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Is Japan Different? Evidence on Momentum and Market Dynamics*

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ABSTRACT

Recent evidence for the US indicates that momentum profits are conditional on market dynamics. This paper documents that the following finding holds for the Japanese market as well: momentum returns are significantly higher when the market stays in the same condition than when it transitions to the other state. This evidence is consistent with the behavioral model of Daniel et al. (1998, *Journal of Finance* 53(6), 1839–1885.). Furthermore, market transitions occurred more frequently in Japan compared to the US. These results explain why average momentum returns have historically been low in Japan, a fact generally referred to as an empirical failure of momentum. Overall, my findings indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan.

I. INTRODUCTION

Past return-based investment strategies, such as the medium-term momentum strategy by Jegadeesh and Titman (1993), have been studied intensively by financial economists over the last two decades. Their success has been documented for different countries (Rouwenhorst 1998, 1999), time periods (Jegadeesh and Titman 2001), and asset classes (Asness et al. 2013). Thus, momentum is one of the 'big three' anomalies besides size (Banz 1981) and value (Rosenberg et al. 1985; Fama and French 1992; Lakonishok et al. 1994).

There are three main stories that can explain such profitable investment strategies.[1] First, the factors that the strategy is based on are proxies for risk not captured by the suggested underlying asset pricing model.[2] Second, the market

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1 Fama and French (1996) identify these three arguments for the explanatory power of their SMB and HML factors.

2 E.g., the CAPM or the Fama-French three-factor model.

is not efficient and the profits are the result of systematic mispricing. Third, the empirical evidence is spurious because of survivorship bias or simply data mining.

In contrast to the size effect,[3] value and momentum have survived most out-of-sample tests. Whereas the debate on the value effect focuses on whether risk (e.g., Petkova and Zhang 2005; Zhang 2005) or mispricing (Lakonishok et al. 1994) is the main driver, I regard the abovementioned third argument as motivation for this article.

Despite the broad evidence of momentum profits around the world, there is one remarkable exception. Several studies argue that medium-term momentum strategies fail in Japan as they do not find any significant premium (e.g., Griffin et al. 2003; Fama and French 2012; Asness et al. 2013) or even observe a negative mean return (Chou et al. 2007). Although these results could be rejected as bad luck, there are other explanations why momentum returns are smaller in Japan or why momentum should not be considered alone. Chui et al. (2010) argue that momentum returns are weaker in countries with low individualism such as Japan or other parts of Asia. Some researchers, such as Fama and French (2012), are skeptical because 'it seems [that] the argument could go the other way' (p. 461), and they see the evidence as a chance result. In contrast, Asness (2011) argues that momentum should be studied in a system with value because they are negatively correlated. A combined 50/50 strategy also works in Japan, so he states that 'momentum in Japan [. . . is] the exception that proves the rule' (p. 67). However, the author gives no theoretical explanation for why value and momentum should be negatively correlated.

In the present article, I investigate why momentum strategies on average do not deliver any significant premium in Japan. In contrast to the majority of studies on momentum, I focus on momentum profits in different market dynamics. According to the behavioral model of Daniel et al. (1998), investors' overconfidence is expected to be higher when the market remains in the same state than when it reverses. Therefore, momentum returns should be higher in market continuations than in market transitions. Asem and Tian (2010) provide mixed evidence, because they can present this pattern for the US but not for Japan.

I instead show that market-dynamic conditional momentum is also present in the Japanese stock market by examining a comprehensive and carefully screened dataset. I observe that momentum returns are significantly higher when the market stays in the same condition than when it transitions to the other state. Furthermore, this pattern is more pronounced after periods of poor market performance. A potential explanation for this contrast might be the result of the option-like payoff of the loser portfolio after market declines. However, the question of why momentum on average exhibits no significant premium remains. Assuming that the distribution of market transitions for Japan is the same as in the US, the magnitude of momentum premiums would

3 See van Dijk (2011) for a comprehensive review of the size effect.

be substantially higher. Overall, my findings indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan. Finally, my results are robust to various specifications and also hold for other countries with low average momentum returns.

My study contributes to the existing literature in at least two ways. To the best of my knowledge, I am the first to provide evidence outside the US that momentum returns are conditional on market dynamics. This is consistent with the behavioral model of Daniel et al. (1998). Moreover, my findings explain why average momentum returns have historically been low in Japan, a fact generally referred to as an empirical failure of momentum.

The remainder of the paper is organized as follows. Section II introduces an overview of potential sources of momentum profits and Section III provides details about data and calculation of momentum returns and other risk factors. Section IV presents descriptive statistics about the risk factors, and Section V shows the main empirical results. Finally, Section VI applies robustness tests, and Section VII concludes.

II. SOURCES OF MOMENTUM PROFITS

There is an ongoing debate among researchers about the sources of momentum profits.[4] Models trying to explain momentum profits with market risk (Jegadeesh and Titman 1993, 2001) or the Fama-French factors (Jegadeesh and Titman 2001; Fama and French 1996; Grundy and Martin 2001) fail.

Besides these standard risk models, some other rational models exist.[5] While these models explain why momentum profits exist, the magnitude of the momentum returns observed (e.g., approximately one percent per month in Jegadeesh and Titman 1993) would require extreme levels of risk aversion for these models (see Chui et al. 2010).

As a consequence, most academic research focuses on behavioral explanations. Barberis et al. (1998) state that conservatism bias might lead to an initial underreaction to new information, followed by momentum profits. According to Grinblatt and Han (2005), underreaction is also caused by the disposition effect, which leads investors to stick with their past losers and sell their past winners too early. George and Hwang (2004) also provide evidence that anchoring on past prices might cause momentum.

Daniel et al. (1998) suggest a model in which traders receive public signals after trading a stock based on a private signal. If the public signal confirms their private signal, the investors attribute the success to their skills; however, they attribute non-confirming signals to bad luck because of a self-attribution bias. Because of this cognitive bias, the traders become overconfident about their stock selection skills, and this overconfidence drives momentum.

4 See, e.g., Jegadeesh and Titman (2011) for an overview.
5 See, e.g., Johnson (2002) or Sagi and Seasholes (2007).

Hong and Stein (1999) model two groups of investors: newswatchers observing some private information and momentum traders acting only on past prices. The private information diffuses slowly over time, causing some initial underreaction and attracting the momentum traders attention. Thus, they cause momentum and an eventual overreaction.

Based on the evidence in Cooper et al. (2004) that momentum profits exist only after periods of positive market performance, Asem and Tian (2010) develop hypotheses about the magnitude of momentum profits in different market dynamics, according to the models of Sagi and Seasholes (2007), Hong and Stein (1999), and Daniel et al. (1998). The empirical evidence that momentum profits are higher when the market remains in the same condition than when the market reverses is consistent only with the behavioral model of Daniel et al. (1998).

In the model of Daniel et al. (1998), a public signal confirming a trade based on a private signal increases overconfidence, while a disconfirming signal either slightly decreases overconfidence or keeps it constant due to self-attribution. Thus, positive public signals following a 'buy' or negative public signals following a 'sell' increase overconfidence.[6] Asem and Tian (2010) assume that investors, on average, traded more based on positive private signals when the past market was positive. Consequently, subsequent positive months should drive overconfidence more than subsequent negative months. Analogously, the investors should have traded more based on negative private signals in a period of bad market performance. Subsequent negative months should then drive overconfidence more than subsequent positive months. Thus, overconfidence can also increase in a bear market if the market continues to decline. As a result, I expect higher overconfidence and thus higher momentum profits when the market remains in the same state than when it reverses.

III. DATA AND CONSTRUCTION OF MOMENTUM RETURNS

A. Data

The sample of Japanese stocks used in this study is derived from Thomson Reuters Datastream. As Ince and Porter (2006) describe, raw return data from Datastream may not be error-free. Following Ince and Porter (2006), Griffin et al. (2010), and Schmidt et al. (2011), I apply several screens to ensure data quality. The static screens ensure that the sample contains only Japanese common equity stocks, as described in detail in Appendix A1.

This screening process leaves 5,043 unique securities. For these securities, I obtain return data from Datastream and accounting data from Worldscope. All

6 Note that Daniel et al. (1998) clearly state that confirming negative public signals ('bad news after a sell', p.1842) also drive investor overconfidence.

items are measured in JPY. To ensure data quality, I limit my analysis to the period from October 1986 to September 2012.[7] Following Ince and Porter (2006) and Schmidt et al. (2011), I apply several dynamic screens to the monthly return data.[8] As a proxy for the risk-free rate, I choose the Japanese one-month interbank rates offered by the British Bankers' Association (BBA).

To qualify for my sample from October of year y to September of year $y + 1$, a security needs a valid value for the market capitalization on March 31 and September 30 of year y, a positive book value at the fiscal year end that falls between April of year $y - 1$ and March of year y, and valid stock returns for the previous 12 months. I define book value as common equity plus deferred taxes, if available.[9]

From the 5,043 unique securities, 4,783 unique securities meet my sample-selection criteria in at least one year. The sample consists of a minimum of 803 stocks in 1986 and a maximum of 3,814 stocks in 2008.

B. Construction of Risk Factors

I construct the risk factors RMRF (see definition below), SMB ('small minus big'), HML ('high minus low'), WML ('winner minus losers'), and MOM ('momentum') following the standard procedures of Fama and French (2012) and Jegadeesh and Titman (2001).

RMRF is the excess return of the market return (RM), a value-weighted return of all sample stocks, over the risk-free rate (RF).

For the construction of the risk factors SMB and HML, I follow the procedure of Fama and French (2012), with the exception of the portfolio construction date. The majority of the companies listed in Japan have March 31 as their financial year end.[10] As I wish to ensure that all accounting information is publicly available at the time of portfolio construction, I choose the end of September, instead of June, as the construction date for the book-to-market (B/M) and size portfolios. At the end of September of each year y, all stocks are sorted independently into two size groups, Big (B) and Small (S), and three B/M groups, High (H), Medium (M), and Low (L). According to Fama and French (2012), I choose the top 90% of the aggregate market capitalization at the end

7 'The base year for the Worldscope Database is 1980, although statistically significant company and data item representation is best represented from January 1985 forward' (Thomson Financial 2013, p.27).

8 Ince and Porter (2006) point out that raw return data from Datastream could especially affect momentum returns. E.g., Datastream repeats the last valid data point for a delisted stock. This fact could, for example, lead this stock to wrongly appear in the winner portfolio when the overall market is down, as it seems to outperform the market.

9 This definition is standard in the Fama-French factor literature, see, e.g., Fama and French (1993) or Fama and French (1996).

10 See also Chan et al. (1991) or Daniel et al. (2001).

of September of year y as the size breakpoint.[11] B/M is calculated as the book value at the fiscal year end, falling between April of year $y - 1$ and March of year y, divided by the market capitalization at the end of March of year y. The breakpoints for the book-to-market ratio are the 30th and 70th percentiles of B/M for the biggest stocks (B), which are also applied to small stocks.

At the intersection of the two size and three B/M groups, I construct six portfolios (S/H, S/M, S/L, B/H, B/M, and B/L). Monthly value-weighted returns are calculated for the next twelve months starting from October of year y until September of year $y + 1$. The portfolios are reformed at the end of September of year $y + 1$. The size factor, SMB, is the difference between the average returns of the three small stock and the three big stock portfolios, while the value factor, HML, is the difference between the average return of the two high B/M and the two low B/M portfolios.

Following Carhart (1997) and Fama and French (2012), I also construct WML. Each month t, I sort stocks by their cumulative performance from month $t - 11$ to month $t - 1$ (it is standard to skip the last month t). Again, the momentum breakpoints for all stocks are the 30th and 70th percentiles of lagged performance for the biggest stocks (B). Here, L denotes losers (bottom 30% of lagged return), N denotes neutral (middle 40%), and W denotes winners (top 30%). The intersection of the size and momentum groups results in the six value-weighted portfolios S/L, S/N, S/W, B/L, B/N, and B/W. Similar to the calculation of HML, WML is the difference between the average return of the two winner and the two loser portfolios.

Additionally, I construct the momentum factor, MOM, according to Jegadeesh and Titman (2001). At the end of each month t, I rank the stocks in my sample based on their cumulative return for month $t - 5$ to month $t - 1$ and assign the stocks to ten portfolios. Portfolio 10 comprises past winners and portfolio 1 comprises past losers. Each portfolio is held for six months. I calculate value-weighted returns to reduce the effect of small stocks. As in Jegadeesh and Titman (2001), I construct overlapping portfolios; in other words, a momentum decile portfolio in any month holds stocks ranked in that decile from the previous six ranking months. Each monthly cohort is assigned an equal weight in this portfolio. MOM is the return difference between portfolio 10 and portfolio 1.

Besides the raw momentum return, I also calculate the Fama and French (1993) adjusted momentum α for each month t as

$$\alpha_t = WML_t - \hat{\beta} \cdot RMRF_t - \hat{s} \cdot SMB_t - \hat{h} \cdot HML_t, \tag{1}$$

where RMRF, SMB, and HML are the common risk factors, as described above. $\hat{\beta}$, $\hat{s}$, and $\hat{h}$ are the estimated loadings from a time series regression of the

11 Fama and French (1993) calculate the median for all NYSE stocks but apply this breakpoint to all NYSE, AMEX, and NASDAQ stocks. They want to avoid a high weight of tiny stocks within the size dimension as NYSE stocks have, on average, a higher market capitalization. Fama and French (2012) mention that the NYSE median roughly corresponds to 90% of the aggregate market cap.

Table 1 Descriptive Statistic Risk Factors

	RM	RF	RMRF	SMB	HML	WML	MOM
Mean	0.06	0.15	–0.08	0.10	0.68	0.02	0.19
Std dev	5.57	0.19	5.58	3.68	2.59	4.73	6.66
t-Mean	0.19	13.41	–0.27	0.49	4.64	0.06	0.50
				Correlations			
RM	1.00						
RF	–0.03	1.00					
RMRF	1.00	–0.07	1.00				
SMB	0.00	0.05	0.00	1.00			
HML	–0.22	–0.03	–0.22	0.02	1.00		
WML	–0.21	–0.06	–0.20	–0.25	–0.07	1.00	
MOM	–0.14	–0.04	–0.14	–0.25	–0.07	0.88	1.00

The table reports summary statistics of the market return (RM), the risk free rate (RF), the excess return of the market over the risk free rate (RMRF = RM – RF), the size factor (SMB), the value factor (HML), and the two momentum factors (WML and MOM). The statistics are computed over the period October 1986 to September 2012.

momentum variable on the common Fama and French (1993) risk factors plus a constant. As medium-term momentum usually cannot be explained by the Fama and French (1993) risk factors (see, e.g., Fama and French 1996), I do not expect my results to be altered by this adjustment.

IV. BASIC EVIDENCE

This section reports the descriptive statistics of the standard risk factors from October 1986 to September 2012 in Japan. Table 1 shows the summary statistics and correlations. The average return of the market (RM) is only slightly higher than the average risk-free rate (RF), resulting in an equity risk premium (RMRF) that is nearly zero. Fama and French (2012) observe even a negative equity risk premium for a slightly earlier time frame.

There is only a small size premium of 0.10% that is not significantly different from zero ($t = 0.49$). In contrast, I document the well-known value premium in Japan. The average HML return is 0.68 and 4.64 standard errors from zero.

Similar to Fama and French (2012) and Asness et al. (2013), I cannot find a premium for WML. Moreover, the slightly different methodology for MOM does not change the result. Comparable to Griffin et al. (2003), I observe only a small premium of 0.19% that is not significantly ($t = 0.50$) different from zero. This evidence leads to the common view that momentum strategies fail in Japan.[12]

12 The contrary evidence of negative medium-term momentum in Chou et al. (2007) can be reconciled with my results because of two major methodological differences. Chou et al. (2007) use equal-weighted momentum portfolios and do not skip one month between portfolio ranking and investment period. Following their approach, the return on WML and MOM would be –0.545% and –0.568% with t-statistics of $t = -2.01$ and $t = -1.83$.

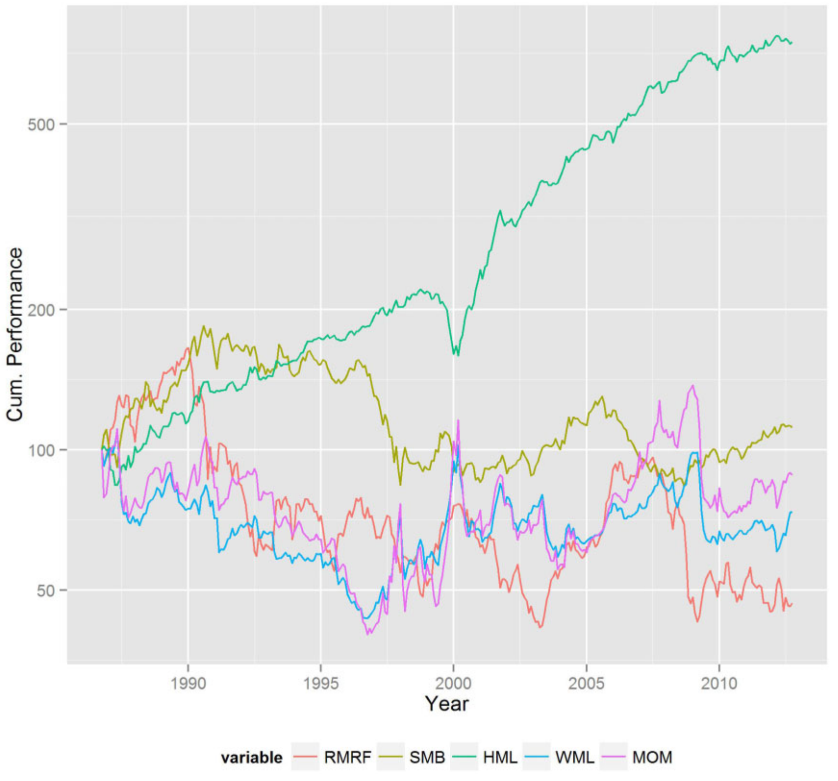

Figure 1 Cumulative Performance of the Risk Factors Premiums. The figure plots the cumulated performance of the monthly time-series of the market (RMRF), SMB, HML, WML and MOM factor. The time series are computed over the period October 1986 to September 2012.

The second part of Table 1 shows the correlations of the risk factors. Besides, the naturally high correlations of the two factors depending on the market (RM and RMRF) and on past returns (WML and MOM), the correlations between the other factors are rather small. There is a small negative correlation between RMRF and HML of –0.22 and between RMRF and WML (MOM) of –0.20 (–0.14). We also see a negative correlation between HML and WML (MOM) of –0.07 (–0.07), but not as negative as in Asness (2011).[13]

Figure 1 visualizes the cumulative performance of my risk factors RMRF, SMB, HML, WML, and MOM from October 1986 to September 2012. The chart illustrates the aforementioned results. The equity risk premium is very volatile,

13 Changing the month of the market capitalization in the denominator of B/M from March to September would push the coefficient down to a level similar to that in Asness (2011) (–0.55). See also Asness and Frazzini (2013) for a detailed analysis of this alternative specification.

and especially in the nineties, we see a lot more market transitions in Japan than we would in the US. The size premium is positive for the beginning of my sample until the early nineties. This result is consistent with the observation of a positive size premium in earlier studies of the Japanese market, as in Chan et al. (1991) or Daniel et al. (2001). After the early nineties, I document a negative performance for SMB. In contrast, I see a nearly stable value effect, interrupted only by a sharp decline in the cumulative value premium during the tech bubble around the year 2000.

WML and MOM both are highly volatile and correlated. The overall cumulative performance is actually negative. The different signs of the two premiums between Table 1 and Figure 1 are due to differences in the arithmetic and geometric averages. Although there are time periods when momentum strategies work well, such as in the mid two thousands or late nineties, there are also months with sharp momentum crashes. These crashes tend to occur when the market rebounds after some months of decline (growth) as in October 1990 or February 2009 (March 2000).

The following section analyzes this dependency of momentum returns on market dynamics.

V. CONDITIONAL MOMENTUM PROFITS

A. Market Dynamics

Following Asem and Tian (2010), I classify each month t the past market as either a BULL market or a BEAR market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month t as a subsequent UP (DOWN) market if the return of the market in month t is non-negative (negative).

This categorization results in 87 (71) subsequent DOWN (UP) market months following BEAR markets and 59 (83) subsequent DOWN (UP) market months following BULL markets. Compared with the US market in Asem and Tian (2010), we see a rather balanced proportion of the different market dynamics. For the US, past BULL markets dominate the sample, with 453 following UP markets and 246 following DOWN markets. The subsequent month is 135 (114) times classified as an UP (DOWN) market after a past BEAR market. This deviating distribution indicates why the average momentum profits could be lower in Japan than in the US.

Panel A of Table 2 shows the momentum profits following past BEAR markets. The mean momentum return is 2.35% ($t = 6.34$) per month when the subsequent market is DOWN and –2.88% ($t = -4.54$) when the subsequent market is UP. I obtain a difference of 5.24% that is highly significant ($t = 7.12$). Thus, momentum profits are higher when the market remains negative. The high momentum profits that occur when the market continues to decline are remarkable, as Cooper et al. (2004) argue that momentum profits do not exist after negative market returns. I report an average momentum mean of 0.00%

Table 2 Market Dynamics and Momentum Profits

	Subsequent DOWN Markets	Subsequent UP Markets	DOWN – UP Markets	Both subsequent Months
Panel A: Past BEAR Market				
Mean	2.35	–2.88	5.24	0.00
t-Mean	6.34	–4.54	7.12	0.00
FF-α	1.49	–1.99	3.48	–0.07
t-FF-α	4.04	–3.46	5.10	–0.20
No. of months	87	71		
Panel B: Past BULL Market				
Mean	–1.35	1.40	–2.74	0.26
t-Mean	–2.84	3.55	–4.45	0.80
FF-α	–1.85	2.36	–4.22	0.61
t-FF-α	–3.74	6.10	–6.70	1.74
No. of months	59	83		
Panel C: Both past conditions				
Mean	0.60	–0.52	1.12	0.02
t-Mean	1.69	–1.32	2.11	0.06
FF-α	–0.05	0.39	–0.45	0.18
t-FF-α	–0.16	1.05	–0.89	0.70

The table reports the WML means, and monthly Fama and French (1993) adjusted return means (FF-α) means for different market dynamics. For each month *t*, I classify the past market either as a BULL market or a BEAR market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month *t* as subsequent UP (DOWN) market if the return of the market in *t* is non-negative (negative). The statistics are computed over the period October 1986 to September 2012.

after BEAR markets; however my results demonstrate that this mean is composed of two highly contrary means depending on the subsequent market state. The Fama and French (1993) adjusted α's have the same signs and significance levels as the raw momentum profits.

The results following BULL markets are shown in Panel B of Table 2. The mean momentum return is –1.35% (t = –2.84) when the market reverses and 1.40% (t = 3.55) when it remains in the same state. As stated earlier, the momentum profits depend on the subsequent market development, but the pattern is not as pronounced as after a BEAR market. The difference in momentum returns is –2.74%, with –4.45 standard errors from zero. The Fama and French (1993) adjusted α's lead to the same result.

In Panel C, I distinguish only between the subsequent month and determine that momentum profits are higher for subsequent DOWN market months. The result indicates that the effect after past BEAR markets dominates the effect after past BULL markets. Although the momentum profits in subsequent DOWN markets and the difference in momentum profits are significant, the effect is not as pronounced as for the both different past market regimes. In addition, the Fama and French (1993) adjusted α's show only a small difference and are not significant.

At the bottom right corner of Table 2, the outcome of Section IV is shown again. Further, the Fama and French (1993) adjusted α demonstrates the lack of momentum profits for an unconditional model. The question remains regarding why average momentum returns for Japan are low, although I document the same significant patterns in different market dynamics as in the US, where significant momentum returns are observed. I believe that the answer lies in the different distribution of market transitions. As mentioned above, UP markets following past BULL markets dominate in Asem and Tian (2010) for the US. This pattern is present only for 28% of the months in Japan, compared with 48% for the US. Assuming that the distribution of market transitions for Japan is the same as that in the US and assuming constant premiums for the particular market dynamics, the mean momentum return would be 0.18% per month for WML and 0.40% for MOM.[14] These returns correspond to substantial higher yearly premiums of 2% or 5%. Overall, my findings indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan.

B. A Potential Explanation

The previous subsection clarified that momentum profits are higher when the market stays in the same condition than when it reverses. As described in Section II, these patterns are consistent with the behavioral model of Daniel et al. (1998). However, the model does not provide an explanation for why the pattern is more pronounced after BEAR markets than after BULL markets.

Daniel and Moskowitz (2013) analyze the occurrence of momentum crashes and argue that these crashes follow periods of market declines, when volatility is high and simultaneous with market rebounds. This situation is analogous to our (BEAR, UP) state, where we observe sharp momentum losses. Daniel and Moskowitz (2013) document that momentum portfolios have significant time-varying exposures to the market. By their nature, the market beta of the momentum portfolio is expected to be higher after a past BULL market than after a BEAR market because it is likely that the portfolio is long in high beta stocks and short in low beta stocks. Furthermore, Daniel and Moskowitz (2013) demonstrate that not only do the market betas of the momentum portfolio differ depending on the past market performance but also that after BEAR markets, the beta of the momentum portfolio is significantly lower when the subsequent market is UP. Daniel and Moskowitz (2013) conclude that, 'in bear markets, the momentum portfolio is effectively short a call option on the market' (p. 19). Moreover, the loser portfolio is the predominant source of this

14 Instead, I report 0.02% and 0.19% in Section IV.

optionality. They argue that this evidence can be seen as consistent with the theory of Merton (1974) that a common stock is a call option on the value of the firm. Especially after a BEAR market environment, the stocks of the loser portfolio are probably not as deep in-the-money as the stocks of the winner portfolio, and consequently have a stronger option-like behavior.

This so-called optionality is only present after BEAR markets and not after BULL markets. Therefore, momentum returns in the US exhibit a substantially higher sensitivity to the subsequent market development after BEAR markets than after BULL markets. To evaluate whether this evidence may also explain the more pronounced pattern after BEAR markets of the last subsection, I replicate the main model of Daniel and Moskowitz (2013) for Japan.

For the ten momentum portfolios, as described in Section III.B, and the difference of the two extreme decile returns (MOM), I estimate the following regressions:

$$R_t = \alpha + \alpha_B I_B + [\beta + I_B(\beta_B + I_U \beta_{B,U})] RMRF_t + \varepsilon_t \quad (2)$$

$$R_t = \alpha + \alpha_L I_L + [\beta + I_L(\beta_L + I_D \beta_{L,D})] RMRF_t + \varepsilon_t \quad (3)$$

In these regressions, I_B and I_L are dummies indicating whether the past cumulative twelve-month return of the market (RM) is negative (I_B) or non-negative (I_L), while I_U and I_D are dummies indicating whether the subsequent month is non-negative (I_U) or negative (I_D). Table 3 shows the results for both regressions.

In Panel A, I estimate the conditional CAPM of equation 2 with I_B as a past BEAR market indicator and I_U as a subsequent UP market indicator. The associated coefficients α_B and β_B indicate whether the intercept and market-beta differ after past BEAR markets while $\beta_{B,U}$ indicates the extent to which the subsequent UP and DOWN market betas differ after such a past BEAR market.

For the momentum portfolio MOM, I determine differences in the market beta depending on the market conditions, consistent with Grundy and Martin (2001) and Daniel and Moskowitz (2013). As expected, I observe a positive beta of 0.185 after BULL markets, while the sign of the beta becomes negative after BEAR markets: if the subsequent market is DOWN, the beta is –0.257 lower, but if the subsequent market is UP, the beta is additional –0.909 (t = –3.76) lower. This results in an overall market beta of $\beta + \beta_B + \beta_{B,U}$ = –0.981 if the market reverses after past BEAR markets, but only in a beta of $\beta + \beta_B$ = –0.072 if the market declines further. The analysis for each of the ten momentum portfolios shows that the prevailing source of this optionality is the loser portfolio. While the UP market beta of the winner portfolio is 0.304 lower than in subsequent DOWN markets, the loser portfolio beta is 0.605 higher, with a point estimate of 1.72.

In Panel B, I analyze the corresponding model after past BULL markets. In accordance with Daniel and Moskowitz (2013), I do not observe the optionality as described above after BULL markets. While I see a considerable change in the market beta of the momentum portfolio MOM between past BEAR markets and

Table 3 Momentum Portfolio Optionality

	1	2	3	4	5	6	7	8	9	10	MOM
Panel A: Past BEAR Market and Subsequent UP Market Indicator											
α	–0.265	0.054	0.014	0.129	0.033	0.150	0.241	0.336	0.341	0.249	0.514
	(–0.83)	(0.24)	(0.08)	(0.88)	(0.27)	(1.46)	(2.16)	(3.09)	(2.62)	(0.92)	(1.03)
α_B	–0.832	–0.831	–0.510	–0.578	–0.392	–0.473	–0.297	–0.366	–0.127	0.404	1.236
	(–1.47)	(–2.11)	(–1.74)	(–2.22)	(–1.82)	(–2.58)	(–1.50)	(–1.90)	(–0.55)	(0.84)	(1.40)
β	1.034	0.931	0.917	0.896	0.921	0.938	0.965	1.014	1.108	1.220	0.185
	(16.10)	(20.90)	(27.56)	(30.37)	(37.75)	(45.20)	(42.92)	(46.46)	(42.34)	(22.45)	(1.85)
β_B	0.081	0.109	0.102	0.065	0.037	–0.010	–0.044	–0.093	–0.119	–0.176	–0.257
	(0.74)	(1.45)	(1.82)	(1.30)	(0.89)	(–0.29)	(–1.17)	(–2.53)	(–2.69)	(–1.92)	(–1.52)
$\beta_{B,U}$	0.605	0.441	0.270	0.280	0.132	0.089	–0.027	–0.108	–0.219	–0.304	–0.909
	(3.89)	(4.09)	(3.35)	(3.93)	(2.24)	(1.77)	(–0.49)	(–2.05)	(–3.46)	(–2.31)	(–3.76)
Panel B: Past BULL Market and Subsequent DOWN Market Indicator											
α	0.292	0.233	0.122	0.193	–0.056	–0.119	–0.117	–0.279	–0.289	–0.044	–0.336
	(0.94)	(1.08)	(0.76)	(1.35)	(–0.48)	(–1.21)	(–1.10)	(–2.68)	(–2.29)	(–0.17)	(–0.69)
α_L	–0.487	–0.178	–0.004	–0.012	0.226	0.249	0.496	0.724	0.671	0.039	0.526
	(–0.81)	(–0.43)	(–0.01)	(–0.04)	(1.01)	(1.31)	(2.43)	(3.63)	(2.76)	(0.08)	(0.56)
β	1.394	1.243	1.144	1.089	1.018	0.969	0.908	0.871	0.888	0.904	–0.491
	(27.17)	(34.85)	(43.33)	(46.25)	(53.23)	(59.62)	(51.93)	(50.94)	(42.71)	(21.19)	(–6.16)
β_L	–0.378	–0.312	–0.254	–0.208	–0.133	–0.025	0.021	0.114	0.209	0.382	0.760
	(–2.85)	(–3.39)	(–3.73)	(–3.41)	(–2.70)	(–0.60)	(0.46)	(2.59)	(3.90)	(3.47)	(3.70)
$\beta_{L,D}$	0.037	0.001	0.055	0.028	0.072	–0.011	0.072	0.057	0.022	–0.133	–0.169
	(0.18)	(0.00)	(0.52)	(0.29)	(0.93)	(–0.17)	(1.03)	(0.84)	(0.26)	(–0.78)	(–0.53)

The table reports the results of a regression of the excess return of ten momentum portfolios and the difference of the two extreme decile returns (MOM) on the excess return of the market (RM) and various indicator variables. In Panel A, I estimate the following regression for each of these portfolios:

$$R_t = \alpha + \alpha_B I_B + [\beta + I_B(\beta_B + I_U \beta_{B,U})]RMRF_t + \varepsilon_t$$

In Panel B, I estimate the following regression for each of these portfolios:

$$R_t = \alpha + \alpha_L I_L + [\beta + I_L(\beta_L + I_D \beta_{L,D})]RMRF_t + \varepsilon_t$$

In these regressions, I_B and I_L are dummies indicating whether the past cumulative twelve-month return of the market (RM) is negative (I_B) or non-negative (I_L). I_U and I_D are dummies indicating whether the subsequent month is non-negative (I_U) or negative (I_D). The statistics are computed over the period October 1986 to September 2012.

past BULL markets in general (0.76), the difference between subsequent UP and DOWN markets is small and not significant (–0.169). The point estimate for the momentum portfolio is $\beta + \beta_L = 0.269$ for subsequent UP markets and $\beta + \beta_L + \beta_{L,D} = 0.1$ for subsequent DOWN markets. Thus, similar to that in the US, the momentum strategy in Japan exhibits a substantially higher sensitivity to the subsequent market development after BEAR markets than after BULL markets.

Overall, these results can be interpreted as consistent with the theory of Merton (1974) that a common stock is a call option on the value of the firm. In particular, the stocks of the loser portfolio are not as deep in-the-money after BEAR markets than after BULL markets and therefore exhibit a stronger option-like behavior. This optionality may explain why the patterns, described in the previous subsection, are more pronounced after BEAR markets than after BULL markets.

VI. ROBUSTNESS CHECKS

A. Alternative Specifications

The results in the previous section demonstrated that momentum profits are responsive to current market dynamics. In this section, I will address some alternative specifications and their effects on my results.[15]

Although the choice of the currency should not significantly affect long-short difference returns, such as the momentum portfolios, the market excess return (RM) can differ significantly depending on the currency used to measure it. Thus, the classification into past BEAR/BULL markets and subsequent UP/DOWN markets may differ when returns are measured in USD. Using USD returns results in a slightly different distribution of market states; however, the main results remain the same and are not affected by the choice of the return currency.

Asem and Tian (2010) have been unable to confirm their results for Japan. However, I have demonstrated that market-dynamic conditional momentum is also present in the Japanese stock market. Because Asem and Tian (2010) do not provide details about their data process, I am unable to explain this contrary evidence. While I trust my comprehensive and carefully screened dataset, this contrary finding could be the result of different time periods covered in the papers. This might indicate that the results are not stable over time. Therefore, I replicate my analysis for the time period between October 1986 and December 2005, which is nearly identical to January 1985 to December 2005 as in Asem and Tian (2010). However, the differences in WML means of 6.49% and –3.15% after BEAR and BULL markets, respectively, are a little more pronounced in this alternative sub-period period.

The momentum strategy definitions of Jegadeesh and Titman (1993), MOM, and the Carhart (1997), WML, are the most common momentum proxies in financial research. To determine whether the alternative definition alters my results, I replace WML with MOM. The MOM means are 2.59%, –3.17%, –0.71%, and 1.51% for (BEAR, DOWN), (BEAR, UP), (BULL, DOWN), and (BULL, UP) states, respectively. Thus, my results are robust to the alternative momentum definition.

B. Alternative Sentiment Definition

In the present article, I document that momentum profits in Japan are higher when the market stays in the same condition than when it reverses. This result

15 The results are not tabulated for brevity and available upon request.

Table 4 Alternative Sentiment Definition

		High Sentiment	Low Sentiment	High-Low
Long leg	mean	–0.21	0.23	–0.44
	t-value	–0.44	0.51	–0.68
Short leg	mean	–0.79	0.77	–1.56
	t-value	–1.39	1.38	–1.96
Long-short	mean	0.58	–0.54	1.12
	t-value	1.72	–1.31	2.10

The table reports average excess returns for the long and short leg of the WML factor following high and low sentiment levels. I classify each return as following a high sentiment month or low sentiment month. A high sentiment month is one in which the value of the Tankan large manufacturing index is above the median value of my sample period and vice versa for the low sentiment months. The statistics are computed over the period October 1986 to September 2012.

is consistent with Daniel et al. (1998), who suppose that confirming public information leads to investor overconfidence. Confirming public information is defined as a subsequent positive month after a BULL market and a subsequent negative month after a BEAR market. However it is possible that variables other than market dynamics can also be used as a proxy for investor overconfidence or more general investor sentiment.

Stambaugh et al. (2012) explore how investor sentiment influences the returns of a broad set of anomalies for a US sample. They argue that the primary form of mispricing (due to short selling impediments) is overpricing, and that overpricing is positively related to sentiment. Thus, mispricing should be more present when sentiment is high and for the stocks in the short leg of the trading strategies. Their results show that the returns for each anomaly are higher, and in contrast to the long leg of the strategy, the short legs are more profitable following high sentiment levels.

In this subsection, I follow Stambaugh et al. (2012) to test the effect of sentiment on momentum returns in Japan. Therefore, I use the Tankan, a short-term business survey of enterprises conducted by the Bank of Japan, as a measure for sentiment. I classify the WML return each month as following a high-sentiment month or low-sentiment month. A high-sentiment month is one in which the value of the Tankan large manufacturing index is above the median value of my sample period and vice versa for the low-sentiment months.[16] Table 4 reports the WML returns as well as the returns of the long and short leg for high- and low-sentiment months.

The results show that WML returns (row 'Long-short') are significantly positive following high sentiment and (insignificantly) negative following low

16 According to Kataoka (2010) the outcome of large manufacturing enterprises, in particular, attracts attention and is used by a large number of studies, e.g., Fatum et al. (2012).

Table 5 Robustness – Market Dynamics and Momentum Profits for other International Markets

Past Market	BEAR		BULL	
Subsequent Month	DOWN	UP	DOWN	UP
Panel A: Korea				
Mean	2.71	–5.95	–0.18	1.95
t-Mean	2.64	–3.05	–0.32	2.88
No. of months	46	31	51	64
Panel B: Taiwan				
Mean	1.62	–4.23	–0.55	2.68
t-Mean	2.07	–3.21	–0.73	3.32
No. of months	37	33	55	67
Panel C: Turkey				
Mean	2.00	–3.84	0.15	0.65
t-Mean	1.90	–3.69	0.21	0.97
No. of months	31	42	56	63

The table reports the WML means for different market dynamics in Korea, Taiwan and Turkey. I classify for each month *t* the past market either as a BULL market or a BEAR market, depending on whether the past cumulative twelve-month return of the market (RM) is non-negative or negative. Furthermore, I classify month *t* as subsequent UP (DOWN) market if the return of the market in *t* is non-negative (negative). The statistics are computed over the period July 1995 to June 2012.

sentiment. The sentiment-related difference in momentum returns is 1.12% per month ($t = 2.10$). The prevailing source of this difference is the short leg of the strategy. While the (insignificant) difference for the long leg is –0.44, the short leg earns 1.56% ($t = -1.96$) less following high sentiment than following low sentiment.

My evidence for sentiment-influenced WML returns in Japan confirms the results of Stambaugh et al. (2012). Furthermore, the results serve as a robustness check, as I replace my proxy for investor overconfidence with the Tankan survey, a proxy for investor sentiment. Although sentiment and overconfidence are not the same, the results point in the same direction as they demonstrate that, under certain circumstances, momentum profits are also present in the Japanese market.

C. International Robustness

Chui et al. (2010) argue that cross-country differences in individualism are related to the average momentum profits in these countries, while I argue that momentum profits depend on market dynamics. In Table 5, I check whether my results also hold in countries with low individualism scores and low average momentum profits. Korea, Taiwan, and Turkey are the only countries besides Japan with negative average momentum profits in Chui et al. (2010), and they are all in the lowest country individualism group. For all three countries, I report significant and positive (negative) momentum premiums after DOWN (UP) markets following past BEAR markets. Except in Turkey, I also see significant and positive momentum profits in UP markets following past BULL markets and negative momentum returns in DOWN markets. Although, the patterns following BULL markets in Turkey are not as pronounced as for the other countries, I still obtain higher momentum profits if the market continues to rise.

VII. SUMMARY

In this paper, I provide the first evidence concerning the profitability of medium-term momentum strategies depending on market dynamics in Japan. While several studies conclude that momentum strategies are an empirical failure in Japan, I argue that momentum must be studied conditional on market dynamics.

First, I determine that momentum returns are significantly higher when the market stays in the same condition than when it transitions to the other state. The mean momentum return following a BULL market is –1.35% per month when the subsequent market is DOWN and 1.40% when the subsequent market is UP. Following BEAR markets, the mean momentum return is 2.35% when the market continues to go DOWN and –2.88% when it reverses. These findings are consistent with the behavioral model of Daniel et al. (1998). However, the question remains regarding why momentum on average exhibits no significant premium. Assuming that the distribution of market transitions for Japan is the same as that in the US and assuming constant premiums for the particular market dynamics, the yearly premiums for WML and MOM would be 2% or 5%, respectively. Overall, my results indicate that different market dynamics, and not different momentum, cause the overall low momentum returns in Japan.

Second, I observe that this pattern is more pronounced after periods of poor market performance. I report a difference of 5.24% after BEAR markets but a difference of only 2.74% after BULL markets. A potential explanation of this asymmetry might be the result of the option-like payoff of the loser portfolio after BEAR markets. I do not observe this optionality after BULL markets.

Third, my findings are robust to various specifications and apply to other countries with low average momentum returns.

My results should be of interest to researchers and practitioners alike. This paper enriches the ongoing debate about the source of momentum profits and shows the market dynamics in which momentum strategies would be profitable. Investors should be aware that momentum strategies might be exposed to sharp momentum crashes in BEAR markets if the market rebounds. On the other hand, this risk is rewarded by high momentum profits if the market remains in the same condition. For the Japanese market, my findings indicate that momentum strategies might be more profitable in the future if the overall market performance is more stable than in the past.

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APPENDIX A

A1 Static Screens

I use Thomson Reuters Datastream constituent lists to build my dataset. To avoid a survivorship bias, I use the intersection of Datastream research lists, Worldscope lists, and dead lists.[17] I restrict my sample to stocks of type equity; companies and securities located and listed in Japan; the primary quotation of a security; and the (major) security with the biggest market capitalization and liquidity for companies with more than one equity security. Furthermore, I exclude securities with quoted currency other than the local JPY or ISIN country code other than 'JP'. To eliminate non-common equity stocks, I search similar to Griffin et al. (2010) for suspicious words in the company name, indicating that the security is more likely a duplicate, preferred stock, dept, etc.[18]

Table A1 Generic filter rules to exclude non-common equity securities, mostly recommended by Ince and Porter (2006) and Griffin et al. (2010)

Non-common equity	Keywords
Duplicates	'DUPLICATE' 'DUPL' 'DUP.' 'DUPE' 'DULP' 'DUPLI' '1000DUPL' 'XSQ' 'XETa' 'DUP' 'DUPL'
Depository Receipts	'ADR' 'GDR'
Preferred Stock	'Stock' 'PREFERRED' 'PF.' 'PFD' 'PREF' 'PF' 'PRF'
Warrants	'WARRANT' 'WARRANTS' 'WTS' 'WTS2' 'WARRT'
Debt	'DEB' 'DB' 'DCB' 'DEBT' 'DEBENTURES' 'DEBENTURE' 'BOND' '%'
Unit Trusts (2 words)	'RLST IT' 'INVESTMENT TRUST' 'INV TST' 'UNIT TRUST' 'UNT TST' 'TRUST UNITS' 'TST UNITS' 'TRUST UNIT' 'TST UNIT'
Unit Trusts (1 word)	'UT' '.IT'
ETF	'ETF' 'ISHARES' 'INAV' 'X-TR' 'LYXOR' 'JUNGE' 'AMUNDI'
Ince and Porter (2006)	'500' 'BOND' 'DEFER' 'DEP' 'DEPY' 'ELKS' 'ETF' 'FUND' 'FD' 'IDX' 'INDEX' 'MIPS' 'MITS' 'MITS.' 'MITT' 'MITT.' 'NIKKEI' 'NOTE.' 'NOTE' 'PERQS' 'PINES' 'PINES.' 'PRTF' 'PTNS' 'PTSHP' 'QUIBS' 'QUIDS' 'RATE' 'RCPTS' 'RECEIPTS' 'REIT' 'RETUR' 'SCORE' 'SPDR' 'STRYPES' 'TOPRS' 'WTS' 'XXXXX' 'YIELD' 'YLD' 'QUIDS'
Expired securities	'EXPIRED' 'EXPD' 'EXPIRY' 'EXPY'

The table lists keywords, which serve as indicators, that a Datastream security is, in contrast to its stock classification in Datastream, not common equity. If a part of the security name is matched to one of the keywords from the second column, the security is most likely not a common stock but the type in the first column of the same row. After a manual review, the identified securities are excluded from the sample.

17 Research lists (FJAP, FTOKYO, FOSAKA, FJASDAQ), Worldscope list (WSCOPEJP), Dead list (DEADJP).

18 See Table A1 for a list of all the used keywords.