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

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*Does financial innovation improve market efficiency? Innovations that facilitate arbitrage are good examples. We use the stocks listed on the newly established single stock futures (SSF) exchanges to introduce a new approach to test for market efficiency. The measure is based on the reduction in the number of excessive unexplained price changes. The evidence is that SSF trading increases market efficiency. After identifying new information associated with large price changes, we show there are fewer unexplained large stock returns for SSF firms than in the pre-listing period, and than in a matched non-SSF sample. The decline is positively related to the extent of trading activity in the single stock futures market. [*G13, G14*]*

■There is a long-standing debate in the economic literature as to the benefits of financial innovations. On one side, there are those who believe that financial innovations have a destabilizing impact on the spot market; speculators can use financial innovations to manipulate asset prices, causing price distortion and increased volatility. Others take the opposite view that financial innovations are beneficial, as they enable arbitrageurs to participate more actively and thus cause prices to converge to fair value more quickly.[1] This is not a trivial question. It addresses whether new financial products, including derivatives, are justified. Whether innovations are more likely to generate destabilizing trades or stabilizing trades is an issue to be settled with empirical data.

On November 8, 2002, after a ban of than two decades, single stock futures (SSF) began trading in the US on two new exchanges, OneChicago and NQLX. In an SSF contract, a buyer commits to buy or a seller to sell a particular stock at a pre-specified price on a pre-specified future date. An SSF has two main advantages over the trading of stocks or a combination of stocks and current derivatives.

First, it reduces, if not eliminates, the short-selling constraints facing traders who want 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 that it affords investors greater leverage because futures contracts require less capital. The margin requirement is low in single stock futures (generally 20%).

Both these features are important to arbitrageurs as well as speculators. Arbitrageurs need to short stocks, and foreclosure of effective short sales has been blamed for market inefficiency, such as, too many large price deviations from fair values.[2] On the other hand, securities that reduce transaction costs 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.

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

[2]The costs of arbitrage, for example, are discussed in Merton (1987), Shleifer and Vishny (1990), and Campbell and Kyle (1993).

We examine the newly established market for single stock futures to provide an empirical test of whether SSF enable greater market efficiency. Our empirical procedure to compare the number of unexplained large price changes is based on two logical ideas. First, given positive transaction and information costs, arbitrageurs are more motivated to enter a market when there may be substantial price deviation and thus expected gain is large. Second, both the formal statement of market efficiency (that market prices reflect all relevant information) and its flip side (that market prices do not change in the absence of information) must be true. We find significantly fewer 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 than in a match sample and than in 250-day pre-listing period. When we look at news around the dates of large returns, we find that the reduction in changes lies mainly in the no-news sample, i.e., futures for which no news explains the price changes. SSF introduction, on the whole, improves spot market efficiency.

In a robustness check, we also conduct standard tests using volatility. The SSF firms have a greater reduction in volatility than the matched firms, and SSF trading volume is positively related to the reduction in volatility.

We see our work as making several contributions to the literature. First, we add empirical evidence to the debate on whether derivatives facilitate speculation or help achieve greater market efficiency. Second, we are among the first to study the newly established market for the single stock futures. In Ang and Cheng (2005), we focus on how OneChicago and NQLX select the futures contracts for listing. Single stock futures allow traders to focus on a particular stock, and provide a better laboratory to test for the impact of futures contracts on underlying stocks. Third, we propose a new framework for studying market efficiency. We take into account the costs of trading by arbitrageurs, and expect that they will concentrate on large price deviations.

I. Single Stock Futures and Empirical 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 US, whether single stock futures were to be treated as stocks or futures once created an unresolved conflict of jurisdiction 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 1980s, resulted in a moratorium prohibiting the sale of futures written on individual stocks and narrowly based indices.

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

Several US exchanges expressed interest after the passage of CFMA,[4] but only two alliances have managed to establish a new exchange for single stock futures. They are OneChicago, a joint venture of the Chicago Mercantile Exchange (CME), the Chicago Board of Option Exchange (CBOE), and the Chicago Board Trade (CBOT), and NQLX, a joint venture of 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.

Although single stock futures could be constructed by using the underlying assets or other currently available derivatives, their existence may be justified by their having at least two advantages. First, they enable traders to short stocks at lower costs. Selling a stock short requires identifying and arranging a stock lender and incurring a carrying cost and the inconvenience of recall and replacement. 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, SSF traders need to post only 20% of margin. The greater leverage in SSF allows investors to mitigate their capital constraints.

The inability of traders to construct short positions at low cost has been long seen as a major cause of market inefficiency. The availability of single stock futures is hypothesized to foster greater efficiency in the stock market. Traders can short what they perceive to be overvalued stocks more easily, or in reaction to negative information more promptly. The alternative hypothesis is that lower transaction costs and greater leverage facilitate destabilizing speculation.

There are two ways to test whether market efficiency improves after the introduction of a financial

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

[4]The American Stock Exchange and Island Trading were known to have an intention to enter the SSF market.

innovation. The first, which is the standard approach, is to test for a deduction in a stock's volatility. This is based on the idea that prices in an inefficient market would be too volatile.

Results of studies of the impact of index futures introduction on the volatility of the stock market are mixed. Edwards (1988a, 1988b) and Bologna and Cavallo (2002) find a reduction in volatility, while Antoniou and Holmes (1990) report an increase. Most authors find insignificant changes, including Santoni (1987), Smith (1989), Becketti and Roberts (1990), 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, arbitrageurs would enter the market only if perceived price deviations are great enough. Thus, improvements in market efficiency might not be observed on days with smaller deviations. Furthermore, arbitrage against an index, which is a portfolio of many stocks, could entail rather high implementation costs. We believe that it is more fruitful to concentrate on instances of large price changes, which is the basis for our approach.

The idea is analogous to the "have the rooms been cleaned?" question. 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 fewer untidy rooms. On days of no large price changes, it would be difficult to tell whether there is no price deviation or whether a potentially large price deviation has been eliminated by successful arbitrage activities. Although interventions by arbitrageurs are not directly observable, a change in the number of days with large returns is.

Concentrating on large price changes has one additional advantage: it allows us to take a closer look at news events surrounding price changes to determine whether the price changes are supported by new information. That is, we should identity the causes of, or the absence of large price changes instead of just relying on summary statistics.

We first identify the presence or absence of news around large price changes, to generate a count of possibly inefficient prices. A nonparametric approach comparing the number of unexplained large stock returns in the listed stocks and the match sample over pre- and post-listing periods should provide a more direct and powerful test of market efficiency.

II. Data Description

The data used in this study come 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. FutureSource.com provides the daily information on SSF traded on NQLX. Daily stock information is from the CRSP database.

Exhibit 1 lists the names of companies with single stock futures that began trading either in November or December 2002, on OneChicago or NQLX, and that were still listed as of the end of December 2003. There are 84 in total. Although there were 81 SSF on OneChicago and 37 on NQLX by December 2002, a significant number of these futures on the two exchanges are written on the same stocks. The list appears diverse, covering 23 industries according to two-digit SIC codes, but there is considerable concentration, with only four industries accounting for 45 SSFs. The four two-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, 2005).

To control for industry and size, we construct a matching sample for the SSF firms. For any SSF firm, we find all the firms that are in the same industry (based on two-digit SIC codes) but 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 of Exhibit 2 compares the number of days with large positive or negative returns for SSF firms and their matches over both the pre- and post-listing periods. Each period consists of 250 trading days before or after the initial listing date.

There are two reasons to include matched firms as benchmarks. One, there could be systematic differences in the number of information events, market, and industry-related, 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 matched sample.

If a stock's return on a particular day is higher than the market mean daily return plus 2.576 times the

Exhibit 1. Industry Distribution of 84 SSFs by End of December 2003

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

Two-Digit SIC Code	Count	Industry, Source: US 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		

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 a normal distribution, there is only a 1% chance (or 2.5 times in 250 days) that the market portfolio

Exhibit 2. Occurrence of Large Daily Returns for SSF-firms and Matched 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 number of days with large returns, and Panel B identifies whether there is news within a 10-day window around the large returns. t-tests and sign tests are used to examine whether the means and the medians are significantly different from zero.

Panel A. The Number of Days with Large Positive/Negative Returns

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

Panel B. Number of Days with Large Returns 'with versus without News'

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

***Significant at the 0.01% level.
**Significant at the 0.05% level.
*Significant at the 0.10% level.

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 the SSF introduction.[5]

Note that we use the return distribution of the market portfolio to identify large stock returns. This enables us to control for market conditions during a certain time period. If we use a stock's own distribution, we risk an endogeneity problem; 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 which could cause us to undercount the large price deviations.

Even though we attempt to match non-SSF and SSF firms on size and industry, we find 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, 2005).

We find that the matched firms experience a significant increase of 0.82 days of large positive returns from the period before to the period after SSF introduction. The SSF firms experience a significant reduction of –1.74 days over the same time period. SSF introduction also reduces the number of large negative stock returns. SSF firms experience a significant reduction of –3.28 day in large negative returns, compared to an insignificant +0.64 day increase for non-SSF firms during the same period. These results are consistent with the hypothesis that lower transaction costs and greater leverage of SSF help arbitrageurs reduce large price deviations.

A large price change could be explained if it is justified by new information (i.e., with news) or unexplained if not supported by news (i.e., no news). We conjecture that the reduction in number of large daily stock returns for SSF firms is mainly due to fewer unexplained price changes. We postulate that:

If SSF introduction facilitates 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 arbitrageurs could now use SSF to make opposite trades against noise trading and reduce unexplained price changes. The presence of SSF should not hinder normal price adjustments when there is indeed new information, however.

To identify whether the large price changes are supported by information, we use a two-step procedure. We first search for all the articles related to a particular company, as published in the *Wall Street Journal,* during a (-5 day, +5 day) event window, where the date of a large price change is day 0. Next, we read the articles to determine, e.g., whether any new information is reported. Examples of information include merger announcements, personnel changes, earnings surprises, dividend news, or restructuring plans.

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, and otherwise as "no news".

Panel B of Exhibit 2 summarizes the number of days with large returns, with or without news. For the SSF firms, 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. For the matched 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, by +1.06 days on average.

Introduction of SSF does not affect the number of days with large negative returns associated with news, but it reduces the corresponding "without news" days. The mean change is –3.05 days, although the median is 0. For the matched firms, there is no significant change in either the "with news" or "without news" subsets in terms of days of large negative returns.

We next examine whether there is a direct connection between SSF trading volume and the decline in unexplained price changes. We calculate the daily average trading volume of SSF within the 250-day post-listing 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.

Exhibit 3 and Exhibit 4 report the results for the high and the low SSF volume subsets respectively.

Stocks with high SSF volume experience a greater reduction in the number of large price changes. For example, the changes in the number of days with large positive and negative returns between the two periods are –2.83 and –5.26 respectively (Exhibit 3, Panel A). Furthermore, the effect occurs predominantly in the

[5]Although other empirical studies indicate that stock returns have long tails and there should be more large returns than under the normal distribution, there are two reasons why no ad hoc adjustment for long tails 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 tails would actually distort the empirical testing. Second, matching the firms should correct for cross- sectional differences in large price changes.

Exhibit 3. Occurrence of Large Daily Returns for Subset with SSF Average Daily 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 number of days with large returns, and Panel B identifies whether there is news within a 10-day window around the large returns. t-tests and sign tests are used to examine whether the means and the medians are significantly different from zero.

Panel A. Number of Days with Large Positive or Negative Returns

		Pre-listing Mean (Median)	Post-listing 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)	5.09 (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	9.462	4.578	7.552

***Significant at the 0.01% level.
**Significant at the 0.05% level.
*Significant at the 0.10% level.

subset with no news (Exhibit 3, Panel B). For the matched sample, there is no evidence of reduction in the number of 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 Exhibit 3 and 4 demonstrate a correlation between SSF trading volume and improved spot market efficiency. We confirm the relationship by estimating an ordinary least squares model of change in the number of days with large returns. 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-listing period.

The industry variable is included to account for industry- wide events. Due to the limited number of observations, we only use one-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-listing period to account for the possibility that stocks with more large returns in one period would allow more room for reduction in the next period.

Exhibit 5 reports the estimated coefficients and statistics from the linear regressions. The degree of decline in the number of large returns is positively related to the number of large returns in the pre-listing period and the market capitalization of the firm. Conditioning on size, industry, and previous number of large returns, the SSF trading volume has a significant impact on reducing the number of large positive or negative returns. Holding all else constant,

Exhibit 3. Occurrence of Large Daily Returns for Subset with SSF Average Daily Trading Volume Above Median (*Continued*)

Panel B. Number of Days with Large Returns, with or with No News

		Pre-listing Mean (Median)	Post-listing 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	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 large positive returns 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 large negative returns 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 large negative returns 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 the 0.01% level.
**Significant at the 0.05% level.
*Significant at the 0.10% level.

the number of large negative returns would fall by 0.15% from before to after SSF introduction for every single contract increase in average daily SSF volume.

IV. Robustness Check and Alternative Tests

In a robustness check, we investigate two alternative definitions of large returns. The first is use a fixed cutoff of -5% for large negative returns and +5% for large positive returns, to classify large returns for both periods instead of the contemporaneous market distribution cutoffs used above. Although variable cutoffs allow for changes in market conditions from one period to another, a straightforward fixed cutoff captures the period-independent portion of trading by arbitrageurs. Some impediments to arbitrage, such as fixed information and transaction costs, are captured by a fixed percentage of price deviations

Exhibit 6 presents estimation results for an OLS model of the number of large returns during the post-listing period. The dependent variable here is the number of large returns during the post-listing period, instead of the percentage change in the number of large returns from the pre- to the post-listing period. The reason is that, under the 5% cutoff, a handful of observations have zero days of large returns during

Exhibit 4. Occurrence of Large Daily Returns for Subset with SSF Average Trading Volume Below Median

This table examines the number of large daily returns for the subset 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 number of days with large returns, and Panel B identifies whether there is news within a 10-day window around the large returns. t-tests and sign tests are used to examine whether the means and the medians are significantly different from zero.

Panel A. Number of Days with Large Positive/Negative Returns

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

Panel B. Number of Days with Large Returns, with or without News

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

***Significant at the 0.01% level.
**Significant at the 0.05% level.
*Significant at the 0.10% level.

Exhibit 5. Percentage Change in Number of Large Returns and SSF Trading Volume

This table estimates percentage change in the number of large returns from pre-listing to post-listing as a function of the number of large returns in the pre-listing period, industry, market capitalization, and SSF average daily volume, using ordinary least squares. 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. t-statistics are in parentheses.

Coefficient (t-stat)	% change in number of large positive returns from pre-listing to post-listing period (%)	% change in number of large negative returns from pre-listing to post-listing period (%)
Number of large returns in the pre-listing 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 $^{\xi}$	83 $^{\xi}$
R-squared	0.3281	0.3657
F-stat	2.29	4.20
Prob>F	0.0252	0.0002

***Significant at the 0.01% level.
**Significant at the 0.05% level.
*Significant at the 0.10% level.

ξ : Excluding one outlier.

pre-listing period. The independent variables are industry, size, number of large returns during the pre-listing period, and average SSF daily trading volume.

Under a fixed cutoff of 5%, holding all else constant, a higher daily SSF trading volume results in fewer large returns during the post-listing period. This result holds for both positive and negative returns. For example, for every one contact increase in daily SSF volume, the number of days with large negative returns on average declines by 0.03, significant at the 5% level. Repeating the analysis at 3%, 4%, and 6% values produces similar results.

The second robustness check is to eliminate the constraint that large returns have to occur within a single day. Inefficient market prices may persist for more than one day, we so examine large two-day returns. The cutoffs for this test are constructed in a similar fashion to our original one-day return cutoffs, but using a distribution of two-day market returns.

Replication of the analysis in Exhibit 2, 3, 4, and 5 supports the conclusion that SSF introduction improves spot market efficiency by reducing the number of unexplained large returns (tables not reported for space reasons). Exhibit 7 summarizes the ratio of the number of two-day large returns for SSF firms to their matched firms. 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, the ratio of the number of large returns declines significantly from the pre- to the post-listing period, mainly because of the subset with above median SSF volume. The ratio drops from 2.50

Exhibit 6. Number of Large Returns Based on Fixed Cutoffs and SSF Trading Volume

This table estimates number of large returns during the post-listing period as a function of the number of large returns in the pre-listing period, industry, market capitalization, and SSF average daily volume, using ordinary least squares. 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-statistics are in parentheses.

Coefficient (t-stat)	Number of large positive returns during post-listing period	Number of large negative returns during post-listing period
Number of large returns in the pre-listing period	0.39*** (10.85)	0.27*** (8.32)
Average of daily SSF contracts in the 250 days after the listing (number of contracts)	-0.02** (-1.98)	-0.03** (-2.07)
1-digit SIC code is 2	4.30** (2.19)	1.96* (1.72)
1-digit SIC code is 3	4.81** (2.40)	2.74*** (2.72)
1-digit SIC code is 4	5.40*** (2.61)	2.88* (1.89)
1-digit SIC code is 5	5.69** (2.32)	2.72*** (3.01)
1-digit SIC code is 6	3.08 (1.54)	1.01 (0.99)
1-digit SIC code is 7	4.12** (1.99)	-0.42 (-0.32)
Market capitalization ($ million)	-0.00002 (-1.46)	-0.000005 (-0.24)
Intercept	-3.61* (-1.83)	-1.27 (-1.37)
Number of observations	83^{ξ}	83^{ξ}
R-squared	0.8034	0.7672
F-stat	24.61	16.37
Prob>F	0.0000	0.0000

***Significant at the 0.01% level.
**Significant at the 0.05% level.
*Significant at the 0.10% level.
ξ : Excluding one outlier.

to 1.90 for the more actively traded SSF. The less actively traded SSF do not show a significant difference from before to after SSF introduction. In short, the two-day results are consistent with the one-day analysis.

We noted earlier that the traditional measurement of improvement in market efficiency, i.e., volatility, will have low power in our case. As a standard approach, however, volatility remains of interest and may provide additional insight, so we conduct several tests using volatilities.

Exhibit 7 summarizes volatilities for the SSF and matched firms in the 250 trading days before and after SSF introduction. Volatility declines significantly for SSF stocks, 32% on average, compared to 28% on average for the matched firms. The Kruskal-Wallis test shows that the reduction in volatility for the SSF firms, in both absolute value and percentage terms, is significantly greater than for non-SSF firms.[6]

At first glance, the decline in volatility for the matched firms in the post-listing period seems to contradict the result in Exhibit 2 that the matched firms have more large return increases in the post-listing

[6]Lee and Tong (1998) report a similar decline in volatility in a study of Australian SSFs.

Exhibit 7. Comparison of Two-day Large Returns for SSF and non-SSF Firms

The table reports the ratio of the number of large two-day returns of the SSF firm to that of its match in both pre-listing and post-listing periods. A stock's two-day return is large positive if it is higher than the market mean two-day return plus 2.576 * standard deviation of market two-day return. A stock's two-day return is large negative if it is lower than the market mean two-day return minus 2.576 times standard deviation of market two-day return. Market mean and standard deviation are measured using the 125 two-day intervals before or after SSF introduction. The Kruskal-Wallis test examines whether there is a significant difference between pre- and post-listing periods If a stock's SSF volume is above the median daily average volume, is labeled as "more actively traded SSF", otherwise it is "less actively traded SSF".

All Firms	Ratio of number of large two-day returns for a SSF firm to that of its match in the pre-listing period Mean (Median)	Ratio of number of large two-day returns for a SSF firm to that of its match in the post-listing 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)

period. The reason is that we define high returns using the distribution of the market portfolio as the benchmark. When a stock's volatility declines, it still can have a greater number of high returns as long as the market portfolio has an even greater reduction in volatility. The overall stock market happens to be less volatile in the post-listing period: a 0.015 standard deviation of market daily return during year 2002, and 0.010 during year 2003.

To examine the association between the change in stock volatility and the trading activity of SSF, we estimate an OLS model of post-listing stock volatility. The dependent variable is stock volatility (standard deviation of daily stock returns) in the 250 days after the listing. The independent variables are industry, volatility in the 250 days before the listing, and size.

Exhibit 9 shows that the SSF trading volume significantly reduces the post-listing 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.[7]

V. Summary and Conclusions

We examine the most recent financial innovation, single stock futures, adding to the empirical evidence on financial derivatives.[8] The evidence is compelling that financial innovations with lower trading costs can

[7]We also estimate the conditional variance of SSF firms using the GARCH method. Modeling the time dependent behavior of volatility over time may be appropriate way to study changing components of variance in the before and after periods. Unreported results show several significant changes in the behavior of the underlying GARCH parameters in the two periods. The source of decline in the variance is not from a reduction in the fixed portion of variance (i.e., the intercept term), but from a significant, decline in the way the variance process is updated. Variances of SSF firms are less dependent on old news, and respond less to recent news.

[8]See Frame and White (2004).

Exhibit 8. Volatility of SSF Firms and Matched 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-tests and sign tests are used to examine whether the means and the medians 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: Chi-squared (*p* value)		18.016 (<0.0001)	12.444 (0.0004)	15.548 (<0.0001)	7.495 (0.006)

***Significant at the 0.01% level.
**Significant at the 0.05% level.
*Significant at the 0.10% level.

Exhibit 9. Stock Return Volatility and SSF Trading Volume

This table estimates volatility in the 250 days after the SSF listing as a function of volatility in the 250 days before the listing, industry, market capitalization, and SSF volume, using ordinary least squares. t-statistics are in parentheses

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 $^{\xi}$
R-squared	0.8147
F	35.45
Prob>F	0.0000

***Significant at the 0.01% level.
**Significant at the 0.05% level.
*Significant at the 0.10% level.

ξ : Excluding one outlier.

have a stabilizing effect on a market. Our results are consistent with a hypothesis that single stock futures, with lower trading costs and higher leverage, better provide relief to arbitragers than speculators. Market efficiency improves for stocks that have been listed on SSF exchanges since the end of 2002. We use a specific news event approach to show that there are fewer unexplained large stock returns for SSF firms in the post-listing period and in a matched sample. The degree of reduction is positively related to the extent of trading activity in the single stock futures market.

Examination of large returns and identification of news events around these large price deviations may continue to provide useful insight into the question of stock market efficiency.■

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