PORTFOLIO PUMPING IN SINGAPORE: MYTH OR REALITY?

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Executive Summary

This research originates from a landmark court case involving the Monetary Authority of Singapore (MAS, plaintiff) and Tan Chong Koay and Pheim Asset Management Sdn Bhd (defendants). In August 2009, a formal civil suit was filed against the defendants for creating a false or misleading appearance relating to the price of a security. On 17 September 2010, the defendants were pronounced guilty of priming the stocks of United Envirotech (UET) over a three-day period from 29 December 2004 to 31 December 2004. At a subsequent appeal hearing on 22 July 2011, the original verdict was upheld by the Court of Appeal.

The case was interesting because it provided the ideal case study to explore the effectiveness of regulatory enforcements on portfolio pumping deterrence. It also helped determine whether portfolio pumping in Singapore was prevalent then and how the trends have evolved over time.

After the introduction, we summarize the key attributes of the MAS case just mentioned. We then explain the regulatory environment that all listed companies in Singapore need to comply with, along with a chronology of events related to changes in the microstructure of the exchange, particularly in the area of managing the closing prices.

In the following chapter, we examine the literature on the subject. Our main takeaway is that the relationship between fund manager compensation and the underlying fund performance creates a natural incentive for managers to temporarily boost prices of their fund holdings, especially if such a relationship is formally set in their compensation contracts.

To test for portfolio pumping activities, our review suggested using two approaches. First, testing a relevant period metric against a control period or a control environment, and second, validating the results by using a regression analysis of a metric against period-defining dummy variables.

As for data, this study was privileged to be granted access to tick-by-tick data of 189 listed companies under the FTSE Straits Times (ST) All-Share Index (including current and delisted companies) from the Singapore Exchange (SGX). The dataset period ranged from January 2003 to December 2013. The data consisted of 35 fields, out of which 16 were found to be relevant. In total, more than 12 billion data points were used for this study. Given that data were spread across multiple files and that each file carried trade information running into several hundreds of thousands of rows, data extraction was not a straightforward exercise. Basic software, such as Microsoft Excel, could not be solely relied on to undertake our analysis given its limitation in handling the enormous volume of data. Hence, we loaded the complete dataset in the desired format onto a Microsoft SQL database server. Most analyses were done on data extracted from this central database. EViews was used as the primary statistical tool to run analysis.

Our research revolved around seven hypotheses. Their description, the subsequent findings, and results interpretation are as follows.

Hypothesis 1 suggested that portfolio pumping would be evident at the broad market level. It should be reflected in abnormal positive returns on the last day of the quarter and abnormal negative returns on the first day of the following quarter.

Based on the last trading day of the quarter, we found reasonable evidence for abnormal positive returns at the end of the year and some limited support at the end of the second quarter. But no reversal of returns was visible. Our volume-based analysis also did not offer any additional insight, suggesting that this hypothesis does not appear to be valid.

Hypothesis 2 tested for portfolio pumping concentrating in the final few minutes of a trade or in the final few transactions.

Although we found strong statistical evidence to suggest that returns in the final 30 minutes of trading in a quarter were positive, it does not appear to be very different from the final 30 minutes of trading on other days of the quarter, thus offering limited support for pumping. But in a separate volume-based regression analysis, a different picture emerged in that trades in the final 30 minutes during quarter-end days were relatively more active, even at the 1% significance level. Thus, results were, at best, mixed for Hypothesis 2.

Hypothesis 3 tested for whether the proportion of buyer-initiated transactions is higher around the last day and final few minutes of trades at quarter-ends than at other periods.

Here we found that on the last day of the quarter, on average, 49% of trades happen to be buyer initiated. This result is higher than the average trades observed on non-quarter-end days in the quarter. When the test was extended to the final 30 minutes of trade, the proportions of buyer-initiated trades were marginally higher at 50%. But, in terms of statistical significance, evidence was not as strong as the complete day trade to suggest the proportion of buyer-initiated trades is higher than on non-quarter-end days. Mixed results were found for Hypothesis 3.

Hypothesis 4 examined whether fund managers are likely to engage in pumping with limited amount of capital.

Using the proportion of small trades (less than 5,000 shares) as the proxy for representing a limited amount of capital, we found the figure to be significantly smaller on both complete day and the final 30 minutes of trading during quarter-end days relative to non-quarter-end days. Hence, no evidence emerged to find this hypothesis to be valid.

Hypothesis 5 examined whether pumping is achieved through the cornering of trades by a select set of traders and clients.

Although we observed both trader and client concentration to be significantly higher on the last trading day of a quarter as compared with other days in the quarter, interestingly, when focused on the final 30 minutes of trading, we saw the trader concentration on the final trading day of a quarter to be significantly lower as compared with other days in the quarter. Mixed results were found for Hypothesis 5.

Hypothesis 6 looked at potential pumping activities on a segmented basis in which we expected such pumping activities to be concentrated on

a. small-cap stocks,

b. Catalist-listed stocks,[1]

c. extreme strong and weak performers, and

d. S-chip stocks.

In this analysis, we found mid-cap stocks to be the only capitalization segment[2] with significant positive returns on the last day of the quarter as measured by absolute and excess returns. Additionally, this stock group is the only capitalization segment to register a negative excess return on the first day of the quarter, although it was not found to be statistically significant. Again, mixed results were found here.

In Hypothesis 7, we tried to determine whether portfolio pumping declined over time, especially after key milestone events around enforcement of portfolio pumping legislation.

We found that the regulatory reform proposal to introduce composition system and mandatory minimum penalties by disciplinary committees for rule violations in the securities market to be associated with a significant reduction in both average absolute and excess returns after its occurrence in February 2008. This hypothesis was thus not rejected.

Having concluded our first round of quantitative analysis, we organized a practitioner round table event on 30 March 2015 with various stakeholders from Singapore. During this event, we spent three hours presenting our findings and seeking advice on how to interpret our findings from these senior portfolio managers, investment analysts, and academics. The feedback was insightful and inspired us to undertake various additional tests.

An important comment we received was that the FTSE mid-cap stock division in our segmental test is actually regarded as small-cap in the eyes of fund managers whereas the FTSE small-cap division would be the equivalent of micro-cap. Given that funds generally have limited exposure to the FTSE small-cap division because of limited free float and liquidity of the shares of these companies, we should ideally not expect to see much pumping activity here.

To better understand the segments in which portfolio pumping is possibly present to a larger extent, we replicated the analysis that we undertook on the FTSE STI, mid-cap, and small-cap divisions with custom groups based on market capitalization. We divided the investment universe of the FTSE STI and FTSE ST Mid Cap Index constituents into three groups based on their market value at the start of each quarter. Market value greater than S$10 billion was treated as Group 1. Market value between S$5 billion to S$10 billion was treated as Group 2, and market

[1]Mainboard and Catalist are two platforms available for listing in Singapore. Mainboard is the primary listing platform under direct supervision of the SGX. Catalist is the sponsor-supervised listing platform, with less rigorous listing criteria facilitating smaller companies with limited operational track record in getting listed easily.
[2]For market capitalization, we studied three stock segments, namely constituents of FTSE STI, FTSE ST Mid Cap, and FTSE ST Small Cap indexes.

value between S$2 billion to S$5billion was treated as Group 3. We introduced the S$2 billion cut-off to be in line with the standard industry definition[3] for a mid-cap stock.

In terms of absolute returns, all three groups appeared to have insignificant positive returns, although it was significantly positive across the groups at the beginning of the quarter. But in terms of excess returns, the variation became clearly visible. Only Group 3, representing the smallest capitalization group with market value of S$2 billion to S$5 billion, seemed to generate significant positive return at the end of the quarter, and although not statistically significant, it also seemed to indicate some reversal. This finding suggests that some signs of potential pumping were evident in Group 3.

Other feedback that we incorporated into this research related to the common characteristics of stocks that could be pumped. In this case, the practitioners suggested that because potential portfolio pumping activities among individual stocks could have been masked out during the market and segmental quantitative tests, it would be ideal if we considered the portfolio pumping situation at the individual stock level and came up with a list of common characteristics.

To address this feedback, we identified specific instances of possible portfolio pumping at the stock level over the 44 quarters of our study and then identified characteristics that mark such stocks. The approach we used is similar to the "gaming proxy" method of Gallagher, Gardner, and Swan (2009).[4]

Additionally, to strengthen our findings, we further adopted a stricter threshold-based approach to identify stocks with possibly the highest level of pumping and observed their characteristics. We achieved that by making use of our two-day inflation[5] metric to define stocks at the end of each quarter and restricted our analysis universe to the top quartile and top decile stocks with the highest level of two-day inflation. Following that, we defined our gaming proxy metric based on this universe as the dependent variable in a logistic regression against a set of stock, trade, and market characteristics.

Our findings suggest that portfolio pumping appears to be higher among stocks that have performed poorly until the second-to-last day of the quarter; other characteristics associated with higher portfolio pumping include stocks with smaller capitalization and lower free-float liquidity as well as being Catalist-listed and being a non-constituent of the MSCI Singapore Free Index (SIMSCI). Such potential pumped stocks also have a significantly higher degree of buyer-initiated trades on the day of pumping with a higher standardized trade volume. The proportion of trades happening in the final 30 minutes on the last day of a quarter also appears significantly higher among possible pumped-up stocks. An additional interesting insight is that even though the S-chip division as a universe did not show any significant signs of portfolio

[3]This S$2 billion cut-off was based on the consensus views of the practitioners who were present during the Singapore round table on 30 March 2015.
[4]Gaming proxy is a dummy variable that takes a value of 1 for a stock in a quarter if the stock earns positive absolute and excess return on the last day of the quarter and also earns a negative absolute and excess return on the first day of the subsequent quarter.
[5]The two-day inflation metric represents the difference in returns between two consecutive trading days. In the event of portfolio pumping at the end of a reference period, say a quarter, we would expect a strong positive return on the last day of the quarter and a strong negative return on the beginning day of the subsequent quarter, thereby making the two-day inflation metric significantly positive.

pumping, it did seem to have a reasonable representation among the stocks with the highest pumping potential, as measured by our two-day inflation metric.

Our main conclusions and policy recommendations based on the findings are as follows.

First, we found evidence from MAS's experience that the successful prosecution of a stock manipulator and the existence of market microstructure that would render portfolio pumping activity to be a relatively expensive affair have a strong positive impact on market integrity.

In arriving at this conclusion, we used milestone-defining dummy variables to segregate the time period before and after key legal and regulatory events and regressed the respective portfolio pumping metric across these milestone-defining dummy variables.

Our results show that the first conviction in September 2010 for portfolio pumping in Singapore, with Pheim Asset Management Sdn Bhd being pronounced guilty, was associated with a significant reduction in average market absolute returns. The same observation was also made with the regulatory reform proposal to introduce composition system and mandatory minimum penalties by disciplinary committees for rule violations in the securities market in February 2008.

We thus recommend other exchanges adopt and refine some of these measures to stifle potential market manipulation activities on closing prices during end of day.

Second, we identified the common profile of the listed companies that have strong potential to be subject to portfolio pumping. Their traits are as follows:

- Mid-cap segment, especially those within the S$2 billion to S$5 billion range
- Lower free-float liquidity
- Not constituents of the SIMSCI
- Part of the worst performance quartile
- Higher daily standardized trade volume
- Significantly higher degree of buyer-initiated trades
- Greater proportion of trades in the final 30 minutes of a quarter-end trading day
- S-chip stocks

With this profile in hand, regulators would be better equipped to divert their supervisory effort to where it matters the most. In particular, given the unexplained statistically significant returns that were uncovered during year-end for both the mid-cap stocks and the worst-performing quartile group of stocks during each quarter, regulators would benefit most from increasing their scrutiny of market surveillance activities, particularly in these two segments.

Third, despite mainstream media reporting on the prevalence of portfolio pumping activities during year-ends, our findings indicate that it was not the case. Although abnormal returns were evident at year-ends, they were definitively not related to portfolio pumping activities and there was limited evidence that they were a result of window dressing activities.

In light of this evidence, and to prevent the possible misperception of investors, regulators should increase the awareness and education of mainstream media in relation to the real situation of portfolio pumping in practice. By closing the knowledge gap among mass media journalists, they will paint a more accurate picture of the current capital market regulatory scene for their readers.

1. Introduction

The genesis for this research project arose from the case of Monetary Authority of Singapore (MAS, plaintiff) versus Tan Chong Koay and Pheim Asset Management Sdn Bhd (defendants) in August 2009[6] when a formal civil suit was filed against the defendants for creating a false or misleading appearance relating to the price of a security. On 17 September 2010, the defendants were pronounced guilty of priming the stocks of United Envirotech (UET) over a three-day period from 29 December 2004 to 31 December 2004. At a subsequent appeal hearing on 22 July 2011, the original verdict was upheld by the Court of Appeal. Using this landmark case, we wanted to explore the effect of enforcement as deterrence to portfolio pumping activities.

Another reason for undertaking this project was to determine whether the assertion by the media that window dressing activities occur at year-ends was actually true. Local newspapers frequently mention[7] near the end of December that stocks are moving up in price because of this type of activity. During the course of our research, we realized that the media may have portrayed window dressing activities incorrectly. In fact, we believe that when the media mention window dressing activities, they are actually referencing portfolio pumping.

Window Dressing and Portfolio Pumping: What's the Difference?

Window dressing occurs when poorly performing stocks in the portfolio are sold and replaced with well-performing stocks. This replacement usually occurs at the end of the year and is aimed at presenting a favorable picture of the portfolio for the fund manager when it is published in the annual report.

Portfolio pumping occurs with the intent of manipulating the prices of the chosen stocks to increase the closing prices around a reference period (usually at quarter-ends and year-ends). For such stocks to be considered "pumped," their prices should subsequently fall when the activity ceases. In other words, once the artificial inflation of stock prices ends, these stocks should return to their market equilibrium prices, typically at the beginning of the subsequent quarters and years. If successful, the higher marking of the prices at the relevant reference period would result in the total position of the "pumped" stocks to be valued higher.

[6]Monetary Authority of Singapore v. Tan Chong Koay and another, SCHC 277, Suit No. 658 of 2008 (High Court, 2010): www.singaporelaw.sg/sglaw/laws-of-singapore/case-law/free-law/high-court-judgments/14308-monetary-authority-of-singapore-v-tan-chong-koay-and-another-2010-sghc-277.

[7]For example, Jonathan Burgos and Chanyaporn Chanjaroen, "Singapore Banker Faces Uphill Battle in Boosting SGX Trading," Bloomberg (13 July 2015); Shihar Aneez, "SE Asia Stocks – Most Edge Up; Singapore Up on Banks," Reuters (23 March 2015); R. Sivanithy, "Thoughts Turn to Window Dressing," *Business Times* (26 March 2015); R. Sivanithy, "STI Lift May Be Due to Early Window Dressing," *Business Times* (27 March 2015); and R. Sivanithy, "Good Chance for Window-Dressing Push on STI," *Business Times* (29 December 2014).

Why Do These Activities Happen?

Our literature review suggests that these types of activities are common. In their illustrious work on the January effect, Rozeff and Kinney (1976) found that the monthly returns of NYSE stocks in January are about seven times the average they are in the other months. Since then, building on this finding, other researchers have also observed various forms of seasonal anomalies in financial markets. These include French (1980), who found some evidence of a weekend effect; Ariel (1987), who suggested that there were anomalies related to the day of the month; and Harris (1989), Akyol and Michayluk (2010), McInish and Wood (1990), Chan (2005), and Aitken, Kua, Brown, Walter, and Izan (1995), all of whom found evidence of the end-of-day effect in such countries as Turkey, Canada, Hong Kong, and Australia.

In relation to our study, Harris (1989) found that these abnormal end-of-day price effects peaked at month-ends and reversed at the turn of the month. Similar results were also discovered by Lakonishok and Smidt (1988), who uncovered that the daily average returns over the last four days at the turn of each month were consistently higher than other days. Zweig (1997) pointed to evidence that the average equity fund beat the S&P 500 Index on the last day of the year by 53 bps and underperformed it the following day by 37 bps.

Common explanations for the return anomalies include the effects of tax-loss selling as observed by Roll (1983), Keim (1983), Reinganum (1983), Sias and Starks (1997), and Hu, McLean, Pontiff, and Wang (2014); the influence of large periodic inflows as found by Harris (1989); and window dressing as suggested by Haugen and Lakonishok (1987) and Musto (1999).

But in the seminal work of Carhart, Kaniel, Musto, and Reed (CKMR 2002), they disagreed with the previous reasoning and attributed the observation of an abnormal positive return on the last day of the quarter and an abnormal negative return on the first day of the subsequent quarter to portfolio pumping. This pumping occurs when a fund manager tries to artificially increase prices of stocks held in a portfolio.

What Motivates Portfolio Pumping Activities?

A common reason is the expectation of generating higher compensation. Brown, Harlow, and Starks (1996) explain this expectation using competition analysis, whereas Bhattacharyya and Nanda (2013) and Xiao, Cheng, and Chen (2005) believe this expectation is a natural outcome of incentives being directly linked to fund performance.

This view is particularly applicable to hedge funds for which the performance fee component is generally a higher proportion of the total fees (Ben-David, Franzoni, Landier, and Moussawi 2013). Interestingly, Asness, Krail, and Liew (2001) found the possibility of incurring a bad reputation through the poor performance of the fund as another reason for undertaking this type of activity. Agarwal, Daniel, and Naik (2007) explain this behavior as drawing on savings by borrowing from future periods when performance matters the most.

In our review, we found three major theories that help explain why portfolio pumping occurs.

The first is known as "leaning for the tape," which was documented by Ippolito (1992) and Sirri and Tufano (1998) when they found a convex relationship between flows and performance in mutual funds. In this case, as noted by CKMR (2002), investor flows tend to favor the top-performing funds in a disproportionate manner, which provides the incentive for such funds to manipulate the closing prices. Furthermore, given the weak persistence of outperformance among such top-performing funds across subsequent quarters, as recorded by Hendricks, Patel, and Zeckhauser (1993) and Zheng (1999), investors are likely to look for gaining maximum flows when the going is good.

The second theory is known as "clutching at straws." Khorana (1996) found evidence of this theory by comparing the turnover and costs of departing fund managers with those of continuing managers; both elements exhibited higher levels for the departing fund manager.[8] He explains that this result is attributable to the fear of possible loss of employment among the departing fund managers, which leads them to engage in portfolio pumping. Another reason why this activity occurs is because poor performers might face significant funds outflows, resulting in stressed force sale of assets to meet redemption requirements (Lakonishok, Shleifer, Thaler, and Vishny 1991; Del Guercio and Tkac 2002).

The third theory is called "beating the benchmark." The reasoning is that as fund managers are evaluated in relation to a benchmark, they are incentivized to manipulate key components of that benchmark (Kocherhans 1995; Zweig 1997). But this argument has found little empirical support.

In the Pheim Asset Management case referenced earlier, court documents indicate that the portfolio pumping activity resulted in three benefits. First, the portfolio value of the defendants' accounts in Malaysia and Singapore increased by S$1,086,989. Second, as a consequence, three Singapore accounts outperformed their benchmark returns. And finally, as a result of the out-performance, Pheim Asset Management earned an additional S$50,000 in fees.

Implications for Market Integrity

Pheim Asset Management was a reputable boutique asset management firm with such heavy-weight clients as the Government of Singapore Investment Corporation (GIC) and Japan's Aizawa Securities. From a fund performance perspective, such agencies as Standard and Poor's and Lipper used to rate the firm as one of the region's most successful asset manager firms on a 3-, 5-, and 10-year return basis.[9]

Because these ratings are meant to be reflective of the skill of a firm in generating alpha returns, any doubts in investors' minds in this regard might taint the perception of Singapore's market integrity. Even more important, if market misconduct practices were discovered and not given due process from an enforcement perspective, it would also provide the wrong signal to the investment community about the desire of the Singapore authorities to guard against such market abuses—the consequence of which could be a strong deterrent[10] for future investor participation in Singapore's capital market. And we have yet to mention the detrimental impact on shareholders of funds who have made their long-term purchase at the inflated prices during quarter-ends as well as any additional unproductive trading on fund costs.

[8]"Departing fund manager" refers to the fund managers who have left the fund management firm.
[9]For details, see www.institutionalinvestor.com/Article/1025864/Search/Pheim-and-fortune.html#.VW12T02JhMs.
[10]An example of such deterrence in action would be the S-Chip saga in Singapore. For details, see www.business.asiaone.com/news/remisiers-feel-the-chill-investors-shun-local-market.

This point is encapsulated in the failed appeal of Tan Chong Koay and Pheim Asset Management versus MAS in 2011 in which the original decision was upheld.[11] Specifically, in keeping with the use of civil penalties instead of a fine, the judges intimated that both fulfilled a similar policy. That function is to protect the integrity of the capital markets and the investors who invest in securities by punishing and deterring malpractice.

Our Findings

Data for this project came directly from the Singapore Exchange (SGX) in the form of tick-by-tick prices, which resulted in more than 12 billion data points. Given that data was spread across multiple files and that each file carried trade information running into several hundreds of thousands of rows, data extraction was not a straightforward exercise. Microsoft Excel is also limited in its ability to handle such a high volume of data. Hence, we loaded the complete dataset in the desired format onto a Microsoft SQL database server. Most analyses were done on data extracted from this central database, with EViews as the primary statistical tool for analysis. The period we studied was from 2003 to 2013 and included all stocks in the FTSE Straits Times (ST) All-Share Index (including current and delisted companies). With the granularity of information, we were able to drill into very detailed execution information undertaken by market participants.

Our key findings are as follows:

1. At the market level, portfolio pumping was not active on the SGX during the period of analysis (2003–2013). Although we cannot fully attribute this result to the regulatory microstructure reforms, it can be inferred that the regulatory structure put in place has done a reasonable job in upholding market integrity in regard to portfolio pumping.[12] But it is important to note that abnormal positive returns during the quarter-end days, which was not accompanied by any subsequent price reversion, was observed.

2. In segmental analysis, we found abnormal positive quarter-end returns thriving in the mid-cap stock segment but not in the large-cap and small-cap stock segments. Our view is that the blue-chip stocks were probably too liquid and expensive for undertaking portfolio pumping activities whereas the small-cap stocks were probably too small in terms of market capitalization to satisfy the investment mandate of most portfolio managers.

3. In testing for the impact of enforcement activities, we concluded from our legal milestone regression test that both the identification and successful conviction of market fraud events have had significant impact on reducing market absolute return during quarter-ends. In the same vein, we concluded from our regulatory reform milestone regression test that having a stronger penalty system in place for offenders did have an influence in reducing both absolute and excess returns during quarter-ends. As for its influence on minimizing portfolio pumping activity, the link remains unclear.

[11]Tan Chong Koay and another v. Monetary Authority of Singapore. Civil Appeal No 186 of 2010 (2011): www.singaporelaw.sg/sglaw/laws-of-singapore/case-law/free-law/court-of-appeal-judgments/14632-tan-chong-koay-and-another-v-monetary-authority-of-singapore-2011-sgca-36.
[12]This, however, does not imply the complete absence of portfolio pumping at the segmental and company level.

4. Contrary to popular belief, portfolio pumping at an overall level is not evident among S-chips, constituents not on the MSCI Singapore Free Index (SIMSCI), and Catalist-listed stocks. Majority shareholder domination and the general lack of institutional interests are possible reasons for the absence of portfolio pumping activities among these stock segments.

5. From a momentum-based approach, there were significant positive returns during quarter-end days for the worst-performing quartile. A plausible reason can be explained from a remuneration and reputational perspective. For example, for appraisal purposes, portfolio managers may be incentivized to pump up the prices of their worst-performing holdings during the quarter-end. But consistent with the other findings, reversion of returns remained elusive.

6. Finally, we found that over time, market integrity with respect to portfolio pumping has improved in the SGX. This finding is inferred from changes in the two-day inflation metric of the gaming proxy population for both the top quartile and decile[13] members.

Policy Recommendations

1. Our findings indicate that the existing operation of the SGX market surveillance and MAS enforcement process is working well in regard to quarter-end closing prices. We recommend other exchanges adopt and refine some of these measures as methods to stifle potential market manipulation activities on closing prices during these periods. These measures include the following:

   a. When manipulation activities are detected, the authorities should ensure a fair and judicial prosecution of the participant. This first step provides the signaling effect to would-be offenders that market activities are being monitored. And if successful in the prosecution process, the second element further reinforces the fact that if found guilty, civil or criminal sanctions will follow, thus further discouraging such activities.

   b. Make it difficult and expensive to undertake portfolio pumping activities. It is highly probable that the adoption of the call auction system for end-of-day pricing in 2000, the randomization of the pre-close time duration, and the implementation of a new algorithm for end-of-day pricing in 2011 affected the opportunities for would-be offenders to undertake such activities.

2. Increase scrutiny of market surveillance activities for mid-cap stocks. Our findings suggest that there are abnormal forces at work in this category for the quarter-end days, albeit without the anticipated price reversion the following day. Specifically,

   a. if portfolio pumping activities did exist in this category, was the expected price reversion masked out by some other factors?

   b. if portfolio pumping activities did not exist, it would be interesting to understand why such abnormal returns were evident for only this category of stocks.

[13]To elaborate, for the top quartile, the average two-day inflation at quarter-ends during 2011 to 2013 dropped to 7% relative to 10% for the entire period under study. For the top decile, the value was 9.5% relative to 13%. As can be observed, the magnitude of suspicious portfolio pumping activity over time has dampened even among the most active entities.

3. Increase scrutiny of market surveillance activities for stocks that are performing worst. In nonsegmented tests, our findings suggest that there were unexplained forces at work for these types of stocks for quarter-end days, which is inconsistent with the window dressing process, in which one would expect the opposite to occur.

4. Our gaming proxy and logistic regression analyses further identified some characteristics that are common among suspicious instances of portfolio pumping activities. Market surveillance could focus on stocks that exhibit these additional traits:

    - Mid-cap segment, especially those in the S$2 billion to S$5 billion range
    - Lower free-float liquidity
    - Not a constituent of the SIMSCI
    - Part of the worst-performing quartile
    - Higher daily standardized trade volume
    - Significantly higher degree of buyer-initiated trades
    - Greater proportion of trades in the final 30 minutes of a quarter-end trading day
    - S-chip stock

5. Increase the awareness and education of mainstream media about hyping up portfolio pumping activities at year-ends. Inevitably, the media play an important role in creating the perception in the minds of investors about the integrity of the stock market. Our findings indicate that although abnormal returns were evident at year-ends, it was not definitively because of portfolio pumping activities and there was limited evidence that it was related to window dressing activities.

2. Singapore's Regulatory Environment

The Pheim Asset Management Saga

Pheim Asset Management Sdn Bhd started investing in shares of UET in April 2004 when it acquired 2,300,000 UET shares at S$0.47 each in an initial public offering (IPO). Subsequently, both Pheim Asset Management Sdn Bhd and Pheim Asset Management (Asia) Pte Ltd continued to purchase more UET shares below the S$0.47 IPO prices.

On 15 December 2004 at a meeting of its investment committee, Pheim Asset Management Sdn Bhd decided to increase its investment in UET shares for three of its accounts. For unknown reasons, these intended purchases were not executed until 29 December 2004.

Ironically, Pheim Asset Management (Asia) Pte Ltd disposed of 207,000 UET shares on or after 23 December 2004 at an average price of S$0.359 per share in order to liquidate an account that was being terminated.

But from 29 December until 31 December, there was a congestion of buy orders done between 3 seconds and 35 minutes before the close of trading on each day, with the representative remisier[14] making the last purchase of UET shares on each day a few seconds before the close of trading. In all, the representative remisier purchased a total of 360,000 UET shares at the cost of S$152,470.95 for Pheim Asset Management Sdn Bhd, representing about 88% of total trades that happened over the specified period.

This trading affected the closing price for the day and year, which resulted in a price increase of about 17%, reaching S$0.445 on 31 December 2004 from a low of S$0.380 on 27 December 2004. Over the same period, the FTSE STI advanced by 0.7% and the FTSE ST Small Cap Index inched up by 0.2%.

The increase in price resulted in the following:

1. The total net asset value of both Pheim Asset Management Sdn Bhd and Pheim Asset Management (Asia) Pte Ltd accounts increased by S$1,086,989.

2. Three Pheim Asset Management (Asia) Pte Ltd accounts outperformed their benchmark returns for 2004 (which would otherwise not have occurred).

3. Pheim Asset Management (Asia) Pte Ltd earned an additional S$50,000 in fees arising from the outperformance.

[14]A remisier is an agent of a stock brokerage who receives a commission for each transaction handled. This mode of payment is different from that of a dealer, who serves a similar function but is a full-time employee of the stock brokerage and on a relatively fixed monthly payroll. Although the origin of the word is French and such structure still exists in the Paris Bourse, this term is more commonly used in the context of the Kuala Lumpur Stock Exchange and the SGX.

Of special mention is the fact that the price of UET eventually reverted downward by about 7%, reaching S$0.415 on the first trading day of the subsequent year, 3 January 2005, with about half the daily average trading volume level of the previous six months, excluding the material days of 29 December 2004 to 31 December 2004.

On the basis of these facts, MAS commenced civil proceedings under Section 197(1)(b) of the Securities and Futures Act (SFA) against Tan Chong Koay and Pheim Asset Management Sdn Bhd. The High Court subsequently imposed a civil penalty of S$250,000 on each of them for having acted with the intent to create a false or misleading appearance with respect to the price of a security (UET shares). Following that, an appeal against the verdict was filed. But it was rejected by the court of appeal based on the following arguments:

- First, the judge did not accept the argument from Pheim Asset Management Sdn Bhd that it purchased UET shares for legitimate commercial purposes with the representative remisier deciding the execution price at his own discretion. The judge also rejected the argument that Pheim Asset Management Sdn Bhd could not purchase UET shares before 29 December 2004 because of equity limits on the relevant accounts.

- Second, any act that aims to create a false or misleading appearance in relation to the market or the price of securities constitutes a legal breach regardless of the original intent. In other words, it is not a requirement under a common law system to prove the underlying criminal intent of the plaintiff. The mere impression of a false or misleading appearance is sufficient.

- Third, the judge further agreed that the sellers of the shares during the relevant period were genuine independent investors who were attempting to offload their investments. But that alone does not automatically mean that the lifting of the "ask" prices represented genuine demand.

- Finally, the judge also found the explanation of using UET shares as a replacement for another recently liquidated counter[15] unconvincing given that the time lag between the completed investment analysis and trade execution was too long to be merely coincidence.

On the basis of these reasons, it was clear that the primary intent was to bolster year-end valuation of certain funds holding UET shares by creating a misleading appearance with respect to the price of UET shares. For the reasons just outlined, the appeal was dismissed.

Although the fines involved were in no way near the sensational seven or eight figures normally associated with similar lawsuits in the United States, this case still earned a landmark status given Pheim Asset Management's stellar track record since inception and also by virtue of its heavyweight institutional clients, which included GIC and Japan's Aizawa Securities.

Indeed, Standard and Poor's and Lipper used to rate Pheim Asset Management as one of the region's most successful investment management houses on 3-, 5-, and 10-year returns. Consulting firm Watson Wyatt Worldwide, conducting an independent study in 2003, concluded

[15]The defendants argued that they traded UET toward the end of the year because they had to wait for shares of Azeus Systems Holdings Limited (Azeus) to be sold off so that a foreign investment limit of 10% and an equity holding limit of 60% were not breached in the relevant accounts. The sale of Azeus was completed on 28 December 2014, but it was proved in the court of law that even if UET shares were purchased earlier, there was no immediate threat to the two fund positioning limits.

that funds of Pheim Asset Management Sdn Bhd and Pheim Asset Management (Asia) Pte Ltd outperformed their respective benchmarks, Kuala Lumpur Composite Index and Straits Times Index (STI), since inception, representing a tenure of 11 and 10 years in a row, respectively.

The implication is simple: If such a reputable fund manager could undertake unethical activities to bolster its returns, this conviction sends a very strong signal that the authorities in Singapore will not be tolerant of would-be market abuses in the years to come.

The outcome of this case leads us to pose the following questions:

1. Because there are many suspicious cases of market abuses (portfolio pumping, insider trading, and accounting frauds) on the SGX during the past decade, why were there so few convicted cases?

2. What impact did this landmark case have on general market integrity?

3. Were there any follow-up developments from the regulators, and how effective were they?

To answer these three questions, we need to understand the specific roles of MAS and the SGX in capital market regulations.

Understanding the Regulatory Environment

In the area of the capital markets, the SFA and the Companies Act form the backbone of Singapore's market conduct enforcement framework. Besides these two major acts, the securities industry is also regulated by other subsidiary legislations. These include the Singapore Code on Take-overs and Mergers (a nonstatutory code enforced by the Securities Industry Council) and the Code on Collective Investment Schemes.

Under the current regulatory regime, MAS is Singapore's de facto central bank. It was established under the Monetary Authority of Singapore Act. Its responsibilities include supervising the banking industry, the securities and futures markets, and the insurance industry.

MAS is also the licensing authority for the capital markets services license. Holders of the license are permitted to carry on a business in the regulated activities of dealing in securities, trading in futures contracts, leveraged foreign exchange trading, fund management, advising on corporate finance, financing securities, and providing custodial services for securities. Trading representative licensing for individuals also falls under the jurisdiction of MAS.

In enforcing its supervisory duties, MAS has the power to seize books and information from a holder of a capital markets services license or its representatives and any other person if it relates to a matter under investigation. Specifically, MAS may require the holder of a capital markets services license or an exempt person to disclose the names of persons behind any acquisition, disposal of securities, and/or disposal of futures contracts. MAS may also require the individual to disclose the nature of any relevant instructions given, which include the following:

1. Requiring an individual to disclose who has acquired, held, or disposed of the financial contracts and whether he or she did so as a trustee or agent of another person, and if so, who that person was and the specific details of the instructions given.

2. Seeking information from officers of listed companies during instances when it becomes pertinent to prohibit trading in the listed securities. And when a contravention of the law is suspected, MAS can order investigations under the Monetary Authority of Singapore Act to ensure regulatory compliance.

3. Issuing directions to the SGX to ensure that market integrity is upheld, systemic risks are properly managed, and the market is functioning in an orderly manner.

4. Carrying out civil enforcement actions in the form of punitive fines on offenders.

MAS undertakes the overall supervisory role within the entire capital market, whereas the day-to-day operation within the securities market lies with the SGX. The roles and operational structure of the SGX revolve around three important documents:

1. The Memorandum and Articles of Association, which define the purpose and operation of the SGX

2. The SGX Rules, which form the legal framework used to regulate trading in securities

3. The SGX Listing Manual, which lists the criteria for listing and the obligations of listed companies

In dealing with breaches of its rules and listing manual, the SGX may issue a reminder (minor case) or a letter of warning (moderate case) to the offender. If the breach is severe, the SGX may publicly censure or charge the offender before the Disciplinary Committee (DC). Any disciplinary actions meted out by the DC will be publicly announced on the website of the SGX.

As for process, prior to charging an offender, a written notice is issued to the offender detailing the particulars of the charge. The charged person may submit a written response. In addition, the charged person may be required to appear before the DC at a date fixed for the hearing of the charge.

At the hearing, the DC hears the charge and decides whether the charge is valid. If it is, the DC then determines the appropriate disciplinary action. The plaintiff or the SGX may appeal to the Appeals Committee (AC). The AC will hear the appeal and decide on the outcome, which is final and binding.

To ensure the independence and proper functioning of these committees on the SGX, the following measures are in place:

1. Committee members are appointed by the board of the SGX. Senior management of the SGX does not play any role in the process.

2. Directors, officers, or employees of the SGX or any of its related companies cannot be appointed as committee members.

3. Within the AC, directors, officers, or employees of sponsors or its subsidiaries cannot make up the majority of the AC's committee members. The same rule also applies to substantial shareholders of the SGX or any directly related parties of the SGX's substantial shareholders.

4. At least one of the committee members must come from a corporate finance practitioner background. This rule is to ensure sufficient technical expertise is present at all times.

5. In the event of any potential conflict of interest in relation to a charge or appeal, the members of the committee must notify the chairman before or during the hearing. The chairman will then decide whether the member concerned should attend the hearing of that charge or appeal. And if the chairman has a potential conflict of interest, he must abstain from the hearing.

The following options are within the scope of the SGX's power to ensure a fair and orderly market:

1. Verbal reminders

2. Letter of warning

3. Reprimand

4. Fine

5. Suspension

6. Expulsion

7. Requirement to attend education or compliance program

8. Imposition of other restrictions or conditions

To monitor market misconduct, the SGX conducts real-time surveillance of the capital markets to detect unusual trading activities. Once the market surveillance team concludes that a case may have breached the provisions of the SFA, it will refer to the MAS and Commercial Affairs Department for further investigation and action.

In addition to real-time market surveillance of the capital markets, the SGX also supervises the compliance of listed companies with the listing, trading, and clearing rules. Any suspected breach is promptly investigated with appropriate disciplinary action taken after considering the following:

1. Severity of the breach
2. Circumstances leading to the breach
3. Compliance track record of the offenders
4. Mitigating factors

Serious offenses may be referred to the DC to decide on appropriate sanctions. It is important to note that the SGX does not possess seizing power; that remains in the hands of MAS and the police. And to be thorough and neutral, any form of investigation will have to follow a formal procedure that takes time and effort, especially during multiple-party collaborations. Final conviction relies on the presence of concrete evidence, which can be difficult to gather. As such, there is a thin line between a random market event and market manipulation.

This difficulty with gathering evidence is possibly why, despite so many suspicious cases of market abuses on the SGX over the past 10 years, there have been very few convictions related to portfolio pumping. Evidence from most cases is generally not concrete enough to be brought to the court for prosecution.[16]

Historical Background of Regulatory Reform Events on the SGX

Maintaining market integrity with aggregate microstructural reforms has been a normal practice for capital market regulators. The SGX has operated in a similar fashion. Its website lists a long set of reforms over the past years. **Table 1** presents some of them that we deemed as relevant toward enhancing market integrity, particularly in regard to closing prices.

Within the list in Table 1 of what we classified as the relevant equity market microstructural reform on the SGX, there are four (21 August 2000, 1 June 2011, 22 July 2011, and 15 August 2011) that are related to the determination of market opening and closing prices. The original intent of these specific reforms was to minimize the potential of end-of-day pricing being manipulated by market participants.

[16]A classic example of the difficulty involved is the Bluemont, Asiasons, and LionGold saga. For details, refer to http://klse.i3investor.com/blogs/kianweiaritcles/38481.jsp.

Table 1. Description of Market Structure Reform on the SGX

Date	Description of Reform
21 Aug 2000	The SGX adopted the call market method to open and close the market.
14 Feb 2008	The SGX issued a consultation paper titled "Composition System and Mandatory Minimum Menalties by Disciplinary Committees for Rule Violations in the Securities Market."
1 Jun 2011	The SGX proposed changes to its opening and closing routines.
7 Jul 2011	The SGX proposed the use of circuit breakers in the securities market and issued a consultation paper to the public.
22 Jul 2011	The SGX proposed a change to the algorithm used for computing indicative equilibrium prices.
1 Aug 2011	The SGX implemented a continuous trading session from 9:00 a.m. until 5:00 p.m.
15 Aug 2011	The SGX rolled out random-end to the pre-close of the closing routine and enacted a change to the algorithm used for computing the single price at which orders at the end of the opening routine, closing routine, and adjustment phase are matched.
25 Oct 2013	The SGX put up an article on its website to correct misconceptions in the media that included the following: ■ The nature of contra trading ■ The three key regulatory tools used by the SGX for maintaining a fair, orderly, and transparent market ■ The difference between investigation and maintaining orderly trading ■ The importance of maintaining confidentiality during misconduct investigations
30 Oct 2013	The SGX posted an article on its website to explain why it suspends, designates, and investigates unusual market movement.
24 Feb 2014	The SGX introduced circuit breakers to deal with fluctuations in prices.

Source: Based on information from the SGX.

Understanding the Closing Price Mechanism on the SGX

There are generally two major types of trading mechanisms in modern day equity markets—namely, continuous trading (also known as continuous auction) and single-price auction (also known as call auction).

Internationally, it is common for security exchanges to adopt continuous trading in their main trading session. Within this continuous trading session, buy and sell orders are submitted to the market and executed in price and time priority against matching orders within a central limit order book. Through the matching process, price discovery and order execution are continously determined.

This method works well during a typical trading day. But it is generally considered less well adapted to trading at the start of the day, when there are a lot of activities as all market participants react to overnight information around the same time. It is also less efficient at the market close, when there is once again a flurry of activities as market participants rush to complete their executions for the day. Because of these issues and advances in computer technology, a single-price auction mechanism began to be commonly adopted for the market opening and closing during the turn of the millennium.

This single-price auction mechanism typically consists of three phases. First, there is an order input phase, in which various buy and sell interests are gathered to trade at a single price. Second, there is a price determination phase, in which that single price is calculated based on a predefined auction algorithm to maximize matching. Third, there is the trade execution phase, in which the orders are matched at the single price in accordance with their order priority.

By aggregating the trading interest of multiple buyers and sellers, a single-price auction generates a consensus price that reflects the interaction between market supply and demand. It also minimizes the probability of having any individual factor affecting the closing price by making it difficult and expensive for any party to influence the outcome of an auction. On top of that, the entire mechanism also allows trades to be executed at fair opening and closing prices, which is an important objective for many capital market stakeholders. Exchanges that have adopted this methodology include the London Stock Exchange in 2000, the American Stock Exchange in 2003, and the Toronto Stock Exchange in 2004. By January 2015, most bourses around the globe have adopted the closing auction session (CAS) mechanism, as shown in **Table 2**.

Table 2. Global Profile of CAS Mechanism Adoption

List of Developed Markets with CAS		List of Developing Markets with CAS	
Australia	Japan	Brazil	Poland
Austria	Netherlands	China (Shenzhen Stock Exchange)	Qatar
Belgium	New Zealand	Colombia	Russia
Canada	Norway	Czech Republic	South Africa
Denmark	Portugal	Greece	South Korea
Finland	Singapore	Hungary	Taiwan
France	Spain	Indonesia	Thailand
Germany	Sweden	Malaysia	Philippines
Ireland	Switzerland	Mexico	Turkey
Israel	United Kingdom	Peru	United Arab Emirates
Italy	United States		
List of Developed Markets without CAS		**List of Developing Markets without CAS**	
Hong Kong		Chile	Egypt
		China (Shanghai Stock Exchange)	India

Source: Based on data from Hong Kong Exchanges and Clearing Limited.

Singapore was, in fact, one of the early adopters of the CAS mechanism when the SGX adopted it on 21 August 2000.

The use of the call auction method is expected to improve both price discovery and market quality. For example, Chang, Rhee, Stone, and Tang (2008) demonstrated that the SGX did experience an unambiguous improvement in its price discovery process for liquid stocks. The improvement was attributable to a significant reduction in price volatility during the opening and closing sessions of liquid stocks, less negative return correlation, and smaller pricing errors.

But in the case of illiquid stocks, the same outcome was not evident. Chang et al. (2008) concluded that although the call auction mechanism did significantly reduce return volatility for illiquid stocks during market opening, the same cannot be said during market close. The authors also found that price manipulation activities (portfolio pumping being one of them) did decline for "active" as well as FTSE STI component stocks. However, illiquid stocks still remain vulnerable to price manipulation given that there might not be enough transaction volume during the closing moments to implement an auction.

This lack of volume is probably the reason why closing prices of illiquid stocks, such as UET, could still be artificially inflated, even in spite of the introduction of the CAS mechanism in August 2000.

To improve the process, SGX undertook two further market microstructural reforms in August 2011. First, it completely revamped the algorithm used to arrive at the indicative equilibrium price within the current call auction mechanism. It was explained that the new algorithm's parameters allow for better accounting of the forces of market supply and demand and is also the same formula used by established bourses, such as the Australian Securities Exchange (ASX) and NASDAQ OMX.

Second, SGX added on to the existing call auction closing mechanism by installing a random end to the pre-close phase of the closing routine. Before this randomization, the pre-close phase of the closing routine used to be a fixed duration of five minutes after the trading session. With the randomization, this end of the pre-close phase will vary in its duration between four and five minutes and will be synchronized across all counters. With this process, it is anticipated that the varying time periods will protect the integrity of the closing price against sudden huge entry and/or withdrawal orders.

3. Literature Review

At a broader level, pricing anomalies in financial market securities, and more specifically in equities, have attracted the special interest of academicians and regulators alike around the world. Although the initial set of studies tried to establish the presence of pricing anomalies in a particular market, some researchers have since focused on deciphering the reasoning behind them, even as others have attempted to evaluate policy effectiveness in tackling such anomalies.

In their seminal work on the January effect, Rozeff and Kinney[17] (1976) highlighted that the average monthly return of an equal-weighted index of NYSE stocks in January is about seven times the average of other months. Building on this work, researchers have observed and reasoned out various other seasonal anomalies in financial markets, including the weekend effect (French[18] 1980), day-of-the-month effect (Ariel[19] 1987), and the popular end-of-day effect (Harris[20] 1989). Such studies have spanned across geographies, with Akyol and Michayluk (2010) commenting on the end-of-day effect on the Istanbul stock exchange, McInish and Wood (1990) testing the effect on the Toronto stock exchange, Chan (2005) researching the Hong Kong stock exchange, and Aitken et al. (1995) examining the Australian exchange.

Of special interest among these seasonal patterns is the turn-of-the-period effect around a month, quarter, or year. Harris (1989) noted that the end-of-day effect peaks at month-ends and the trend reverses at the turn of the month. Similarly, Lakonishok and Smidt (1988) laid out that average daily returns over the four days surrounding the turn of the month, starting from the last day of the previous month, are consistently higher than other days, based on their analysis of the DJIA over 90 years. At the fund level, Zweig (1997) pointed out that an average equity fund beats the S&P 500 on the last day of a year by 53 bps and underperforms it the next day by 37 bps, on average.

In this section, we explore the literature on the explanatory factors behind such anomalies, with a focus on anomalies driven by market manipulation activities and specifically those arising as a result of portfolio pumping.[21] We discuss in detail the analytical methodologies adopted by researchers to identify such instances and the metrics used to establish the presence of portfolio pumping. We also lay out characteristics of the markets, stocks, and funds that are subject to portfolio pumping.

[17]Rofezz and Kinney (1976) analyzed monthly returns of NYSE stocks in 1904–1974 and found an equal-weighted index generated an average monthly return of 3.5% in January compared with 0.5% for other months. In fact, returns in January were found to explain more than one-third of average annual returns.
[18]French (1980) noted that average returns on Mondays were significantly negative relative to returns on Fridays. This finding is counterintuitive because Monday should ideally capture returns of three days (including the weekend close).
[19]Ariel (1987) observed that average returns for stocks is positive only just prior to and during the first half of the month, whereas it is not significantly different from zero for the second half of the month.
[20]Harris (1989), in a study of NYSE transactions, showed prices systematically rise at the end of the day, especially with the last trade.
[21]The SEC terms it "marking the close." It is also referred to as marking up, leaning for the tape, and painting the tape, among others.

Reasons for the Anomalies

Roll (1983) opined that tax-loss selling contributes to turn-of-the-year effects, especially among small-cap stocks, as prior year losers witness increased selling pressure near the year-end driven by investor tax considerations. A relief rally is seen once the pressure abates with the turn of the year.[22] Keim[23] (1983) validated the theory based on his observation of a significantly higher proportion of trades occurring at bid prices (being seller driven) in December and the trend reversing in January. Reinganum (1983), while finding support for the tax-loss selling argument, noted that small-cap stocks that are least likely to be sold for tax reasons (being among prior year winners) also exhibit the turn-of-the-year effect, suggesting there are factors beyond tax-loss selling that are influencing prices at the year-end. Introducing an ownership dimension to the argument, Sias and Starks (1997) observed that tax-loss selling is restricted to only stocks with high individual ownership[24] and indicated that stocks with higher institutional ownership could act differently. In fact, they found that stocks with higher institutional ownership tend to generate abnormally higher returns over the last four days of a year and significantly lower returns over the first four days of a year.[25] Hu et al. (2014) reasoned the turn-of-the-year effect is a behavioral phenomenon because they observed a dip in both institutional buying and selling toward year-ends, with the latter effect dominating, resulting in greater abnormal returns.

Harris (1989) offered the influence of large periodic inflows from such sources as pension funds as an alternative explanation for the turn-of-the-period effects. He observed significant positive returns from stocks at the end of every month and a reversal of the trend at the start of the next month.[26]

Apart from these structural and behavioral arguments, deliberate actions of fund managers to manipulate prices and holdings at period-ends are also viewed as a contributing factor. Haugen and Lakonishok (1987) believed that fund managers might try to weed out losers from the portfolio and add winners just prior to disclosure to investors, a manipulation commonly referred to in the literature as window dressing, so that they are viewed favorably. In a similar vein, Musto[27] (1999) pointed out that fund managers might want to present a different risk profile of their portfolio than what they generally maintain; accordingly, they may then want to tweak their holdings prior to reporting.

In their seminal paper on the subject, CKMR (2002) refuted the claims of tax-loss selling, periodic inflows, or window dressing as the definitive argument for abnormal quarter-end

[22]Roll pointed out that higher transaction costs and a lower level of liquidity in small-cap stocks might prevent arbitrageurs from exploiting this trend and profiting from it.

[23]Keim (1983) offered tax-loss selling as a possible explanation for the January effect. Similarly, Ritter (1988) observed instances of a lower buy-to-sell ratio for investors in December and a strong rise in the ratio in January.

[24]Starks, Yong, and Zheng (2006) find evidence for the tax-loss selling argument in municipal bond closed-end funds, which carry a high level of retail participation. They also observed it to be specifically higher for funds from brokerage firms, for which tax counseling plays a definitive role.

[25]Based on empirical observation of all firms listed on NYSE from 1978 to 1992.

[26]Harris based his observation on a single year and did not test specifically for quarterly or yearly effects.

[27]Musto (1999) observed retail money market funds selling corporate bonds and buying sovereign bonds near quarter-ends. Musto (1997) also showed that the yield of commercial papers maturing after a year-end is much higher than those maturing just prior to a reporting period. Such an investment premium does not exist in T-bills, indicating that money market fund managers do not want to hold risky securities in their portfolios going into reporting.

behavior in stocks.[28] They attributed the observation of an abnormal positive return on the last day of the quarter and an abnormal negative return on the first day of the subsequent quarter to portfolio pumping,[29] by which a fund manager deliberately attempts to increase prices of stocks held in the portfolio.

Motivation for Portfolio Pumping

Brown et al. (1996) likened mutual fund managers to competitors in a tournament in which they are placed against each other and constantly evaluated. If fund management fees or fund manager compensation are directly linked to fund performance, there is a natural incentive for managers to engage in portfolio pumping (Bhattacharyya and Nanda 2013; Xiao et al. 2005). Ben-David et al. (2013) highlighted that the incentive is higher for hedge funds, for which management fees tend to be directly related to performance. Even if fund managers are not directly rewarded through compensation, poor performance tends to create a bad reputation for funds and their managers (Asness et al. 2001). Therefore, managers seek to draw on some saved performance (in the nature of withheld reserves[30]) from earlier periods and borrow some from future periods to present their best returns during the crucial evaluation times (Agarwal et al.[31] 2007).

Accordingly, there are three major theories associated with the motivation for portfolio pumping, which in turn determines the type of fund managers who may indulge in it. Among others, Ippolito (1992) and Sirri and Tufano (1998) documented a convex relationship between flows and performance, especially with respect to mutual funds. They noted that investor flows tend to disproportionately move in favor of a few top-performing funds at the expense of others. Thus, CKMR (2002) highlighted a greater incentive for better-performing funds and fund managers to manipulate closing prices to end the year among the top performers. They called this tendency "leaning for the tape." This incentive becomes even more critical in the context of weak persistence among the best-performing funds, as recorded by Hendricks et al.[32] (1993) and Zheng[33] (1999). Accordingly, the current and prior best performers might look to stretch their lead to the furthest extent possible through pumping (CKMR 2002).

Gallagher et al. (2009) noted that although mutual fund investors place considerable importance on fund manager rankings and reward the best performers, they do not necessarily penalize poor performers. But with pension funds, poor performers might face significant outflows (Lakonishok et al. 1991; Del Guercio and Tkac 2002) and could be forced into a stress sale of

[28]CKMR highlighted the existence of abnormal returns around quarter-ends too (and, hence, tax-loss selling at year-ends cannot be the sole argument for anomalies) but not at the month-end level (so, monthly periodic inflows cannot also be the reason for anomalies).

[29]CKMR (2002) referred to the phenomenon as "leaning for the tape." Ippolito (1992), Sirri and Tufano (1998), and Bernhardt and Davies (2005), among others, have also validated instances of portfolio pumping.

[30]Agarwal, Daniel, and Naik (2007) point out that fund managers might underreport results in the earlier part of the year so that they can use them in the later part of the year if actual performance turns bad because fund manager performance evaluation mostly happens around the end of the year.

[31]Agarwal et al. (2007) observed that hedge funds underreport their prior month performances by creating reserves and draw from January returns by engaging in the pumping of stock prices at the end of the year to present higher returns at the end of December.

[32]Hendricks et al. (1993) empirically observed best-performing funds to continue to be among the best performers over one to eight quarters whereas persistence of poor performers tended to continue for a longer period.

[33]Zheng (1999) showed that the best-performing managers in a quarter tend to be among the worst-performing managers in 30 months.

assets (Agarwal et al. 2007). This situation is well reflected in the observation of Khorana (1996) that funds managed by departing fund managers exhibit greater turnover and costs (prior to their departure) compared with funds managed by continuing managers, possibly driven by a threat of losing employment. These circumstances might force poor performers to indulge in pumping, with their motivation called "clutching at straws."

Kocherhans (1995) and Zweig (1997) believe that investors evaluate funds, especially pension funds, in relation to a benchmark; accordingly, fund managers might engage in pumping to ensure the "beating of the benchmark." But this argument, though intuitive, has found limited empirical support. CKMR (1999) showed that although the extent of fund outperformance is higher on the last day of a year, it tends to be in line with expected levels.[34]

Scope of Coverage in the Literature

The motivating factors for portfolio pumping have been well tested in literature across asset classes and funds (mutual funds, pension funds, money market funds, and hedge funds). Most studies seem to suggest the existence of pumping, even as they vary in terms of its relative levels of presence across fund, manager, and stock universe.

However, academic research remains largely concentrated on the developed world, with limited studies on emerging markets. Among the first such studies, Bhana (1994) presented instances of market manipulation in the Johannesburg stock exchange. Drawing on the methodologies of CKMR (2002), Xiao et al. (2005) evaluated instances of portfolio pumping among Chinese security investment funds over 1998–2003. They found limited evidence of pumping at the market level, although they established its presence among the top stock holdings of the best-performing funds. Ko and Lee (2008) and Kim and Sohn (2012) recognized portfolio pumping in the South Korean markets, with the former finding instances of it in publicly offered growth funds and the latter among the best-performing funds.

In the absence of a direct audit trail of trades by fund managers, most studies have had to adopt an indirect approach to gauge portfolio pumping. Ben-David et al. (2013) established pumping by hedge funds around month-ends through the observation of abnormal returns in prices of stocks with a high level of hedge fund ownership.[35] Similarly, Xiao et al.[36] (2005) and Agarwal et al.[37] (2007) made use of fund net asset value (NAV) returns to establish pumping. Taking advantage of the periodic portfolio disclosures by funds, Duong and Meschke[38] (2008) identified instances of pumping among the best-performing funds and the worst-performing funds through the specific observation of constituent stock performance at quarter-end and the

[34]CKMR (1999) showed that a significantly larger proportion of funds beat the S&P 500 on the last day of the year and a significant number of them underperformed the index the next day. However, they argued it was a symptom of the distribution of returns rather than an intentional effort by managers to beat it. Using a distribution function approach, they point to the proportion of funds beating the S&P 500 as being in line with expected outcomes.

[35]Ben-David et al. (2013) regressed stock returns adjusted following the Daniel, Grinblatt, Titman, and Wermers (1997) method against independent variables based on hedge fund ownership. They also looked at intra-day trade data to establish pumping being concentrated around the last few minutes of a trading day.

[36]Xiao et al. (2005) regressed daily fund performance against period-end dummies.

[37]Agarwal et al. (2007) regressed gross monthly fund returns against period dummies and other control factors.

[38]Duong and Meschke (2008) recorded their findings based on fund holdings of US domestic equity funds over 1993–2006.

first day of the subsequent quarter. Going a step further, CKMR (2002) and Gallagher et al.[39] (2009) used intra-day trade data to validate pumping activities to be concentrated around the last few minutes of the final trading day of a quarter.

Apart from making a general observation about the existence of portfolio pumping, Duong and Meschke (2008), in a time-series observation, documented a reduction in pumping activity in the United States since 2001. They attributed the reduction to increased scrutiny by the SEC and a rise in investor awareness since the publication of CKMR (2002).[40] Similarly, Gallagher et al. (2009) showcased a reduction in pumping activities on the ASX in two rounds: first, after the introduction of the CAS in 1997, and second, with a change in the algorithm to measure closing price introduced in 2002.[41] Xiao et al. (2005) drew support from wider media coverage in China to explain their lack of evidence of portfolio pumping at the overall market level.[42]

In terms of analytical methodologies, apart from a first-cut review of metric performance around period-ends with visual inspection, two broad quantitative techniques have been adopted.

The first technique is testing for differences. Hypothesis testing has been used by some researchers to compare the performance of a relevant metric over the testing period (around month-, quarter-, or year-end) against a control period (trading days other than the testing period) or a control environment (expected outcomes in the absence of pumping). For instance, Meier and Schaumburg (2006) used a hypothesis test to evaluate the actual performance of a fund against the performance of a buy-and-hold strategy of disclosed fund holdings. Bhana (1994) adopted a non-parametric hypothesis test comparing block trades over the testing period (15 to 6 days from a quarter-end) versus the control period (days prior to –15).

The second technique uses regression analysis. Regression analysis of a chosen metric against period-end and period-beginning dummies (assigning a value of 1 for a period-end and 0 for other days) is a common technique that has been adopted by CKMR (2002) and Duong and Meschke (2008), among others. Bernhardt and Davies[43] (2009) and Bhattacharyya and Nanda[44] (2013) both used a theoretical modeling approach to establish favorable conditions for portfolio pumping and its potential impact.

[39]Gallagher et al. (2009) used actual fund trades data for Australian funds to identify instances of pumping.

[40]Similarly, Hillion and Suominen (2004) reasoned that the introduction of the closing call auction in the Euronext Paris stock exchange significantly reduced manipulation activities in Paris. Earlier, Christie and Schultz (1994) observed a reduction in use of the odd-eighth quote by NASDAQ market makers after an article about their possible collusion (to keep spreads high) was widely publicized.

[41]Gallagher et al. (2009) reasoned that the introduction of the closing price auction by ASX and its subsequent methodology change in 2002 led to a significant increase in liquidity in the ASX, thereby reducing the extent to which fund managers can influence prices.

[42]Xiao et al. (2005) believed an article published in a Chinese magazine in 2000 titled "Fund Inside Story of a Plot" to have been the game changer.

[43]Bernhardt and Davies (2009) developed a model to show how investors rewarding the best performers in a quarter with more flows create an incentive for managers to invest in stocks with significant holdings to extend their short-run fund performance. But they argued that the run is short lived and the next quarter begins with a significant return deficit that cannot be overcome, which leads to weak persistence.

[44]Bhattacharya and Nanda (2013) developed a model that factors in managerial compensation structure's influence on trading. They contend that a manager who is rewarded based on short-term NAV returns is likely to pump and to do so with stocks he or she has a bigger holding of.

In the literature, time-series analysis of portfolio pumping has generally involved a milestone-based approach within a regression analysis. In this regard, researchers have predominantly used milestone-defining dummy variables in isolation or along with the period-defining dummy variables to gauge the significance of a milestone in explaining a chosen portfolio pumping metric. For instance, Duong and Meschke (2008) defined a dummy variable called "post-2001" that carried a value of 1 for all values post 2001.[45] The variable was used as part of the regression analysis to evaluate whether portfolio pumping had declined significantly since 2001. Gallagher et al. (2009) also adopted a similar approach by defining dummy variables for two milestones to be used in their analysis—the introduction of the CAS in the ASX and the change of algorithm for the CAS.

Metrics to Establish Portfolio Pumping

In their seminal paper, CKMR (2002) used fund NAV returns as the first-level check to establish pumping. They carried out a regression of daily returns on Lipper fund indexes as well as their own custom fund indexes against period-end and period-beginning dummy variables.[46] They noted a strong positive relationship with the former and a significant negative relationship with the latter.

Duong and Meschke (2008) highlighted a limitation in the approach of CKMR (2002) in that they thought that constituents affecting a fund's NAV at quarter-end could be different from those affecting the NAV the next day. They contended that a mere observation of NAV would not be sufficient and there was a need for evaluation at the individual fund constituent level. Accordingly, they created a portfolio pumping metric that weights by market value fund portfolio constituent returns over the last 30 minutes of a day provided the returns are positive and a reversal occurs the next day. The metric is subsequently regressed against the period-end dummies. Along these lines, Gallagher et al. (2009) adopted a more rigorous metric called the "gaming proxy" to establish pumping in Australia. The proxy's binary variable carries a value of 1 if a stock generates a positive return in the last 30 minutes of trade, outperforms the index for the period, and registers a negative return in absolute and relative (to the index) terms at the close of the first half-hour of trade the next day. The proportion of stocks in the study with a gaming proxy value of 1 is treated as the dependent variable in a regression against the period-end dummies.

Bernhardt and Davies (2005) believed the observation of a proportion of stocks outperforming a benchmark (an alternate dependent variable used by CKMR[47] 2002) understated the impact because portfolio pumping is also reflected in the market index. They suggested an absolute approach and pointed out that an equal-weighted index of stocks outperform on the last trading day compared with any other day and more so with respect to the first trading day of a quarter. Noting a rise in abnormal returns in line with mutual fund ownership of stocks,[48] they attributed the source of abnormal returns to pumping by fund managers, which is in line with Sias and

[45]On the basis of the visual inspection of the portfolio pumping metric declining significantly since 2001, Duong and Meschke (2008) adopted 2001 as a milestone year in their analysis and formally tested it in the regression analysis.
[46]Drawing from CKMR (2002), Xiao et al. (2005) adopted a similar approach with Chinese securities investment funds.
[47]CKMR (2002) regressed the proportion of funds outperforming the S&P 500 against period-end and period-beginning dummy variables.
[48]Bernhardt and Davies (2005) compared abnormal returns based on equal-weighted indexes from CRSP against the ratio of total mutual fund holding of corporates to the market value of total equities, sourced from the US Fed.

Starks (1997). This finding was subsequently validated by Duong and Meschke[49] (2008). Using a regression of stock returns on quarter-end days adjusted following the Daniel, Grinblatt, Titman, and Wermers (DGTW 1997) method against hedge fund ownership dummy variables, Ben-David et al. (2013) also established the influence of institutional ownership on abnormal returns of stocks, pointing to possible pumping by these funds. They also used information on fund portfolio disclosures to create a metric termed "blip" that marked the difference in constituent returns between the last day of a quarter and the next day, weighted by quarter-end disclosed weights. The metric was subsequently adjusted for volatility and market returns and found to be significantly different from zero, pointing to the possibility of pumping.

CKMR (2002) derived support for their "leaning for the tape" hypothesis by finding a strong positive relationship when regressing a long–short portfolio of the top and bottom 10% performing funds[50] against the period-end dummies. O'Neal (2001) adopted a more complex two-level regression in which he regressed residuals for six days surrounding a month-end against period-based dummy variables, with the residuals, in turn, being obtained from regressing daily fund returns against six Russell-style indexes.

Apart from using fund and stock returns, CKMR (2002) also provided support for their argument by using actual trade data, including on an intra-day frequency. The proportion of trades occurring at or above the ask price[51] (buyer-driven trades) on a trading day and the fraction of trade volume in the last 30 minutes of a day versus an average day[52] were among the metrics tested for being significantly higher at quarter-ends compared with other days. Akyol and Michayluk (2010) treated a proportion of small trades among final trades as their trade-based metric, whereas Bhana (1994) took the number of block trades and the proportion of block trades among total trades to evaluate market manipulation in South Africa. Gallagher et al. (2009) used a gross (net) trades metric, defined as buy trades plus (minus) sell trades by funds, as a dependent variable against period-end dummies.

Hu et al. (2014), researching for portfolio pumping on a monthly basis, used an abnormal buy measure, created an excess of trading value of institutional buys on the last day of a month over the average buys in the last five days of the month, and expressed it as a proportion of the average buys in the last five days of the month. They then regressed the difference in returns between the last day of the quarter and the next day against the metric to identify the extent to which the price inflation is driven by pumping activity.[53]

[49]Duong and Meschke (2008) observed a positive relationship between their portfolio pumping metric and the level of institutional ownership in a stock. As indicated earlier, they also noted a reduction in extent of pumping post-2001.
[50]Best- and worst-performing funds are identified on a daily basis by using a rolling three-month and one-year return of funds.
[51]Harris (1989) and Lakonishok and Smidt (1988), among others, have adopted this metric to evaluate instances of portfolio pumping.
[52]An average day is defined as six months prior and six months after the specific day in question, excluding quarter-end trading days.
[53]The analysis is supplemented by a regression of the buy proportion of trades [defined as buy/(buy + sell) trades] against period-end dummy variables.

Building the Robustness of the Analysis

At the basic level, researchers have sought to bring robustness to their analysis through the effective selection of a dataset. With a historical trend of low trading activity[54] around days –5 to –1 until the end of the quarter, Bhana (1994) used trading days –15 to –6 as the primary period of observation rather than the standard approach of evaluating the last day of the quarter. Furthermore, Bhana (1994) also excluded from his analysis companies with extreme positive or negative news in the last 20 days of a quarter to control for effects other than market manipulation. Similarly, Hu et al. (2014) verified the year-end flow pattern into funds to exclude the unwarranted effect of flows on trade activity influencing their results.[55]

Ben-David et al. (2013) made adjustments to fine-tune the quality of their variables and metrics, including risk adjustment of stock returns using the DGTW approach. They also adjusted their blip metric for volatility and market factors. To take care of the tournament-style evaluation of fund managers, Duong and Meschke (2008) tightened their portfolio pumping metric by only including a particular fund holding if its relative weight in the portfolio was greater than 3% and its holding was at least 2% greater than any other fund in that investment style.

Most academics have used control variables in their regression analysis, capturing size, momentum, liquidity, and ownership, among other factors, to establish pumping with greater certainty and across dimensions. Ben-David et al. (2013) used returns over the first day of the month as an explanatory variable to predict returns on the last day of the month to control for cases in which a low return at the beginning of the month and a high return at the end of the month is a simple recurring phenomenon.[56] Apart from considering the extent of mutual fund ownership levels in their regression analysis to explain stock returns, Duong and Meschke (2008) used a fund Herfindahl index variable to infer that pumping is more visible among stocks with concentrated fund ownership. Furthermore, they considered several interaction terms, including interaction variables[57] of a period dummy and momentum factors, and concluded that a reduction in pumping was stronger among the best-performing funds after 2001.

At a more refined level, researchers have sought to undertake additional analysis or eliminate alternative explanations. CKMR (2002) used a two-step regression[58] approach to validate that higher abnormal fund returns on the last trading day of a quarter indeed influenced the significantly lower returns the next day. Similarly, in establishing the "leaning for the tape" hypothesis,

[54]Liquidity on the Johannesburg stock exchange for small-cap stocks is quite low and trading is limited in the final days of a quarter.

[55]Ben-David et al. (2013) excluded funds that witnessed significant flows from their analysis to eliminate effects of flow-driven abnormal returns. Also, at the trade level, they excluded all corrected trades, including those trades happening outside of trading hours.

[56]Duong and Meschke (2008) include VIX (CBOE Volatility Index) as a regression variable to control for simple volatility driving abnormal returns.

[57]Interaction variables involving the 2001 period dummy and past performance quintile dummies are used.

[58]CKMR (2002) established that the negative effect at the beginning of quarters actually represents a turnaround of the positive effect of the previous day and not some random effect. For this analysis, they adopted a two-step regression. In the first step, they regressed each day's return against the previous day's return across stocks for each day. This approach would provide an auto-correlation coefficient for each day. They subsequently regressed these auto-correlation coefficients obtained for each day against a period-beginning dummy variable. If it is a turnaround effect, the dummy variable should have a statistically significant positive value.

CKMR (1999) rejected the possibility of the "beating the benchmark" approach[59] explaining the identified portfolio pumping phenomenon. Duong and Meschke (2008) explicitly ruled out the impact of window dressing in explaining abnormal returns by analyzing their portfolio pumping metric excluding prior-year winners and losers.

Dimensions of Portfolio Pumping

Through the analysis of the top 10% of fund performers versus other funds, CKMR (2002) showed that the best-performing funds drive abnormal returns in stocks because these funds gain the most from portfolio pumping.[60] Duong and Meschke (2008) validated pumping by the best-performing funds[61] but also found evidence for it being carried out by the poor performers, although they contended the economic impact was higher for the former. In contrast, Agarwal, Gay, and Ling (2014) and Patel and Sarkissian[62] (2013) discovered evidence that poor performers are more prone to pumping than their stronger counterparts. Ben-David et al. (2013) added a refined dimension by highlighting that past underperformers that appear to be outperforming in the current evaluation period tend to engage most in pumping because they are trying to take maximum advantage of their position.[63] Agarwal et al. (2007) viewed the extent of pumping as a function of the compensation arrangements in place for the fund manager. By adopting a regression of monthly hedge fund returns against fund manager compensation characteristics,[64] they showed that funds at the threshold of earning the best incentives or facing a stringent set of penalties are more likely to engage in pumping. Accordingly, the best- and the worst-performing funds are the more likely candidates for pumping.

At the stock level, the results have been mixed. In an intuitive observation, Agarwal et al. (2007) and Gallagher et al. (2009) found that funds pump stocks in which they hold significant

[59]CKMR (1999) allocated funds into cross-sectional groups based on their year-to-date relative return until the second-to-last day in a year and full year relative return. The count of funds falling under each subgroup was compared with predictions based on unconditional distribution. CKMR (2002) rejected the "beating the benchmark" hypothesis after visual inspection of distribution of returns of funds around the S&P 500.

[60]CKMR (2002) created a long–short portfolio by going long the top 10% of best-performing funds and shorting an equal-weighted portfolio of other funds on a daily basis based on the last 12-months and last 3-months returns. They subsequently regressed the same against the period-end and period-beginning dummy variables. They found the long–short portfolio generated significant positive return on the last day of the year and quarter and generated significant negative returns on the first day of the subsequent year and quarter, driven by the long portfolio of the top 10% of fund performers.

[61]Duong and Meschke (2008) perform a quintile-based analysis in which they group each fund belonging to a style into quintiles based on their past 11 months of performance and consider it as a dependent variable in regressing their portfolio pumping metric against period-end dummies.

[62]In plotting fund quintile performance based on year-to-date performance until second-to-last day of the year versus excess returns earned on the last trading day and first trading day of next year, Patel and Sarkissian (2013) observe a U-shaped and inverse U-shaped phenomenon.

[63]This finding ties in well with the argument for weak persistence of fund outperformance highlighted by Hendricks et al. (1993) and Zheng (1999).

[64]Agarwal et al. (2007) considered the "moneyness" of the compensation contract, the delta on offering, year-to-date performance, lockup period for fund contributions, and restriction periods, among other factors, in a regression of hedge fund returns against period dummies.

ownership. Through an analysis of the winning fund portfolio,[65] CKMR (2002) pointed to extreme winner and loser stocks being picked for pumping by funds.[66] The winners offer the maximum benefit, whereas the losers generally tend to be held by a few select funds; by using them, the managers could boost their fund returns effectively without increasing the returns of the funds at large. This approach is in line with the argument of Duong and Meschke (2008) on pumping being concentrated in stocks with a high concentration of fund ownership. Xiao et al. (2005) adopted a similar approach to that of CKMR and found that only the best-performing stocks are possibly being used for pumping in China.

In terms of capitalization, the trend is broadly unanimous with CKMR (2002) and Duong and Meschke (2008), among others, establishing pumping as being driven by the small-cap funds, whereas Bernhardt and Davies (2009) and Xiao et al. (2005) present a case for small-cap stocks. The latter view is tied to a related observation of a higher instance of portfolio pumping in illiquid stocks and funds exposed to illiquid stocks, as found by Agarwal et al.[67] (2007). Duong and Meschke (2008) specifically noted the stocks with a lesser number of market makers are pumped to a larger extent. In a similar observation, Bernhardt and Davies (2009) found that funds with a specialized focus are more likely to invest in illiquid stocks; accordingly, they are more likely to engage in portfolio pumping because such trades are less costly to execute.

Growth funds and aggressive growth funds that generally tend to invest with a greater small-cap focus appear to be more likely candidates for pumping than value funds, according to an analysis by Meier and Schaumburg (2006) and Gallagher et al.[68] (2009). Although Harris (1989) found evidence of greater pumping at lower price levels, subsequent research by Akyol and Michayluk (2010) and others did not garner much support for this hypothesis.

Performing a regression of their adjusted blip metric against fund characteristics, Ben-David et al. (2013) showed that younger funds, smaller-sized funds, and funds that are less diversified in nature are more prone to pumping. Meier and Schaumburg (2006) added that funds with a higher turnover, a higher expense ratio, and larger cash holdings seem to have a greater likelihood of being pumped. Agarwal et al. (2007) opined that the funds with greater opportunities to pump are more likely to use the opportunities. Using a sample of hedge funds, they contended that funds with a wider volatility of monthly returns are more prone to pumping.

Commenting on managerial skill levels, Agarwal et al. (2014), through comparison of actual fund performance and implied performance based on disclosed prior period-end holdings,[69] highlighted that low-skilled managers are more susceptible to engaging in manipulative activi-

[65]CKMR (2002) divided stocks into a 5 × 5 matrix based on capitalization and recent performance until two days prior to end of year. They then created a long–short portfolio in each group with long on stocks that are in the portfolio of the top 10% of fund performers and short in others. Subsequently, they compute two-day inflation for each year as the last day return/first day return of the next year. This approach is standardized across a normal two-day return across years to test whether the two-day inflation at the end of year is significantly different from other days.

[66]In an earlier paper, CKMR (1999) considered a portfolio of returns on stocks held in the top 10% of winning funds (until the second-to-last day of a quarter) over the last day of the quarter and first day of the subsequent quarter and tested for it being significantly different from zero.

[67]Bernhardt and Davies (2009), Akyol and Michayluk (2010), and Gallagher et al. (2009) have also drawn similar conclusions.

[68]CKMR (2002) and Duong and Meschke (2008), among others, have also found support in favor of growth funds.

[69]Assuming that the holdings from the prior month-end were retained, the performance of such a portfolio is compared with actual monthly fund returns. A 12-month moving average of the same is treated as a measure of manager skill and used as a regressor variable to explain the return differential between actual and implied performance.

ties. In evaluating the influence of team structure on pumping activity, Patel and Sarkissian (2013) found that a fund with multiple managers (team-based fund management) tends to act more ethically than single-managed fund managers because the team structure reduces the extent of incentives, creates moral pressure, and ensures enhanced monitoring.

Extending the analysis a step further, Ben-David et al. (2013) explored the persistence of pumped funds and stocks. They found that funds that indulge in pumping continue to do so, although it seems the same stocks are generally not picked for pumping in subsequent quarters. Going beyond the fund characteristics, they also commented that pumping by funds is more likely during times of market lows because those times offer a better opportunity to earn investor attention on their skills. Evaluating pumping against market conditions, Gallagher et al. (2009) found that the trend intensifies after and around market highs because flows are generally higher during these periods and managers make every effort to corner the maximum flows.

4. Hypothesis Development

Drawing inspiration from our literature review presented in the previous section, we developed seven hypothesis statements on portfolio pumping that we wanted to test for in the context of Singapore.

H1: Portfolio Pumping Will Be Evident at the Broad Market Level

A. Stocks would earn abnormal positive returns on the last day of the quarter, and

B. stocks would earn abnormal negative returns on the first day of the quarter.

The literature clearly suggests a continued presence of portfolio pumping in the United States and other markets, despite some researchers documenting a decline in activity over time. Therefore, the first hypothesis is that the overall stock universe would exhibit evidence of portfolio pumping, which would be characterized by abnormal positive returns on the last day of the quarter and a reversal of these returns in the following day.

We proposed to test whether standardized average returns of an equal-weighted index of stocks on the last trading day of the quarter and the first trading day of the subsequent quarter (standardized over days excluding the first and the last day of a quarter) are significantly greater and less than zero, respectively. This approach would be in line with the methodology adopted by Xiao et al. (2005), among others.

We validated our analysis with regressions of daily stock returns against period-end and period-beginning dummy variables, as defined by CKMR (2002). Accordingly, the period-end dummy variable was assigned a value of 1 at specified period-ends, such as a quarter- or year-end, and a value of 0 on other days. Similarly, the period-beginning dummy variable carried a value of 1 on period-beginning days and a value of 0 otherwise. If our hypothesis held, we expected to observe a significant positive relationship with quarter-end dummy variables and a significant negative relationship with quarter-beginning dummy variables.

Apart from observing price behaviour, we also took a closer look at volume during period-ends. Gallagher et al. (2009) observed abnormally high trading activity during quarter-ends, specifically during year-ends. We performed the same regression of standardized trade volume with period-end and period-beginning dummies to note unusual instances of volume surge in our dataset.

H2: Portfolio Pumping Is Concentrated in the Final Few Minutes of Trading or in the Final Few Transactions

Executing a portfolio pumping strategy involves its own cost, especially on a stock that is liquid, which means fund managers wanting to boost the prices of their holdings are likely to engage in pumping in the final few minutes of the last trading day of the quarter. Observing the last few minutes of trading or the last few transactions is an effective way to identify instances of portfolio pumping.

We replicated the analysis undertaken to evaluate pumping on the last day of a quarter during the final few minutes of trading and final set of transactions to explore the presence of any abnormal behaviour. In general, researchers have observed transactions over the last 30 minutes (Duong and Meschke 2008; Gallagher et al. 2009, among others) to establish pumping. We began with the same approach.

H3: Proportion of Buyer-Initiated Transactions Is Higher during the Final Few Minutes of Trading at Quarter-Ends Than during Other Periods

Furthermore, if the trades are initiated by fund managers in the final few minutes of the last trading day of a quarter just to boost prices, a larger fraction of concluded trades are expected to be driven by the buyers. Accordingly, we hypothesized that the proportion of trades at ask price or more would be higher at quarter-ends than otherwise, in line with observation of CKMR (2002).

H4: Fund Managers Are Likely to Engage in Pumping with a Limited Amount of Capital

If portfolio pumping exists, fund managers are likely to execute such a pumping strategy with smaller trade volumes than normal if their only intention is to enhance prices temporarily. Accordingly, we drew from Akyol and Michayluk (2010) and adopted their metric, proportion of small trades among final trades, to gauge fund manager behavior. We expected it to be significantly higher on the last trading day of the quarter as opposed to any other normal day. We adopted a definition of small trades in line with the historical trading pattern at the SGX. We also stress tested it for robustness with multiple threshold values.

To validate H3 and H4, we performed a regression on the proportion of trades at ask price or higher and the proportion of small trades among final trades, respectively, against period-end dummies. Significant results supporting our hypotheses will mean the influence of portfolio pumping as a defining activity in explaining any abnormal returns observed at quarter-ends.

H5: Pumping Will Be Achieved by Cornering of Trades by Select Set of Traders and Clients

Given the wealth of data in terms of individual trader activity (activity by trader ID) and also the clients backing it (by way of client ID), we took a step further and extended our analysis to trades at the trader and client levels. *Ex post* studies of portfolio pumping instances generally found evidence of select traders and clients cornering a significant share of trades in the final few minutes of trading on the last day of a reporting period. Our analysis is among the first to evaluate the concentration of trades at the trader and client level and will provide insights on whether the cornering of trades occurs in Singapore. Observing the activity at the trader and client level provided more direct evidence of pumping than indirect observations based on price and volume behavior.

H6: Portfolio Pumping Will Be Concentrated on Small-Cap Stocks, Catalist-Listed Stocks, Extreme Strong and Weak Performers, and S-Chip Stocks

We wanted to understand the nature of stocks for which evidence of pumping is relatively stronger. Bernhardt and Davies (2009) and Xiao et al. (2005), among others, have highlighted a higher incidence of pumping among small-cap, illiquid, and growth stocks. In terms of momentum, CKMR (2002) pointed to extreme winner and loser stocks being picked for pumping by funds. Drawing inspiration from these analyses, we replicated our hypothesis testing and regression analysis with period-end and period-beginning dummies bifurcating our stock universe across capitalization, turnover, style, and momentum factors.

Additionally, our data universe enabled us to test for significant difference in pumping activity between stocks across operational jurisdictions. We tested whether the S-chip stocks (stocks operationally based out of mainland China and listed in Singapore) are more prone to pumping than their local counterparts. Again, we believe our analysis is the first to compare pumping activity in onshore and offshore stocks.

H7: Portfolio Pumping Is Expected to Have Declined over Time, Especially after Key Milestone Events around Enforcement of Portfolio Pumping Legislation

Duong and Meschke (2008) observed a significant reduction in portfolio pumping activity in the United States after 2001. They attributed the trend to increased scrutiny by the Fed and widespread publicity of CKMR (2002), the first draft version of which was published in June 1999. Using 2001 as a binary dummy variable (they assigned a value of 1 to all observations occurring after 2001 and a value of 0 to prior-period values), the authors found a significant negative relationship between the variable and their portfolio pumping metric. Similar conclusions were drawn by Gallagher et al. (2009), who found that ASX's introduction of a closing call auction (in February 1997) and the change of its algorithm (in September 2001) helped reduce abnormal returns at quarter-ends. To our knowledge, there is no specific literature that has looked at effectiveness of enforcement action of portfolio pumping legislation. So, we began by gauging the impact of portfolio pumping after key milestone enforcement actions.

Specifically, we believe the Pheim Asset Management case to be a landmark event in the history of enforcement related to portfolio pumping in Singapore, and we tracked the effect of its developments on portfolio pumping activity during our study period. Similarly, we also used market microstructure reforms introduced by SGX as milestones to determine how pumping activities have evolved in response to regulatory actions.

We adopted the methodology used by Gallagher et al. (2009) by introducing period-defining dummy variables for the milestone events. We then used them as explanatory variables in running regression analysis on our portfolio pumping metric.

5. Research Design and Analysis

In this section, we discuss the data source, provide descriptive statistics and visual analysis, and offer detailed data analysis.

Data Source

This study was privileged to be granted access to tick-by-tick data of 189 listed companies in the FTSE ST All-Share Index (including current and delisted companies) from SGX. The data consisted of 35 fields, out of which 16 were found relevant for this study. The period ranged from January 2003 to December 2013. In total, more than 12 billion data points were used for this study.

Data were made available in Microsoft Excel files, with one file dedicated to each trading day. As the first step, these raw files had to be cleaned and put in the right format, such as in the case of date-related fields and presentation structure, to enable optimal and effective analysis. Given that data were spread across multiple files and that each file included information about trades that took up several hundreds of thousands of rows, data extraction was not a straightforward exercise. Excel also has limitations in handling such a high volume of data. Hence, we loaded the complete dataset in the desired format to a SQL database server. Most analyses were done on data extracted from this central database. This approach ensured the effective storage of all data in a single location and also facilitated custom extraction through SQL queries. EViews was used as the primary statistical tool to run analysis. In certain cases, cleaned Excel files had to be used directly for analysis because of limitations in data structure, such as identifying trades that are buyer initiated or the need for custom data series at the granular level—for example, to determine trader and client concentration levels using the Herfindahl index. This step required extensive coding in Visual Basic for Applications to derive and analyze relevant metrics. **Table 3** lists the data fields and a description of each that were in the data provided.

Broad market analysis was carried out using daily pricing (open, high, low, and close) and volume (shares) data from Bloomberg for the 189 listed companies in the FTSE ST All-Share Index from the SGX.

Table 3. List of Data Fields in the Tick-by-Tick Trades Provided by SGX

Data Field	Description
Date	Date when the transaction took place
Time	Time when the transaction took place, rounded up to the nearest second
Security	Name of the listed company
Transtype	Type of transaction entered, which includes four subcategories: ■ Amend—a transaction entered to modify and overwrite a previously entered transaction ■ Delete—a transaction entered to cancel a previously entered transaction ■ Enter—any new transaction entry ■ Trade—confirmed execution of a previously entered transaction
Is Bid	Long or short transaction, which includes two subcategories: ■ False—any short transaction ■ True—any long transaction
Volume	Number of shares involved in the transaction
Price	Price of the stock in the transaction
Value	Aggregate value of the transaction; obtained when price is multiplied by volume
House (masked)	Brokerage house through which the transaction gets executed; because of the sensitivity of information, the name of the individual brokerage house is masked and replaced with a unique ID
Trader (masked)	Trading representative through whom the transaction gets executed; because of the sensitivity of information, the name of the individual trading representative is masked and replaced with a unique ID
Client (masked)	Identity of the trading account holder; because of the sensitivity of information, the identity of the individual account holder is masked and replaced with a unique ID
Listing date	Date of IPO
Board	Listing platform of the stock issue: main (Mainboard) or secondary (Catalist)
Currency	Currency denomination of the stock issue
Shares on issue	Total number of shares issued
Sector	Industry classification of the stock issue

Descriptive Statistics and Visual Analysis

Our dataset from 2003 to 2013 enabled us to search for evidence of portfolio pumping over 44 quarters. **Table 4** presents a snapshot of the absolute and excess returns of the universe on the last trading day of each quarter over the analysis period. The table also provides the same information for the first trading day of the subsequent quarter. Average return represents a simple equal-weighted average of returns of all stocks in the universe. Excess returns are computed in relation to the FTSE STI.

Average absolute return on the last day of the quarter is about 20 bps, whereas average excess return is slightly lower at 17 bps. Interestingly, on the first day of the quarter, average returns are positive and higher at 65 bps and 16 bps for absolute and excess returns, respectively. This result is in contrast to the expectation of what it would be in the event of portfolio pumping. If fund managers had temporarily raised prices at the end of the quarter to inflate their fund performance, then the price change is expected to reverse in the first trading day of the subsequent quarter. But there is no such tendency visible in the dataset.

Table 4. Absolute and Excess Returns of Stock Universe on the Last Trading Day and the First Trading Day of a Quarter

	Last Day of Quarter						First Day of Quarter					
	Absolute Returns (%)			Excess Returns (%)			Absolute Returns (%)			Excess Returns (%)		
Quarter	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases
Q1 2003	–2.21	–1.19	7.95	1.56	2.58	72.73*	1.52	0.00	44.79	0.51	–1.01	38.64
Q2 2003	–0.65	–0.65	19.57	1.65	1.65	82.61*	0.28	0.00	26.00	–0.20	–0.48	26.09
Q3 2003	0.02	0.00	29.47	–0.21	–0.23	29.47	–0.36	0.00	25.24	–0.29	0.07	54.74
Q4 2003	0.42	0.00	34.38*	0.40	–0.02	34.38*	2.30	1.63	68.27	0.63	–0.04	47.92
Q1 2004	0.30	0.00	37.76	–0.33	–0.63	29.59	1.44	0.82	56.60	0.71	0.09	55.10
Q2 2004	0.33	0.00	33.33	–0.06	–0.39	33.33	0.20	0.00	27.27	–0.13	–0.33	29.41
Q3 2004	0.46	0.00	44.12*	–0.10	–0.56	41.18	0.13	0.00	21.82	0.18	0.05	58.82
Q4 2004	0.12	0.00	34.58	–0.19	–0.31	34.58	0.74	0.00	43.48	0.59	–0.15	46.73
Q1 2005	0.40	0.00	40.00*	–0.52	–0.92	27.27	0.25	0.00	33.05	0.13	–0.12	35.45
Q2 2005	0.61	0.00	36.61*	–0.12	–0.73	34.82	–0.42	0.00	24.17	–0.15	0.27	61.61
Q3 2005	0.28	0.00	31.30	0.11	–0.17	31.30	0.07	0.00	26.83	0.19	0.12	63.48
Q4 2005	0.60	0.00	37.93*	0.46	–0.14	37.93*	1.42	0.79	53.23	0.41	–0.22	45.69
Q1 2006	0.68	0.00	43.22*	0.24	–0.44	43.22	0.90	0.00	40.94	0.22	–0.68	40.34
Q2 2006	2.22	1.01	60.98*	0.25	–0.96	39.84	–0.30	0.00	28.24	–0.35	–0.05	30.08
Q3 2006	0.53	0.00	37.30*	0.55	0.02	76.98*	0.26	0.00	39.55	–1.07	–1.33	29.37*
Q4 2006	1.55	0.54	52.31*	0.91	–0.10	48.46*	3.25	1.61	60.87	1.35	–0.29	45.38
Q1 2007	0.51	0.00	41.67*	0.54	0.03	63.64*	0.53	0.00	37.14	0.24	–0.29	39.39
Q2 2007	0.59	0.00	47.41*	0.24	–0.35	47.41	0.11	0.00	34.27	0.08	–0.03	36.30
Q3 2007	0.84	0.40	50.74*	1.07	0.63	75.74*	1.79	1.16	61.81	0.40	–0.23	45.59
Q4 2007	1.46	0.90	63.64*	0.45	–0.11	46.15*	–0.35	0.00	23.84	0.26	0.61	60.84
Q1 2008	–0.69	0.00	28.47	0.12	0.81	61.11	0.55	0.00	44.74	–0.75	–1.30	31.94*
Q2 2008	–0.22	0.00	31.72	0.06	0.28	55.86	–1.37	–1.00	13.07*	0.01	0.38	60.00
Q3 2008	0.25	0.00	36.99	0.35	0.10	58.90	1.04	0.00	40.26	0.84	–0.20	42.47

(continued)

Table 4. Absolute and Excess Returns of Stock Universe on the Last Trading Day and the First Trading Day of a Quarter (continued)

	Last Day of Quarter						First Day of Quarter					
	Absolute Returns (%)			Excess Returns (%)			Absolute Returns (%)			Excess Returns (%)		
Quarter	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases
Q4 2008	−0.27	0.00	24.49	0.24	0.51	63.27	3.35	3.09	63.23	−0.52	−0.78	39.46
Q1 2009	1.83	0.00	46.94*	0.23	−1.60	38.10	0.59	0.00	30.97	0.46	−0.13	32.65
Q2 2009	−0.75	0.00	20.41	−1.44	−0.69	17.01	0.78	0.91	56.13	−0.05	0.08	50.34
Q3 2009	−1.04	−0.68	25.00	−1.39	−1.03	25.00	−1.48	−1.19	14.10*	−0.91	−0.62	38.51*
Q4 2009	0.54	0.00	43.71*	−0.08	−0.62	35.76	1.59	0.93	55.97	1.70	1.04	82.12
Q1 2010	−0.96	−1.04	15.69	0.61	0.53	63.40*	1.37	1.05	60.25	−0.55	−0.87	30.07*
Q2 2010	0.16	0.00	38.71	−0.02	−0.18	38.06	−0.82	−0.81	20.86*	−0.29	−0.28	45.16*
Q3 2010	−0.46	0.00	25.16	−0.19	0.27	52.90	1.39	0.98	64.42	0.32	−0.09	46.45
Q4 2010	−0.30	0.00	29.19	0.40	0.70	75.78*	1.86	1.29	69.23	0.43	−0.14	45.96
Q1 2011	−0.38	0.00	29.70	−0.72	−0.34	29.09	0.88	0.64	57.23	0.41	0.17	55.15
Q2 2011	0.97	0.53	53.89*	−0.35	−0.79	24.55	0.27	0.00	44.00	−0.33	−0.60	40.12
Q3 2011	−1.08	−1.01	17.86	0.14	0.21	55.95	−2.70	−2.59	8.52*	−0.69	−0.58	44.05*
Q4 2011	0.14	0.00	33.93	1.13	0.99	78.57*	1.94	1.52	73.86	0.35	−0.08	47.62
Q1 2012	0.75	0.00	45.56*	0.20	−0.55	40.83	0.80	0.00	47.46	0.61	−0.19	49.70
Q2 2012	1.27	1.03	73.84*	0.16	−0.08	48.26	1.09	0.96	63.33	−0.03	−0.16	46.51
Q3 2012	0.06	0.00	33.33	0.03	−0.03	33.33	0.49	0.00	40.11	0.57	0.08	69.54
Q4 2012	0.70	0.00	26.40	1.47	0.77	74.16*	2.20	1.57	80.11	1.11	0.48	64.61
Q1 2013	−0.31	−0.06	28.89	−0.16	0.09	50.56	−0.07	0.00	33.51	−0.05	0.02	60.56
Q2 2013	0.61	0.49	58.79*	−0.43	−0.55	35.71	−0.24	0.00	31.05	0.06	0.30	56.59
Q3 2013	−1.27	−0.97	16.13	0.05	0.35	60.22	0.54	0.00	47.42	0.11	−0.43	46.77
Q4 2013	0.38	0.00	39.89*	−0.07	−0.45	34.04	0.60	0.00	46.43	0.37	−0.23	47.34

(continued)

Table 4. Absolute and Excess Returns of Stock Universe on the Last Trading Day and the First Trading Day of a Quarter (continued)

	Last Day of Quarter						First Day of Quarter					
	Absolute Returns (%)			Excess Returns (%)			Absolute Returns (%)			Excess Returns (%)		
Quarter	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases
Averages												
Overall	0.20	−0.02	36.57*	0.17	−0.06	47.30*	0.65	0.30	42.81	0.16	−0.19	46.92
Average for quarters												
Q1	−0.01	−0.21	33.26	0.16	−0.04	47.23	0.80	0.23	44.24	0.18	−0.39	42.64
Q2	0.47	0.22	43.20*	0.00	−0.25	41.59	−0.04	0.00	33.49	−0.12	−0.08	43.84
Q3	−0.13	−0.20	31.58	0.04	−0.04	49.18	0.11	−0.15	35.46	−0.03	−0.29	49.07
Q4	0.49	0.13	38.22*	0.47	0.11	51.19*	1.72	1.13	58.05	0.61	0.02	52.15
Average for regime												
2003–2007	0.34	0.04	37.75*	0.32	0.02	48.74*	0.72	0.34	39.11	0.14	−0.25	44.37
2008–2013	0.04	−0.08	35.15	−0.02	−0.15	45.56	0.55	0.26	47.25	0.18	−0.11	49.99
Average for each year												
2003	−0.61	−0.46	22.84	0.85	1.00	54.80*	0.94	0.41	41.08	0.16	−0.36	41.84
2004	0.31	0.00	37.45*	−0.17	−0.47	34.67	0.63	0.21	37.29	0.34	−0.08	47.52
2005	0.47	0.00	36.46*	−0.02	−0.49	32.83	0.33	0.20	34.32	0.14	0.01	51.56
2006	1.24	0.39	48.45*	0.49	−0.37	52.13*	1.03	0.40	42.40	0.04	−0.59	36.29
2007	0.85	0.32	50.86*	0.58	0.05	58.23*	0.52	0.29	39.26	0.25	0.02	45.53
2008	−0.23	0.00	30.42	0.19	0.43	59.79	0.89	0.52	40.32	−0.11	−0.48	43.47
2009	0.15	−0.17	34.01	−0.67	−0.98	28.97	0.37	0.16	39.29	0.30	0.09	50.91
2010	−0.39	−0.26	27.19	0.20	0.33	57.54*	0.95	0.63	53.69	−0.02	−0.35	41.91
2011	−0.09	−0.12	33.84	0.05	0.02	47.04	0.10	−0.11	45.90	−0.06	−0.27	46.73
2012	0.69	0.26	44.78*	0.46	0.03	49.14*	1.14	0.63	57.75	0.56	0.05	57.59
2013	−0.15	−0.13	35.93	−0.15	−0.14	45.13	0.21	0.00	39.60	0.12	−0.09	52.82

(continued)

Table 4. Absolute and Excess Returns of Stock Universe on the Last Trading Day and the First Trading Day of a Quarter (continued)

	Last Day of Quarter						First Day of Quarter					
	Absolute Returns (%)			Excess Returns (%)			Absolute Returns (%)			Excess Returns (%)		
Quarter	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases
Averages by category												
Capitalization												
Large	0.16	0.02	43.91	0.12	−0.02	48.30*	0.50	0.38	53.59	0.01	−0.11	48.52
Mid	0.32	0.17	43.49*	0.28	0.13	52.52*	0.48	0.32	46.67	−0.01	−0.17	45.29
Small	0.17	−0.06	30.36	0.13	−0.10	44.39	0.78	0.31	41.23	0.29	−0.18	46.96
S-chip												
Yes	0.13	−0.05	44.93	0.09	−0.09	45.04	0.87	0.68	56.04	0.38	0.19	52.96
No	0.22	−0.02	47.21*	0.18	−0.06	47.66*	0.61	0.27	49.94	0.12	−0.22	45.90
SIMSCI												
Yes	0.16	0.02	47.00	0.12	−0.02	48.26	0.42	0.36	49.04	−0.07	−0.13	46.38
No	0.22	−0.01	46.89	0.18	−0.05	47.04	0.70	0.30	51.25	0.21	−0.19	46.97
Momentum												
1 (worst)	0.36	0.00	32.50*	0.32	−0.04	45.17*	0.07	0.02	36.62	−0.42	−0.47	39.57
2	0.13	0.02	37.15	0.09	−0.01	47.96	0.52	0.31	43.42	0.03	−0.18	43.21
3	0.23	0.07	38.79	0.19	0.03	48.52*	0.71	0.49	50.92	0.22	0.00	50.81
4 (best)	0.11	−0.10	37.75	0.07	−0.14	47.34	1.27	0.62	50.24	0.79	0.13	53.99
Listing												
Mainboard	0.22	0.00	47.36*	0.18	−0.04	47.94*	0.64	0.33	50.84	0.15	−0.15	47.17
Catalist	−0.02	−0.14	41.52	−0.06	−0.18	39.89	0.68	0.27	51.00	0.19	−0.22	44.28

(continued)

Table 4. Absolute and Excess Returns of Stock Universe on the Last Trading Day and the First Trading Day of a Quarter (continued)

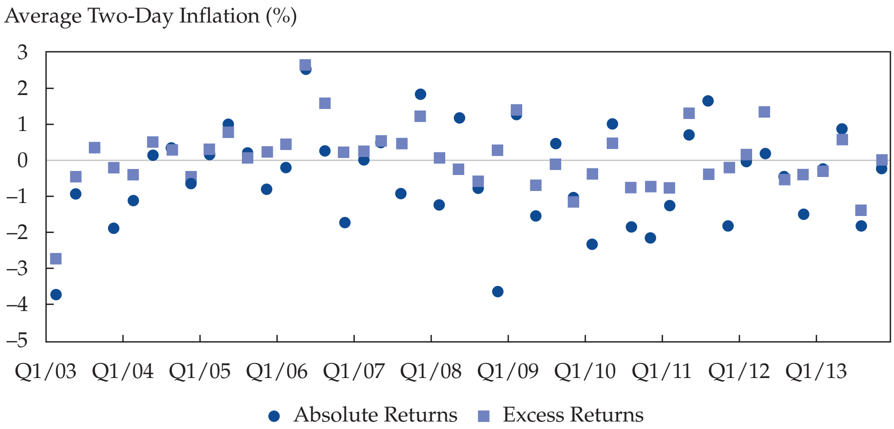
	Last Day of Quarter						First Day of Quarter					
	Absolute Returns (%)			Excess Returns (%)			Absolute Returns (%)			Excess Returns (%)		
Quarter	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases
Milestone												
Post 2006	0.28	0.03	37.99*	0.13	–0.13	47.87*	0.62	0.30	43.62	0.14	–0.18	47.42
Post 2009	0.02	–0.06	35.44	0.14	0.06	49.71*	0.60	0.29	49.24	0.15	–0.16	49.76
Post 2011	0.27	0.06	40.35*	0.16	–0.06	47.14*	0.68	0.32	48.68	0.34	–0.02	55.20

*Represents favorable significance of average value at the 5% level. It implies returns are significantly greater than zero on the last day of the quarter or significantly less than zero on the first day of the quarter.

Looking at the individual quarters in greater detail, **Figure 1** presents a scatterplot of average two-day inflation around quarter-ends in terms of both absolute and excess returns. Two-day inflation for a quarter is defined as the average returns of all constituents on the last day of a quarter minus the average returns earned by all constituents on the first day of the subsequent quarter. In the event of pumping, we would expect the two-day inflation to be significantly positive, as computed by a significant positive return on the last day of the quarter and a reversal of return (accordingly, a significantly negative return) on the first day of the subsequent quarter.

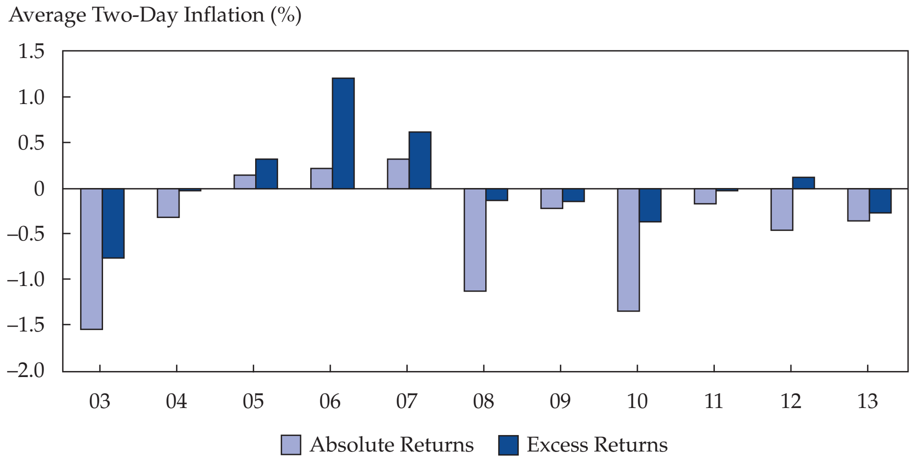
We observed that average two-day inflation on both absolute and excess returns was largely negative in nature, especially during the second half of the study period. **Figure 2** presents the information aggregated by year, and the trend is more evident.

Figure 1. Average Two-Day Inflation around Quarter-Ends by Quarter



Source: Based on data from Bloomberg Finance L.P. and the SGX.

Figure 2. Average Two-Day Inflation around Quarter-Ends by Year



Source: Based on data from Bloomberg Finance L.P. and the SGX.

Table 4 also shows that the proportion of positive return quarters was higher on the first day of the quarter as opposed to the last day. In fact, over the complete period of our study, there were only two quarters over which average excess returns on the last day of the quarter were significantly positive and on the first day of the subsequent quarter were significantly negative.

Looking more closely at the individual calendar quarters, we observed positive returns on the last day of the quarter to be strongest in Q4. But on the first day of the subsequent quarter, marking the beginning of the year, average returns were much higher. Thus, even if we assumed the positive excess returns in Q4 (year-ends) to be reflective of portfolio pumping, no immediate reversal is visible at the turn of the year. This result could possibly be attributable to the impact of other overriding factors potentially masking the reversal trend. With other calendar quarters, the quarter-end returns were either minuscule or not favorable.

Since 2008, which marked the end of the global financial crisis (GFC), there has been an increased focus on regulation globally. Dividing our sample period into pre-GFC (2003–2007) and post-GFC (2008–2013), we observed that returns on the last day of the quarter fell significantly in the latter period. In fact, average excess returns were slightly negative at 2 bps on the last trading day of a quarter during 2008–2013, a sharp fall from 32 bps in the prior period. This result could possibly be reflective of increased regulation, greater enforcement, and media scrutiny of fund managers in recent years. We will evaluate this subject later in the study.

The trend is also well reflected in the averages for each year. Average absolute and excess returns over 2003–2007 were found to be significantly greater than zero on the final day of the quarter. The trend changes significantly in the period starting in 2008, with the exception of 2012, when both average absolute and excess returns generated strong positive returns at quarter-ends.

In terms of capitalization, mid-cap stocks generated absolute and excess returns of 32 bps and 28 bps, on average, on the last trading day of a quarter. These returns are almost twice the equivalent return of 16 bps and 12 bps earned by the large-cap stocks. Mid-cap stock returns were also found to be statistically higher than zero at the 5% significance level. Furthermore, mid-cap stocks generated a marginal, albeit not statistically significant, negative excess return on the first day of the subsequent quarter, possibly representing a reversal of any pumping activity. But large-cap stocks generated a strong positive excess return at the turn of the quarter. Interestingly, the return profile of small-cap stocks appeared to be closer to large-caps than mid-caps.

S-chip stocks earned an average excess return of 9 bps on the final trading day of a quarter, half the return earned by non-S-chip stocks (18 bps). The excess return of the latter group was also found to be significantly greater than zero at the 5% significance level.

Stocks forming a part of the current SIMSCI had a lower level of excess returns compared with the remaining stocks in the universe. Because stocks in the SIMSCI are predominantly large-cap stocks, the results are in line with the observation made earlier.

Stocks that were among the worst performers of the quarter until the second-to-last day of the quarter had the strongest level of excess returns on the final trading day of a quarter. The bottom performer quartile of stocks for the quarter earned an excess return of 32 bps, on average, on the final trading day. They also lost 42 bps, on average, the first trading day of the subsequent quarter. Although not statistically significant, they mark the only group with a negative return on the first trading day of a quarter.

Mainboard-listed stocks earned an excess return of 18 bps on the final trading day of a quarter, whereas Catalist-listed stocks lost 6 bps. At the turn of the quarter, both groups earned positive excess returns.

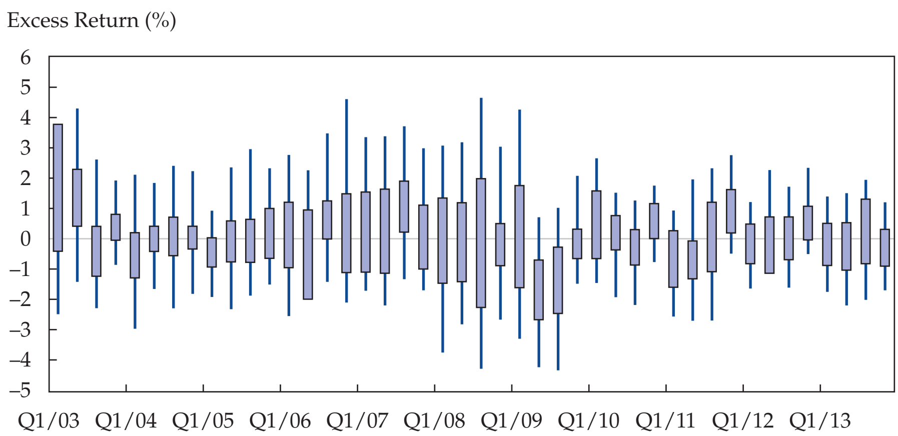
Over the period of our analysis, 2006, 2009, and 2011 could be viewed as key milestone years in terms of portfolio pumping and market manipulation regulation in Singapore. Abnormal trades in shares of UET by Tan Chong Koay and his firm, Pheim Asset Management Sdn Bhd, in the final trading days and minutes of 2004 year-end received media attention starting in 2006 when the first investigation began. In several ways, this case was considered the first widely publicized instance of potential portfolio pumping activity in the Singapore market. In 2009, MAS filed a formal civil suit against Pheim Asset Management Sdn Bhd for alleged portfolio pumping. An appeal from Tan Chong Koay and the firm contesting the verdict that indicted them for portfolio pumping was dismissed in 2011. Absolute and excess returns appeared to decline significantly at quarter-ends after 2009. But they appeared to increase after 2011, probably influenced by the strong positive returns in 2012.

Concentrating specifically on the last day of a quarter, we explore the variation in excess returns of individual stocks in various quarter periods of the study and present the result in **Figure 3** as a box plot. The figure shows the variation in excess returns between the 10th and 90th percentile value of excess returns for each quarter and the box limits represent Q1–Q3 values.

Two distinct trends are visible. There is a specific cyclicality in excess returns over time, with the cycle expanding over Q1 2005 to Q3 2007 and again over Q2 2009 to Q3 2011. Second, variation in excess returns has declined in recent years compared with the earlier period of analysis. Specifically, variation has been relatively quiet since 2010.

Although we have established some visual support for possible pumping at the end of the quarter, a reversal trend is strictly not visible on the first trading day of a quarter. One possible explanation could be a possible delay in reversal because of other factors. If this reason were true, we would expect a reversal to be seen on subsequent days in a quarter.

Figure 3. Excess Return Variation across Stocks by Quarter on the Last Trading Day



Source: Based on data from Bloomberg Finance L.P. and the SGX.

Figure 4 presents the average excess returns for the study's universe 10 days prior and 10 days after a quarter-end. Although average excess returns on Day 0 (last day of the quarter) and Day 1 (first day of the quarter) are positive, interestingly, Day 2 (second day of the quarter), on average, showed a negative excess return. In fact, it is the only day of average negative returns in the 10 days following a quarter-end, which could possibly be an effect of a delayed reversal.

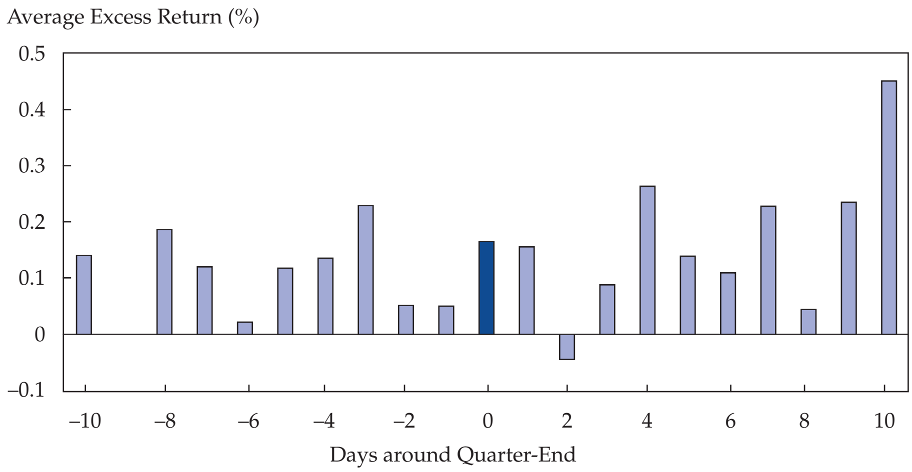
This finding is corroborated by **Figure 5**, which presents our two-day inflation metric computed with returns on the last day of a quarter and returns from multiple days following the start of the next quarter, ranging from T+1 day (first day of the next quarter) to T+5 days (five days subsequent into quarter), for each year studied (2003–2013). In general, we found two-day inflation to be negative across most years for most days, with the exception of T+2 days, for which we observed quite a few cases with positive returns. This finding needs detailed testing to determine whether the average negative return on day T+2 marks a reversal of return. We will test the same later in the report.

In unreported results, performing the analysis with cumulative returns over the set of multiple days (T+1 to T+5 days) did not show any sign of reversal of returns. We would expect cumulative returns to be close to zero if the significant positive returns on the last day of a quarter vanished subsequently over T+1 to T+5 days. But we find no supportive evidence in this regard.

Drawing inspiration from Gallagher et al. (2009), we next observed patterns in traded volume around a quarter-end. They observed significant pick-up in trade activity in Australia around quarter-end and specifically around fiscal year-end. **Figure 6** presents the average standardized traded volume of stocks in our universe around a quarter-end for –10 days to +10 days of a quarter-end.

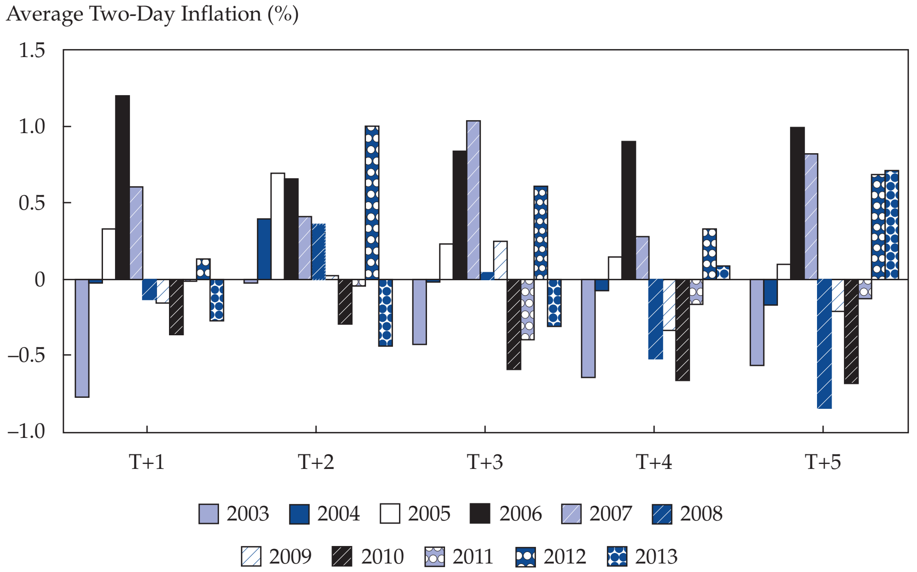
Volume for each stock in the universe is standardized against volume over its prior six months and subsequent six months, as adopted by CKMR (2002). Standardized volume for each stock is averaged across all stocks in the universe and the pattern is charted. Contrary to our expectations, we did not observe increased trading activity on the final trading day of a quarter. Instead, trade volume fell a few days prior to a quarter-end and gradually picked up with the start of the subsequent quarter.

Figure 4. Average Excess Return of the Universe around Quarter-End



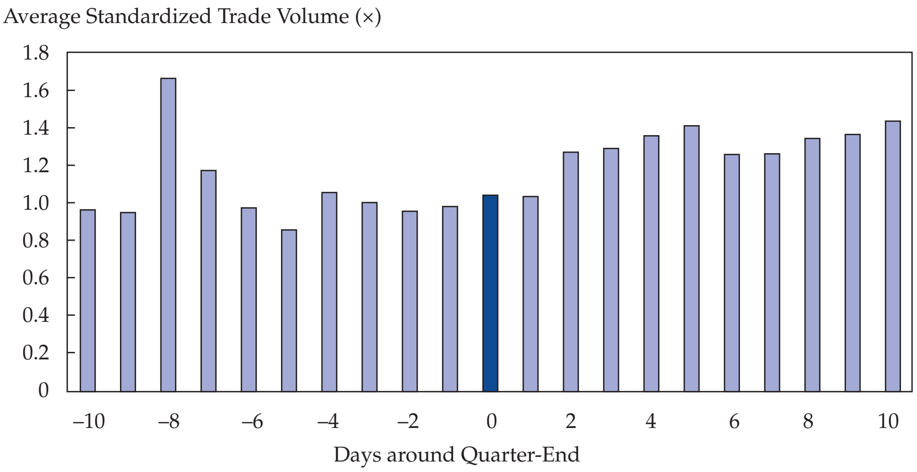
Source: Based on data from Bloomberg Finance L.P. and the SGX.

Figure 5. Average Two-Day Inflation (Excess Returns) around Quarter-Ends Based on Returns on Last Day of the Quarter and Multiple Subsequent Days in the Following Quarter



Source: Based on data from Bloomberg Finance L.P. and the SGX.

Figure 6. Average Standardized Trade Volume around a Quarter-End



Source: Based on data from Bloomberg Finance L.P. and the SGX

Pumping involves significant cost for fund managers. Therefore, if fund managers engage in portfolio pumping, their activity is likely to be concentrated in the final few minutes of the last trading day to derive maximum benefit. Academic literature, including the work of CKMR (2002), specifically concentrates on the final 30 minutes of trading on the final trading day of a quarter or a year. **Table 5** presents average returns and standardized trading volume of stocks on the last trading day and during the final 30 minutes of trading on the last trading day of a

Table 5. Returns and Volume on the Last Trading Day and during the Final 30 Minutes of Trading on the Last Day of a Quarter

	Absolute Returns (%)						Average Standardized Volume					
	Last Trading Day			Last 30 Minutes of Trading			Last Trading Day			Last 30 Minutes of Trading		
Quarter	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases	Mean	Median	Proportion of Positive Cases
Overall	0.20	−0.02	36.57	0.08	0.00	20.48	0.85	0.38	60.64	1.08	0.37	57.86
Q1	−0.01	−0.21	33.26	0.01	0.00	18.74	0.81	0.36	55.95	1.00	0.32	54.27
Q2	0.47	0.22	43.20	0.07	0.00	21.00	0.78	0.36	55.18	0.98	0.38	53.01
Q3	−0.13	−0.20	31.58	0.14	0.00	22.76	1.04	0.58	62.66	1.30	0.52	59.56
Q4	0.49	0.13	38.22	0.11	0.00	19.41	0.60	0.16	57.73	0.85	0.18	54.06
2003–2007	0.34	0.04	37.75	0.13	0.00	19.71	0.90	0.43	63.44	1.09	0.40	59.97
2008–2013	0.04	−0.08	35.15	0.02	0.00	21.40	0.80	0.33	57.56	1.07	0.34	55.53

quarter. In the final 30 minutes of trading on the last day of a quarter, stocks in our universe earn an average return of 8 bps, compared with 20 bps for the complete day. The proportion of stocks with positive returns is lower in the final 30 minutes of trading in a quarter compared with the overall day because several stocks that could have traded earlier in the day may not trade in the final few minutes.

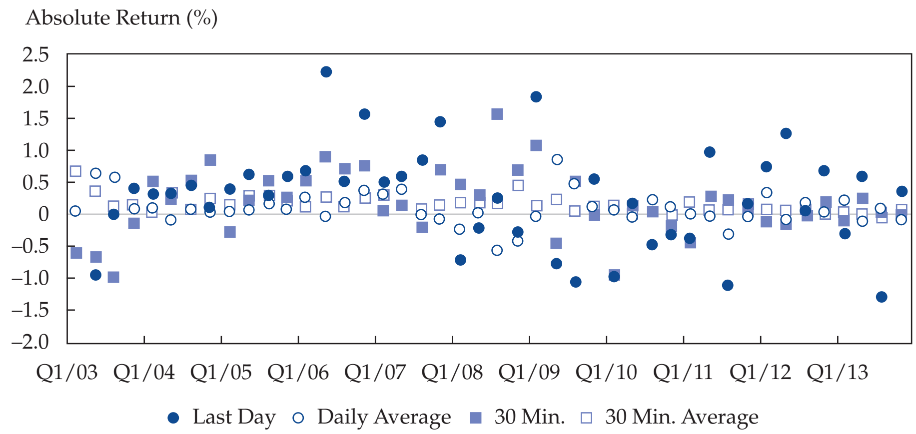
Interestingly, we observed returns during the final 30 minutes of trading to be consistently positive across all quarters as opposed to the full final trading day, for which Q1 and Q3 have negative average returns. In terms of standardized trade volume, it was higher in the final 30 minutes of trading on the last trading day in relation to the complete day. The trend is also consistent across individual quarters. Year-end volumes were lower (at about 60% of normal levels) because they were likely influenced by half-day trading activity if the last trading day of the year happened to be New Year's Eve.

Although returns on the last day and final 30 minutes of the last trading day of a quarter were significantly greater than zero, we also needed to establish whether they were abnormal in nature. In other words, they also needed to be significantly different from the rest of the days in the quarter.

We started with a visual observation of returns and volumes on the last trading day and during the final 30 minutes of trading in a quarter compared with the average for the quarter until the second-to-last day. For the purpose of the scatterplot, we considered averages excluding companies that did not trade on a particular day to get a true sense of activity.

As highlighted in **Figure 7**, final day returns were higher than the corresponding quarter average across most quarters. Returns during the final 30 minutes of trading were higher than their corresponding quarter averages in the earlier years but seemed to converge in the later quarters.

Figure 7. Comparison of Last Day and Final 30 Minutes of Returns with Quarter Averages



Source: Based on data from Bloomberg Finance L.P. and the SGX.

A similar analysis at the standardized volume level is presented in **Figure 8**. Traded volumes on the last trading day generally were higher than quarter averages. Q4 numbers were systematically low because most instances were half-day trading days because they fall on New Year's Eve. Traded volume in the final 30 minutes of trading was higher than the respective quarter averages in standardized terms; it was also higher than the observation for the complete day on most occasions.

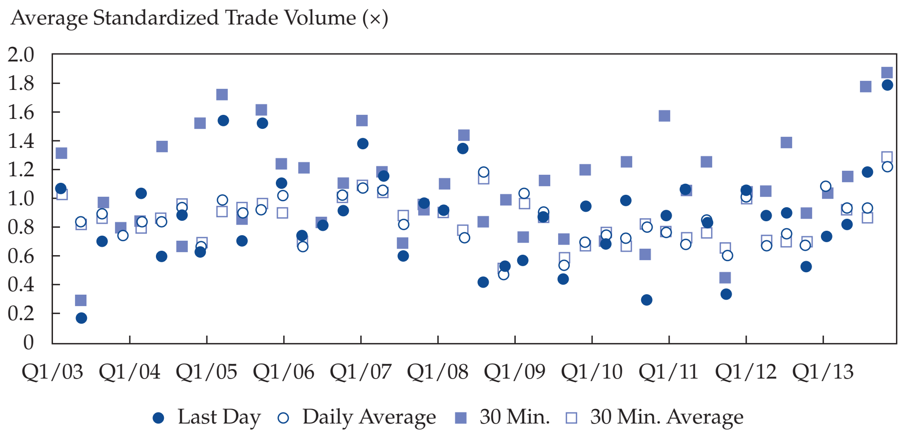
Apart from observing returns and volume pattern on the final trading day and in the final few minutes of trading, we explored other facets of trader behavior to gather more circumstantial evidence to validate our analysis. A trader wanting to purchase stocks to artificially boost prices is likely to place a quote at or above the current ask price to ensure that the quote gets converted into a definite trade.

Drawing from CKMR (2002), **Figure 9** presents the proportion of trades happening at or above ask price on the final trading day and during the final 30 minutes of trading in a quarter compared with the respective quarterly averages.

If quotes were random in nature, we would expect 50% of trades to be at or above ask price.[70] As shown in Figure 9, the quarter averages hovered around 50%, which is in line with expectation. Trades on the last day appear to carry a mixed trend, with certain quarters carrying a higher proportion of buyer-initiated trades (trades at or above ask price) and certain quarters falling short of the quarter averages. The trend is more concrete over the final 30 minutes of trading when the extent of buyer-initiated trades was higher than the average for the quarter.

Similarly, given the cost involved in artificially boosting stock prices, fund managers with a pumping intention are likely to make trades of a smaller volume denomination than in the case of a genuine purchase. **Figure 10** presents a scatterplot of the proportion of small trades among

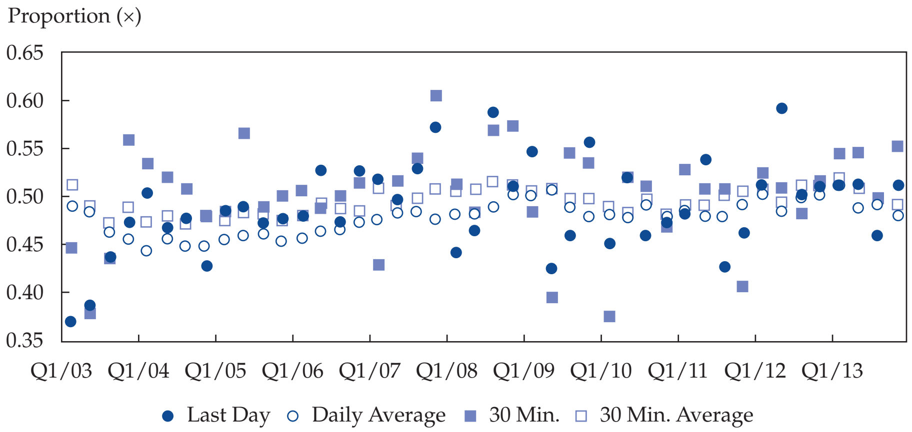
Figure 8. Comparison of Last Day and Final 30 Minutes of Volume with Quarter Averages



Source: Based on data from Bloomberg Finance L.P. and the SGX.

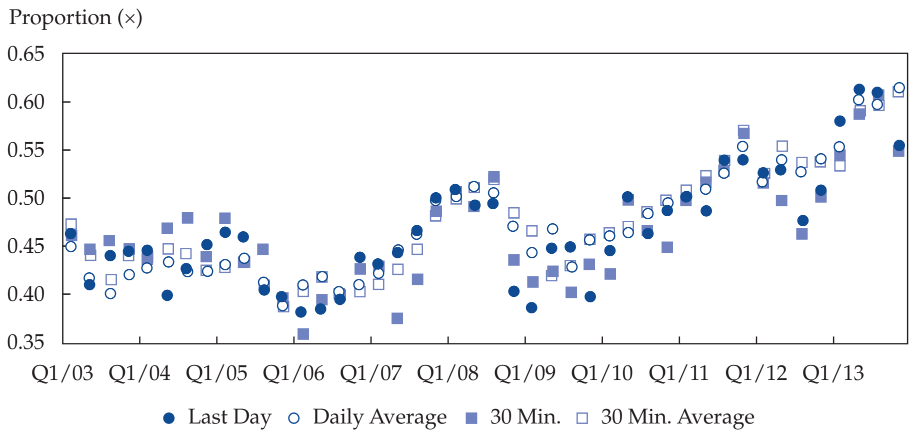
[70]If a buy order was received that exceeded the current best ask price and it was executed, then the trade is considered to have happened at above ask price. The trade price will be driven by the new buy order.

Figure 9. Comparison of Last Day and Final 30 Minutes of Trades Above Ask Price with Quarter Averages



Source: Based on data from Bloomberg Finance L.P. and the SGX.

Figure 10. Comparison of Last Day and Final 30 Minutes of Proportion of Small Trades with Quarter Averages



Source: Based on data from Bloomberg Finance L.P. and the SGX.

total trades in the final trading day and final 30 minutes of trading in relation to the respective quarter averages. Akyol and Michayluk (2010) used this metric to evaluate the presence of pumping on the Istanbul stock exchange.

We define small trades as trades of less than 5,000 shares. As one would intuitively expect with improved market penetration and liquidity over time, we see a structural increase in the proportion of trades of less than 5,000 shares. The quarter averages have steadily risen. But the pattern of trade on the last trading day or in the final few minutes of trading is not very evident from the chart. In unreported analysis, assuming a threshold of 500 or 1,000 shares to define small trades also provides a similar picture.

Overall, visual inspection and summary statistics seem to offer mixed signals. In general, returns on the final trading day were positive and higher than quarter averages. The trend was also visible in the final 30 minutes of trading. The proportion of trades in the final 30 minutes of the last trading session of a quarter as well as trades happening at or above ask price in that period also had higher than expected averages. But small trades as a proportion of total trades exhibited no evidence of pumping. Furthermore, a reversal of abnormal returns in the initial days of the subsequent quarter was missing consistently across the board. This result calls for a detailed quantitative analysis.

Methodology

For a more formal analysis, we adopted hypothesis testing as our primary research technique. This approach involved comparing the chosen portfolio pumping metric value on the final trading day or final 30 minutes of trading (termed the observed value) in a quarter with the expected average value (termed control value) for the quarter. We generally adopted a one-tail test when we tested that the observed value was greater than the control value. A two-tailed test was used when we tested for the observed value to be different from the control value and when we could draw definite interpretation for the observed value being on both sides of the control value. We ran the hypothesis tests at a 95% confidence level (5% significance level). When appropriate, we commented on significance at the 10% level.

We validated our findings using regression analysis. We predominantly adopted multi-linear regression using the ordinary least-squares technique. The chosen portfolio pumping metric served as the dependent variable and we performed a regression of it against period-defining dummy variables, a technique popularized by CKMR (2002) and subsequently adopted in numerous studies. A period-defining dummy variable assumes a value of 1 for the defined period and 0 otherwise. For instance, a quarter-end dummy variable assumes a value of 1 on last trading day of a quarter and 0 on other days. Similarly, a year-end variable assumes a value of 1 on the last trading day of a year and 0 on other days. **Table 6** presents a list of the period-defining dummy variables used in our analysis.

Table 6. List of Period-Defining Dummies Used in Regression Analysis

Variable	Description
QEND + YEND	Takes a value of 1 for all quarter-ends, including year-ends
QBEG + YBEG	Takes a value of 1 for all quarter-beginnings, including year-beginnings
QEND	Takes a value of 1 for all quarter-ends, excluding year-ends
QBEG	Takes a value of 1 for all quarter-beginnings, excluding year-beginnings
YEND/Q4END	Takes a value of 1 for all year-ends
YBEG/Q4BEG	Takes a value of 1 for all year-beginnings
Q3END	Takes a value of 1 for last trading day of Q3
Q3BEG	Takes a value of 1 for first day following last trading day of Q3
Q2END	Takes a value of 1 for last trading day of Q2
Q2BEG	Takes a value of 1 for first day following last trading day of Q2
Q1END	Takes a value of 1 for last trading day of Q1
Q1BEG	Takes a value of 1 for first day following last trading day of Q1

In general, we adopted three levels of regression with the dummy variables.

Level 1: Capturing overall quarter-end (beginning) effect

Portfolio Pumping Metric = $b_0 + b_1$*(QEND+YEND) + b_2*(QBEG+YBEG) (1)

Level 2: Splitting year-end (beginning) and quarter-end (beginning) effect

Portfolio Pumping Metric = $b_0 + b_1$*YEND + b_2*YBEG + b_3*QEND
+ b_4*QBEG (2)

Level 3: Splitting individual quarter-end (beginning) effect

Portfolio Pumping Metric = $b_0 + b_1$*Q1END + b_2*Q1BEG + b_3*Q2END
+ b_4*Q2BEG+ b_5*Q3END + b_6*Q3BEG + b_7*Q4END + b_8*Q4BEG (3)

With respect to milestone-based testing, we used milestone dummy variables on a standalone basis or in addition to period-defining dummy variables to define the milestone. For instance, the Milestone 1 dummy variable assumes a value of 0 for all days prior to the milestone occurrence period and takes a value of 1 for the subsequent period.

For the purpose of our analysis, we based our tests on two different sets of milestones. The first set of milestones was based on the Pheim Asset Management case. We believe five events in the unfolding of the case were critical and we considered them to be milestone events and assigned them each a milestone dummy variable (called Mile *i*). Mile *i* takes a value of 1 from the first trading day of the subsequent month following Event *i*. For instance, if Milestone 1 occurred in June 2006, the corresponding Mile 1 variable will assume a value of 1 from the first entry in July 2006 and a value of 0 for all prior entries.

Table 7 lists the milestones along with relevant dates and the period from which the corresponding dummy variable assumes a value of 1.

The second set of milestones relate to key SGX regulation aimed at improving the trading environment and curbing market manipulation. They are denoted by Mile M*i*, where each Mile M*i* represents a dummy variable assuming a value of 1 for days after the occurrence of the milestone and 0 otherwise. **Table 8** presents this milestone set.

We performed regression analysis with these milestones at two levels.

Level 1: Capturing milestone effects on a standalone basis

Portfolio Pumping Metric = $b_0 + b_1$*Mile 1 + b_2*Mile 2 + b_3*Mile 3
+ b_4*Mile 4 + b_5*Mile 5 (4)

Level 2: Capturing milestone effects in addition to year-end (beginning) and quarter-end (beginning) effects

Portfolio Pumping Metric = $b_0 + b_1$*Mile 1 + b_2*Mile 2 + b_3*Mile 3
+ b_4*Mile 4 + b_5*Mile 5 + b_6*YBEG + b_7*YEND + b_8*QBEG + b_9*QEND (5)

Table 7. List of Key Milestones Captured in Our Regression Analysis Related to the Pheim Asset Management Case

Milestone Dummy Code	Milestone Description	Event Period	Start Date for Assuming Value of 1
Mile 1	First investigation begins of Pheim Asset Management Sdn Bhd and its founder Tan Chong Koay by MAS and Securities Commission of Malaysia (SCM) for possible market manipulation.	Q1 and Q2 2006	1 Jul 2006
Mile 2	MAS officially files a civil suit against Pheim Asset Management Sdn Bhd under Section 197(1)(b) of the SFA for trading with the intention of creating a false or misleading appearance in the price of UET shares.	Aug 2009	1 Sep 2009
Mile 3	Pheim Asset Management Sdn Bhd and Tan Chong Koay pronounced guilty by the Singapore High Court.	17 Sep 2010	1 Oct 2010
Mile 4	Appeal filed by Pheim Asset Management Sdn Bhd and Tan Chong Koay to set aside the verdict was rejected by the Singapore Court of Appeal.	22 Jul 2011	1 Aug 2011
Mile 5	Tan Chong Koay banned by the MAS from participating in capital market activities for four years.	29 Nov 2012	1 Dec 2012

Table 8. List of Key Milestones Used in Our Regression Analysis Related to Improvements in Trading Environment Introduced by the SGX

Milestone Dummy Code	Milestone Start Date/ Date of Assuming Value of 1	Milestone Description
Mile M1	1 Mar 2006	■ Proposal announcement for a reduction in minimum bids structure of stocks
Mile M2	1 Jun 2007	■ Proposal announcement to move Catalist market from an exchange control setup to a sponsor-supervised setup
Mile M3	1 Mar 2008	■ Proposal announcement for introduction of composition system and mandatory minimum penalties by disciplinary committees for rule violations in the securities market ■ Implementation of proposal for reduction in minimum bids structure ■ Implementation of sponsor-governed setup of Catalist market
Mile M4	1 Oct 2009	■ Proposal announcement for an additional reduction in minimum bids structure of stocks
Mile M5	1 Nov 2010	■ Proposal announcement for introduction of continuous all-day trading for the SGX securities market from 9:00 a.m. to 5:00 p.m. without break time
Mile M6	1 Sep 2011	■ Proposal announcement and implementation of publication of real-time indicative equilibrium prices during the pre-open and pre-close phases and random end to the pre-close of the closing routine between four and five minutes after 5:00 p.m. ■ Proposal announcement for introduction of circuit breakers ■ Proposal announcement and implementation of change to the algorithm used by the SGX ST to compute the indicative equilibrium price ■ Implementation of composition system and mandatory minimum penalties by disciplinary committees for rule violations in the securities market ■ Implementation of additional reduction in minimum bids structure of stocks ■ Implementation of continuous all-day trading for the SGX securities market from 9:00 a.m. to 5:00 p.m. without break time

The chosen portfolio pumping metric for both hypothesis testing and regression analysis depends on the individual hypotheses we set out to test. As a process, we computed a portfolio pumping metric value for each stock in the universe on a daily basis and then subsequently aggregated them across the universe for each day by taking an average with an equal weighting for all stocks. The aggregated metric value was used to perform hypothesis testing as well as regression analysis. **Table 9** provides an overview of the portfolio pumping metrics adopted in our analysis.

Apart from looking for evidence of portfolio pumping at the broad universe and sub-universe levels, we also attempted to identify cases of portfolio pumped stocks to sketch the characteristics of such stocks. In effect, the idea was an attempt to look at pumping from the opposite direction. Rather than looking at whether pumping exists among a certain subset of stocks with certain

Table 9. Portfolio Pumping Metrics Used in the Analysis

Hypothesis	Description	Portfolio Pumping Metric
H1	Portfolio pumping will be evident at the broad market level.	*Returns:* Equal-weighted average of two-day inflation of absolute and excess daily returns of all stocks in the universe; two-day inflation is defined as the difference in daily returns on two consecutive trading days. *Returns:* Equal-weighted average of absolute and excess daily returns of all stocks in the universe. *Volume:* Equal-weighted average of standardized daily trade volume of all stocks in the universe. Standardized trade volume is defined as daily trade volume as a proportion of average trade volume in the six months preceding and succeeding the day under consideration.
H2	Portfolio pumping will be concentrated in the final few minutes of trading or in the final few transactions.	*Returns:* Equal-weighted average of absolute and excess daily returns of all stocks in the universe during the final 30 minutes of trading. *Volume:* Equal-weighted average of standardized trade volume across all stocks in the universe during the final 30 minutes of trading.
H3	The proportion of buyer-initiated transactions will be higher around the final few minutes of trading at quarter-ends than at other periods.	Equal-weighted average of proportion of trades happening at or above ask price based on (1) the complete day and (2) the final 30 minutes of trading.
H4	Fund managers will engage in pumping with a limited amount of capital.	Equal-weighted average of proportion of small trades among total trades during (1) the complete day and (2) the final 30 minutes of trading. Small trades are defined as trades of less than 5,000 shares.
H5	Pumping will be driven by certain traders and clients by cornering trades in identified stocks.	Equal-weighted average of trader and client concentration during (1) the complete day and (2) the final 30 minutes of trading.
H6	Portfolio pumping will be concentrated in small-cap stocks, Catalist-listed stocks, extreme strong and weak performers, S-chip stocks, and non-SIMSCI stocks.	Equal-weighted average of absolute and excess daily returns of all stocks during (1) the complete day and (2) the final 30 minutes of trading with the universe restricted by capitalization, momentum, and index inclusion factors.
H7	Portfolio pumping is expected to have declined over time, especially after key milestone events around enforcement of portfolio pumping legislation.	Equal-weighted average of absolute and excess daily returns of all stocks in the universe during (1) the complete day and (2) the final 30 minutes of trading.

characteristics, we attempted to first identify cases of possible portfolio pumped stocks and then decipher their characteristics. For this, we drew inspiration from Gallagher et al. (2009) and adopted a metric similar to their "gaming proxy" metric. They defined gaming proxy to be a dummy variable that gets a value of 1 if a stock has a positive absolute and excess return (relative to a benchmark index) in the final 30 minutes of trading in a quarter and a negative absolute and excess return in the first 30 minutes of trading on the first trading day of the subsequent quarter. Gaming proxy values of stocks for various quarters were regressed against a set of stock and manager characteristics to narrow down factors that generally make up the pumped-up stocks. A logistic regression was used.

We adopted a similar approach with an exception. We defined our primary gaming proxy based on the complete last day of a quarter (instead of just the final 30 minutes) and the complete first day of the subsequent quarter (instead of the first 30 minutes of trading). Accordingly, in our study, we assigned a value of 1 to a stock for a particular quarter if it earned a positive return as well as a return greater than the FTSE STI on the last day of the quarter and earned a negative return as well as a return less than the STI on the first day of the subsequent quarter. For a robustness check, we also verified our results with the original definition of gaming proxy, as defined by Gallagher et al. (2009). We then adopted a logistic regression in line with Gallagher et al. (2009) to regress the gaming proxy variable against a defined set of stock, trade, and market characteristics. **Table 10** presents the list of stock, trade, and market characteristics we considered for the study.

Table 10. Stock, Trade, and Market Characteristic Variables Considered in Our Analysis

Code	Nature of Variable	Description
Dependent variable		
GAMING_PROXY	Dummy	Assumes a value of 1 if absolute and excess (relative to FTSE STI) returns on the last trading day of a quarter is greater than zero and absolute and excess returns on the first trading day of the subsequent quarter is negative.
Stock characteristics		
MOMENTUM	Categorical	Assumes an integer value from 1 to 4 (both inclusive) representing the performance quartile of the stock in the quarter until the second-to-last day of the quarter. A value of 1 includes the bottom 25% performers and 4 the top 25% performers.
MOMENTUM_1	Dummy	Takes a value of 1 if the momentum variable takes the value of 1, otherwise 0.
MOMENTUM_2	Dummy	Takes a value of 1 if the momentum variable takes the value of 2, otherwise 0.
MOMENTUM_3	Dummy	Takes a value of 1 if the momentum variable takes the value of 3, otherwise 0.
MOMENTUM_4	Dummy	Takes a value of 1 if the momentum variable takes the value of 4, otherwise 0.
CAPITALIZATION	Categorical	Assumes an integer value of 1, 2, or 3 depending on market capitalization of a stock: 1 for large-caps, 2 for mid-caps, and 3 for small-caps. Inclusion in capitalization categories based on constituent presence on FTSE STI, FTSE ST Mid Cap Index, and FTSE ST Small Cap Index.

(continued)

Table 10. Stock, Trade, and Market Characteristic Variables Considered in Our Analysis (continued)

Code	Nature of Variable	Description
LARGE_CAP	Dummy	Takes a value of 1 if the capitalization variable takes the value of 1, otherwise 0.
MID_CAP	Dummy	Takes a value of 1 if the capitalization variable takes the value of 2, otherwise 0.
SMALL_CAP	Dummy	Takes a value of 1 if the capitalization variable takes the value of 3, otherwise 0.
DOMICILE	Dummy	Takes a value of 1 if a stock is a constituent of FTSE ST S-Chip Index representing China-domiciled stocks listed in Singapore, otherwise 0.
LISTING_BOARD	Dummy	Takes a value of 1 if a stock is listed on the Mainboard platform of the SGX, otherwise 0.
SIMSCI_ INCLUSION	Dummy	Takes a value of 1 if a stock is a constituent of MSCI Singapore Free Index (SIMSCI), otherwise 0.
Trade and market characteristics		
ASK_PRICE_FULL	Ratio	Proportion of stock trades happening at or above ask price (buyer-initiated trades) on the last day of a quarter.
SMALL_TRADES_ FULL	Ratio	Proportion of stock trades involving volume of less than 5,000 shares on the last day of a quarter.
TRC_FULL	Ratio	Trader concentration ratio on the last day of the quarter represented by a trader Herfindahl index.[a]
CRC_FULL	Ratio	Client concentration ratio on the last day of the quarter represented by a client Herfindahl index.[a]
ASK_PRICE_30MIN	Ratio	Proportion of stock trades happening at or above ask price (buyer-initiated trades) in the final 30 minutes of trading on the last day of a quarter.
SMALL_TRADES_ 30MIN	Ratio	Proportion of stock trades involving volume of less than 5,000 shares in the final 30 minutes of trading on the last day of a quarter.
TRC_30MIN	Ratio	Trader concentration ratio in the final 30 minutes of trading on the last day of the quarter represented by a trader Herfindahl index.[a]
CRC_30MIN	Ratio	Client concentration ratio in the final 30 minutes of trading on the last day of the quarter represented by a client Herfindahl index.[a]
LIQUIDITY	Ratio	Average daily trading volume of a stock in a quarter divided by the total number of issued shares for the stock.
LIQUIDITY_FREE_ FLOAT	Ratio	Average daily trading volume of a stock in a quarter divided by the total number of free-float shares for the stock.
STD_VOLUME	Ratio	Traded volume on the last day of a quarter standardized over the previous six months of subsequent six months of trading excluding quarter-end days. This ensures that the standardized value is adjusted for any structural shift in trade volume pattern.
PROP_TRADES_ 30MIN	Ratio	Proportion of trades in a stock happening in the final 30 minutes of trading on the last day of a quarter.
MARKET_ RETURNS	Ratio	Return generated by FTSE STI over the quarter.

[a]A Herfindahl index involves taking the square of market share of individual participants in individual stocks and then summing across all participants to arrive at the participant group-level concentration in individual stocks. A higher value of the concentration level represents more concentrated participation whereas a lower value represents a wider set of participation.

Data Analysis

Drawing from the methodology discussed in the previous section, we began by identifying whether there was significant evidence of portfolio pumping at the overall market level. To do so, we did hypothesis tests at two levels. We verified first whether our metric values were significantly different from zero and second whether they were significantly different from non-quarter-end days. We began this analysis with two-day average inflation, defined as the difference in daily returns between two consecutive trading days. For instance, two-day average inflation on 31 March would be the difference in daily returns on 31 March and 1 April, assuming both days are trading days.

If portfolio pumping is present, we expected significant positive returns on the last day of a quarter and significant negative returns on the first day of the subsequent quarter. Correspondingly, we expected the two-day average inflation around a quarter-end to be significantly greater than zero and also significantly different from non-quarter-end days. We performed the analysis with both absolute and excess returns. **Table 11** presents the results of the hypothesis test with the two-day average inflation around quarter-ends at the overall universe level. Clearly, there is no evidence of pumping with the two-day inflation metric.

Next, we broke the two-day inflation into its two days and ran individual hypothesis tests for returns on the last day of a quarter and returns on the first day of a quarter. This test would help us understand whether the relative absence of evidence is consistent across both days or mixed in nature. If pumping exists, we would expect the last day returns to be significantly positive and the first day returns to be significantly negative. **Table 12** presents the results.

Between the two days, we observed on both an absolute (at a 10% significance level) and excess return (at a 5% significance level) basis that returns were significantly positive. With excess returns, they were also significantly greater than the non-quarter-end days, hinting at abnormal

Table 11. Hypothesis Test of Two-Day Inflation around Quarter-End

	Test for Average Returns Being	
	Greater than Zero	Greater than Non-Quarter-End Days
Absolute returns		
Average returns	–0.44	
t-Statistic	–2.17	0.19
p-Value	0.02	0.42
Excess returns		
Average returns	0.01	
t-Statistic	0.08	–0.16
p-Value	0.47	0.44

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

Table 12. Hypothesis Test of Daily Returns on the Last and First Trading Day of a Quarter

	Test for Average Returns on Last Trading Day of a Quarter Being		Test for Average Returns on First Trading Day of a Quarter Being	
	Greater than Zero	Greater than Non-Quarter-End Days	Less than Zero	Less than Non-Quarter-End Days
Absolute returns				
Average returns	0.20		0.65	
t-Statistic	1.60	0.99	3.71	4.10
p-Value	0.06**	0.16	0.00	0.00
Excess returns				
Average returns	0.17		0.16	
t-Statistic	1.75	1.30	1.86	1.49
p-Value	0.04*	0.10**	0.03	0.07

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

positive returns being generated on the last trading day of a quarter. But the first day of the quarter did not exhibit any reversal in returns. In fact, in terms of both absolute and excess returns, they appeared to be significantly positive.

Given our observation of average negative excess returns on day T+2 in Figure 4, we repeated the hypothesis test of first and last day returns with returns on day T+2. **Table 13** presents the results.

Although the average excess return on day T+2 was negative, it was not found to be statistically significant. Absolute returns were actually positive. This result provides limited support for pumping at the market level.

To decipher whether the pattern was different between year-end and non-year-end quarters and also to validate our earlier findings, we ran regression analysis based on daily absolute and excess returns at three levels (termed "models"), as discussed earlier in the Methodology section.

Results of the regression equation are presented in **Table A1** in the Appendix. In Model 1 of the regression equation, both quarter-end and quarter-beginning effects were positive and significantly greater than zero, in line with the hypothesis tests. Splitting into individual quarters, we observed the period-end effect to be predominantly driven by the year-end effect. Q2END effect also was significantly positive with absolute returns while failing with excess returns. Q2BEG and Q3BEG effects with excess returns were negative, but they did not follow an abnormal positive return at the end of the previous quarters (Q2END and Q3END effects were in fact negative). Q4END effects were significantly positive across both absolute and excess return counts. But Q4BEG, representing the first trading day of the year, was also strongly positive under both return metrics, possibly suggesting an influence of other factors. It appears that even if pumping prevailed at the end of the year, the reversal influence at the start of the year could have possibly been masked by a different event.

Table 13. Hypothesis Test of Daily Returns on Day T+2 of a Quarter

	Test for Average Returns Being	
	Greater than Zero	Greater than Non-Quarter-End Days
Absolute returns		
Average returns	−0.44	
t-Statistic	2.25	2.00
p-Value	0.01	0.03
Excess returns		
Average returns	−0.05	
t-Statistic	−0.41	−0.81
p-Value	0.34	0.21

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

There could be a possible issue with adopting a simple approach (deduction of FTSE STI returns from the absolute return of a stock) to determine excess return for a stock. The reason is because mid- and small-cap stocks in our universe tended to have a greater level of volatility in returns and, hence, might have affected our analysis. To address this concern and to add robustness, we replicated the earlier analysis with beta-adjusted excess returns. For this purpose, beta was computed on a daily basis for all stocks based on the comovement of daily stock returns with the FTSE STI over the past six months. Regression output under this approach is available in **Table A2** in the Appendix. We note that the results are broadly consistent with the earlier analysis of simple excess returns computation. Q4END effect continued to be significantly positive while Q4BEG effect also remained significantly positive. There was not much of value from other quarters.

Turning our attention to volume-based analysis, **Table A3** in the Appendix provides the results of regressions of the daily average standardized trade volume of stocks in our universe against period-defining dummies. There was no definite trend visible in the three regression models, which is in line with the conclusions from the visual analysis discussed earlier (Figure 8). Among the individual quarters (Model 3), Q1END, Q2END, and Q3END coefficients were positive, although only the Q3END coefficient was significant at the 5% level. Q4END is understandably negative because the last trading day of the year happens to fall mostly on New Year's Eve when trading is restricted to half-day.

Summing up, based on the last trading day of the quarter, we found reasonable evidence for abnormal positive returns at the end of the year and some limited support at the end of Q2. But no reversal of returns was visible. Volume-based analysis did not offer any additional insight.

Final 30 Minutes of Trading

Next, we looked at returns and volume patterns in the final 30 minutes of trading on the last trading day of the quarter. **Table 14** presents the results from hypothesis tests for returns in the final 30 minutes of trading on the final day of the quarter being significantly greater than zero and being greater than the final 30 minutes of returns on non-quarter-end days. There was strong statistical evidence to suggest that returns in the final 30 minutes of trading in a quarter were positive. But it was not very different from the final 30 minutes of trading during other days of the quarter, thus offering limited support for pumping.

Table A4 in the Appendix presents the results of regressions of daily returns over the final 30 minutes of trading against period-defining dummies. Among the individual quarter effects (Model 3), only the Q3END coefficient was positive and significant. The Q4END coefficient was positive, although not significant. Q1END and Q2END coefficients were actually negative. At the market level, returns during the final 30 minutes of trading showed very little sign of being pumped.

A similar analysis with standardized trade volume presents a different picture. Details of the regression results are in **Table A5** in the Appendix. Model 1 shows that quarter-end effects were positive and significant while quarter-beginning effects were significantly negative. Model 3 indicates that all non-year-end quarter-ends shared the trend of being significantly positive. The Q4END coefficient was positive but not significant.

To validate this finding of significantly higher activity in the final 30 minutes of trading at quarter-ends, we simply divided traded volume in the final 30 minutes of trading by the total trade volume for the day per stock and then averaged it across all stocks to arrive at the metric value for the day. This result was regressed against the period-end dummies. Results from this analysis are also presented in Table A5 in the Appendix (right side of the table). Model 3 indicates that all four quarter-end coefficients were significant and positive. In fact, they were significant at the 1% significance level, suggesting that trades in the final 30 minutes were much more active on quarter-end days.

Table 14. Hypothesis Test of Final 30 Minutes of Returns around Quarter-End

	Test for Average Returns Being	
	Greater than Zero	Greater than Non-Quarter-End Days
Absolute returns		
Average returns	0.21	
t-Statistic	2.71	0.79
p-Value	0.00*	0.22

Notes: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level. Companies with no trades in the final 30 minutes of trade are excluded.

Buyer-Initiated Trades

With returns and volume data presenting a mixed picture, we looked for more evidence of pumping by determining whether individual trades were buyer or seller initiated. In general, the buyer or seller could initiate a trade. We consider a trade to be buyer initiated if a buyer makes a bid at or above the best ask price existing at the moment of making the quote. We looked at the proportion of such buyer-initiated trades on the last day of the quarter and during the final 30 minutes of trading in the quarter and compared it with the corresponding values on non-quarter-end days in the quarter. **Table 15** presents the results of this hypothesis test.

We found that on the last day of the quarter, on average, 49% of trades were buyer initiated. This result is higher than the average trades observed on non-quarter-end days in the quarter and the results are significant at the 5% level. Based on the final 30 minutes of trading, the proportion of buyer-initiated trades was marginally higher at 50%. But in terms of statistical significance, evidence was not as strong as with the complete day trades to suggest that the proportion of buyer-initiated trades was higher than non-quarter-end days.

Table A6 in the Appendix presents the corresponding regression results based on the proportion of trades happening at or above ask price. On the basis of complete day analysis, YEND and QEND coefficients (Model 2) emerge significant. Drilling one level deeper (Model 3), we observed Q2END and Q4END to be significant. On the basis of the final 30 minutes of trading, only the YEND coefficient appeared to be significant at the 5% level.

Table 15. Hypothesis Test of the Proportion of Trades above Ask Price

	Test for Average Proportion of Trades above Ask Price on Quarter-End Days	
	Based on Complete Day	Based on Final 30 Minutes of Trading
Greater than non-quarter-end days		
Average returns	0.49	0.50
t-Statistic	1.81	1.19
p-Value	0.04*	0.12

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

Small Trades Activity

Other evidence commonly used in the literature to establish pumping is to highlight a significant jump in the proportion of small trades among total trades at quarter-ends. Portfolio pumping involves cost and if fund managers need to push up the prices of stocks artificially, they will do so with a smaller order size compared with genuine buys. **Table 16** presents the results of the hypothesis test to determine whether the proportion of small trades among total trades was significantly larger at quarter-ends than on other days. The test is based on the assumption of a trade size of less than 5,000 being treated as a small trade.

Table 16. Hypothesis Test of Proportion of Small Trades

	Test for Average Proportion of Small Trades among Total Trades on Quarter-End Days Being Greater than Non-Quarter-End Days	
	Based on Complete Day	Based on Final 30 Minutes of Trading
Average returns	0.47	0.47
t-Statistic	–1.29	–2.25
p-Value	0.10	0.01

Notes: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level. Small trades represent trades of less than 5,000 shares.

In the results of this test, we did not observe any evidence of pumping, and in fact, based on both complete final day of trading in a quarter and the final 30 minutes of trading, the proportion of small trades was actually significantly smaller than on non-quarter-end days. This result is quite contrary to expectations under the presence of portfolio pumping. In unreported results, we observed a similar trend with other threshold levels for small trades, namely order size being less than 1,000 shares.

The regression results in **Table A7** in the Appendix mimic the hypothesis test results. Evidence of an increased proportion of small trades was not observed across any quarter-ends, including the year-end.

With not much evidence of portfolio pumping at the market level, except for heightened activity in the final 30 minutes of trading and some abnormal positive return at year-end, without any corresponding reversal the following day, we turned our attention to specific segments of the market in which we looked for similar evidence of portfolio pumping.

Segmental Analysis

Table 17 shows hypothesis test results for absolute and excess returns on the last day of the quarter for large-, mid-, and small-cap segments being greater than on non-quarter-end days. The table also shows a similar analysis for returns on the first day of the quarter to verify whether they are significantly lower than non-quarter-end days. In terms of both absolute and excess returns, mid-cap stocks were the only capitalization segment with significant positive returns on the last day of the quarter. Furthermore, the mid-cap stock group was the only capitalization segment to register a negative excess return on first day of the quarter, although it was not found to be statistically significant. Large-caps achieved non-significant positive returns at the end of the quarter and also positive returns on the first day of the quarter.

Interestingly, the trend in small-caps seems to be closer to large-caps rather than the mid-caps. Although this result was a bit surprising at first glance, it is not unintuitive. Given that funds generally have limited exposure to the small-cap segment because of limited free float and the liquidity of shares of these companies, we should ideally not expect to see much pumping activity here. Although Table 17 uses the constituents of the FTSE STI, FTSE ST Mid Cap Index,

Table 17. Hypothesis Test of Absolute and Excess Returns on Capitalization Segments

	Tests for Average Returns on the Last Day of the Quarter Being Greater than Non-Quarter-End Days			Tests for Average Returns on the First Day of the Quarter Being Less than Non-Quarter-End Days		
	Large-Cap	Mid-Cap	Small-Cap	Large-Cap	Mid-Cap	Small-Cap
Absolute returns						
Average	0.16	0.32	0.17	0.50	0.48	0.78
t-Statistic	0.57	1.87	0.68	2.83	2.78	4.39
p-Value	0.28	0.03*	0.25	0.00	0.00	0.00
Excess returns						
Average	0.12	0.28	0.13	0.01	–0.01	0.29
t-Statistic	1.16	2.34	0.71	–0.14	–0.14	2.09
p-Value	0.13	0.01*	0.24	0.44	0.45	0.02

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

and FTSE ST Small Cap Index to define large-, mid-, and small-cap stocks, respectively, from a fund's perspective, their investment universe could be largely limited to the FTSE STI and FTSE ST Mid Cap Index constituents. Therefore, to better understand the segments in which portfolio pumping is possibly present to a larger extent, we replicated the analysis with custom groups based on market capitalization. We divided this investment universe of FTSE STI and FTSE ST Mid Cap Index constituents into three groups based on their market value at the start of each quarter: market value greater than S$10 billion is Group 1, value between S$5 billion and S$10 billion is Group 2, and value between S$2 billion and S$5billion is Group 3. We introduced a S$2 billion cutoff, in line with the standard industry definition for a mid-cap stock. **Table 18** presents the results of this test.

In terms of absolute returns, all three groups had insignificant positive returns at the end of the quarter and significantly positive returns at the beginning of the quarter. But in terms of excess returns, the variation was clearly visible. Only Group 3, representing the smallest capitalization group with market value of S$2 billion to S$5 billion, generated significant positive return at the end of the quarter. Furthermore, the group earned a return lower than the average day in a quarter at the beginning of the quarter. Although not statistically significant, in the context of returns on the first day of a quarter generally being strongly positive, the lower-than-average return at the beginning of the quarter for Group 3 did show some signs of potential pumping.

Between S-chip and non-S-chip stocks, **Table 19** shows that contrary to expectation, non-S-chip stocks exhibited abnormal positive excess returns at the end of the quarter while it was not significant with S-chip stocks. But a reversal of returns at the start of year remains elusive for both categories.

Between SIMSCI and non-SIMSCI constituent stocks, both groups did not show significant positive returns at the end of the quarter, as shown in **Table 20**. Non-SIMSCI stocks exhibited significant negative excess returns at the beginning of the quarter but did not receive enough support for pumping at the end of the quarter.

Table 18. Hypothesis Test of Returns on Capitalization Groups

	Tests for Average Returns on the Last Day of the Quarter Being Greater than Non-Quarter-End Days			Tests for Average Returns on the First Day of the Quarter Being Less than Non-Quarter-End Days		
	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3
Absolute returns						
Average	0.06	0.06	0.23	0.53	0.58	0.49
t-Statistic	0.51	−0.08	1.14	3.06	3.09	2.71
p-Value	0.31	0.47	0.13	0.00	0.00	0.00
Excess returns						
Average	0.02	0.02	0.19	0.04	0.09	0.00
t-Statistic	0.49	0.26	2.12	1.62	0.75	−0.01
p-Value	0.31	0.40	0.02*	0.06	0.23	0.49

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

Table 19. Hypothesis Test of Returns on S-Chip and Non-S-Chip Stocks

	Test for Average Returns on the Last Day of the Quarter Being Greater than Non-Quarter-End Days		Test for Average Returns on the First Day of the Quarter Being Less than Non-Quarter-End Days	
	S-Chip	Non-S-Chip	S-Chip	Non-S-Chip
Absolute returns				
Average	0.13	0.22	0.87	0.61
t-Statistic	0.12	1.18	3.77	3.98
p-Value	0.45	0.12	0.00	0.00
Excess returns				
Average	0.09	0.18	0.38	0.12
t-Statistic	0.17	1.43	2.37	1.12
p-Value	0.43	0.08**	0.01	0.13

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

Similarly, as shown in **Table 21**, there is not much to distinguish between Mainboard- and Catalist-listed stocks. Mainboard-listed stocks exhibited positive excess returns at the end of the quarter without any reversal at the beginning of the quarter.

The worst-performing quartile group (Group 1), marking the poorest-performing set of stocks in the quarter until the second-to-last day, was the only group with significant positive absolute and excess returns at the end of the quarter at the 5% significance level. In addition, the second worst-performing quartile stocks showed significant positive excess returns at the 10% significance level. At the beginning of the quarter, only the worst-performing quartile exhibited negative return, although it was statistically insignificant. **Table 22** presents these results.

Table 20. Hypothesis Test of Returns on SIMSCI and Non-SIMSCI Constituents

	Test for Average Returns on the Last Day of the Quarter Being Greater than Non-Quarter-End Days		Test for Average Returns on the First Day of the Quarter Being Less than Non-Quarter-End Days	
	SIMSCI	Non-SIMSCI	SIMSCI	Non-SIMSCI
Absolute returns				
Average	0.16	0.22	0.42	0.70
t-Statistic	0.53	1.08	2.05	4.42
p-Value	0.30	0.14	0.02	0.00
Excess returns				
Average	0.12	0.18	–0.07	0.21
t-Statistic	0.96	1.23	–1.68	1.83
p-Value	0.17	0.11	0.05*	0.04

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

Table 21. Hypothesis Test of Returns on Mainboard- and Catalist-Listed Stocks

	Test for Average Returns on the Last Day of the Quarter Being Greater than Non-Quarter-End Days		Test for Average Returns on the First Day of the Quarter Being Less than Non-Quarter-End Days	
	Mainboard	Catalist	Mainboard	Catalist
Absolute returns				
Average	0.22	–0.02	0.64	0.68
t-Statistic	1.24	–0.38	4.03	2.66
p-Value	0.11	0.35	0.00	0.01
Excess returns				
Average	0.18	–0.06	0.15	0.19
t-Statistic	1.65	–0.74	1.44	0.99
p-Value	0.05*	0.23	0.08	0.16

Note: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level.

Table 22. Hypothesis Test of Returns on Momentum Groups

	Test for Average Returns on the Last Day of the Quarter Being Greater than Non-Quarter-End Days				Test for Average Returns on the First Day of the Quarter Being Less than Non-Quarter-End Days			
	1	2	3	4	1	2	3	4
Absolute returns								
Average	0.36	0.13	0.23	0.11	0.07	0.52	0.71	1.27
t-Statistic	3.32	1.15	0.82	–1.65	1.67	3.67	5.11	4.60
p-Value	0.00*	0.13	0.21	0.05	0.05	0.00	0.00	0.00
Excess returns								
Average	0.32	0.09	0.19	0.07	–0.42	0.03	0.22	0.79
t-Statistic	4.49	1.47	1.01	–2.48	–1.06	1.06	2.21	2.95
p-Value	0.00*	0.07**	0.16	0.01	0.15	0.15	0.02	0.00

Notes: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level. Momentum groups represent the worst-performing quartile (Group 1) in the quarter until the second-to-last day; Group 4 represents the best-performing quartile.

Trader and Client Concentration

It is difficult and costly to pump stocks when multiple traders and clients are involved because any attempt to artificially inflate the stock price may be quickly eroded with more parties vying for the stock.

Accordingly, pumping activity, if any, is likely to be dominant in stocks in which trade participant concentration is high. Given our rich dataset of tick-by-tick data from the SGX along with broker and client codes, we evaluated trader and client concentration in stocks around quarter-end to determine whether they are different from other non-quarter-end days. In fact, in the Pheim Asset Management case, it was highlighted that more than 90% of trades in UET during the final few days in 2004 were managed by Pheim Asset Management, which led to an increase in share price by more than 17% in the final three days of trading in 2004. Incidentally, the stock price fell by around 13% in the first three days of the subsequent quarter, with the first day accounting for 6%.

Table 23 presents the hypothesis test results with average trader concentration levels for all stocks in the universe. Trader concentration was obtained using the Herfindahl Index approach. It involves taking the square of the market share of individual participants (here, traders) in individual stocks and then summing across all participants to arrive at the participant group (here, trader) concentration level in individual stocks. A higher value of the concentration level represents more concentrated participation, whereas a lower value represents a wider set of participation. In the event of pumping, we would expect trader concentration to be significantly higher at quarter-ends rather than non-quarter-end days. We observed trader concentration to be significantly higher on the last trading day of a quarter compared with other days in the quarter. But in terms of the final 30 minutes of trading, trader concentration on the final trading day of a quarter was significantly lower compared with other days in the quarter.

Table 24 presents a similar analysis replicated with client concentration. Results are pretty much in line with observations based on trader concentration. Considering the final complete trading day of a quarter, concentration levels are found to be significantly higher compared with non-quarter-end days.

Table A8 and **Table A9** in the Appendix present our standard regression analysis with period-defining dummies using trader concentration and client concentration levels as dependent variables. On the basis of the complete trading day as well as the final 30 minutes of trading, we observed that only the year-end variable (Q4END) had a significantly positive coefficient whereas the quarter-end effects for other quarters were negative or insignificant. On the basis of the complete trading day, we also observed a significant reversal in concentration levels at the beginning of the year. With the final 30 minutes of trading, a reversal was observed at the beginning of the year but not found to be significant.

Overall, analysis based on trader and client concentration largely tied in with the broader observation seen earlier, with some evidence of abnormal returns evident in the year-end quarter but negligible across other quarter-ends.

Table 23. Hypothesis Test of Trader Concentration

	Test for Average Trader Concentration on Quarter-End Days Being Greater than Non-Quarter-End Days	
	Based on Complete Day	Based on Final 30 Minutes of Trading
Average	0.25	0.40
t-Statistic	1.46	–2.52
p-Value	0.08**	0.01

Notes: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level. Trader concentration determined using the Herfindahl index approach to create a trader index.

Table 24. Hypothesis Test of Average Client Concentration

	Test for Average Client Concentration on Quarter-End Days Being Greater than Non-Quarter-End Days	
	Based on Complete Day	Based on Final 30 Minutes of Trading
Average	0.24	0.39
t-Statistic	1.30	–2.12
p-Value	0.10**	0.02

Notes: If applicable, values marked with a single asterisk (*) are significant at the 5% level, and values marked with a double asterisk (**) are significant at the 10% level. Client concentration determined using the Herfindahl index approach to create a client index.

Milestone Tests

Moving from the cross-sectional analysis discussed thus far, we now turn to how evidence for portfolio pumping traversed over time. Specifically, given the importance of the Pheim Asset Management case in the evolution of market manipulation enforcement in Singapore, we considered key events associated with the case as the first set of milestones based on which we evaluated instances of pumping. We adopted a multiple linear regression analysis by regressing average absolute and excess returns of the universe against milestone dummies (hereafter referred to as mile) in isolation and along with period-defining dummies. In the event of a milestone being a trigger in reducing portfolio pumping, we would expect a significant negative coefficient for the corresponding milestone dummy.

Table A10 in the Appendix presents the regression results. With respect to absolute returns, Mile 3 (representing the first conviction for portfolio pumping in Singapore with Pheim Asset Management Sdn Bhd being pronounced guilty) was found to be the most significant event. Since the event in September 2010, we observed a significant reduction in average absolute returns. Mile 1 (representing the first investigation by MAS and SCM of Pheim Asset Management with respect to portfolio pumping in Q1 and Q2 2006) also was found to be a significant event. In terms of excess returns, only Mile 2 (referring to first filing of a suit by the SGX against Pheim Asset Management Sdn Bhd for market manipulation) was significant.

Our alternate set of milestones relates to key regulatory proposals announced and implemented by the SGX in promoting a better trading environment and curbing market manipulation. We adopted a similar approach using a multiple linear regression with the milestone dummies (Mile M*i*) in isolation and along with period-defining dummies. **Table A11** in the Appendix presents the results. With the passage of Mile M2 (proposal to introduce a composition system and mandatory minimum penalties by disciplinary committees for rule violations in the securities market), we observed a significant reduction in absolute and excess returns.

Individual Stocks Analysis

So far, our analysis has provided mixed support for the existence of portfolio pumping. Even if it did, a reversal of returns on the first day or first few days of subsequent quarters have been nonexistent at the market and market group levels. To draw a more definitive conclusion, we identified specific instances of possible portfolio pumping at the stock level during the 44 quarters of our study and identified characteristics that mark such stocks. Several stock-level as well as trade characteristics, including those taken up for evaluating pumping in the initial part of this section, were considered.

For our analysis, we identified potential instances of pumping by adopting an approach similar to the "gaming proxy" method of Gallagher et al. (2009). Gaming proxy is a dummy variable that takes a value of 1 for a stock in a quarter if the stock earns positive absolute and excess return on the last day of the quarter and also earns a negative absolute and excess return on the first day of the subsequent quarter. We defined gaming proxy as our dependent variable in a logistic regression against a set of stock, trade, and market characteristics, which are listed in Table 10 in the Research Methodology section.

Before getting started with the regression, we observed the cross-correlation levels among the identified set of variables. **Table A12** in the Appendix presents the results. There was a nearly perfect correlation between the trader and client concentration levels based on the complete day (TRC_FULL and CRC_FULL) and final 30 minutes of trading (TRC_30MIN and CRC_30MIN) metrics. To avoid multicollinearity issues affecting our analysis, we removed client concentration metrics from our analysis (CRC_FULL and CRC_30MIN). There was also a high correlation between the total liquidity (LIQUIDITY) and free-float liquidity (LIQUIDITY_FREE_FLOAT) metrics. But given that they might potentially offer varying signals, we decided to retain them both in our analysis. The other cross-correlation values were relatively less significant.

Table A13 in the Appendix presents the results of a logistic regression. Portfolio pumping appeared to be higher among stocks that performed poorly until the second-to-last day of the quarter, had smaller capitalization, had lower free-float liquidity, were Catalist-listed, and were not a constituent of the SIMSCI (Model 1A). Such potentially pumped stocks also had a significantly higher degree of buyer-initiated trades (ASK_PRICE_FULL) on the day of pumping with a higher standardized trade volume (STD_VOLUME). Interestingly, trader concentration (and incidentally, client concentration) was not found to be a significant factor in explaining portfolio pumped stocks. Pumped-up stocks also did not appear to be clustered around a specific domicile (such as being China domiciled or Singapore domiciled) and there was no statistical evidence that the pumping happened with limited capital (fewer number of traded shares).

Restricting the trade-based factors to the final 30 minutes of trading instead of the complete last day of the quarter also provided a similar conclusion (Model 2A). The proportion of trades happening in the final 30 minutes on the last day of a quarter was significantly higher among possible pumped-up stocks. Factoring in both sets of parameters (relating to the complete last day of the quarter and final 30 minutes of trading) jointly offered largely the same conclusion (Model 3A).

The results are broadly in line with our earlier hypotheses tests and help validate our findings. Although we did not observe much of a return reversal at the start of a quarter at the overall market level, an analysis of possible pumped-up stocks (which tend to have abnormally positive returns at a quarter-end and a reversal of returns on the next trading day) revealed that they did exhibit characteristics similar to observations from our earlier analysis that evaluated abnormal activity at the end of the quarter. This result lends significant credibility to our findings and positions us to conclude with confidence.

One area of difference from earlier results was the significance of Catalist-listed stocks among the pumped-up universe. This finding is in contrast to our earlier observation of significant positive average returns on the last day of a quarter among Mainboard stocks and a corresponding average negative (although not significant) return among Catalist stocks (Table 21). With trader and client concentration levels, we observed that the trend of abnormally higher concentration levels on the last day of a quarter and abnormally lower concentration levels in the final 30 minutes of trading on the last day of a quarter that came through in the logistic regression with the gaming proxy variable was in line with our earlier conclusion. But the concentration level did not emerge as a significant factor to explain potential pumped-up stocks.

Despite establishing a significant negative relationship between capitalization size and the presence of pumping, our capitalization variable, being categorical in nature, was not able to precisely validate our previous finding of mid-cap stocks having significantly higher abnormal positive returns on the last day of the quarter as compared with the large- and small-caps. To achieve this validation, we broke down our two categorical variables, momentum and capitalization, into category value–wise dummy variables and replicated the regression models discussed earlier.

As required for a categorical variable with *n* possible values, we created *n*–1 dummy variables and reran the logistic regression analyses. This approach was necessary to avoid the issue of multicollinearity in our analysis. Furthermore, given that our previous finding pointed to pumping being likely higher among the worst 25% performers of the quarter (until the second-to-last day) and among the mid-caps, we accordingly placed them as the implied variables. Accordingly, the momentum variable was replaced by three dummy variables—MOMENTUM_2, MOMENTUM_3, and MOMENTUM_4—in our analysis, making the worst 25% performer group (MOMENTUM_1) implied. Similarly, LARGE_CAP and SMALL_CAP were the capitalization dummy variables considered in our analysis, whereas MID_CAP was taken as an implied variable. In effect, a significant negative coefficient for the explicitly included variables would automatically denote the significance of the implied variables.

Models 1B, 2B, and 3B bring out the analysis with the newer set of dummy variables in place of the categorical variables. As expected, we observed a significantly strong negative correlation between the newly introduced momentum and capitalization dummy variables. This result validated the presence of pumping being higher among the worst performers and among the mid-caps.

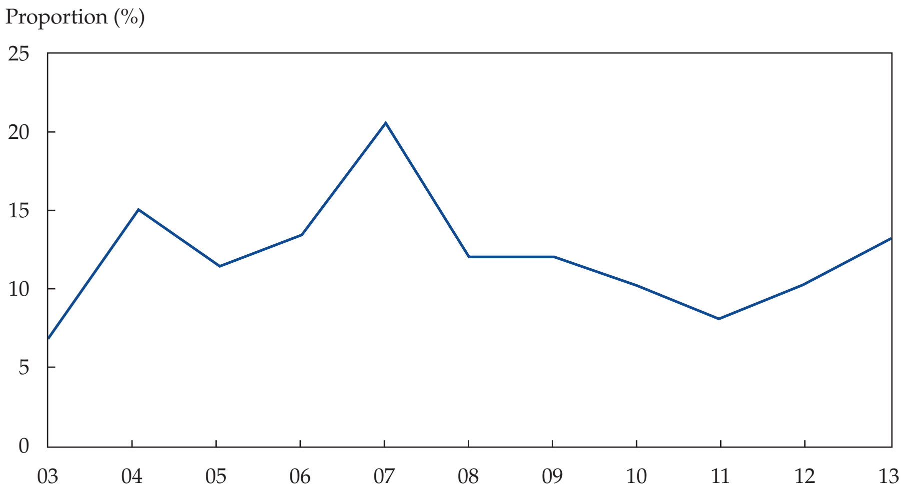
In unreported results, we also replicated the analysis with just the absolute return definition for the gaming proxy. In effect, the gaming proxy variable assumed a value of 1 for a stock-quarter if the stock earned positive absolute returns on the last day of the quarter and a negative absolute return on the first day of the subsequent quarter. The results were in line with the broader definition of the gaming proxy. Apart from the already identified set of significant variables, the MARKET_RETURNS variable also turned significant with a negative coefficient under the narrow definition of the gaming proxy. This result possibly implies a higher instance of pumping in down-trending markets, as recognized by Ben-David et al. (2013).

We then attempted a time-series analysis of the gaming proxy to understand how it has worked out over time and, more importantly, to validate some of our earlier findings with abnormal returns. **Figure 11** presents a snapshot of the proportion of stocks likely to have been pumped (gaming proxy variable assuming a value of 1) from 2003 to 2013. We observed a general decline in such instances since 2007, although there was an uptick in 2012 and 2013. **Figure 12** shows the proportion of possible pumping in individual quarters for each year in the dataset.

Interestingly, although abnormal returns on the last day of the quarter were the highest in Q4 (year-end quarters), from a gaming proxy perspective, the extent was more evenly spread across quarters, with Q2 and Q3 quarter-ends having the maximum number of such instances and Q4 actually registering the least frequency of a value of 1 for the gaming proxy variable. This result could be largely attributable to the previously highlighted trend of an abnormally high instance of absolute (and also to a great extent, excess) returns on the first day of the year possibly concealing more such pumping instances in year-end quarters.

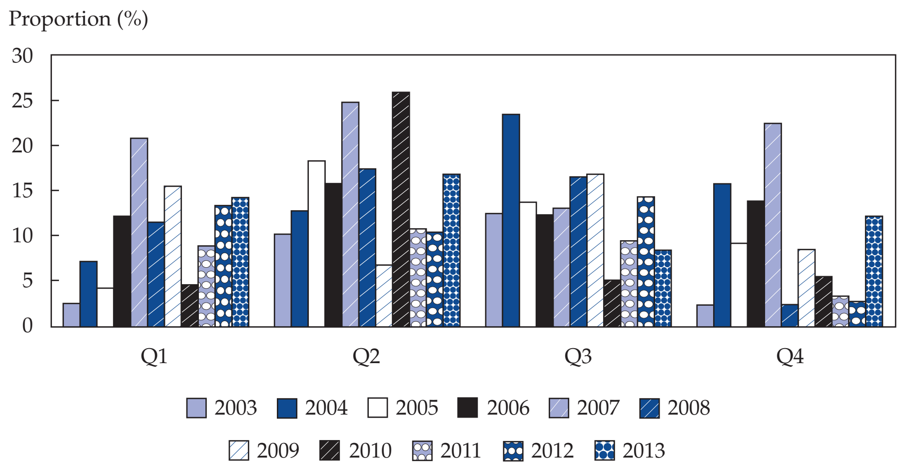
For a more formal analysis of a time-series study of gaming proxy, we introduced key milestone events as independent dummy variables in the logistic regression analysis. But given that we have so far dealt with two different sets of milestones covering the same study period, for the

Figure 11. Proportion of Possible Pumped-Up Stocks over Study Period



Source: Based on data from Bloomberg Finance L.P. and the SGX.

Figure 12. Proportion of Possible Pumped-Up Stocks by Quarter over Study Period



Source: Based on data from Bloomberg Finance L.P. and the SGX.

purpose of the logistic regression, we combined the two to create a single series of milestone dummy variables. **Table 25** presents the combined set of milestones.

Table A14 in the Appendix presents the results of the logistic regression factoring in the combined set of milestone dummy variables along with the originally identified set of stock, trade, and market characteristics. Mile C (equivalent of Mile M3), representing the proposal to introduce a composition system and mandatory minimum penalties by disciplinary committees for rule violations in the securities market, was found to have a significant (at the 5% level) negative relationship with the gaming proxy variable. Mile E (equivalent of Mile 3 and Mile M5),

Table 25. Combined List of Key Milestones Relating to the Pheim Asset Management Case and Regulations by the SGX to Improve the Trading Environment

Combined Milestone Code	Date of Assuming a Value of 1 under Combined Milestone	Milestone Reference Based on the SGX Trade Rules	Date of Assuming a Value of 1 under the SGX Trade Milestone	Milestone Reference Based on Pheim Asset Management Case	Date of Assuming a Value of 1 under Pheim Asset Management Case Milestone
Mile A	1 Jul 06	Mile M1	1 Mar 06	Mile 1	1 Jul 06
Mile B	1 Jun 07	Mile M2	1 Jun 07		
Mile C	1 Mar 08	Mile M3	1 Mar 08		
Mile D	1 Oct 09	Mile M4	1 Oct 09	Mile 2	1 Sep 09
Mile E	1 Nov 10	Mile M5	1 Nov 10	Mile 3	1 Oct 10
Mile F	1 Sep 11	Mile M6	1 Sep 11	Mile 4	1 Aug 11
Mile G	1 Dec 12			Mile 5	1 Dec 12

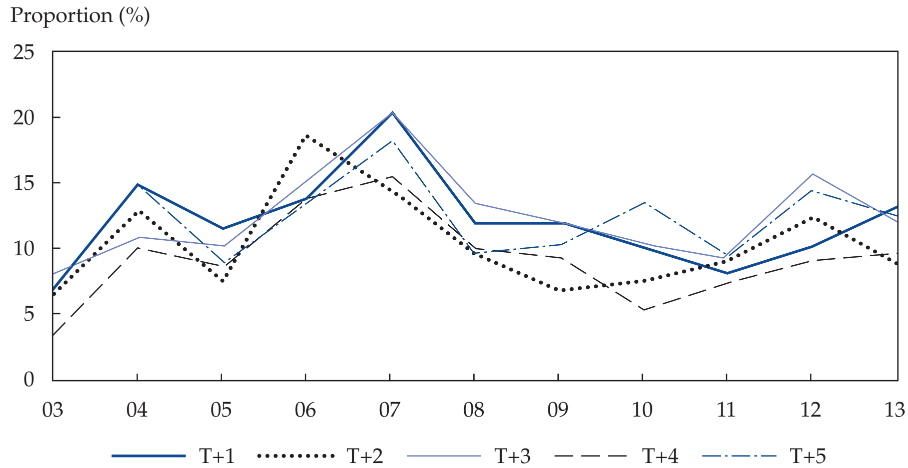
representing the pronouncement of Tan Chong Koay and Pheim Asset Management Sdn Bhd as guilty by the court and the SGX proposal for the introduction of continuous all-day trading for the SGX securities market from 9:00 a.m. to 5:00 p.m. without a break time, was also found to be significantly (at the 10% level) negative (Models 4, 5, 6A, 6B). Version 2 models (Models 4B, 5B, and 6B), which consider the breakdown of categorical momentum and capitalization variables into dummy ones, also placed the same set of milestones as significant. None of the other milestones were significant.

In Figure 4 and Figure 5, we noticed the T+2 day return of a quarter was negative, probably signaling a reversal after possible pumping at the end of the previous quarter. Drawing from this observation, we looked at several variations of the gaming proxy definitions based on the number of days into the new quarter when the reversal of pumped-up returns could have occurred. **Figure 13** presents the proportion of stocks likely to have been pumped during the study period with various possible number of days when the reversal could have occurred, ranging from T+1 day (our base case presented in Figure 11) to T+5 days.

For instance, T+2 captured the proportion of stocks that registered positive absolute and excess returns on the last day of the quarter and a negative absolute and excess return on day T+2. The results are fairly consistent across the various number of day assumptions for the reversal of returns, supporting the stability and robustness of our analysis. There was a general decline in the proportion of possible pumped-up stocks since 2007 and a slight uptick in 2012.

Table A15 in the Appendix presents the regression of these various definitions of the gaming proxy against milestone-dummy variables and the identified set of stock, trade, and market characteristics. In line with observations in Figure 13, the results are consistent for various definitions of the gaming proxy. Recent worst-performing stocks, mid-cap stocks, and Catalist-listed stocks with limited free-float liquidity showed consistently a relatively higher level of support for possible pumping. The trend of a higher proportion of buyer-initiated trades, greater proportion of trades in the final 30 minutes of trading on the last trading day of a quarter, and lower trader concentration are also facets of possible pumped-up stocks. In terms of milestones, Mile C, representing the proposal to introduce a composition system and mandatory minimum penalties by disciplinary committees for rule violations in the securities market, was found to be consistently significantly negative across the various definitions of the gaming proxy.

Figure 13. Proportion of Possible Pumped-Up Stocks over Study Period with Multiple Number of Days for Reversal of Returns



Sources: Based on data from Bloomberg Finance L.P. and the SGX.

Using Stricter Thresholds

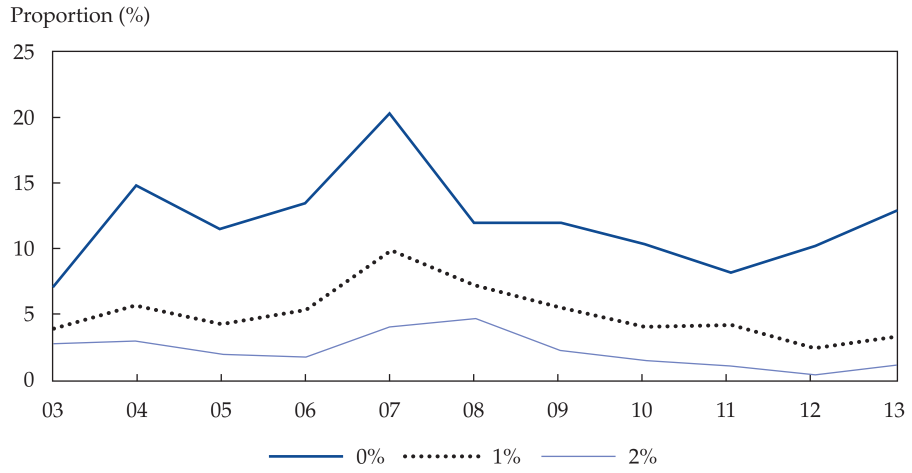
A mere positive return on the last day of a quarter and a negative return on the following day is not necessarily evidence enough for pumping. In certain cases, it could be a simple random effect and accordingly, the gaming proxy variable might include significant noise.

So, to minimize the effect of false signals, we introduced a couple of stricter definitions for the gaming proxy, defined as gaming proxy_strict1 and gaming proxy_strict2. Gaming proxy_strict1 was assigned a value of 1 only if absolute and excess returns on last day of the quarter exceeded 1% and both the returns on the next day fell below –1%. A similar definition was assigned to gaming proxy_strict2, with 2% and –2% as the threshold. **Figure 14** presents the results. As expected, with a tighter threshold level, we observed the proportion of possible pumped-up stocks to be lower across the board. But the broad trend is similar to the levels peaking around 2007–2008. Over the 2012–13 period, a simple threshold shows an uptick in the proportion of pumped-up stocks, but the rise is not as significant with the stricter thresholds, suggesting a general decline in any pumping activity if present.

Table A16 in the Appendix presents the logistic regression results for various definitions of the gaming proxy against milestone-dummy variables and the identified set of stock, trade, and market characteristics with a stricter returns threshold of 1% for the gaming proxy variable. The results are broadly in line with our observations from the base assumption of the gaming proxy in Table A15. Interestingly, small trades as a proportion of total trades turned out to be a significant negative variable with a stricter threshold, indicating that pumping was probably done with limited capital through a fewer number of shares.

An alternative to the stricter threshold–based approach is to identify stocks with the highest level of pumping and to observe their characteristics. For this approach, we made use of our two-day inflation metric to define stocks at the end of each quarter and observe characteristics

Figure 14. Proportion of Possible Pumped-up Stocks for Various Threshold Levels for Absolute and Excess Returns



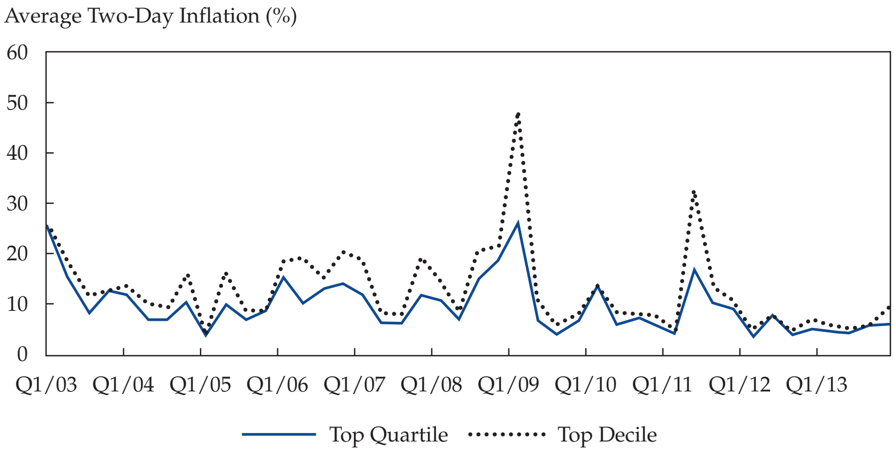
Sources: Based on data from Bloomberg Finance L.P. and the SGX.

of the top-quartile and top-decile stocks with the highest level of two-day inflation. **Figure 15** charts the average two-day inflation across quarters for the top-quartile and top-decile sets of stocks at quarter-ends. Excluding a couple of quarters with extreme values, the trend is broadly flat, with an average two-day inflation of around 10% and 13% for top-quartile and top-decile stocks, respectively. But we noted that in the past few years, there has been a decline in the average two-day inflation of the groups, which is in line with the trend for the overall universe observed earlier and shown in Figure 1 and Figure 2. For reference, average two-day inflation for the top-quartile and top-decile groups over the last three years of the study period (2011–2013) stood at 7% and 9.5%, respectively.

Table A17 and **Table A18** in the Appendix present the standard logistic regression results for various definitions of the gaming proxy against milestone-dummy variables and the identified set of stock, trade, and market characteristics for the identified set of top-quartile and top-decile pumped stocks. The results are broadly in line with the base case and the stricter threshold–based analysis discussed earlier. But it also brings out some interesting contradictions. Domicile, which was not a significant factor in the earlier discussions, now turns significantly negative, implying that the most pumped-up stocks came from the S-chip universe. Although as a universe, the S-chip group did not show a significant sign of pumping, it seems to have a reasonable representation among the stocks with the highest potential pumping, as measured by our two-day inflation metric.

Small trades as a proportion of total trades emerged significantly more negative in the latter set of analysis (based on top quartile and top decile) compared with the earlier set of analysis, offering more support to the view that it is costly to engage in pumping and possibly cannot be managed with small trades. Similarly, more trades among the most pumped stocks seemed to be driven by buyer-initiated trades, with more trades closing at or above ask price.

Figure 15. Average Two-Day Inflation across Quarters among the Top-Quartile and Top-Decile Stocks (Determined in Terms of Two-Day Inflation)



Sources: Based on data from Bloomberg Finance L.P. and the SGX.

Between the quartile- and decile-based analyses, two contradictions are observed. First, with the basket of the top 10% of stocks (in each quarter) with the highest two-day inflation, the proportion of trades in the final 30 minutes on the last trading day of a quarter turned insignificant, implying more balanced trading of these stocks over time on the final trading day of a quarter. Second, the trader concentration ratio in the final 30 minutes of trading on the last trading day of the quarter, which was significantly negative across all earlier analysis as well as with quartile-based analysis, turned insignificant with the decile analysis.

We noted earlier that a pick-up in trading activity in the final 30 minutes of trading on the last trading day of a quarter led to trader concentration being generally low in that period. But the decile analysis indicated that stocks that experience the top 10% most significant two-day inflation at quarter-ends did not need to be part of wide trader participation. Although it does not turn significantly positive to satisfactorily conclude that trades were cornered by a few select traders, insignificance of the contrary does offer some support for a possible pumping in these stocks.

Validation of Results

To increase the robustness of our gaming proxy analysis, we carried out a couple of additional tests. First, we negated the argument that positive returns at quarter-end and negative returns on the first day of the subsequent quarter observed among our gaming proxy universe was a structural phenomenon. To test this view, we introduced quarter-beginning returns (QTR_BEG_RETURN) as a dependent variable in our standard logit regression model. We did two versions: one based on quarter-beginning absolute returns and one based on excess returns. **Table A19** in the Appendix presents the result. With absolute returns, the factor QTR_BEG_RETURN turned positive significantly, indicating that a potentially pumped stock in a quarter began the quarter with a positive return. This result is not surprising given that we already noted returns on the first day of a quarter to be significantly positive on average for the entire universe. More importantly, this finding negates any structural argument of such pumped-up stocks observing negative quarter-beginning returns and positive quarter-end returns. With excess return, the factor did not emerge as significant, giving confidence to our base results.

A second robustness technique we adopted was to exclude from our analysis companies with significant news flow to negate the argument that the significant positive return observed at the end of the quarter could be driven by some news associated with the company and not by pumping. We considered the number of stories on the companies using data from Bloomberg Finance L.P. We standardized the news story count for each month based on the preceding six-month and subsequent six-month story count levels. Here again, we considered two versions. If the standardized score happened to be greater than 0.5 or 1, we excluded the companies from our gaming proxy analysis. For this purpose, we used the stricter version of the gaming proxy logit regression with a threshold of 2%. This implies that a company for a particular quarter will earn a value of 1 for the gaming proxy if absolute and excess returns were significantly greater than 2% at quarter-end and earn a negative return of less than –2% on both counts on the first trading day of the subsequent quarter. About 10% of the identified instances of potential pumping were removed with this analysis. **Table A20** in the Appendix presents the results. We noted that the results broadly hold with the base case. But variables corresponding to the proportion of trades in the final 30 minutes on the last trading day and standardized trade volume turned insignificant with this analysis. The latter is quite expected given that trades are likely to be higher for stocks with greater news flow.

Finally, we tested for the persistence of stocks, traders, and clients to pump stocks. Specifically, we explored the turnover of stocks in two subsequent quarters to capture the extent to which the same set of stocks tended to repeat being among the pumped-up universe. We also computed the number of times a company came up as being pumped during the study period. We ran a similar analysis for trader and client groups. With the company analysis, we also ran our standard logit regression with a flag for the stock having been pumped in the previous quarter as a dependent variable. In unreported results, we did not find any significant sign of persistence among stocks, traders, or clients.

6. Conclusions

At the market level, portfolio pumping was not active on the SGX during the period of analysis (2003–2013). Although we cannot fully attribute this result to the regulatory microstructure reforms, it can be inferred that the regulatory structure put in place has done a decent job in upholding market integrity in regards to portfolio pumping.[71]

But it is important to note that abnormal positive returns during the quarter-end days that was not accompanied by any subsequent price reversion was observed. The presence of these bullish sentiments is further validated by the significant presence of more buyer-initiated transactions during quarter-end days. Additionally, subsequent regression analysis using the final 30 minutes pricing data at quarter-end days revealed the end-of-year dummy to be significantly positive. Similar results were validated in regression analysis on both average trader and client concentration.

In segmental analysis, we found that these bullish sentiments thrived in the mid-cap stock segment and not in both the large-cap and small-cap stock segments. Our view is that the large-cap stocks were probably too liquid for undertaking portfolio pumping activities, whereas the small-cap stocks were probably too small in terms of market capitalization to satisfy the investment mandate of most portfolio managers. This view was further validated when we repeated our analysis on customized stock segments via a market-capitalization approach.

Because these abnormal returns without subsequent price reversions were found only in the mid-cap stocks, it is unclear whether the expected price reversion was being masked by some other factor or the abnormal returns were attributable to some other reasons.

In testing for small trades, the results suggested that if portfolio pumping were to occur on the SGX, it would have involved larger lot sizes (greater than 5,000 shares) and thus be a relatively costly exercise. This result provides additional evidence of the nonexistence of portfolio pumping at the market level.

In testing for the impact of enforcement activities, our legal milestone regression test indicated that both the identification and successful conviction of market fraud events have had a significant role in reducing market absolute returns during quarter-ends. But it is unclear as to whether it minimizes portfolio pumping activities.

At the same time, our regulatory reform milestone regression test indicated that having a stronger penalty system in place for offenders did have an influence in reducing both market absolute and excess returns during quarter-ends. As for its influence on minimizing portfolio pumping activity, it similarly remains unclear.

Contrary to popular belief, portfolio pumping activity was inactive among S-chips, non-SIMSCI constituents, and Catalist-listed stocks. Majority shareholder domination and the general lack of institutional interests are possible reasons for the absence of portfolio pumping activities among these stock segments.

[71]This statement does not imply the complete absence of portfolio pumping at the segmental and company level.

In nonsegmented analysis, there were significantly positive returns during quarter-end days for the worst-performing quartile. A plausible reason can be inferred from a remuneration and reputational perspective. For example, for appraisal purposes, portfolio managers may be incentivized to pump up the prices of their worst-performing holdings during the quarter-end. But consistent with the other findings, the reversion of returns remained elusive.

To validate our results, we used an alternative method: a combination of a gaming proxy and logistic regression. As expected, stocks from the mid-cap segment, with lower free-float liquidity and not constituents of the SIMSCI, experienced a significantly higher degree of buyer-initiated trades. This result suggests that these stocks displayed greater potential to be pumped during the quarter-end days.

Other attributes that characterized this pool of suspicious instances included generating poor performance until the second-to-last day of the quarter and having a higher daily standardized trade volume as well as a greater proportion of trades happening in the final 30 minutes on the last day of a quarter. One interesting note was the domicile factor. Even though the S-chip universe as a whole was relatively free of portfolio pumping, as mentioned before, many of the most suspicious instances (top quartile and decile of the gaming proxy population) originated from the S-chip segment.

Finally, we found that over time, market integrity with respect to portfolio pumping has improved in the SGX. This finding is inferred from changes in the two-day inflation metric of the gaming proxy population. For the top quartile, the average two-day inflation during 2011 to 2013 dropped to 7%, compared with 10% for the entire period under study. For the top decile, that value was 9.5% compared with 13%. As can be observed, the magnitude of suspicious portfolio pumping activity over time has dampened even among the most active entities.

Furthermore, our turnover analysis across subsequent quarters did not uncover any significant sign of persistence of suspicious pumping activity among stocks, traders, or clients. These demonstrated that throughout time, pumping activities if present are not clustered around any particular group of stocks, carried out by any specific group of traders, or ordered by some common individuals (clients).

Our work leads us to conclude that the regulatory microstructures that are in place have done a good job in upholding the integrity of the SGX because it is a relatively costly exercise now to engage in portfolio pumping.

7. Policy Recommendations

1. Our findings indicate that the existing operation of the SGX market surveillance and MAS enforcement process is working well in regard to quarter-end closing prices. We recommend other exchanges adopt and refine some of these measures as methods to stifle potential market manipulation activities on closing prices during these periods. These measures include the following:

    a. When manipulation activities are detected, the authorities should ensure a fair and judicial prosecution of the participant. This first step provides the signaling effect to would-be offenders that market activities are being monitored. And if successful in the prosecution process, the second element further reinforces the fact that if found guilty, civil or criminal sanctions will follow, thus further discouraging such activities.

    b. Make it difficult and expensive to undertake portfolio pumping activities. It is highly probable that the adoption of the call auction system for end-of-day pricing in 2000, the randomization of the pre-close time duration, and the implementation of a new algorithm for end-of-day pricing in 2011 affected the opportunities for would-be offenders to pump stocks.

2. Increase scrutiny of market surveillance activities for mid-cap stocks. Our findings suggest that there were abnormal forces at work in this category for the quarter-end days, albeit without the anticipated price reversion the following day. Specifically,

    a. if portfolio pumping activities did exist in this category, was the expected price reversion masked out by some other factor?

    b. if portfolio pumping did not exist, it would be interesting to understand why such abnormal returns were evident for only this category of stocks.

3. Increase scrutiny of market surveillance activities for stocks that are performing worst. In nonsegmented tests, our findings suggest that there were unexplained forces at work for these types of stocks for quarter-end days, which is inconsistent with the window dressing process, in which one would expect the opposite to occur.

4. Our gaming proxy and logistic regression analyses further identified some characteristics that are common among suspicious instances of portfolio pumping activities. Market surveillance could focus on stocks that exhibit these additional traits:

    - Mid-cap segment, especially those within the S$2 billion to S$5 billion range
    - Lower free-float liquidity
    - Not a constituent of the SIMSCI
    - Part of the worst-performing quartile
    - Higher daily standardized trade volume

- Significantly higher degree of buyer-initiated trades
- Greater proportion of trades in the final 30 minutes of a quarter-end trading day
- S-chip stocks

5. Increase the awareness and education of mainstream media about hyping up portfolio pumping activities at year-ends. Inevitably, the media play an important role in creating the perception in the minds of investors about the integrity of the stock market. Our findings indicate that although abnormal returns were evident at year-ends, it was not definitively because of portfolio pumping activities, and there was limited evidence that it was related to window dressing activities.

Appendix

This section contains tables presenting the output of the regression analyses discussed in Section 5. Output Tables A1 to A9 consist of three regression model outputs representing the three levels of analysis discussed in the Research Methodology section. Tables A10 and A11 present the regression output for daily absolute and excess returns against milestone dummies discussed in Table 7 and Table 8, respectively. Table A12 presents a cross-correlation of stock, trade, and market characteristic variables that are listed in Table 10. Table A13 presents logistic regression results for our gaming proxy variable against the identified set of stock, trade, and market characteristic variables. Tables A14, A15, and A16 include key milestone event dummy variables in the logistic regression. Tables A17 and A18 restrict the analysis to the top quartile and top decile of stocks, respectively, based on two-day inflation returns. Table A19 includes quarter-beginning returns as a dependent variable in our standard logit regression model to capture instances of any structural pattern explaining the abnormal returns. Table A20 extends the robustness of our gaming proxy analysis by removing companies that have a significant number of news stories.

For each of the independent variables considered in the respective regression models, the output covers the coefficient value in the first row and the standard error in parentheses in the second row. If the coefficient is significant at the 5% or 10% levels (p-values of less than 0.05 and 0.1, respectively), a marking in the form of * (asterisk) or ** (double asterisk), respectively, is placed adjacent to it. If the level of significance is supportive of portfolio pumping, the regression coefficient and the markings are placed in bold and italicized. Period-end coefficients having a value greater than 0 and period-beginning coefficients having a value of less than 0 are considered favorable and supportive of pumping. With respect to milestone dummies as well as the stock, trade, and market characteristic variables, we draw interpretation for both significant positive and negative coefficients.

Table A1. Regression of Absolute and Excess Returns against Period-Defining Dummies

	Absolute Returns	Excess Returns
Model 1	$R_{it} = b_0 + b_1$*(QBEG + YBEG) + b_2*(QEND + YEND)	
Constant	0.08*	0.05*
	(0.01)	(0.01)
QBEG + YBEG	0.55*	0.09*
	(0.04)	(0.04)
QEND + YEND	***0.12****	***0.09****
	(0.04)	(0.04)
Model 2	$R_{it} = b_0 + b_1$*YBEG + b_2*YEND + b_3*QBEG + b_4*QEND	
Constant	0.08*	0.05*
	(0.01)	(0.01)
YBEG	1.63*	0.55*
	(0.09)	(0.08)
YEND	***0.39****	***0.44****
	(0.09)	(0.08)
QBEG	0.16*	***–0.08*****
	(0.05)	(0.05)
QEND	0.03	–0.03
	(0.05)	(0.05)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END+ b_3*Q2BEG + b_4*Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END	
Constant	0.08*	0.05*
	(0.01)	(0.01)
Q1BEG	0.67*	0.10
	(0.09)	(0.09)
Q1END	–0.04	0.07
	(0.09)	(0.09)
Q2BEG	–0.11	***–0.17****
	(0.09)	(0.09)
Q2END	***0.43****	–0.13*
	(0.09)	(0.09)
Q3BEG	***–0.08****	***–0.16****
	(0.09)	(0.09)
Q3END	–0.29*	–0.02
	(0.09)	(0.08)
Q4BEG	1.63*	0.55*
	(0.09)	(0.08)
Q4END	***0.39****	***0.44****
	(0.09)	(0.08)

Table A2. Regression of Beta-Adjusted Excess Returns against Period-Defining Dummies

	Beta-Adjusted Excess Returns
Model 1	$R_{it} = b_0 + b_1$*(QBEG + YBEG) + b_2*(QEND + YEND)
Constant	−0.06*
	(0.01)
QBEG + YBEG	0.19*
	(0.04)
QEND + YEND	***0.09****
	(0.04)
Model 2	$R_{it} = b_0 + b_1$*YBEG + b_2*YEND + b_3*QBEG + b_4*QEND
Constant	−0.06*
	(0.01)
YBEG	0.78*
	(0.08)
YEND	***0.41****
	(0.08)
QBEG	−0.03
	(0.05)
QEND	−0.03
	(0.05)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END +b_3*Q2BEG + b_4*Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END
Constant	−0.06*
	(0.01)
Q1BEG	0.14**
	(0.09)
Q1END	0.09
	(0.09)
Q2BEG	***−0.15****
	(0.09)
Q2END	−0.13**
	(0.09)
Q3BEG	−0.06
	(0.09)
Q3END	−0.03
	(0.09)
Q4BEG	0.78*
	(0.08)
Q4END	***0.41****
	(0.08)

Table A3. Regression of Standardized Trade Volume against Period-Defining Dummies

	Daily Average Standardized Traded Volume
Model 1	$R_{it} = b_0 + b_1$*(QBEG+YBEG) + b_2*(QEND + YEND)
Constant	0.85*
	(0.00)
QBEG + YBEG	−0.03**
	(0.03)
QEND + YEND	0.01
	(0.03)
Model 2	$R_{it} = b_0 + b_1$*YBEG +b_2*YEND + b_3*QBEG + b_4*QEND
Constant	0.85*
	(0.00)
YBEG	0.07**
	(0.05)
YEND	−0.20*
	(0.05)
QBEG	***−0.07****
	(0.03)
QEND	***0.09****
	(0.03)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END+ b_3*Q2BEG + b_4*Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END
Constant	0.85*
	(0.00)
Q1BEG	−0.15*
	(0.05)
Q1END	0.05
	(0.05)
Q2BEG	***−0.21****
	(0.05)
Q2END	0.03
	(0.05)
Q3BEG	0.17*
	(0.05)
Q3END	***0.19****
	(0.05)
Q4BEG	0.07**
	(0.05)
Q4END	−0.20*
	(0.05)

Table A4. Regression of Final 30-Minute Returns against Period-Defining Dummies

	Daily Final 30-Minute Trading Period Returns
Model 1	$R_{it} = b_0 + b_1$*(QBEG + YBEG) + b_2*(QEND + YEND)
Constant	0.10*
	(0.00)
QBEG + YBEG	0.02
	(0.03)
QEND + YEND	0.01
	(0.03)
Model 2	$R_{it} = b_0 + b_1$*YBEG + b_2*YEND + b_3*QBEG + b_4*QEND
Constant	0.10*
	(0.00)
YBEG	0.21*
	(0.06)
YEND	0.03
	(0.05)
QBEG	–0.04
	(0.03)
QEND	0.00
	(0.03)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END + b_3*Q2BEG + b_4*Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END
Constant	0.10*
	(0.00)
Q1BEG	0.08**
	(0.05)
Q1END	–0.05
	(0.05)
Q2BEG	–0.20*
	(0.05)
Q2END	–0.05
	(0.05)
Q3BEG	0.01*
	(0.06)
Q3END	***0.10****
	(0.05)
Q4BEG	0.21*
	(0.06)
Q4END	0.03
	(0.05)

Table A5. Regression of Final 30-Minute Trade Volume against Period-Defining Dummies

	Daily Standardized Trade Volume in the Final 30 Minutes	Proportion of Trades in the Day in the Final 30 Minutes
Model 1	$R_{it} = b_0 + b_1$*(QBEG + YBEG) + b_2*(QEND + YEND)	
Constant	0.86*	0.11*
	(0.00)	(0.00)
QBEG + YBEG	***−0.07****	0.00*
	(0.03)	(0.00)
QEND + YEND	***0.25****	***0.03****
	(0.03)	(0.00)
Model 2	$R_{it} = b_0 + b_1$*YBEG + b_2*YEND + b_3*QBEG + b_4*QEND	
Constant	0.86*	0.11*
	(0.00)	(0.00)
YBEG	−0.01	0.00
	(0.06)	(0.00)
YEND	0.03	***0.04****
	(0.06)	(0.00)
QBEG	***−0.09****	0.00*
	(0.03)	*(0.00)*
QEND	***0.33****	***0.02****
	(0.03)	(0.00)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END+ b_3*Q2BEG + b_4*Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END	
Constant	0.86*	0.11*
	(0.00)	(0.00)
Q1BEG	***−0.18****	0.00
	(0.06)	(0.00)
Q1END	***0.28****	***0.02****
	(0.06)	(0.00)
Q2BEG	***−0.10****	0.01*
	(0.06)	(0.00)
Q2END	***0.22****	***0.02****
	(0.06)	(0.00)
Q3BEG	0.01	0.00
	(0.06)	(0.00)
Q3END	***0.48****	***0.02****
	(0.06)	(0.00)
Q4BEG	−0.01	0.00
	(0.06)	(0.00)
Q4END	0.03	***0.04****
	(0.06)	(0.00)

Table A6. Regression of Proportion of Trades Happening at or above Ask Price against Period-Defining Dummies

	Based on Complete Day	Based on Final 30 Minutes
Model 1	$R_{it} = b_0 + b_1$*(QBEG + YBEG) +b_2*(QEND + YEND)	
Constant	0.48*	0.50*
	(0.00)	(0.00)
QBEG + YBEG	0.03*	0.02*
	(0.00)	(0.00)
QEND + YEND	***0.01****	***0.01****
	(0.00)	(0.00)
Model 2	$R_{it} = b_0 + b_1$*YBEG + b_2*YEND + b_3*QBEG + b_4*QEND	
Constant	0.48*	0.50*
	(0.00)	(0.00)
YBEG	0.07*	0.06*
	(0.01)	(0.01)
YEND	***0.02****	***0.02****
	(0.01)	(0.01)
QBEG	0.02*	0.01*
	(0.00)	(0.01)
QEND	***0.01****	0.00
	(0.00)	(0.01)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END + b_3*Q2BEG + b_4*Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END	
Constant	0.48*	0.50*
	(0.00)	(0.00)
Q1BEG	0.04*	0.03*
	(0.01)	(0.01)
Q1END	0.01	0.00
	(0.01)	(0.01)
Q2BEG	0.01**	0.01
	(0.01)	(0.01)
Q2END	***0.02****	0.00
	(0.01)	(0.01)
Q3BEG	0.01*	0.01
	(0.01)	(0.01)
Q3END	0.00	***0.01*****
	(0.01)	(0.01)
Q4BEG	0.07*	0.06*
	(0.01)	(0.01)
Q4END	***0.02****	***0.02****
	(0.01)	(0.01)

Table A7. Regression of Proportion of Small Trades against Period-Defining Dummies

	Based on Complete Day	Based on Final 30 Minutes
Model 1	$R_{it} = b_0 + b_1$*(QBEG + YBEG) + b_2*(QEND + YEND)	
Constant	0.49*	0.49*
	(0.00)	(0.00)
QBEG + YBEG	−0.01*	−0.01**
	(0.00)	(0.00)
QEND + YEND	−0.01**	−0.01*
	(0.00)	(0.00)
Model 2	$R_{it} = b_0 + b_1$*YBEG + b_2*YEND + b_3*QBEG + b_4*QEND	
Constant	0.49*	0.49*
	(0.00)	(0.00)
YBEG	−0.03*	−0.03*
	(0.01)	(0.01)
YEND	−0.01	−0.01
	(0.01)	(0.01)
QBEG	0.00	0.00
	(0.00)	(0.01)
QEND	0.00	−0.01*
	(0.00)	(0.01)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END+ b_3*Q2BEG + b *Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END	
Constant	0.49*	0.49*
	(0.00)	(0.00)
Q1BEG	−0.02*	−0.01
	(0.01)	(0.01)
Q1END	−0.01	−0.02*
	(0.01)	(0.01)
Q2BEG	0.01	0.01
	(0.01)	(0.01)
Q2END	0.00	−0.01**
	(0.01)	(0.01)
Q3BEG	0.01	0.00
	(0.01)	(0.01)
Q3END	0.00	−0.01
	(0.01)	(0.01)
Q4BEG	−0.03*	−0.03*
	(0.01)	(0.01)
Q4END	−0.01	−0.01**
	(0.01)	(0.01)

Table A8. Regression of Average Trader Concentration against Period-Defining Dummies

	Based on Complete Day	Based on Final 30 Minutes
Model 1	$R_{it} = b_0 + b_1$*(QBEG + YBEG) + b (QEND + YEND)	
Constant	0.23*	0.40*
	(0.00)	(0.00)
QBEG + YBEG	0.00**	***−0.01****
	(0.00)	(0.00)
QEND + YEND	***0.01****	0.01*
	(0.00)	(0.00)
Model 2	$R_{it} = b_0 + b_1$*YBEG + b_2*YEND + b_3*QBEG + b_4*QEND	
Constant	0.23*	0.40*
	(0.00)	(0.00)
YBEG	***−0.02****	−0.01
	(0.01)	(0.01)
YEND	***0.05****	***0.03****
	(0.01)	(0.01)
QBEG	0.00	***−0.01****
	(0.00)	(0.01)
QEND	−0.01	−0.03*
	(0.00)	(0.01)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END+ b_3*Q2BEG + b_4*Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END	
Constant	0.23*	0.40*
	(0.00)	(0.00)
Q1BEG	0.00	−0.01
	(0.01)	(0.01)
Q1END	0.00	−0.01
	(0.01)	(0.01)
Q2BEG	0.02*	0.00
	(0.01)	(0.01)
Q2END	0.00	−0.03*
	(0.01)	(0.01)
Q3BEG	***−0.01****	***−0.01****
	(0.01)	(0.01)
Q3END	−0.02*	−0.04*
	(0.01)	(0.01)
Q4BEG	***−0.02****	−0.01
	(0.01)	(0.01)
Q4END	***0.05****	***0.03****
	(0.01)	(0.01)

Table A9. Regression of Average Client Concentration against Period-Defining Dummies

	Based on Complete Day	Based on Final 30 Minutes
Model 1	$R_{it} = b_0 + b_1$*(QBEG + YBEG) + b_2*(QEND + YEND)	
Constant	0.23*	0.39*
	(0.00)	(0.00)
QBEG + YBEG	***–0.01****	***–0.01****
	(0.00)	(0.00)
QEND + YEND	0.00	–0.01*
	(0.00)	(0.00)
Model 2	$R_{it} = b_0 + b_1$*YBEG + b_2*YEND + b_3*QBEG + b_4*QEND	
Constant	0.23*	0.39*
	(0.00)	(0.00)
YBEG	***–0.03****	–0.01
	(0.01)	(0.01)
YEND	***0.04****	***0.03****
	(0.01)	(0.01)
QBEG	***–0.01*****	***–0.01*****
	(0.00)	(0.01)
QEND	–0.01*	–0.02*
	(0.00)	(0.01)
Model 3	$R_{it} = b_0 + b_1$*Q1BEG + b_2*Q1END+ b_3*Q2BEG + b_4*Q2END + b_5*Q3BEG + b_6*Q3END + b_7*Q4BEG + b_8*Q4END	
Constant	0.23*	0.39*
	(0.00)	(0.00)
Q1BEG	0.00	0.00
	(0.01)	(0.01)
Q1END	–0.01	–0.01
	(0.01)	(0.01)
Q2BEG	0.01	0.00
	(0.01)	(0.01)
Q2END	0.00	–0.03*
	(0.01)	(0.01)
Q3BEG	***–0.02****	***–0.02****
	(0.01)	(0.01)
Q3END	–0.03*	–0.04*
	(0.01)	(0.01)
Q4BEG	***–0.03****	–0.01
	(0.01)	(0.01)
Q4END	***0.04****	***0.03****
	(0.01)	(0.01)

Table A10. Regression of Absolute and Excess Returns against Pheim Asset Management Case Milestone and Period-Defining Dummies

	Absolute Returns	Excess Returns
Model 4	$R_{it} = b_0 + b_1$*Mile 1 + b_2*Mile 2 + b_3*Mile 3 + b_4*Mile 4 + b_5*Mile 5	
Constant	0.04*	0.06*
	(0.02)	(0.01)
Mile 1	***−0.03****	0.02**
	(0.02)	(0.01)
Mile 2	0.01	***−0.03****
	(0.02)	(0.02)
Mile 3	***−0.08****	−0.03
	(0.03)	(0.02)
Mile 4	−0.01	0.02
	(0.02)	(0.02)
Mile 5	0.04*	0.02
	(0.02)	(0.02)
Model 5	$R_{it} = b_0 + b_1$*Mile 1 + b_2*Mile 2 + b_3*Mile 3 + b_4*Mile 4 + b_5*Mile 5 + b_6*YBEG + b_7*YEND + b_8*QBEG + b_9*QEND	
Constant	0.03*	0.06*
	(0.05)	(0.01)
Mile 1	***−0.03****	0.02**
	(0.02)	(0.01)
Mile 2	0.01	***−0.03****
	(0.02)	(0.02)
Mile 3	***−0.08****	−0.03
	(0.03)	(0.02)
Mile 4	0.00	0.02
	(0.02)	(0.02)
Mile 5	0.03	0.01
	(0.02)	(0.02)
YBEG	1.63*	0.55*
	(0.09)	(0.08)
YEND	***0.40****	***0.44****
	(0.09)	(0.08)
QBEG	0.17*	***−0.07*****
	(0.05)	(0.05)
QEND	0.03	−0.03
	(0.05)	(0.05)

Table A11. Regression of Absolute and Excess Returns against the SGX Regulatory Action Milestone and Period-Defining Dummies

	Absolute Returns	Excess Returns
Model 4	$R_{it} = b_0 + b_1$*Mile M1 + b_2*Mile M2 + b_3*Mile M3 + b_4*Mile M4 + b_5*Mile M5	
Constant	0.13*	0.06*
	(0.01)	(0.01)
Mile M1	0.18*	0.09*
	(0.02)	(0.02)
Mile M2	***–0.33****	***–0.11****
	(0.03)	(0.03)
Mile M3	0.08*	0.03**
	(0.03)	(0.02)
Mile M4	0.04*	***–0.03*****
	(0.02)	(0.02)
Mile M5	***–0.13****	–0.03
	(0.03)	(0.02)
Mile M6	0.10*	0.04*
	(0.02)	(0.02)
Model 5	$R_{it} = b_0 + b_1$*Mile M1 + b_2*Mile M2 + b_3*Mile M3 + b_4*Mile M4 + b_5*Mile M5 + b_6*Mile M6 + b_7*YBEG + b_8*YEND + b_9*QBEG + b_{10}*QEND	
Constant	0.12*	0.06*
	(0.01)	(0.01)
Mile M1	0.18*	0.09*
	(0.02)	(0.02)
Mile M2	***–0.33****	***–0.11****
	(0.03)	(0.03)
Mile M3	0.09*	0.04*
	(0.03)	(0.02)
Mile M4	0.03**	***–0.04****
	(0.02)	(0.02)
Mile M5	***–0.13****	–0.03
	(0.03)	(0.02)
Mile M6	0.10*	0.04*
	(0.02)	(0.02)
YBEG	1.63*	0.55*
	(0.09)	(0.08)
YEND	***0.40****	***0.44****
	(0.09)	(0.08)
QBEG	0.16*	***–0.08*****
	(0.05)	(0.05)
QEND	0.03	–0.03
	(0.05)	(0.05)

Table A12. Cross-Correlation of Stock, Trade, and Market Characteristics Considered in Our Analysis

	Stock, Trade, and Market Characteristics																	
	MOMENTUM	CAPITALIZATION	DOMICILE	LISTING_BOARD	SIMSCI_INCLUSION	ASK_PRICE_FULL	ASK_PRICE_30MIN	SMALL_TRADES_FULL	SMALL_TRADES_30MIN	TRC_FULL	TRC_30MIN	CRC_FULL	CRC_30MIN	LIQUIDITY	LIQUIDITY_FREE_FLOAT	STD_VOLUME	PROP_TRADES_30MIN	MARKET_RETURNS
MOMENTUM	1.00	−0.08	−0.04	0.01	0.05	0.02	0.04	0.03	0.03	−0.02	0.00	−0.01	0.00	−0.03	−0.04	0.08	0.03	0.00
CAPITALIZATION	−0.08	1.00	0.12	−0.18	−0.72	−0.05	−0.09	−0.38	−0.34	0.19	0.19	0.16	0.17	0.08	0.06	−0.03	−0.11	−0.01
DOMICILE	−0.04	0.12	1.00	0.13	−0.11	−0.04	−0.04	−0.12	−0.11	−0.04	−0.03	−0.04	−0.04	0.06	0.01	−0.03	−0.03	−0.01
LISTING_BOARD	0.01	−0.18	0.13	1.00	0.15	0.15	0.16	0.24	0.22	−0.01	0.07	−0.01	0.07	−0.15	−0.18	−0.02	0.08	0.00
SIMSCI_INCLUSION	0.05	−0.72	−0.11	0.15	1.00	0.04	0.06	0.26	0.24	−0.18	−0.21	−0.16	−0.20	−0.03	−0.03	0.05	0.05	0.01
ASK_PRICE_FULL	0.02	−0.05	−0.04	0.15	0.04	1.00	0.67	0.47	0.42	0.35	0.38	0.33	0.38	0.01	−0.04	0.08	0.29	−0.06
ASK_PRICE_30MIN	0.04	−0.09	−0.04	0.16	0.06	0.67	1.00	0.42	0.44	0.13	0.47	0.12	0.47	0.02	−0.03	0.05	0.32	−0.05
SMALL_TRADES_FULL	0.03	−0.38	−0.12	0.24	0.26	0.47	0.42	1.00	0.86	0.16	0.21	0.17	0.21	−0.06	−0.06	−0.02	0.33	−0.05
SMALL_TRADES_30MIN	0.03	−0.34	−0.11	0.22	0.24	0.42	0.44	0.86	1.00	0.08	0.29	0.08	0.29	−0.05	−0.05	0.00	0.27	−0.05
TRC_FULL	−0.02	0.19	−0.04	−0.01	−0.18	0.35	0.13	0.16	0.08	1.00	0.47	0.98	0.47	−0.05	−0.02	−0.04	0.14	−0.06
TRC_30MIN	0.00	0.19	−0.03	0.07	−0.21	0.38	0.47	0.21	0.29	0.47	1.00	0.45	0.99	−0.03	−0.03	−0.03	0.23	−0.03
CRC_FULL	−0.01	0.16	−0.04	−0.01	−0.16	0.33	0.12	0.17	0.08	0.98	0.45	1.00	0.46	−0.06	−0.03	−0.03	0.14	−0.06
CRC_30MIN	0.00	0.17	−0.04	0.07	−0.20	0.38	0.47	0.21	0.29	0.47	0.99	0.46	1.00	−0.03	−0.03	−0.03	0.23	−0.04
LIQUIDITY	−0.03	0.08	0.06	−0.15	−0.03	0.01	0.02	−0.06	−0.05	−0.05	−0.03	−0.06	−0.03	1.00	0.89	−0.04	0.00	0.02
LIQUIDITY_FREE_FLOAT	−0.04	0.06	0.01	−0.18	−0.03	−0.04	−0.03	−0.06	−0.05	−0.02	−0.03	−0.03	−0.03	0.89	1.00	−0.03	−0.03	0.02
STD_VOLUME	0.08	−0.03	−0.03	−0.02	0.05	0.08	0.05	−0.02	0.00	−0.04	−0.03	−0.03	−0.03	−0.04	−0.03	1.00	−0.02	0.03
PROP_TRADES_30MIN	0.03	−0.11	−0.03	0.08	0.05	0.29	0.32	0.33	0.27	0.14	0.23	0.14	0.23	0.00	−0.03	−0.02	1.00	−0.03
MARKET_RETURNS	0.00	−0.01	−0.01	0.00	0.01	−0.06	−0.05	−0.05	−0.05	−0.06	−0.03	−0.06	−0.04	0.02	0.02	0.03	−0.03	1.00

Table A13. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$					
Generic Model Factors	Model 1A	Model 2A	Model 3A	Model 1B	Model 2B	Model 3B
MOMENTUM	−0.16*	−0.17*	−0.18*			
	(0.03)	(0.03)	(0.03)			
MOMENTUM_2				−0.40*	−0.39*	−0.40*
				(0.11)	(0.11)	(0.11)
MOMENTUM_3				−0.48*	−0.49*	−0.50*
				(0.11)	(0.11)	(0.11)
MOMENTUM_4				−0.67*	−0.70*	−0.72*
				(0.11)	(0.11)	(0.11)
CAPITALIZATION	−0.69*	−0.64*	−0.69*			
	(0.05)	(0.05)	(0.05)			
LARGE_CAP				−0.46*	−0.42*	−0.41*
				(0.14)	(0.14)	(0.14)
SMALL_CAP				−1.05*	−0.96*	−1.01*
DOMICILE	−0.02	0.01	0.01	0.12	0.13	0.13
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
LISTING_BOARD	−0.71*	−0.77*	−0.80*	−1.52*	−1.58*	−1.61*
	(0.13)	(0.13)	(0.14)	(0.11)	(0.10)	(0.11)
SIMSCI_INCLUSION	−0.50*	−0.44*	−0.47*	0.16	0.16	0.15
	(0.12)	(0.12)	(0.12)	(0.14)	(0.14)	(0.14)
ASK_PRICE_FULL	1.71*		0.82*	1.37*		0.52*
	(0.19)		(0.24)	(0.19)		(0.23)
SMALL_TRADES_FULL	−0.19		−0.16	−0.16		−0.19
	(0.16)		(0.29)	(0.16)		(0.29)
TRC_FULL	0.19		0.31	−0.04		0.12
	(0.21)		(0.24)	(0.21)		(0.24)
ASK_PRICE_30MIN		1.42*	1.08*		1.28*	1.06*
		(0.16)	(0.20)		(0.16)	(0.20)
SMALL_TRADES_30MIN		−0.37*	−0.35		−0.34	−0.26
		(0.15)	(0.27)		(0.15)	(0.27)
TRC_30MIN		−0.01	−0.16		−0.18	−0.27
		(0.17)	(0.20)		(0.17)	(0.20)
LIQUIDITY	0.33	0.22	0.24	0.20	0.10	0.09
	(0.26)	(0.28)	(0.28)	(0.29)	(0.31)	(0.31)
LIQUIDITY_FREE_FLOAT	−0.21**	−0.22	−0.23**	−0.43*	−0.45*	−0.46*
	(0.12)	(0.14)	(0.14)	(0.15)	(0.16)	(0.16)
STD_VOLUME	0.04*	0.05*	0.05*	0.02	0.03	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.16)	(0.02)
PROP_TRADES_30MIN		1.37*	1.26*		1.15*	1.10*
		(0.22)	(0.23)		(0.16)	(0.23)
MARKET_RETURNS	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)

Table A14. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics Along with Key Milestone Events

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$					
Generic Model Factors	Model 4A	Model 5A	Model 6A	Model 4B	Model 5B	Model 6B
MOMENTUM	−0.17*	−0.18*	−0.18*			
	(0.04)	(0.04)	(0.04)			
MOMENTUM_2				−0.33*	−0.32*	−(0.33)*
				(0.11)	(0.11)	(0.11)
MOMENTUM_3				−0.41*	−0.42*	−0.44*
				(0.11)	(0.11)	(0.11)
MOMENTUM_4				−0.58*	−0.61*	−0.63*
				(0.11)	(0.11)	(0.11)
CAPITALIZATION	−0.60*	−0.56*	−0.60*			
	(0.06)	(0.05)	(0.06)			
LARGE_CAP				−0.52*	−0.46*	−0.46*
				(0.14)	(0.15)	(0.15)
SMALL_CAP				−0.84*	−0.76*	−0.78*
				(0.10)	(0.09)	(0.10)
DOMICILE	0.00	0.03	0.03	0.15	0.16	0.16
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)
LISTING_BOARD	−0.68*	−0.72*	−0.77*	−1.28*	−1.32*	−1.37*
	(0.14)	(0.14)	(0.14)	(0.12)	(0.12)	(0.12)
SIMSCI_INCLUSION	−0.46*	−0.41*	−0.43*	0.16	0.15	0.14
	(0.12)	(0.12)	(0.12)	(0.14)	(0.15)	(0.15)
ASK_PRICE_FULL	1.75*		0.85*	1.51*		0.66*
	(0.20)		(0.25)	(0.19)		(0.24)
SMALL_TRADES_FULL	−0.05		−0.02	0.11		0.09
	(0.16)		(0.30)	(0.17)		(0.29)
TRC_FULL	0.00		0.17	−0.29		−0.08
	(0.21)		(0.25)	(0.21)		(0.25)
ASK_PRICE_30MIN		1.47*	1.11*		1.39*	1.09*
		(0.16)	(0.20)		(0.16)	(0.20)
SMALL_TRADES_30MIN		−0.25	−0.34		−0.11	−0.25
		(0.15)	(0.27)		(0.16)	(0.27)
TRC_30MIN		−0.15	−0.24		−0.38*	−0.37**
		(0.18)	(0.20)		(0.18)	(0.20)
LIQUIDITY	0.25	0.14	0.15	0.09	−0.01	−0.02
	(0.26)	(0.28)	(0.29)	(0.29)	(0.30)	(0.31)
LIQUIDITY_FREE_FLOAT	−0.24**	−0.26**	−0.27**	−0.43*	−0.44*	−0.46*
	(0.13)	(0.14)	(0.14)	(0.15)	(0.15)	(0.16)

(continued)

Table A14. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics Along with Key Milestone Events (continued)

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$					
Generic Model Factors	Model 4A	Model 5A	Model 6A	Model 4B	Model 5B	Model 6B
STD_VOLUME	0.04*	0.05*	0.04*	0.02	0.03**	0.02
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
PROP_TRADES_30MIN		1.42*	1.31*		1.28*	1.20*
		(0.22)	(0.23)		(0.23)	(0.24)
MARKET_RETURNS	0.00	0.00	0.00	−0.01	−0.01**	−0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MILE_A	−0.05	0.02	−0.01	−0.28	−0.23	−0.27
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
MILE_B	0.25	0.17	0.17	0.21	0.15	0.14
	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)	(0.22)
MILE_C	−0.41*	−0.41*	−0.37*	−0.48*	−0.48*	−0.46*
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
MILE_D	−0.09	−0.07	−0.08	−0.07	−0.05	−0.05
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
MILE_E	−0.34	−0.38**	−0.38**	−0.36**	−0.40**	−0.40**
	(0.21)	(0.22)	(0.22)	(0.21)	(0.22)	(0.22)
MILE_F	0.20	0.24	0.24	0.20	0.24	0.23
	(0.20)	(0.20)	(0.21)	(0.20)	(0.20)	(0.21)
MILE_G	0.07	0.00	0.01	0.07	−0.01	0.00
	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)

Table A15. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics with Milestone-Dummy Variables across Multiple Number of Days for Reversal of Returns

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$				
Generic Model Factors	T+1	T+2	T+3	T+4	T+5
MOMENTUM_2	−0.33*	−0.52*	−0.48*	−0.42*	−0.52*
	(0.11)	(0.12)	(0.11)	(0.12)	(0.11)
MOMENTUM_3	−0.44*	−0.57*	−0.48*	−0.38*	−0.51*
	(0.11)	(0.12)	(0.11)	(0.12)	(0.11)
MOMENTUM_4	−0.63*	−0.52*	−0.51*	−0.42*	−0.65*
	(0.11)	(0.11)	(0.11)	(0.12)	(0.11)
LARGE_CAP	−0.46*	−0.36*	−0.12	−0.65*	−0.30*
	(0.15)	(0.16)	(0.14)	(0.16)	(0.15)
SMALL_CAP	−0.78*	−0.77*	−0.83*	−1.01*	−0.84*
	(0.10)	(0.10)	(0.09)	(0.11)	(0.10)
DOMICILE	0.16	0.16	0.28	0.48	0.16
	(0.13)	(0.13)	(0.12)	(0.13)	(0.12)

(continued)

Table A15. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics with Milestone-Dummy Variables across Multiple Number of Days for Reversal of Returns (continued)

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$				
Generic Model Factors	T+1	T+2	T+3	T+4	T+5
LISTING_BOARD	−1.37*	−1.29*	−1.25*	−1.39*	−1.14*
	(0.12)	(0.12)	(0.12)	(0.13)	(0.12)
SIMSCI_INCLUSION	0.14	0.07	−0.24	0.15	−0.15
	(0.15)	(0.16)	(0.15)	(0.16)	(0.15)
ASK_PRICE_FULL	0.66*	0.56	1.11*	0.39	1.08
	(0.24)	(0.26)	(0.24)	(0.27)	(0.24)
SMALL_TRADES_FULL	0.09	−0.55**	−0.78*	−0.15	−0.95
	(0.29)	(0.32)	(0.30)	(0.33)	(0.30)
TRC_FULL	−0.08	−0.21	−0.68*	−0.26	−0.53*
	(0.25)	(0.27)	(0.26)	(0.28)	(0.26)
ASK_PRICE_30MIN	1.09*	1.04*	0.65*	0.58*	0.40*
	(0.20)	(0.21)	(0.20)	(0.22)	(0.20)
SMALL_TRADES_30MIN	−0.25	−0.08	0.33	0.14	0.73*
	(0.27)	(0.29)	(0.28)	(0.30)	(0.27)
TRC_30MIN	−0.37**	−0.42**	−0.37**	−0.24	−0.31
	(0.20)	(0.22)	(0.20)	(0.22)	(0.20)
LIQUIDITY	−0.02	−0.28	−0.83*	−0.37	−0.23
	(0.31)	(0.35)	(0.35)	(0.39)	(0.32)
LIQUIDITY_FREE_FLOAT	−0.46*	−0.27**	−0.02	−0.25*	−0.17*
	(0.16)	(0.16)	(0.12)	(0.17)	(0.14)
STD_VOLUME	0.02	0.08	0.08*	0.09*	0.08*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
PROP_TRADES_30MIN	1.20*	1.43*	1.28*	0.78*	0.92*
	(0.24)	(0.25)	(0.24)	(0.27)	(0.24)
MARKET_RETURNS	−0.01	0.00	−0.01**	0.00	−0.01*
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
MILE_A	−0.27	−0.19	−0.12	−0.37**	−0.53*
	(0.18)	(0.18)	(0.18)	(0.20)	(0.20)
MILE_B	0.14	0.02	0.17	0.40**	0.68*
	(0.22)	(0.22)	(0.21)	(0.24)	(0.23)
MILE_C	−0.46*	−0.79*	−0.54*	−0.69*	−0.89*
	(0.18)	(0.20)	(0.18)	(0.20)	(0.18)
MILE_D	−0.05	−0.16	−0.08	−0.11	0.32**
	(0.17)	(0.21)	(0.17)	(0.20)	(0.17)
MILE_E	−0.40**	0.42**	−0.19	−0.09	−0.16
	(0.22)	(0.23)	(0.21)	(0.24)	(0.19)
MILE_F	0.23	0.09	0.48	0.24	0.11
	(0.21)	(0.20)	(0.19)	(0.22)	(0.18)
MILE_G	0.00	−0.12	−0.37	−0.06	−0.05
	(0.16)	(0.16)	(0.15)	(0.17)	(0.15)

Table A16. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics with Milestone-Dummy Variables with a Stricter Threshold of 1% for Gaming Proxy

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$				
Generic Model Factors	T+1	T+2	T+3	T+4	T+5
MOMENTUM_2	−0.53*	−1.15*	−0.92*	−0.91*	−0.76*
	(0.16)	(0.19)	(0.17)	(0.21)	(0.17)
MOMENTUM_3	−0.76*	−1.04*	−0.68*	−0.72*	−0.80*
	(0.16)	(0.18)	(0.16)	(0.20)	(0.17)
MOMENTUM_4	−0.89*	−0.67*	−0.76*	−0.54*	−0.78*
	(0.16)	(0.16)	(0.15)	(0.18)	(0.16)
LARGE_CAP	−0.37	−0.63*	−0.45**	−0.95*	−0.47**
	(0.23)	(0.27)	(0.24)	(0.29)	(0.26)
SMALL_CAP	−0.72*	−0.50*	−0.93*	−1.08*	−0.97*
	(0.13)	(0.14)	(0.13)	(0.16)	(0.14)
DOMICILE	0.38	0.19	0.36*	0.65*	0.29
	(0.17)	(0.20)	(0.18)	(0.21)	(0.18)
LISTING_BOARD	−1.66*	−1.57*	−1.56*	−1.63*	−1.39*
	(0.15)	(0.16)	(0.15)	(0.18)	(0.16)
SIMSCI_INCLUSION	−0.32	−0.11	−0.59	−0.24	−0.33
	(0.24)	(0.27)	(0.25)	(0.29)	(0.27)
ASK_PRICE_FULL	0.81*	0.62**	1.51*	0.81*	1.20*
	(0.32)	(0.36)	(0.34)	(0.40)	(0.35)
SMALL_TRADES_FULL	−0.78**	−1.17*	−1.47*	−0.14	−2.54*
	(0.41)	(0.47)	(0.46)	(0.50)	(0.47)
TRC_FULL	0.29	−0.10	−0.77*	−0.28	−0.52
	(0.31)	(0.36)	(0.36)	(0.40)	(0.36)
ASK_PRICE_30MIN	1.15*	1.28*	0.48	0.67**	0.10
	(0.28)	(0.32)	(0.29)	(0.35)	(0.29)
SMALL_TRADES_30MIN	−0.10	0.27	0.43	−0.64	1.06*
	(0.38)	(0.42)	(0.42)	(0.47)	(0.41)
TRC_30MIN	−0.71**	−0.74*	−0.54**	−0.36	0.15
	(0.28)	(0.32)	(0.30)	(0.35)	(0.28)
LIQUIDITY	0.13	−0.76	−0.96*	−0.91	−0.42
	(0.36)	(0.62)	(0.57)	(0.74)	(0.54)
LIQUIDITY_FREE_FLOAT	−0.68*	−0.42*	−0.13	−0.50	−0.29
	(0.20)	(0.26)	(0.21)	(0.31)	(0.23)
STD_VOLUME	0.02	0.09*	0.12*	0.10*	0.08*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
PROP_TRADES_30MIN	0.60**	0.90*	0.91*	0.53	0.55
	(0.33)	(0.36)	(0.35)	(0.40)	(0.36)
MARKET_RETURNS	−0.03	−0.02*	−0.02*	−0.02	−0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

(continued)

Table A16. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics with Milestone-Dummy Variables with a Stricter Threshold of 1% for Gaming Proxy (continued)

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$				
Generic Model Factors	T+1	T+2	T+3	T+4	T+5
MILE_A	−0.14	−0.14	0.15	−0.86*	−0.28
	(0.24)	(0.24)	(0.23)	(0.34)	(0.27)
MILE_B	0.02	0.03	−0.14	0.81*	0.35
	(0.29)	(0.30)	(0.29)	(0.39)	(0.32)
MILE_C	−0.50*	−1.17*	−0.44*	−0.76*	−0.79*
	(0.25)	(0.28)	(0.25)	(0.29)	(0.27)
MILE_D	−0.29	−0.18	−0.41	−0.32	−0.02
	(0.26)	(0.33)	(0.26)	(0.32)	(0.27)
MILE_E	−0.14	0.32	−0.32	−1.20*	−0.11
	(0.32)	(0.36)	(0.34)	(0.57)	(0.32)
MILE_F	−0.21	−0.16	0.33	1.00**	−0.16
	(0.31)	(0.32)	(0.32)	(0.56)	(0.31)
MILE_G	−0.19	−0.34	−0.49**	0.03	0.20
	(0.28)	(0.30)	(0.27)	(0.32)	(0.27)

Table A17. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics with Milestone-Dummy Variables with Top-Quartile Performers Based on Two-Day Inflation Returns

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$				
Generic Model Factors	T+1	T+2	T+3	T+4	T+5
MOMENTUM_2	−0.60*	−1.01*	−1.03*	−1.28*	−0.68*
	(0.19)	(0.22)	(0.21)	(0.27)	(0.20)
MOMENTUM_3	−0.58*	−1.13*	−0.77*	−0.65*	−0.96*
	(0.19)	(0.23)	(0.19)	(0.22)	(0.21)
MOMENTUM_4	−1.08*	−0.76*	−0.75*	−0.45*	−0.74*
	(0.20)	(0.18)	(0.17)	(0.19)	(0.18)
LARGE_CAP	−0.47*	−0.59*	−0.30	−0.97*	−0.63*
	(0.29)	(0.35)	(0.28)	(0.32)	(0.33)
SMALL_CAP	−0.89*	−0.65*	−0.92*	−1.18*	−0.84*
	(0.16)	(0.16)	(0.15)	(0.17)	(0.16)
DOMICILE	0.65*	0.01	0.49*	0.74*	0.46*
	(0.21)	(0.25)	(0.20)	(0.23)	(0.21)
LISTING_BOARD	−1.97*	−1.58*	−1.75*	−2.00*	−1.54*
	(0.18)	(0.18)	(0.18)	(0.20)	(0.18)

(continued)

Table A17. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics with Milestone-Dummy Variables with Top-Quartile Performers Based on Two-Day Inflation Returns (continued)

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$				
Generic Model Factors	T+1	T+2	T+3	T+4	T+5
SIMSCI_INCLUSION	−0.03	−0.37	−0.65*	−0.11	−0.37
	(0.29)	(0.35)	(0.29)	(0.31)	(0.33)
ASK_PRICE_FULL	0.92*	1.49*	1.64*	0.88**	1.21*
	(0.40)	(0.45)	(0.41)	(0.48)	(0.42)
SMALL_TRADES_FULL	−0.97**	−1.90*	−1.75*	0.19	−2.47*
	(0.52)	(0.60)	(0.54)	(0.60)	(0.57)
TRC_FULL	0.01	−0.73	−0.88*	−0.93*	−1.12*
	(0.40)	(0.47)	(0.44)	(0.52)	(0.47)
ASK_PRICE_30MIN	1.18*	0.93*	0.78*	0.87*	0.63**
	(0.35)	(0.39)	(0.35)	(0.42)	(0.35)
SMALL_TRADES_30MIN	−0.23	0.39	0.83	−1.08*	0.92**
	(0.47)	(0.55)	(0.49)	(0.58)	(0.49)
TRC_30MIN	−0.65**	−1.21*	−0.86*	−0.70	−0.21
	(0.35)	(0.41)	(0.36)	(0.42)	(0.36)
LIQUIDITY	0.27	−0.78	−3.56*	−0.28	−2.12*
	(0.36)	(0.79)	(0.82)	(0.62)	(0.86)
LIQUIDITY_FREE_FLOAT	−0.92*	−0.86**	0.24	−0.69*	−0.23
	(0.24)	(0.36)	(0.24)	(0.30)	(0.33)
STD_VOLUME	0.06	0.10*	0.14*	0.14*	0.11*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
PROP_TRADES_30MIN	−0.23	1.10*	1.12*	1.13*	0.83*
	(0.43)	(0.43)	(0.40)	(0.44)	(0.42)
MARKET_RETURNS	−0.01**	−0.01	−0.02*	−0.01	−0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
MILE_A	−0.84*	−0.83*	−0.63*	−0.99*	−0.96*
	(0.35)	(0.35)	(0.32)	(0.39)	(0.38)
MILE_B	0.39	0.45	0.35	0.57	0.73
	(0.43)	(0.43)	(0.39)	(0.46)	(0.45)
MILE_C	−0.34	−0.98*	−0.75*	−0.84*	−0.91*
	(0.33)	(0.37)	(0.32)	(0.37)	(0.34)
MILE_D	−0.19	−0.15	0.02	0.16	0.33
	(0.32)	(0.40)	(0.33)	(0.37)	(0.33)
MILE_E	−0.08	0.55	−0.10	−0.17	−0.19
	(0.39)	(0.43)	(0.38)	(0.44)	(0.37)
MILE_F	0.08	−0.05	0.34	0.19	0.07
	(0.37)	(0.36)	(0.34)	(0.41)	(0.35)
MILE_G	0.15	−0.01	−0.27	0.07	0.16
	(0.30)	(0.30)	(0.27)	(0.32)	(0.28)

Table A18. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics with Milestone-Dummy Variables with Top-Decile Performers Based on Two-Day Inflation Returns

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$				
Generic Model Factors	T+1	T+2	T+3	T+4	T+5
MOMENTUM_2	−0.87*	−1.52*	−1.37*	−1.76*	−0.55*
	(0.28)	(0.37)	(0.31)	(0.44)	(0.27)
MOMENTUM_3	−1.01*	−1.21*	−1.08*	−0.95*	−1.05*
	(0.29)	(0.33)	(0.27)	(0.32)	(0.32)
MOMENTUM_4	−1.29*	−0.82*	−1.40*	−0.46**	−1.17*
	(0.28)	(0.25)	(0.27)	(0.25)	(0.29)
LARGE_CAP	−0.98*	−1.26*	−0.46	−1.19*	−1.32*
	(0.47)	(0.60)	(0.44)	(0.52)	(0.55)
SMALL_CAP	−1.14*	−0.95*	−1.05*	−0.99*	−1.13*
	(0.21)	(0.22)	(0.21)	(0.23)	(0.22)
DOMICILE	0.77*	−0.12	0.33	0.79*	0.28
	(0.29)	(0.39)	(0.32)	(0.32)	(0.34)
LISTING_BOARD	−2.04*	−1.84*	−1.96*	−2.08*	−1.53*
	(0.24)	(0.25)	(0.24)	(0.27)	(0.25)
SIMSCI_INCLUSION	0.04	−0.15	−0.86**	−0.17	0.01
	(0.45)	(0.55)	(0.46)	(0.48)	(0.51)
ASK_PRICE_FULL	1.48*	2.27*	1.76*	0.86	1.77*
	(0.56)	(0.62)	(0.57)	(0.67)	(0.66)
SMALL_TRADES_FULL	−1.60*	−2.81*	−1.55*	−0.63	−2.28*
	(0.76)	(0.90)	(0.74)	(0.88)	(0.93)
TRC_FULL	−0.43	−1.19**	−0.79	−0.75	−2.08*
	(0.58)	(0.68)	(0.60)	(0.73)	(0.78)
ASK_PRICE_30MIN	0.95*	0.23*	0.45	0.82	0.99**
	(0.50)	(0.55)	(0.49)	(0.62)	(0.57)
SMALL_TRADES_30MIN	−0.48	0.74	1.09**	0.03	−0.07
	(0.69)	(0.79)	(0.66)	(0.84)	(0.85)
TRC_30MIN	−0.37	−0.86	−0.81	−1.53*	−0.80
	(0.49)	(0.56)	(0.51)	(0.66)	(0.59)
LIQUIDITY	0.13	−0.03	−3.33*	−0.30	−5.84*
	(0.55)	(0.71)	(1.38)	(0.82)	(1.69)
LIQUIDITY_FREE_FLOAT	−1.30*	−1.39*	−0.21	−1.45*	0.29
	(0.37)	(0.43)	(0.50)	(0.48)	(0.53)
STD_VOLUME	0.04**	0.13*	0.14*	0.15*	0.13*
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
PROP_TRADES_30MIN	−0.39	0.46	0.18	0.15	0.77
	(0.59)	(0.62)	(0.58)	(0.69)	(0.62)
MARKET_RETURNS	−0.02**	−0.02**	−0.03*	−0.02	−0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

(continued)

Table A18. Regression of Gaming Proxy against Stock, Trade, and Market Characteristics with Milestone-Dummy Variables with Top-Decile Performers Based on Two-Day Inflation Returns (continued)

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$				
Generic Model Factors	T+1	T+2	T+3	T+4	T+5
MILE_A	−0.84**	−1.03*	−1.05*	−1.12*	−1.17*
	(0.49)	(0.53)	(0.51)	(0.54)	(0.57)
MILE_B	0.25	0.76	0.58	0.63	0.36
	(0.61)	(0.63)	(0.62)	(0.65)	(0.72)
MILE_C	−0.50	−1.40*	−0.77	−1.21*	−0.66
	(0.49)	(0.53)	(0.48)	(0.55)	(0.58)
MILE_D	−0.20	0.16	−0.07	0.23	0.43
	(0.49)	(0.56)	(0.50)	(0.56)	(0.50)
MILE_E	−0.04	0.20	0.08	0.17	−0.31
	(0.60)	(0.62)	(0.57)	(0.62)	(0.57)
MILE_F	0.21	−0.07	0.15	−0.22	0.19
	(0.55)	(0.57)	(0.50)	(0.58)	(0.55)
MILE_G	0.26	0.16	−0.06	0.27	0.15
	(0.42)	(0.47)	(0.40)	(0.47)	(0.43)

Table A19. Regression of Gaming Proxy against Standard Characteristics with Quarter-Beginning Returns Included as Dependent Variable

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$	
Generic Model Factors	Absolute Returns	Relative Returns
MOMENTUM_2	−0.35*	−0.34*
	(0.11)	(0.11)
MOMENTUM_3	−0.45*	−0.44*
	(0.11)	(0.11)
MOMENTUM_4	−0.66*	−0.64*
	(0.11)	(0.11)
LARGE_CAP	−0.47*	−0.47*
	(0.15)	(0.15)
SMALL_CAP	−0.79*	−0.79*
	(0.10)	(0.10)
DOMICILE	0.15	0.15
	(0.13)	(0.13)
LISTING_BOARD	−1.38*	−1.37*
	(0.12)	(0.12)
SIMSCI_INCLUSION	0.15	0.15
	(0.15)	(0.15)

(continued)

Table A19. Regression of Gaming Proxy against Standard Characteristics with Quarter-Beginning Returns Included as Dependent Variable (continued)

	Gaming $proxy_{it} = b_0 + \Sigma b_i$*$Characteristic_i$	
Generic Model Factors	Absolute Returns	Relative Returns
ASK_PRICE_FULL	0.67*	0.67*
	(0.24)	(0.24)
SMALL_TRADES_FULL	0.08	0.08
	(0.29)	(0.29)
TRC_FULL	−0.05	−0.06
	(0.25)	(0.25)
ASK_PRICE_30MIN	1.09*	1.09*
	(0.20)	(0.20)
SMALL_TRADES_30MIN	−0.24	−0.24
	(0.27)	(0.27)
TRC_30MIN	−0.37**	−0.37**
	(0.20)	(0.20)
LIQUIDITY	−0.02	−0.02
	(0.31)	(0.31)
LIQUIDITY_FREE_FLOAT	−0.47*	−0.46*
	(0.16)	(0.16)
STD_VOLUME	0.02	0.02
	(0.02)	(0.02)
PROP_TRADES_30MIN	1.20*	1.20*
	(0.24)	(0.23)
MARKET_RETURNS	−0.01**	−0.01
	(0.00)	(0.00)
MILE_A	−0.29	−0.27
	(0.18)	(0.18)
MILE_B	0.16	0.15
	(0.22)	(0.22)
MILE_C	−0.46*	−0.45*
	(0.18)	(0.18)
MILE_D	−0.04	−0.05
	(0.17)	(0.17)
MILE_E	−0.43	−0.40
	(0.22)	(0.22)
MILE_F	0.26	0.24
	(0.21)	(0.21)
MILE_G	0.00	0.00
	(0.16)	(0.16)
QTR_BEG_RETURN	0.03*	0.02
	(0.01)	(0.01)

Table A20. Regression of Gaming Proxy against Standard Characteristics with a Stricter Definition of Gaming (2%) and with Companies with Significant News Flow Removed

	Gaming proxy$_{it}$ = b_0 + Σb_i*Characteristic$_i$	
Generic Model Factors	Standardized News Count >0.5	Standardized News Count >1.0
MOMENTUM_2	−0.90*	−0.77*
	(0.26)	(0.25)
MOMENTUM_3	−0.70*	−0.74*
	(0.24)	(0.24)
MOMENTUM_4	−1.24*	−1.19*
	(0.27)	(0.26)
LARGE_CAP	−0.41	−0.46
	(0.38)	(0.36)
SMALL_CAP	−0.98*	−0.99*
	(0.20)	(0.20)
DOMICILE	0.33	0.27
	(0.29)	(0.29)
LISTING_BOARD	−1.79*	−1.81*
	(0.23)	(0.23)
SIMSCI_INCLUSION	−0.56	−0.25
	(0.39)	(0.36)
ASK_PRICE_FULL	1.00*	0.92**
	(0.48)	(0.48)
SMALL_TRADES_FULL	−0.77	−0.78
	(0.61)	(0.60)
TRC_FULL	0.46	0.47
	(0.46)	(0.45)
ASK_PRICE_30MIN	1.23*	1.36*
	(0.45)	(0.44)
SMALL_TRADES_30MIN	−0.29	−0.40
	(0.57)	(0.57)
TRC_30MIN	−0.79**	−0.85**
	(0.44)	(0.44)
LIQUIDITY	−0.56	−0.19
	(0.97)	(0.84)
LIQUIDITY_FREE_FLOAT	−1.59*	−1.70*
	(0.48)	(0.45)
STD_VOLUME	0.01	0.02
	(0.03)	(0.03)
PROP_TRADES_30MIN	−0.02	0.06
	(0.50)	(0.49)

(continued)

Table A20. Regression of Gaming Proxy against Standard Characteristics with a Stricter Definition of Gaming (2%) and with Companies with Significant News Flow Removed (continued)

	Gaming proxy$_{it} = b_0 + \Sigma b_i$*Characteristic$_i$	
Generic Model Factors	Standardized News Count >0.5	Standardized News Count >1.0
MARKET_RETURNS	−0.04	−0.04*
	(0.01)	(0.01)
MILE_A	−0.69**	−0.71**
	(0.42)	(0.42)
MILE_B	0.47	0.45
	(0.49)	(0.49)
MILE_C	−0.55	−0.48
	(0.37)	(0.36)
MILE_D	−0.59	−0.65
	(0.44)	(0.43)
MILE_E	−0.31	−0.31
	(0.58)	(0.58)
MILE_F	−0.85	−0.45
	(0.68)	(0.61)
MILE_G	0.80	0.40
	(0.61)	(0.54)

List of Acronyms

List of Undefined Acronyms Used in This Publication

Acronym	Description
DJIA	Dow Jones Industrial Average
FTSE	Financial Times Stock Exchange
NASDAQ OMX	National Association of Securities Dealers Automated Quotations *Aktiebolaget Optionsmäklarna*/Helsinki Stock Exchange
NYSE	New York Stock Exchange
SQL	Structured Query Language

References

Agarwal, Vikas, Naveen D. Daniel, and Narayan Y. Naik. 2007. “Why Is Santa So Kind to Hedge Funds? The December Return Puzzle!” BNP Paribas Hedge Fund Centre Working Paper Series HF-026.

Agarwal, Vikas, Gerald D. Gay, and Leng Ling. 2014. “Window Dressing in Mutual Funds.” *Review of Financial Studies*, vol. 27, no. 11 (November): 3133–3170.

Aitken, M., A. Kua, P. Brown, T. Walter, and H.Y. Izan. 1995. “An Intraday Analysis of the Probability of Trading on the ASX at the Asking Price.” *Australian Journal of Management*, vol. 20, no. 2 (December): 115–154.

Akyol, Ali C., and David Michayluk. 2010. “Day End Returns on the Istanbul Stock Exchange.” Annual Conference of the Multinational Finance Society, Barcelona, Spain (June).

Ariel, Robert A. 1987. “A Monthly Effect in Stock Returns.” *Journal of Financial Economics*, vol. 18 (March): 161–174.

Asness, Cliff, Robert Krail, and John Liew. 2001. “Do Hedge Funds Hedge?” *Journal of Portfolio Management*, vol. 28, no. 1 (Fall): 6–19.

Ben-David, Itzhak, Francesco Franzoni, Augustin Landier, and Rabih Moussawi. 2013. “Do Hedge Funds Manipulate Stock Prices?” *Journal of Finance*, vol. 68, no. 6 (December): 2383–2434.

Bernhardt, Dan, and Ryan J. Davies. 2005. “Painting the Tape: Aggregate Evidence.” *Economics Letters*, vol. 89, no. 3 (December): 306–311.

———. 2009. “Smart Fund Managers? Stupid Money?” *The Canadian Journal of Economics/Revue canadienne d'economique*, vol. 42, no. 2 (May): 719–748.

Bhana, Narendra. 1994. “Window Dressing by Institutional Investors on the Johannesburg Stock Exchange: An Empirical Analysis.” *Investment Analysts Journal*, vol. 23, no. 39 (Winter): 61–67.

Bhattacharyya, Sugato, and Vikram Nanda. 2013. “Portfolio Pumping, Trading Activity and Fund Performance.” *Review of Finance*, vol. 17, no. 3 (May): 885–919.

Brown, Keith C., W. Van Harlow, and Laura T. Starks. 1996. “Of Tournaments and Temptations: An Analysis of Managerial Incentives in the Mutual Fund Industry.” *Journal of Finance*, vol. 51, no. 1 (March): 85–110.

Carhart, Mark M. 1997. “On Persistence in Mutual Fund Performance.” *Journal of Finance*, vol. 52, no. 1 (March): 57–82.

Carhart, Mark M., Ron Kaniel, David K. Musto, and Adam V. Reed. 1999. “Mutual Fund Returns and Market Microstructure.” Working paper, The Rodney L. White Center for Financial Research, The Wharton School, University of Pennsylvania (June).

———. 2002. “Leaning for the Tape: Evidence of Gaming Behavior in Equity Mutual Funds.” *Journal of Finance*, vol. 58, no. 2 (April): 661–693.

Chan, Alex W.H. 2005. “Relationship between Trading at Ask Price and the End-of-Day Effect in Hong Kong Stock Exchange.” *Investment Management and Financial Innovations*, vol. 4 (Winter): 124–136.

Chang, Rosita P., S. Ghon Rhee, Gregory R. Stone, and Ning Tang. 2008. “How Does the Call Market Method Affect Price Efficiency? Evidence from the Singapore Stock Market.” *Journal of Banking and Finance*, vol. 32, no. 10 (October): 2205–2219.

Christie, William G., and Paul H. Schultz. 1994. "Why Do NASDAQ Market Makers Avoid Odd-Eighth Quotes?" *Journal of Finance*, vol. 49, no. 5 (December): 1813–1840.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers. 1997. "Measuring Mutual Fund Performance with Characteristic-Based Benchmarks." *Journal of Finance*, vol. 52, no. 3 (July): 1035–1058.

Del Guercio, Diana, and Paula A. Tkac. 2002. "The Determinants of the Flow of Funds of Managed Portfolios: Mutual Funds versus Pension Funds." *Journal of Financial and Quantitative Analysis*, vol. 37, no. 4 (December): 523–557.

Duong, Truong X., and Felix Meschke. 2008. "The Rise and Fall of Portfolio Pumping among U.S. Mutual Funds." Working paper, Carlson School of Management, University of Minnesota (May).

French, Kenneth. 1980. "Stock Returns and the Weekend Effect." *Journal of Financial Economics*, vol. 8, no. 1 (March): 55–69.

Gallagher, David R., Peter Gardner, and Peter L. Swan. 2009. "Portfolio Pumping: An Examination of Investment Manager Trading and Performance." *Pacific-Basin Finance Journal*, vol. 17, no. 1 (January): 1–27.

Harris, Lawrence. 1989. "A Day-End Transaction Price Anomaly." *Journal of Financial and Quantitative Analysis*, vol. 24, no. 1 (March): 29–45.

Haugen, R., and J. Lakonishok. 1987. *The Incredible January Effect: The Stock Market's Unresolved Mystery.* Homewood, IL: Dow Jones-Irwin.

Hendricks, Daryll, Jayendu Patel, and Richard Zeckhauser. 1993. "Hot Hands in Mutual Funds: Short-Run Persistence of Performance, 1974–1988." *Journal of Finance*, vol. 48, no. 1 (March): 93–130.

Hillion, P., and M. Suominen. 2004. "The Manipulation of Closing Prices." *Journal of Financial Markets*, vol. 7, no. 4 (October): 351–375.

Hu, Gang, David R. McLean, Jeffrey Pontiff, and Qinghai Wang. 2014. "The Year-End Trading Activities of Institutional Investors: Evidence from Daily Trades." *The Review of Financial Studies*, vol. 27, no. 5 (May): 1593–1614.

Ippolito, Richard A. 1992. "Consumer Reaction to Measures of Poor Quality: Evidence from the Mutual Fund Industry." *Journal of Law and Economics*, vol. 35, no. 1 (April): 45–70.

Keim, Donald. 1983. "Size-Related Anomalies and Stock Return Seasonality: Further Empirical Evidence." *Journal of Financial Economics*, vol. 12, no. 1 (June): 13–32.

Khorana, Ajay. 1996. "Top Management Turnover: An Empirical Investigation of Mutual Fund Managers." *Journal of Financial Economics*, vol. 40, no. 3 (March): 403–427.

Kim, S.S., and P.D. Sohn. 2012. "Do Fund Managers Inflate Their Performance via Pumping Behavior? Evidence from Korean Fund Market." *Korean Journal of Financial Studies*, vol. 41: 233–261.

Ko, K.S., and J.S. Lee. 2008. "The Effect of Portfolio Pumping and Performance Transfer of Korean Equity Funds." *Journal of the Korean Data Analysis Society*, vol. 10: 1613–1628.

Kocherhans, Thomas C. 1995. "Securities Exchange Act Release No. 36556." Securities and Exchange Commission (6 December).

Lakonishok, J., and S. Smidt. 1988. "Are Seasonal Anomalies Real? A Ninety-Year Perspective." *Review of Financial Studies*, vol. 1, no. 4 (Winter): 403–425.

Lakonishok, J., A. Shleifer, R. Thaler, and R. Vishny. 1991. “Window Dressing by Pension Fund Managers.” *American Economic Review*, vol. 81, no. 2 (May): 227–231.

McInish, T.H., and R.A. Wood. 1990. “An Analysis of Transactions Data for the Toronto Stock Exchange.” *Journal of Banking and Finance*, vol. 14, no. 2–3 (August): 441–458.

Meier, Iwan, and Ernst Schaumburg. 2006. “Do Funds Window Dress? Evidence for U.S. Domestic Equity Mutual Funds.” Working paper, HEC Montreal and Kellogg School of Management (May).

Musto, David K. 1997. “Portfolio Disclosures and Year-End Price Shifts.” *Journal of Finance*, vol. 52, no. 4 (September): 1563–1588.

———. 1999. “Investment Decisions Depend on Portfolio Disclosures.” *Journal of Finance*, vol. 54, no. 3 (June): 935–952.

O’Neal, Edward S. 2001. “Window Dressing and Equity Mutual Funds.” Working paper, Wake Forest University (June).

Patel, Saurin, and Sergei Sarkissian. 2013. “Deception and Managerial Structure: A Joint Study of Portfolio Pumping and Window Dressing Practices.” Working paper, McGill University (November).

Reinganum, Marc R. 1983. “The Anomalous Stock Market Behavior of Small Firms in January: Empirical Tests for Tax-Loss Selling Effect.” *Journal of Financial Economics*, vol. 12, no. 1 (June): 89–104.

Ritter, Jay. 1988. “The Buying and Selling Behavior of Individual Investors at the Turn of the Year.” *Journal of Finance*, vol. 43, no. 3 (July): 701–717.

Roll, Richard W. 1983. “Vas ist das? The Turn-of-the-Year Effect and the Return Premium of Small Firms.” *Journal of Portfolio Management*, vol. 9, no. 1 (Winter): 18–28.

Rozeff, Michael S., and William R. Kinney. 1976. “Capital Market Seasonality: The Case of Stock Returns.” *Journal of Financial Economics*, vol. 3, no. 4 (October): 379–402.

Sias, Richard W., and Laura T. Starks. 1997. “Institutions and Individuals at the Turn-of-the-Year.” *Journal of Finance*, vol. 52, no. 4 (September): 1543–1562.

Sirri, Erik, and Peter Tufano. 1998. “Costly Search and Mutual Fund Flows.” *Journal of Finance*, vol. 53, no. 5 (October): 1589–1622.

Starks, Laura, Li Yong, and Lu Zheng. 2006. “Tax-Loss Selling and the January Effect: Evidence from Municipal Bond Closed-End Funds.” *Journal of Finance*, vol. 61, no. 6 (December): 3049–3067.

Xiao, Xinrong, Peng Cheng, and Jean Chen. 2005. “Window Dressing of Chinese Securities Investment Funds.” Paper presented at the European Financial Management Association 2005 Annual Meeting (29 June–2 July).

Zheng, L. 1999. “Is Money Smart? A Study of Mutual Fund Investors’ Fund Selection Ability.” *Journal of Finance*, vol. 54, no. 3 (June): 901–933.

Zweig, Jason. 1997. “Watch Out for the Year-End Fund Flimflam.” *Money*, vol. 26, no. 11 (November): 130–133.

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