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Weekend Effect and Short Sales: Evidence from Hong Kong

Jinghan Cai University of Scranton, United States

Jibao He Shenzhen Stock Exchange, China

Le Xia BBVA, Hong Kong and Renmin University of China, China

Weili Zhai* Shenzhen University, China

Abstract: Using a unique short selling setting in Hong Kong stock market, we test the Chen and Singal (2003) hypothesis that speculative short sellers add to the selling pressure on Mondays and hence add to the weekend effect. We document that, first, the weekend effect exists in Hong Kong stock market, regardless of the existence of short sale constraints; second, after introducing short selling, the individual stocks face more significant weekend effect. The reported result is robust over different estimation models, and over different choices of control groups. Our findings strongly support the Chen and Singal (2003) hypothesis.

Keywords: Short sales; Weekend effect; Hong Kong stock market.

JEL Classification: G10; G15

1. Introduction

The weekend effect, also known as day-of-the-week effect, is probably one of the most studied fields in market anomaly literature. Generally, the weekend effect refers to the systematically lower Monday returns, or higher Friday returns, or both. Related literature begins from French (1980), which studies the S&P 500 Index over the period 1953 through 1977, and from Gibbons and Hess (1981), which study the S&P 500 Index and CRSP value- and equally-weighted indices for NYSE and AMEX securities over the period 1962 through 1978. Later on, there has been much evidence in support of the systematic lower returns on Mondays. Keim and Stambaugh (1984) find that Friday returns are lower when there is Saturday trading. Ariel (1990) finds that a significantly larger number of stocks rises preholiday than postholiday. Wang *et al.* (1997) find that the lower returns systematically occur on Mondays in the second half of a month.

In addition to the U.S. stock market, researchers have also documented weekend effects in other equity markets. Hindmarch *et al.* (1984) find a weekend effect in the Canadian market. Jaffe and Westerfield (1985) find weekday effects similar to those in the U.S. market for the Canadian, British, Japanese, and Australian equity markets. Condoyanni *et al.* (1989) find significantly negative Monday or Tuesday returns in a study including seven developed markets. Chang *et al.* (1993) find significantly negative Monday returns in 13 of 23 international markets. Dubois and Louvet (1996) provide further evidence of the existence of low Monday returns for developed markets in an examination of eleven indices from nine countries during the period 1969 through 1992. Cai *et al.* (2006) document similar pattern as in Wang *et al.* (1997) that weekend effects mainly occur in the second half of a month in Chinese stock market.

Many researchers try to propose potential explanations of the weekend effect. Keim and Stambaugh (1984) establish that the phenomenon has been a regular feature of the financial landscape for many years and they reject the possibility that it arises from measurement error. Keim (1989) finds that the bid-ask bounce can explain about 17 percent of the weekend effect. Lakonishok and Maberly (1990), Abraham and Ikenberry (1994) and Chan *et al.* (2004) attribute part of the weekend effect to the differential trading patterns or holding preferences of institutions and individuals. Sias and Starks (1995) also document an association between the weekend effect and institutional ownership.

More recently, Chen and Singal (2003) propose a new explanation that the weekend effect might be linked to short sales. They argue that unlike a long position whose potential loss is limited, a short position faces theoretically unlimited downside risks. Thus the short positions require closer monitoring. Since the short sellers cannot adjust positions in non-trading hours, they tend to close their positions by weekend to avoid the potential losses occurring in the long period of non-trading, and rebuild the positions on Mondays. Empirically, they find that stocks with high

*Corresponding Author

short interest experience a relatively greater weekend effect than stocks with low short interest, which directly supports their hypothesis.

However, recently some researchers issue evidence that does not support Chen and Singal (2003)'s hypothesis. For example, Blau *et al.* (2007) do not find that short selling is more abundant on Mondays. Angel *et al.* (2003) distinguish short sales by dealers from that by customers, but they find no evidence that Monday-Friday return differences are closely linked to the Monday-Friday differences in either type of short selling. In sum, the empirical evidences of Chen and Singal (2003)'s hypothesis are still mixed.

To clarify whether short sales play a significant role in explaining the weekend effect, we extend the empirical tests of the relationship of weekend effect and short sales from the case of Hong Kong. The novelty of our paper lies in the fact that Hong Kong's short-selling regulation provides a unique experiment to directly test the impact of short-selling behavior on weekend effect. It is argued in the literature that most of the empirical works about short-sales constraints, including Chen and Singal (2003), suffer from the problem of using an imperfect proxy or short-sales constraints (see Chang *et al.* (2007)), thus reducing the reliability of the results. However, in our study, we provide a natural experiment in which we can directly compare the day-of-the-week effect of the same stock before and after the event that the stock changes its status of being non-shortable to shortable. Considering the fact that mixed results are presented, this paper will contribute to the literature through exhibiting more solid evidences. Empirically, we document that, first, the weekend effect exist in Hong Kong stock market, regardless of the existence of short sell constraints; second, after introducing short selling, the individual stocks face more significant weekend effect, which strongly support the Chen and Singal (2003) hypothesis. The results are invariant of different estimation methods.

The rest of the paper is arranged as follows: Section 2 explains the data source and sample characteristics; Section 3 shows the empirical results, and section 4 concludes.

2. The Data Source and Sample Characteristics

2.1. Hong Kong Stock Market

The Hong Kong Stock Market is a pure order-driven market. Security prices are determined by the buy and sell orders submitted by investors in the absence of designated market makers. Limit orders are placed through brokers and are consolidated into the electronic limit-order book and executed through an automated trading system, known as the Automatic Order Matching and Execution System (AMS). The limit orders for a specified price and quantity are stored in the system and executed using strict price and time priority. Although the trading system only accepts limit orders, investors could submit market orders to their brokers who will place them in the form of limit orders that match the best price on the other side of the book.

2.2. Short Selling Mechanism in Hong Kong

The HKEx allows only the stocks satisfying certain requirements to be sold short. The qualified stocks are listed on the designated list. Any stocks not on the list are prohibited from short sales. This restriction differentiates HKEx from almost all other major stock markets such as, NYSE and the NASDAQ, where all stocks can be shorted. The HKEx publishes the designated list of stocks allowing for short-selling on quarterly basis since 1994. On announcement, every name on the list is automatically permitted to sell short, which aggregately produces a series of events for this study.

2.3. Data Source Description and Matching process

The data we use in this paper is from two sources. Daily adjusted returns of individual stocks are from Datastream. And the designated short-selling stock list is from Hong Kong stock exchange (HKEx short list database). However, since the data recording process is separate in the two sources, we conduct the steps to match the two dataset, and identify 1145 events as our raw dataset. The detailed procedure can be seen in Appendix A.

2.4. Selection Criteria

In order to enter our sample, an addition event must satisfy the following two conditions simultaneously: (1) Before the announcement day of an event, the stock must have at least 120 trading days. (2) For every addition event there is no other addition or deletion event of the same stock that occurs over its pre and post long-term estimation window of 180 days (roughly half a year). After that, we have a final sample of 814 addition events during the sample period of 1996-2008. The distribution of addition events is displayed in Table 1.

Table-1. Addition events distribution

year	No.of events	Percentage
1996	82	10.07
1997	111	13.64
1998	93	11.43
1999	7	0.86
2000	45	5.53
2001	27	3.32
2002	29	3.56
2003	33	4.05
2004	40	4.91
2005	61	7.49
2006	92	11.30
2007	167	20.52
2008	27	3.32
All	814	100.00

3. Short Sales and the Weekend Effects: Empirical Results

Chen and Singal (2003) explain the weekend effect by introducing the potential impacts from the acts of short sellers. It is well known that stock returns for unhedged short positions are theoretically unbounded. Also, researchers such as Asquith and Muelbroek (1996), DeChow *et al.* (2001) have noted that unhedged short positions face higher risks. All these facts indicate that an uncovered short exposure needs more closely watching to minimize the chance of large losses due to price increase. Therefore, non-trading hours will incur more risks than usual because short sellers are unable to adjust their positions. Based on these arguments, Chen and Singal (2003) believe that short sellers tend to close positions before weekend, and reopen short positions on Mondays. This leads to lower average Monday returns and higher Friday returns.

3.1. OLS Results

Following Chen and Singal (2003), we define the weekend effect as the difference between Friday and preceding Monday returns hereinafter. Thus, the following regression is identified:

$$r_{ijt} = \beta_{ij1} + \beta_{ij2}dum2_t + \beta_{ij3}dum3_t + \beta_{ij4}dum4_t + \beta_{ij5}dum5_t + \varepsilon_{ijt} \qquad (1)$$

where r_{ijt} is the daily stock return for event stock *i*, day *t*, and estimation window *j* (*j*=pre, post), and is defined as: $r_{ijt} = \log(p_{ijt}) - \log(p_{ijt-1})$, and p_{ijt} is the close price of stock *i*, day *t*, and estimation window *j* (*j*=pre, post). Dum2-dum5 is the dummy variable for Tuesday to Friday, respectively. We run equation (1) for the pre-event window and the post-event window for each event-stock *i*, and $\hat{\beta}_{ij5}$ thus captures the average difference between Fridays and Mondays in the pre-event window and post-event window respectively. Results are exhibited in Table 2.

Table-2. OLS regression

Results in Table 2 are based on the following regression equations:

$$r_{ijt} = \beta_{ij1} + \beta_{ij2}dum2_t + \beta_{ij3}dum3_t + \beta_{ij4}dum4_t + \beta_{ij5}dum5_t + \varepsilon_{ijt}$$

where r_{ijt} is the daily stock return for event stock *i*, day *t*, and estimation window *j* (*j*=pre, post), and is defined as: $r_{ijt} = \log(p_{ijt}) - \log(p_{ijt-1})$, and p_{ijt} is the close price of stock *i*, day *t*, and estimation window *j* (*j*=pre, post). Dum2-dum5 is the dummy variable for Tuesday to Friday, respectively. Means are compared using paired-t-test and medians are compared using signrank test.

	Pre-event $\beta_{i,5}$ (%)	**Post-event $\beta_{i,5}$ (%)**	**Post-event $\beta_{i,5}$ -Pre-event $\beta_{i,5}$ (%)**
# of observations	814	814	
Mean (p-value)	0.200 (0.001)	0.332 (0.000)	0.133 (0.017)
Median (p-value)	0.107 (0.000)	0.239 (0.000)	0.132 (0.008)
# positive	444	506	440
# negative	369	307	373

The following patterns are documented in Table 2. First, unconditional weekend effect exist, regardless of the existence of short sale constraints. It can be shown from the first column, which indicates that the estimated coefficient of Friday dummy, i.e., the mean return gap (Friday return minus Monday return) is 0.2%, with the median is 0.107%. Both are significant at 1% level.

3.2. GARCH Results

However, a rich amount of literature documents time varying volatility in stock return data, and rejects a homoskedastic error structure for conditional distributions (see French *et al.* (1987), for example). Moreover, Sterge (1989) observes that financial futures return data, exhibits volatility clustering. These findings arouse the necessity to use modeling techniques that capture these distributional properties. GARCH model (Bollerslev, 1986) is thus a natural candidate. Recent weekend effect literature has extensively applied GARCH to capture the above-mentioned distribution property (see Najand and Yung (1994), among others). Specifically, the model is expressed as follows:

$$\begin{gathered} r_{ijt} = \beta_{ij1} + \beta_{ij2} dum2_t + \beta_{ij3} dum3_t + \beta_{ij4} dum4_t + \beta_{ij5} dum5_t + \varepsilon_{ijt} \\ \varepsilon_{ijt} \mid \Phi_{ij,t-1} \sim N(0, h_{ijt}) \qquad (2) \\ h_{ijt} = \alpha_{ij0} + \alpha_{ij1}\varepsilon^2_{ijt-1} + \alpha_{ij2} h_{ij,t-1} \end{gathered}$$

where r_{ijt} is the daily stock return for event stock *i*, day *t*, and estimation window *j* (*j*=pre, post), and is defined as: $r_{ijt} = \log(p_{ijt}) - \log(p_{ijt-1})$, and p_{ijt} is the close price of stock *i*, day *t*, and estimation window *j* (*j*=pre, post). Dum2-dum5 is the dummy variable for Tuesday to Friday, respectively. Φ_{ijt-1} is the period t-1 information set for event stock *i*, and h_{ijt} is the variance of the errors of event stock i, day t and estimation window *j* (*j*=pre, post). Again, we run equation (2) for the pre-event window and the post-event window for each event-stock *i*, and $\hat{\beta}_{ij5}$ thus captures the average difference between Fridays and Mondays in the pre-event window and post-event window respectively.

The GARCH results are shown in Table 3. Similar with that of Table 2, we again observe the existence of the unconditional weekend effect: the mean Friday-Monday return gap before event (i.e., with short sale constraints) is 0.140%, and the median is 0.090%, both are significant at 1% level. Moreover, after the removal of short sale constraint, the level weekend effect is stronger, in the sense that the mean (median) Friday-Monday return gap is 0.299% (0.200%), and the gap of the change around the removal of short sale constraint is 0.161% (0.110%), which is significant at 1% (5% for median). The results are highly consistent with Chen and Singal (2003)'s prediction.

Table-3. GARCH (1, 1) result

Results in Table 3 are based on the following GARCH (1,1) model:

$$r_{ijt} = \beta_{ij1} + \beta_{ij2} dum2_t + \beta_{ij3} dum3_t + \beta_{ij4} dum4_t + \beta_{ij5} dum5_t + \varepsilon_{ijt}$$

$$\varepsilon_{ijt} \mid \Phi_{ij,t-1} \sim N(0, h_{ijt}) \qquad (2)$$

$$h_{ijt} = \alpha_{ij0} + \alpha_{ij1}\varepsilon^2_{ijt-1} + \alpha_{ij2} h_{ij,t-1}$$

where r_{ijt} and dum2-dum5 are the same as defined in equation (1). Φ_{ijt-1} is the period t-1 information set for event stock *i*, and h_{ijt} is the variance of the errors of event stock i, day t and and estimation window *j* (*j*=pre, post). Again, we run equation (2) for the pre-event window and the post-event window for each event-stock *i*,. Means are compared using paired-t-test and medians are compared using signrank test.

	Pre-event $\beta_{i,5}$ (%)	**Post-event $\beta_{i,5}$ (%)**	**Post-event $\beta_{i,5}$ -Pre-event $\beta_{i,5}$ (%)**
# of effective observations	682	669	557
Mean (p-value)	0.140 (0.001)	0.299 (0.000)	0.161 (0.001)
Median (p-value)	0.090 (0.002)	0.200 (0.000)	0.110 (0.016)
# positive	370	412	302
# negative	312	257	254

3.3. Volatility Adjusted Weekend Effect

Presently trading activity change around the removal of short sale constraints is under hot debate. Researchers have come up to consistent results around some of the measures. For example, Chen and Rhee (2010), and Boehmer *et al.* (2008) prove that the existence of short sale constraints causes the reduction of the speed of price adjustment to information, which unanimously predict that the removal of short sale constraints will lead to higher price efficiency. However, different papers provide divergent results on volatility change. For example, Chang *et al.* (2007) document an increase in the volatility after the removal of short sale constraints, while Cai *et al.* (2012) observe a decline in volatility. In this paper, we do not directly distinguish this feature; however, we are still interested in controlling the potential impact of volatility change on the level of weekend effect. In order to do so, the "idiosyncratic volatility adjusted return" is use. Following Ang *et al.* (2006), we calculate the idiosyncratic volatility by regressing the market model:

$$r_{i,t} = \beta_{i,1} + \beta_{i,2} Mrtn_t + \varepsilon_{i,t} \qquad (3)$$

for each stock i in both the pre-event window and post-event window. $r_{i,t}$ is the daily stock return for stock i, day t, and $Mrtn_t$ is the daily return of Hang Seng Index in day t. Idiosyncratic volatility (vol) is defined as the standard deviation of residuals for pre-/post-event periods of event stock i. We then apply both OLS and GARCH (1,1) model to capture the size of the weekend effect, as described in section 3.1 and 3.2. The results are shown in Table 4.

Table-4. Idiosyncratic volatility adjusted return

We calculate the idiosyncratic volatility by regressing the market model:

$$r_{i,t} = \beta_{i,1} + \beta_{i,2} Mrtn_t + \varepsilon_{i,t}$$

for each stock i in both the pre-event window and post-event window. $r_{i,t}$ is the daily stock return for stock i, day t, and $Mrtn_t$ is the daily return of Hang Seng Index in day t. Idiosyncratic volatility (vol) is defined as the standard deviation of residuals for pre-/post-event periods of event stock i. OLS results are based on the following regression equations:

$$r_{ijt} = \beta_{ij1} + \beta_{ij2} dum2_t + \beta_{ij3} dum3_t + \beta_{ij4} dum4_t + \beta_{ij5} dum5_t + \varepsilon_{ijt}$$

where r_{ijt} is the daily stock return for event stock *i*, day *t*, and estimation window *j* (*j*=pre, post),. Dum2-dum5 is the dummy variable for Tuesday to Friday, respectively. The studied value in is the estimated $\hat{\beta}_{j,5} / vol_{ij}$, which is the idiosyncratic volatility adjusted return. GARCH (1,1) model is:

$$r_{ijt} = \gamma_{ij1} + \gamma_{ij2} dum2_t + \gamma_{ij3} dum3_t + \gamma_{ij4} dum4_t + \gamma_{ij5} dum5_t + \varepsilon_{ijt}$$

$$\varepsilon_{ijt} \mid \Phi_{ij,t-1} \sim N(0, h_{ijt})$$

$$h_{ijt} = \alpha_{ij0} + \alpha_{ij1} \varepsilon^2_{ij,t-1} + \alpha_{ij2} h_{ij,t-1}$$

where r_{ijt} is the daily stock return for event stock *i*, day *t*, and estimation window *j* (*j*=pre, post), $\Phi_{ij,t-1}$ is the period t-1 information set for event stock i, and $h_{i,t}$ is the variance of the errors of event stock i, estimation window j (*j*=pre, post).. The studied value in is the estimated $\hat{\gamma}_{ij5} / vol_{ij}$. Means are compared using paired-t-test and medians are compared using signrank test.

	Post-event –Pre-event volatility adjusted return	
Model	OLS	GARCH (1,1)
# of observations	814	557
Mean (p-value)	0.028 (0.031)	0.072 (0.038)
Median (p-value)	0.047 (0.015)	0.035 (0.004)

Table 4 shows that, regardless of whether OLS or GARCH (1,1) is used, the change of volatility adjusted return around the event is significant for both mean and median comparisons. Specifically, the mean change around event is 0.028, using OLS model, and 0.072, using GARCH (1,1) model. Both changes are significant at 5% level. Median changes are highly consistent. The results in Table 4 show that the potential impact of volatility change does not explain the observed weekend effect change. After controlling for volatility, we still observe more prominent weekend effect after stocks are allowed to short.

3.4. EGARCH Result

While GARCH models capture volatility clustering and leptokurtosis, it is also noted that as the distribution is assumed to be symmetric, GARCH class models fail to capture the "leverage effect" (Black, 1976), which occurs when stock prices change are negatively correlated with changes in volatility. This problem has been addressed by many extensions of GARCH model, among which the Exponential GARCH (EGARCH) by Nelson (1991) is one of the most successful extensions. The EGARCH has been widely used in recent day-of-the-week literature, such as Savva *et al.* (2006), Anwar and Mulyadi (2009), etc. In this paper we also adopt the EGARCH model to further check whether the existence of level effect can explain the significant increase of weekend effect around the short sale constraint lift. The settings of the EGARCH model are as follows:

$$r_{ijt} = \beta_{ij1} + \beta_{ij2}dum2_t + \beta_{ij3}dum3_t + \beta_{ij4}dum4_t + \beta_{ij5}dum5_t + \varepsilon_{ijt}$$

$$\varepsilon_{i,t} \mid \Phi_{i,t-1} \sim N(0, h_{i,t}) \qquad (4)$$

$$\ln h_{i,t}^2 = \alpha_{i,0} + \alpha_{i,1}\left|\frac{\varepsilon_{i,t-1}}{h_{i,t-1}}\right| + \phi_i \frac{\varepsilon_{i,t-1}}{h_{i,t-1}} + \gamma_i \ln h_{i,t-1}^2$$

where r_{ijt} is the daily stock return for event stock *i*, day *t*, and estimation window *j* (*j*=pre, post), and is defined as: $r_{ijt} = \log(p_{ijt}) - \log(p_{ijt-1})$, and p_{ijt} is the close price of stock *i*, day *t*, and estimation window *j* (*j*=pre, post). Dum2-dum5 is the dummy variable for Tuesday to Friday, respectively. Φ_{ijt-1} is the period t-1 information set for event stock *i*, and h_{ijt} is the variance of the errors of event stock i, day t and and estimation window *j* (*j*=pre, post). Results of EGARCH model are exhibited in Table 5.

Table-5. EGARCH (1, 1) result

Results in Table 5 are based on the following EGARCH (1,1) model:

$$r_{ijt} = \beta_{ij1} + \beta_{ij2}dum2_t + \beta_{ij3}dum3_t + \beta_{ij4}dum4_t + \beta_{ij5}dum5_t + \varepsilon_{ijt}$$

$$\varepsilon_{ijt} \mid \Phi_{ij,t-1} \sim N(0, h_{ijt})$$

$$\ln h_{ijt}^2 = \alpha_{ij0} + \alpha_{ij1}\left|\frac{\varepsilon_{ij,t-1}}{h_{ij,t-1}}\right| + \phi_{ij} \frac{\varepsilon_{ij,t-1}}{h_{ij,t-1}} + \gamma_{ij} \ln h_{ij,t-1}^2$$

where r_{ijt} is the daily stock return for event stock *i*, day *t*, and estimation window *j* (*j*=pre, post), $\Phi_{ij,t-1}$ is the period t-1 information set for event stock i, and $h_{i,t}$ is the variance of the errors of event stock i, estimation window j (*j*=pre, post). Means are compared using paired-t-test and medians are compared using signrank test.

Means are compared using paired-t-test and medians are compared using signrank test.

	Pre-event $\beta_{i,5}$ (%)	**Post-event $\beta_{i,5}$ (%)**	**Post-event $\beta_{i,5}$ -Pre-event $\beta_{i,5}$ (%)**
# of effective observations	814	814	814
Mean (p-value)	0.168 (0.000)	0.302 (0.000)	0.134 (0.016)
Median (p-value)	0.094 (0.000)	0.185 (0.000)	0.091 (0.015)
# positive	448	503	435
# negative	366	311	378

Similar with that of previous tables, results in Table 5 further confirm that after the stocks are allowed to be shorted, the weekend effect becomes more prominent. We observe that the mean difference between post-event and pre-event weekend effects is 0.134%, while the median difference is 0.091%, both significant at 5% level. The results imply that the observed phenomenon is robust over the selection of different time series models.

3.5. Control Group

One more type of potential criticism towards our results is about the comparison of our observed results and feasible control groups. Namely, even if there is significantly more prominent weekend effect after the lift of short sale constraints, it is well possible that other stocks that have not encountered the change of short sale constraint condition also experience a higher weekend effect due to some unobserved reasons other than short selling restrictions. In order to clarify such type of situation, we introduce the following two types of control groups, namely market benchmark and market cap matched control groups.

3.5.1 Market Benchmark Control Group

We set the selection criteria for the market benchmark control group as follows:

(1) we sort the effective dates of our 814 sample events and document that these sample events actually occur in 62 different dates.

(2) For each of the 62 dates, we set up the pre-event and post-event window as -/+180 trading days around the event *t* (*t*=1,2,…,62), calculated from Hang Seng Index.

(3) To select the control group for event t, we first drop those stocks that have the effective day on day *t* (which are actually the test group). Moreover, if a stock has any on-list or de-list event that falls with in the 180-day

window around event *t*, this stock is further excluded from the control group of event t. All the other stocks on the main board of HKEx serve as control group. We repeat this procedure for *t*=1,2,…,62, and end up with 22692 control events for the 814 events. The control stocks are actually the market portfolio excluding those stocks that have either on-list or de-list events during the examination window, which we are able to compare with as benchmark portfolio.

This type of control group is called hereinafter the market benchmark control group. Descriptive statistics of the market benchmark control group, as well as the test group are shown in Table 6.

Table-6. Descriptive statistics of test group and control group

Table 6 shows the comparison of several firm specific financial information between test group, the ***market benchmark*** control group and the ***market cap matched*** control group. The selection criteria for ***market benchmark*** are: (1) we sort the effective dates of our 814 sample events and document that these sample events actually occur in 62 different dates. (2) For each of the 62 dates, we set up the pre-event and post-event window as -/+180 trading days around the event t (t=1,2,…,62), calculated from Hang Seng Index. (3) To select the control group for event t, we first drop those stocks that have the effective day on day t (which are actually the test group). Moreover, if a stock has any on-list or de-list event that falls with in the 180-day window around event t, this stock is further excluded from the control group of event t. All the other stocks on the main board of HKEx serve as control group. We repeat this procedure for t=1,2,…,62, and end up with 22692 control events for the 814 events. The control stocks are actually the market portfolio excluding those stocks that have either on-list or de-list events during the examination window, which we are able to compare with as ***market benchmark***. The selection criteria for ***market cap matched*** control group are: (1) for each of the 62 dates, namely date i, we calculate the mean of the market capitalization ($mktcap_i$) of the test group for the month of date i. (2) Then we search in the market benchmark control group and keep those stocks with market capitalization falling in the range of [0.9* $mktcap_i$, 1.1* $mktcap_i$] as the market cap matched control group for event date *i*. (3) We sum up the market cap matched control group for event date *i* for all i=1,2,…,62, and get the ***market cap matched*** control group.

Group	**Test group**		**Control group (market benchmark)**		**Control group (market cap matched)**	
No. of obs.	814		22692		814	
	Mean	Median	Mean	Median	Mean	Median
Market capitalization	6091.43	1638.39	19659.01	833.62	4666.72	3291.99
Net debt	341556	17929	982541	22971	680066	72638
Total asset	6112036	2228034	27075143	2263683	10347921	5210255
Profit	242262	132526	1179680	93079	544071	270819
Price-to-book ratio	2.34	1.46	1.91	1.09	1.59	1.26
Profit/total asset	0.06	0.05	0.16	0.04	0.06	0.06

3.5.2. Market Capitalization Matched Control Groups

However, a closer look at the market benchmark control reveals that the composition of stocks for the market benchmark control group is quite different from that of the test group. Most prominent difference is the size of the market. The mean of market capitalization for the market benchmark is 19659 million HK$, much higher than 6091 million for the test group, while the median of the market benchmark is only 833.62 mil HK$, much lower than 1638 mil for the test group. This is not surprising. The test group contains the medium-size stocks in the market, while the market benchmark contains the largest-, as well as the smallest-size stocks. The largest stocks in Hong Kong stock market enter the list at the very beginning of the short-selling mechanism, and will almost never be deleted from the list, because they are mainly the blue chip stocks and are the major indices component. So their names do not appear in our event list, and will always enter the market benchmark control group. On the other hand, the smallest stocks will not stand a chance to be entering the short sale list, either, for they are not the indices components, nor are they the underlying stock of options, warrants, etc. So the smallest stock will also be staying in the market benchmark, too. The different composition of test group and market benchmark control group may be the potential source of bias.

In order to alleviate the composition bias, we construct a second control group, namely the market capitalization matched control group. The procedure of selecting this group is as follows: (1) for each of the 62 dates, namely date i, we calculate the mean of the market capitalization ($mktcap_i$) of the test group for the month of date i. (2) Then we search in the market benchmark control group and keep those stocks with market capitalization falling in the range of [0.9* $mktcap_i$, 1.1* $mktcap_i$][1] as the market cap matched control group for event date *i*. (3) We sum up the market cap matched control group for event date *i* for all i=1,2,…,62, and get the *market cap matched* control group. The descriptive statistics for the *market cap matched* control group are also shown in Table 6.

[1] We adjust the range for various values of the cutoff points of the market cap, including [0.95, 1.05], [0.85, 1.15], [0.80, 1.20], [0.75, 1.25] and [0.70, 1.30], and the regression results are highly consistent with the presented one.

3.5.3. Regression Results for Test Group and Different Control Groups

Based on the two control group we have identified, we then run regression on equation (1) again

$$r_{ijt} = \beta_{ij1} + \beta_{ij2}dum2_t + \beta_{ij3}dum3_t + \beta_{ij4}dum4_t + \beta_{ij5}dum5_t + \varepsilon_{ijt} \qquad (1)$$

for each event *i* (i=1, 2,…, 23506, for test group and ***market benchmark*** control group, and i=1,2,…, 1534 for test group and ***market cap matched*** control group), window *j* (*j*=pre, post), day *t*, Then, we construct the gap of Friday-Monday return for event *i* as:

$$gap_i = \hat{\beta}_{i5,post} - \hat{\beta}_{i5,pre} \qquad (5)$$

(***i***=1, 2,…, 23506 for test group and ***market benchmark*** control group, and *i*=1,2,…, 1534 for test group and ***market cap matched*** control group)

Based on these construct, we run the following cross-sectional regression

$$gap_i = \alpha + \beta Edum_i + \gamma X_i + \varepsilon_i \qquad (6)$$

where $Edum_i$ is the event dummy which equals to one for the test group and zero for control group. X_i's are firm specific control variables, including a firm's market capitalization (in logs), net debt, total asset (in logs), Price-to-book ratio and the ratio of profit over total asset. The results are shown in Table 7.

Table-7. Test group vs control groups

Table 7 shows the regression results for test group versus two different types of control groups. First, we then run regression on equation (1) again

$$r_{ijt} = \beta_{ij1} + \beta_{ij2}dum2_t + \beta_{ij3}dum3_t + \beta_{ij4}dum4_t + \beta_{ij5}dum5_t + \varepsilon_{ijt} \qquad (1)$$

for each event *i* (i=1, 2,…, 23506, for test group and ***market benchmark*** control group, and i=1,2,…, 1534 for test group and ***market cap matched*** control group), window *j* (*j*=pre, post), day *t*, Then, we construct the gap of Friday-Monday return for event *i* as:

$$gap_i = \hat{\beta}_{i5,post} - \hat{\beta}_{i5,pre} \qquad (5)$$

(***i***=1, 2,…, 23506 for test group and ***market benchmark*** control group, and *i*=1,2,…, 1534 for test group and ***market cap matched*** control group)

Based on these construct, we run the following cross-sectional regression

$$gap_i = \alpha + \beta Edum_i + \gamma X_i + \varepsilon_i \qquad (6)$$

where *Edumi* is the event dummy which equals to one for the test group and zero for control group. Xi's are firm specific control variables, including a firm's market capitalization (in logs), net debt, total asset (in logs), Price-to-book ratio and the ratio of profit over total asset. Panel A is the regression results for eq(6) using the market benchmark control group and Panel B uses the market cap matched control group.

Panel-A. With market benchmark control group

Group	With market benchmark control group							
Edum (10^{-2})	0.129** (2.28)	0.121** (2.11)	0.155*** (2.67)	0.161*** (2.80)	0.157*** (2.71)	0.155*** (2.67)	0.138** (2.35)	0.156*** (2.67)
Log-market cap (10^{-2})		0.023*** (4.67)					0.023*** (4.45)	
Net debt (10^{-11})			0.117 (0.26)				-0.088 (-0.20)	0.036 (0.08)
Log total asset (10^{-2})				0.006 (1.10)				0.006 (1.12)
Profit (10^{-11})					0.278 (0.24)			
Profit/total asset (10^{-2})						-0.003 (-1.48)	-0.002 (-1.37)	-0.003 (-1.153)
Constant (10^{-2})	0.037 (0.37)	-0.161*** (-3.95)	0.003 (0.29)	-0.088 (-1.02)	0.003 (0.29)	0.003 (0.33)	-0.159*** (-3.80)	-0.009 (-1.02)

Panel-B. With market cap matched control group

Group	With market cap matched control group							
Edum (10^{-2})	0.148** (2.13)	0.160*** (2.24)	0.170** (2.41)	0.135* (1.94)	0.153** (2.18)	0.167** (2.37)	0.155** (2.14)	0.131* (1.86)
Log-market cap (10^{-2})		0.015 (0.34)					-0.013 (-0.29)	
Net debt (10^{-11})			5.280 (0.77)				4.530 (0.65)	7.830 (1.22)
Log total asset (10^{-2})				-0.045 (-1.44)				-0.049 (-1.55)
Profit (10^{-11})					-5.510*** (-2.61)			
Profit/total asset (10^{-2})						-0.111 (-0.28)	-0.105 (-0.15)	-0.060 (-0.15)
Constant (10^{-2})	-0.015 (-0.36)	-0.140 (-0.38)	-0.013 (-0.32)	0.686 (1.41)	0.021 (0.47)	-0.003 (-0.06)	0.103 (0.27)	0.746* (1.86)

Note: *, **, and *** represent significance level of 10%, 5% and 1% respectively. In parentheses are the t-values using heteroskadasticity adjusted standard errors.

Panel A of Table 7 shows the results with market benchmark control group. After controlling all the potential firm specific variables, the event dummy is positive and significant at acceptable level. The results indicates that stocks in the market benchmark control group face no significant Friday-Monday return gap change, and, as documented above, this economically large and statistically significant Friday-Monday return gap change appear only in our sample events. This effect is significant over different control variable. Moreover, Panel B of Table 7 further confirms that the stock composition does not explain the observed pattern. The results by using the market capitalization matched group are highly consistent with those using the market benchmark control group.

4. Discussion and Conclusions

The topic about weekend effect is a research field full of discussions and controversies. Ever since French (1980), many researchers have documented the existence of the weekend effect and provided numerous potential explanations. Recently, Chen and Singal (2003) propose an explanation that the weekend effect might be linked to short sales. They argue that since the short sellers cannot close positions in weekends, they tend to close their positions before weekend and re-open them on Mondays to avoid the potential losses. However, other papers, such as Christophe *et al.* (2009), and Blau *et al.* (2007) declare no empirical evidence to support Chen and Singal (2003)'s explanations.

In this paper, we examine the relationship between short sales and weekend effect using the unique short sale settings of Hong Kong stock market. We explore the level change of weekend effect before and after a stock is allowed to short, and empirically document that: (1) in the case when stocks are not shortable, the weekend effect still exists. The Friday returns are, on average, 0.2% higher than Monday returns if OLS is used and 0.14% higher if GARCH (1,1) model is used. (2) if a stock is allowed to short, we will observe a more prominent weekend effect. The change of Friday-Monday return gap is 0.097% higher after the removal of short sale constraints if OLS is used and 0.161% higher if GARCH (1,1) is used. (3) The documented empirical results are robust over different settings of model selection, as well as different choices of control variables. These findings are highly consistent with Chen and Singal (2003)'s hypothesis that the short selling behavior will attribute to the level of weekend effect in that short sellers tend to close short positions on Fridays and open them on Mondays to avoid potential losses occurring during the long non-trading weekend.

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Appendix 1: Matching Process of Datastream and Designated List

According to the match condition of the two datasets, the list of stocks can be grouped into four categories according to their presence-related characteristics:

Normal Group : Every stock in this group share the same “stock_code” in both HKEx short list database and Datastream database (DS), but not necessary the same name. Furthermore, the underlying stocks’ reported base_dates (first-appearing dates) in DS are invariably earlier than their on_list effective dates and their DS reported current status are active. It means that there are continuous records for these stocks during the research periods. Now we have 907 events of this type.

Dead-or-suspended Group: Every stock in this group has the status of ‘dead’ or ‘suspended’ in Datastream database while it still has an earlier base-date than on_list effective dates. For these stocks, We further ensure they have the same names in both HKEX and Datastream. Now we have 68 events of this kind. Five of these 68 events are questionable because of the mismatch of their names in HKEX dataset and Datastream database.

Replace Group: All these stocks are actually dead. And in Datasteam their stock codes are still in use by some new listed stocks. So we manually match their names in one sub-database of Datastream in which the stock codes are missing. This sub-database was mainly made up of the dead stocks. All these stocks are put into the questionable group as well as the five cases of Dead-or-suspended group.

No-match: It is impossible to find their HKEX reported stock codes in Datastream. So again, we manually match their names in the missing-code database of Datastream. Like above, we put all these stocks into the questionable group for further checking. For all the events in the questionable group, we manually match their names in HKEX database with those in Datastream. Fortunately, 34 events are savaged.

So the available dataset now includes all the events available for further processing, which includes 1048 events of normal group, 63 events of Dead-or-suspended Group and 34 savaged events.