 doi:10.20944/preprints201809.0474.v1

The R^2 and the Seven Events in Hong Kong: A New Look at Return Synchronicity and Price Efficiency

Jinghan Cai, Fengyun Li, Iordanis Petsas[1]

This paper identifies a dilemma in the relationship between R^2 and price efficiency: After comprehensively studying the R^2 change around 7 well-known corporate events, neither the traditional understanding of R^2 as price inefficiency, nor the behavioral way of R^2 as price efficiency can explain the observed R^2 change around the events. We adopt an alternative methodology to replace the standard difference-in-difference regression and directly decompose the R^2 change. We find that, due to the endogeneity of events, the changes of R^2 are over-estimated. We further propose that in the event study setting, the R^2 change may be simply the consequence of the inflow/outflow of some trend-chasing investors, and it may be detached from price (in) efficiency. Empirical evidences are consistent with this hypothesis.

Introduction

The R^2 of a stock is derived from regressing the stock's returns on one or multiple market indices or common factors. Academia's attention on R^2 can date back to Roll (1988), who finds a low R^2, implying high firm-specific return variations, is driven either by private information or simply noise unrelated to specific information. French and Roll (1986) note that the key distinction between public and private information is that public information affects prices the moment it becomes known, while private information is only revealed through trading. Subsequently, Morck, Yeung and Yu (2000) (MYY hereafter) start a large body of research on R^2. They propose that stronger property rights promote informed arbitrage, which capitalizes detailed firm specific information. Therefore, R^2 is a measure of inverse price informativesness. This R^2-based inefficiency measure has gained increasing popularity in recent years and is widely used in various

[1] Jinghan Cai and Iordanis Petsas are from Department of Economics and Finance, University of Scranton. Fengyun Li is from School of Finance, Renmin University of China. Jinghan Cai and Iordanis Petsas acknowledge financial supports from Faculty Internal Funds, University of Scranton. Please send correspondence to Iordanis Petsas, email: iordanis.petsas@scranton.edu.

empirical studies of corporate investment and emerging market development, e.g., Wurgler, (2000), Durnev, et al. (2004), Durnev, Morck, and Yeung (2004), Jin and Myers (2006).

In contrast to the standard wisdom as stated by MYY, there indeed exists the opposite understanding of the relationship between R^2 and price efficiency. Hou, Peng and Xiong (2013) (HPX hereafter) argue that if stock price fluctuations are driven by investor overreactions, lower return R^2 is associated with stronger medium-term price momentum and long-term price reversal, two commonly believed signs of market inefficiency. In short, the sentiment-driven (retail) investors would react and result in a positive relationship between R^2 and price efficiency. Along this line, many papers have also provided supporting evidences (Kelly, 2014, Thoh, Yang and Zhang, 2007 among others).

In this paper, we argue that more attention should be paid when R^2 is applied as either a measure of price inefficiency, or a measure of price efficiency, especially in the event studies. The motivation is driven by two well-studied events in the literature: stock splits and the lift of short-selling constraints. In the literature, stock splits are proved to be related with a larger investor base. Due to the influx of uninformed investors, who also tend to be small retail investors[2], after the splits, the liquidity improves, trading becomes more active, and the probability of informed trading decreases, implying a lowered price efficiency. If one believes in the MYY explanation that R^2 is a price inefficiency measure, it is not surprising to see that Chang, et al (2015) find out that R^2 increases after the splits.

Another corporate event that draws our attention is the removal of short sales constraints. As Morck, Yeung and Yu (2013) articulate, "(some) countries ban short selling, presumably reducing the value of roughly half of all nonpublic information." In other words, the existence of short sales bans excludes a large chunk of the information from being impounded into the stock prices. Therefore, not surprisingly, when the short sales bans are removed, the price efficiency will improve. Both theories (Diamond and Verrechia, 2003) and empirical results (Chen and Rhee, 2013, among others) find unanimously consistent results (i.e., after the removal of short sales constraints, the price becomes more informative).

[2] In this paper, we use "noise traders" and "retail investors" interchangeably.

Based on these observations, if again we believe in MYY's explanation, we would predict that the R^2 would decrease. However, in a recent paper, Cai and Xia (2014) use the Hong Kong Stock market data and document that the R^2 actually increases after the removal of short sales constraints. Cai and Xia are not alone: A more recent paper, Kan and Gong (2017), uses the SHO pilot program in the U.S. market, and finds similar results as in Cai and Xia (2014). These papers in the literature put the understanding of R^2 and price inefficiency into a dilemma. Neither the MYY's interpretation nor the HPX's can explain the conflicted results between the splits and short selling constraints events raised above.

In this paper, we apply Hong Kong Stock Market data, and adopt seven corporate events (stock splits, revers splits, addition to Hang Seng index, deletion from Hang Seng index, allowing short selling, banning short selling, as well as rights offerings) to give a comprehensive examination about the empirical relationship between R^2 and information. Specifically, we re-examine how the R^2 will respond to these 7 events, since in the literature, there are some empirical papers that provide opposite evidences compared with Chang et al (2005) and Cai and Xia (2014), Kang and Gong (2017)[3]. We would like to firstly assure Chang/Cai/Kan results are robust enough to exhibit the existence of the dilemma. Then, we extend the exploration to other corporate events. Initially, we indeed find the following results as shown in Table 1, which are consistent with the literature.

(Insert Table 1)

Moreover, the results in Table 1 indicate that the said dilemma indeed exists: The R^2 and price efficiency movements are not consistent within these seven events. Neither MYY nor HPX can explain what happens around these events. We therefore suggest that researchers should be careful when adopting R^2 to represent either the price inefficiency or the price efficiency, at least under the event study context.

We try to reconcile the seemingly discordant results in two ways: first, we identify an endogeneity problem of the timing for the events, which leads to an over-estimated R^2 change. After controlling for the endogenous timing of the events, only 4 out of the above 7 corporate events have robust

[3] For example, Bris, Goetzmann and Zhu (2007), etc.

R^2 changes. Second, we provide the following behavioral explanation: The R^2 increase (decrease) exhibited above may simply be due to the inflow (outflow) of the investors who are more "indexed" traders.

First, none of the above seven events are purely exogenous. Firms may choose to proceed with these events at different market conditions. For example, more firms may tend to split their shares when market goes up, and they are more likely to consolidate (reverse split) the shares when the market goes down. Another example is, the Hong Kong Stock Exchange puts more firms in the shortable list in the bull market, but more firms are removed from the list in the bear market. It is obvious that the seven events are endogenous decisions, depending on the market condition. Based on these facts, we use a probit model and figure out that the R^2-increase events (split, addition to Hang Seng Index, allowing short selling and rights issuing) are more likely to occur when the market return goes up and the market return volatility is low, and the R^2-decrease events (reverse split, deletion from Hang Seng Index, banned short selling) are more likely to occur when the market return goes down and the market return volatility is high. Subsequently, in the post-event window of the R^2-increase events, market returns and volatility reverse, and we observe lower market returns and significantly higher market volatility. In parallel to that, in the post-event window of the R^2-decrease events, we observe higher market returns and lower market volatility. The market change is unlikely to be the results of the events, rather, it comes from the endogenous timing of the events. The consequence of the endogeneity problem is that, the R^2 changes might be significantly over-estimated. We decompose the R^2 changes and find out that a large fraction of the change comes from the market volatility change, rather than any firm-specific factors. After we control for the market change, we find no significant R^2 changes around allowing/banning short selling, or around rights offerings. So, our following discussions are based on the events of stock split/consolidation, addition to/deletion from Hang Seng Index.

In order to control for possible endogeneity issues, one standard methodology is to choose a control group as benchmark, and use methods like difference-in-difference regressions (DID). However, we argue that, despite of the popularity of DID, it is not impeccable in the procedure of selecting the control stocks. While controlling for the market change, it is possible that some control groups may exhibit undesirable features that we wish to avoid. More specifically, we also choose a control group, and figure out that around some events, the control stocks exhibit significant R^2 changes due to some unknown reasons. Therefore, the DID procedure actually uses some biased bench mark. Our method avoids this potential drawback of DID.

In our explanation about the R^2 changes, we argue that the investor composition around the above-mentioned events. In the case of stock splits, lowered price would result in a larger investor base, and more retail investors are attracted into trading the split stock. According to Nofsinger (2014), retail investors tend to be more active when index return goes dup, implying that retail investors are more "indexed" investors, compared with other investors. Using Chinese stock market data, Cai, He, He and Zhai (2018) actually find out that the retail investors' participation positively commoves with the market on an event study basis, which gives direct supports to our paper. Therefore, when firms split (consolidate, or reverse split) their shares, their investor base increases (decreases), and more small retail investors enter (leave) the stock, accompanied by the increase (decrease) of R^2.

Another event is the addition to/deletion from the Hang Seng Index. The vast popularity of Hang Seng index-linked investment products, such as mutual funds, futures, and options, suggests that the index is a preferred habitat for some investors and a natural category for many more. When a stock is added to the Hang Seng index, it enters a category (habitat) used by many investors and is buffeted by fund flows in and out of that category (habitat). If arbitrage is limited, these fund flows raise the correlation of the included stock's return with the returns of other stocks in the Hang Seng Index, and thus, become more (less) synchronous of the index, leading to a higher (lower) R^2. Moreover, according to Chen, Singal and Noronha (2005), addition to major stock index leads to a higher level of investor awareness, which also attracts more retail investors. The R^2 tends to increase (decrease), correspondingly.

In short, our above stories argue that the R^2change may reflect the change of investor composition, which may not necessarily be related to price efficiency. If our above stories about different types of corporate events and their potential impact on R^2 are true, we would observe that the trading volume will move to the same directions as the R^2. We directly test the change of trading volume,

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 September 2018 doi:10.20944/preprints201809.0474.v1

and indeed find a positive co-movement beween R^2 and trading volume. This result provides consistent evidence supporting the investor composition hypothesis of R^2.

The rest of the paper is arranged as follows. Section 2 reviews the literature. Section 3 shows the data, and basic information of Hong Kong Stock market. Section 4 discusses the empirical results, and section 5 concludes.

2. Literature Review

2.1 R^2

Whether R^2 is a proxy of price efficiency or noise? Ever since MYY, evidences have been mounting on both sides of the discussion. On the one hand, following French and Roll (1986) and Roll (1988), firm-specification fluctuation reflects more than just public news, and they credit private arbitrage for much stock price fluctuation. Higher firm-specific variation in higher-income countries might reflect arbitrageurs' falling costs or rising trading revenues. As discussed in Morck, Yeung and Yu (2013), R^2 tends to be low after emerging markets lower inward foreign portfolio investment barriers (Li et al. 2004); receive increased equity investment inflows from the United States (Bae, Bailey and Mao 2006); announce stock market liberalizations (Bae, Bailey and Mao 2006); or allow cross-listings or closed-end country funds into the United States, the United Kingdom (Bae, Bailey and Mao2006), or Hong Kong (Gul, Kim and Qiu 2010). These findings also fit the pattern if foreign arbitrageurs raise the intensity and sophistication of informed trading.

On the other hand, another stream of literature shows that higher R^2 is correlated with higher price efficiency. For example, Gassen, Skaife and Veenman (2017) find that much of the differences in R^2 both within and across countries is driven the differences in liquidity, subverting findings in prior research suggesting that stocks' low R^2s result from transparent information environments. HPX provide evidence consistent with greater pronounced overreaction-driven price momentum among low-R^2 stocks. Dasgupta, Gan and Gao (2010) provide both theory and evidence that R^2 can increase when transparency improves. Chan and Chan (2014) investigate the SEOs as events and find that the stock prices are more informative when R^2 is higher.

 doi:10.20944/preprints201809.0474.v1

Some seemingly contradicted empirical findings can be reconciled if we scrutinize the cost of information production industry. In a dynamic model with discrete fixed costs of information gathering and processing, Veldkamp (2006) uses a dynamic model with discrete fixed costs of information production and argues that competition biases information suppliers toward producing information useful for estimating the fundamental values of many firms because this has more buyers than information about one stock. Higher fixed costs of information production extenuate this, leading to even less production of information about individual firms. Thus, where arbitrage fixed costs are higher, more investors trade *en masse* on the basis of the same information about the same subset of stocks, rendering returns more synchronous. For example, Piotroski and Roulstone (2004) find that stocks followed by more analysts comove more in the United States. Chan and Hameed (2006) find similar results in emerging markets. All these findings can be understood within the context of Veldkamp (2006) that analysists' forecasts contain information about industry or economy-levels. However, Veldkamp (2006)'s model is still silent on other firm specific event studies which are unrelated with information production cost (e.g., stock splits).

Two papers consider the relationship between R^2 and liquidity, which are similar to our paper's arguments. Chan, Hameed and Kang (2013) discuss the "relative synchronicity" hypothesis which predicts that stock return co-movement, or the R^2 measure, positively affects the liquidity of a stock, as market makers learn more information from the market if the stock has more correlated fundamentals. They provide evidence that stock price synchronicity affects stock liquidity positively. Also, they find that improvement in liquidity following additions to the S&P 500 Index is related to the stock's increase in return co-movement. In short, Chan, Hameed and Kang (2013) argue that R^2 increase would lead to an improved liquidity. However, unlike the addition to index events, other events in our paper, such as the stock split/reverse split events are not related with any fundamental changes. Therefore, other theories of the positive correlation between R^2 and liquidity are needed. Our empirical results that R^2 are positively correlated with trading volume, are consistent with theirs, but we provide an alternative explanation that this may be the evidence that more indexed investors participate in trading after these events.

2.2 Stock split

Why do firms bother to take actions to split, or to consolidate (reverse split) its outstanding shares? The trading range hypothesis (see Copeland, 1979, Lakonishok and Lev, 1987) argues that the management would like to bring the stock price into a certain optimal range and hence the stability and liquidity of the stock will improve after a split due to an increase in the ownership base. Merton (1987) argues that a larger investor base will result in a higher firm value by reducing cost of capital, ceteris paribus. Empirical studies find supportive evidence that firms that take actions to expand their shareholder base indeed benefit from a low cost of capital (e.g., Grullon, Kanatas, and Weston, 2004, among others). Existing literature further ascertains that a larger investor base would lower the price informativeness. For example, Peress (2010) argues that the extent to which investors are encouraged to acquire firm-specific information depends on the size of shareholder base. The intuition is that the enlarged investor base increases risk sharing by spreading the risk among a large number of investors. As investors' expected losses decrease, they have less incentives to gather information with respect to the uncertainty about firm payoff. In other words, information production in general is negatively related to the degree of risk sharing. Empirically, Guo, Zhou and Cai (2008) use Tokyo Stock Exchange data and find out that the stock splits tend to increase the trading activity, to enhance the market liquidity, to reduce the information asymmetry, and to lower the probability of informed trading. Using 5,104 NYSE/AMEX/Nasdaq stock splits from 1994 to 2007, Chang et al (2015) find that the adjusted Probability of INformed Trading (adjPIN, see Duarte and Young, 2009) decreases significantly after stock splits, also supporting the prediction that stock splits will result in lower price efficiency.

2.3 Addition to Index

The act of adding a stock to the major index should not change investors' perceptions of the covariance of the included stock's fundamental value with other stocks' fundamental values. The stated goal of an index is to represent the market's economy, not to signal a view about future cash flows. However, deletions from the index are another matter. Stocks are usually removed from the index because a firm is merging, being taken over, or nearing bankruptcy. There might be some differences between the stock split and reverse split cases. We include both events in our study.

The major stock index in Hong Kong Stock market is the Hang Sang index. The traditional wisdom, derived from economies without frictions and with rational investors, holds that the price synchronicity with the market should not change, since addition to the Hang Seng index does not change the cash flows of the firm. On the other hand, as argued in Barberis, Shleifer and Wurgler (2005), in economics with frictions or with irrational investors, and in which there are limits to arbitrage, comovement in prices is delinked from comovement in fundamentals. This suggests a second broad class of "friction-based" and "sentiment-based" theories of comovement. Barberis, Shleifer and Wurgler (2005) examine three specific views of comovement that can be described in these terms. The first is the category view, analyzed by Barberis and Shleifer (2003). They argue that, to simplify portfolio decisions, many investors first group assets into categories such as small-cap stocks, oil industry stocks, or junk bonds, and then allocate funds at the level of these categories rather than at the individual asset level. If some of the investors using categories are noise traders with correlated sentiment, and if their trading affects prices, then as they move funds from one category to another, their coordinated demand induces common factors in the returns of assets that happen to be classified into the same category, even when these assets' cash flows are uncorrelated.

Another kind of comovement is the habitat view, starting from the observation that many investors choose to trade only a subset of all available securities. Such preferred habitats could arise because of transaction costs, international trading restrictions, or lack of information. As these investors' risk aversion, sentiment, or liquidity needs change, they alter their exposure to the securities in their habitat, thereby inducing a common factor in the returns of these securities. This view of comovement predicts that there will be a common factor in the returns of securities that are held and traded by a specific subset of investors, such as individual investors.

In both cases, when a stock is added to the Hang Seng index, it enters a category (habitat) used by many investors and is buffeted by fund flows in and out of that category (habitat). If arbitrage is limited, these fund flows raise the correlation of the included stock's return with the returns of other stocks in the Hang Seng Index, and thus, become more (less) synchronous of the index, leading to a higher (lower) R^2.

2.3 Short selling ban

Short selling bans have been widely studied starting from Miller (1977), who argues that short-selling bans drive up the price because holders of negative information are kept out of the market. Harrison and Kreps (1978) follow Miller (1977) and construct a model to show that when the short-selling constraints are binding, a stock can be overvalued. Diamond and Verrecchia (1987) predict that a short sale ban widens the bid-ask spread, thereby suggesting a negative liquidity effect. Correspondingly, Marsh and Payne (2012) find a deterioration in liquidity, trade, and market quality in the shorting ban in the 2008 financial crisis period in London. Beber and Pagano (2013) find that a ban causes a deterioration of liquidity and a slower speed of price discovery. Boehmer, Jones, and Zhang (2013) find that large American stocks experience a decline of trades, wider bid-ask spreads, and lower liquidity conditions from August to October 2008. All these above studies confirm that the negative liquidity effect remained true in the urgent and somewhat discretionary shorting bans during the 2008 crisis. However, some other papers provide different opinions: Zhang and Ikeda (2017) and Cai, Ko, Li and Xia (2018) use the case of Hong Kong Stock Exchange and find out that the liquidity may get better after short selling is banned (and liquidity worsens after the lift of short selling ban). Cai, Ko, Li and Xia (2018) argue that this is due to the fact that retail investors leave the market when short selling is allowed. According to the above results, the impact of short selling ban on liquidity is ambiguous.

2.3 Rights offerings

Rights offerings are one of the major ways for Seasoned Equity Offerings (SEOs), but they are also minimally studied (Holderness and Pontiff, 2016). In a rights offering, existing shareholders are given the right, but not the obligation, to purchase newly issued securities which are proportional to their fractional ownership in the firm. In comparison to rights offerings, another way of SEO, known as public placement, refers to selling the new shares to the public. However, unlike public placements, rights offerings may cause value-destructive effects. For example, Wu and Wang (2002) find negative cumulative abnormal returns after rights offerings. However, existing evidence, e.g., Balachandran et al (2013), argues that high quality firms tend to issue rights offerings. How different investors will respond to rights offerings? This question remains unclear and puzzling.

 doi:10.20944/preprints201809.0474.v1

3. Hong Kong Stock market and the data

In this paper, we choose Hong Kong Stock Market for at least the following reasons. First, Hong Kong stock market provides a good case where a variety of corporate events can be found, including stock splits, reverse splits, addition to/deletion from Hang Seng Index, etc. More importantly, Hong Kong has a unique mechanism of short selling. Hong Kong Stock Exchange (HKEx) allows short-selling of stocks if they are on the designated list. The list is adjusted quarterly, therefore, we can have a series of events where some stocks are added to the list while others are deleted from the list. This mechanism differs from any other events of short selling around the world, in the sense that, in other markets (U.K, U.S, etc.) the short selling bans are most likely the passive results due to the threat from financial crisis. In the U.S. market, the Regulation SHO pilot program is an exception, which removed short-selling price tests for randomly-selected stocks ("pilot stocks") in May 2005, before removing such tests for all stocks in July 2007. However, the SHO pilot program occurs at one time slot, which is essentially one single event, which is not an ideal setting. Moreover, Hong Kong has many cases of rights offerings, which are relatively rare in U.S. stock market.

In this paper, the information of the events about stock split, reverse split and rights offerings are provided by HKEx. The sample period is from January 1996 to December, 2016. 559 reverse split events and 236 split events are identified, and 765 rights offerings are identified. The Hang Seng Index addition/deletion events are from Hang Seng Indexes Company Limited website[4]. The sample period is from January 1995 to December, 2017. There are 49 deletion events, and 66 addition events. The short-selling status change data are from HKEx[5]. The sample period is from January 1996 to December, 2008. There are 812 deletion events and 1150 addition events. The individual stock information is from Datastream. We use the local code (LOC) item from Datastream to match the events and the individual stock data. For an above event, we use the [-120 trading days, announcement date] as the pre-event window, and [effective date, 120 trading days] as the post-event window. Moreover, in order to remain in our sample, we require that there are no fewer than 60 observations in either the pre- or post-event window. The final number of events used in our sample is shown in Table 1.

---

[4] https://www.hsi.com.hk/HSI-Net/HSI-Net

[5] we are grateful to Le Xia for sharing this data with us.

 doi:10.20944/preprints201809.0474.v1

4. Empirical Results

4.1 The change of R^2

We start with the direct comparison for the R^2 between the pre- and post-windows for the seven events. Using the 120-day window around the events, we run the following market model

$$r_{it\in j=\{pre,post\}} = \alpha_{ij} + \beta_{ij} r_{mt} + \varepsilon_{it}, \quad t=1, 2, \ldots, T_{ij} \tag{1}$$

where r_{it} is the continuously compounded return for stock-event i on day t, if t is in window j (pre- or post-event window), r_{mt} is the Hang Seng index return on day t, and ε_{it} is the error term. T_{ij} is the total number of observations for stock-event i in window j={pre, post}. The R^2 is then

$$R_{ij}^2 = \frac{\beta_{ij}^2 V_{ij}}{\beta_{ij}^2 V_{ij} + SSE_{ij}} \tag{2}$$

where β_{ij} is the beta value estimated from equation (1), V_{ij} is the market return variation measure for stock-event i, from window j, and more specifically, $V_{ij} = \frac{T_{ij}-1}{T_{ij}} \sum_{s=1}^{T_{ij}} (r_{mt} - \overline{r_{mt}})^2$, and SSE_{ij} is the sum of squared residuals for stock-event i, from window j. For simplicity's sake, we omit the subscripts when there is no confusion. For each stock-event, we have one pre-event window R^2, and a post-event window one. Table 2 shows the direct comparison between the mean and median of the R^2 for pre- and post-event windows.

(Insert Table 2)

We can see from Table 2 that, consistent with the existing literature, we do fine significant R^2 increases in mean or median after stock splits, addition to Hang Seng Index, allowing short selling and rights offerings. Correspondingly, the R^2 decreases significantly after the events of reverse splits, deletion from Hang Seng Index, and banning short selling. The results are highly consistent with Cai and Xia (2014), Chang, et al (2015), and Kan and Gong (2017).

4.2 Endogenous timing of the events

It is not surprising that the above seven events are not strictly exogenous. In the literature, the standard way to get rid of the endogeneity problem in an event study is to select a control group and run a difference-in-difference regression (DID). In this paper, we use an alternative method that can directly calibrate the subsequent impact from the market. To begin with, we first test the endogeneity of the seven events by directly running the following probit regression:

$$Prob(\mathbf{1}) = \alpha + \beta_1 MktRtn_i + \beta_2 MktStd_i + \varepsilon_i \qquad (3)$$

where Prob(**1**) is a dummy variable which equals 1 if event i leads to R^2 increase, including stock split, addition to Hang Seng index, allowing short selling, and rights offerings, and 0 if event i leads to R^2 decrease, including stock consolidation, deletion from Hang Seng Index and disabling short selling. $MktRtn_i$ is the average daily Hang Seng Index return for stock-event i in the pre-event window; and $MktStd_i$ is the Hang Seng Index return standard deviation for stock-event i in the pre-event window. ε_i is the error term. The results are shown in Table 3.

(Insert Table 3)

Equation (3) embeds the null hypothesis that the events themselves are purely exogenous, and they are not subject to the impact of the prevailing market condition. However, the results from Panel A, Table 3 shows that, firms are more likely to split their shares, to be added to Hang Seng Index, to be allowed to short selling, and to conduct rights offerings when the market return is higher and the market volatility is lower. The results are significant. We further examine the comparison of market return and volatility between the pre-event and post-event window. The results are shown in Panels B and C of Table 3. We can see that there are reversals in both return and volatility. After the R^2 increase (decrease) events, the market returns are significantly lower (higher), and the market volatilities are significantly higher (lower). It is very unlikely that the individual stock events would significantly impact the market, therefore, the reason of this return/volatility reversal may come from the timing of the events. However, as a result, the endogeneity of events will lead to an imprecise estimation of the R^2.

4.3 Decomposition of R^2 change

In our paper, we directly decompose the R^2 change and examine the magnitude of the endogeneity problem.

We know from earlier discussion that the market-model R^2 is constructed as follows:

$$R^2 = \frac{\beta^2 V}{\beta^2 V + SSE} \tag{4}$$

where β is the beta value estimated from regressing the individual stock return on the market return, V is the market return variation measure, more specifically, $V = \frac{T-1}{T}\sum_{i=1}^{T}(r_{mt} - \overline{r_{mt}})^2$, where r_{mt} is the market return on day t, t=1, 2,…,T, and *SSE* is the sum of squared residuals. For simplicity's sake, we omit all the subscripts.

After a log-linearization, the R^2 change is approximately (see appendix for a detailed explanation of the procedure):

$$\widetilde{R^2} = \widetilde{\beta^2} + \tilde{V} - R^{2*}\widetilde{\beta^2 V} - (1 - R^{2*})\widetilde{SSE} \tag{5}$$

where the tilde expression in equation (5) is defined as follows: for a variable x, $\tilde{x} = \frac{x - x^*}{x^*}$, or the percentage deviation of x about x^*, where x^* is the steady state value of x. In equation (5), we use the pre-event window as the steady state. The results of the decomposition are shown in Table 4.

(Insert Table 4 here)

In Panel A of Table 4, we can see that, the R^2 increase events lead to 15.39% higher R^2. The steady state R^{2*}=10%, $\widetilde{\beta^2} = -20.82\%$, which leads to a reduction R^2. $\tilde{V} = 35.86\%$, therefore $R^{2*}\widetilde{\beta^2 V}$ is close to zero and can be neglected. $(1 - R^{2*})\widetilde{SSE} = (1 - 10\%)4.19\%$=3.77%. The above decomposition shows that, the majority of R^2 increase is from the market return variation $\tilde{V}$. We can decompose the R^2 decrease in Panel B of Table 4 analogously, and about half of the R^2 decrease is from the market return variation $\tilde{V}$. The results imply that, the exogenous market return variation plays an important role in explaining the R^2 change, and the R^2 change due to the firm-specific event is over-estimated.

4.4 The design of FR^2

The standard methodology to control the endogeneity problem in an event is the difference-in-difference regression (DID). However, DID is not impeccable, in the sense that, first, DID is not able to directly calibrate the impact from the market, and second, while removing the market wide factors, the sample-specific properties of the control group will be attributed to the test group, so that some extra errors may occur. In our paper, we adopt a new methodology that fixes the market impact in the estimation of the R^2 change. We name this fixed version of R^2 the "fixed-R^2", or FR^2, for short. For stock *i*, $FR^2_{i,j=pre,post}$ is defined as follows:

$$FR^2_{i,j=pre,post} = \begin{cases} R^2_{i,pre}, & if\ j = pre \\ \dfrac{\beta^2_{i,post} V_{i,pre}}{\beta^2_{i,post} V_{i,pre} + SSE_{i,post}}, & if\ j = post \end{cases}$$

V is the market return variation measure, more specifically, $V = \frac{T-1}{T} \sum_{i=1}^{T} (r_{mt} - \overline{r_{mt}})^2$, where r_{mt} is the market return on day t, t=1, 2,…,T, and *SSE* is the sum of squared residuals. The logic of FR^2 is, in the post-event window, we use the pre-event market variation to replace the post-event value, so that there is no market variation difference. By using this alternative method, we are able to (1) calibrate the magnitude of the endogeneity problem, and (2) to prevent any control-sample-specific errors, which is explained in Table 5.

(Insert Table 5)

Panel A of Table 5 shows the comparison around the seven events between the standard R^2 and fixed-R^2 (FR^2). We can see that, in most of the R^2 increase events, the standard post-event R^2, i.e., R^2_{post} tends to be over-estimated. For example, in the stock split case, the standard R^2_{post} is 9.39%, while the FR^2_{post}, which has excluded the market movement, is only 6.87%. In comparison to that, for the R^2 decrease events, the R^2_{post} tends to be under-estimated. For example, in the reverse split case, the R^2_{post} is 4.93%, while the FR^2_{post} is only 5.25%. Based on the fixed-R^2, we re-examine the R^2 change around the seven events, and figure out that allowing/banning short selling and rights offerings do not result in significant change in the fixed-R^2 at 5% level. The observed the R^2 change (see Table 2) is therefore from the change in market volatility. In comparison to that, the stock split/reverse split, addition to/deletion from Hang Seng Index events still have significant impact on the R^2. Therefore, in the rest of the papers, we will focus on the mechanism of these four events.

Panel B of Table 5 shows the comparison around between the standard R^2 and fixed-R^2 (FR^2) for a control group. In finding out the control group, we match the price, market value and trading volume for a stock-event in the test group from the same industry[6]. We can see that, the match is effective, in the sense that the selected control group stocks show similar magnitudes of R^2. Also, for 5 of the 7 events, there are no significant changes in fixed-R^2 around the events. However, for banning short selling and rights offerings events, there are significant differences in the fixed-R^2 around the events, due to some unknown reasons. If standard DID is applied, these changes would be attributed to the attributed to the test group. The results from Panel B of Table 5 provide evidence for the potential drawbacks of DID, and our methodology is free of this issue.

4.5 A behavioral explanation of the R^2 change

We have shown that the stock split and addition to Hang Seng Index would lead to a significant increase in R^2, while the reverse split and deletion from Hang Seng Index would lead to a significant decrease. Instead of explaining the findings from the perspective of price efficiency or inefficiency, we tackle this question from the angle of investor composition.

First, when firms split their shares, the investor base increases and more retail investors come and trade the stock. Retail investors tend to be overconfident, which is learned through past success.

[6] We vary the selection criteria and find different control groups, for robustness sake, and the results are highly consistent with the presented ones.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 September 2018 doi:10.20944/preprints201809.0474.v1

The more successes people experience, the more they will attribute it to their own ability. Nofsinger (2014) states that, during bull markets when index return goes up, individual investors will attribute too much of their success to their own abilities, which makes them overconfident. As a consequence, overconfident behaviors will be more pronounced in bull markets (See also Gervais and Odean, 2001, and Daniel, Hirshleifer and Subrahmanyam, 2002). Chuang and Susmel (2011) find that retail investors trade more aggressively following market gains than institutional investors. This overconfidence would result in the fact that individual investors' fund flows are positively correlated with the market movement. We therefore would observe a higher comovement (higher R^2) after the stock split. The reverse split works analogously. Cai, He, He and Zhai (2008) indeed find that the retail investor participation is positively correlated with the R^2, which directly supports out findings.

Another event is the addition to/deletion from the Hang Seng Index. The vast popularity of Hang Seng index-linked investment products, such as mutual funds, futures, and options, suggests that the index is a preferred habitat for some investors and a natural category for many more. When a stock is added to the Hang Seng index, it enters a category (habitat) used by many investors and is buffeted by fund flows in and out of that category (habitat). If arbitrage is limited, these fund flows raise the correlation of the included stock's return with the returns of other stocks in the Hang Seng Index, and thus, become more (less) synchronous of the index, leading to a higher (lower) R^2.

The above arguments imply that, the R^2 increase or decrease after these events might be the result from the fact that some market-trend chasing investors (retail investors or category/habitat traders) enter or quit the market. However, it is empirically hard to directly test the influx or outflow of the investors. What we choose are the following tests that may indirectly related to the investor composition hypothesis.

H1: After the stock split and addition to Hang Seng Index, the entering of trend-chasing retail investors and category traders may increase the beta and/or decrease the sum of squared residuals (SSE).

H2: After the reverse split and deletion Hang Seng Index, the withdrawal of trend-chasing retail investors and category traders may decrease the beta and/or increase the sum of squared residuals (SSE).

(Insert Table 6)

Table 6 shows the beta and SSE change around the events. Unlike the traditional wisdom that retail investors are noise trades and they tend to increase the errors in the market mode, we find that there are some mild evidences support the opposite direct of the traditional wisdom, in that when stock splits, retail investors come and trade, but the underlying stock's beta increases, and SSE drops (although insignificant). The reverse split shows consistent results, that a beta decrease (although insignificant) and SSE increase are found after the reverse split. These findings shows consistent results as in Cai, He, He and Zhai (2018). As to the Hang Seng Index addition/deletion, we find that after addition of HSI, beta increases and SSE tends to decrease. After deletion from HSI, beta decreases and SSE tends to increase. Overall, H1 and H2 are mildly supported.

Another potential way to show the relationship between the R^2 and investor composition is through trading volume. Since we argue that the R^2 change is from the influx/outflow of trend-chasing investors, it is therefore true that

H3: Trading volume is positively correlated with the R^2.

(Insert Table 7)

Table 7 shows the results of the following regressions:

$$vol_{i\in R_{+}^{2},j=pre,post} = \alpha_1 + \beta_1 post_{i,j} + \varepsilon_{ij} \qquad (1)$$

$$vol_{i\in R_{-}^{2},j=pre,post} = \alpha_2 + \beta_2 post_{i,j} + u_{ij} \qquad (2)$$

$$\Psi_{i\in R_{+}^{2},j=pre,post} = \gamma_1 + \beta_1 post_{i,j} + \theta_1 vol_{i,j} + \rho_1 post_{i,j} * vol_{i,j} + \eta_{ij} \qquad (3)$$

$$\Psi_{i\in R_{-}^{2},j=pre,post} = \gamma_2 + \beta_2 post_{i,j} + \theta_2 vol_{i,j} + \rho_2 post_{i,j} * vol_{i,j} + \mu_{ij} \qquad (4)$$

where $vol_{i \in R^2_+, j=pre,post}$ is the mean dollar trading volume of event i, if i is an R^2 increase event (stock split and addition to Hang Seng Index), for window j = pre, post; $vol_{i \in R^2_-, j=pre,post}$ is the mean dollar trading volume of event i, if i is an R^2 decrease event (stock reverse split and deletion from Hang Seng Index) for window j = pre, post. $\Psi_{i \in R^2_+, j=pre,post} = \log \frac{R^2_{i \in R^2_+, j=pre,post}}{1-R^2_{i \in R^2_+, j=pre,post}}$, and $\Psi_{i \in R^2_-, j=pre,post} = \log \frac{R^2_{i \in R^2_-, j=pre,post}}{1-R^2_{i \in R^2_-, j=pre,post}}$, where $R^2_{i \in R^2_+, j=pre,post}$ is the R^2 of stock-event i, if i is an R^2 increase event (stock split and addition to Hang Seng Index), for window j = pre, post, and $R^2_{i \in R^2_-, j=pre,post}$ are defined analogously. $post_{i,j}$ is a dummy variable which equals 1 if j=post, and 0 otherwise. $vol_{i,j}$ is the mean dollar trading volume of event i in window j. The models are estimated using seemingly unrelated regression.

We can see from models (1) and (2) of Table 7 that, after the R^2 increase events, the trading volume inceases, while after the R^2 decrease events, the trading volume decreases. Moreover, in models (3) and (4) of Table 7, the marginal impacts of trading volume on R^2 are both significantly positive. This supports H3 that the R^2 is indeed commoving positively with trading volume, which is consistent with the investor composition hypothesis of R^2.

4 Conclusion

This paper explores the R^2 change around 7 corporate events, namely stock splits, revers splits, addition to Hang Seng index, deletion from Hang Seng index, allowing short selling, banning short selling, as well as rights offerings. We adopt an alternative methodology to DID, and this alternative methodology directly decompose the change of R^2. We find that after controlling the endogeneity of events, only four events lead to significant changes in R^2. Specifically, stock splits and addition to HSI tend to increase the R^2, while reverse split and deletion from HSI tend to decrease the R^2. This finding arouses a clear conflict about the relationship between the R^2 and price efficiency. We argue that it might be the case that the R^2 change is due to the investor composition: R^2 increase (decrease) is the result of the inflow (outflow) of the trend-chasing investors, and the R^2 change might be detached to the price efficiency explanation.

Reference

Bae K-H, Bailey W, Mao C. 2006. Stock market liberalization and the information environment. Journal of International Money and Finance 25(3):404–28

Barberis, N., Shleifer, A., 2003. Style investing. Journal of Financial Economics 68, 161–199.

Barberis, Nicholas, Andrei Shleifer, Jeffrey Wurgler (2005) Comovement, Journal of Financial Economics, 75 283-317

Beber, A. and Marco Pagano, 2013, Short-selling Bans around the World: Evidence from the 2007-2009 Crisis, Journal of Finance 68, 343-381.

Boehmer, E., C. Jones, and X. Zhang, 2010, Shackling Short Sellers: The 2008 Shorting Ban, Working Paper.

Bris, A., Goetzmann, W. N., and Zhu, N. (2007). Efficiency and the bear: Short sales and markets around the world. Journal of Finance, 62(3), 1029–1079.

Cai, Jinghan, Jia He, Jibao He and Weili Zhai (2018) Individual investors and R^2, working paper

Cai, Jinghan, Chiu Yu Ko, Yuming Li and Le Xia (2018) Hide and seek: Uninformed traders and short sales constraints, Annals of Economics and Finance, forthcoming

Cai, Jinghan and Le Xia, (2014) When R^2 meets the short sales constraints, Economic Letters, 125(3) 336-339

Chan, Kalok, and Yue-Cheong Chan, 2014, Price informativeness and stock return synchronicity: Evidence from the pricing of seasoned equity offerings, Journal of Financial Economics, 114(1)36-53

Chan K, A. Hameed, (2006) Stock price synchronicity and analyst coverage in emerging markets. *Journal of Financial Economics*, 80(1):115–47

Chan K, A. Hameed, and Wenjing Kang, 2013, Stock price synchronicity and liquidity, Journal of Financial Markets, 16 (3)414-438

Chen, C.X, and S.G. Rhee, 2010, Short Sales and Speed of Price Adjustment: Evidence form the Hong Kong Stock Market, Journal of Banking and Finance 34, 471-483.

Chen, Honghui, Gregory Noronha Vijay Singal (2005). The Price Response to S&P 500 Index Additions and Deletions: Evidence of Asymmetry and a New Explanation, 59 (4)1901-1930

Chuang, W.I. and Rauli Susmel (2011) Who is the more overconfident trader? Individual vs. institutional investors, *Journal of Banking and Finance*, 35(7), 1626-1644

Chang, E.C., Tse-Chun Lina Xiaorong Ma, (2015) The Tradeoff between Risk Sharing and Information Production in Financial Markets: Evidence from Stock Splits, Working paper

Copeland, T.E., 1979. Liquidity changes following stock splits. Journal of Finance 34, 115–141.

Daniel, K., D. Hirshleifer, A. Subrahmanyam (1998) Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839-1886.

Daniel, Kent, David Hirshleifer and Avanidhar Subrahmanyam (2002), overconfidence, arbitrage, and equilibrium asset pricing, Journal of Finance 56(3), 921-965

Dasgupta, Sudipto, Jie Gan, and Ning Gao (2010), Transparency, price informativeness, and stock return synchronicity: Theory and evidence, Journal of Financial and Quantitative Analysis 45, 1189-1220.

Diamond, D.W. and R.E. Verrecchia, 1987, Constraints on Short-Selling and Asset Price Adjustment to Private Information, Journal of Financial Economics 18, 277-311.

Duarte, J., & Young, L. (2009). Why is pin priced? Journal of Financial Economics, 91(2), 119–138.

Durnev, Artyom, Randall Morck, Bernard Yeung, and Paul Zarowin (2003), Does greater firm-specific return variation mean more or less informed stock pricing? Journal of Accounting Research 41, 797-836.

Durnev, Artyom, Randall Morck, and Bernard Yeung (2004), Does firm-specific information in stock prices guide capital budgeting? Journal of Finance 59, 65-105.

French, K.R. and Roll, R. (1986) Stock Return Variances: The Arrival of Information and Reaction of Traders. Journal of Financial Economics, 17, 5-26

Gassen, Joachim, Hollis Skaife and David Veenman (2017) Illiquidity and the measure of stock price synchronicity, working paper

Gervais, S., and Odean, T., (2001) Learning to be overconfident. Review of Financial Studies 14, 1-27.

Grullon, G, G. Kanatas, and J. Weston, (2004) Advertising, Breadth of Ownership, and Liquidity, with Gustavo Grullon and George Kanatas. Review of Financial Studies 17 (Spring 2004) 439-46.

Gul F, Kim J-B, Qiu A. 2010. Ownership concentration, foreign shareholding, audit quality, and stock price synchronicity: evidence from China Journal of Financial Economics 95(3):425–42

Guo, Fang, Kaiguo Zhou and Jinghan Cai (2008) Stock splits, liquidity, and information asymmetry—An empirical study on Tokyo Stock Exchange, Journal of Japanese and International Economies, 22, 417-438

Harrison, J. M. and D.M. Kreps, 1978, Speculative Investor Behavior in a Stock Market with Heterogeneous Expectations, Quarterly Journal of Economics 92, 323-336.

Holderness, Clifford and Jeffrey Pontiff (2016) Shareholder nonparticipation in valuable rights offerings: New findings for an old puzzle, Journal of Financial Economics, 120(2) 252-268

Hou, Kewei, Lin Peng, and Wei Xiong (2013) Is R2 a measure of market inefficiency? Working paper, 2013

Jin, Li and Stewart C. Myers (2006), R2 around the world: new theory and new tests, Journal of Financial Economics 79(2), 257-292.

Kang, Shuo and Stephen Gong (2017), Does High Stock Return Synchronicity Indicate High or Low Price Informativeness? Evidence from a Regulatory Experiment, International Review of Finance

Kelly, Patrick (2014), Information efficiency and firm-specific return variation, Working paper, Arizona State University.

Lakonishok, J., Lev, B., 1987. Stock splits and stock dividends: Why, who, and when. Journal of Finance 42, 913–932.

Li K, Morck R, Yang F, Yeung B. 2004. Firm-specific variation and openness in emerging markets. Review of Economics and Statistics 86(3):658–69

Marsh, I, and R. Payne, 2012, Banning Short Sales and Market Quality: The UK's Experience, Journal of Banking and Finance 36, 1975-1986.

Merton, R., 1987. A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483–511.

Miller, E., 1977, Risk, Uncertainty, and Divergence of Opinion, Journal of Finance 32, 1151-1168.

Morck, Randall, Bernard Yeung, and Wayne Yu (2000), The information content of stock markets: Why do emerging markets have synchronous stock Price movements? Journal of Financial Economics 58, 215-260.

Morck, Randall, Bernard Yeung, and Wayne Yu (2013), R2 and the economy, Annual Review of Financial Economics, vol 5, 143-166

Peress, Joel, 2010, The Tradeoff between Risk Sharing and Information Production in Financial Markets

Piotroski J, Roulstone D. 2004. The influence of analysts, institutional investors, and insiders on the incorporation of market, industry, and firm-specific information into stock prices. Accounting Review, 79(4):1119–51

Roll, Richard (1988), R^2, Journal of Finance 43, 541-566.

Teoh, Siew Hong, Yong Yang and Yinglei Zhang (2007), R-squared: Noise or firm-specific information, Working paper, University of California, Irvine.

Veldkamp L. 2006. Information markets and the comovement of asset prices. Review of Economic Studies 73(3):823–45

Wu, Xueping and Zheng Wang (2002) Why Do Firms Choose Value-Destroying Rights Offerings? Theory and Evidence from Hong Kong. Working paper.

Wurgler J. 2000. Financial markets and allocation of capital. Journal of Financial Economics 58(1/2):187–214

Zhang, Yan and Shin Ikeda (2016) Effects of short sale ban on financial liquidity in crisis and non-crisis periods: a propensity score-matching approach, Applied Economics, 49 (28) 2711-2718

 doi:10.20944/preprints201809.0474.v1

Appendix: Log-linearization of the R^2

We start with this market model

$$r_{it} = \alpha + \beta r_{mt} + \varepsilon_{it}, \quad t=1, 2,\ldots,T \tag{1}$$

where r_{it} is the continuously compounded return for stock i on day t, r_{mt} is the market return on day t, and ε_{it} is the error term. The R^2 is then

$$R^2 = \frac{\beta^2 V}{\beta^2 V + SSE} \tag{2}$$

where β is the beta value estimated from equation (1), V is the market return variation measure, more specifically, $V = \frac{T-1}{T}\sum_{i=1}^{T}(r_{mt} - \overline{r_{mt}})^2$, and SSE is the sum of squared residuals.

Take natural *log* on both sides of (2), we have:

$$\log(R^2) = \log(\beta^2) + \log(V) - \log(\beta^2 V + SSE) \tag{3}$$

Take Taylor first order expansion of (3)

$$\log(R^{2*}) + \frac{R^2 - R^{2*}}{R^{2*}} = \log(\beta^{2*}) + \frac{\beta^2 - \beta^{2*}}{\beta^{2*}} + \log(V^*) + \frac{V - V^*}{V^*} - \left[\log(\beta^{2*}V^* + SSE^*) + \frac{\beta^2 V \quad + SSE \quad - (\beta^{2*}V^* + SSE^*)}{\beta^{2*}V^* + SSE^*}\right] \tag{4}$$

Since $\log(R^{2*}) = \log(\beta^{2*}) + \log(V^*) - \log(\beta^{2*}V^* + SSE^*)$

(4) can be simplified to:

$$\frac{R^2 - R^{2*}}{R^{2*}} = \frac{\beta^2 - \beta^{2*}}{\beta^{2*}} + \frac{V - V^*}{V^*} - \frac{\beta^2 V + SSE - (\beta^{2*}V^* + SSE^*)}{\beta^{2*}V^* + SSE^*}$$

(4′)

For notational ease, define the tilde expression of variable $\tilde{x} = \frac{x-x^*}{x^*}$, or the percentage deviation of x about x^*, which is the steady state value of x. So, equation (4′) can be expressed as:

$$\widetilde{R^2} = \widetilde{\beta^2} + \tilde{V} - \frac{\beta^2 V - \beta^{2*}V^*}{\beta^{2*}V^* + SSE^*} - \frac{SSE - SSE^*}{\beta^{2*}V^* + SSE^*}$$

$$= \widetilde{\beta^2} + \tilde{V} - \frac{\beta^{2*}V^*}{\beta^{2*}V^* + SSE^*}\frac{\beta^2 V - \beta^{2*}V^*}{\beta^{2*}V^*} - \frac{SSE^*}{\beta^{2*}V^* + SSE^*}\frac{SSE - SSE^*}{SSE^*}$$

So, we have

$$\widetilde{R^2} = \widetilde{\beta^2} + \tilde{V} - R^{2*}\frac{\beta^2 V - \beta^{2*}V^*}{\beta^{2*}V^*} - (1 - R^{2*})\frac{SSE - SSE^*}{SSE^*}$$

$$\widetilde{R^2} = \widetilde{\beta^2} + \tilde{V} - R^{2*}\widetilde{\beta^2 V} - (1 - R^{2*})\widetilde{SSE}$$

(5)

where the R^{2*} is the steady-state R^2.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 September 2018 doi:10.20944/preprints201809.0474.v1

Table 1: Summary of the Events, R^2, and Price efficiency

	Event	Frequency	R^2 change Direction	Price efficiency	Is MYY correct?	Is HPX correct?
(1)	Stock Split	219	⇑	⇓	Yes	No
(2)	Reverse split	484	⇓	⇑	Yes	No
(3)	Addition of Hang Seng index	45	⇑	⇑	No	Yes
(4)	Deletion from Hang Seng index	35	⇓	⇓	No	Yes
(5)	Allowing Short selling	905	⇑	⇑	No	Yes
(6)	Disabling Short selling	669	⇓	⇓	No	Yes
(7)	Rights issue	579	⇑	⇑	No	Yes

Note: Contents in "price efficiency" column are derived from the literature. Literature review section gives more descriptions.

Table 2: R^2 Comparison

We start with the direct comparison for the R^2 between the pre- and post-windows for the seven events. we run the following market model

$$r_{it\in j=\{pre,post\}} = \alpha_{ij} + \beta_{ij} r_{mt} + \varepsilon_{it}, \quad t=1, 2,\ldots,T_{ij} \qquad (1)$$

where r_{it} is the continuously compounded return for stock-event i on day t, if t is in window j (pre- or post-event window), r_{mt} is the Hang Seng index return on day t, and ε_{it} is the error term. T_{ij} is the total number of observations for stock-event i in window j={pre, post}. The R^2 is then

$$R_{ij}^2 = \frac{\beta_{ij}^2 V_{ij}}{\beta_{ij}^2 V_{ij} + SSE_{ij}} \qquad (2)$$

where β_{ij} is the beta value estimated from equation (1), V_{ij} is the market return variation measure for stock-event i, from window j, and more specifically, $V_{ij} = \frac{T_{ij}-1}{T_{ij}} \sum_{s=1}^{T_{ij}} (r_{mt} - \overline{r_{mt}})^2$, and SSE_{ij} is the sum of squared residuals for stock-event i, from window j.

	Event	# obs	mean R^2_{pre}	mean R^2_{post}	t-value for the log difference	median R^2_{pre}	median R^2_{post}	Signrank test	R^2 Direction
(1)	Split	219	5.30	9.39	5.90***	1.85	*5.29*	5.73***	⇑
(2)	Reverse split	484	6.42	4.93	-3.57***	2.95	*2.32*	-3.44***	⇓
(3)	Addition of HS index	45	26.78	34.72	3.04***	22.58	*31.89*	2.70***	⇑
(4)	Deletion from HS index	35	26.52	17.34	-2.88***	19.00	*14.40*	-2.95***	⇓
(5)	Allowing Short selling	905	12.48	14.89	5.25***	8.57	*11.63*	5.29***	⇑
(6)	Disabling Short selling	669	11.89	9.32	-6.10***	8.39	*6.59*	-5.52***	⇓
(7)	Rights issue	579	8.62	9.83	2.42**	4.48	*5.14*	2.85***	⇑

Note: Table 4 shows the direct comparison for means and medians of the mean daily dollar volume in windows around the events. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

doi:10.20944/preprints201809.0474.v1

Table 3: Endogenous timing of events

Panel A of Table 3 is based on the following probit model

$$Prob(\mathbf{1}) = \alpha + \beta_1 MktRtn_i + \beta_2 MktStd_i + \varepsilon_i$$

where Prob(1) is a dummy variable which equals 1 if event i leads to R^2 increase, including stock split, addition to Hang Seng index, allowing short selling, and rights issue, and 0 if event i leads to R^2 decrease, including stock consolidation, deletion from Hang Seng Index and disabling short selling. The sample contains only pre-event window in Panel A, Table 3.

Panels B and C of Table 3 shows the market condition change in the pre- and post-120-trading-day window of R^2 increase events and R^2 decrease events, respectively.

Panel A: Market condition and events

	(1)	(2)	(3)
Market return	1.305***		0.733***
	[11.45]		[5.30]
Market Return Stdev.		-34.50***	-24.40***
		[-12.56]	[-7.30]
constant	0.215***	0.785***	0.617***
	[9.19]	[15.37]	[10.29]
N	3002	3000	3000
chi2	136.2	160.8	189.2
p	0.000	0.000	0.000

*, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Panel B: Market change in the pre- and post-event window of R^2 increase events

# obs: 1754		Pre	Post	Paired t-value/ z-value
Market return	Mean	0.0406	0.0008	-6.84***
	Median	0.0791	0.0286	-8.05***
Market Return Stdev.	Mean	0.0147	0.0171	11.61***
	Median	0.0123	0.0138	8.07***

*, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Panel C: Market change in the pre- and post-event window of R^2 decrease events

 doi:10.20944/preprints201809.0474.v1

# obs: 1243		Pre	Post	Paired t-value/ z-value
Market return	Mean	-0.0502	0.0404	9.16***
	Median	0.0038	0.0680	8.02***
Market Return Stdev.	Mean	0.0187	0.0172	-6.96***
	Median	0.0170	0.0146	-9.36***

*, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Table 4: Decomposition of R^2 before and after the events

In this table, we first calculate the mean R^2, β^2, V, and SSE for the pre- and post event windows for the R^2 increase and R^2 decrease events, respectively.

$\boldsymbol{Panel\ A}$: $\boldsymbol{R^2\ increase}$	$\boldsymbol{R^2}$	$\boldsymbol{\beta^2}$	$\boldsymbol{V}$	$\boldsymbol{SSE}$
pre	0.100	0.877	0.032	0.243
post	0.115	0.694	0.043	0.232
change	15.39%	-20.82%	35.86%	-4.19%
$\boldsymbol{Panel\ B}$: $\boldsymbol{R^2\ decrease}$	$\boldsymbol{R^2}$	$\boldsymbol{\beta^2}$	$\boldsymbol{V}$	$\boldsymbol{SSE}$
pre	0.088	0.615	0.051	0.293
post	0.070	0.551	0.044	0.312
change	-20.71%	-10.52%	-14.63%	6.59%

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 September 2018 doi:10.20944/preprints201809.0474.v1

Table 5: R^2 Comparison revisited using FR^2

Panel A of Table 5 shows the comparison around the events using both standard R^2 and fixed- R^2, or FR^2. For stock i, $FR^2_{i,j=pre,post}$ is defined as follows:

$$FR^2_{i,j=pre,post} = \begin{cases} R^2_{i,pre}, & if\ j = pre \\ \dfrac{\beta^2_{i,post} V_{i,pre}}{\beta^2_{i,post} V_{i,pre} + SSE_{i,post}}, & if\ j = post \end{cases}$$

where we use the [-120 day, announcement date] as the pre-event window, and [effective date, 120 days] as the post-event window.

Panel A: Test group

	Event	# obs	Mean R^2_{pre}	Mean FR^2_{post}	Mean R^2_{post}	t-value for R^2_{pre}= FR^2_{post}	Median R^2_{pre}	Median FR^2_{post}	Median R^2_{post}	Signrank for R^2_{pre}= FR^2_{post}	R^2
(1)	Split	219	5.30	6.87	*9.39*	5.90***	1.85	3.57	*5.29*	3.36***	⇑
(2)	Reverse split	484	6.42	5.25	*4.93*	-3.08***	2.95	2.71	*2.32*	-2.46**	⇓
(3)	Addition of HS index	45	26.78	34.81	*34.72*	4.08***	22.58	33.31	*31.89*	3.64***	⇑
(4)	Deletion from HS index	35	26.52	16.67	*17.34*	-4.35***	19.00	12.63	*14.40*	-3.70***	⇓
(5)	Allowing Short selling	905	12.48	12.24	*14.89*	-0.70	8.57	7.04	*11.63*	-1.18	NA
(6)	Disabling Short selling	669	11.89	11.24	*9.32*	-1.59	8.39	7.47	*6.59*	-1.91*	NA
(7)	Rights issue	579	8.62	9.41	*9.83*	1.91*	4.48	4.52	*5.14*	1.46	NA

*, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Panel B: Control group

			Mean				Median			
	Event	# obs	R^2_{pre}	FR^2_{post}	R^2_{post}	t-value for $R^2_{pre}= FR^2_{post}$	R^2_{pre}	FR^2_{post}	R^2_{post}	Signrank for $R^2_{pre}= FR^2_{post}$
(1)	Split	219	8.02	7.89	*9.89*	-0.18	3.37	4.36	*5.29*	0.57
(2)	Reverse split	484	5.40	5.53	*5.06*	0.38	2.14	2.09	*2.25*	-0.09
(3)	Addition of HS index	45	21.34	20.44	*20.35*	-0.64	17.34	17.39	*15.52*	-0.54
(4)	Deletion from HS index	35	15.77	14.99	*15.05*	-0.41	9.62	7.53	*8.23*	-0.60
(5)	Allowing Short selling	905	10.35	7.75	*10.48*	-8.54***	5.94	3.39	*5.78*	-8.76***
(6)	Disabling Short selling	669	8.68	7.72	*6.34*	-2.89***	5.11	3.40	*3.20*	-3.63***
(7)	Rights issue	579	7.73	7.44	*7.87*	0.70	2.82	2.48	*2.68*	-0.21

*, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Table 6: The change of beta and SSE

This table shows the beta and the sum of squared residuals change around the R^2 increase and R^2 decrease events.

	β^2			SSE		
Panel A*: R^2 *increase	**Before**	**After**	**t-value**	**Before**	**After**	**t-value**
Stock split	0.62	0.75	2.92***	0.348	0.318	-1.03
Addition to HSI	0.82	0.87	1.23	0.0894	0.0802	-0.80
Both	0.65	0.77	3.10***	0.303	0.276	-1.09
Panel B*: R^2 *decrease	**Before**	**After**	**Diff**	**Before**	**After**	**Diff**
Reverse split	0.57	0.56	-0.33	0.354	0.430	2.87***
Deletion from HSI	0.71	0.59	-2.17**	0.0156	0.0210	0.64
Both	0.58	0.57	-0.65	0.338	0.409	2.90***

*, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 25 September 2018 doi:10.20944/preprints201809.0474.v1

Table 7: R^2 and Trading volume

Table 7 shows the results of the following regressions:

$$vol_{i\in R_+^2, j=pre,post} = \alpha_1 + \beta_1 post_{i,j} + \varepsilon_{ij} \quad (1)$$

$$vol_{i\in R_-^2, j=pre,post} = \alpha_2 + \beta_2 post_{i,j} + u_{ij} \quad (2)$$

$$\Psi_{i\in R_+^2, j=pre,post} = \gamma_1 + \beta_1 post_{i,j} + \theta_1 vol_{i,j} + \rho_1 post_{i,j} * vol_{i,j} + \eta_{ij} \quad (3)$$

$$\Psi_{i\in R_-^2, j=pre,post} = \gamma_2 + \beta_2 post_{i,j} + \theta_2 vol_{i,j} + \rho_2 post_{i,j} * vol_{i,j} + \mu_{ij} \quad (4)$$

where $vol_{i\in R_+^2, j=pre,post}$ is the mean dollar trading volume of event i, if i is an R^2 increase event (stock split and addition to Hang Seng Index), for window j = pre, post; $vol_{i\in R_-^2, j=pre,post}$ is the mean dollar trading volume of event i, if i is an R^2 decrease event (stock reverse split and deletion from Hang Seng Index) for window j = pre, post. $\Psi_{i\in R_+^2, j=pre,post} = \log\frac{R^2_{i\in R_+^2, j=pre,post}}{1-R^2_{i\in R_+^2, j=pre,post}}$, and $\Psi_{i\in R_-^2, j=pre,post} = \log\frac{R^2_{i\in R_-^2, j=pre,post}}{1-R^2_{i\in R_-^2, j=pre,post}}$, where $R^2_{i\in R_+^2, j=pre,post}$ is the R^2 of stock-event i, if i is an R^2 increase event (stock split and addition to Hang Seng Index), for window j = pre, post, and $R^2_{i\in R_-^2, j=pre,post}$ are defined analogously. $post_{i,j}$ is a dummy variable which equals 1 if j=post, and 0 otherwise. $vol_{i,j}$ is the mean dollar trading volume of event i in window j. The models are estimated using seemingly unrelated regression. t-values are in brackets.

	(1)	(2)	(3)	(4)
Dependent variable	$vol_{i\in R_+^2, j}$	$vol_{i\in R_-^2, j}$	$\Psi_{i\in R_+^2, j}$	$\Psi_{i\in R_-^2, j}$
$\beta_1 (post_{i,j}\ for\ vol_{i\in R_+^2, j}/R^2_{i\in R_+^2, j})$	0.759***		-0.612	
	[6.75]		[-1.56]	
$\beta_2 (post_{i,j}\ for\ vol_{i\in R_-^2, j}/R^2_{i\in R_-^2, j})$		-0.850***		1.314***
		[-7.66]		[3.40]
$\rho_1 (post_{i,j} * vol_{i,j}\ for\ R^2_{i\in R_+^2, j})$			0.101**	
			[2.18]	
$\rho_2 (post_{i,j} * vol_{i,j}\ for\ R^2_{i\in R_-^2, j})$				-0.191***
				[-3.76]
$\theta_1 (vol_{i,j}\ for\ R^2_{i\in R_+^2, j})$			0.390***	
			[16.03]	
$\theta_2 (vol_{i,j}\ for\ R^2_{i\in R_-^2, j})$				0.461***
				[19.70]
Constant	7.623***	8.037*	-6.754***	-7.239***
	[134.7]	[141.2]	[35.02]	[-37.04]
Marginal effect for Vol.			0.415***	0.411***

 doi:10.20944/preprints201809.0474.v1

			[20.01]	[19.67]
		χ^2		χ^2
Test for equality for:	$\beta_1 = \beta_2$	79.36***	$\beta_1 = \beta_2$	10.48***
			$\rho_1 = \rho_2$	13.92***
			$\theta_1 = \theta_2$	13.54***
# of observations	2116	2116	2090	2090

*, **, and *** represent significance level of 10%, 5%, and 1%, respectively.