The Pricing of CBOT Exchange Seat

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Abstract

This paper analyzes the behavior of the CBOT seat prices for the post-1975 period. Based on the time-series property of seat returns and the empirical link between seat returns and economic factors, we develop a conditional multi-factor model, where the price of risks are assumed to be linearly generated from the ARIMA estimates of the factor values. Particularly, we find the close short-run and long-run link between the CBOT seat price and CBOT trading volume. Importantly, the CBOT seat returns appear to exhibit significant power in predicting stock market returns, the growth of CBOT trading volume, the growth of industrial production, and interest rate. Based on the dynamic pricing model including three factors by Fama and French, we find that excess seat returns are time-varying with some expected factor variables, such as expected size premium (SMB^e), expected CBOT trading volume (VOL^e), and expected interest rate (INT^e). Seat returns are particularly sensitive to the size premium shock (SMB^u). We conclude that the pricing mechanism of CBOT seats is similar to that of a well-diversified stock market portfolio.

Keywords: CBOT Seat Return, CBOT Trading Volume, Time-Varying Expected Return, Conditional Multi-factor Model. ARIMA

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I. Introduction

The major role of commodity futures exchanges, such as the Chicago Board of Trade, is to provide a market for managing the price risk of commodities. If the risk of commodity prices increase, *ceteris paribus*, there will be a higher demand for trading in futures exchanges. It is likely that the commodity price uncertainty is subject to underlying economic uncertainties. Since the profits of traders on the exchanges are generated mostly from trading volume, cash flows to trader on exchanges should be associated with the degree of uncertainty in economic fundamentals. Such a connection can be easily understood through a comment by the ***Economist*** (2003) on the boom in commodity futures markets, "*War, terrorist threats, volatile stock markets and wobbly economy: terrible, isn't it? Not for derivative exchanges, which have been booming as investors seek to manage their risk in uncertain times (…-omitted-…). Traders are raking in money, whichever way markets go*."

Commodity trading volumes vary by business conditions. In particular, the price uncertainty in economic downturns tends to increase. In this case, in order to hedge the price risk of commodities, more trading activities might take place, and leads to an increase in trading volume. Voluminous studies have examined the contemporaneous relation between asset price variability and trading volume. Among others, Clark (1973), Telser (1981), Tauchen and Pitts (1983), and Grammatikos and Saunders (1986), and Barro (1986) have studied this relation for futures markets.[1] They all report a positive relation between price uncertainty and the overall volume of futures trading. It has been argued that the linkage holds for both overall price levels and individual commodity prices.

Since the profits of exchange members are mainly derived from trading volume, and trading volume is contingent on the overall variability of prices that fluctuate subject to the uncertainty of business conditions, we argue that commodity exchange seat prices should change in response to common macroeconomic shocks.[2] In fact, both trading volume and profitability of brokerage firms on the commodity futures exchanges fluctuate together over business conditions. In this sense, trading volumes can be regarded as a function of business conditions, which is consistent with evidence reported in recent empirical literature (Amihud and Mendelson (1986) and Chordia, Roll, and Subrahmanyam (2001)).

Since trading volume is a major source of cash flows to traders on commodity futures exchanges and seat holders are entitled to future cash flows to be earned from trading activities, we can devise a simple pricing equation for a commodity exchange seat, such that the model explicitly account for the effects of any common macroeconomic shocks.

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[1] Following the work of Clark (1973), most empirical models tend to follow the specification related to the "Mixture of Distribution Hypothesis" (MDH) that posits a joint dependence of returns and volume on an underlying latent event. See Epps and Epps (1976) and Andersen (1996) for stock markets.

[2] 84% of the CBOT contracts in 2003 were generated from financial/ stock index, which are the most volatile products, while only 16% came from agricultural products.

$$P_t = E\left(\sum_{i=1}^{\infty} \frac{CF_{t+i}(f_{1,t+i}, f_{2,t+i}, ..., f_{k,t+i})}{\prod_{j=1}^{i}(1+r_{t+j}(f_{1,t+i}, f_{2,t+i}, ..., f_{k,t+i}))^j} \Big| I_t \right) + \nu_t \qquad (1)$$

Let P_t denote the seat price at time t. $CF_{t+i}(f_{1,t+i}, f_{2,t+i}, ..., f_{k,t+i})$ represents the cash flow to a seat member i at time t+i as a function of k factor $f_{1,t+i}, f_{2,t+i}, ..., f_{k,t+i}$ at time t+i. The time-varying discount rate at time t+j is denoted by $r_{t+j}(f_{1,t+i}, f_{2,t+i}, ..., f_{k,t+i})$ as a function of k factors $f_{1,t+i}, f_{2,t+i}, ..., f_{k,t+i}$ at time t+j. I_t represents information set available at time t. ν_t and E represent the unexpected part of seat price and expectation operator, respectively. The unexpected term ν_t can reflect systematic forecasting errors of markets. The systematic forecasting errors may be due to structural changes, market sentiments, and irrational bubbles.

Seats as capital assets have value since they bring their holders with future cash flows. The unexpected term may reflect noise or market sentiment. As manefisted by the NYSE, the model is consistent with the view that "seat prices reflect the interplay of supply and demand, the profitability of the brokerage business, the level of trading volume on the exchanges, general economic conditions, and so forth." A key implication of the model is that actual seat prices are determined by both changes in cash flows and discount rates driven by underlying state factor uncertainties. Thus, the model enables us to posit that actual seat returns are determined by underlying economic factors.

Relatively only a few papers have examined the behavior of exchange seat prices. Among others, Schwert (1977a) investigated the effect of public regulations on the profit of brokers who trade on the NYSE and the ASE. Using the monthly data from 1926 to 1972, he examined the time series properties of seat prices based on the market model. He modeled seat price as a function of new information about future levels of stock prices and share trading volume. He also assessed the impact of the SEC Act in 1934 Act on seat returns, and rejected the capture hypothesis that NYSE and ASE brokers gain from regulatory supervision at the expense of consumers. Relying on the market model, Schwert (1977b) test the efficiency of seat prices by examining the significance of unexpected parts of stock market prices and trading volume in explaining the seat return. He concludes that the behavior of seat prices resembles that of capital assets that process unexpected surprise quickly. However, he was unable to find any evidence that seat returns have predictive power on stock market returns.

Keim and Madhavan (2000) analyze the information content of NYSE seat prices using annual seat prices from 1869 to 1998, and higher-frequency micro-trading data including bids and offers from 1973 to 1994. They confirm the prior evidence of no predictive power of seat return on stock market returns. Under the three factor model of Fama and French (1993), their evidence on the relationship between NYSE trading volume and seat returns is mixed across sample periods.

However, they argue that seat market volumes are negatively related to future stock market returns. Using the notion of Merton (1980), they conjecture that an increase in seat market activity is associated with less market volatility and, hence, a lower expected return. It is worth noting that their supporting evidence was obtained from a model where multiple economic risk factors (book-to-market, default premium, term premium, and dividend yield) are allowed. Interestingly, in their conditional model there are some conditional economic factors that became highly significant, while the market factor bacame insignificant for the overall period and the most recent period. This evidence hints that the underlying economic factors can be more important than the market factor in explaining seat returns.

Following the approach by Schwert (1977b), Chiang et al. (1987) analyze the information contents of seat prices in three commodity exchanges such as COMEX, CBOT, and CME. They offer evidence that commodity exchange seat prices also behave at random like capital assets. They also found that current stock market return is related to current seat returns of CME and CBOT, but they found no evdence that commodity exchange seat returns have predictive power on future stock market return. Adding three explanatory variables, such as expected trading volume, unexpected trading volume, and commodity futures index, to the base market model, they showed both unexpected and expected trading volume are related to CBOT seat return. Interestingly, in their specification, expected trading volume turned out to be highly negatively associated with seat return.[3] This seems to be a quite interesting result, since the significant relation of expected trading volume to seat return can be interpreted as evidence that expected commodity seat return is time-varying with expected trading volume. That is, if expected return is time-varying, even in efficient market, expected change in underlying factors can be associated with seat returns contemporaneously.[4] Their finding seems to be consistent with the recent study on NYSE seat prices by Keim and Madhavan (2000), who report that lagged innovations in seat market liquidity (seat volume) are negatively related to NYSE market excess returns, implying the trading activity in the seat market can be positively related to stock market liquidity, and hence higher stock values and lower expected returns (Amihud and Mendelson (1986) and Chordia, Roll, and Subrahmanyam (2001)).

Put differently, seat trading volume in stock exchanges might be related to the overall market liquidity factor, while that in commodity exchanges might be related more directly to the overall economy. Therefore, a key question in this regard will be what underlying factors drive expected trading volume, and, in turn, time-varying expected returns on commodity exchange seats. In this

[3] The absolute value of estimated coefficient is very large (0.217). Thus, a 10% increase in expected trading volume results in 2.17% decrease in seat returns.

[4] Under the time-varying expected return framework of Merton (1980), the negative relationship of seat return to expected trading volume growth is possible if expected trading volume growth can be a proxy for unobserved underlying factors.

regard, it is worthwile to note a recent study by Chordia, Roll, and Subrahmanyam (2001) who find evidence that liquidity and trading activity are influenced by overall economic conditions such as long-term and short-term interest rates and macroeconomic announcements. They document that liquidity plummets significantly in down markets, and a decrease in trading activity is related to an increase in market volatility. Their finding suggests that trading volume on exchanges can convey information on a certain time-varying economic factor.[5]

Despite the past studies about exchange membership prices, we identify some research gaps that should yet be filled in the following aspects. First, none provides evidence on the behavior of CBOT seat prices over the period including the post-1983. Chiang et al. (1987) only examine the behavior of CBOT seat price for the pre-1982 period. However, it is known the CBOT has undergone various significant structural changes especially since 1970s.[6] Thus, it is essential to revisit the issue of how the CBOT seats are priced since a series of recent structural changes might

[5] From micro perspectives, Battalio and Bagnoli (1995) investigate CBOT membership prices and the value of specialization over the period from 1982 to 1986. By comparing the estimated value and the market value of an Associate membership, they conclude that there is no discernable value to specialization. Jarrell (1984) examines the effect of 1975 deregulation on the NYSE seat value. He finds that after 1975 deregulation NYSE seat value declined dramatically despite an unexpected increase in volume, and that only the publicly traded national brokerage firms benefited from deregulation. Pashigian (1986) examines the effect of jurisdictional conflicts on the seat prices on the CBOT, the CME, and the CBOE, and shows the seat prices respond significantly to decisions surrounding the conflicts.

[6] In 1973 the CBOE was established, and Futures on GNMAs were launched as a first financial futures instrument. In 1974 CFTC was established as a self-supervisory agent. The supervisory logistic was reauthorized by Congress in 1978, 1982, and 1986. In 1997 CBOT launched DJIA futures and options on futures contracts. On September, 28, 1998, the board of directors of CBOT established side-by-side open outcry and electronic trading, providing trading opportunities for those members and firms who wished to trade on the CBOT's electronic trading system Project A during the day. In 1992 the trading system was eclipsed by Eurex, the all-electronic German/Swiss derivative exchange.

have a significant impact on the nature and behavior of CBOT seat prices. Second, most of existing studies except Keim and Madhavan (2000) employ a single factor market model or its variants under the assumption of constant expected return (Schwert (1987); Chiang, et. al. (1987)). The single factor market model cannot fully capture the time-variation of expected return.[7] An alternative is to embody the time-variation of expected return by combining the economic factor model and the latent variable model.[8] Such a model specification has its own merit in the sense that time-varying expected return can be fully implemented with economic uncertainties, as evidenced in existing literature. In their study on NYSE seat returns, we see the key conclusion by Keim and Madhavan (2000) was drawn based on the conditional economic factor model as a variant of the Fama-French three factor model.[9] Moreover, they conjecture seat trading volume might proxy for an underlying economic risk factor.[10] Chiang, et al. (1987) also find the inverse relationship between expected volume and CBOT seat return, implying an increase in expected trading volume results in a lower expected seat return. Such an anomalous phenomenon (judging from the constant

[7] Model alternatives span the economic factor model (Chen, Roll, and Ross (1986)), the three factor model (Fama and French (1993)), and the latent variable model (Gibbons and Ferson (1985), Campbell (1987), Harvey (1991), Campbell and Hamao (1992), Ferson, Foerster, and Keim (1993), Ferson and Harvey (1999)).

[8] Elton, Gruber, and Blake (1995) report the importance of fundamental economic variables in explaining the cross-section of expected returns.

[9] Views, different from Fama and French (1993), can be found in Carhart (1997), Lo and MacKinlay (1990), White (2000), Campbell (1996), Ferson and Harvey (1999), and Campbell (2000) for a comprehensive review.

[10] In contrast, in their study on commodity exchange seat returns, Chiang et al. (1987) report that expected trading volume on futures contracts is related to seat return. This is in sharp contrast with the evidience on the stock exchanges, of which expected trading volume is not related to seat returns.

expected return view) may be reconciled only if expected trading volume on CBOT can proxy for an economic risk factor. A higher expected trading volume may be associated with a lower expected volatility of unknown economic factors, thus resulting in a lower expected return. This conjecture is consistent with the observation by Chordia, Roll, and Subrahmanyam (2001). The fact that trading activity conveys information on market conditions prompts us to develop our conditional expected return model based on economic fundamental risk factors.

The potential contributions of our study are deemed two-fold. First, this paper is the first to develop a pricing equation for a commodity exchange seat based on a set of economic fundamental factors. In particular, we examine the dynamic relation between seat return and ex ante factors. Second, we extend the sample period onto the post-1983, which is more adequate to examine the impact of major structural changes around commodity futures exchanges including advances in trading technologies, rising global competitions, developments of versatile derivatives, and dramatic ownership structure changes (demutualization, mergers, etc).

In order to effectively fill the above gaps, we employ a wide spectrum of monthly data over the period 1975 – 1999 including CBOT full membership price, trading volume on CBOT exchange, industrial production index, personal consumption expenditure, 3-month T-bill rate, 1-year T-bond rate, 20-year government bond rate, AAA-rated corporate bond yield, BAA-rated corporate bond yield, consumer price index, S&P500 index, SMB (size premium: small stock return – large stock return), HML (book-to-market premium: high B/M return – low B/M return), NBER business cycles (peak and trough), and so forth. The CBOT full membership prices and trading volume data are obtained directly from the CBOT, the macroeconomic data are taken from home site of the FRB at St. Lous, the S&P 500 index is from CRSP database, and SMB and HML data are from the home page of French. The sample period covers from 1975:1 to 1999:8.

As a result of analysis, we find strong evidence supporting the typical pricing behavior of the CBOT seat as a capital asset. Interestingly, CBOT seat returns turned out to show the predictable power of fundamental variables including future stock market returns, CBOT trading volume, industrial production, and interest rate. In particular, we observe that there is the short- and long-run relationship between CBOT seat price and CBOT trading volume. In asset pricing context, we also find that excess seat returns are time-varying with expected size premium (SMB^e), expected interest rate (INT^e), and expected CBOT trading volume (VOL^e). Moreover, it is shown that expected seat returns are positively associated with expected size premium (SMB^e) and negatively related to expected interest rate (INT^e).

The rest of the paper is organized as follows. In the section II we assess the importance of economic forces in explaining the CBOT seat prices. We thereby examine the dynamic relationship of CBOT seat returns to major economic fundamentals. Key focus will be put on the relationship between CBOT trading volume and CBOT seat returns. The section III provides a multi-factor model of seat prices based on economic fundamentals. In the section IV we analyze the return and risk characteristics of seat prices. In the section V, we conclude the paper.

II. Linkage of Seat Prices to Economic Fundamentals

1. Dynamic Long-run Relationship between CBOT Volume and Seat Prices

Before proceeding with the model for pricing the exchange seat, we check the significance of trading volume on the CBOT in explaining the price of seats. This can be seen from Figure 1 showing the association of time-series patterns of the logarithmic CBOT seat prices and the logarithmic CBOT trading volume. A glance at the Figure 1 suggests that CBOT seat prices are somewhat related to CBOT trading volume. Especially, the two series appear to share the long-run trend. The graph reinforces the conjecture that the CBOT trading volume, as a major source of the exchange's profit, plays a certain role in determining the CBOT seat prices.

Certainly, the volume of futures contract traded on the CBOT can be seen as a major driver for determining the market price of seats. In this section, we put special emphasis on the dynamic relation between CBOT trading volume and seat prices. As a preliminary test, we conduct the Perron unit root tests for levels and differences of two variables. Table 1 reports the results of the test. Even after controlling the unknown structural breaks, we find that levels of log seat prices and log volume are I(1), and differencing the level data leads to I(0) stationary series.

Place [Table 1] around here.

We conduct the Johansen cointegration test to see whether there is a long-run equilibrium relation between CBOT volume and seat prices. We introduced a dummy variable for controlling the 1987 stock market crash. The dummy takes 1 for the period 1987:7 to 1987:11, and elsewhere zero. The lag length was set to nine (in level), at which the length of lags residuals satisfy the normality condition. We allowed an intercept only out of cointegrating space. The results are reported in Table 2. Based on the L-max and Trace statistics, we are 95% confident that there exists 1 cointegrating vector. Under the restriction of 1 cointegrating vector, we estimated the vector error correction model. The estimation results are available in Panel B of Table 2. The estimated cointegrating vector in the set of seat price and trading volume in logarithmic form is (lseat, lvol) = (5.895, -3.373). Notably seat returns are significantly influenced by the adjustment of long-run disequilibrium (t=-3.05), unlike trading volume. In other words, trading volume is weakly exogenous for the long-run cointegration relation. Looking at the estimates of short-run dynamic adjustment terms, we can confirm that seat returns precede trading volume in Granger sense. Especially, the 1987 crisis dummy is significant only for the CBOT seat return variable. The estimation results show that CBOT seat price has dropped by 9.5% during 3 months due to the stock market crash.

Place [Table 2] around here.

2. Permanent-Transitory Decomposition

As long as we found that seat price and trading volume are cointegrated, we are interested in extracting out common components between seat price and volume. Adopting the decomposition technique proposed by Gonzalo and Granger (1995) and Johansen (1991), we divide economic variables into permanent and temporary components. In an econometric sense, the permanent component is assumed as an I(1) process (integrated of order 1), while temporary component is deemed to follow I(0) process. If x and y are all integrated of order 1, they are cointegrated if there exists a linear combination of x and y, which is I(0). We provide a re-interpretation of the cointegration relation from the factor economy perspective. Let's assume x and y that are characterized as follows. $y_t = cf_t + e_{yt}$, and $x_t = f_t + e_{xt}$. We assume that $f_t \to I(1)$, $e_{xt} \to I(0)$, $e_{yt} \to I(0)$, and c is a constant coefficient. We constructed the system such that the system (x_t, y_t) own a common I(1) factor, f_t. In this particular factor system, if there is a common I(1) factor, there can exist a vector (1, -c) such that linear combination of x and y, $z_t = y_t - cx_t = e_{yt} - ce_{xt}$, becomes stationary. The reverse is also true (as shown by Stock and Watson (1988)): if x and y are cointegrated, there must exist a common stochjastic factor representation.

Based on this proposition, Gonzalo and Granger (1995) develop a technique for extimating common stochastic factors and then P-T components under the VECM framework. Let's consider a (px1) vector of I(1) time series with mean zero, X_t. We assume that the rank of cointegration is r, implying that there exists a matrix $\beta_{p\times r}$ of rank r, such that $\beta' X_t$ is I(0). Then, the vector X_t can be expressed as a VECM representation as follows.

$$\Delta X_t = \Gamma_1 X_{t-1} + ... + \Gamma_k X_{t-k} + \alpha\beta' X_{t-1} + e_t , \qquad (2)$$

This VECM implies that the elements of X_t can be explained by smaller number of I(1) variables (in this case, p-r). Using the estimated VECM, Gonzalo and Granger (1995) shows that common (long memory or permanent) factors can be identified based on the following equation.

$$f_t = \alpha'_{\perp} X_t , \text{ where } \alpha'_{\perp} \alpha = 0 \text{ and k = p – r.} \qquad (3)$$

These are the linear combinations of ΔX_t that do not contain the levels of the error correction term. Once the common factor f_t is identified, by inverting the the matrix $(\alpha_{\perp}, \beta)'$, we obtain the P-T decomposition as follows.

$$X_t = \beta_{\perp}(\alpha'_{\perp} \beta_{\perp})^{-1} \alpha_{\perp}' X_t + \alpha(\beta'\alpha)^{-1} \beta' X_t \qquad (4)$$

By reflecting the short-run adjustment process, the decomposition can be re-written as follows.

$$X_t = \beta_{\perp}(\alpha'_{\perp} \psi\beta_{\perp})^{-1} \alpha_{\perp}' X_t + \alpha(\beta'\psi\alpha)^{-1} \beta' X_t , \text{ where } \psi = (\mathrm{I} - \Gamma_1 - ... - \Gamma_k) \qquad (5)$$

The estimation of PT components can be done by the maximum likelihood estimation of vector error correction model.

We applied this technique to decomposing trading volume and seat price into permanent and temporary components. PT decompositions are based on the estimates from the VECM in Table 2. In particular, the MA representation of the estimated VECM yields the orthogonal alpha and common stochastic trend. In order to see which component of trading volume causes the seat return, we conducted the Granger causality test using five differenced components such as the common stochastic factor (Δf_t) , the permanent component of seat price (ΔP_t^S), the temporary component of seat price (ΔT_t^S), the permanent component of volume (ΔP_t^V), and the temporary component of volume(ΔT_t^V). By allowing upto 4 lags, the test was applied to seat return (R_t) and excess seat return ($R_t - r_{ft}$), respectively. Results from causality tests between components and seat returns are shown in Table 3.

Place [Table 3] around here.

The results seem to deliver a uniform message, irrespective of the choice of dependent variable. In particular, seat return is caused by both permanent components for seat return and volume growth. Moreover, seat return is also caused by the temporary component of seat price. In contrast, seat return is not caused by temporary component of trading volume. Conventionally, the permanent component is considered unpredictable, since it is characterized as a random walk. On the contrary, the temporary component is regarded as predictable, since it is stationary and can be modelled as a usual ARMA process. We observe that the temporary component of trading volume is not useful for predicting seat returns. Thus, the predictable ability of trading volume for future seat return can be limited in ex ante sense. Despite the limit, the causality from the permanent component of trading volume to the seat return suggests that seat return can be strongly influenced by a permanent shock in trading volume factor. This fact is likely to help us formulate a factor pricing model that includes trading volume as a crucial factor in a system of finite asset pricing factors.

3. Causality Analysis between CBOT Seat Returns and Economic Factors

The success of modeling the behavior of seat prices depends on the identification of legitimate set of factors. Thus, before proceeding with the development of a seat pricing model, we examine the causality between CBOT variables (seat returns and trading volume growth rates) and economic fundamental variables. The criteria for choosing the variables are based on the prior empirical literature related to the pricing of capital assets. Together with CBOT trading volume, the economic variables encompass stock market return, the growth rate of industrial production, the growth rate of real consumption, interest rate, CPI inflation rate, the size premium factor (SMB), and the value premium factor (HML).[11] Firstly, we examine the causality from trading volume to seat return. Secondly, we investigate the relationship between trading volume and real activity.

Our prediction about the causality under the efficiency assumption is that seat prices precede trading volume and real activity. However, if the opposite is true, the preceding variables might contain certain information about time-variation of expected return to seats.

Place [Table 4] around here.

Table 4 contains the results of Granger-causality tests. Variables of interest encompass the CBOT trading volume, the stock market return, the growth rate of industrial production, the growth rate of real consumption, interest rate, CPI inflation rate, SMB, and HML factor. The lag lengths of causality tests are tried at 2, 4, and 6, respectively.

The first test is to investigate whether CBOT seat returns cause other economic fundamental variables. The interesting findings are that CBOT seat returns are significant in predicting CBOT trading volume, stock market return, industrial production, interest rate, and CPI inflation rate. However, the reverse causality direction is not detected except interest rate, for which causality is bi-directional. The reverse causality going from interest rate to CBOT seat price is likely to come out due to the leasing arrangement for the CBOT seat. We consider this test result as new evidence on the

[11] The growth rate of the variables and the inflation rate are defined as the first difference of logarithmic level series.

information contents of the CBOT seat price as a predictor of future economic activity and stock market.

The second causality test was conducted to see whether CBOT trading volume can also predict the future economic activity and stock market. There appears strong evidence on the causality from CPI inflation and SMB factor to CBOT trading volume. However, there is also marginally significant evidence on the causal direction from CBOT volume to CPI inflation. Particular importance of CPI inflation can be easily understood from the nature of the commodity futures tradng which is frequently used for the hedging of price risk. The relationship between CBOT trading volume and inflation rates is expected to be strong since traders tend to use the commodity futures contract to hedge against unfavorable movements of commodity prices in the future. The causality from size premium (SMB) to CBOT trading volume is very interesting. The rationale for the causal linkage is likely to be justifiable as long as the size premium can be a proxy of the risk factor that can influence the trading activity on the commodity futures market.

III. Economic Factors and Expected Seat Return

1. Identification of Economic Factors

In the prior sections, we paid particular attention to demonstrating that CBOT seat price fluctuates according to states of economy. Based on the major observations, we propose a model of time-varying expected return on the CBOT seat of which the return is generated with a finite number of risk factors. The setting of return generating mechanism is motivated by the fundamental reasoning that both cash flows and discount rates are determined by underlying economic shocks as implied in the forementioned equation (1). This spirit is generally consistent with those of prior studies including Chen Roll, and Ross (1976), Breeden (1979), Fama and Gibbons (1982), Stulz (1986), Burmeister and McElroy (1988), Elton, Gruber, and Blake (1995), Pesaran and Timmermann (1995), Campbell (1996), Ferson and Harvey (1999), and Campbell (2000).

We take an exploratory approach to identifying a legitimate set of economic factors. As a preliminary set of economic factors for explaining excess seat returns (ESR), we initially consider 10 economic factors and two states of business cycles: excess market return (EMR), size premium (SMB), value premium (HML), CBOT trading volume growth rate (VOL), the growth rate of industrial production (INP), CPI inflation rate (CPI), the growth rate of real personal consumption expenditure (CON), short-term interest rate (INT), default spread defined as difference between BAA bond rate and AAA bond rate (DSP), term spread defined as difference between 10-year T-bond rate and 1-year T-bill rate (TSP), the peak of business cycles (Peak), and the trough of business cycles (Trough). Most variables are selected from related literature that may affect expected cash flows and expected discount rates of seat prices as one of capital assets.[12]

Place [Table 5] around here.

Table 5 shows the estimated correlation matrix among selected variables. Overall, correlations among variables except interest-related ones appear relatively low. Pairs with relatively higher correlations include CPI-INT, INT-TSP, CPI-TSP, DSP-INT, and DSP-INP. The degrees of correlations for the pairs seem to be consistent with our casual expectation.

Place [Table 6] around here.

Table 6 reports the results of OLS regressions for excess seat returns using different subsets of independent variables. In order to control the effect of infrequent trading of seat memberships, we embedded the lagged dependent term into the regressors. The overall explanatory powers range from 7% to 12%. Relatively significant economic variables include EMR, SMB, HML, RVOL, and INT. As expected, all three factors of Fama and French turned out significant in explaining excess seat returns. This evidence reinforces our premise that exchange seats are also a capital asset by nature.

These Fama-French factor variables are treated as major fundamental factors driving the price of

[12] We may change the set of economic variables based on the results from prior sections. For example, if trading volume shows a significant power, independent of real activity, in explaining seat prices, we may include trading volume as a factor.

CBOT seat. Business cycle variables are relatively insignificant, probably because there exist alternative variables absorbing their effects. Among three factors of Fama and French, size premium (SMB) appears more significant than any other two factors such as value premium (HML) and excess market return (EMR). Interestingly, trading volume growth rate shows incremental significance even after controlling other key factors. Presumably this feature may distinguish the CBOT seats from other capital assets. It is likely that CBOT seat prices can be better explained by including another factor.

The asset pricing model stipulates the ex ante relation between return on capital assets and factors. In order to define ex ante measures of factor variables, we assume that investors have full knowledge of the ARIMA techniques in forming the expectation of economic factors. Thus, the ex ante parts of economic factors can be separated out by fitting the ARIMA models to the data. In order to control for the possible abrupt structural changes, we estimated the ARIMA model with intervention terms. The estimated results are presented in Table 7.

Place [Table 7] around here.

Consistent with our usual expectation, the model-fitting of excess stock market return produced a white noise process (after controlling for interventions). Unlike excess stock market return, excess seat returns are best modelled as AR(3) process. The estimated model of trading volume is an ARMA model, where there are seasonal multiplicative factors in the moving average terms. It is worth mentioning the intervention term is significant in December 1975 for the trading volume model. The drop of trading volume at that time may be attributed to the first oil crisis and deregulation measures. Another interesting variable is size premium (SMB). SMB is best modelled as AR(1) with three interventions. Significant interventions took place in 1978:10, 1983:8, and 1983:10. The abrupt shocks all led to a decrease in size premia. This is probably because of the second oil shock. We also see some seasonal spikes in estimated models for interest-ralated variables (INT, DSP, and TSP).

Place [Table 8] around here.

Table 8 shows the results from OLS regressions using expected and unexpected parts of variables for excess seat returns and excess market returns. We included EMR for estimating the excess seat return model, but not for excess market return model. The explanatory power of the full model for seat return is 12.4%, while that of the full model for market returns is 32.6%. Seat returns are related to SMB^e, VOL^e, and INT^e. Stock markets are significantly explained by economic fundamentals including INT^e, CON^e, CPI^e, DSP^e. For both regression equations, all expected variables turned out jointly significant. However, the unexpected variables for excess seat returns are jointly insignificant. In spite that the stock market return is more explained by unexpected parts, the proportion of variations explained by expected parts with respect to the full model is larger in seat returns. Even based on the regression analysis, we end up with key fundamental factors: EMR, SMB, HML, RVOL, and INT. These key variables will be considered in the dynamic asset pricing model to be discussed in the next section.

2. Dynamic Asset Pricing Model

In order to derive the pricing model of the exchange seat, we consider five economic risk factors such as the unexpected market premium (EMR^u), the unexpected size premium (SMB^u), the unexpected value premium (HML^u), the unexpected interest rate (INT^u), and the unexpected futures trading volume (VOL^u). The first three factors are the same as factors in Fama-French, and the last two are included as additional factors. We define symbols as follows.

r : asset returns.

f_j^u : innovation of unidentified factor j.

η : Idiosyncratic term.

I : information set available to investors.

x = SMB, HML, INT, VOL, EMR.

I_x : information subset pertaining to X.

E : conditional expectation operator.

β_x : loading to factor X (a measure of systematic risk).

λ_x : price of risk to factor X.

Γ^e : expected risk premium to unidentified factors.

$E(X_{t+1} \mid I_{xt})$: t+1 expected value of factor X conditional on information I_x .

α_x : the constant risk premium to factor X.

Using the notations defined above and the assumption of 5 identifiable factors and k unidentifiable factors, we describe the return generating mechanism as the following equation (6).

$$r_{t+1} = E(r_{t+1} \mid I_t) + \beta_{emr} EMR^u{}_{t+1} + \beta_{smb} SMB^u{}_{t+1} + \beta_{hml} HML^u{}_{t+1} + \beta_{int} INT^u{}_{t+1} + \beta_{vol} VOL^u{}_{t+1} + \sum_{j=1}^{k} \beta_j f^u_{jt+1} + \eta_{t+1} \tag{6}$$

Therefore, expected returns on assets can be expressed as a sum of factor risk premia, where risk premium to a particular factor is the product of factor loading and unit price of risk to the factor.

$$E(r_{t+1} \mid I_t) = \sum_x \beta_x \lambda_{xt} + \Gamma^e_t, \quad x = EMR, \; SMB, \; HML, \; INT, \; VOL. \tag{7}$$

The price of risk to factors is assumed to change linearly with the ARIMA prediction of factor variable X, conditioned on information I_x. This formulation is similar to the specification of the latent variable models (Gibbons and Ferson (1985), Campbell (1987), Harvey (1991), Campbell and Hamao (1992), Ferson, Foerster, and Keim (1993), Ferson and Harvey (1999)). Unlike the latent variable models that use a linear combination of lagged conditioning variables for defining the price of risks to factors (so called “linear risk premium hypothesis”), in our model the price of risks are assumed to be proportional to the ARIMA estimates of factors. This specification can be advantageous in that time-varying risk premia can be more precisely tracked by optimally predicted variables. By this definition, we obtain equation (8) for pricing each risk factor.[13]

$$\lambda_{xt} = \alpha_x + \gamma_x E_t(X_{t+1} \mid I_{xt}) \tag{8}$$

Substituting (8) for (7), we obtain equations (9) and (10) that represent the equilibrium relationship expected return and factor risks.

$$\begin{aligned} E(r_{t+1} \mid I_t) = \alpha_t + \beta_{smb}\gamma_{smb}E_t(SMB_{t+1}) + \beta_{hml}\gamma_{hml}E_t(HML_{t+1}) + \beta_{\text{int}}\gamma_{\text{int}}E_t(INT_{t+1}) + \\ \beta_{vol}\gamma_{vol}E_t(VOL_{t+1}) + \beta_{emr}\gamma_{emr}E_t(EMR_{t+1}) \end{aligned} \tag{9}$$

$$\alpha_t = \Gamma_t^e + \beta_{smb}\alpha_{smb} + \beta_{hml}\alpha_{hml} + \beta_{\text{int}}\alpha_{\text{int}} + \beta_{vol}\alpha_{vol} + \beta_{emr}\alpha_{emr} \tag{10}$$

By combining (10) with (6), we come up with an empirical model (11), which will be used for estimation.

$$\begin{aligned} r_{t+1} = a + bE_t(EMR_{t+1}) + cE_t(SMB_{t+1}) + dE_t(HML_{t+1}) + eE_t(INT_{t+1}) + fE_t(VOL_{t+1}) + \\ g\hat{U}_{emr,t+1} + h\hat{U}_{smb,t+1} + i\hat{U}_{hml,t+1} + j\hat{U}_{int,t+1} + k\hat{U}_{vol,t+1} + \eta_{t+1} \end{aligned} \tag{11}$$

Restrictions to the empirical model are: $a = \Gamma^e + \sum_x \beta_x \alpha_x, x = smb, hml, int, vol, emr$; $b = \beta_{emr}\gamma_{emr}$; $c = \beta_{smb}\gamma_{smb}$; $d = \beta_{hml}\gamma_{hml}$; $e = \beta_{int}\gamma_{int}$; $f = \beta_{vol}\gamma_{vol}$; $g = \beta_{emr}$; $h = \beta_{smb}$; $i = \beta_{hml}$; $j = \beta_{int}$; $k = \beta_{vol}$.

As argued, the conditional expected value of a factor X can be estimated using the ARIMA

[13] We define $E(X_{t+1} \mid I_t) = X_{t+1}^e$.

technique. In the same way, the end-of-period shock in a factor X can be estimated using a Box-Jenkins univariate ARIMA model for series X. Hence the unexpected value of a factor X can be computed as $X_{t+1}^{u} = X_{t+1} - E(X_{t+1} \mid X_t, X_{t-1}, ...)$.

In the universe of capital assets, the equation (11) can be estimated as a system by using SUR (seemingly unrelated regression) technique. If we are interested in the pricing of two assets such as CBOT seat returns (r_s) and stock market returns (r_m), we may establish two estimable systems (System 1 and System 2) as follows.[14] System 1 assumes only four factors such as SMB, HML, INT, and VOL. The first system is obtained by ignoring the stock market factor. It follows that the coefficients of EMR^e and EMR^u are restricted to zero.

<System 1>

$$\begin{pmatrix} r_{st+1} \\ r_{mt+1} \end{pmatrix} = \begin{pmatrix} a_s + b_s E_t(SMB_{t+1}) + c_s E_t(HML_{t+1}) + d_s E_t(INT_{t+1}) + e_s E_t(VOL_{t+1}) + f_s \hat{U}_{smb,t+1} + \\ g_s \hat{U}_{hml,t+1} + h_s \hat{U}_{\text{int},t+1} + i_s \hat{U}_{vol,t+1} \\ a_m + b_m E_t(SMB_{t+1}) + c_m E_t(HML_{t+1}) + d_m E_t(INT_{t+1}) + e_s E_t(VOL_{t+1}) + f_m \hat{U}_{smb,t+1} + \\ g_m \hat{U}_{hml,t+1} + h_m \hat{U}_{\text{int},t+1} + i_m \hat{U}_{vol,t+1} \end{pmatrix} + \begin{pmatrix} \eta_{st+1} \\ \eta_{mt+1} \end{pmatrix} \qquad (12)$$

We can distinguish the return generating mechanisms of seat and stock market by assuming different sets of factors as given below.

<System2>

[14] The stock market portfolio was chosen as a representative of a well-diversified capital asset for the purpose of comparison with CBOT seat.

$$\begin{pmatrix} r_{st+1} \\ r_{mt+1} \end{pmatrix} = \begin{pmatrix} a_s + b_s E_t(EMR_{t+1}) + c_s E_t(SMB_{t+1}) + d_s E_t(HML_{t+1}) + e_s E_t(INT_{t+1}) + f_s E_t(VOL_{t+1}) + \\ \quad g_s \hat{U}_{emr,t+1} + h_s \hat{U}_{smb,t+1} + i_s \hat{U}_{hml,t+1} + j_s \hat{U}_{\text{int},t+1} + k_s \hat{U}_{vol,t+1} \\ a_m + c_m E_t(SMB_{t+1}) + d_m E_t(HML_{t+1}) + e_m E_t(INT_{t+1}) + f_m E_t(VOL_{t+1}) + \\ \quad + h_m \hat{U}_{smb,t+1} + i_m \hat{U}_{hml,t+1} + j_m \hat{U}_{\text{int},t+1} + k_m \hat{U}_{vol,t+1} \end{pmatrix} + \begin{pmatrix} \eta_{st+1} \\ \eta_{mt+1} \end{pmatrix} \tag{13}$$

System 2 relaxes the restriction imposed on the seat return equation of the system 1, allowing the terms of the expected and unexpected excess market returns. But the equation for stock market return leaves the same as in System 1. As a result, only restriction is $b_m = g_m = 0$ on the equation of stock market return.

IV. Evidence on the Relationship between Seat Return and Fundamental Factors

We perform the multivariate SUR estimation on the set of seat return (R_s) and stock market return (R_m) (proxied by S&P 500). In the specification, we examine four major hypotheses as follows. First, we are interested in checking the validity of the assumption that the sum of unidentified factor premia is constant across assets (H_1). This hypothesis can be evaluated by testing the equality of constant terms in the 2 equation system. Second, we ask a question of whether unit factor risk premia and systematic risks are equal across assets (H_2). This test is helpful when we evaluate the relative risks of assets in consideration. Basically, we raise a question of whether CBOT seat and stock market index have the same risk. Third, we are concerned about time-variation of expected asset returns (H_3). This test can be done by jointly evaluating the significance of coefficients of expected factor value. Fourth, we test whether systematic shocks are jointly significant across assets (H_4). The key hypotheses are summarized as follows.

(H_1) H_{1a}: Constancy of unidentified factors across assets

(H_2) H_{2a}: Equality of unit factor risk premia across assets

(H_3) H_{3a}: Equality of the sensitivities to systematic shocks aross assets

H_{3b}: No time-varying risk premia for seat return

H_{3c}: No time-varying risk premia for both asset returns

(H_4) H_{4a}: No systematic factor risks to seat return

H_{4b}: No systematic factor risks to stock market return

H_{4c}: No systematic factor risks to both asset returns

Table 9 reports the results from the SUR estimation for System 1. The estimation is made against the equation (11) by restricting the coefficients of EMR^e and EMR^u to zero. From Table 9, we know that excess seat returns are time-varying with expected size premium (SMB^e), expected interest rate (INT^e), and expected CBOT volume (VOL^e). Moreover, excess seat returns are positively associated with expected size premium (SMB^e) and expected CBOT volume (VOL^e), while they are negatively related to expected interest rate (INT^e). Excess seat returns are particularly sensitive to the SMB shock. It is of particular importance to note that E(VOL) is highly associated with seat returns. In contrast, excess market returns are time-varying with both expected size premium (SMB^e) and expected interest rate (INT^e). However, excess market returns are sensitive to both shocks to size premium and value premium factors. Excess stock market returns are sensitive to shocks to size and value premia.

As a result of the Wald tests, we were able to reject most of null hypotheses. However, we were able to reject the hypothesis of the constancy of unidentified factors across assets, which is consistent with the model implication. The empirical evidence of different factor risk premia between seat and stock market index enables us to argue that risk exposures are also divergent. Moreover, we find that the sensitivities to systematic risks are also not equal. More importantly, the evidence suggests that both expected seat returns and stock market returns are time-varying with a finite number of risk factor. This reinforces the argument that exchange seats are a capital asset.

Wald tests on the restrictions show that (1) unit premium for interest factor are equal between seat and stock market, (2) the constant risk premuim hypothesis is rejected, and (3) the sensitivities to shocks are jointly different across assets.

Place [Table 9] around here.

Table 10 contains the results from the estimation of System 2. There are slight differences between Systems 1 and 2. System 2 uses different explanotary variables between seat return and market return equations. Particularly, there are trading volume variable and market return variable for the seat return equation. It turns out that one of Fama-French factors, HML^e, is insignificant in explaining excess seat returns. However, expected trading volume is highly significant and positively related to seat return.[15] It implies that seat returns are generated by local factors as well as regular asset factors. In this system, we also reject the hypothesis that excess seat returns are constant, and we find that excess seat returns are time-varying with expected SMB, and expected interest rate. Moreover, it turns out that CBOT seats are a more risky asset than the general stock market portfolio.

Place [Table 10] around here.

In order to evaluate the restriction between System 1 and System 2, we conducted the likelihood ratio test. The likelihood ratio is given by the formula, $2(\ln(L_{S2}) - \ln(L_{S1})) \sim \chi^2(\#restrictions)$. The number of restrictions is given as 2. Since the log likelihood values of System 1 and System 2 are 849.78 and 851.11, respectively, the likelihood ratio is 0.66, which is insignificant. Thus,System 1 can be a parsimonious alternative..

V. Conclusion

This paper analyzes the behavior of the CBOT seat prices for the period from 1975:1 to 1999:8.

[15] This evidence is not consistent with that of Chaing, et al. (1987). The divergent result may arise due to different model specifications: their static single factor model vs. our dynamic conditional multi-factor model.

Based on the time-series property of seat returns and the empirical link between seat returns and economic factors, we develop a conditional multi-factor model, where the price of risks are assumed to be linearly generated from the ARIMA estimates of the factor values. Particularly, we find a close short-run and long-run link between the CBOT seat price and CBOT trading volume. Importantly, the CBOT seat returns appear to exhibit significant power in predicting stock market returns, the growth of CBOT trading volume, the growth of industrial production, interest rate, and CPI inflation rate. Moreover, the CBOT trading volume showed a bidirectional causal relation to CPI inflation rate. Based on the dynamic pricing model, we find that excess seat returns are time-varying with some expected factors, such as expected size premium (SMB^e), expected CBOT trading volume (VOL^e), and expected interest rate (INT^e). Seat returns are particularly sensitive to the size premium shock (SMB^u). In conrtrast, excess stock market returns are shown to be time-varying with expected size premium (SMB^e) and expected interest rate (INT^e). Excess stock market returns are highly sensitive to shocks to size premium and value premium factors. Overall, we conclude that the pricing mechanism of CBOT seats is similar to that of a well-diversified stock market portfolio, suggesting the exchange seat is priced as a capital asset.

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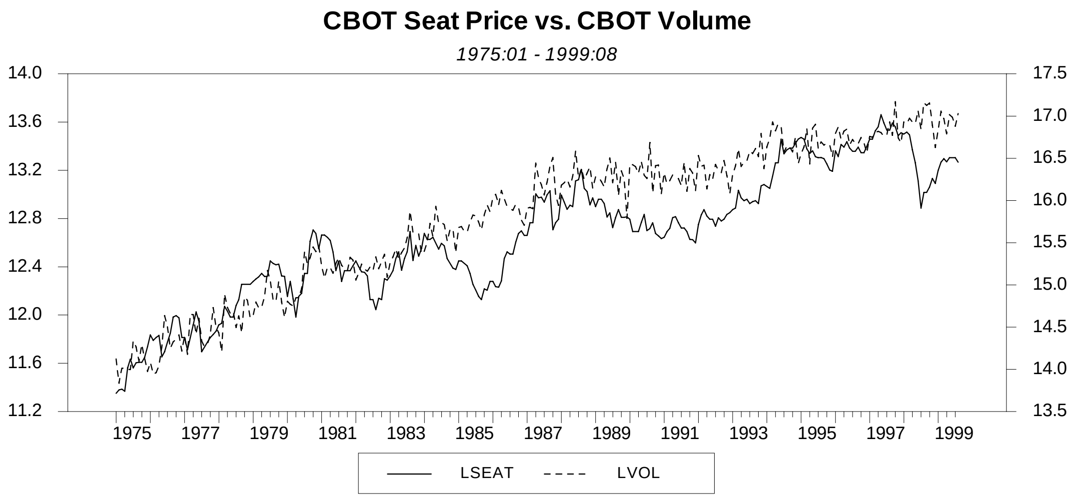
<Figure 1> CBOT Seat Price and CBOT Trading Volume



<Table 1> Perron Unit Root Test

Model	Description	Log Seat Price	Log Volume	Seat Return	Volume Growth Rate
IO1	Time Break	1998:02	1980:05	1987:12	1987:09
	$t_{\alpha}(\alpha=1)$	-4.406	-3.283	-18.320**	-7.579**
	Optimal Lag	2	12	0	12
IO2	Time Break	1994:01	1989:07	1987:12	1987:09
	$t_{\alpha}(\alpha=1)$	-4.532	-4.614	-18.300**	-7.583**
	Optimal Lag	2	12	0	12
AO	Time Break	1998:08	1987:02	1976:02	1990:08
	$t_{\alpha}(\alpha=1)$	-4.187	-4.227	-10.776**	-7.325**
	Optimal Lag	2	12	2	12

Note: Critical values are drawn from Perron (1997). * and ** represent significance at the 5% and 1% levels, respectively. The Perron test takes an intervention analysis approach by allowing intervention dummies in intercepts and slopes. There are three types of test statistics available: IO1 = t-statistic in the model of innovation outlier with a change in intercept, IO2 = t-statistic in the model of innovation with a change in intercept and in the slope, and AO = t-statistic in the model of additional outlier with a change in the slope only but both segments of the trend function are joined at the time break.

<Table 2> Results of ML Estimation of the VECM using the Johansen Procedure

Panel A. Johansen Multivariate Cointegration Test

Eigen Value	L-Max	Trace	$H_0 : r$
0.0391	11.44*	14.90*	$r = 0$
0.0120	3.46	3.46	$r \le 1$

Panel B. VECM Estimation

$$\begin{pmatrix} \Delta S_t \\ \Delta V_t \end{pmatrix} = \begin{pmatrix} -0.082 \\ (-3.05)^{**} \\ 0.054 \\ (1.021) \end{pmatrix} (5.895, \quad -3.373) \begin{pmatrix} S_{t-1} \\ V_{t-1} \end{pmatrix} + \begin{pmatrix} -0.008 & -0.017 \\ (-0.137) & (-0.531) \\ 0.035 & -0.574 \\ (0.291) & (-8.928)^{**} \end{pmatrix} \begin{pmatrix} \Delta S_{t-1} \\ \Delta V_{t-1} \end{pmatrix} + \begin{pmatrix} 0.133 & -0.011 \\ (2.207)^{*} & (-0.303) \\ 0.290 & -0.469 \\ (2.458)^{**} & (-6.577)^{**} \end{pmatrix} \begin{pmatrix} \Delta S_{t-2} \\ \Delta V_{t-2} \end{pmatrix} + \begin{pmatrix} -0.104 & 0.034 \\ (-1.703)^{+} & (0.911) \\ -0.221 & -0.244 \\ (-1.853)^{+} & (-3.301)^{**} \end{pmatrix} \begin{pmatrix} \Delta S_{t-3} \\ \Delta V_{t-3} \end{pmatrix} +$$

$$\begin{pmatrix} 0.009 & 0.042 \\ (0.145) & (1.128) \\ -0.118 & -0.290 \\ (-0.999) & (-3.943)^{**} \end{pmatrix} \begin{pmatrix} \Delta S_{t-4} \\ \Delta V_{t-4} \end{pmatrix} + \begin{pmatrix} 0.033 & 0.054 \\ (0.550) & (1.433) \\ 0.182 & -0.211 \\ (1.558) & (-2.868)^{**} \end{pmatrix} \begin{pmatrix} \Delta S_{t-5} \\ \Delta V_{t-5} \end{pmatrix} + \begin{pmatrix} -0.009 & -0.031 \\ (-0.149) & (-0.823) \\ 0.062 & -0.282 \\ (0.533) & (-3.867)^{**} \end{pmatrix} \begin{pmatrix} \Delta S_{t-6} \\ \Delta V_{t-6} \end{pmatrix} + \begin{pmatrix} 0.101 & 0.001 \\ (1.710)^{+} & (0.036) \\ 0.078 & -0.201 \\ (0.674) & (-2.934)^{**} \end{pmatrix} \begin{pmatrix} \Delta S_{t-7} \\ \Delta V_{t-7} \end{pmatrix} +$$

$$\begin{pmatrix} -0.012 & 0.007 \\ (-0.199) & (0.232) \\ -0.281 & -0.141 \\ (-2.425)^{*} & (-2.411)^{*} \end{pmatrix} \begin{pmatrix} \Delta S_{t-8} \\ \Delta V_{t-8} \end{pmatrix} + \begin{pmatrix} -0.095 \\ (-2.025)^{*} \\ 0.078 \\ (0.839) \end{pmatrix} D_{1987} + \begin{pmatrix} 0.300 \\ (3.102)^{**} \\ -0.161 \\ (-0.849) \end{pmatrix} + \begin{pmatrix} \varepsilon_{st} \\ \varepsilon_{vt} \end{pmatrix}$$

Panel C. Residual Analysis

Test for Normality: $\chi^2(4) = 6.491 (p = 0.17)$

Test for Autocorrelation: LM(1) $\chi^2(4) = 2.047 (p = 0.73)$; LM(4) $\chi^2(4) = 3.587 (p = 0.46)$

Note : D_{1987} is a dummy, which takes 1 for the period 1987:9 – 1987:11, zero otherwise. * indicates 5% significance.

<Table 3> P-T Decomposition and Granger Causality

$X_t = \beta_\perp(\alpha_\perp^{'}\psi\beta_\perp)^{-1}\alpha_\perp X_t + \alpha(\beta^{'}\psi\alpha)^{-1}\beta^{'} X_t$, where $\psi = (\mathrm{I} - \Gamma_1 - \ldots\Gamma_8)$

$\alpha_\perp^{'} = (0.5483 \quad 0.8363)$

Loadings to the common trend: $\beta_\perp(\alpha_\perp^{'}\psi\beta_\perp)^{-1} = \begin{pmatrix} 0.102 \\ 0.179 \end{pmatrix}$

Impact matrix: $C(1) = \begin{pmatrix} 0.102 & 0.156 \\ (0.992) & (7.377)^{**} \\ 0.179 & 0.273 \\ (0.992) & (7.377)^{**} \end{pmatrix}$

Seat Return	Δf_t	ΔP_t^S	ΔT_t^S	ΔP_t^V	ΔT_t^V
R_t	3.295 (p=0.01)	3.286 (p=0.01)	18.255 (p=0.00)	3.295 (p=0.01)	0.268 (p=0.89)
$R_t - r_{ft}$	3.271 (p=0.01)	3.262 (p=0.01)	17.375 (p=0.00)	3.271 (p=0.01)	0.266 (p=0.89)

Note: Δf_t =change in common stochastic factor, ΔP_t^S =change in permanent component of seat price, ΔT_t^S =change in temporary component of seat price, ΔP_t^V =change in permanent component of trading volume, ΔT_t^V =change in temporary component of trading volume

<Table 4> Causality Analysis between CBOT Seat Returns and Economic Factors

Lags in the Regression	CBOT Trading Volume	Stock Market Return	Industrial Production	Real Consumption	Interest Rate	CPI Inflation	SMB	HML
	(A.1) Granger Causality Direction: Seat Return → Economic Variables							
2	2.577+	3.948*	5.446**	0.494	5.298**	1.879	0.122	0.855
4	3.036*	2.115+	3.887**	0.711	3.995**	0.838	0.746	0.413
6	2.678*	2.333*	3.470**	0.690	3.806**	1.805+	0.525	0.760
Lags	(A.2) Granger Causality Direction: Economic Variables → Seat Return							
2	0.113	1.237	1.898	1.384	6.144**	1.132	1.089	1.465
4	0.192	0.718	0.895	1.369	5.047**	1.532	1.205	1.472
6	1.842+	0.544	0.584	1.420	3.495**	1.576	0.815	1.122
Lags	(B.1) Granger Causality Direction: CBOT Trading Volume → Economic Variables							
2	--	1.073	0.292	0.018	1.001	2.631+	1.552	2.590+
4	--	1.275	0.204	0.208	0.574	2.292+	1.577	2.673*
6	--	1.222	0.533	0.378	0.939	2.478*	1.436	2.435*
Lags	(B.2) Granger Causality Direction: Economic Variables → CBOT Trading Volume							
2	--	0.837	0.423	1.520	0.242	4.082*	8.799**	0.117
4	--	1.649	1.117	2.253+	0.333	4.043**	4.797**	0.896
6	--	1.911+	0.725	1.500	0.471	3.484**	4.025**	0.663

Note: Numbers in parentheses are F-statistics based on the Granger causality regressions. +, *, and ** indicate significance at 10%, 5%, and 1%, respectively.

<Table 5> Correlation Matrix

	ESR	EMR	SMB	HML	VOL	INP	CPI	CON	INT	DSP	TSP	Peak	Trough
ESR	1												
EMR	0.117	1											
SMB	0.175	0.275	1										
HML	0.032	-0.411	-0.121	1									
RVOL	0.153	-0.077	0.004	0.082	1								
RINP	0.030	-0.192	-0.007	0.120	0.048	1							
RCPI	-0.073	-0.163	0.025	0.084	0.112	-0.057	1						
RCON	0.089	0.009	0.184	0.026	-0.005	0.270	-0.214	1					
INT	-0.164	-0.130	-0.022	0.042	-0.020	-0.187	0.500	-0.149	1				
DSP	0.015	0.080	0.137	0.060	0.004	-0.293	0.208	-0.003	0.593	1			
TSP	0.148	0.080	0.069	0.096	0.034	0.104	-0.486	0.144	-0.685	-0.107	1		
Peak	-0.104	-0.003	-0.053	0.001	0.034	0.008	0.179	-0.008	0.170	0.046	-0.154	1	
Trough	0.122	0.085	0.172	-0.087	0.108	-0.154	-0.113	0.080	0.002	0.160	0.060	0.000	1

<Table 6> Estimating the OLS regressions for Excess CBOT Seat Returns

Reg.	constant	R(-1)	EMR	SMB	HML	VOL	INP	CON	INT	DSP	TSP	Peak	Trough	DW	R^2
(1)	0.022	-0.087	0.002	0.003	0.002	0.058	0.751	0.164	-8.882	28.57	-4.717	-0.063	0.054	2.03	0.117
	(1.03)	(-1.51)	(1.62)	(2.05)*	(1.32)	(2.35)*	(0.98)	(0.18)	(-2.16)*	(1.56)	(-0.59)	(-1.36)	(1.29)		
(2)	-0.003	-0.058	0.002	0.004	0.002	0.062	--	--	--	--	--	-0.085	0.057	2.03	0.087
	(-0.64)	(-1.01)	(2.07)*	(2.23)*	(1.55)	(2.52)*						(-1.83)+	(1.40)		
(3)	0.025	-0.073	0.002	0.004	0.002	0.059	--	--	-5.060	--	--	-0.065	0.059	2.03	0.106
	(2.04)*	(-1.29)	(1.80)+	(2.31)*	(1.55)	(2.42)*			(-2.49)*			(-1.40)	(1.46)		
(4)	0.029	-0.067	0.001	0.004	--	0.064	--	--	-5.515	--	--	--	--	2.03	0.087
	(2.37)*	(-1.17)	(1.30)	(2.62)**		(2.63)**			(-2.7)**						
(5)	0.028	-0.069	0.002	0.004	0.002	0.062	--	--	-5.494	--	--	--	--	2.03	0.093
	(2.25)*	(-1.21)	(1.76)+	(2.64)*	(1.45)	(2.55)*			(-2.7)**						

Note: Numbers in parentheses are t-statistics. DW indicates the Durbin-Watson statistic. +, *, and ** indicate significance at 10%, 5%, and 1%, respectively. R(-1) represents a lagged dependent variable.

<Table 7> Estimating ARIMA-Intervention Models for Economic Variables

Var	ARIMA Models	R^2	MSE
ESR	$(y_t - 0.0054) = -0.325I_{1pt} - 0.093I_{2pt} + (1 - 0.114B^2 + 0.132B^3)^{-1}e_t$ (1.19) (4.27)** (3.99)** (1.98)* (−2.30)* $I_{1pt} = 1987:10$, $I_{2pt} = 1989:7$	0.122	0.006
EMR	$(y_t - 1.012) = -24.012I_{1pt} - 17.00I_{2pt} + e_t$, $I_{1pt} = 1987:10$, $I_{2pt} = 1998:8$ (4.27)** (5.90)** (4.18)**	0.150	16.67
SMB	$(y_t - 1.115) = -11.13I_{1pt} - 1.203I_{2pt} - 2.225I_{3pt} + (1 - 0.149B)^{-1}e_t$, $I_{1pt} = 1978:10$ $I_{2pt} = 1983:8$, $I_{3pt} = 1983:10$	0.170	5.736
HML	$(y_t - 0.335) = (1 + 0.169B)e_t$ (1.58) (2.94)**	0.027	7.154
VOL	$(y_t - 0.013) = -0.209I_{1pt} + 0.196I_{2pt} + 0.294I_{3pt} + (1 + 0.533B)^{-1}(1 - 0.376B^2)(1 + 0.310B^{12})e_t$ (2.87)** (5.48)** (4.40)** (2.68)** (9.59)** (6.04)** (5.44)** $I_{1pt} = 1975:12$, $I_{2pt} = 1985:1$, $I_{3pt} = 1978:3$	0.462	0.019
CON	$(y_t - 0.0029) = -0.029I_{1pt} + 0.019I_{2pt} + 0.019I_{3pt} - 0.019I_{4pt} - 0.018I_{5pt} + e_t$, (10.58)** (6.03)** (3.97)** (3.94)** (3.92)** (3.71)** $I_{1pt} = 1987:1$, $I_{2pt} = 1986:12$, $I_{3pt} = 1986:9$, $I_{4pt} = 1985:10$, $I_{5pt} = 1986:10$	0.247	$.23\text{x}10^{-4}$
INP	$(y_t - 0.0028) = -0.021I_{1pt} + [(1 - 0.168B - 0.175B^2)(1 - 0.131B^3)]^{-1}e_t$, $I_{1pt} = 1980:5$ (4.00)** (3.55)** (2.83)** (3.00)** (2.20)*	0.154	$.38\text{x}10^{-4}$
CPI	$(y_t - 0.0033) = -0.01I_{1pt} + [(1 - 0.731B)(1 - 0.315B^{12})]^{-1}(1 - 0.152B)e_t$, $I_{1pt} = 1980:7$ (3.62)** (5.65)** (11.5)** (5.47)** (1.68)+	0.571	$.46\text{x}10^{-5}$
INT	$(1 - B)y_t = -0.0004(1 - B)I_{1pt} + [(1 - 0.459B + 0.225B^2 + 0.06B^3)(1 + 0.218B^6)]^{-1}(1 - 0.252B^{12}$ (1.77)+ (7.67)** (3.42)** (0.09) (3.63)** (4.23)** $I_{1pt} = 1980:5$	0.968	$.79\text{x}10^{-6}$
DSP	$(y_t - 0.0008) = [(1 - 0.975B)(1 - 0.918B + 0.250B^2 + 0.074B^3)]^{-1}e_t$ (1.62)+ (73.51)** (3.33)** (4.33)** (1.25)	0.942	$.90\text{x}10^{-8}$
TSP	$(1 - B)y_t = (1 + 0.187B^{12})^{-1}(1 + 0.469B)e_t$ (3.29)** (8.91)**	0.931	$.63\text{x}10^{-7}$

Note: Numbers in parentheses are t-statistics. +, *, and ** indicate significance at 10%, 5%, and 1%, respectively. I_p represents an intervention pulse variable. B represents a backshift operator.

<Table 8> OLS Regressions Using Expected and Unexpected Variables

	Excess Seat Return	Excess Market Return
Constant	0.017(0.68)	0.04(3.94)***
EMR	0.001(1.42)	--
SMB^e	0.005(2.49)*	0.001(1.60)
HML^e	0.003(.28)	-0.002(0.42)
VOL^e	0.053(2.0)*	0.002(0.17)
INT^e	-7.73(1.65)+	-6.057(2.9)**
CON^e	-0.66(0.36)	-2.88(3.6)**
INP^e	0.19(0.24)	-0.531(1.50)
CPI^e	0.99(0.52)	-2.093(2.50)*
DSP^e	21.7(1.12)	21.72(2.55)*
TSP^e	-1.43(0.15)	-9.54(2.29)
SMB^u	0.005(1.64)+	0.004(3.48)**
HML^u	0.002(1.13)	-0.004(5.4)**
VOL^u	0.035(0.75)	0.031(1.52)
INT^u	-17.21(1.31)	-11.7(2.03)
CON^u	0.94(0.84)	0.708(1.42)
INP^u	0.65(0.53)	-0.421(0.76)
CPI^u	-2.37(0.80)	-0.996(0.76)
DSP^u	-4.34(0.07)	40.64(1.46)
TSP^u	30.06(1.39)	3.415(0.35)
DW	2.12	2.00
R^2	0.124	0.326
F-test for all expected	2.362*	53.199**
F-test for all unexpected	1.123	26.637**

Note: Numbers in parentheses are t-statistics. DW indicates the Durbin-Watson statistic. +, *, and ** indicate significance at 10%, 5%, and 1%, respectively.

<Table 9> Results from the SUR Estimation: System 1

Panel A. SUR Estimation

	Constant	SMB^e	HML^e	INT^e	VOL^e	SMB^u	HML^u	INT^u	VOL^u	SSE
	a_i	b_i	c_i	d_i	e_i	f_i	g_i	h_i	i_i	
Seat	0.030	0.005	-0.0004	-5.541	0.063	0.006	0.002	-16.53	0.056	1.801
($i = s$)	(2.35)*	(3.21)**	(0.03)	(2.72)**	(2.52)*	(2.39)*	(1.03)	(1.41)	(1.26)	
Stock	0.017	0.002	-0.003	-2.178	-0.007	0.005	-0.006	-7.37	0.016	0.413
($i = m$)	(2.80)**	(2.38)*	(0.72)	(2.23)*	(0.62)	(4.25)**	(6.75)**	(1.31)	(0.77)	

Panel B. Test Results of Hypotheses

	Hypotheses	Description	Chi-square Test (p)
H_1	H_{1a}: $a_s = a_m$	Constancy of unidentified factors across assets	χ^2 (1)=0.910 (0.33)
H_2	H_{2a}: $b_s = b_m, c_s = c_m, d_s = d_m, e_s = e_m$	Equality of unit factor risk premia across assets	χ^2 (4)=13.748 (0.008)**
	H_2b: $f_s = f_m, g_s = g_m, h_s = h_m, i_s = i_m$	Equality of the sensitivities to systematic shocks aross assets	χ^2 (4)=17.783 (0.001)**
H_3	H_{3a}: $b_s = c_s = d_s = e_s = 0$	No time-varying risk premia for seat return	χ^2 (4)=25.226(0.000)**
	H_{3b}: $b_m = c_m = d_m = e_m = 0$	No time-varying risk premia for stock market return	χ^2 (4)=12.265 (0.015)*
	H_{3c}: $b_s = c_s = d_s = e_s = b_m = c_m = d_m = e_m = 0$	No time-varying risk premia for both asset returns	χ^2 (8)=35.010 (0.000)**
H_4	H_{4a}: $f_s = g_s = h_s = i_s = 0$	No systematic factor risks to seat return	χ^2 (4)=9.302 (0.05)*
	H_{4b}: $f_m = g_m = h_m = i_m = 0$	No systematic factor risks to stock market return	χ^2 (4)=76.157 (0.000)**
	H_{4c}: $f_s = g_s = h_s = i_s = f_m = g_m = h_m = i_m = 0$	No systematic factor risks to both asset returns	χ^2 (8)=84.926 (0.000)**

Note: Numbers in parentheses in Panel A are t-statistics. SSE indicates the sum-of-squared-errors. +, *, and ** indicate significance at 10%, 5%, and 1%, respectively. The likelihood value for System 1 is 849.78.

<Table 10> Results from the SUR Estimation: System 2

Panel A. SUR Estimation

	Constant a_i	EMR^e b_i	SMB^e c_i	HML^e d_i	INT^e e_i	VOL^e f_i	EMR^u g_i	SMB^u h_i	HML^u i_i	INT^u j_i	VOL^u k_i	SSE
Seat	0.025	0.006	0.004	-0.001	-5.524	0.067	0.0008	0.005	0.003	-15.610	0.052	1.763
($i = s$)	(1.93)+	(2.307)*	(2.43)*	(0.12)	(2.72)**	(2.69)**	(0.64)	(1.87)+	(1.49)	(1.34)	(1.18)	
Stock	0.017	--	0.002	-0.003	-2.178	-0.007	--	0.005	-0.006	-7.372	0.016	0.414
($i = m$)	(2.80)**		(2.38)*	(0.72)	(2.24)*	(0.62)		(4.25)**	(6.75)**	(1.31)	(0.77)	

Panel B. Test Results of Hypotheses

	Hypotheses	Description	Chi-square Test (p)
H_1	H_{1a}: $a_s = a_m$	Constancy of unidentified factors across assets	χ^2 (1)=0.294 (0.58)
H_2	H_{2a}: $c_s = c_m, d_s = d_m, e_s = e_m, f_s = f_m$	Equality of unit factor risk premia across assets	χ^2 (4)=11.38 (0.022)*
	H_{2b}: $h_s = h_m, i_s = i_m, j_s = j_m, k_s = k_m$	Equality of the sensitivities to systematic shocks aross assets	χ^2 (4)=18.52 (0.000)**
H_3	H_{3a}: $b_s = c_s = d_s = e_s = f_s = 0$	No time-varying risk premia for seat return	χ^2 (5)=29.17(0.000)**
	H_{3b}: $c_m = d_m = e_m = f_m = 0$	No time-varying risk premia for stock market return	χ^2 (4)=12.26 (0.015)*
	H_{3c}: $b_s = c_s = d_s = e_s = f_s = c_m = d_m = e_m = f_m = 0$	No time-varying risk premia for both asset returns	χ^2 (9)=41.17 (0.000)**
H_4	H_{4a}: $g_s = h_s = i_s = j_s = k_s = 0$	No systematic factor risks to seat return	χ^2 (5)=9.428 (0.09)+
	H_{4b}: $h_m = i_m = j_m = k_m = 0$	No systematic factor risks to stock market return	χ^2 (4)=76.156 (0.000)**
	H_{4c}: $g_s = h_s = i_s = j_s = k_m = h_m = i_m = j_m = k_m = 0$	No systematic factor risks to both asset returns	χ^2 (9)=85.51(0.000)**

Note: Numbers in parentheses in Panel A are t-statistics. SSE indicates the sum-of-squared-errors. +, *, and ** indicate significance at 10%, 5%, and 1%, respectively. The likelihood value for System 2 is 851.11.