International Journal of Business and Economics, 2018, Vol. 17, No. 2, 179-191

Pricing Dynamics between Single Stock Futures and the Underlying Spot Security

Vaneesha Boney
University of Denver, U.S.A.

Christos Giannikos*
Department of Economics and Finance, Baruch College, City University of New York, U.S.A.

Hany Guirguis
Manhattan College, U.S.A.

Abstract

This paper examines the pricing dynamics between single stock futures (SSF) and the underlying spot security. The sample period in this analysis allows us to examine this relationship across a market cycle and regulation changes that would potentially impact this relationship. We find that the spot market leads the SSF market and contributes roughly 70% to price discovery. Unlike what has been documented in prior research, this relationship holds during significant periods of market distress. However, we find that the pricing contribution deteriorated in 2010, and this state persisted through the end of our sample period. We posit that this is the result of a change in regulation SHO, which amended existing restrictions on short selling. Specifically, this change likely increased the rebate rate charged by brokers for locating the stock to be shorted and subsequently caused SSF in our sample to trade in backwardation, thus disrupting the pricing relationship previously found.

Key words: price dynamics; price discovery; single stock futures; financial crisis

JEL classification: C20; G00; G10; G12

1. Main Ideas, Model, and Data

After being banned for more than two decades, Single Stock Futures (SSF) began trading on the OneChicago and NQLX exchanges on November 8, 2002, though NQLX suspended SSF trading in December 2004. However, OneChicago, a

*Correspondence to: One Baruch Way, B10-225, New York, NY 10010. Email: Christos.Giannikos@baruch.cuny.edu. Tel.: 646-312-3492. Fax: 646-312-3451. We thank an anonymous reviewer of IJBE for all comments and suggestions that helped to greatly improve the paper.

fully electronic exchange, continues to serve these contracts. Unlike more traditional futures contracts such as those written on a currency, commodity, or an index, SSF are contracts written on individual stocks.

SSF contracts are said to have many benefits, which have driven the modest yet steady growth in their volume since their listing return to the exchanges. SSF act like a synthetic stock loan, serving as a means to loan the underlying stock and locate stock when selling short, of which the latter proves beneficial when dealing with hard to borrow (HTB) stocks. Without SSF, the act of short selling can be expensive and fairly complicated, and by using them to short a position, traders are also exempt from the uptick rule. In addition, SSF may be an effective risk management tool. For example, in a market downturn an investor can avoid liquidating shares by selling an equivalent amount of SSF, thus offsetting potential losses in the underlying position. Another benefit of this strategy is positive tax consequences: by delaying a sale, the investor potentially delays the realization of a short-term gain.

SSF also allow for Exchange Futures for Physical (EFP) transactions during which an investor simultaneously sells a stock (or shorts the stock) and buys SSF to create a long position, effectively creating an equivalent delta position. Traders may find this a more cost efficient way of hedging given there are no limitations on investors' ability to short the stock. Traders often do not hold the actual stock needed to sell, and thus they utilize the short sale market. Moreover, using SSF to acquire a position in stock is generally less costly when using margin, because they carry a 20% margin requirement compared to the minimum 50% requirement for stock.

While not an exhaustive list, the aspects above are some of the capital efficiencies of using SSF and some of the reasons why they have become an important strategy tool of professional traders. Although there is a limited amount of academic research on SSF, these contracts are becoming more popular in terms of participation and volume. We aim to determine the impact of information content of the SSF market on the prices of underlying stocks, and vice versa. Our work builds on Shastri et al. (2008), however, one of our major contributions to this literature is documenting how the pricing dynamic changes over a longer period of time. Our sample allows us to observe this dynamic over a market cycle and a change in regulation that potentially can impact this relationship. Giannikos et al. [2013] document a significant change in the price discovery relationship between the stock and credit default swap markets. Prior to the crisis of 2007, they find that the stock market contribution amounted to roughly 2/3 of price discovery, while the credit default swap (CDS) market contributed roughly 1/3. However, between 2007 and 2008 the CDS market played the dominant role. Our analysis aims to document whether such changes will occur in the SSF market.

A flurry of academic papers has examined the introduction and use of SSF. Early papers analyzing this phenomenon are mainly descriptive or analyze the trading costs and behaviors associated with these instruments. Ang and Cheng [2005] examine the selection process of SSF, developing a model that shows that the likelihood of an individual stock being chosen for inclusion in this market increases with its market capitalization, volatility, and turnover. They conclude that the goal of security selection in the SSF market is to increase the probability of post-listing success. Jones and Brooks [2005] give an overview of how the SSF market developed in its reintroduction infancy, providing numerous reasons why these instruments have seemingly failed to reach their potential in the retail market. One reason given is low trading volume, which permits the underlying asset price to close above the SSF settlement price, which is an apparent contradiction of the carry arbitrage model.

These two findings taken together imply that without an increase in interest and subsequent volume, it may be difficult for the SSF market to support large trades and for SSF prices to reflect the instruments' true value. This has led other researchers to examine information and price discovery in the SSF market. For example, Fung and Tse [2008] measure the informational efficiency of SSF traded on the Hong Kong Exchange using intraday bid/ask quotes. Their study shows that nearly 80% of quotes are inferior to quotes on the underlying stock, but they find that SSF are fairly priced after adjusting for the cost of carry.

Pan [2008] examines the efficiency of using SSF as a means for U.S. investors to access foreign markets. While there is a growing appetite for foreign exposure by U.S. investors, Pan points out that operating in foreign markets exposes U.S. investors to the risk of falling outside the protections and safeguards of the U.S. SEC. Pan notes that the ongoing effort by the SEC to negotiate 'mutual exchange' agreements with foreign countries would allow the SEC and native administrations to jointly regulate exchanges. However, coordinating these efforts consumes a great deal of time and resources. Ultimately, Pan shows that by using SSF, U.S. investor are able to gain access to foreign markets without losing SEC protection. He argues that the SEC should promote the use of SSF rather than negotiating mutual exchange agreements, potentially saving a great deal of time and effort.

Shastri et al. [2008] examine stock market quality given the introduction of SSF and the information content of SSF relative to the spot market. They utilize the 'information shares' model introduced by Hasbrouck [1995] in which the portion of price discovery attributable to the market is measured in terms of its contribution to the innovations' variance of the efficient spot market price. Their main conclusion is that the market quality of the underlying stocks benefits from the presence of SSF, that SSF account for roughly 24% of price discovery, and that this contribution does not vary according to the exchange where the underlying stock is traded. They also indicate that the price discovery contribution improves as SSF spreads grow narrower.

The goal of this paper is to examine how the price discovery relationship between SSF and the underlying spot market changes over time and how it is impacted by periods of market distress. This paper builds on the work of Shastri, Thirumalai and Zutter [2008] who examine the information content associated with single stock futures (SSF) and the underlying stock. Our paper contributes to the literature in four important ways. First, it has been documented that the dynamics of the price discovery relationship can vary over time and across market conditions. Namely, Giannikos et al. [2013] examine the price discovery dynamics of three markets: the stock, bond, and CDS markets. They test how market stress (the financial crisis of 2007-2008) impacts the price discovery relationship in these markets. Examining the relationship of CDS (credit default spread) relative to bond market spreads, they find that spreads in the CDS market dominate the bond market in price discovery and that this relationship is relatively stable over time. However, findings for the equity market differ. They show that prior to the financial crisis the stock market played the dominant role in price discovery, however, this role becomes significantly weaker in times of financial distress and over this period the CDS market serves as the dominant source of information relative to the stock market. Moreover, Shastri et al. [2008] provide evidence that informed traders prefer the futures market when volatility in the underlying stock market is low, thus contributing to the increased information share for the futures market. However, the Shastri et al analysis does not include periods of significant financial distress and profound changes in regulation. Thus, they are not able to assess how this relationship is impacted by a market cycle. This paper contributes to the literature by providing some understanding of the dynamics of the pricing relationship across varying market conditions, which are important for traders using these instruments on a daily basis to implement various portfolio strategies. Moreover, because strategies utilizing SSF often include shorting stocks, we indirectly examine whether there is any correlation between changes in regulation affecting the ability and potential cost of shorting stock and the pricing relationship between SSF and underlying asset. Understanding their relationship over time can have significant economic implications for the practitioner who utilizes SSF for hedging purposes and/or closely monitors the dissemination of new information for making investment decisions.

Second, the SSF market has expanded considerably since its reintroduction in 2002. It now contains a more inclusive and diverse population of underlying stocks. Our initial sample of SSF is almost two times greater than the sample available to Shastri et al. [2008].

Third and finally, it is a stylized notion that the futures market often leads the spot market. However, with respect to SSF we expect that the opposite relationship is just as likely, given the way that markets are made and how prices are calculated for SSF.

OneChicago's SSF prices are calculated by the following formula (Source: OneChicago website for 1C contracts, http://www.onechicago.com/):

$$F = S * (1 + r) - Div, \tag{1}$$

where F is the SSF price, S is the spot price of the underlying stock, r is the implied interest rate demanded by market makers, and Div is the dividend.

Unlike what we will call "traditional" futures markets, which are characterized by significant participation, sustained trading volume, and are driven to a great extent by supply/demand, trading in the SSF market is not as vibrant. The average daily contract volume for SSF was roughly 38,800 contracts in 2013, as provided by OneChicago. It represents the combined trades from the Central Limit Order Book (CLOB) and the Exchange BETS Platform (Block Exchange for Physical Trading System). The former accounts for roughly 1300 daily contracts, and the latter accounts for 37,500 average daily contracts.

SSF liquidity providers meet the demands of [primarily] large block traders, who place orders through the exchanges' BETS (Block and EFP Trading System) platforms. As each order is placed, these liquidity providers determine an implied interest rate. Key factors for determining this implied rate include general collateral and whether the stock is HTB (hard to borrow). This implied rate is then added to the spot price. Moreover, unlike a traditional futures contract that may in fact have more volume than the underlying security, SSF volume is less robust and sporadic throughout the day. These factors may impact the dynamics of the price discovery relationship over time and across market conditions, which, to our knowledge, has yet to be examined for SSF. We suspect that unlike traditional futures contracts, where the futures generally lead the spot market, the spot market for the underlying asset may lead and significantly contribute to the SSF price. This prominent finding would run counter to what we generally see in futures markets.

Daily data on contract prices, as well as highs and lows, are provided by OneChicago between January 2006 and December 2011 for the 30 stocks that trade on the DJIA as of January 2006. These particular stocks were chosen given they are highly visible and liquid. Accordingly, pricing anomalies potentially found in this analysis are less likely to be attributed to illiquidity or lack of participation. Daily closing prices of the underlying securities are provided by CRSP. Our market volatility measure is the daily VIX, provided by the CBOE. Exhibit 1 provides descriptive statistics for the data utilized in this analysis.

Exhibit 1 shows various descriptive statistics for thirty SSF and their underlying stock prices on the DJIA. All data in this series are daily and cover the period from January 2006 to December 2011. Exhibit 1 reveals the significant fluctuations in prices of the stocks and SSF as illustrated by the standard deviation, maximum, and minimum values. For example, the stock price of General Electric fluctuated between $5.91 and $42.14.

In this paper we examine the following two important aspects of the dynamic relationship between SSF and the underlying spot security. First, what is the relative share of price discovery associated with the SSF market for the underlying securities included in our sample? Second, how does the price discovery contribution change over time given periods of financial turbulence and regulation changes?

Exhibit 1. Shows the Ticker for Each Stock Used in the Analysis and Its Comparable SSF. The Average Closing Price, Standard Deviation in Price Over our Sample Period, as well as Minimum and Maximum Values are Listed for Each One

Stock					Single Stock Futures			
	MEAN	SD	MIN	MAXIMUM	MEAN	SD	MIN	MAXIMUM
AA	23.07	11.41	5.20	48.23	23.17	11.54	3.75	48.59
AIG	42.17	20.59	0.34	72.96	39.10	22.77	0.06	73.86
AXP	45.85	11.37	9.78	65.79	46.06	11.66	9.78	66.45
BA	72.77	16.59	29.17	107.63	72.86	17.14	12.60	108.97
C	23.47	19.62	0.97	56.63	23.45	19.68	1.02	56.80
CAT	70.42	19.57	15.70	116.02	70.21	19.84	11.55	116.42
DD	43.70	8.28	16.09	56.99	43.48	8.59	9.65	56.92
DIS	32.54	5.28	12.36	44.27	32.58	5.47	8.46	44.37
GE	25.20	9.90	5.91	42.14	24.96	10.32	4.11	42.54
XOM	75.78	11.40	28.15	95.99	76.29	10.16	10.16	96.43
HD	31.95	5.42	17.82	42.46	31.90	5.58	8.33	42.75
HON	48.44	8.93	23.15	62.95	48.40	9.17	17.97	63.36
HPQ	42.84	6.42	21.55	54.58	43.00	6.53	12.70	54.55
IBM	123.37	25.70	75.19	194.73	123.31	25.54	20.44	194.87
INT	23.40	5.22	10.32	52.31	23.29	5.04	3.28	52.51
JNJ	63.14	3.84	46.32	72.73	62.89	4.75	30.60	72.93
JPM	42.00	6.12	15.21	53.24	42.09	6.30	11.13	53.78
KO	55.79	7.22	38.35	71.75	55.63	7.25	12.32	71.58
MCD	61.96	13.39	35.18	100.96	61.77	13.21	13.56	101.28
MMM	79.63	10.05	41.42	98.17	79.53	10.27	19.95	98.22
MO	41.61	26.51	14.51	90.36	41.49	26.68	8.00	90.71
MRK	39.31	8.21	20.27	61.57	39.17	8.46	15.94	62.00
MSF	27.13	3.80	10.09	37.47	27.09	4.22	6.06	37.83
PFE	20.39	4.10	11.65	28.60	20.31	4.21	4.41	28.70
PG	63.21	4.92	44.07	75.17	63.18	5.42	14.90	77.76
T	31.87	5.50	21.68	42.95	31.77	5.73	5.60	43.00
UTX	69.67	9.33	37.45	91.78	69.66	9.46	18.58	91.79
VZ	35.40	4.58	26.02	46.22	35.21	4.98	8.77	46.53
WMT	51.41	4.03	42.15	63.10	51.38	4.23	12.18	72.41
GM	19.00	14.12	0.55	42.94	18.67	14.37	0.23	43.11

Our study quantifies price discovery in terms of the adjustments made by the SSF reflected in the underlying securities to eliminate any divergence from the efficient price caused by permanent shocks.

Following Gonzalo and Granger [1995], we capture the adjustment process by deriving the common integrating factor of the two markets. Their methodology has two appealing characteristics. First, the normalized coefficients on the common integrating factor can be interpreted as the relative contribution of each market to price discovery. Second, the null hypothesis that these coefficients are statistically different from zero can be tested by the χ^2 statistic.

We are in need of an estimation technique to measure the relative contribution of each market to price discovery. Thus, we use the Gonzalo and Granger [1995] estimation of the common long-memory components that are driving movements in the co-integrated series. The same technique was used in a very similar way by Giannikos, Giurguis and Suen [2013] to also address relative contributions of different markets to price discovery.

Gonzalo and Granger decompose the series (X_t) of a (p $_X$ 1) vector of (I) time series (in an error correction model) as follows:

$$X_t = A_1 f_t + A_2 \beta' X_{t-1`}, \tag{2}$$

where f_t is a ($k \times 1$) vector of common integrating factors representing the permanent components of X_t; A_1 and A_2 are loading matrices; ($A_2 \beta' X_{t-1`}$) is a vector containing the temporary components of X_t; and k = p - r. Gonzalo and Granger [1995] also show that the vector f_t is identifiable up to a non-singular transformation provided that the two following conditions hold:

a. f_t is a linear function of the observable variable X_t:

$$f_t = B_1 X_t. \tag{3}$$

$A_2 \beta' X_{t-1`}$ (which are the temporary components) do not Granger-cause the permanent components ($A_1 f_t$) at low frequencies. This means that $A_1 f_t$ is the only linear combination of X_t such that the temporary component has no long-run effect on X_t:

$$f_t = \phi X_t = \alpha^{`}_{\perp} X_t. \tag{4}$$

The orthogonality condition ($\alpha^{`}_{\perp}\alpha = 0$) satisfies the 2nd requirement given it concentrates out the effect of the error correction term on X_t. Thus, equation (4) can be written as:

$$\underset{p\times k}{X_t = A_1} \; \underset{k\times p}{\alpha'_{\perp}} \; \underset{p\times 1}{X_t} \; + \underset{p\times r}{A_2} \; \underset{r\times p}{\beta'} \; \underset{p\times 1}{X_{t-1`}}, \tag{5}$$

where $A_1 = \beta_{\perp}(\alpha^{`}_{\perp}\beta_{\perp})^{-1}$ and $A_2 = \alpha(\beta'\alpha)^{-1}$.

The existence of a *single* trend or integrating common factor to govern the long-run movements of co-integrated series is necessary for market integration (Rivera and Helfand, 2001). The markets would not be integrated in the long run if there were more than one integrating factor, because different prices would be governed by different components. Accordingly, market integration requires exactly p−1 co-integrating relationships in addition to one integrating factor that will be common to all variables in the error correction model. Once we identify the integrating factor, we can interpret this as the implicit efficient price or the source of the permanent changes in the co-integrated markets.

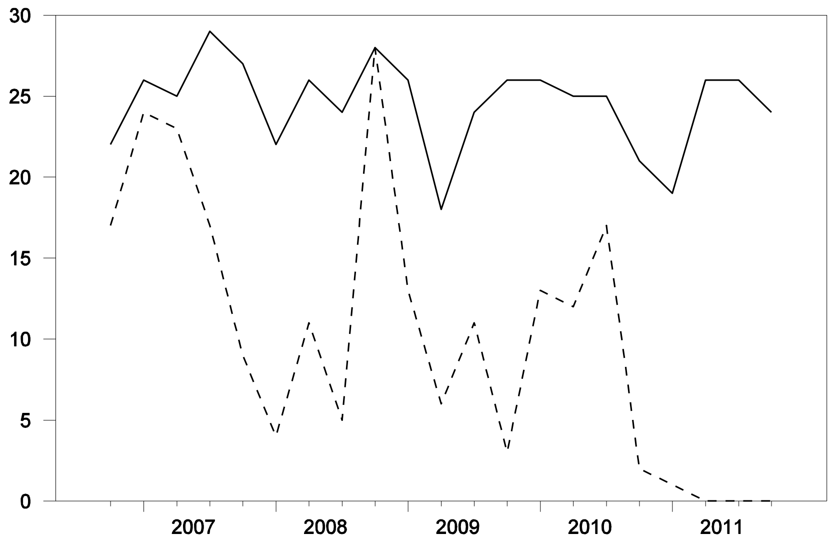
To determine what price discovery relationships exist between the two variables, we utilize the χ^2 test statistic (Q_{SS}) introduced by Gonzalo and Granger [1995]. This method tests the null hypothesis that the coefficients corresponding to each market are statistically not different from zero. If the coefficient of the common factor is statistically different from zero for only one market, then this market contributes 100% to price discovery. The intuition behind such a result is that the leading or dominant market processes news of shocks faster than other markets, and so its prices do not respond to changes in the other markets. The non-leading markets, however, do respond to deviations from the dominant market's price, thus restoring the long-run equilibrium. If the coefficients of the common factor are statistically significant for more than one market, then the relative magnitude of their normalized values can be used to quantify price leadership among the markets.

We next examine whether price discovery in the two markets changed due to the global financial crisis by employing the rolling window technique. This means that we analyze co-integration for each fiscal quarter independently. For example, the test statistics for the first quarter of 2007 are based on daily prices of the thirty stocks and their single futures from October 2 to March 30 of that year. Our rolling window test provides a detailed study of the price discovery for twenty-one quarters between 2006:04 and 2011:04. The main advantage of this technique is that it can identify changes in the price discovery dynamics of the markets without splitting the sample on an arbitrary date.

2. Empirical Procedure and Results

We begin our analysis by tackling the problem of spurious regression pointed out by Granger and Newbold (1974). We test for this property in the thirty companies with complete data using the Philips-Perron (PP) test [1988], independently in each quarter of the sample period. The PP test is a generalized form of the Dickey-Fuller test, with no requirement that the disturbance term be serially uncorrelated and homogenous. Non-stationarity in the variables is accounted for by taking the first difference in the case of one unit root and the second difference in the case of two unit roots. The number of lags of the unit root test is determined by the Akaike Information Criterion (AIC). Exhibit 2 shows the number of companies whose stocks or SSF have one unit root; the dates on the horizontal axis are the end dates of each quarter.

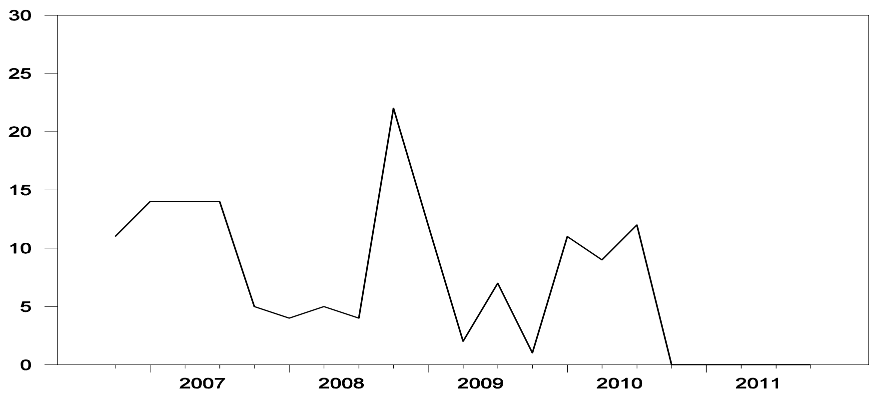
Exhibit 2: Phillips-Perron Unit Root Test Indicating the Number of Stocks (___) and Single Stock Futures (---) Whose Price Series have One Unit Root over our Sample Period. The x-axis is Time (year), and y-axis represents the Number of Occurrences.



The vertical axis displays the number of companies whose price series have one unit root, for stocks (___) and SSF (_ _ _) utilizing the Philips-Perron (PP) unit root tests at the 10% significance level. There are 26 companies whose stock prices have one unit root across the entire sample period. Exhibit 2 reveals that at the 10% significance level, most of the stock prices have one unit root that can be removed by taking the first difference. However, SSF exhibit more stationary behavior, especially during the last five quarters from 2010:04 to 2011:04. For the time periods when both the stock prices and their SSF have one unit root, we proceed under the assumption that all the series are integrated of order 1 (i.e., they are I(1)) and conduct the co-integration analysis to test for price discovery between the two markets.

We start by performing Johansen's co-integration trace test. In each iteration, we utilize Johansen's test to determine the number of co-integrating vectors. It should be noted that the lag in the original VAR model is two, and that our model is specified with a constant term restricted to the co-integrated space. Exhibit 3 reports the number of companies for which Johansen's trace test indicates that only one co-integrating relationship exists between the stocks and their SSF at the 10% significance level.

Exhibit 3. On the Vertical Axis is a Johansen co-integration Trace Test Determining the Number of Co-integrating Vectors over our Sample Period between our Sample of Stocks and Their SSF. The Horizontal Axis is Time



We conduct tests with two lags in the original VAR model, and our model is specified with a constant term restricted to the co-integrated space. As expected, the stocks and their SSF are not co-integrated during the last 5 quarters of our sample. This would indicate that there has been a structure change in the stochastic process of SSF that significantly weakened their long-term relationship with the related stocks. We do not believe the change in this relationship is explained by market distress as seen in Giannikos et al. [2013]. If the financial crisis and lack of accompanying market stability were the culprit, then we would expect to see the co-integration deteriorate prior to 2010. Instead, we believe this relationship may be the result of a change in regulation - namely, in 2010 there was an amendment to regulation SHO.

Initially adopted in January 2005, this amendment requires broker-dealers, among other things, to 'locate' borrowed shares prior to affecting a short sale. The amendment required brokers to implement clear, written, and formal policies around initiating a short sale. This change may have effectively caused an increase in the fee (rebate rate) that brokers charge the short seller to short the stock and may have also caused more stocks to be designated as Hard To Borrow (HTB) for a time. This is material, because it likely caused backwardation in SSF, or caused SSF to trade negative to the underlying stock. For example, a trader buying SSF at the bid wanting to affect a 100% hedge would need to sell/short the underlying stock. Having to borrow the stock makes the trader subject to the rate charged by the clearing house. This market rate undoubtedly increases in the case where the stock is HTB. Because the stock and SSF will trade at parity upon expiry, SSF would trade at a negative bid, or discount to the stock, to compensate for the fees paid to the locating broker. We believe this likely caused the break down in the pricing relationship discovered through our analysis.

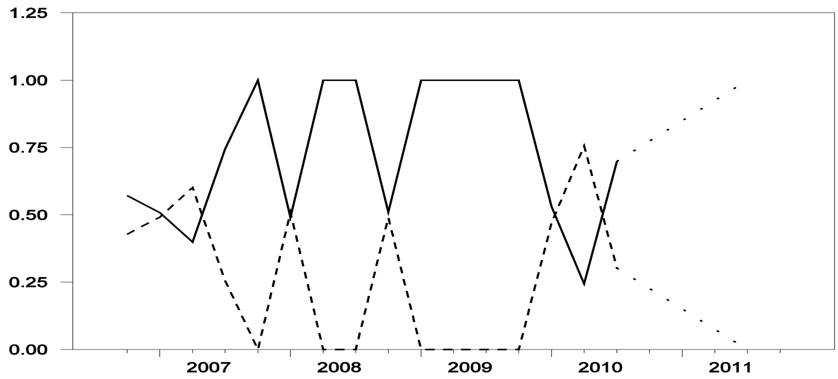
We now look for the common integrating factor between stock prices and their corresponding SSF for the thirty companies. We estimate the unique common factor from the VECM, where the number of co-integrating relationships is p−1. We also calculate Q_{GG} statistics to decide whether each coefficient of the common factor is statistically significant. To quantify the contribution of the stocks and their futures, we normalize the significant coefficients and calculate the overall share of price discovery over all thirty companies in each quarter. For example, the contributions of stock prices and SSF prices to the overall price discovery in quarter *j* can be calculated as follows:

$$Overall\ Price\ Discovery_{Stock,j} = \frac{(N_{Stock})_j + \sum_{i=1}^{30} (w_{Stock})_{i,j}}{(N_{Stock})_j + \sum_{i=1}^{30} (w_{Stock})_{i,j} + (N_{Futures})_j + \sum_{i=1}^{30} (w_{Futures})_{i,j}} \tag{6}$$

$$Overall\ Price\ Discovery_{Future,j} = \frac{(N_{Future})_j + \sum_{i=1}^{10} (w_{Future})_{i,j}}{(N_{Stock})_j + \sum_{i=1}^{30} (w_{Stock})_{i,j} + (N_{Futures})_j + \sum_{i=1}^{30} (w_{Futures})_{i,j}} \tag{7}$$

Here, *i* refers to one of the thirty companies, and $(N_{Stock})_j$ is the number of companies (out of thirty) for which the coefficient of the stock price is statistically different from zero, but the coefficient of the SSF price is statistically insignificant (meaning that 100% of the price discovery is contributed by the stock prices). Similarly, $(N_{Futures})_j$ is the number of times that the SSF coefficient is statistically different from zero, but the stock coefficient is not. In both cases, the normalized coefficient of the informative market is exactly 1. The terms $(w_{Stock})_i$ and $(w_{Futures})_i$ are the normalized coefficients when both markets have a significant coefficient in the common integrating factor. Exhibit 4 plots the overall price discovery coefficients of the stock and the SSf markets for each of the 21 quarters.

Exhibit 4. This Exhibit Presents the Price Discovery Weights/Contributions of the Stock Price Relative to the SSF Price. The Exhibit Shows this Relationship in Each of the 21 Quarters over the Sample Period. The x-axis Shows the 21 Quarters in Our Rolling Window, and the y-axis Represents Price Discovery Percentage



The vertical axis displays the overall price discovery weights of stock prices and SSF prices in each of the 21 quarters (rolling window). It should be noted that the sum of the overall price discovery of the two markets adds up to one at each quarter. The exhibit shows the dominance of the stock price in the discovery process up until 2010, as previously noted. The disappearance of the long-term relationship between the stock prices and their SSF from 2010:04 to 2011:04 indicates that the SSF market ceased to respond to new information or exogenous shocks during the last five quarters of our sample. Accordingly, stock prices became the main source of price discovery in the market.

While we do not explicitly test for this, we have seen that regulatory changes can impact the price discovery relationship. Fattouh, Sen, and Sen [2013] find that regulation reduces liquidity and impedes the price discovery mechanism. Hendershott and Jones [2003] note that when regulation was put in place preventing the Island Electronic Communication Network from displaying its limit order book, the overall market quality of the ETF fell as spreads increased and the price discovery mechanism eroded. The point of the regulation was to create a fair and competitive marketplace, however, this came with unintended consequences. This too, may be the case with the SSF pricing mechanism. Regulation SHO is intended to prevent potentially manipulative and/or abusive short selling practices from driving down markets. Unfortunately, an unintended consequence of that regulation is that financial instruments whose pricing is partially determined by market driven borrowing rates are impacted by the ability and ease of shorting stock. Accordingly, regulation that impacts this (short sale) market may decrease the SSF's price discovery mechanism.

3. Conclusion

Based on a practical understanding of how the markets for SSF operate, we began this analysis by suggesting that the spot market for the underlying stock should lead the SSF market. Prior literature has concluded that the *futures* market leads and significantly contributes to price discovery in the spot market. This literature also suggests that the relationship can vary with market conditions, and that the relationship can change during a market downturn {Giannikos et al [2008]}. In line with Shastri et al. [2008], we find that the spot market leads the SSF market and contributes to roughly 70% of the price discovery of the futures contracts. The results hold during a period of market turbulence. However, we document a breakdown in this relationship, beginning in 2010, which persisted through the end of our sample period. A potential explanation for this is an amendment to regulation SHO, which further tightened the requirements around locating stock and introduced circuit breaker policies when shorting a stock. This regulation should have effectively increased the rate charged by locating brokers, thus impacting SSF pricing. Our results indicate that the active participants in the SSF market, particularly those using the instrument for hedging purposes, proceeded with caution when dealing with HTB stocks and that they paid close attention to changes in regulation that could impact or set new limits on the ability to short securities.

References

Ang, J. S. and Y. Cheng, (2005), “Single Stock Futures: Listing Selection and Trading Volume,” *Finance Research Letters*, 2(1), 30-40.

Fattouh, B., A. Sen and A. Sen, (2013), *Diesel Pricing Reforms in India: A Perspective on Demand*, Oxford Energy Comment, August.

Fung, J. K. W. and Y. Tse, (2008), “Efficiency of Single Stock Futures: An Intraday Analysis,” *Journal of Futures Markets*, 28(6), 518-536.

Giannikos, C., H. Guirguis, and M. Suen, (2013), “The 2008 Financial Crisis and the Dynamics of Price Discovery among Stock Prices, CDS Spreads and Bond Spreads for US Financial Firms,” *Journal of Derivatives*, 21(1), 27-48.

Gonzalo, J. and C. Granger, (1995), “Estimation of Common Long-Memory Components in Cointegrated Systems,” *Journal of Business and Economic Statistics*, 13(1), 27-35.

Granger, C. W. J. and P. Newbold, (1974), “Spurious Regressions in Econometrics,” *Journal of Econometrics*, 2(2), 111-120.

Hasbrouck, J., (1995), “One Security, Many Markets: Determining the Contributions to Price Discovery,” *Journal of Finance*, 50(4), 1175-1199.

Jones, T. and R. Brooks, (2005), “An Analysis of Single Stock Futures Trading in the US,” *Financial Services Review*, 14, 85-95.

Pan, E., (2008-9), “Single Stock Futures and Cross-Border Access for US Investors,” *Journal of Law, Business and Finance*, 221, 221-262.

Phillips, P. and P. Perron, (1988), “Testing for a Unit Root in Time Series Regression,” *Biometrica*, 75(2), 335-346.

Rivera, G. G. and S. M. Helfand, (2001), “The Extent, Pattern, and Degree of Market Integration: A multivariate Approach for the Brazilian Rice Market,” *American Journal of Agricultural Economics*, 83(3), 576-592.

Shastri, K., R. S. Thirumalai, and C. Zutter, (2008), “Information Revelation in the Futures Market: Evidence from Single Stock Futures,” *Journal of Futures Markets*, 28(4), 335-353.