Financial Innovations and Market Efficiency:
The Case of Single Stock Futures***

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Abstract

Market efficiency improves for stocks that are listed on the newly established single stock futures (SSF) exchanges. After identifying information associated with large price changes, we show that the number of unexplained large stock returns decreases for SSF firms in comparison to the pre-SSF period, and to the matched non-SSF sample. The reduction is positively related to the extent of trading activity in the single stock futures market.

Financial Innovations and Market Efficiency: The Case of Single Stock Futures

There has been a long-standing debate in the economic literature about the benefits of financial innovations that have lower trading costs. On the one hand, some believe that financial innovations have a destabilizing impact on the spot market: speculators can use the financial innovations to manipulate asset prices, causing price distortion and increased volatility. On the other hand, others take the opposite view that financial innovations are beneficial as they enable the arbitragers to participate more actively and cause prices to converge to fair value sooner[1]. The outcome of this debate is important. It addresses the question of whether new financial products, including derivatives, are justified. Whether innovations are more prone to generate destabilizing or stabilizing trades is an issue to be settled with empirical data.

On November 8, 2002, after being banned for more than two decades, single stock futures (SSF hereafter) began trading in the U.S. on two new exchanges, OneChicago and NQLX. In a SSF contract, a buyer (seller) commits to buy (sell) a particular stock at a pre-specified price on a pre-specified future date. It has two main advantages over the trading of stocks or combination of stocks and extant derivatives. First, it reduces, if not removes, the short selling constraints facing those

[1] Examples supporting the stabilizing view include Friedman (1953), Powers (1970), Danthine (1978), and Schwartz and Laatsch (1991), while the opposite view is supported by Cox (1979) and Figlewski (1981).

who desire to short the underlying stock. Entering into a short position in single stock futures is as convenient as acquiring a long position. The second advantage is a greater leverage effect since future contracts require less capital. The margin requirement is low in single stock futures (generally 20%). Both of these features are important to arbitragers as well as speculators. Arbitragers need to short stocks, and lack of effective short sales has been blamed for market inefficiency, e.g., too many large price deviations from the fair values[2]. On the other hand, securities that lower the transaction cost also facilitate "destabilizing" speculation. Thus, like a two-edged sword, introduction of single stock futures could stabilize or destabilize the spot market. Depending on who the dominant investors are, the issue of single stock futures and market efficiency is ultimately an empirical question.

In this paper, we study the newly established market for single stock futures and provide an empirical test of whether SSF lead to greater market efficiency. We concentrate on an empirical procedure that examines the number of unexplained large price changes. The procedure is based on the intuitive assumption that arbitragers are more motivated to enter the market when the expected gain is greater. We find a significant reduction in the number of large positive and negative stock returns for the 84 single stock futures listed on OneChicago or NQLX during the first 250 days of SSF trading. This comparison is made relative to a match sample, and to the 250-day pre-SSF period. We further identify the presence or absence of news

[2] For example, the costs to arbitrage are discussed in Campbell and Kyle (1993), Merton (1987), and Shleifer and Vishny (1990).

around the dates of large returns, and we find that the reduction mainly lies in the no-news sample, i.e., the unexplained price changes. SSF introduction, on the whole, improves spot market efficiency. As a robustness check, we have also conducted standard tests using volatility. The SSF firms have a greater reduction in volatility than the matches, and a higher SSF trading volume is positively related to the reduction in volatility.

This paper makes several contributions to the literature. First, it adds empirical evidence to the debate of whether derivatives facilitate speculation or help achieve greater market efficiency. Second, it is among one of the first studies of the newly established market for the single stock futures. Unlike broad based index futures, single stock futures allow traders to focus on a particular stock, and shall provide a more ideal laboratory to test for the impact of futures contracts on market efficiency. Third, we propose an alternative approach to study market efficiency. We take into account the costs of trading by arbitragers, and expect that they would concentrate their efforts on large price deviations.

The rest of the paper is organized as follows. In Section I, we discuss the role of single stock futures and the empirical testing strategy. Section II describes the data, and the results are presented in Section III. In Section IV, we conduct robustness tests. Section V summarizes and concludes.

I. Single Stock Futures and Testing Strategy

Single stock futures are contracts written for delivery of a particular stock of a certain quantity on a specific date. Although futures on stock indexes have been traded in the U.S., whether single stock futures were to be treated as stocks or futures created the unresolved conflict of jurisdictions between the Securities and Exchange Commission (SEC) and the Commodity Futures Trading Commission (CFTC). The Shad-Johnson accord, reached between these regulators in the early 80s, resulted in a moratorium prohibiting the sale of futures written on individual stocks and narrow based indices.

In the meantime, SSF have been offered by over a dozen exchanges around the world[3]. Some, such the Universal Stock Futures on LIFFE (London International Financial Futures Exchange), would even include U.S. stocks in their listings. Partly due to this reality and the threat to the dominance of U.S. exchanges, the Commodity Futures Modernization Act (CFMA) was signed in December 2000 and lifted the ban on SSF trading.

Several U.S exchanges had expressed interests after the passage of CFMA[4], however, only two alliances have managed to carry out the task of planning and establishing the new exchanges for single stock futures. They are: OneChicago, a joint venture of the Chicago Mercantile Exchange (CME), the Chicago Board of

[3] The list includes: Sydney, OM Stockholm, Hong Kong, South Africa, India, and London, etc.

[4] For instance, the American Stock Exchange and Island Trading were known of having had the intention to enter SSF market.

Option Exchange (CBOE) and the Chicago Board of Trade (CBOT), and NQLX, a joint venture between NASDAQ and LIFFE. On November 8, 2002, single stock futures commenced trading on OneChicago and NQLX. OneChicago listed 42 stocks, and NQLX listed 20 in November 2002. The list quickly increased to 81 on OneChicago and 37 on NQLX in the next month.

Like other derivatives, single stock futures could be constructed from using the underlying assets or other derivatives, e.g., options. Single stocks futures may justify its existence by having at least two advantages. First, it enables traders to short stocks at lower costs. Selling a stock short requires identifying and arranging a stock lender, incurring a carrying cost and the inconvenience of recall and replacement. By contrast, for the single stock futures, there is no limit on the quantity to short. The uptick rule in shorting stocks does not apply to single stock futures. In effect, single stock futures level the playing field between long and short traders. Second, the SSF traders only need to post 20% of the margin. The greater leverage in SSF allows investors to mitigate the capital constraint.

The traders' inability to construct short positions at low costs is a major contribution to market inefficiency. The availability of single stock futures enables traders to short more easily, thus should foster greater efficiency in the stock market. The traders can short what they perceived to be overvalued stocks, or short in reaction to negative information more promptly. On the other hand, lower transaction costs and greater leverage also facilitate "destabilizing" speculation.

There are two ways to test whether there is an increase in market efficiency. The first, which is the standard approach, is to test for a decrease in the stock's volatility. Studies of the impact of index futures on the volatility of the stock market are mixed. Edward (1988a, 1988b) and Bologna and Cavallo (2002) find a decrease in volatility, while an increase is reported in Antoniou and Holmes (1990). The majority of the studies find insignificant changes, for example, Becketti and Roberts (1990), Santoni (1987), Smith (1989), and Baldauf and Santoni (1991). One possible reason for these inconclusive results is that the standard volatility test may have low testing power. Facing implementation costs, arbitragers would choose to participate only if the perceived price deviation is large enough. Thus, the improvement in market efficiency might not be observed in days with smaller deviations. We believe that it would be more fruitful to concentrate on instances of large price changes, which is the basis for the second approach, i.e., our approach.

Our approach is analogous to "have the rooms been cleaned?" strategy. Guests can observe untidy rooms and infer that the rooms have not been cleaned, but they cannot tell whether a tidy room has been cleaned or had not been occupied the previous night. Nevertheless, one may still judge the improvement in the performance of the cleaning staff by observing a reduction in the number of untidy rooms. In days of no large price changes, it would be difficult to tell whether there is no price deviation or a potentially large price deviation is reduced or eliminated by successful arbitrage activities. Although the successful intervention by arbitragers is not directly observable, the change in the number of days with large returns is.

Concentrating on large price changes has one further advantage: it allows us to take a closer look at the news events surrounding the price changes to determine whether the price changes are supported by new information. We identify the presence or absence of news around large price changes, and generate a count of the instances of possibly inefficient prices. A nonparametric approach comparing the large stock returns, between the listed stocks and the match sample over the pre- and post-SSF periods, can provide a more powerful test for market efficiency.

II. Data Description

The data used in this study comes from several sources. The lists of single stock futures are made available by the two exchanges on their websites. The daily price, volume and open interest of SSF traded on OneChicago are collected from the website of OneChicago. The daily information on SSF traded on NQLX is provided by FutureSource.com. Daily stock information is from the CRSP database.

Table 1 lists the names of companies with single stock futures that began trading either in November or December 2002, on OneChicago or NQLX, and were still listed as of the end of December 2003. There are 84 in total. The list appears diverse, covering 23 two-digit SIC industries, however, there is considerable concentration, with only 4 industries accounting for 45 SSFs. The four 2-digit SIC codes and industries are: 28(Chemical and allied products), 35(Industrial machinery and equipment), 36(Electrical and electronic equipment), and 73(Business services). Since the exchanges select the listings to ensure the exchanges' successful opening, the listed firms are all very actively traded in the stock market (Ang and Cheng, 2004).

Insert Table I here

To control for the industry and size, we construct a match sample for the SSF firms. For any SSF firm, we find all the firms that are in the same industry (by 2-digit SIC codes) that were not listed on OneChicago or NQLX in November or December 2002. We then choose the firm whose market capitalization is closest to the SSF firm as the match firm. The market capitalization is measured as the number of shares outstanding multiplied by the stock price as of the month end preceding the listing month.

III. Analysis of Results

Panel A in Table II compares the number of days with large positive or negative returns for SSF firms and their matches over both pre- and post-SSF periods. Each period consists of 250 trading days before or after the initial listing date. There are two purposes for including match firms as benchmarks. One, there could be systematic difference in the number of information events before and after the SSF introduction. Comparing the SSF and the non-SSF firms during the same time period helps mitigate this effect. Two, there are cross sectional differences among SSF firms and this type of heterogeneity is reduced with a match sample.

Insert Table II here

If a stock's return on a particular day is higher than the market mean daily return plus 2.576 times the standard deviations of the market daily return, we say that the stock has a large positive return on that day. If a stock's return on a particular day is lower than the market mean daily return minus 2.576 times the standard deviations of the market daily return, we say that the stock has a large negative return on that day. That is, under normal distribution, there is only a one percent chance (or 2.5 times in 250 days) that the market portfolio return is a large positive or negative return. The mean and standard deviation of market daily return are calculated as the mean and standard deviation of the daily return of the value-weighted market portfolio (available on CRSP) during the 250 trading days before or after SSF introduction[5]. Note that we use the return distribution of the market portfolio to classify large stock returns. This enables us to control for market conditions during the same period. If we use a stock's own distribution, an endogenity problem arises: if there are many large price changes for a stock, the estimated parameters of the stock's return distribution, such as standard deviation, will be too high and in turn result in an undercount of the large price deviations.

[5] Although previous empirical studies indicate that stock returns have long tails and the number of large returns is expected to be greater than that under the normal distribution, there are two reasons why no ad hoc adjustment for long tail is necessary. First, the observed long tail may be the result of large price deviations that were not corrected by arbitrage. Since our purpose is to study how SSF may facilitate arbitrage, making ad hoc corrections for long tail would actually distort the empirical testing. Second, matching firms should capture cross sectional difference in large price changes.

In spite of our attempt to match non-SSF with SSF firms on size and industry, the non-SSF firms have fewer large returns than SSF firms. For example, SSF firms, on average, have 27.08 days of large positive returns before SSF introduction, while non-SSF firms have 17.49 days of large positive returns during the same time period. This is understandable, given the fact that SSF are selected on their ability to generate trades and thus the underlying stocks tend to be more volatile (Ang and Cheng, 2004). We find that the match firms experience a statistically significant increase of 0.82 days of large positive returns from before to after SSF introduction. By contrast, SSF firms experience a statistically significant decrease of –1.74 days over the same time period. SSF introduction also reduces the number of large negative stock returns. SSF firms experience a statistically significant reduction of –3.28 days, compared to an insignificant +0.64 day increase for non-SSF firms during the same period. These results are consistent with the conjecture that lower transaction costs and greater leverage of SSF help arbitragers reduce large price deviations.

A large price change could be explained if justified by new information (i.e., with news) or unexplained if not supported by news (i.e., without news). As shown above, SSF introduction reduces the number of large daily stock returns, and we further conjecture that the reduction is mainly due to the decrease in the number of unexplained price changes. We postulate that: *if SSF introduction facilitates greater efficiency in the stock market, there should be a statistically significant reduction in the number of large positive or negative returns in the "no news" category, but no* *reduction in the "with news" cases.* That is, informed investors and arbitragers could now use SSF to make opposite trades against noise trading and reduce unexplained price changes. However, SSF do not hinder normal price adjustments when there is indeed new information.

To identify whether the large price changes are supported by information, we employ a two-step procedure. We first search and obtain all the articles related to a particular company, as published in the *Wall Street Journal,* during the (-5 day, +5 day) event window, with the date of large price changes as day 0. Next, we read the articles to determine if any new information is reported. The examples of information include mergers and acquisitions, personnel changes, earnings surprises, dividend news, restructuring, etc. We go through the same procedure for both SSF and non-SSF firms. We classify the large returns as "with news" if new information is reported within the event window, otherwise they are classified as "without news".

Panel B in Table II summarizes the number of days with large returns, with or without news. We find that there is no change in the number of "with news" large positive returns, but there is a significant *decline* in the number of "without news" large positive returns, by -1.72 days on average. By contrast, for the match firms, there is no significant change in the number of days with large positive returns in the "with news" subset, instead, there is a significant *increase* in the "without news" sample, i.e., +1.06 days on average. Introduction of SSF does not affect the number of days with large negative returns associated with news, but it decreases the corresponding "without news" days. The mean change is –3.05 days although the median is 0. For the match firms, there is no significant change in either the "with news" or "without news" subsets in terms of days of large negative returns.

Having shown that SSF introduction improves market efficiency by reducing the number of large unexplained price changes, we then examine whether there is a direct connection between SSF trading volume and the decrease of unexplained price changes. We calculate the daily average trading volume of SSF within the 250-day period, in units of the number of contracts. We rank all SSF by their average trading volume and divide the sample into high (above median) and low (below median) volume subsets. Table III and Table IV report the results for the high and low SSF volume subsets respectively.

Insert Table III here

Insert Table IV here

We find that stocks with high SSF volume experience a greater decrease in large price changes. For example, the mean changes in days of large positive and negative returns are –2.83 and –5.26 respectively. Furthermore, the decrease is mainly from the subset with no news. For the matching sample, there is no evidence of reduction in large price changes. Stocks with low SSF volume show much weaker results. There is no statistically significant reduction in the number of days with positive or negative large price changes, with or without news.

The results in Table III and Table IV demonstrate a correlation between SSF trading volume and improvement in spot market efficiency. We further confirm the relationship by running a cross sectional multivariate regression. The dependent variable is the percentage change in the number of days with large returns from before to after SSF introduction. The independent variables include industry dummy variables, size or market capitalization of the firms, and the number of large returns in the pre-SSF period. The industry variable is to account for industry wide events. Due to the limited number of observations, we only use 1-digit SIC codes. Market capitalization can be important because larger firms may receive more press coverage and attract more traders. We include the number of large returns in the pre-SSF period as a variable to account for the possibility that stocks with a higher number of large returns in one period may have more room for reduction in the next period. Table V reports regressions for the change in the number of days with positive and negative large returns. The magnitude of decrease in the number of large returns is positively related to the number of large returns in the pre-SSF period and the market capitalization of the firm. Conditioning on size, industry and prior number of large returns, the volume of SSF trading has a significant impact on the reduction in large positive or negative returns. For example, holding everything else constant, the number of large negative returns will decrease by 0.15% from before to after SSF introduction, for every 1 contract increase in average daily SSF volume.

Insert Table V here

IV. Robustness check and Alternative Tests

As a robustness check, we investigate two alternative definitions of large returns. First, instead of the contemporaneous market distribution cutoffs used above, we use a fixed cutoff to classify large returns for both periods. In particular, we use -5% for large negative returns and +5% for large positive returns. Although variable cutoffs allow for changes in market conditions from one period to another, a fixed cutoff is straightforward and captures the period-independent portion of trading by arbitragers. Some impediments to arbitrage, such as fixed information and transaction costs, are better captured by a fixed percentage of price deviation. We choose the 5% threshold for the purpose of illustration. We also repeat the analysis at 3%, 4% and 6%, and obtain similar results.

As shown in Table VI, under the fixed cutoff, there are significantly fewer cases of large returns in the post-SSF period, for both SSF and match firms. The reason is that the stock market happens to be less volatile in the later period. For example, the standard deviation of market daily return is 0.015 during year 2002, and 0.010 during year 2003. However, we do find that the reductions in both large positive and negative returns among SSF firms are significantly greater than those in the match samples. Specifically, SSF firms have a reduction of –11.15 and –11.85 days for the number of large positive and negative returns respectively, while non-SSF firms only have a reduction of –5.12 and –6.12 days.

Insert Table VI here

The second robustness check is to remove the constraint that these large returns have to occur within one single day. Since there is a possibility that inefficient market prices may persist for more than one day, we examine large 2-day returns. The cutoff for this test is constructed in a similar fashion to the 1-day return cutoff, only using 2-day market returns. We replicate Tables II, III, IV and V, and draw the similar conclusion that SSF introduction improves spot market efficiency by reducing the number of unexplained large returns. These tables are not reported because of space constraints. Instead, we summarize the ratio of the number of 2-day large returns for a SSF firm to that of its match firm in Table VII. We also examine the subsets with SSF volume above median ("more actively traded SSF") and below median ("less actively traded SSF"). For the overall sample, there is a significant decrease in the ratio of the number of large returns from the pre-SSF to post-SSF period. Again, the decrease mainly comes from the subset with SSF volume above the median. The ratio decreases from 2.50 to 1.90 for the more actively traded SSF. However, the less actively traded SSF do not show a significant difference from before to after SSF introduction. In short, the 2-day results are consistent with the one-day analysis.

Insert Table VII here

As discussed earlier, the traditional measurement of improvement in market efficiency, i.e., volatility, will have low power. Nevertheless, as a standard approach, volatility is still of interest and may provide additional insight. In the rest of the paper, we conduct several tests using volatilities. The volatility for the SSF and match firms in the 250 trading days before and after SSF introduction are summarized in Table VIII. There is a significant decrease in volatility for SSF stocks, i.e., 32% on average. During the same time periods, the match firms also exhibit a decrease of volatility, 28% on average. The Kruskal-Wallis test shows that the decrease in the volatility of SSF firms, in both absolute value and percentage, is statistically significantly greater than that of non-SSF firms[8].

At first glance, the decrease in volatility of the match firms seems to contradict the result in Table II that the match firms' number of large returns increases in the post-SSF period. The reason is that our classification of "large returns" uses the distribution of the market portfolio as the benchmark. When there is a reduction in volatility for a stock, the number of its "large returns" can still increase as long as the market portfolio has an even greater reduction in volatility.

Insert Table VIII here

To examine the association between the change in stock volatility and the trading activity of SSF, we run a regression of post-SSF spot volatility controlling for industry, prior volatility and size. The dependent variable is the volatility (standard deviation of daily stock returns) in the 250 days after the listing. Table IX shows that the trading volume of SSF significantly reduces the post-SSF stock volatility, conditional on the prior volatility, industry and size. This result is consistent with the hypothesis that participants in the SSF market help to stabilize prices[6].

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8 The decrease in volatility is also reported in a study of Australian SSFs by Lee and Tong (1998).

6 We also estimate the conditional variance of SSF firms via the GARCH method. Since GARCH models the time dependent behavior of volatility over time, the approach may be appropriate to study the change in the components of variance between the before and after period. The unreported results show several significant changes in the behavior of the underlying GARCH parameters in the two

Insert Table IX here

V. Summary and Conclusions

This paper finds that market efficiency improves for stocks listed on SSF exchanges since the end of 2002. We use a news event approach to show that the number of unexplained large stock returns decreases for SSF firms, in comparison to the pre-SSF period, and to the match sample. The magnitude of reduction is positively related to the extent of trading activity in the single stock futures market.

We study the most recent financial innovation, SSF, adding to the literature on empirical studies of financial derivatives[7]. In our analysis of SSF, we provide evidence that financial innovations with lower trading costs can have a stabilizing effect. Our results are consistent with the hypothesis that single stock futures, with lower trading costs and a higher leverage, relieve the arbitragers more than attract the speculators. In addition, we show that examining large returns and identifying news events around these large price deviations could provide useful insight into the study of stock market efficiency.

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periods. We find the source of decrease in the variance, is not from a decrease in the fixed portion of variance (i.e. the intercept term), but from a significant decline in the way variance process is updated. Variances of SSF firms are less dependent on old news, as well as respond less to recent news.

[7] See Frame and White (2004).

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Table I
Industry distribution of the 84 SSF by the end of December, 2003

These 84 SSFs have been started trading in November or December, 2002, on OneChicago or NQLX.

2-digit SIC code	COUNT	Industry (Source: U.S. Census Bureau)	Short Names of the Companies
13	3	Oil and Gas Extraction	Halliburton; Newmont Mining; Schlumberger
20	2	Food and Kindred Products	Coca-Cola; PepsiCo
21	1	Tobacco Manufactures	Altria Group
26	2	Paper and Allied Products	International Paper; 3M
28	11	Chemicals and Allied Products	Amgen; Biogen; Biogen Idec; Bristol-Myers Squibb; Cephalon; DuPont; Genzyme; Johnson & Johnson; Merck; Pfizer; Procter & Gamble
29	2	Petroleum and Coal Products	ChevronTexaco; Exxon Mobil
33	2	Primary Metal Industries	Alcoa; Novellus Systems
35	10	Industrial Machinery and Equipment	Apple; Applied Materials; Brocade Communications Systems; Caterpillar; Dell; Emulex; Hewlett-Packard; International Business Machines; Micron Technology; SanDisk
36	13	Electrical and Electronic Equipment	Altera; Broadcom Corp; Cisco Systems; General Electric; Intel; Linear Technology; Motorola; Maxim Integrated Products; NVIDIA; QUALCOMM; Qlogic; Texas Instruments; Xilinx
37	6	Transportation Equipment	Boeing; Ford Motor; General Motors; Honeywell International; Northrop Grumman; United Technologies
38	2	Instruments and Related Products	Eastman Kodak; KLA-Tencor
48	3	Communications	SBC Communications; AT&T; Verizon Communications
52	1	Building Materials, Hardware, Garden Supply, & Mobile	Home Depot
53	1	General Merchandise Stores	Wal-Mart Stores
57	1	Furniture, Home Furnishing and Equipment Stores	Best Buy
58	3	Eating and Drinking Places	Krispy Kreme Doughnuts; McDonald's; Starbucks
60	3	Depository Institutions	Bank of America; Citigroup; J.P. Morgan Chase
61	1	Nondepository Credit Institutions	American Express
62	3	Security, Commodity Brokers, and Services	Goldman Sachs Group; Merrill Lynch; Morgan Stanley
63	1	Insurance Carriers	American International Group
67	1	Holding and Other Investment Offices	Bank One
73	11	Business Services	AOL-Time Warner; Check Point Software Tech; eBay; Microsoft; Oracle; PeopleSoft; Siebel Systems; Symantec; Tyco International; VERITAS Software; Yahoo!
79	1	Amusement and Recreational Services	Walt Disney
All	84		

Table II
Occurrence of large daily returns for SSF-firms and their match firms

A stock's daily return is large positive if it is higher than the market mean daily return plus 2.576 times standard deviation of market daily return. A stock's daily return is large negative if it is lower than the market mean daily return minus 2.576 times standard deviation of market daily return. The market mean and standard deviation are measured within the 250 trading days before or after SSF introduction. "2.576" is used because it is the cutoff point for *p* value no greater than 0.01, under normal distribution. Panel A examines the number of days with large returns, and Panel B identifies whether there are news within the 10-day window around the large returns. t-test and rank test are used to examine whether the mean and the median are significantly different from zero.

Panel A: The number of days with large positive/negative returns

		Pre-SSF Mean (Median)	Post-SSF Mean (Median)	Post minus Pre Mean (Median)
	Number of observations	84	84	84
Number of days with large positive returns	SSF firms	27.08 (22.50)	25.34 (21.00)	-1.74* (-2.50)*
	Match firms	17.49 (13.00)	18.31 (13.50)	0.82*** (1.50)***
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	18.457 (<0.0001)	10.853 (0.001)	11.33 (0.0008)
Number of days with large negative returns	SSF firms	25.54 (19.50)	22.26 (19.00)	-3.28** (-0.50)
	Match firms	16.15 (10.00)	16.79 (14.00)	0.64 (1.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	14.222 (0.0002)	8.751 (0.003)	4.43 (0.04)

***, **, *: significant at 1%, 5% and 10% respectively.

Table II continued

Panel B: The number of days with large returns, with or without news

		Pre-SSF Mean (Median)	Post-SSF Mean (Median)	Post minus Pre Mean (Median)
	Number of observations	84	84	84
Number of days with large positive returns and with news	SSF firms	4.58 (3.00)	4.57 (3.00)	-0.01 (0.00)
	Match firms	2.56 (1.00)	2.32 (1.00)	-0.24 (0.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	13.50 (0.0002)	7.68 (0.0056)	0.35 (0.55)
Number of days with large positive returns and with *no* news	SSF firms	22.50 (18.50)	20.77 (17.00)	-1.72* (-2.00)*
	Match firms	14.92 (11.00)	15.99 (12.50)	1.06** (1.00)***
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	12.11 (0.0005)	7.01 (0.008)	9.64 (0.002)
Number of days with large negative returns and with news	SSF firms	4.85 (3.00)	4.62 (3.00)	-0.22 (0.00)
	Match firms	2.23 (0.00)	2.11 (0.00)	-0.12 (0.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	9.33 (0.002)	6.13 (0.01)	0.01 (0.93)
Number of days with large negative returns and with no news	SSF firms	20.69 (15.50)	17.64 (15.00)	-3.05** (0.00)
	Match firms	13.92 (9.00)	14.68 (11.50)	0.76 (1.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	8.89 (0.003)	6.39 (0.01)	3.81 (0.05)

***, **, *: significant at 1%, 5% and 10% respectively.

Table III
Occurrence of large daily returns for subsets with SSF average daily trading volume above median

This table examines the number of large daily returns for subsets with SSF average trading volume above median. SSF trading volume is the daily average within the 250 trading days after being listed. A stock's daily return is large positive if it is higher than the market mean daily return plus 2.576 times standard deviation of market daily return. A stock's daily return is large negative if it is lower than the market mean daily return minus 2.576 times standard deviation of market daily return. The market mean and standard deviation are measured within the 250 trading days before or after SSF introduction. "2.576" is used because that is the cutoff point for *p* value no greater than 0.01, under normal distribution. Panel A examines the number of days with large returns, and Panel B identifies whether there are news within the 10-day window around the large returns. t-test and rank test are used to examine whether the mean and the median are significantly different from zero.

Panel A: The number of days with large positive/negative returns

		Pre-SSF Mean (Median)	Post-SSF Mean (Median)	Post minus Pre Mean (Median)
	Number of observations	42	42	42
Number of days with large positive returns	SSF firms	29.83 (27.00)	27.00 (25.00)	-2.83* (-3.00)**
	Match firms	18.55 (13.00)	19.14 (14.00)	0.59 (1.50)*
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	10.796 (0.001)	5.090 (0.024)	7.808 (0.005)
Number of days with large negative returns	SSF firms	28.24 (25.00)	22.98 (24.50)	-5.26*** (-3.00)***
	Match firms	17.52 (10.00)	17.38 (14.00)	-0.14 (0.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	9.462 (0.002)	4.578 (0.032)	7.552 (0.006)

***, **, *: significant at 1%, 5% and 10% respectively.

Table III continued
Panel B: The number of days with large returns, with or without news

		Pre-SSF Mean (Median)	Post-SSF Mean (Median)	Post minus Pre Mean (Median)
	Number of observations	42	42	42
Number of days with positive extremes and with news	SSF firms	5.94 (4.00)	5.97 (4.00)	0.03 (0.00)
	Match firms	2.55 (0.00)	1.87 (0.00)	-0.68 (0.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	13.41 (0.0003)	9.181 (0.002)	0.42 (0.52)
Number of days with positive extremes and with *no* news	SSF firms	23.89 (21.00)	21.03 (19.00)	-2.86* (-3.00)**
	Match firms	16.00 (12.50)	17.27 (13.50)	1.27* (1.50)*
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	3.83 (0.05)	0.51 (0.48)	8.73 (0.003)
Number of days with negative extremes and with news	SSF firms	6.15 (4.00)	5.99 (4.00)	-0.16 (0.00)
	Match firms	2.79 (0.00)	2.17 (0.00)	-0.62 (0.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	8.735 (0.003)	12.336 (0.0004)	0.01 (0.93)
Number of days with negative extremes and with no news	SSF firms	22.08 (20.00)	16.99 (17.00)	-5.10*** (-2.00)*
	Match firms	14.73 (10.00)	15.21 (13.00)	0.48 (0.50)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	4.08 (0.04)	0.25 (0.62)	6.92 (0.01)

***, **, *: significant at 1%, 5% and 10% respectively.

Table IV

Occurrence of extreme daily returns for subsets with SSF average trading volume below median

This table examines the number of large daily returns for subsets with SSF average trading volume below median. SSF trading volume is the daily average within the 250 trading days after being listed. A stock's daily return is large positive if it is higher than the market mean daily return plus 2.576 times standard deviation of market daily return. A stock's daily return is large negative if it is lower than the market mean daily return minus 2.576 times standard deviation of market daily return. The market mean and standard deviation are measured within the 250 trading days before or after SSF introduction. "2.576" is used because that is the cutoff point for p value no greater than 0.01, under normal distribution. Panel A examines the number of days with large returns, and Panel B identifies whether there are news within the 10-day window around the large returns. t-test and rank test are used to examine whether the mean and the median are significantly different from zero.

Panel A: The number of days with large positive/negative returns

		Pre-SSF Mean (Median)	Post-SSF Mean (Median)	Post minus Pre Mean (Median)
	Number of observations	42	42	42
Number of days with large positive returns	SSF firms	24.33 (19.00)	23.69 (20.00)	-0.64 (0.00)
	Match firms	16.43 (12.50)	17.48 (13.50)	1.05* (2.00)**
	K-W test of the difference between SSF firms and matches: Chi-squared (p value)	8.184 (0.004)	6.287 (0.012)	3.736 (0.053)
Number of days with large negative returns	SSF firms	22.83 (18.00)	21.55 (18.00)	-1.28 (1.00)
	Match firms	14.79 (10.00)	16.19 (14.50)	1.40 (0.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (p value)	6.196 (0.013)	4.675 (0.031)	0.011 (0.916)

***, **, *: significant at 1%, 5% and 10% respectively.

Table IV continued

Panel B: The number of days with large returns, with or without news

		Pre-SSF Mean (Median)	Post-SSF Mean (Median)	Post minus Pre Mean (Median)
	Number of observations	42	42	42
Number of days with large positive returns and with news	SSF firms	3.22 (3.00)	3.17 (3.00)	-0.05 (0.00)
	Match firms	2.58 (1.00)	2.77 (1.00)	0.19 (0.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	6.099 (0.014)	4.814 (0.028)	0.038 (0.845)
Number of days with large positive returns and with *no* news	SSF firms	21.11 (15.00)	20.52 (16.00)	-0.59 (1.00)
	Match firms	13.85 (10.50)	14.71 (12.00)	0.86* (1.00)**
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	5.845 (0.016)	3.026 (0.082)	1.756 (0.185)
Number of days with large negative returns and with news	SSF firms	3.53 (3.00)	3.26 (3.00)	-0.26 (0.00)
	Match firms	1.67 (0.50)	2.05 (1.00)	0.38 (0.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	5.136 (0.023)	3.121 (0.077)	0.003 (0.960)
Number of days with large negative returns and with no news	SSF firms	19.30 (14.00)	18.29 (14.00)	-1.01 (1.00)
	Match firms	13.12 (9.00)	14.14 (11.00)	1.02 (1.00)
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	3.806 (0.051)	2.719 (0.099)	0.022 (0.883)

***, **, *: significant at 1%, 5% and 10% respectively.

Table V
Regression of percentage change in number of large returns onto the SSF volumes and other factors

This table regresses percentage change in number of large returns from pre-SSF to post-SSF period onto number of large returns in the pre-SSF period, industry, market capitalization and SSF average daily volume. The numbers in the parenthesis are the t-statistics. A stock's daily return is large positive if it is higher than the market mean daily return plus 2.576 times standard deviation of market daily return. A stock's daily return is large negative if it is lower than the market mean daily return minus 2.576 times standard deviation of market daily return.

Coefficient (t-stat)	% change in number of large positive returns from pre-SSF to post-SSF period (%)	% change in number of large negative returns from pre-SSF to post-SSF period (%)
Number of large returns in the pre-SSF period	-0.53**	-1.90***
	(-2.02)	(-3.16)
Average of daily SSF contracts in the 250 days after the listing (number of contracts)	-0.11**	-0.15***
	(-2.36)	(-3.29)
1-digit SIC code is 2	13.52	20.12
	(0.71)	(1.25)
1-digit SIC code is 3	22.43	47.15**
	(1.31)	(2.19)
1-digit SIC code is 4	23.67	69.73*
	(1.25)	(1.94)
1-digit SIC code is 5	65.33**	46.74*
	(2.19)	(1.88)
1-digit SIC code is 6	2.55	13.97
	(0.13)	(0.80)
1-digit SIC code is 7	9.26	28.23
	(0.53)	(1.54)
Market capitalization ($ million)	-0.00015**	-0.00028***
	(-2.21)	(-2.77)
Intercept	8.82	43.87**
	(0.48)	(2.39)
Number of observations	83 ^	83 ^
R-squared	0.3281	0.3657
F-stat	2.29	4.20
Prob>F	0.0252	0.0002

***, **, *: Significant at 1%, 5% and 10% respectively.

^ : Excluding one outlier.

Table VI
Occurrence of large daily returns for SSF-firms and their match firms using +5% and –5% as the cutoffs

A stock's daily return is large positive if it is higher than 5%. A stock's daily return is large negative if it is lower than –5%. t-test and rank test are used to examine whether the mean and the median are significantly different from zero.

		Pre-SSF Mean (Median)	Post-SSF Mean (Median)	Post minus Pre Mean (Median)
Number of observations		84	84	84
Number of days with large positive returns	SSF firms	17.64 (13.00)	6.49 (4.00)	-11.15*** (-10.00)***
	Match firms	9.14 (5.00)	4.02 (2.00)	-5.12*** (-3.50)***
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	23.05 (<0.0001)	7.93 (0.0049)	24.31 (<0.0001)
Number of days with large negative returns	SSF firms	16.01 (10.00)	4.17 (3.00)	-11.85*** (-8.00)***
	Match firms	8.65 (5.00)	2.54 (1.00)	-6.12*** (-4.00)***
	K-W test of the difference between SSF firms and matches: Chi-squared (*p* value)	15.05 (0.0001)	9.17 (0.0025)	14.21 (0.0002)

***: significant at 1% level.

Table VII

Comparison of two-day large returns between SSF and non-SSF firms

The table reports the ratio of the number of large 2-day returns of the SSF firm to that of its match in both pre-SSF and post-SSF periods. A stock's 2-day return is large positive if it is higher than the market mean 2-day return plus 2.576 * standard deviation of market 2-day return. A stock's 2-day return is large negative if it is lower than the market mean 2-day return minus 2.576 * standard deviation of market 2-day return. The market mean and standard deviation are measured using the 125 2-day intervals before or after SSF introduction. The Kruskal-Wallis test examines whether there is significant difference between pre- and post-SSF periods. We rank all the SSF-firms by their daily average volumes within the 250 trading days after being listed. If a stock's SSF volume is above the median, we call it "more actively traded SSF"; otherwise we call it "less actively traded SSF".

All Firms	Ratio of number of large 2-day returns for a SSF firm to that of its match in the pre-SSF period Mean (Median)	Ratio of number of large 2-day returns for a SSF firm to that of its match in the post-SSF period Mean (Median)	Kruskal-Wallis test Chi-squared (p value)
All Firms			
Large positive returns	2.36	2.12	3.89
	(1.71)	(1.44)	(0.05)
Large negative returns	2.81	2.17	4.27
	(2.11)	(1.31)	(0.04)
More actively traded SSF			
Large positive returns	2.50	1.90	3.45
	(1.90)	(1.46)	(0.07)
Large negative returns	2.69	1.91	3.06
	(2.16)	(1.19)	(0.08)
Less actively traded SSF			
Large positive returns	2.22	2.35	0.42
	(1.63)	(1.44)	(0.51)
Large negative returns	2.94	2.45	1.30
	(2.00)	(1.33)	(0.25)

Table VIII
Volatility of SSF firms and their match firms

Volatility is measured as the standard deviation of daily stock returns over 250-trading days before or after SSF listing. The Kruskal-Wallis test examines whether there is a significant difference between SSF firms and match firms. t-test and rank test are used to examine whether the mean and the median are significantly different from zero.

	Number of observations	Volatility over 250 trading days prior to the listing Mean (Median)	Volatility over 250 trading days after the listing Mean (Median)	Difference in volatility Mean (Median)	Ratio of post volatility/prior volatility –1 Mean (Median)
SSF firms	84	0.0340 (0.0295)	0.0226 (0.0216)	-0.0115*** (-0.0097)***	-0.32*** (-0.33)***
Matches	84	0.0270 (0.0237)	0.0191 (0.0176)	-0.008*** (-0.006)***	-0.28*** (-0.29)***
Kruskal-Wallis Test		18.016 (<0.0001)	12.444 (0.0004)	15.548 (<0.0001)	7.495 (0.006)

***, **, *: significant at 1%, 5% and 10% respectively.

Table IX
The stock return volatility and SSF average daily volume

This table regresses the volatility in the 250 days after the SSF listing onto the volatility in the 250 days before the listing, industry, market capitalization and SSF volume. The numbers in the parenthesis are the t-statistics.

Coefficient (t-stat)	Volatility (standard deviation of daily stock returns) in the 250 days after the listing
Volatility (standard deviation of daily stock returns) in the 250 days prior to the listing	0.45*** (6.76)
Average of daily SSF contracts in the 250 days after the listing (number of contracts)	-0.00002** (-2.27)
1-digit SIC code is 2	0.0031 (1.02)
1-digit SIC code is 3	0.0061** (1.98)
1-digit SIC code is 4	0.0087** (2.60)
1-digit SIC code is 5	0.0062** (2.07)
1-digit SIC code is 6	0.0032 (1.05)
1-digit SIC code is 7	0.0031 (0.96)
Market capitalization ($ million)	$-1.56\text{x}10^{-8}$*** (-2.78)
Intercept	0.0046 (1.28)
Number of observations	83^
R-squared	0.8147
F	35.45
Prob>F	0.0000

***, **, *: significant at 1%, 5% and 10% respectively.
^: Excluding one outlier.