highest conditional market beta in bear markets.

Finally for the Val-Mom portfolio, only the bear market conditional beta and the constant are statistically significant in line with all previous regressions. This proves that the Val-Mom portfolio is not susceptible to momentum crashes in the Japanese equity market.

Table 6: *Conditional CAPM, Regression 5 investigating the bear-market to market-variance interaction effects. In the estimated regression, the variable I_P and any interaction terms it is included in is multiplied by 1200 to put them in annualized percentage terms.*

		Portfolios:				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_P	I_P	0.105**	−0.017	−0.045	−0.151***	−0.031
		(2.0)	(-0.4)	(-0.8)	(-2.9)	(-1.4)
β_B	$\mathrm{I}_B \cdot R_E$	0.767***	0.633***	0.639***	−0.127	−0.083**
		(8.9)	(8.6)	(7.2)	(-1.5)	(-2.3)
β_V	$\sigma_M^2 \cdot R_E$	0.246***	0.247***	0.258***	0.012	−0.012
		(9.1)	(10.8)	(9.3)	(0.4)	(-1.1)
β_P	$\mathrm{I}_P \cdot R_E$	−0.093***	−0.102***	−0.118***	−0.025*	0.001
		(-6.2)	(-8.0)	(-7.7)	(-1.7)	(0.1)
1	Constant	0.702***	0.868***	1.027***	0.326	0.352***
		(2.9)	(4.2)	(4.1)	(1.4)	(3.1)
Observations	563	563	563	563	563	500
R^2	0.037	0.405	0.395	0.281	0.067	0.059
Adjusted R^2	0.030	0.401	0.391	0.276	0.060	0.051
Note:						*p<0.1; **p<0.05; ***p<0.01

To summarize Tables 2-6, the WML momentum strategy in the Japanese equity market is effectively also short on volatility and the payoff structure is comparable to that of an option. Furthermore, it performs poorly in market rebounds and in panic periods with high volatility and poor lagged market returns. We conclude that there is evidence for momentum crashes in the Japanese equity market.

We established in Section 2.1 that the Japanese equity market had undergone important structural and regulatory changes after 1997. As a result of this, the cross section of the returns may have changed across these periods. We therefore run the same 5 regressions on the data prior to 1997 and after in order to conduct a robustness check of the results from Tables 2-6. The output of these new regressions along with their analysis can be found in Appendix 2.

Overall, the results of Appendix 2 are widely consistent with our findings from Tables 2-6 and confirm the evidence of momentum that we uncovered. There are certain interesting findings that arise from these secondary regressions. First of all, WML returns do not significantly change during reversals after a bear market after 1997 unlike in Table 4. Next, the WML portfolio still shows a "shorting" behavior on volatility during bear markets in all sub-samples. Additionally, the panic indicator estimator interaction remains significant pre- 1997 but not in the period after for WML. Finally, the Val- Mom portfolio has extremely different estimations of the volatility variable and its interactions before and after 1997. Pre- 1997 it experiences significantly negative reductions in returns from volatility and post- 1997 it has negligible and insignificant estimators. Since the other portfolios do not demonstrate the same change in results across the 2 periods, we can guess that the market changes and regulations had a greater effect on the value factor than on momentum with regards to volatility.

Although evidence of momentum crashes was found, the strength of simple OLS regressions may be called into question. Beck (2001) argues the limitations of standard OLS regressions and highlights the prevalence of heteroskedasticity in time series cross-sectional data which may cloud results.

In fact, heteroskedasticity may well be present in the data. The presence of various economic shocks both positive and negative contribute to heteroskedasticity and with such a long time series studies, it is certain that we captured such shocks.

We thus implement a White Test in order to evaluate heteroskedasticity in Table 7. Moreover, we plot the residuals of regression 5 (Table 6) for all portfolios to informally assess the degree of heteroskedasticity in that regression, these can be found in Appendix 2.

Table 7: *White test results per portfolio for regression 5. The test measures heteroskedasticity in the sample and is statistically significant when p-values are lower than 0.05.*

	Portfolios			
	Loser	Winner	WML	Val-Mom
White Test P-value	$9.91\text{x}10^{-8}$	$2.528\text{x}10^{-6}$	0.049	0.0016

Table 7 demonstrates that heteroskedasticity occurs in Regression 5 for all the relevant portfolios. However, the White test does lose explanatory power when more variables are added to the model. Since regression 5 contains 5 variables we must analyze the residual plots from Appendix 3 to confirm the finding. For each portfolio's residual plot, it appears that the variance of residuals is much greater around the mean and has a much lower variance when the fitted values are more extreme. We conclude from this subsection that the data possesses some heteroskedasticity. As such a new model accounting for non- constant variance in the data must be tested in order to produce robust standard errors.

We hence implement a Fama-MacBeth model for regression 1, 2 and 5. Fama-Macbeth regressions were developed by Eugene Fama and James MacBeth in 1973 to provide standard errors corrected for cross sectional correlation. The Fama-MacBeth regression estimates the betas and risk premia for all risk factors in the model. To implement the regression, 2 steps are needed:

First perform a time series regression by dividing the data into equal sub-periods and regress each portfolio's excess returns on the risk factors to estimate the exposure within the chosen period.

$$R_{i,t} = \alpha_{i,t} + \beta_0 R_{E,i,t} + \dots + \varepsilon_{i,t}$$

Next, regress each portfolio return against the estimated explanatory variables $\widehat{\beta}_i$ in the cross-sectional regression at every point in time t to determine the factor risk premia.

$$R_{i,T} = \alpha_{0,T} + \widehat{\beta_0}\gamma_{E,i,T} + \dots + \varepsilon_{i,T}$$

The estimated factor risk premia are calculated as the time series averages of the estimates at each point in time:

$$\widehat{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\widehat{\gamma_t}$$

For the Fama-Macbeth regression in this study, the cross sectional returns will be regressed monthly in step 1. The smaller period division helps account for different economic conditions in each period that could cause heterogeneity. As a result of the period division, there was not enough portfolio return data in order to make strong statistical conclusions. Hence, we used 25 portfolios sorted by size and momentum from the Kenneth and French website. Neutralizing momentum portfolios with size allows for a wider cross section and a better understanding of whether market risk premium is priced in during different market states. The drawback of using Kennth and French portfolios is that the data only starts from October 1991, this is a smaller period sample than the Asness AQR data.

Table 8: *Fama MacBeth regression of CAPM for the Kenneth and French 25 portfolios sorted on size and momentum. Data runs from October 1991 to March 2023.*

Coefficient	Variable	Momentum Returns
β_0	R_E	0.157^{***}
		(0.008)
1	Constant	-0.213^{***}
		(0.031)
Observations	9,725	
R^2	0.018	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 8, shows that the market risk premium is priced in the cross section of momentum. In fact, the market beta is positive with a value of 0.157 and highly significant. Compared to the CAPM in Table 2, the market beta of the WML portfolio was -0.093, the coefficient's sign is inverted and has a smaller absolute value. This would indicate that, inversely to our previous findings, momentum strategies generate higher returns in bull markets. Secondly, the CAPM fails to generate positive alphas, this highlights the generally poor performance of momentum in Japan.

Table 9: *Fama MacBeth regression of Regression 2 for the Kenneth and French 25 portfolios sorted on size and momentum. Data runs from October 1991 to March 2023.*

Coefficient	Variable	Momentum Returns
α_B	I_B	-0.309^{***}
		(0.075)
β_0	R_E	0.097^{***}
		(0.008)
β_B	$I_B \cdot R_E$	0.089^{***}
		(0.005)
1	Constant	-0.048^{*}
		(0.029)
Observations	9,725	
R^2	0.016	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 9 shows the results from Regression 2, we note that the cross section of momentum maintains a positive market risk premium in bull markets (β_0) and in bear markets ($\beta_0 + \beta_B$). Both predictors are statistically significant to a 1% confidence interval. This demonstrates that the cross section of momentum is actually more correlated with the market in bearish periods. This is inconsistent with the findings from Table 3, there we find that the bear market beta was negative for the WML portfolio. The bear market premium (α_B) is negative and significant which indicates that on average momentum cross sectional returns decrease by 0.309% in bear markets. Overall, the results from this regression illustrate momentum strategies as particular poor performers in bear markets.We note that the R^2 for the regression is extremely low and indicates poor explanatory power of the model.

Table 10: *Fama MacBeth regression of Regression 6 (See Below) for the Kenneth and French 25 portfolios sorted on size and momentum. Data runs from October 1991 to March 2023. In the estimated regression, the variable I_P and any interaction terms it is included in is multiplied by 1200 to put them in annualized percentage terms.*

Coefficient	Variable	Momentum Returns
α_P	I_P	-0.229^{***}
		(0.010)
α_V	σ^2_M	0.696^{***}
		(0.054)
β_0	R_E	0.155^{***}
		(0.010)
β_P	$I_P \cdot R_E$	0.00001
		(0.001)
1	Constant	-1.031^{***}
		(0.103)
Observations	9,725	
R^2	0.022	
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 10 outlines the results of a slightly modified version of Regression 5:

$$R_i = (\alpha_0 + \alpha_P I_{P,t} + \alpha_V \sigma^2_{M,t-1}) + (\beta_0 + \beta_P I_{P,t}) R_{E,t} + \varepsilon_t \tag{6}$$

The results highlight that the market risk premium stays positive in bull markets with a beta of 0.155. Unlike previous findings, the market volatility risk premium is positive and quite high. Although at first sight this contradicts the short volatility, written call behavior of momentum, in panic periods characterized by negative ex ante market returns and high volatility, the average returns of momentum cross sectional returns decrease by -0.229%. Finally, the cross sectional market beta does not change significantly in panic periods, therefore market risk premium is not priced in during panic states. This also signifies that the decrease in momentum cross sectional returns during panic periods is not achieved through a change in market betas during said periods challenging the findings of Daniel and Moskowitz (2016).

We observe that the R^2 of the regression is still minimal and shows poor explanatory power, which harms the validity of the results. Nevertheless, we find relatively similar conclusions to that of our OLS regression but with much higher statistical significance using the Fama MacBeth regressions. The market risk premium is priced in during bull and bear markets but not during panic periods. During bear markets, the cross- sectional momentum returns decrease with volatility.

5. Discussion

The results of our OLS regressions show mitigated results and statistical strength especially with regards to the WML portfolio. With the robustness check from the event study regressions in Appendix 2 and the Fama Macbeth cross-sectional regressions we confirmed the validity of the findings. On one hand, we established that the written call optionality behavior was present in bear markets. On the other, we found weak evidence of momentum crashes. Notwithstanding, the models used in the regressions failed to generate meaningful R^2 measures for both WML and Val-Mom portfolios in all OLS regressions and in the Fama MacBeth regressions which never surpassed 0.075.

As a result the conclusions of this study should be evaluated with discretion. We can however try to provide brief explanations for the anomalies, compare the results to similar studies and examine the limitations of the research.

First of all, regarding the OLS regressions, the momentum portfolios were sourced from an updated data library for the Asness et al. (2013) study. When comparing this paper's portfolio summary statistics to the very same one from the 2013 paper, we can see that the portfolio characteristics have changed in our new sample time period. This is most likely due to the market behavior in the new period we introduced from 2011-2023. Our new sample includes the Covid-19 pandemic and a long extended period of extremely low and even negative interest rates in the 2010s. In our sample, across all portfolios, the returns, standard deviation and sharpe ratios have all considerably lowered. For example in the Asness et al. paper the momentum WML portfolio had a return of 1.7% a standard deviation of 18.6% and a sharpe ratio of 0.09, in this paper the values for the WML portfolio are 0.13%, 5.09% and 0.03 respectively.

Next, we compare our regression results with the ones from the “Momentum Crashes” paper by Daniel and Moskowitz (2016). The overall conclusions of the paper are largely consistent with ours. The WML momentum strategy has difficulty yielding statistically significant positive returns. Both papers find evidence of a statistically significant optionality behavior of the WML in bear markets. The main difference in conclusions is that Daniel and Moskowitz find significant market beta changes in panic periods in Japanese markets, we find the same pattern in our OLS regressions but not with the Fama Macbeth ones. We discover evidence in our Fama MacBeth regressions that panic states affect the cross sectional returns directly and not through the market beta. Nevertheless, we discover a similar bear market-market variance interaction effect as the paper. Finally, like our study, the “Momentum Crashes” paper cannot completely argue the existence of momentum crashes in Japanese markets because the WML portfolio might be such a poor performer in the first place.

With regards to the optionality of momentum strategy returns, academic literature offers various explanations. Sunstein and Zeckhauser (2011) and Loewenstein et al. (2001) outline several investor behavioral biases that could affect pricing. Namely, in situations of extreme market conditions, individuals are inclined to act irrationally and fearfully. They appear to only focus on the losses, generally disregarding probabilities. Merton (1974) proposes a different theory; corporate liabilities can be represented as a combination of a risk free asset and a put option on the firm’s assets. As such, the optionality behavior of corporate debt could persist into the risk return profile of the WML momentum strategy.

Finally, academic research has called into question the statistical power of conditional capital asset pricing models which our paper relies on. Lewellen and Nagel (2006) explain that the conditional CAPM does not provide satisfactory explanations for asset-pricing anomalies such as momentum and the value premium. This is due to the fact that betas vary significantly over time. The betas’ volatility implies that conditional CAPMs are better when performed on short-window regressions (of about half a year). Considering that our paper used around a 49 year sample to estimate betas, our models must have captured a lot of noise and exogenous factors that could have clouded the results. The Fama MacBeth regressions should have in part addressed this issue. This is because, in the first step of the Fama MacBeth regression, we ran monthly time series regressions on the momentum portfolios which should fulfill the short-window condition of Lewellen and Nagel. If we follow Lewellen and Nagel’s warning then only our Fama MacBeth results are robust and we must conclude that the market betas in panic states show no statistical effect and this weakens the evidence for momentum crashes.

One potential limitation that the Fama Macbeth regressions do not address is the possible autocorrelation occurring in the data. As section 2.1 points out, a common business practice in Japan is cross-shareholding across different industries and business types. If this occurs between firms in different sub portfolios, an exogenous shock to a firm in the winner's portfolio would affect the loser portfolio even though the loser firms should not be directly exposed to the shock. One way to address this issue could be to implement a new variable measuring the share of the firm held by Japanese corporations. Another approach could be to use more sophisticated models such as the GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) that could address both the heteroskedasticity and the autocorrelation in the data.

6. Conclusion

The paper set out to determine the existence of momentum crashes and examine the performance of commonly used momentum strategies in the Japanese equity market. Terciles of momentum portfolios were created along with a winners-minus-losers portfolio and an equally weighted value and momentum portfolio. The Nikkei-225 was used as a proxy to represent the equity market. The analysis was organized with the use of various conditional CAPM OLS regressions and Fama MacBeth regressions.

In summary, simple momentum strategies prove to be unsuccessful in the Japanese markets. All fail to beat the market returns and the WML portfolio even realizes a loss across the 49 year holding period. The equally weighted value and momentum portfolio is the best performer in the study but even it fails to beat the market. We conclude the value is a better factor to trade with in the Japanese equity markets.

We find evidence of a written put option behavior in the returns of the WML portfolio consistent with previous academic literature, highlighting a vulnerability to market variance effects. Furthermore, the study provides weak evidence of the existence of momentum crashes in the Japanese market in line with published academic literature. Although some evidence of momentum crashes was uncovered, it is not as evident as momentum crashes in other economically developed equity markets and remains an economic oddity.

Further research should aim to investigate the behavioral environment of the Japanese market. Since momentum crashes only show a weak presence, perhaps investor sentiment and biases play a smaller role in the Japanese equity market. Moreover, this study could be replicated with more sophisticated models that correct for certain data imperfections like the violation of i.i.d. Additionally, one could examine the cross sectional variations of momentum further, for instance looking at whether certain industries exhibit a greater propensity to momentum crashes. If cross-shareholding is indeed a relevant factor, then momentum crashes should affect the whole market and not just certain sectors. Finally, alternative momentum strategies could be investigated similar to Denis Chaves's idiosyncratic momentum strategy (2012). Alternatively, if Merton (1974) proves to be correct, a portfolio construction based on momentum and debt level could provide some interesting results.

7. References

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8. Appendix

Appendix 1: Worst Performing months for the WML Portfolio

Table 11: *Worst performing months for the WML portfolio between March 1974 and March 2023, all values are in percentages*

Date	WML Return	Market Return	2y Market Return
31/10/1985	-22.9	1.9	35.1
31/01/1998	-20.5	9.0	-23.2
30/09/1981	-19.9	-4.6	21.4
30/06/1987	-19.2	-2.4	94.2
31/03/2000	-17.0	1.9	18.6
31/05/2000	-16.6	-9.1	14.9
31/08/1992	-15.0	13.5	-48.7
28/02/1991	-14.8	13.4	-26.2
30/04/1986	-14.8	-0.2	45.1
31/05/1987	-14.6	6.4	87.3

Appendix 2: Regression Comparison for pre- and post- 1997

Table 12: *CAPM regression on all portfolios from March 1974 to December 1996. All results are in percentages and standard errors are in brackets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
β_0	R_E	0.783***	0.737***	0.726***	−0.057	−0.048*
		(0.052)	(0.046)	(0.055)	(0.050)	(0.029)
1	Constant	4.327***	4.147***	4.121***	−0.206	0.233
		(0.401)	(0.356)	(0.428)	(0.392)	(0.219)
Observations		269	269	269	269	186
R^2		0.463	0.493	0.394	0.005	0.015
Adjusted R^2		0.461	0.491	0.392	0.001	0.010
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 13: *CAPM regression on all portfolios from January 1997 to March 2023. All results are in percentages and standard errors are in brackets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
β_0	R_E	0.814***	0.658***	0.638***	−0.176***	−0.103***
		(0.044)	(0.032)	(0.042)	(0.053)	(0.020)
1	Constant	−0.039	−0.049	0.177	0.216	0.311***
		(0.244)	(0.176)	(0.229)	(0.288)	(0.112)
Observations		314	314	314	314	314
R^2		0.518	0.573	0.427	0.035	0.075
Adjusted R^2		0.516	0.571	0.425	0.032	0.073
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 14: *Regression 2 on all portfolios from March 1974 to December 1996. All results are in percentages and standard errors are in brackets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	0.399	−1.228	−1.804*	−2.203**	−0.754
		(0.907)	(0.803)	(0.968)	(0.886)	(0.465)
β_0	R_E	0.674***	0.729***	0.774***	0.099	0.012
		(0.076)	(0.067)	(0.081)	(0.074)	(0.041)
β_B	$I_B \cdot R_E$	0.282**	0.090	−0.024	−0.306***	−0.113**
		(0.110)	(0.098)	(0.118)	(0.108)	(0.057)
1	Constant	3.731***	4.202***	4.438***	0.707	0.579**
		(0.515)	(0.456)	(0.550)	(0.504)	(0.281)
Observations		249	249	249	249	186
R^2		0.475	0.507	0.408	0.041	0.039
Adjusted R^2		0.469	0.501	0.401	0.029	0.023
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 15: *Regression 2 on all portfolios from January 1997 to March 2023. All results are in percentages and standard errors are in brackets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	0.353	0.112	0.584	0.231	0.006
		(0.493)	(0.361)	(0.463)	(0.574)	(0.226)
β_0	R_E	0.695***	0.667***	0.760***	0.065	−0.053*
		(0.066)	(0.048)	(0.062)	(0.077)	(0.030)
β_B	$I_B \cdot R_E$	0.220**	−0.015	−0.214**	−0.434***	−0.091**
		(0.089)	(0.065)	(0.084)	(0.104)	(0.041)
1	Constant	−0.134	−0.099	−0.113	0.021	0.287**
		(0.317)	(0.232)	(0.297)	(0.369)	(0.146)
Observations		314	314	314	314	314
R^2		0.528	0.573	0.442	0.087	0.090
Adjusted R^2		0.523	0.569	0.436	0.078	0.081
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 16: *Regression 3 on all portfolios from March 1974 to December 1996. All results are in percentages and standard errors are in brackets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	−0.767	−1.153	−1.487	−0.720	−0.748
		(1.278)	(1.136)	(1.369)	(1.246)	(0.649)
β_0	R_E	0.674***	0.729***	0.774***	0.099	0.012
		(0.076)	(0.067)	(0.081)	(0.074)	(0.041)
β_B	$I_B \cdot R_E$	0.157	0.098	0.010	−0.147	−0.113
		(0.146)	(0.130)	(0.157)	(0.143)	(0.075)
β_U	$I_B \cdot I_U \cdot R_E$	0.368	−0.024	−0.100	−0.468*	−0.002
		(0.285)	(0.253)	(0.305)	(0.278)	(0.141)
1	Constant	3.731***	4.202***	4.438***	0.707	0.579**
		(0.514)	(0.457)	(0.551)	(0.502)	(0.281)
Observations		249	249	249	249	186
R^2		0.479	0.507	0.409	0.052	0.039
Adjusted R^2		0.471	0.499	0.399	0.037	0.018
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 17: *Regression 3 on all portfolios from January 1997 to March 2023. All results are in percentages and standard errors are in brackets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	−0.076	0.058	0.875	0.952	−0.019
		(0.711)	(0.520)	(0.667)	(0.826)	(0.327)
β_0	R_E	0.695***	0.667***	0.760***	0.065	−0.053*
		(0.066)	(0.048)	(0.062)	(0.077)	(0.030)
β_B	$I_B \cdot R_E$	0.147	−0.025	−0.165	−0.312**	−0.095*
		(0.124)	(0.091)	(0.116)	(0.144)	(0.057)
β_U	$I_B \cdot I_U \cdot R_E$	0.171	0.022	−0.116	−0.288	0.010
		(0.204)	(0.150)	(0.192)	(0.237)	(0.094)
1	Constant	−0.134	−0.099	−0.113	0.021	0.287**
		(0.317)	(0.232)	(0.297)	(0.368)	(0.146)
Observations		314	314	314	314	314
R^2		0.529	0.573	0.442	0.091	0.090
Adjusted R^2		0.523	0.567	0.435	0.079	0.078
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 18: *Regression 4 on all portfolios from March 1974 to December 1996. All results are in percentages and standard errors are in brackets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	-0.830	-1.302	-1.162	-0.332	0.002
		(1.103)	(0.985)	(1.185)	(1.065)	(0.544)
α_V	σ^2_M	0.734**	0.051	-0.382	-1.116***	-0.503***
		(0.366)	(0.327)	(0.393)	(0.353)	(0.184)
β_0	R_E	0.601***	0.716***	0.811***	0.209**	0.089*
		(0.092)	(0.083)	(0.099)	(0.089)	(0.051)
β_B	$\mathrm{I}_B \cdot R_E$	0.208	0.075	0.013	-0.195	-0.048
		(0.127)	(0.114)	(0.137)	(0.123)	(0.062)
β_V	$\sigma^2_M \cdot R_E$	0.051	0.010	-0.026	-0.077**	-0.049**
		(0.040)	(0.036)	(0.043)	(0.038)	(0.020)
1	Constant	3.017***	4.134***	4.807***	1.790***	1.176***
		(0.621)	(0.555)	(0.667)	(0.599)	(0.339)
Observations		249	249	249	249	186
R^2		0.484	0.507	0.411	0.080	0.087
Adjusted R^2		0.474	0.497	0.399	0.062	0.062
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 19: *Regression 4 on all portfolios from January 1997 to March 2023. All results are in percentages and standard errors are in brackets.*

		Portfolios				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_B	I_B	0.064	0.167	0.846*	0.782	-0.011
		(0.531)	(0.389)	(0.498)	(0.612)	(0.245)
α_V	σ^2_M	0.213	-0.038	-0.193	-0.406**	0.013
		(0.145)	(0.106)	(0.136)	(0.167)	(0.067)
β_0	R_E	0.661***	0.643***	0.792***	0.131	-0.054
		(0.073)	(0.054)	(0.069)	(0.084)	(0.034)
β_B	$\mathrm{I}_B \cdot R_E$	0.172*	-0.045	-0.170*	-0.342***	-0.093**
		(0.097)	(0.071)	(0.091)	(0.112)	(0.045)
β_V	$\sigma^2_M \cdot R_E$	0.023	0.014	-0.021	-0.043**	0.001
		(0.018)	(0.013)	(0.017)	(0.021)	(0.008)
1	Constant	-0.465	-0.030	0.186	0.652	0.267
		(0.392)	(0.288)	(0.368)	(0.452)	(0.181)
Observations		314	314	314	314	314
R^2		0.533	0.575	0.447	0.113	0.090
Adjusted R^2		0.525	0.568	0.438	0.098	0.075
Note:		*p<0.1; **p<0.05; ***p<0.01				

Table 20: *Regression 5 on all portfolios from March 1974 to December 1996. All results are in percentages and standard errors are in brackets.* I_P *and its interactions have been multiplied by 1200 to convert coefficients to percentage*

		Portfolios:				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_P	I_P	0.568***	0.245**	0.151	−0.417***	−0.197***
		(0.131)	(0.122)	(0.146)	(0.118)	(0.060)
β_B	$I_B \cdot R_E$	0.649***	0.679***	0.569***	−0.080	0.053
		(0.185)	(0.172)	(0.205)	(0.166)	(0.083)
β_V	$\sigma_M^2 \cdot R_E$	0.197***	0.227***	0.217***	0.020	0.003
		(0.040)	(0.038)	(0.045)	(0.036)	(0.018)
β_P	$I_P \cdot R_E$	−0.093***	−0.102***	−0.118***	−0.025*	0.001
		(0.015)	(0.013)	(0.015)	(0.015)	(0.006)
1	Constant	1.068***	1.470***	1.503***	0.436	0.669***
		(0.406)	(0.378)	(0.451)	(0.364)	(0.217)
Observations	249	249	249	249	249	186
R^2	0.508	0.391	0.367	0.259	0.065	0.093
Adjusted R^2	0.500	0.381	0.356	0.247	0.050	0.073
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 21: *Regression 5 on all portfolios from January 1997 to March 2023. All results are in percentages and standard errors are in brackets.*I_P *and its interactions have been multiplied by 1200 to convert coefficients to percentage*

		Portfolios:				
Coefficient	Variable	Losers	Middle	Winners	WML	Val- Mom
α_P	I_P	0.052	−0.024	−0.040	−0.092	0.006
		(0.051)	(0.039)	(0.050)	(0.058)	(0.023)
β_B	$I_B \cdot R_E$	0.838***	0.586***	0.600***	−0.237**	−0.144***
		(0.097)	(0.074)	(0.094)	(0.109)	(0.043)
β_V	$\sigma_M^2 \cdot R_E$	0.328***	0.301***	0.333***	0.004	−0.022
		(0.035)	(0.027)	(0.034)	(0.040)	(0.016)
β_P	$I_P \cdot R_E$	−0.136***	−0.126***	−0.154***	−0.018	0.010
		(0.018)	(0.013)	(0.017)	(0.020)	(0.008)
1	Constant	0.019	0.162	0.398	0.379	0.262**
		(0.287)	(0.218)	(0.279)	(0.323)	(0.128)
Observations	314	314	314	314	314	314
R^2	0.511	0.503	0.514	0.369	0.098	0.087
Adjusted R^2	0.505	0.497	0.508	0.361	0.086	0.075
Note:				*p<0.1; **p<0.05; ***p<0.01		

Table 12 shows that pre-1997, CAPM does not hold for the WML portfolio, it however does for all sub-portfolios and their market beta decreases over the momentum terciles. In Table 13, post-1997, all market betas are significant, the betas also decrease across terciles. This is consistent with the findings of Table 2. The market beta for the WML portfolio is still negative in both periods but of a higher magnitude post-1997. Finally, the Val-Mom portfolio also has negative betas consistent with Table 2 across the whole sample but it shows a greater absolute value of market beta post-1997.

In Table 14, results pre-1997 show significant negative effect on returns during bear markets both through α_B and $\square_B$ for the WML portfolio. This is consistent with our findings from Table 3 although pre- 1997, α_B is quite large in comparison to the full sample regression. A similar bear market coefficient is found in Table 15. The main difference in results with regards to the sub-portfolios is that post-1997, the winners portfolio exhibit a beta decrease in bear markets which is significant but inconsistent with Table 3. This indicates that the Winners perform much better after 1997. Post- 1997, the WML beta also shows a decrease in bear markets and at a larger magnitude than in Table 3.

Table 16 displays very little statistical significance for the WML portfolio with regards to regression 3 except for the coefficient $\square_U$ (-0.468). This does show weak evidence for momentum crashes and is consistent with our previous findings. We can see the drivers of the effect because $\square_U$ for the Loser portfolio is positive and for the Winner it is quite small and negative. A similar pattern is present in the results in Table 17, post-1997, however there is no statistical significance and it is lower in magnitude. Overall, these findings are consistent with Table 4. The Val- Mom portfolio does show significance in some coefficients but not the critical $\square_U$ one, therefore it shows no optionality in bear markets and is in line with results from Table 4.

In both Tables 18 and 19, we find statistical significance for a negative variance effect for the WML portfolio, consistent with our findings from Table 5. However pre- 1997 we note that the bear market beta ($\square_0$ + $\square_B$) is marginally positive whereas post- 1997 it is negative. Variance has no statistical effect on the sub portfolios except for the Loser portfolio pre- 1997 where returns actually increase with volatility, also consistent with previous findings. The Val-Mom portfolio is the worst performer with regards to volatility pre- 1997 and it becomes the best post-1997. This might be what drives the insignificance of its variance coefficients in Table 5 and shows that the 1997 market changes had large impacts on the Val-Mom portfolio in terms of variance effects.

In Tables 20 and 21, all sub portfolios show consistent reduced performance in panic periods as found in Table 6. The coefficient $\square_P$ for the loser portfolio were lower in magnitude than the Winner's which is also consistent. This confirms the evidence of momentum crashes that was found. During panic periods, the winner portfolio performs significantly worse then the losers and should make the WML returns crash. Despite this, only the panic coefficients in Table 20 are statistically significant, which would mean that the WML portfolio only experiences momentum crashes pre-1997 and not after. This occurs even though the sub-portfolios show the expected behavior in both periods. Lastly, with regards to the Val- Mom portfolio, it shows some significance of the α_P estimator pre- 1997 which only occurs in that period and demonstrates that the portfolio received reduced returns in times of panic periods. The Val-Mom portfolio also shows significance of the $\square_B$ coefficient post- 1997 in line with the findings of Table 6.

Appendix 3: Residual plots for regression 5 for the Loser, Winner, WML and Val-Mom portfolios