A Note on a Cointegrating Vector for US Interest Rate Swaps

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Abstract

This note explores the temporal relationship among US interest rate swap spreads, US corporate credit spreads, LIBOR and the shape of the Treasury yield curve by performing cointegration test and estimating an error correction model. One cointegrating relationship is found, implying that a single common factor underlies these time series and a stable long-run linear relationship exists among them. In addition, the obtained cointegrating vector provides evidence for the existence of complex dynamics between the swap and the equity markets in the US.

Key words: Cointegration; Error correction; Interest rate swap.

1. Introduction

It has been recognized that the differentials between interest rate swaps and their Treasury counterparts with the same maturity, or swap spreads, are generally influenced by the interplay of several complex factors. In this empirical study we examine the dynamic interactions between US interest rate swap spreads, London Interbank Offered Rates (LIBOR), corporate credit spreads and the shape of the Treasury yield curve. Because all of these variables are $I(1)$ variables[3], standard vector autoregression (VAR) methods in levels or first differences are inappropriate for our purpose. Therefore, we conduct cointegration analysis to see if there is any long-run relationship among the variables. If cointegration exists, it implies a special long-run relationship among them and the variables cannot wander far away from each other arbitrarily over time.

While Duffie and Singleton (1997) answer the substantive questions that one would have regarding the dynamic relationships between fixed income market variables and the swap spread at weekly intervals, this note has the potential to extend this knowledge down to smaller time horizons and it would be interesting to know how the dynamic relationships change as the time intervals shorten.

In order to examine the cointegrating relationship among the variables, we perform the Johansen (1988) cointegration tests. The finding of exactly one cointegrating relationship, which is obtained from the fixed income and the credit markets, suggests that there is an error correction representation of the model. Error correction model (ECM) is deemed as an effective way of characterizing the dynamic multivariate interactions when cointegrating relationships are present. Results from the ECM estimation confirm that the selected variables are well modelled as a cointegrated system, shedding light on the relative importance of lagged innovations in the variables, as well as deviations of the variables from their long-run cointegrating relationship, to innovations in the swap spreads.

The note is organized as follows. The second section gives an overview of the existing literature on the determinants of swap spreads and outlines the theoretical considerations for the variables in our study. In section 3 we describe the dataset on the fixed-income market variables of our choice. Then we present the econometric models of cointegration and error correction. Section 4 contains the interpretations of the empirical estimation results. In particular, further exploration shows that the obtained cointegrating vector is highly correlated with the Nasdaq stock market index, indicating complex dynamics between the swap and the equity markets that has not been documented before. The final section provides concluding remarks.

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[3] That is, the hypothesis of a unit root cannot be rejected.

2. Determinants of swap spreads

Since the inception of swap contracts in 1981, the market for swaps has experienced tremendous growth in the past two decades. It has grown into one of the biggest and most liquid markets in the world. The notional amount of outstanding transactions was estimated to be $50 trillion in 1999. By the end of 2002, it was about $80 trillion according to Bank for International Settlements. Moreover, the swap curve obtained from interest rate swaps is being widely adopted as the best alternative to Treasuries as the primary benchmark for the term structure of interest rates.

Recent studies show mixed interactions between swap spreads, credit risk and liquidity factor. Duffie and Singleton (1997) develop a term structure model for swap yields, which account for both counterparty default risk and liquidity risk. Other papers, such as by He (2001) and Solnik (2001), argue that swap contracts are essentially risk-free due to the extensive use of collateral nowadays. Variation in swap spreads is ascribed to the change in liquidity risk by Grinblatt (2001). Minton (1997) also finds weak evidence that swap rates are sensitive to the credit spread between AAA and BAA rated bond yields. At the same time, in this strand of literature, results reporting credit risk in the interest rate swap market can be found in Cossin and Pirotte (1997) and Liu, Longstaff, and Mandell (2002).

Our main concern is to investigate whether there is a *stable* long-run relationship between the US interest rate swap spreads and a few key underlying variables (among inexhaustible many) that are related to the dynamics of swap spreads. Because many of the same factors may affect both the yield of Treasuries and the swap rate, it would be tricky to make precise assumptions about what causes the swap spread to alter. This note, therefore, incorporates the following relevant variables: the 10-year US interest rate swap spreads (SS_{10}), 6-month LIBOR rates (LIBOR), the shape of the Treasury yield curve (SLOPE), corporate credit spreads (CREDIT) and the modified duration of the corporate bonds in the relevant credit category (DURATION). With the availability of daily data we are able to answer the question — compared to the already established literature how the dynamics change at shorter time intervals[1].

The economic merits of investing in Treasuries and receiving fixed payments under a swap contract are virtually the same, if investors have funds that are of short-term nature. For them, swaps are not just a method of hedging but also considered as an investment opportunity for generating profits. As a result, regardless of interest rate levels, swap spreads with shorter maturities usually experience less volatilities. Swaps are becoming liquid in the medium-term zone. Due to these considerations, we essentially focus on the swaps with ten year maturity.

It is observed that banks are the most important market participants in the swap market. The credit risk of the banking system depends strongly on the creditworthiness of the corporate sector. Whenever credit spreads increase, credit risk of the banking system also rises and so does the risk premium that has been priced into the swap rates. Swap spreads have generally been lingering within the range defined by AA- and A-rated new-issue spreads in the domestic and international bond market, and longer-dated interest rate swaps are influenced significantly by the corporate bond market. Accordingly, corporate credit spreads are indispensable in our analysis.

But it is worth emphasizing the dual nature of the credit risk involved. On the one hand, interest rate swaps are assumed to be close to risk-free — the general swap rate is only for highly rated counterparties, and there is no principal to default on. Counterparties lose money only if they are net receivers when the other party defaults. In addition, many swap agreements require collateral. On the other hand, the floating rate used most often in the swap market to reference a swap rate is the LIBOR rate and this means that swaps can be thought of as derivatives on LIBOR rates. Although LIBOR is a standardized rate, set by the British Banker's Association, it is an *unsecured* rate, at which major international banks can borrow funds from each other without posting collateral. Therefore, having little credit risk of their own, swaps do reflect certain credit risk.

The reason to consider 6-month LIBOR is twofold: first, it is commonly used for the floating leg of the US dollar interest rate swaps; second, it is widely viewed as an "effective proxy

[1] Weekly data are commonly used in other papers.

for banking liquidity". Swap rates can be derived as the weighted average of the expected future LIBOR rates, i.e. the LIBOR forward rates over the life of the contract. At the time a swap contract is entered into, the contract is valued at its fair value if it is attributed a value of zero at the beginning. This occurs only if the present value of future net payments is equal to zero. Usually the implied forward rates change daily with the movements of the yield curve. It means that in the course of time the swap will acquire a positive or a negative value, which corresponds to the present value of the future flow of payments.

Since the yield curve of the US Treasury is taken as reflecting the market expectation on future interest rates, there should be a relationship between the shape of the yield curve and the swap spreads. In an environment of steep yield curve, issuers of fixed-rate debt have higher incentives to reduce their interest burden by swapping into synthetic floating-rate debt. This creates a supply surplus (more floating-rate payers) on the swap market, resulting in lower swap rates and narrower swap spreads. In contrast, with an inverted yield curve, rising swap rates and wider swap spreads should be expected.

The two-year and the ten-year on-the-run (OTR) Treasury yields can be used to generate the slope of the yield curve, which may serve as a proxy for the liquidity factor. As displayed in Figure 1, swap spreads almost always move in the opposite direction of SLOPE. For instance, in the first half of the year 2000, swap spreads widened out substantially as Treasury curve flattened due to the continuing shrinkage in the supply of long-term notes. On the contrary, the Fed easing moves in later years caused the Treasury curve to steepen and led to narrowing swap spreads.

Last but not least, the inclusion of the duration variable builds on our belief that the use of swaps as a duration management tool by investors is progressively becoming a pronounced driver of swap spreads. From Figure 1 it seems that DURATION and SS_{10} tend to exhibit opposite trending behavior. Next we will investigate in the following sections whether there is a cointegrating vector between the variables mentioned above and what interesting features it might possess.

3. Cointegration analyses

Cointegration procedures help to retain all the information on potential equilibrium relationship between nondeterministic time series without any initial data transformations. In this section we are interested in obtaining a constant parameter vector β, a cointegrating vector, if there is any, by adopting the Johansen's maximum likelihood (ML) method.

3.1. Data

The data used in this study are primarily Liquid US Corporate Index (LUCI) data from Credit Suisse First Boston[1]. LUCI is a market capitalization weighted index of over 500 High Grade US Corporate bonds. The index is separated into categories based on ratings by Moody's Investor Service and Standard & Poor's. All data within the various rating categories are the weighted average of all bonds within the grouping. There is no "missing" data within the LUCI index because all trading days are included and end of day prices are given by traders. Only closures of the market cause any gaps in the data series.

The estimations utilize daily data from January 4, 1999 to March 8, 2002[2], including 10-year USD swap spreads, LUCI-A benchmark spreads, LUCI-A modified duration[3], OTR Treasuries for both two-year and ten-year maturities, and 6-month LIBOR. Credit components are proxied by LUCI-A benchmark spreads, which are the weighed average credit spreads of the A-rated US corporate bonds. Note that the LUCI-A rating categories are near the ten-year average weighted maturity, we also add the modified duration of LUCI-A category into the analysis. The inclusion of the LUCI data enables us to obtain finer results, since such daily data were not available until

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[2] Before August 1998, US swap spreads had been traded within a stable range.

[3] Modified durations have already taken convexity into account.

the last few years. Figure 1 contains the plots of the variables SLOPE, LIBOR, CREDIT and DURATION in contrast to SS_{10}.

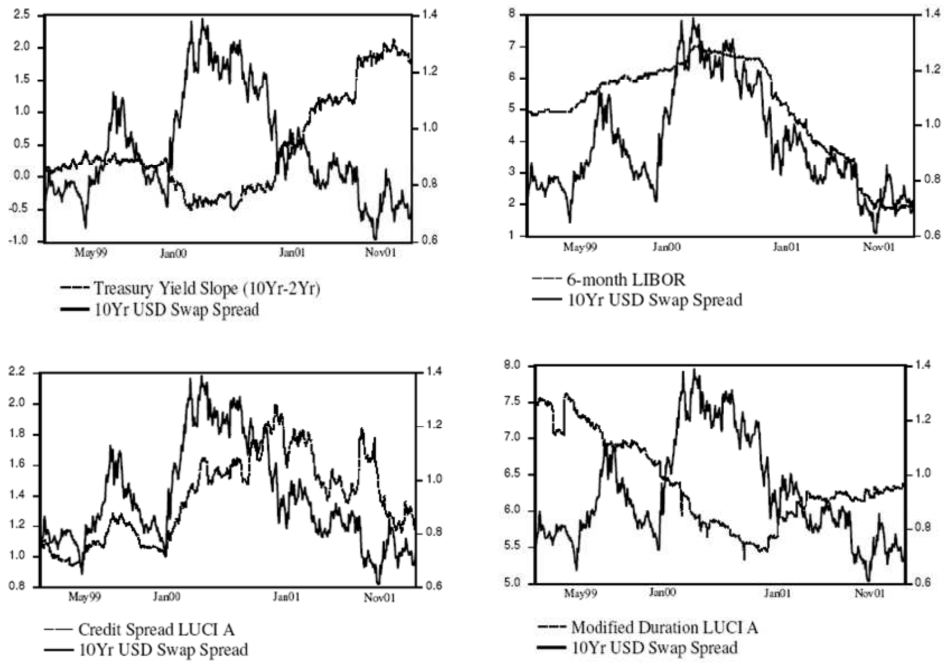

Fig. 1. SS10, SLOPE, LIBOR, DURATION and CREDIT (1999-2002)

3.2. Methodology

Empirically the variables in a vector autoregression (VAR) model should be stationary or transformed into stationary variables for the asymptotic theory to be valid. A VAR in first-differences would be appropriate when the variables are integrated of order one (while not cointegrated). However, if they are *cointegrated* then the lagged equilibrium error(s) should be included as regressor(s) into a dynamic specification of an error correction model (ECM)[1].

The choice of lag length is a crucial step in the construction of a VAR model to be evaluated. We use several information criteria to choose the lag structure of the model. In Table 1, three lags (in terms of levels of the variables) over other orders are suggested unambiguously by the sequential modified likelihood ratio test statistic (LR), Akaike's final prediction error criterion (mean square prediction error, or FPE) and Akaike information criterion (AIC). As pretests, we also conduct unit root tests to assess the order of integration of each variable sequence. Augmented Dickey-Fuller (ADF) test results are shown in Table 2. As most financial time series, the variables of our focus are all non-stationary, *I*(1) variables.

Opting for three lags, we proceed to implement Johansen's (1988) multivariate cointegration test as follows. Let's consider a standard VAR model:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + A_3 Y_{t-3} + \varepsilon_t, \tag{1}$$

[1] Engle and Granger (1987).

where Y stands for a (5 × 1) vector of SS_{10} (10-year swap spreads), SLOPE (slope of the Treasury yield curve), CREDIT (LUCI-A credit spreads), LIBOR (6-month LIBOR), and DURATION (LUCI-A modified duration) respectively, and ε_t is a vector of white noises with mean zero and finite variance. This VAR can be represented by:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + \Pi\, Y_{t-1} + \varepsilon_{t,} \tag{2}$$

where Δ is the first difference operator, $\Pi = A_1 + A_2 + A_3 - I$, and coefficient matrix

$$\Gamma_i = -\sum_{j=i+1}^{3} A_j\,,\ i = 1, 2. \tag{3}$$

The number of distinct cointegrating vectors can be obtained by checking the rank of Π or the significance of the eigenvalues of Π. Johansen's method is to estimate the Π matrix from Equation (2) and use likelihood ratio test to test the hypothesis that there are at most r cointegrating vectors[1].

Two restricted maximum likelihood ratio test statistics are employed: the Trace test statistic and the Maximal Eigenvalue test statistic (Johansen and Juselius, 1990). The trace statistics test the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r (the number of cointegrating relationships) against a general alternative[2]. While in the maximal eigenvalue test, the null hypothesis is that there is no cointegrating relationship among the variables and the alternative hypothesis is that one cointegrating vector exists.

Table 1

VAR Lag Order Selections

Lag	LogL	LR	FPE	AIC
0	-504.98	NA	2.54E-06	1.31
1	8223.36	17322.56	5.31E-16	-20.98
2	8349.73	249.18	4.10E-16	-21.24
3	8386.68	72.38*	3.98E-16*	-21.27*
4	8403.06	31.88	4.06E-16	-21.25
5	8419.71	32.19	4.15E-16	-21.23
6	8435.59	30.50	4.25E-16	-21.21
7	8446.56	20.93	4.41E-16	-21.17
8	8460.02	25.50	4.54E-16	-21.14
9	8475.54	29.22	4.65E-16	-21.12
10	8489.29	25.70	4.79E-16	-21.09
11	8499.92	19.74	4.97E-16	-21.05
12	8506.40	11.94	5.21E-16	-21.00

Notes: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion.

[1] It is most commonly used. In-depth discussions of the methodology and procedure can be found in many texts.

[2] For instance, you can test the null hypothesis $r \leq 0$ against the alternative $r = 1, 2, 3$ or 4.

Table 2

Summary of the Augmented Dickey-Fuller Tests

Variable	t-statistic	p-value
SS_{10}	-1.63	0.47
SLOPE	0.06	0.96
CREDIT	-1.56	0.50
LIBOR	1.68	0.99
DURATION	-1.90	0.33

Notes: (1) The null hypothesis is that each variable has a unit root. (2) Critical values are for a sample size of 800. (3) Critical values: 1% level is -3.44; 5% level is -2.86; 10% level is -2.57. (4) p-values are MacKinnon one-sided p-values.

3.3. Estimation of the long-run cointegrating relation

Table 3 contains the cointegration rank test of the data. All in all, the results of both the trace and maximal eigenvalue tests indicate one cointegrating vector ($r = 1$) at both 5% and 1% levels. The existence of one cointegrating vector asserts that there is one linear combination between swaps spreads and the other four variables for which the variance is bounded. By Granger's representation theorem (Engle and Granger, 1987), Π in Equation (2) can be represented by $\Pi = \alpha\beta'$, with both α and β (5×1) being column vectors. The elements in α are known as the adjustment parameters. $\beta = (\beta_1, \beta_2, \beta_3, \beta_4, \beta_5)'$ is the cointegrating vector, such that $\beta'Y_t$ is stationary or integrated of order zero. The Johansen MLE of the cointegrating coefficients is presented in Table 4. When the system is in long-run equilibrium, we have $\beta'Y_t = 0$. Then we are able to obtain the following equation for swap spreads after normalizing the cointegrating coefficient on swap spreads[1].

$$SS_{10} = -1.008 - 0.059 \times SLOPE + 0.969 \times CREDIT + 0.012 \times LIBOR + 0.098 \times DURATION \quad (4)$$

Table 3

Cointegration Rank Test

Hypothesized No. of CE (s)	Eigenvalue	Trace Statistic	5% Critical Value	1% Critical Value
None**	0.06	97.51	76.07	84.45
At most 1	0.03	44.79	53.12	60.16
At most 2	0.02	22.32	34.91	41.07
At most 3	0.01	10.14	19.96	24.60
At most 4	0.01	4.07	9.24	12.97
Hypothesized No. of CE (s)	**Eigenvalue**	**Max Statistic**	**5% Critical Value**	**1% Critical Value**
None**	0.06	52.72	34.40	39.79
At most 1	0.03	22.46	28.14	33.24
At most 2	0.02	12.18	22.00	26.81
At most 3	0.01	6.07	15.67	20.20
At most 4	0.01	4.07	9.24	12.97

Notes: ** denotes rejection of the hypothesis at the 1% level. Both the Trace and Max-eigenvalue tests indicate one cointegrating equation at both 5% and 1% levels.

[1] As the cointegrating vector is not unique, normalization is necessary.

Table 4

Johansen Cointegration Test

Adjustment coefficients (α's)	
ΔSS_{10}	0.0003 (0.004)
ΔSLOPE	-0.02 (0.01)
ΔCREDIT	0.01 (0.003)
ΔLIBOR	0.04 (0.01)
ΔDURATION	-0.01 (0.01)

Normalized Cointegration Coefficients (β's)

SS_{10}	SLOPE	CREDIT	LIBOR	DURATION	C
1.00	0.06 (0.17)	-0.97 (0.21)	-0.01 (0.08)	-0.10 (0.10)	1.01 (1.15)

Note: Standard errors are in parentheses.

4. Estimation of an error correction model

According to Engle and Granger (1987), an error correction representation which incorporates levels and differences of variables can be adopted for a cointegrated system. In this section we illustrate how the above cointegration result may be utilized within an ECM framework[1]. To this end, denoting the cointegration error as e[2], we write the ECM-VAR representation as:

$$\Delta Y_t = \sum_{j=1}^{n} \alpha_j e_{j,t-1} + \sum_{i=1}^{m} A_i \Delta\, Y_{t-i} + \varepsilon_t. \quad (5)$$

Here A is an m × m coefficient matrix, which consists of the short-run parameters — the coefficients on the lagged first-difference terms. The number of cointegrating vectors and the number of lags in lagged first-difference terms are designated by n and m respectively, with $n = 1$ and $m = 2$ as determined in the previous section. The residual from the cointegrating regression, e_{t-1}, is built into the specification and labelled as the *error correction* term. It is a measure of the error or deviation from equilibrium. Each element of α is one feedback coefficient and measures the speed of adjustment of each variable towards the equilibrium. As a result, the long-run behavior of the variables is restricted to converge to their long-run equilibrium while short-run adjustments are also allowed.

4.1. Interpretation of the estimation

Results from the ECM estimation for swap spreads are reported in Table 5. If written out, the equation is:

$$\begin{aligned}\Delta SS_{10,t} &= 0.0003 \times e_{t-1} + 0.20 \times \Delta SS_{10,t-1} - 0.16 \times \Delta SS_{10,t-2} - 0.02 \times \Delta SLOPE_{t-1} - \\ &- 0.02 \times SLOPE_{t-2} + 0.08 \times \Delta CREDIT_{t-1} + 0.003 \times \Delta CREDIT_{t-2} + 0.04 \times \\ &\times \Delta LIBOR_{t-1} + 0.02 \times \Delta LIBOR_{t-2} - 0.01 \times \Delta DURATION_{t-1} - 0.002 \times DURATION_{t-2} + \varepsilon_{1,t}. \quad (6)\end{aligned}$$

In particular, the cointegration error based on the cointegrating vector is given by:

$$\begin{aligned}et\text{-}1 &= 1.008 + SS10,t\text{-}1 + 0.059 \times SLOPEt\text{-}1 - 0.969 \times CREDITt\text{-}1 - 0.012 \times \\ &\times LIBORt\text{-}1 - 0.098 \times DURATIONt\text{-}1. \quad (7)\end{aligned}$$

[1] Due to the error correction mechanism, the ECM is proved to be superior to VAR in forecasting economic courses when the included time series are cointegrated.
[2] It measures the extent to which the system of the variables is out of equilibrium. It is also called the "equilibrium error".

Our results, which emerged from the analysis of daily LUCI data, are not completely in agreement with those of Duffie and Singleton (1997). Using weekly data they find very different responses of swap spreads to liquidity shocks and to credit shocks, with significant impact from liquidity effect in the short run while credit effect being a major determinant only over longer horizons. The cointegrating regression indicates that swap spreads are positively correlated with all the variables, except for the slope of the Treasury yield curve. CREDIT is statistically significant and adjusts almost one for one with SS_{10} in the long run, given ceteris paribus conditions. This is consistent with Duffie and Singleton's conclusion. Thus, it implies that credit spread is the main economic determinant of the behavior of swap spreads over the long run. Meanwhile this long-run equilibrium relationship prevents any of the variables from deviating too far out of the line and it describes the tendency of this system to move toward a particular point over time.

In contrast, responding to short-term shocks, the first lags of the first-difference terms of SS_{10}, CREDIT and LIBOR all display positive as well as strong statistical influence on SS_{10}. The SLOPE term (or liquidity effect) only has a marginally significant, negative short-run effect on SS_{10}. Moreover, DURATION lends little explanatory power to the daily movements of SS_{10}, showing no statistical significance in the regression results. Although the error correction term enters the ECM, the term does not play a statistically (nor economically) significant role in explaining innovations in the subsequent SS_{10}, while the coefficient on the lagged swap spread innovation is large and positive.

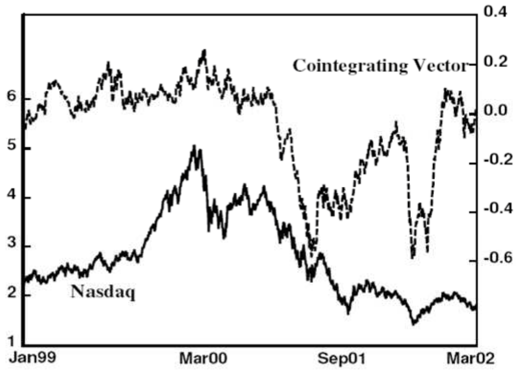

Fig. 2. Nasdaq vs. Cointegrating Vector

4.2. Further exploration of the cointegrating vector

We compare this cointegrating vector with the time series of Nasdaq composite index. Figure 2 shows that the cointegrating vector exhibits strikingly similar movement patterns to those of Nasdaq composite index during the sample period. For instance, it can be seen that as the Nasdaq stock market fell to its lowest level in years in the wake of September 11, the cointegrating vector also made huge plunge around the same time. It appears that there is a strong *positive* correlation (*0.57*) between the two time series. We deduce that this result renders empirical evidence that complex dynamics exists between the swap and equity markets in the US.

5. Conclusions

Given the extensive use of swaps in pricing, balance sheet management, hedging, and trading, the understanding of swap spreads therefore deserves more attention. We have explored the dynamics of interest rate swap spreads within a cointegrated system by using daily data for swap spreads, credit spreads, the shape of the Treasury yield curve, 6- month LIBOR rates and relevant duration measurement for the time period spanning from January 1999 to March 2002. Our analysis presents evidence that these variables from the fixed income markets closely linked to the swap rates are cointegrated with swap spreads.

This note contributes to the literature in the following ways. First, we demonstrate in a framework of ECM that swap spreads at daily intervals react to the long-run corrective restoring force apart from the short-run fluctuations in all the variables. In fact, the finding establishes that the short-run change in the slope of the Treasury yield curve only has a marginally significant, negative effect on swap spreads; while the short-run changes in corporate credit spreads, 6-month LIBOR, and the swap spread itself all exert positive, significant impact on the movement of swap spreads. At the same time, there is substantial impact from credit effect over the long run.

Furthermore, with the error correction term derived from the cointegrating regression, we believe that the presence of a stable long-run relationship reflects the common responses of the variables to changes in economic fundamental factors. Additional work can be done by making use of the knowledge of e_t on how to improve the forecast of one or all of the variables.

Most importantly, it is worthy to note that the cointegrating vector obtained from the fixed-income and credit markets exhibits a high degree of correlation with the Nasdaq composite index. The establishment of such a simple but sound correlation strongly suggests that the understanding of the USD swap market should be extended to the equity market as well.

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