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Dynamic Stock Market Interactions between the Canadian, Mexican, and the United States Markets: The NAFTA Experience

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Abstract

This paper explores the dynamic linkages that portray different facets of the joint probability distribution of stock market returns in NAFTA (i.e., Canada, Mexico, and the US). Our examination of interactions of the NAFTA stock markets considers three issues. First, we examine the long-run relationship between the three markets, using cointegration techniques. Second, we evaluate the dynamic relationships between the three markets, using impulse-response analysis. Finally, we explore the volatility transmission process between the three markets, using a variety of multivariate GARCH models. Our results also exhibit significant volatility transmission between the second moments of the NAFTA stock markets, albeit not homogenous. The magnitude and trend of the conditional correlations indicate that in the last few years, the Mexican stock market exhibited a tendency toward increased integration with the US market. Finally, we do note that evidence exists that the Peso and Asian financial crises as well as the stock-market crash in the US affect the return and volatility time-series relationships.

Journal of Economic Literature Classification: G10, C30, C50

Keywords: NAFTA stock markets, cointegration, impulse response, volatility transmission

1. Introduction

Over the past twenty years, international equity markets grew increasingly interdependent (e.g., Jeon and Chiang, 1991; Kasa, 1992; Rangvid, 2001). Regional and global cooperation, deregulation, and market liberalization contributed to international financial integration and interdependence (Fraser and Oyefeso, 2005; Aggarwal and Kyaw, 2005). Advances in computer technology and information processing also reduced the segmentation of domestic equity markets and increased their ability to react promptly to news originating in the rest of the world. Finally, new, common trading blocs, such as the European Union (EU), the Association of Southeast Asian Nations (ASEAN), the Southern Common Market (MERCOSUR) and the North American Free Trade Agreement (NAFTA), and new, integrated economic systems such as the European Monetary Union (EMU) enhanced the interdependence between national equity markets of those member states (Chen, Firth, and Rui, 2002).

The growth and reach of international trade and finance reveal two important stylized facts. First, although the growth in trade preceded the growth of finance, the growth and spread of international finance eventually surpassed that of trade (Krugman and Obstfeld, 2009; Feenstra and Taylor, 2008). Second, much trade growth reflected the creation of regional trade groups (e.g., ASEAN, MERCOSUR, EU, and NAFTA). Feenstra and Taylor (2008) show that intraregional trade dominates interregional trade, which fostered research dedicated to regional financial markets. Not surprisingly, much recent research examines international financial markets with a regional emphasis (e.g., Asian and Latin American financial markets in emerging markets and the EU and NAFTA in developed countries).

The changing patterns of international trade precipitated larger capital flows across markets, further enhancing the integration and globalization process. MacDermott (2007) concludes that NAFTA increased foreign direct investment (FDI) flows into the US by approximately 0.96%, while flows into Mexico and Canada rose by 1.73 and 1.54 percent. Globerman and Shapiro (1999) and Karp and Sanchez (2000) report similar, but smaller, country-specific results. The rapid growth of financial-market integration portends obvious implications for international portfolio diversification, international asset pricing, hedging strategies, and regulatory policy.[1]

Previous research largely conducted investigations of international equity market linkages along two lines. First, researchers consider whether cointegration (Engle and Granger, 1987; Johansen 1988, 1991, 1995; Johansen and Juselius, 1990) exists among international equity markets. Evidence of cointegration indicates that stock markets follow the same long-run stochastic trend, implying that any diversification gains across international markets only occurs at short-run horizons when markets can temporarily diverge from their long-run path.[2]

The efficient-market hypothesis in its strong form argues that a stock's price incorporates all the known, relevant information about the company. Thus, only "news" about that company moves this period's stock price. Granger (1992) argued "… for the same reason one would not expect a pair of stock prices to be cointegrated, as this would contradict the efficient market hypothesis." (p. 11). Consider two regional stock markets that make a market in the same firm. The law of one price implies the same price in the two markets, ignoring transactions costs and making any needed exchange rate adjustment. Thus, cointegration between the two prices should

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[1] For example, the current global financial crisis highlights the lack of supernational regulation, which will likely change in the near future.

[2] Numerous studies exist that examine stock market integration using cointegration techniques. An abbreviated list includes the following: Taylor and Tonks (1989), Eun and Shim (1989) Jeon and Chiang (1991), Becker et al. (1995), Kasa (1992), Arshanapalli and Doukas (1993), Chorhay et al. (1993), Blackman et al. (1994), Arshanapalli et al. (1997), Richards (1995), Choudhry (1996), Masih and Masih (1997), Roca (1999), Ghosh et al. (1999), Pan et al. (1999), Chang (2001), Ostermark (2001), Chen et al. (2002), Manning (2002), Sharma and Wongbangpo (2002), Aggarwal and Kyaw (2005) and Fraser and Oyefeso (2005).

exist. The cointegration studies that we cite consider market indexes rather than individual stock prices. As a consequence, if countries contain similar industry mixes, then cointegration between stock market indexes in different countries may make sense.

Second, researchers explore the time-series properties of the conditional second moments of the returns, which prove important in many financial applications. Engle (1982) set in motion the extension of traditional time-series tools such as autoregressive moving average (ARMA) models for the conditional mean to essentially analogous models for the conditional variance. Autoregressive conditional heteroskedasticity (ARCH) models now commonly capture the volatility dynamics of financial time series.[3]

The empirical success of ARCH models in fitting univariate time series motivated many researchers to extend these models into multivariate contexts. That financial volatilities move together over time, across assets and markets is a stylized fact. Multivariate modeling should lead to more relevant empirical models and deeper insights into financial markets than working with separate univariate models. The motivation for multivariate GARCH models relies on the fact that international stock prices react, at least in part, to the same information, and consequently, exhibit nonzero covariances, conditional on the information set available. In finance, multivariate GARCH modeling opens the door to better decision tools in various areas such as asset pricing, portfolio selection, hedging, and Value-at-Risk forecasts. Although a huge literature exists on univariate models for volatility dynamics, asymmetry, and fat-tails, much fewer works concentrate on their multivariate extensions.

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[3] This literature includes the ARCH and GARCH models of Engle (1982) and Bollerslev (1987) and their various nonlinear generalizations, such as nonlinear GARCH models of Bera and Higgins (1992), EGARCH models of Nelson (1991), threshold GARCH models of Glosten et al. (1993), quadratic GARCH models of Sentana (1995), threshold ARCH models of Zakoian (1994), and so on. Bollerslev et al. (1992), Bera and Higgins (1993), Bollerslev et al. (1994) survey the literature on ARCH models.

Cointegration analysis only provides a binary outcome: markets are either integrated or segmented. Bekaert and Harvey (1995) emphasize, however, that market integration involves a complex dynamic process. Conditional correlations, rather than cointegration, may more adequately and completely describe the process. The multivariate GARCH framework allows the modeling of the conditional correlations and covariances, analyzing the multilateral feedback among markets, and examining the dynamic links between market information and volatility. Further, unlike the cointegration approach, which does not go beyond linkages between the first moments, the multivariate GARCH approach measures the extent of market integration through both the first and the second moments of the returns in the stock exchanges.[4]

This paper explores the dynamic linkages that portray different facets of the joint probability distributions of stock market returns in NAFTA (i.e., Canada, Mexico, and the US). Our examination of interactions of the NAFTA stock markets considers three issues. First, we examine the long-run relationship between the three markets, using the cointegration techniques of Johansen and Juselius (1990). Second, we evaluate the dynamic relationships between the three markets, using impulse-response analysis. Finally, we explore the volatility transmission process between the three markets, using a variety of multivariate GARCH models. Further, the extant literature offers two approaches to multivariate GARCH models. One, researchers employ models that directly specify the structure of the conditional covariance matrix, such as the VECH model of Bollerslev et al. (1988) and the BEKK model of Engle and Kroner (1995). Two,

[4] Important examples of multivariate volatility models include diagonal multivariate and VECH-representation GARCH models of Bollerslev et al. (1988), the constant-correlation multivariate GARCH (CC-MGARCH) models of Bollerslev (1990), the BEKK (named after Baba, Engle, Kraft and Kroner) models of Engle and Kroner (1995), and the dynamic conditional correlation models of Engle (2002) and Tse and Tsui (2002). Several applications of multivariate (mostly bivariate) GARCH models to the investigation of linkages between stock markets exist. They include, among others, Hamao et al. (1990), King and Wadhwani (1990), Theodosiou and Lee (1993), Karolyi (1995), Koutmos (1996), Lin et al. (1994), Engle and Susmel (1993), Koutmos and Booth (1995), Booth et al. (1997), Worthington and Higgs (2004), In et al. (2001), Liu et al. (1996), Liu et al. (1998), Ang and Bekaert (2002), Brooks and Ragunathan (2003), Wang et al. (2004), and Cotter (2004).

researchers employ models that specify the conditional correlations, such as the constant conditional correlation (CCC) model of Bollerslev (1990) and the dynamic conditional correlation (DCC) model of Engle (2002). Bauwens et al. (2003) provide an overview of the various issues.

The rest of the paper unfolds as follows. Section 2 briefly reviews the extant literature on NAFTA stock markets. Section 3 contains a concise discussion of the data used in our analysis. Section 4 explores the long-run dynamics of the returns in the North American markets, using the cointegration tests of Johansen and Juselius (1990). Section 5 examines the short-run linkages, using the generalized impulse response analysis by Pesaran and Shin (1998).[5] As previously noted, however, integration analysis based upon the cointegration methodology assesses the linkages between the NAFTA stock markets based upon the first unconditional moments of the returns series. This paper's principal contribution assesses the NAFTA stock market linkages, focusing on the second moments using a multivariate GARCH approach. Section 6 introduces the framework of multivariate GARCH used in this paper. Following the work of Golsten et al. (1993), we consider specifications that allow for leverage or asymmetric effects in the conditional innovations. Further, given the widely recognized rejection of normality for GARCH models, we also consider the *t*-distribution with its thicker tails than the Gaussian distribution and estimate each specification with multivariate Gaussian and *t*-distributions. We report the results of the estimation of the various specifications of the multivariate GARCH models in Section 7. Finally, Section 8 summarizes and concludes.

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[5] This methodology dominates the more traditional orthogonalized approach developed by Sims (1980), such as the Cholesky factorization, in that the impulse response functions prove invariant to the ordering of variables in the vector autoregressive model. Dekker et al. (2001) compare the traditional approach to impulse response functions developed by Sims (1980) to the generalized approach by Pesaran and Shin (1998) and finds that the generalized approach gives more realistic results, particularly for those markets with close geographical and economic links.

2. Existing Empirical Analysis of NAFTA Stock Markets

Existing empirical studies of these North American stock markets pay attention predominantly to the long-run linkages and co-movements between the three markets (e.g., Attenberry and Swanson, 1997; Ewing et al., 1999, 2001; Gilmore and McManus, 2004; Darrat and Zhong, 2005; Ciner, 2006; Ortiz et al., 2007; Aggarwal and Kyaw, 2005; and Phengpis and Swanson, 2006). Ewing et al. (1999) find no evidence of cointegration among stock market price indices in the three NAFTA countries, even after including a dummy variable to account for the implementation of NAFTA in January 1994. In a related study, Ewing et al. (2001) report no evidence of daily volatility transmission among NAFTA stock markets during the pre-NAFTA period (1992:06:02–1993:12:31). They do, however, detect significant volatility transmission from the US to the Canadian and Mexican stock markets, but not vice versa, during the post-NAFTA period (1994:01:03–1999:10:28). These two studies jointly imply that the passage of NAFTA enhanced the short-run linkages, but not necessarily long-run linkages among the members' stock markets.

In contrast, other related studies report evidence of cointegration among NAFTA stock markets, especially after the passage of NAFTA. Darrat and Zhong (2005), using weekly data from 1989 to 1999, find no evidence of cointegration during the pre-NAFTA period, but evidence of cointegration during the post-NAFTA period.Gilmore and McManus (2004), who study only the post-NAFTA period (1994–2002), report a cointegrating relationship based on both weekly and monthly data. These studies collectively suggest that NAFTA implementation improved equity market integration and linkages among the member nations. Further, Atteberry and Swanson (1997) test for short- and long-run relations among the three NAFTA stock markets for each annual sub-sample from 1985 to 1994 with daily data. The results indicate consistently strong contemporaneous determination, especially between Canada and the US, but intermittent existence of cointegrating relations from one year to the next. They suggest that the exceptionally strong statistical significance of cointegrating relations in 1993 and 1994 potentially reflect economic uncertainty affecting investors' perceptions of the effects of NAFTA passage on domestic economies similar to the effect of the US stock market crash of 1987.

Phengpis and Swanson (2006) conclude that the passage of NAFTA probably reinforced economic interdependence among member countries, but it did not contribute to the long-run interdependence among the members' stock markets through consistent cointegrating relation(s). Cointegration appears time-varying, but statistically short lived. It emerges strongly during periods of economic uncertainty. These results support those in Ewing et al. (1999) who report no evidence of cointegration, even accounting for NAFTA passage in 1994. These results differ, however, from Darrat and Zhong (2005) and Gilmore and McManus (2004) who report evidence of cointegration during different pre-determined post-NAFTA periods. Thus, the long-run interrelations among NAFTA stock markets may prove sample-dependent, or specifically, time-varying. Thus, proper investigation may require dynamic, rather than static, analysis such as rolling or recursive cointegration methodology.

Ciner (2006), using weekly data from January 2, 1994 to November 17, 2004, reports the results of testing for long-term linkages between the three markets before and after the stock market crash. Following Brooks and Del Negro (2004), Ciner (2006) identifies the breakpoint as March 1, 2000 and specifies the period between January 2, 1994 and February 29, 2000 as the pre-crash period and March 1, 2000 to November 17, 2004 as the post-crash period. Ciner (2006) conducts the empirical analysis separately for each sub-period as well as for the full sample and finds that the NAFTA equity markets support cointegration only in the pre-crash period. The test statistics indicate that the stable relation between the indexes fell apart and no evidence exists of cointegration in the post-crash period. In fact, the evidence against cointegration in the latter part of the sample exhibits such strength that it overturns the favorable results in the full sample.

Ortiz et al. (2007) analyze returns and volatility dynamics among the NAFTA capital markets using a vector error-correction model (VECM), which integrates GARCH effects in a process of dynamic conditional correlations. Their findings suggest that at least one long-run statistically significant equilibrium relationship exists between returns observed in the NAFTA capital markets. This evidence matches that in Darrat and Zhong (2005) and Gilmore and McManus (2004). Their findings also suggest that (a) the U.S. market influences the short run dynamics of the Canadian and Mexican markets; (b) the Canadian market influences the short run dynamics of the U.S. and Mexican markets; and (c) the Mexican market does not influence the short run dynamics of the other two markets. Furthermore, the results from the dynamic conditional correlation model suggest that (a) the Canadian market influences volatility of the Mexican market, but the Mexican market does not influence volatility of the Canadian market; and (b) the US market influences volatility in the Mexican and Canadian markets and the Mexican market, but not the Canadian market, affects the volatility of US market. These results confirm the dominant role of the US market in the North American area and suggest that these three markets do not reflect full integration.

With the exception of Ortiz et al. (2007), the investigation of volatility transmission between the three North American markets rarely appears in the literature. Karolyi (1995) examines the short-run dynamics of returns and volatility for stocks traded on the New York and Toronto stock exchanges within a bivariate GARCH structure and finds that inferences about the magnitude and persistence of return innovations that originate in either market and that transmit to the other market depend importantly on how researchers model the cross-market dynamics in volatility. Adler and Qi (2003) investigate the process of integration between the Mexican and North American equity markets between 1991 and 2002, using a model that combines the domestic and international versions of CAPM.

The extent of interdependence between the Canadian, Mexican, and US stock markets directly affects North American capital integration. That is, did the enactment of NAFTA lead to more integrated North American capital markets? NAFTA greatly reduced or eliminated tariffs and other trade barriers on products and services of the three North American nations.[6] In addition, NAFTA promoted capital flows across borders by relaxing restrictions on cross-country investment and ownership of foreign stocks. The integration of capital markets between the three North American countries in the post NAFTA period affects investors, corporate managers, and policy makers. Integrated capital markets imply reduced long-term diversification benefits available to market participants, where short term correlations overstate the benefits of diversification for long term investors. Hedging strategies depend on relatively isolated, idiosyncratic shocks to stock markets. If shocks to returns and volatilities in the US travel quickly across the Canadian and Mexican borders, then the benefits of diversification are bounded and significantly diluted.

Chen and Zhang (1997) find that countries with strong economic ties (i.e., greater bilateral trade) exhibit co-movement of financial markets. As noted, intraregional trade dominated interregional trade, where NAFTA is no exception. Intraregional trade increased dramatically among the three NAFTA nations. Between 1993 and 2004, total trade between the United States and its NAFTA partners increased 129.3 percent (110.1 percent with Canada and

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[6] Although implemented on January 1, 1994, it did not experience full force until 2000.

100.9 percent with Mexico); yet total trade between the United States and non-NAFTA partners increased 123.8 percent in the same period.[7] Hufbauer and Schott (2005) argues that overall, NAFTA did not cause trade diversion, aside from a few select industries such as textiles and apparel, where the rules of origin negotiated in the agreement specifically made U.S. firms prefer Mexican manufacturers. NAFTA intensified the already strong trade ties between Mexico and the US and Canada (Daniels and Vanhoose, 2004). For example, Canada's trade shares of both exports and imports with respect to Mexico doubled between 1994 and 2006. The US's trade shares with respect to Mexico increased by approximately 35 percent. Mexico also dramatically increased its trade shares over the same time period with Canada, but less so with respect to the US. Canada and the US were major trading partners before and after NAFTA.

3. Data

We employ daily closing price indices for the stock markets in Canada, Mexico, and the US (i.e., the S&P TSX Composite Index in Canada, the IPC index in Mexico, and the S&P500 index in the US, respectively.[8] The series came from Commodities Systems Inc. Following the common

[7] For details, see http://www.census.gov/foreign-trade/balance/c2010.html and http://www.ic.gc.ca/epic/site/tdo-dcd.nsf/en/Home

[8] The Indice de Precios y Cotizaciones (IPC) includes 35 stocks that trade on the Mexico Stock Exchange (Bolsa Mexicana de Valores). The IPC, the main index of stock market performance, expresses market yield based on the price variations from a balanced, weighted, and representative sample of the total stock certificates quoted on the Mexico Stock Exchange. Analysts update the sample on a yearly basis and include approximately 35 issuers from different sectors of the economy. Applied in its current structure since 1978, the IPC accurately expresses the status of the stock exchange market and constitutes a highly reliable index. The IPC reflects market capitalization. That is, the IPC weights the participation of each of the issuers that constitute the sample, based on the market value of the outstanding shares. The Mexico Stock Exchange defines the calculation and adjustment of rights method. The IPC updates automatically in real time, as a consequence of the execution of registered trades of the stock certificates included in the sample during the capital market auction session. The S&P TSX Composite Index currently includes a list of the largest companies on the Toronto Stock Exchange as measured by market capitalization. The Toronto Stock Exchange listed companies in this index comprise about 71 percent of market capitalization for all Canadian-based companies listed on the TSX. The S&P 500 contains the stocks of 500 large capitalization corporations, mostly US. The index proves the most notable of the many indices owned and maintained by Standard & Poor's, a division of McGraw-Hill. S&P 500 index forms part of the broader S&P 1500 and S&P Global 1200 stock market indices. Only the stock of large publicly held companies that trade on the two largest US stock markets, the New York Stock Exchange, and Nasdaq appear in the index.

practice, we denominate all indices in local currency. The data cover January 1, 1992 to December 31, 2007. We remove information from the other two markets, when the other market does not open. This yields a total of 3,790 observations for each series over 16 years. This time span involves periods of significant market volatility in all three markets, as well as periods of relative calm. The daily returns equal the first difference of logarithmic prices multiplied by 100.

Figure 1 plots the three indices. Visual inspection suggests that the stock market crash of 2001 only affected the US and Canadian markets. Figure 2 plots the returns time series. Visual inspection suggests that the three series of returns exhibit stationarity around the mean. Moreover, a strong tendency for the volatility of the stock index returns to cluster exists. That is, large (small) returns generally follow large (small) returns, suggesting that volatility changes over time. Volatility clustering, a characteristic feature found in many asset returns, continues to receive continual documentation since the initial observation of Mandelbrot (1963) and Fama (1965).

Table 1 reports some descriptive statistics of the returns series, detailing the first four sample moments of each series. The summary statistics offer several preliminary insights into the data. The performance of the three equity markets displays average positive returns. The risk-return pattern appears consistent with the implications of finance theory. Mexico achieved the highest average return (0.079 per cent), followed by Canada (0.036 per cent), and then the US (0.033). For sample standard deviations, Mexico experienced a higher unconditional volatility (1.672) compared to the US (1.034 per cent) and Canada (0.923). As expected, all three series exhibit heavy tails and positive excess kurtosis. Thus, the distributional properties of the returns series generally appear non-normal. All three markets possess negative skewness, indicating that large negative shocks occur more frequently than large positive shocks. The IPC, however, illustrates only slight negative skewness, while the S&P TSX shows heavy negative skewness. All returns series display a measure of kurtosis than exceeds three and fail the Jarque-Bera test of normality. In all cases, the p-values reject the null hypothesis of normality at the one-percent level. We also check the normality assumption with the multivariate test of Doornik and Hansen (1994), based on Shenton and Bowman (1977). For each of the *n* series, we transform the measure of skewness, $\sqrt{b_{1j}}$ for j = 1, …, n, to a standard normal Z_{1j} as in D'Agostino (1970), while we transform the measure of kurtosis, b_{2j}, from a gamma to a chi-square distribution and then to a standard normal Z_{2j} using the Wilson and Hilferty (1931) cubed-root transformation. Doornik and Hansen (1994) propose the following test statistic:

$$E_p = Z_1'Z_1 + Z_2'Z_2 , \tag{1}$$

where $Z_1 = (Z_{11},...Z_{1j},...Z_{1n})'$ and $Z_2 = (Z_{21},...Z_{2j},...Z_{2n})'$. Under the null hypothesis of normality, the test statistic is approximately distributed as chi-square with *2n* degrees of freedom. The Doornik-Hansen test statistic equals 4,340.23, which is significant at the one-percent level. This indicates that a significant departure from normality in the joint returns distribution of the returns exists. We test for the presence of intertemporal dependencies in the returns and squared returns using the Ljung-Box portmanteau test. Table 2 summarizes the results.

The Ljung-Box (LB) statistic tests the hypothesis that autocorrelations up to the nth lag are jointly statistically significant. The calculated LB statistics at six, twelve, eighteen, and twenty-four lags, given by LB-Q(6), LB-Q(12), LB-Q(18), and LB-Q(24), firmly reject the hypothesis of linear independence at the one-percent level in each of the three returns, implying that the conditional mean of the distribution of each return depends on past returns. Similarly, we also firmly reject the hypothesis of independence in each of the three squared returns at the one-percent level. The LB statistics for the squared returns at six, twelve, eighteen, and twenty-four lags, given by LB-$Q^2(6)$, LB-$Q^2(12)$, LB-$Q^2(18)$, and LB-$Q^2(24)$, exceed by several times those of the returns themselves. That is, higher-moment dependencies prove much more pronounced. Significant serial correlations in squared returns typically imply volatility clustering and time-varying variances. Hosking (1980) derives the multivariate analogue to the LB portmanteau test statistic for autocorrelation. The test statistic is given as follows:

$$\mathrm{H}(m) = T^2 \sum_{t=1}^{M} (T - j)^{-1} tr\left\{ C^{-1}(0) C(j) C^{-1}(0) C'(j) \right\}, \tag{2}$$

where $C(j)$ equals the sample autocovariance matrix of order j. Under the null hypothesis of no dependence in the returns or squared returns, the test statistic is asymptotically distributed as a chi-square with n^2m degrees of freedom, where n equals the number of series and m equals the number of lags. Table 3 reports the observed H(m) and $\mathrm{H}^2(m)$ statistics calculated at six, twelve, eighteen, and twenty-four lags for the returns and squared returns. All test statistics are statistically significant at the one-percent level, implying that serial correlation in the returns and a significant amount of serial dependence in the squared returns exist, which provides strong evidence of conditional heteroskedasticity.

The (unconditional) correlation coefficient of returns provides one indicator of the co-movements of international stock indices and a rough measure of market interdependence. The correlation coefficients between returns fall in the moderate range, but prove significant at the one-percent level. The correlation between Mexico and US equals 0.529, slightly higher than the correlation between Mexico and Canada (0.474). The highest correlation, as expected, occurs between Canada and the US (0.691).

4. Cointegration Analysis

4.1 The Johansen Multivariate Approach

If a long-run relationship exists between two or more variables, then bounds encompass any deviation from the long-run equilibrium path. If true, then the variables are cointegrated. We analyze the long-term relationship between the three North American stock markets using the multivariate cointegration techniques of Johansen (1988, 1991) and Johansen and Juselius (1990). Their approach uses maximum likelihood estimators of the cointegrating vectors for a vector autoregressive process with Gaussian errors. This procedure incorporates the whole error structure of the underlying multivariate process, including different short-run and long-run dynamics of a system of economic variables. Cointegration allows an analysis of the equilibrium relation among non-stationary series, while abstracting from the short-term deviations from that long-run equilibrium. This section briefly describes the estimation method and the empirical results.

Johansen and Juselius (1990) consider a *p*-dimensional, k^{th} order unrestricted vector autoregression (VAR) as follows:

$$X_t = A_0 + A_1 X_{t-1} + ... + A_k X_{t-k} + \varepsilon_t \qquad t = 1,\ldots,T, \tag{3}$$

where X_t equals a (*p x* 1) vector of non-stationary variables, A_i, $i = 1,...,k$ equals a (*p x p*) matrix of parameters, and ε_t equals a vector of innovations drawn from a *p*-dimensional i.i.d. normal distribution with mean zero and covariance Σ.

Letting Δ represent the first-difference operator, we can reformulate equation (3) as a vector error-correction model (VECM) as follows:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-1} + \varepsilon_t, \tag{4}$$

where $\Gamma_m = -I + \sum_{i=1}^{m} A_i$ for m = 1,…,k-1, $\Pi = -I + \sum_{i=1}^{k} A_i$, and I equals the identity matrix.

We seek cointegration by examining the rank of Π since, as Johansen (1990, 1991) and Johansen and Juselius (1990) show, the rank r of Π determines the number of stationary linear combinations of X_t. Three possibilities exist. First, if the rank r of Π equals zero, the VECM reduces to a standard vector autoregressive (VAR) model in first-differences. All elements of X_t are I(1) and no stationary long-run relationships exist among them. Second, if Π possesses full rank, $r = p$, then all elements of X_t are I(0) and no stochastic trends exist in the series, contrary to the original I(1) specification. Finally, if Π possesses rank $0 < r < p$, then r cointegrating vectors exist. The (p x r) matrices α and β each of rank r exist such that $\Pi = \alpha\beta'$, where the columns of the matrix α equal adjustment factors and the rows of the matrix β equal the cointegrating vectors, where $\beta' X_t$ follows an I(0) process even though each element of X_t includes individually I(1). The cointegrating vectors capture the long-run relationships in the system. Johansen (1988, 1991) shows that only the cointegration vectors in β enter equation (4), otherwise ΠX_{t-1} is not I(0). This implies effectively that the last ($p - r$) columns of α equal zero. Thus, the problem of determining how many $r \leq p$ cointegration vectors exist in β equivalently tests how many columns of α equal zero.

Johansen (1988, 1991) shows that the estimation procedure simplifies by reformulating model (4) as follows:

$$R_{0t} = \alpha\beta' R_{1t} + \zeta_t, \qquad (5)$$

where R_{0t} and R_{1t} equal vectors of residuals from the auxiliary regressions:

$$\Delta X_t = \hat{\pi}_0 + \hat{\vartheta}_1 \Delta X_{t-1} + \hat{\vartheta}_2 \Delta X_{t-2} + \ldots + \hat{\vartheta}_{p-1} \Delta X_{t-(p-1)} + R_{0t}, \text{ and} \qquad (6)$$

$$X_{t-1} = \hat{\theta}_0 + \hat{\xi}_1 \Delta X_{t-1} + \hat{\xi}_2 \Delta X_{t-2} + \ldots + \hat{\xi}_{p-1} \Delta X_{t-(p-1)} + R_{1t} . \quad (7)$$

We can estimate these two equations by OLS. The sample variance-covariance matrices of the OLS residuals R_{0t} and R_{1t} equal the following: $S_{11} = (1/T)\sum_{t=1}^{T} R_{1t} R'_{1t}$, $S_{00} = (1/T)\sum_{t=1}^{T} R_{0t} R'_{0t}$, $S_{01} = (1/T)\sum_{t=1}^{T} R_{0t} R'_{1t}$, $S_{10} = S'_{01}$.

The maximum likelihood estimator of β in (3) comes from solving for the eigenvalues of the equation:

$$\left| \lambda S_{11} - S_{10} S_{00}{}^{-1} S_{01} \right| = 0 , \quad (8)$$

which gives the p eigenvalues, $1 > \hat{\lambda}_1 > \ldots > \hat{\lambda}_p > 0$ and the corresponding eigenvectors $\hat{V}$ = ($\hat{v}_1$, ..., $\hat{v}_p$) normalized such that $\hat{V}' S_{11} \hat{V} = I$. The eigenvalues $\hat{\lambda}_1$, ..., $\hat{\lambda}_p$ correspond to the squared canonical correlations between the "levels" residuals and the "difference" residuals, as defined above. The eigenvectors $\hat{v}_1$, ..., $\hat{v}_p$ determine the linear combinations $\hat{v}'_i z_t$, $i = 1, \ldots, k-1$.

Johansen (1988, 1991) proposes two methods for testing for the number of cointegration vectors: the trace and maximum eigenvalue tests. The trace test equals a likelihood ratio test for maximum r cointegration vectors against the alternative of n vectors as follows:

$$\lambda_{\text{trace}} = -T \sum_{i=r+1}^{p} \ln(1 - \hat{\lambda}_i) , \quad (9)$$

where $\hat{\lambda}_{r+1}$, ..., $\hat{\lambda}_n$ equal the (n-r) smallest eigenvalues of the squared canonical correlations. The maximum eigenvalue test possesses an identical null hypothesis, while the alternative hypothesis equals r+1 cointegration vectors. That is,

$$\lambda_{\max} = -T \ln(1 - \hat{\lambda}_{r+1}) , \quad (10)$$

where $\hat{\lambda}_{r+1}$ equals the largest eigenvalue. Both tests possess a non-standard asymptotic distribution. The critical values for λ_{trace} and $\lambda_{\max}$ come from MacKinnon et al. (1999), who compute numerical distribution functions of these two statistics. They find that the resultant critical values prove more reliable than those in Osterwald-Lenum (1992).

4.2 Empirical results[9]

Cointegration analysis requires nonstationary variables. Traditional statistical tests used for inference assume stationary ergodic processes. The usual distributional results and tests of significance prove invalid and potentially misleading, when considering non-stationary series. Unit-root tests provide a simple method for testing whether a series is non-stationary and, therefore, a useful check of appropriateness and statistical reliability of the time-series models. We use the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), including a constant and a linear deterministic trend in the test equation. The lag length choice uses the Akaike information criterion (AIC). The findings of the ADF tests consistently indicate I(1) stock index values (in natural logs) as well as I(0) return series, proving consistent with prior work. We also examine for unit roots in the series of the indexes and the respective returns using the Phillips-Perron (PP) test (Phillips and Perron, 1988), which depends on a weaker assumption that the error terms do not necessarily conform to independently, identically distributed values. Monte Carlo studies suggest that the PP test possesses more power than the ADF test. The PP test also includes a constant and a linear deterministic trend in the test equation and employs the Bartlett kernel spectral estimation method with the Newey-West bandwith. Table 4 reports results of the unit-root analysis. The PP test results provide consistent findings with those of the ADF test.

[9] We generated our results, using CATS in RATS (2005), version 2.

Further, the results of the ADF and PP tests prove robust to the exclusion of the linear deterministic trend.

The empirical implementation of the Johansen cointegration tests requires the determination of the appropriate lag length in the VAR model. The Monte Carlo results in Cheung and Lai (1993) indicate that both trace and maximal-eigenvalue statistics are robust to over-parameterization in k. For under-parameterization of k, however, a serious upward bias for both trace and maximal-eigenvalue statistics seriously distort the cointegration tests. Thus, choosing less than the optimal value of k can affect our inferences concerning the cointegration rank and, hence, the number of potential cointegrating vectors of our model. The empirical results in Cheung and Lai (1993) also suggest that the lag selection criteria help to choose the right lag length.

We use the multivariate versions of the sequential modified likelihood ratio (LR) test statistic at the 5-percent level, the Akaike information criterion (AIC), the final prediction error (FPE), the Schwarz information criterion (SIC), and Hannan-Quinn information criterion (HIQ) to determine the lag length. Table 5 reports the results of lag length analysis. The first three criteria suggest a model with 3 lags, while the last two criteria suggest a model with 1 lag. As an additional criterion, we also check for residual autocorrelation in all estimated models. Since the residuals from the model with 3 lags do not exhibit significant autocorrelations, we proceed the analysis with a VAR specification of 3 lags.

Tables 6 to 8 report the results of the Johansen cointegration tests, where we consider three alternative models that differ on the trend assumptions. In model 1, the series exclude deterministic trends and the cointegrating equations include intercepts. In model 2, the series include deterministic trends, but the cointegrating equations include only intercepts. In model 3, both the series and the cointegrating equations include linear deterministic trends. In each table, r measures the rank of the Π matrix (i.e., the order of cointegration). MacKinnon et al. (1999) provide the critical values. The results of the cointegration tests prove robust to the different specifications of the deterministic components. The trace and maximum eigenvalue tests cannot reject the null hypothesis of no-cointegration among the stock indexes of Canada, Mexico, and the US ($r = 0$) against the alternative hypothesis of one or more cointegrating vectors ($r > 0$) at the 5-percent level. That is, the stock indexes of the three countries in North America do not share long-run equilibrium relationships. These results conflict with those of Ortiz et al. (2007), Darrat and Zhang (2005) and Gilmore and McManus (2004).

We test for the normality of the residuals, using the Doornik-Hansen (1994) method and reject the null hypothesis of normality at the 1-percent level. Since non-normality of residuals does not bias the results for the Johansen's cointegration tests, the test results prove valid (Gonzalo, 1994).

We also test for ARCH effects in the residuals, using Hosking's (1980) multivariate tests and reject the null hypothesis of no autoregressive conditional heteroskedasticity (ARCH) effects at the 1-percent level. Rahbek, Hansen, and Dennis (2002) and Juselius (2006), however, report that the cointegration tests prove robust against moderate ARCH.

4.3 Recursive Cointegration Analysis

The stock markets of North America experienced frequent and substantial external and internal shocks during the 1992 to 2008 period. They include, among others, the Asian financial crisis of 1997, the Peso crisis of 1994, the Russian financial crisis of 1997, the stock market crash of 2000, and the September 11, 2001 attacks. This history suggests that finding empirical evidence to support one stable long-run relationship between the three markets may prove unlikely. Given the lack of support for a long-run relationship between the three North-American indexes and the conflicting past evidence in the literature, the issue of temporal stability of the cointegration relationship warrants further examination. That is, we may find periods of time when a long-run relationship did exist. In what follows, we perform recursive cointegration analysis, using the method of Hansen and Johansen (1999).

Hansen and Johansen (1999) analyze not only the extent, but also the dynamics, of the long-run relationships. They perform the analysis for an initial period and then update as new data augment the initial sample. Specifically, they compute tests statistics over the initial chosen sample 1, …, T_1 where $T_1 < T$, extend the sample by one period and recalculate the statistics for the period 1 to (T_1+1), and so on until they reach T.

We estimate the recursive cointegration analysis under two VAR representations of equation (4). First, in the unrestricted or "X-representation," we re-estimate all the parameters of the VECM during the sequence of recursive estimations. Second, in the restricted or "R-representation," we hold the short-term parameters Γ_i fixed to their full sample values and only re-estimate the long-run parameters in equation (4). In the "R-representation," rejections of stability reflect changes in the long-run structure, while in the "X-representation," rejections of stability reflect either shifts in the short-run dynamics or changes in the long-run structure. We employ three tests as follows: (1) the fluctuation test of the eigenvalues; (2) the test of β constancy, and 3) the trace test statistics.

Hansen and Johansen (1999) suggest a preliminary graphical procedure to assess the constancy of the long-run parameters over time in cointegrated vector autoregressive models. The procedure uses recursive estimates of the r largest eigenvalues, which provide information about the adjustment coefficients α_i and the cointegrated vectors β_i. The non-constancy of these parameters will thus reflect the time path of the estimated eigenvalues. We transform the eigenvalues λ_i i = 1, …, r into $\xi_i = \ln(\lambda_i / 1 - \lambda_i)$ to obtain a better approximation of their limiting distribution. Figure 3 presents the results for the three estimated cointegration models and, although not a formal test of parameter stability, they indicate non-constancy of the parameters. We use the one-year period in 1992 as the base period. In all three models, the estimates of ξ_1 decrease and stabilize in the second half of the sample. In the first half of the sample, however, large changes in ξ_1 occur, suggesting that some observations, especially in 1995 and 2000 exert a larger effect on parameter estimates.

Following Hansen and Johansen (1999), we use the time path of the transformed estimated eigenvalues to construct the fluctuation test of the eigenvalues. The eigenvalues constancy test plots the sample path of the $\tau_i(t_1)$ defined as follows:

$$\tau_i(t_1) = \frac{t}{T}\left|\left(T^{-1}\Sigma_{ii}^0\right)^{-\frac{1}{2}}\xi_i\right|, \; i = 1,\ldots,r \text{ and } t_1 = 1, \ldots, T_1, \tag{11}$$

where Σ_{ii}^0 equals the variance of the transformed eigenvalues. This supremum test provides a rather conservative signal, implying that the rejecting the test provides a strong signal of non-constant eigenvalues (Juselius, 2006).

Figures 4 to 6 present both the X- and R-representations of the test results for each of the estimated models. We calculate the test for the first eigenvalue. For ease of interpretation, we rescale the calculated statistics by the 5-percent critical value (1.36) of their asymptotic distribution (Ploberger et al., 1989). Rescaled values greater than 1 at a given data point provide evidence against the hypothesis of a constant eigenvalue at that data point. We reject the hypothesis of constant eigenvalues, because of the fluctuation either in the 1997-1998 (Asian financial crisis) period (model 1), the 2000-2001 (stock-market crash) period (model 2), or the 1995-1996 (Pesos crisis) period (model3).

We next examine the constancy of β (Hansen and Johansen, 1999; Juselius, 2006), by recursively testing if the full-sample estimate of β, denoted by β_0, falls in the space spanned by $\hat{\beta}^{(t_1)}$ where $\hat{\beta}^{(t_1)}$ equals the estimate of β based on the period chosen for comparison. The test requires that the rank of Π equals $p_1 < r$. The test statistic equals the following:

$$-2\log Q(H_{\beta}\left|\beta^{(t_1)}\right.) = t_1 \sum_{i=1}^{r} \ln \frac{1-\hat{\rho}_t^{(t_1)}}{1-\hat{\lambda}_i^{(t_1)}}, \tag{12}$$

where $\hat{\lambda}_i^{(t_1)}$ solves the eigenvalue problem $\left|\lambda S_{11}^{(t_1)} - S_{10}^{(t_1)}(S_{00}^{(t_1)})^{-1} S_{01}^{(t_1)}\right| = 0$ and $\hat{\rho}_t^{(t_1)}$ solves the eigenvalue problem $\left|\rho\beta_0' S_{11}^{(t_1)}\beta_0 - \beta_0' S_{10}^{(t_1)}(S_{00}^{(t_1)})^{-1} S_{01}^{(t_1)}\beta_0\right| = 0$ for the various samples considered. The statistic is asymptotically distributed as χ^2 with $r(p_1 - r)$ degrees of freedom, where p_1 equals the dimension of β and r equals the rank of the cointegration matrix.

Figures 7 to 9 illustrate the time path of the tests for $\beta_0 \in \text{span}\left\{\hat{\beta}^{(n)}\right\}$ for each of the three models, scaled by the 5-percent critical value. Test values below one indicate non-rejection of the null hypothesis that the β estimates for the corresponding recursive estimation period do not statistically differ from the βs derived from the full sample at the 5-percent significance level. Each figure portrays both the X- and R-representations. For both representations, the test statistics fluctuate throughout most of the estimation period, although exceeding 1 in only a few instances. In model 1, for example, instability occurs mainly in the 1995-to-2000 (Asian financial crisis) period. Conversely, model 2 rejects constant β estimates in the 1993-to-1995 (Peso crisis) period and in the 2000-to-2001 (stock-market crash) period. Finally, model 3 detects instability mainly in the 1993-to-1996 (Peso crisis) period. Thus, as we add observations from these sub-periods to the base sample, the estimated β parameters prove time varying.

We finally consider a recursive trace test as follows:

$$\tau(r) = -t_1 \sum_{i=1}^{r} \ln(1-\hat{\lambda}_i) \quad r = 1,\ldots,p,\ t_1 = T_1,\ldots,T. \tag{13}$$

For each of the three models, Figures 10 to 12 illustrate the time path of the recursive trace test for the hypothesis of less than one cointegration vector, scaled by the 5-percent critical value. The rescaled trace statistics suggest rejection of the null hypothesis of no cointegration, if it exceeds 1. In addition, the slope of the rescaled trace statistic determines the direction of co-movements between the three stock markets. An upward slope indicates rising co-movement, while a downward slope reveals declining co-movement between the three markets. In the R-representation of model 1 and 2 (but not model 3), we observe a strengthening of the relationship in the mid-nineties, as the three North-American markets appear to display a movement toward cointegration. This, however, reverses at the end of the nineties. In general, therefore, the results of the recursive trace tests prove congruent with the results from the traditional cointegration analysis. Therefore, we find no evidence of a common long-term trend between the three North-American equity indices, and no evidence of a possible strengthening of any such trend.

5. Generalized Impulse Response Functions

The finding that no long-term equilibrium relationship exists between the three North-American markets does not necessarily imply that no relationship exists between these markets. We examine the short-run relationship between the three stock markets returns in this section by applying the generalized impulse response analysis introduced by Koop et al. (1996) and Pesaran and Shin (1988). Impulse response functions can provide insights into how significantly shocks in a particular market may affect other markets though dynamic interactions among markets. The generalized impulse response functions, however, differ from the traditional, orthogonalized impulse response analysis, such as the one based on Choleski factorization for the orthogonalization of VAR innovations. That is, the generalized approach proves invariant to the ordering of variables in the VAR system, and hence yields results that do not depend on the ordering.

We can express the VAR model of daily stock market returns in standard form as follows:

$$R_t = C + \sum_{s=1}^{p} B_s R_{t-s} + \varepsilon_t, \ \ t = 1,2,...,T, \tag{14}$$

where R_t equals a column vector of daily returns on the market indexes at time t, C equals the column vector of constant terms, B_s equal matrices of coefficients such that the i^{th}, j^{th} component of B_s measures the effect of a change in the j^{th} market on the i^{th} market after s periods and ε_t equals a column vector of innovations such that $E(\varepsilon_{it}) = 0$, $E(\varepsilon_{it}^2) = \sigma_{ij}$, and $E(\varepsilon_{is}\varepsilon_{jt}) = 0$ for $s \neq t$. Equation (14) assumes a return generating process, where the return of each capital market depends on a constant term, its own lagged returns, the lagged returns of other capital markets, plus a serially uncorrelated and potentially contemporaneously correlated error term, ε_{it}. The return of a market incorporates not only its own past information, but also the past information of other markets. We can transform the VAR system in equation (14) into an infinite moving average representation as follows:

$$R_t = \sum_{s=0}^{\infty} \Phi_s \varepsilon_{t-s}, \ \ t = 1,2,...,T, \tag{15}$$

where Φ_s equals a matrix of moving average coefficients obtained recursively from B_s in equation (14). In equation (15), the return of a market depends on its own past shocks plus the shocks from other markets. The i^{th}, j^{th} component of Φ_s shows the response of the i^{th} market in s periods after a unit random shock in the j^{th} market.

Pesaran and Shin (1998) show that the generalized impulse response function equals the following:

$$\psi_j^g(p) = \sigma_{jj}^{-1/2} C_p \Sigma e_j , p = 0, 1, 2, \ldots, s \tag{16}$$

where σ_{jj} equals the j^{th}, j^{th} element in the variance-covariance matrix Σ and e_j equals a ($n \times 1$) vector with one as its j^{th} element and zero elsewhere.[10]

Figure 13 presents the estimated generalized impulse responses (along with two standard deviation bands) and Tables 9 to 11 provide the numbers (standard errors in parenthesis).[11] Some notable findings emerge. First, the responses exhibit large magnitudes, using the conventional definition of significant responses as those that exceed 0.20 unit standard deviations (Dekker et al., 2001; Yang et al., 2003; Masih and Masih, 2001).

Second, stock returns respond immediately to a shock in other markets, implying that the markets process information quickly, but do not show long-lasting effects. In all cases, the response dies out within two days.

Third, the response of each market to shocks in its own market always exceeds the response to shocks in other markets. For example, the response of US returns to shocks in the US market prove more than double the response of US returns to shocks originating in the Mexican

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[10] This differs from the more traditional impulse response function $\psi_j^o(p) = C_p P e_j$, p = 0,1,2, …, which occurs using the Choleski decomposition $PP' = \Sigma$, where P equals an ($n \times n$) lower triangular matrix.

[11] We calculate confidence bands using Monte Carlo integration techniques, since impulse responses prove highly non-linear functions of the estimated parameters. We set the number of Monte Carlo repetitions to 1000.

market. The response of Mexican returns to shocks in the US market equals about half the response of the Mexican returns to shocks originating in its own market.

Fourth, the US holds the leading role, in the sense that the Canadian (Mexican) market responds more to shocks stemming from the US than from Mexico (Canada). Nonetheless, the US market also responds to shocks originating in Mexico and Canada. Hence, the US market leads, but is not autonomous.

6. The Multivariate GARCH: Method and Econometrics

Shocks affect not only returns, but also volatilities. The autoregressive conditional heteroskedasticity (ARCH) model originally developed by Engle (1982) and generalized by Bollerslev (1986) provides the most popular method for modelling volatility of stock market returns. In recent years, many studies, starting with Bollerslev, Engle and Wooldridge (1988), extend the univariate generalized autoregressive conditional heteroskedasticity (GARCH) model of Bollerslev (1986) to the multivariate case for modelling the volatility of multiple asset returns.[12]

6.1 Issues and Stylized Facts

Multivariate GARCH models provide several advantages over univariate GARCH models (Bauwens et al., 2006). First, they explicitly accommodate inter-market dependencies in the conditional mean and/or conditional variance equations, thereby avoiding multi-step estimation procedures for univariate models. Second, they improve the efficiency and the power of the tests for cross-market co-movements and spillovers. Third, they produce meaningful analysis of many

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[12] One can model the interdependence across markets using both univariate and multivariate GARCH models. Papers that employ univariate GARCH models include Hamao et al. (1990) and Hahm (2004), who model the volatility spillovers across stock markets; Jiang and Chiang (2000) and Fang (2001), who model the volatility spillovers across stock and foreign exchange markets; and Najand and Yung (1997), who model the price dynamics in exchange rates, stock index, and Treasury bonds in futures markets.

issues in asset pricing and portfolio allocation that require a multivariate context (Bollerslev et al., 1992). Fourth, they accommodate covariances that capture the inter-relatedness of economic variables and their behavior in reacting to the same information (Bera and Higgins, 1993).

Two problems exist in extending the univariate GARCH models to a multivariate framework (Bauwens et al., 2006). First, the number of parameters to estimate grows rapidly with the dimension of the model, the "curse of dimensionality." Second, finding a specification that maintains the positive definiteness of the covariance matrix may prove difficult. Recent contributions to the multivariate GARCH literature confront these difficulties by imposing a variety of simplifying restrictions (Bauwens et al., 2006).

Several important stylized facts emerge from empirical research on asset returns. First, researchers typically observe asymmetry in volatilities and covariances. Asymmetric volatility, a well know phenomenon, receives much discussion in the literature, especially the asymmetric effects of shocks on the second moment of stock returns in univariate GARCH models. Black (1976) and Christie (1982) propose the "leverage-effect" explanation for such asymmetry in variance. As equity values fall, the weight attached to debt in a firm's capital structure rises, *ceteris paribus*. This induces equity holders, who bear the residual risk of the firm, to perceive the stream of future income accruing to their portfolios comes with relatively more risk. Campbell and Hentschel (1992) and Poterba and Summers (1986) provide the alternative "volatility-feedback"' hypothesis. Assuming constant dividends, stock prices should fall when volatility rises, when expected returns increase with stock return volatility.[13]

[13] Pagan and Schwert (1990), Nelson (1991), Campbell and Hentschel (1992), Engle and Ng (1993), Glosten et al. (1993), and Henry (1998), among others, report evidence of asymmetry in equity-return volatility using univariate GARCH models. Kroner and Ng (1998), Braun et al. (1995), Henry and Sharma (1999), Engle and Cho (1999) and Brooks and Henry (2000), Ang and Chen (2001), Kearney and Poti (2006) among others, use multivariate GARCH models to capture time variation and asymmetry in the variance–covariance structure of asset returns.

Second, researchers also typically observe skewness and kurtosis in asset returns. Financial returns rarely follow normal distributions. The estimation of multivariate GARCH models commonly maximizes a Gaussian likelihood function. We can justify the normality assumption because the Gaussian quasi-maximum likelihood (QML) estimator proves inefficient, but consistent, provided we specify the conditional mean and the conditional variance correctly (Bollerslev and Wooldridge, 1992). Various techniques exist to deal with the questionable normality assumption. Harvey et al. (1994), Fiorentini et al. (2003), and Kan and Zhou (2006) replace the multivariate Gaussian density with the Student density, which incorporates fat tails.[14] Since the *t*-distribution adds only one more parameter, this parsimonious extension, which nests the normal as a special case, captures the observed fat tails or leptokurtic characteristics of financial data. Furthermore, although symmetric, the *t*-distribution's highly volatile sample skewness can generate the skewness of the data with high probability. Kan and Zhou (2006) note that the finite sample variation of the sample skewness of a *t*-distribution proves very large for small degrees of freedom. Thus, a high probability for observing large sample skewness occurs even though the true distribution is symmetric.

6.2 Econometric Framework

The econometric model that we use to investigate returns and volatility dynamics between the three North-American stock markets includes two parts -- the mean and covariance models.

<u>The Mean Model.</u> Equation (17) models the North-American index returns as a VAR(3) process:

[14] Several other alternative distributions appear in empirical research, including the mixture of multivariate normal densities (Vlaar and Palm, 1993; Haas et al., 2006), the generalized hyperbolic distribution (Barndorff-Nielsen and Shepard, 2001; Mencía and Sentana, 2004), the multivariate skew-Student density (Bauwens and Laurent, 2005), and the asymmetric multivariate Laplace (Kozubowski and Podgorski, 2001; Cajigas and Urga, 2006). Bollerslev and Wooldridge (1992) note, however, that if the researcher chooses an incorrect non-normal distribution, then the parameter estimates of the multivariate GARCH are not even consistent.

$$R_t = \mu + \sum_{i=1}^{3} \Gamma_i R_{t-i} + \varepsilon_t \,.^{15} \tag{17}$$

We can write equation (17) in extended form as follows:

$$\begin{bmatrix} r_t^{US} \\ r_t^{MEX} \\ r_t^{CAN} \end{bmatrix} = \begin{bmatrix} \mu^{US} \\ \mu^{MEX} \\ \mu^{CAN} \end{bmatrix} + \begin{bmatrix} \gamma_{11}^1 & \gamma_{12}^1 & \gamma_{13}^1 \\ \gamma_{21}^1 & \gamma_{22}^1 & \gamma_{23}^1 \\ \gamma_{31}^1 & \gamma_{32}^1 & \gamma_{33}^1 \end{bmatrix} \begin{bmatrix} r_{t-1}^{US} \\ r_{t-1}^{MEX} \\ r_{t-1}^{CAN} \end{bmatrix} + \begin{bmatrix} \gamma_{11}^2 & \gamma_{12}^2 & \gamma_{13}^2 \\ \gamma_{21}^2 & \gamma_{22}^2 & \gamma_{23}^2 \\ \gamma_{31}^2 & \gamma_{32}^2 & \gamma_{33}^2 \end{bmatrix} \begin{bmatrix} r_{t-2}^{US} \\ r_{t-2}^{MEX} \\ r_{t-2}^{CAN} \end{bmatrix}$$

$$+ \begin{bmatrix} \gamma_{11}^3 & \gamma_{12}^3 & \gamma_{13}^3 \\ \gamma_{21}^3 & \gamma_{22}^3 & \gamma_{23}^3 \\ \gamma_{31}^3 & \gamma_{32}^3 & \gamma_{33}^3 \end{bmatrix} \begin{bmatrix} r_{t-3}^{US} \\ r_{t-3}^{MEX} \\ r_{t-3}^{CAN} \end{bmatrix} + \begin{bmatrix} \varepsilon_t^{US} \\ \varepsilon_t^{MEX} \\ \varepsilon_t^{CAN} \end{bmatrix}, \tag{18}$$

where R_t equals a 3x1 vector of daily returns, with r_t^{US}, r_t^{MEX} and r_t^{CAN}, representing the returns from S&P 500, IPC, and S&P/TSX indexes, respectively; μ equals a 3x1 vector of constants; Γ_i i = 1,2,3 equal 3x3 matrices of parameters; and ε_t equals a 3x1 vector of innovations or "news."

The multivariate structure of equation (17) provides measures of the significance of the own and cross-mean spillover. The off-diagonal elements, $\gamma_{i,j}^1$, $\gamma_{i,j}^2$, and $\gamma_{i,j}^3$ for $i = 1,\ 2,\ 3$ capture the effects of interactions in means, also known as return spillover. The diagonal elements, $\gamma_{i,i}^1$, $\gamma_{i,i}^2$, and $\gamma_{i,i}^3$ for $i = 1,\ 2,\ 3$ measure the effects of own past returns. If the off-diagonal elements equal zero, then the model excludes the return transmission across the markets, which we can test using Wald statistics.

<u>The Covariance Model.</u> In the GARCH framework, the conditional distribution of ε_t varies with time with the following specification:

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[15] Note that we do not incorporate the error correction terms into the mean equations because we do not reject the null hypothesis of no cointegration.

$$\varepsilon_t \left| \Omega_{t-1} \sim D(0, H_t) \right., \tag{19}$$

where H_t equals a (3x3) time-varying conditional covariance matrix.

Several well known multivariate GARCH specifications include the VECH model of Bollerslev et al. (1988), the CCC model of Bollerslev (1990), the DCC model of Engle (2002), the BEKK model of Engle and Kroner (1995), the Asymmetric BEKK model of Kroner and Ng (1998), the Vector Autoregressive Moving Average GARCH (VARMA-GARCH) model of Ling and McAleer (2003), the VARMA Asymmetric GARCH (VARMA-AGARCH) model of McAleer et al. (2008), and the multivariate EGARCH of Koutmos and Booth (1995). Each model offers certain advantages and disadvantages, and each model imposes different restrictions and specifications on the conditional covariance.

We model the variance-covariance matrix $H_t = \lfloor h_{ij,t} \rfloor$ as an asymmetric BEKK-GARCH(1,1) model (Kroner and Ng, 1998). The BEKK specification ensures a positive-definite H_t by imposing quadratic forms on the matrices of coefficients. This sufficiently general specification allows the conditional variances and covariances to interact with each other and although computationally complex, does not require the estimation of a large number of parameters. We can write the asymmetric BEKK parameterization as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + G'\eta_{t-1}\eta'_{t-1}G, \tag{20}$$

where C, A, B, and G equal 3x3 matrices of parameters with a lower-triangular C; H_t equals the 3x3 conditional covariance; $\varepsilon_t = [\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}]$ equals a vector of unexpected shocks from the VAR(3) model; and $\eta_t = [\eta_{1t}, \eta_{2t}, \eta_{3t}]$ equals a vector that contain the Glosten et al. (1993) series defined as η_{it} = min[ε_{it}, 0], where η_{it} equals ε_{it}, if ε_{it} when negative and zero otherwise, and h_{ijt} equals the conditional second moment series. In expanded form, we can write the asymmetric BEKK GARCH (1,1) model as follows:

$$
\begin{aligned}
H_t = & \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix}' \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \\
& + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} & \varepsilon_{2,t-1}\varepsilon_{3,t-1} \\ \varepsilon_{3,t-1}\varepsilon_{1,t-1} & \varepsilon_{3,t-1}\varepsilon_{2,t-1} & \varepsilon^2_{3,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \\
& + \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} & h_{13,t-1} \\ h_{21,t-1} & h_{22,t-1} & h_{23,t-1} \\ h_{31,t-1} & h_{32,t-1} & h_{33,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \\
& + \begin{bmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{bmatrix}' \begin{bmatrix} \eta^2_{1,t-1} & \eta_{1,t-1}\eta_{2,t-1} & \eta_{1,t-1}\eta_{3,t-1} \\ \eta_{2,t-1}\eta_{1,t-1} & \eta^2_{2,t-1} & \eta_{2,t-1}\eta_{3,t-1} \\ \eta_{3,t-1}\eta_{1,t-1} & \eta_{3,t-1}\eta_{2,t-1} & \eta^2_{3,t-1} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{bmatrix}
\end{aligned}
\tag{21}
$$

The symmetric specification restricts $g_{ij} = 0$ for all $i, j = 1, 2, 3$, and $i \neq j$. Kroner and Ng (1998) analyze the asymmetric properties of time-varying covariance matrix models, identifying three possible forms of asymmetric behavior.[16] First, the covariance matrix displays own-variance asymmetry, if the sign of the innovation in $R_{i,t}$ affects the conditional variance of $R_{i,t}$. Second, the covariance matrix exhibits cross-variance asymmetry, if the sign of the innovation in $R_{j,t}$, for $i \neq j$, affects the conditional variance of $R_{i,t}$. Third, if the sign of the innovation in return affects the covariance of returns, the model displays covariance asymmetry.

[16] As a preliminary test, we apply the Engle and Ng (1993) test for asymmetry in volatility to each of the three return series. We find that each returns series exhibits negative sign and size bias, suggesting asymmetry and "bad news" matters more than "good news." The *t*-ratios for the negative sign bias equal 4.2606 (US), 3.1024 (Mexico), and 3.6336 (Canada). The *t*-ratios for the negative size bias equal -12.0266 (US), -11.7938 (Mexico), and -8.5936 (Canada). The chi-square values of the joint test (df = 3) computed as TR^2 equal 698.579 (US), 610.907 (Mexico) and 480.553 (Canada).

We can expand equation (21) by matrix multiplication. The i^{th} conditional variance, $h_{ii,t}$, i = 1, 2, 3, equals the following:

$$\begin{aligned} h_{11,t} = {} & c_{11}^2 + a_{11}^2\varepsilon_{1,t-1}^2 + a_{21}^2\varepsilon_{2,t-1}^2 + a_{31}^2\varepsilon_{3,t-1}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + 2a_{11}a_{31}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{21}a_{31}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{11}^2h_{11,t-1} + b_{21}^2h_{22,t-1} \\ & + b_{31}^2h_{33,t-1} + 2b_{11}b_{21}h_{12,t-1} + 2b_{11}b_{31}h_{13,t-1} + 2b_{21}b_{31}h_{23,t-1} + g_{11}^2\eta_{1,t-1}^2 \\ & + g_{21}^2\eta_{2,t-1}^2 + g_{31}^2\eta_{3,t-1}^2 + 2g_{11}g_{21}\eta_{1,t-1}\eta_{2,t-1} + 2g_{11}g_{31}\eta_{1,t-1}\eta_{3,t-1} \\ & + 2g_{21}g_{31}\eta_{2,t-1}\eta_{3,t-1} \end{aligned} \tag{22}$$

$$\begin{aligned} h_{22,t} = {} & c_{12}^2 + c_{22}^2 + a_{12}^2\varepsilon_{1,t-1}^2 + a_{22}^2\varepsilon_{2,t-1}^2 + a_{32}^2\varepsilon_{3,t-1}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + 2a_{12}a_{32}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{22}a_{32}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{12}^2h_{11,t-1} + b_{22}^2h_{22,t-1} \\ & + b_{32}^2h_{33,t-1} + 2b_{12}b_{22}h_{12,t-1} + 2b_{12}b_{32}h_{13,t-1} + 2b_{22}b_{32}h_{23,t-1} + g_{12}^2\eta_{1,t-1}^2 \\ & + g_{22}^2\eta_{2,t-1}^2 + g_{32}^2\eta_{3,t-1}^2 + 2g_{12}g_{22}\eta_{1,t-1}\eta_{2,t-1} + 2g_{12}g_{32}\eta_{1,t-1}\eta_{3,t-1} \\ & + 2g_{22}g_{32}\eta_{2,t-1}\eta_{3,t-1} \end{aligned} \tag{23}$$

$$\begin{aligned} h_{33,t} = {} & c_{13}^2 + c_{23}^2 + c_{33}^2 + a_{13}^2\varepsilon_{1,t-1}^2 + a_{23}^2\varepsilon_{2,t-1}^2 + a_{33}^2\varepsilon_{3,t-1}^2 + 2a_{13}a_{23}\varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ & + 2a_{13}a_{33}\varepsilon_{1,t-1}\varepsilon_{3,t-1} + 2a_{23}a_{33}\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{13}^2h_{11,t-1} + b_{23,t-1}^2h_{22,t-1} \\ & + b_{33}^2h_{33,t-1} + 2b_{13}b_{23}h_{12,t-1} + 2b_{13}b_{33}h_{13,t-1} + 2b_{23}b_{33}h_{23,t-1} + g_{13}^2\eta_{1,t-1}^2 \\ & + g_{23}^2\eta_{2,t-1}^2 + g_{33}^2\eta_{3,t-1}^2 + 2g_{13}g_{23}\eta_{1,t-1}\eta_{2,t-1} + 2g_{13}g_{33}\eta_{1,t-1}\eta_{3,t-1} \\ & + 2g_{23}g_{33}\eta_{2,t-1}\eta_{3,t-1} \end{aligned} \tag{24}$$

Similarly, we can write the i^{th}, j^{th} conditional covariance, $h_{ij,t}$, $i \neq j$, $i, j = 1, 2, 3$ as follows:

$$\begin{aligned} h_{12,t} = h_{21,t} = {} & c_{11}c_{12} + a_{12}a_{11}\varepsilon_{1,t-1}^2 + a_{22}a_{21}\varepsilon_{2,t-1}^2 + a_{32}a_{31}\varepsilon_{3,t-1}^2 \\ & + (a_{12}a_{21} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + (a_{12}a_{31} + a_{32}a_{11})\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\ & + (a_{22}a_{31} + a_{32}a_{21})\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{12}b_{11}h_{11,t-1} + b_{22}b_{21}h_{22,t-1} \\ & + b_{32}b_{31}h_{33,t-1} + b_{22}b_{11}h_{12,t-1} + b_{32}b_{11}h_{13,t-1} + b_{12}b_{21}h_{21,t-1} \\ & + b_{12}b_{31}h_{31,t-1} + b_{32}b_{21}h_{23,t-1} + b_{22}b_{31}h_{32,t-1} + g_{12}g_{11}\eta_{1,t-1}^2 \\ & + g_{22}g_{21}\eta_{2,t-1}^2 + g_{32}g_{31}\eta_{3,t-1}^2 + (g_{12}g_{21} + g_{11}g_{22})\eta_{1,t-1}\eta_{2,t-1} \\ & + (g_{12}g_{31} + g_{32}g_{11})\eta_{1,t-1}\eta_{3,t-1} + (g_{22}g_{31} + g_{32}g_{21})\eta_{2,t-1}\eta_{3,t-1} \end{aligned} \tag{25}$$

$$
\begin{aligned}
h_{13,t} = h_{31,t} &= c_{11}c_{13} + a_{13}a_{11}\varepsilon^2_{1,t-1} + a_{23}a_{21}\varepsilon^2_{2,t-1} + a_{33}a_{31}\varepsilon^2_{3,t-1} \\
&+ (a_{13}a_{21} + a_{23}a_{11})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + (a_{13}a_{31} + a_{33}a_{11})\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\
&+ (a_{23}a_{31} + a_{33}a_{21})\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{13}b_{11}h_{11,t-1} + b_{23}b_{21}h_{22,t-1} \\
&+ b_{33}b_{31}h_{33,t-1} + b_{23}b_{11}h_{12,t-1} + b_{33}b_{11}h_{13,t-1} + b_{13}b_{21}h_{21,t-1} \\
&+ b_{13}b_{31}h_{31,t-1} + b_{33}b_{21}h_{23,t-1} + b_{23}b_{31}h_{32,t-1} + g_{13}a_{11}\eta^2_{1,t-1} \\
&+ g_{23}g_{21}\eta^2_{2,t-1} + g_{33}g_{31}\eta^2_{3,t-1} + (g_{13}g_{21} + g_{23}g_{11})\eta_{1,t-1}\eta_{2,t-1} \\
&+ (g_{13}g_{31} + g_{33}g_{11})\eta_{1,t-1}\eta_{3,t-1} + (g_{23}g_{31} + g_{33}g_{21})\eta_{2,t-1}\eta_{3,t-1}
\end{aligned} \tag{26}
$$

$$
\begin{aligned}
h_{23,t} = h_{32,t} &= c_{12}c_{13} + c_{22}c_{23} + a_{13}a_{12}\varepsilon^2_{1,t-1} + a_{23}a_{22}\varepsilon^2_{2,t-1} + a_{32}a_{33}\varepsilon^2_{3,t-1} \\
&+ (a_{12}a_{23} + a_{13}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + (a_{13}a_{32} + a_{33}a_{12})\varepsilon_{1,t-1}\varepsilon_{3,t-1} \\
&+ (a_{23}a_{32} + a_{33}a_{22})\varepsilon_{2,t-1}\varepsilon_{3,t-1} + b_{12}b_{12}h_{11,t-1} + b_{23}b_{22}h_{22,t-1} \\
&+ b_{32}b_{33}h_{33,t-1} + b_{23}b_{12}h_{12,t-1} + b_{33}b_{12}h_{13,t-1} + b_{13}b_{22}h_{21,t-1} \\
&+ b_{33}b_{21}h_{31,t-1} + b_{33}b_{22}h_{23,t-1} + b_{23}b_{32}h_{32,t-1} + g_{13}g_{12}\eta^2_{1,t-1} \\
&+ g_{23}g_{22}\eta^2_{2,t-1} + g_{32}g_{33}\eta^2_{3,t-1} + (g_{12}g_{23} + g_{13}g_{22})\eta_{1,t-1}\eta_{2,t-1} \\
&+ (g_{13}g_{32} + g_{33}g_{12})\eta_{1,t-1}\eta_{3,t-1} + (g_{23}g_{32} + g_{33}g_{22})\eta_{2,t-1}\eta_{3,t-1}
\end{aligned} \tag{27}
$$

We estimate the VAR(3)-BEKK-GARCH(1,1) model by non-linear maximum likelihood method. This requires the specification of the distribution for the 3-dimentional innovations. We assume two distributional forms for the innovations. First, the most common and convenient distribution is the multivariate normal. In this case, the log-likelihood function equals the following:

$$
L(\theta) = -\frac{T}{2}K\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\ln|H_t| + \hat{\varepsilon}_t' H_t^{-1}\hat{\varepsilon}_t), \tag{28}
$$

where T represents the number of observations, K equals the number of variables, and θ represents the vector of unknown parameters in the conditional means, and the *C, A*, *B*, and *G* matrices describe the conditional variance.

Second, we use the multivariate Student-*t* density, which accommodates leptokurtic data. Compared to the multivariate normal distribution, the multivariate Student-*t* distribution does not impose a computational burden and only adds one additional parameter, the degrees of freedom (υ), in the calculation of the log-likelihood function. That is,

$$L(\theta) = \sum_{i=1}^{T}\left[ln\Gamma\left(\frac{\upsilon+K}{2}\right) - ln\Gamma\left(\frac{\upsilon}{2}\right) - \frac{K}{2} ln(\upsilon-2)\pi \right] - \frac{1}{2}\sum_{i=1}^{T}\left[ln\left|H_t\right| + (\upsilon+K) ln\left(1+\frac{\hat{\varepsilon}_t' H_t^{-1}\hat{\varepsilon}_t}{\upsilon-2}\right)\right], \tag{29}$$

where Γ is the (complete) gamma function and υ equals the degrees of freedom. The m^{th} moment of the multivariate Student-*t* distribution exists, if $\upsilon > m$. Consequently, we impose the restriction that $\upsilon > 2$. As υ approaches infinity, the multivariate Student-*t* distribution approaches the multivariate normal distribution. Although symmetric, the multivariate Student-*t* distribution exhibits fatter tails than the multivariate normal distribution. The coefficient of excess (relative to the normal) kurtosis is given by $\kappa = 2/(\upsilon-4)$.

7. The Multivariate GARCH: Estimation Results

This section reports the results of our estimations. Table 12 reports the parameter estimates for the standard (symmetric) BEKK specification and the asymmetric BEKK specification, using both distributional assumptions. We estimate the models for the first moment simultaneously with those for the second moment using the BFGS (Broyden, 1970;-Fletcher, 1970;-Goldfarb, 1970; Shanno, 1970) algorithm.

Table 13 presents the log-likelihood statistics, AIC, BIC, the Doornik-Hansen (1994) multivariate tests of normality, and the Hosking (1980) multivariate tests of serial dependence in standardized and squared standardized residuals. The multivariate statistics for the standardized residuals prove insignificant at conventional level, indicating the model specification properly addresses the serial correlation problem. The multivariate statistics for the squared standardized residuals, however, prove significant in the standard BEKK specification, but not significant in the asymmetric version. This suggests that only the asymmetric version of the BEKK model adequately describes the first two moments of the returns series. This observation receives further confirmation from the likelihood ratio test.

As the standard BEKK model nests inside the asymmetric BEKK model, we can easily test one against the other using the likelihood ratio test. The results clearly suggest that asymmetric effects importantly affect the conditional covariances between the returns in the North American markets. The likelihood ratio test statistic equals 234 under the normality assumption and 140 under the Student-*t* distribution assumption. Moreover, with the degrees of freedom equal to 9, we soundly reject the null hypothesis at conventional significance levels. Thus, the model specification with asymmetric effects in covariances dominates the standard BEKK model. Furthermore, using the likelihood ratio test, we can reject the normally distributed asymmetric BEKK model in favor of the *t*-distributed asymmetric BEKK model. The likelihood ratio statistic equals 400, which is significant at conventional significance levels. Consequently, we rely on the asymmetric BEKK specification driven by leptokurtic innovations when interpreting our results.[17]

Interestingly, we reject the null hypothesis of independent conditional means and independent conditional variances of the three returns series. The LR test for the hypothesis that all off-diagonal elements of the *A*, *B,* and *G* matrices equal zero is 3110.77. The likelihood ratio test for the hypothesis that all off-diagonal elements of Γ_1, Γ_2, and Γ_3 equal zero is 55.76. The likelihood ratio that all off-diagonal elements of Γ_1, Γ_2, and Γ_3 and *A*, *B,* and *G* equal zero is

[17] We also consider various conditional volatility models to compare with the BEKK specification. They include the Diagonal VECH model of Bollerslev et al. (1988), the CCC model of Bollerslev (1990), the DCC model of Engle (2002), the VARMA-GARCH model of Ling and McAleer (2003), and the VARMA-AGARCH model of McAleer et al. (2008). We estimate the latter two models using both the CCC specification and the DCC specification. We do not report the full estimation results for economy of space, but in Table 14, we present the maximized log-likelihood (under the normal and the *t*-distribution) and the AIC and BIC of the estimated models.

3150.59. Thus, we model the three return series simultaneously (i.e., the asymmetric BEKK version with multivariate *t*-distribution dominates the separate sequence of three univariate asymmetric *t*-distributed GARCH models).

From Table 12, Panel 1, the following observations emerge. First, we can predict the returns, which reflect their own past returns. The returns of the US and the Mexican indexes depend upon their own first two lags, while the returns of the Canadian index depend upon its own three lags. The Wald test statistics that all own lagged returns equal zero are 16.4141 for the US market, 106.7191 for the Mexican market, and 44.5410, all significant at the one-percent level. Predictable returns may reflect market imperfections, time-varying risk premiums, or irrational behavior in markets. Second, no evidence exists of return spillovers from the Mexican stock market to the US stock market. The Wald test statistics for the null hypothesis that all lagged Mexican returns in the US return equation equal zero is 1.5156. Evidence does exist at the one-percent level, however, of return spillovers from the Mexican stock market to the Canadian stock market, and *vice versa*, at the five-percent level. The Wald test statistic for the null hypothesis that all lagged Mexican returns in the Canadian return equation equal zero is 11.8726 and that all lagged Canadian returns in the Mexican return equation equal zero is 8.8090, rejecting the null hypotheses at the one- and five-percent levels. Similarly, evidence of return spillovers also exists from the Canadian stock market to the US stock market at the five-percent level, and *vice versa*, at the one-percent level. The Wald test statistic for the null hypothesis that all lagged Canadian returns in the US return equation equal zero is 9.1355 and that all lagged US returns in the Canadian return equation are zero is 52.3494, rejecting the null hypotheses at the five- and one-percent levels. Overall, the US and Mexican markets prove relatively more isolated, in terms of returns spillovers, than the US and Canadian markets or even the Canadian and Mexican markets.

The characteristics of the time-varying variance-covariance H_t reflect the A, B, and G matrices. We focus our attention on the results of the estimation of the t-distributed asymmetric BEKK. We make the following observations. First, our results show significant volatility transmission between the second moments of NAFTA stock markets. We reject the null hypothesis at the one-percent level that the cross-variance effects between the US and Mexico equals zero (i.e., $a_{12}=a_{21}=b_{12}=b_{21}=g_{12}=g_{21}$), using the Wald test. Similarly, we reject the null hypotheses at the one-percent levels that the cross-variance effects between the US and Canada equal zero (i.e., $a_{13}=a_{31}=b_{13}=b_{31}=g_{13}=g_{31}$), and that that the cross-variance effects between Canada and Mexico equal zero (i.e., $a_{23}=a_{32}=b_{23}=b_{32}=g_{23}=g_{32}$).

Second, the diagonal elements of the A, B, and G matrices prove highly significant (g_{33}, the exception), which implies that volatility in returns responds to its own past shocks and volatility. Kearney and Patton (2000) observe, however, that we cannot interpret the estimated parameters c_{ij}, a_{ij}, b_{ij} and g_{ij} for all i , j = 1, 2, 3 individually.

The relevant parameters involve nonlinear functions of the original parameters c_{ij}, a_{ij}, b_{ij}, and g_{ij} to generate the constant terms and coefficients of the lagged conditional variances and covariances, lagged squared and cross residuals, lagged squared asymmetric shocks and cross-asymmetric shocks. Statistical inference requires obtaining the first two moments of these nonlinear functions (i.e., the expected value and the standard error of the non-linear combinations of c_{ij}, a_{ij}, b_{ij}, and g_{ij}). We compute the expected value of a non-linear function of random variables as the function of the expected value of the variables, under the assumption of unbiased estimated parameters. Since we use the Maximum Likelihood approach to estimate, the consistent maximum likelihood estimates exhibit a useful property. To wit, if $\hat{\beta}_{MLE}$ consistently estimates β, then $h(\hat{\beta}_{MLE})$ consistently estimates $h(\beta)$. Hence, to produce a consistent estimate of, say a_{ij}^2, we simply square the maximum likelihood estimate of a_{ij}. To calculate the standard errors of this non-linear function, we apply the delta method and use a first-order Taylor approximation, which yields an approximate formulation of the variance of the non linear functions under fairly general assumptions (Oehlert, 1991).[18]

Table 15 displays the linearized parameter estimates for the *t*-distributed asymmetric BEKK model. In Panels 1 and 2, we report the estimates of the three variance equations and the estimates of the covariance equations, respectively. In what follows, US = 1, Mexico = 2, and Canada = 3. Hence, h_{11}, h_{22}, and h_{33} denote the conditional variance for the US, Mexican, and Canadian equity return series, respectively, while h_{12}, h_{13}, and h_{23} denote the conditional covariance between the US and Mexican, the US and Canadian, and the Mexican and Canadian equity returns series.

An analysis of the results requires a preliminary taxonomy of the transmission channels. We can visualize two transmission channels. First, consider the transmission of volatility, which includes a) a direct volatility transmission, where $h_{ii,t}$ responds to $h_{ii,t-1}$ (its own volatility) and/or to $h_{jj,t-1}$ (volatility in the other markets) and b) an indirect volatility transmission, where

[18] Applying the delta method to a function of one variable, $h(\theta)$, yields $var(h(\theta) = \left(dh/d\theta \right)^2 var(\theta)$. Similarly, applying the delta method to a function of two variables, $h(\theta_1,\ \theta_2)$, yields $var\left[h(\theta_1,\ \theta_2)\right] = \left(\partial h/\partial\theta_1 \right)^2 var(\theta_1)$ $+ \left(\partial h/\partial\theta_2 \right)^2 var(\theta_2) + 2\left(\partial h/\partial\theta_1 \right)\left(\partial h/\partial\theta_2 \right) cov(\theta_1, \theta_2)$.

$h_{ii,t}$ responds to any covariance $h_{ij,t-1}$, for $i \neq j$, i and j = 1 ,2, 3. Second, consider now the transmission of shocks, which includes a) a direct shock transmission, where $h_{ii,t}$ responds to $\varepsilon^2_{ii,t-1}$ (its own shock) and/or to $\varepsilon^2_{jj,t-1}$ (shock in the other markets) and b) an indirect shock transmission, where $h_{ii,t}$ responds to any of the cross terms $\varepsilon_{i,t-1}\varepsilon_{j,t-1}$ for $i \neq j$, i and j = 1, 2, 3.

The results indicate that the conditional variance of US returns responds directly to its own past volatility and its own past shocks as well as to past shocks originating from the Canadian market. Volatility and shocks from the Mexican market do not significantly affect the conditional variance of US returns. US returns exhibit own-variance asymmetry, cross-variance asymmetry, and covariance asymmetry. Shocks originating in the US market prove asymmetric, given the significance of the coefficient on $\eta^2_{1,t-1}$. That is, negative shocks in the US market increase the volatility of US returns about ten times more than positive shocks. Positive and negative shocks originating in the Canadian markets do not affect the US return asymmetrically, however. In addition, the conditional variance of the US returns displays indirectly cross-variance asymmetry with respect to shocks in the Canadian market, given the significance of the coefficients on the cross term $\varepsilon_{1,t-1}\varepsilon_{3,t-1}$ and its corresponding asymmetric term $\eta_{1,t-1}\eta_{3,t-1}$. Finally, US returns also exhibit covariance asymmetry, as the coefficients on $\eta_{1,t-1}\eta_{2,t-1}$, $\eta_{1,t-1}\eta_{3,t-1}$, and $\eta_{2,t-1}\eta_{3,t-1}$ prove significant in the covariance equation.

The behavior of the Mexican market volatility differs substantially from that of the US market. The volatility of the Mexican returns responds directly to both its past shocks and its own past volatility. Further, while the conditional variances of US and Canadian returns do not directly affect the volatility of the Mexican returns, shocks originating in the US and Canadian markets directly affect the volatility of Mexican returns. This finding implies that a mechanism exists that directly transmits shocks from the US and the Canadian markets to the Mexican market, which we conjecture may reflect US and Canadian investors operating in the Mexican market Furthermore, all the coefficients on the covariance and cross-shocks terms prove significant. This implies that an indirect mechanism exists for volatility and shock transmission from the US and Canadian markets to Mexican market. Mexican returns also exhibit own-variance asymmetry, as indicated by the significance of the coefficient on $\eta_{2,t-1}^2$, cross-variance asymmetry, through the Mexican and Canadian cross-shocks term $\eta_{2,t-1}\eta_{3,t-1}$, and covariance asymmetry, as the coefficient estimates of $\eta_{1,t-1}\eta_{2,t-1}$, $\eta_{1,t-1}\eta_{3,t-1}$, and $\eta_{2,t-1}\eta_{3,t-1}$ prove significant in the covariance equation between US and Mexican returns (the h_{12} equation) and the parameter estimates of $\eta_{1,t-1}$, $\eta_{2,t-1}$, and $\eta_{2,t-1}^2$ prove significant in the covariance equation between Canadian and Mexican returns (the h_{23} equation).

The results for the Canadian market indicate that Canadian returns respond directly to their own past shocks and their own past volatility. No evidence emerges, however, of own-variance asymmetry. Instead, evidence exists of cross-variance asymmetry through the significance of the US and Mexican cross-shocks term $\eta_{1,t-1}\eta_{2,t-1}$. Some evidence also exists of covariance asymmetry, as the parameter estimates of $\eta_{2,t-1}^2$ and $\eta_{1,t-1}\eta_{2,t-1}$ prove significant in the covariance equation between Canadian and Mexican returns (the h_{23} equation), and the parameter estimate of $\eta_{1,t-1}^2$ proves significant in the covariance equation between US and Canadian returns (the h_{13} equation).

Table 16 reports the parameter estimates of negative shocks on the variances and covariances of returns (e.g., the effect of $\varepsilon_{1,t-1}^2$ on $h_{11,t}$ equals a_{11}^2 for $\varepsilon_{1,t-1} > 0$, and $a_{11}^2 + g_{11}$ for $\varepsilon_{1,t-1} < 0$).

Figures 14 and 15 present the plots of the respective conditional variances for the US, Mexican, and Canadian equity markets return series and the conditional covariances, implied by the estimates of the t-distributed asymmetric BEKK model, respectively. Clearly, the variances and covariances cluster over time. The conditional variances and covariances do not remain constant over time and appear especially volatile between 1997 and 2003 (Asian financial crisis and stock-market crash). The Mexican market also exhibited high volatility of the conditional variance between 1994 and 1995 (Peso crisis). Volatilities move together. Covariances between any two of the three returns are higher (lower) in times of high (low) volatility and include, in some instances, large positive spikes.

Previous studies suggest that correlations vary over time and that they increased since the mid-1990s due to wider financial integration (Bekaert and Harvey, 1997, 2002). Following De Goeji and Marquering (2004), we examine whether the time variability in covariances is only due to the variation in variances. The conditional correlation coefficient $\rho_{ij,t}$ between return *i* and return *j* at time *t* is defined as follows:

$$\rho_{ij,t} = \frac{cov(r_{i,t}, r_{j,t})}{\sqrt{var(r_{i,t})}\sqrt{var(r_{j,t})}}. \tag{30}$$

If $\rho_{ij,t}$ does not change over time, then the covariance's variability exclusively reflects the variances' variations. As such, modeling of time-varying covariance proves uninteresting, as the variances capture all the dynamics.

Figure 16 displays the evolution of the estimated conditional correlation coefficients. The plots of the series appear to refute a constant conditional correlation, as considerable variability occurs over time. More trend, however, appears when we included the Mexican market. That is, the correlations between the US and Canadian markets seem to rise from 0.6 to 0.8 over the sample period, whereas the correlations between the Mexican and the US or Canadian markets appear to rise from 0.4 to 0.8 and from 0.2 to 0.6, respectively. A formal test of the constancy of the correlation coefficients regresses the conditional correlation coefficients on a constant and lagged conditional correlation coefficients, rejecting the hypotheses of constant correlation coefficients. The estimates on the lagged conditional correlation coefficients prove significantly different from zero, with *t*-ratios equal to, respectively, 274.8890 (S&P500 and IPC), 287.0184 (S&P500 and S&P/TSX), and 249.7295 (IPC and S&P/TSX).

We can draw some observations about the estimated conditional correlation coefficients. First, the conditional correlations between each pair of returns, on average, are positive. The mean values equal 0.4994 (S&P500 and IPC), 0.6460 (S&P500 and S&P/TSX), and 0.4274 (IPC and S&P/TSX) and their associated standard errors equal 0.0028, 0.0018, and 0.0027, respectively. A simple *t* test concludes that these values significantly differ from zero. Second, the conditional correlations between the returns show large variations during episodes of financial crisis. Kaminsky and Reinhart (2000) suggest that these rapid and sharp movements in correlations make the financial market a likely channel of contagion. Third, the magnitude of the conditional correlations indicates that in the last few years, the Mexican stock market became more integrated with the US and Canadian markets. In the early 1990s, the conditional correlations between the US and Mexican stock markets follow a downward trend, and show an average value of about 0.4. Now, in the early 2000s, we observe an upward trend and with average value of about 0.6. We see the same pattern, although with a smaller magnitude, in the evolution of the conditional correlations between the Mexican and the Canadian markets.

8. Conclusion

This paper explores the first and second moment interactions among the NAFTA stock markets, using daily data over the period 1992-2007. We focus the analysis on three issues. First, we examine the long-run relationships between the markets. Second, we consider the short-run relationship between them. And, third, we investigate the return and volatility transmission process between them.

We address the first issue using the standard cointegration techniques of Johansen and Juselius (1990) and the recursive cointegration techniques of Hansen and Johansen (1999). Standard cointegration analysis fails to discover evidence that the NAFTA stock indexes share long-run equilibrium relationships. We do not reverse this finding with the recursive cointegration analysis. These latter finding show a strengthening of the relationships between the three markets in the mid-nineties, as the NAFTA markets appear to move toward cointegration. This movement, however, reverses by the end of the 1990s. In general, the results of the recursive cointegration tests prove compatible with the traditional cointegration findings. We conclude, therefore, that no evidence exists of a common long-term trend between the three NAFTA equity indices, and no evidence exists of any move toward such a trend relationship.

We address the second issue with the generalized impulse response analysis of Pesaran and Shin (1998). We find that the responses prove quite large in scale, using the conventional 0.20 unit standard deviations definition of significant responses on stock returns. The responses occur immediately, but do not exhibit long-lasting effects. In all cases, the responses die out within two days. We also find that the response of each market to shocks in its own market always exceeds the response to shocks in other markets. The US holds a leading role, in that the Canadian (Mexican) market responds more sensitively to shocks stemming from the US than from Mexico (Canada). The generalized impulse responses show, however, that the US market does respond to shocks originating in Mexico and Canada. Hence, the US market leads, but is not autonomous and independent.

We address the third issue by modelling the joint distribution of the three stock returns using a vector autoregression methodology with innovations, using a multivariate asymmetric BEKK-GARCH(1,1) process. We estimate the model under two distributional forms for the innovations -- the multivariate normal distribution and the multivariate Student-*t* density. The multivariate normal distribution, the most common and convenient, does not accommodate leptokurtic data. The multivariate Student-*t* density does accommodate leptokurtic data. Our preliminary findings, based on LR tests, indicate that the BEKK specification with asymmetric effects in covariances dominates the standard symmetric BEKK model. Furthermore, we reject the normally distributed asymmetric BEKK model in favor of the *t*-distributed asymmetric BEKK model. The asymmetric BEKK results support significant returns and volatility spillovers between the three stock markets. Our results exhibit significant volatility transmission between the first moments of the NAFTA stock markets. Although we find no evidence of return spillovers from the Mexican to the US stock market, we do find evidence of return spillovers from the Mexican to the Canadian stock market, from the Canadian to the US stock market, from the Canadian to the Mexican stock market, and from the US to the Canadian stock market. This evidence suggests that based on the first moments, the US and the Mexican markets prove relatively more isolated than the US and Canadian or even the Canadian and Mexican markets.

Our results also exhibit significant volatility transmission between the second moments of the NAFTA stock markets, albeit not homogenous. US returns exhibit own-variance asymmetry, cross-variance asymmetry, and covariance asymmetry. The conditional variance of US returns responds directly to its own past volatility and shocks as well as to shocks originating in the Canadian market. In contrast, volatility and shocks from the Mexican market do not significantly and directly affect the conditional variance of US returns. The conditional variance of the Mexican returns also responds directly to its own past volatility and shocks. The conditional variance of US and Canadian returns does not directly affect the volatility of the Mexican returns. Shocks originating in the US and Canadian markets, however, directly affect the volatility of the Mexican returns. Mexican returns also exhibit own-variance asymmetry, cross-variance asymmetry, and covariance asymmetry. The conditional variance of Canadian returns also responds directly to its own past volatility and shocks. No evidence exists, however, of own-variance asymmetry. Instead, evidence exists of cross-variance asymmetry and some evidence of covariance asymmetry.

The magnitude and trend of the conditional correlations indicate that in the last few years, the Mexican stock market exhibited a tendency toward increased integration with the US market. In the early 1990s, the conditional correlations between the US and Mexican stock markets followed a downward trend, with an average value of approximately 0.4. Conversely, in the early 2000s, the trend reversed, now rising, with an average value of 0.6. The same pattern, although with slightly lower magnitude, also appears in the evolution of the conditional correlations between the Mexican and the Canadian markets. The finding of volatility transmission between the three NAFTA markets, and the pattern of correlations that emerges, can provide important practical importance to financial market participants and may guide those participants in making optimal portfolio decisions. In the NAFTA stock markets, the benefits of portfolio diversification are not yet exhausted.

Finally, we do note that evidence exists that the Peso and Asian financial crises as well as the stock-market crash in the US affect the return and volatility time-series relationships. Consequently, future empirical work can consider the possibility of one-time structural shifts in the return and volatility relationships, occurring near the Peso and Asian financial crises as well as the US stock-market crash. Accommodating such one-time structural shifts may permit an underlying cointegrating relationship to achieve significance, alter the short-run relationships between the NAFTA markets, and affect the return and volatility transmission process.

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Table 1: Summary Statistics of the Return Series

	Canada	Mexico	US
Mean	0.036319	0.079641	0.033206
Median	0.064505	0.077828	0.055146
Maximum	4.683352	12.15364	5.573247
Minimum	-8.465626	-14.31446	-7.113885
Std. Dev.	0.923267	1.672076	1.034008
Skewness	-0.717208	-0.090087	-0.152942
Kurtosis	9.682723	8.433533	6.915857
Jarque-Bera	7375.34(0.00)	4666.11(0.00)	2435.62(0.00)

Note: Daily returns equal the first difference of logarithmic prices in percent.

Table 2: Ljung-Box Statistics Applied to Returns and Squared Returns

	Returns		
	Canada	**Mexico**	**US**
LB-Q(6)	37.725	38.566	20.900
LB-Q(12)	56.545	54.637	41.278
LB-Q(18)	64.074	67.999	44.632
LB-Q(24)	68.701	70..072	52.736
	Squared Returns		
	Canada	**Mexico**	**US**
LB-Q^2(6)	465.92	549.81	724.73
LB-Q^2(12)	719.16	709.21	1105.1
LB-Q^2(18)	913.47	864.11	1453.6
LB-Q^2(24)	1114.1	936.38	1731.8

Note: LB-Q and LB-Q^2 equal the Ljung-Box statistics for the returns and squared returns, respectively. Number of lags appears in parentheses.

Table 3: Multivariate Ljung-Box Statistics for Returns and Squared Returns

Returns		Squared Returns		Critical Values
H(6)	239.62	**H^2(6)**	1522.70	72.15[54]
H(12)	335.00	**H^2(12)**	2339.24	133.26[108]
H(18)	406.32	**H^2(18)**	3058.04	192.70[162]
H(24)	457.54	**H^2(24)**	3650.41	251.29[216]

Note: H and H^2 equal the Hosking (1980) multivariate analogue to the LB-Q and LB-Q^2 tests for autocorrelation. Number of lags appears in parentheses. The 5-percent critical values appear with degrees of freedom in brackets.

Table 4: Unit Root Tests

	Indexes		Returns	
	ADF	**PP**	**ADF**	**PP**
S&P 500	-1.41	-1.23	-11.58	-63.84
S&P TSX	-2.18	-2.06	-10.68	-56.40
IPC	-2.54	-2.40	-11.48	-55.81

Note: ADF and PP equal the augmented Dickey-Fuller (1979) with a constant and a linear deterministic time trend and the Phillips-Perron (1988) tests for non-stationarity. The critical values for the ADF and PP tests equal -3.12, -3.41, and -3.96 at the 10-, 5-, and 1-percent levels, respectively.

Table 5: VAR Lag Order Selection Criteria

Lag	LogL	LR	FPE	AIC	SIC	HQIC
0	-15953.4	NA	0.929	8.4403	8.4452	8.4421
1	-15867.7	171.32	0.8923	8.3997	**8.4195**	**8.4067**
2	-15852.9	29.44	0.8896	8.3967	8.4313	8.4090
3	-15842.5	**20.88**	**0.8889**	**8.3959**	8.4454	8.4135
4	-15835.6	13.60	0.8900	8.3970	8.4614	8.4199
5	-15830.6	9.963	0.8918	8.3991	8.4784	8.4273
6	-15826.5	8.22	0.8941	8.4017	8.4958	8.4352
7	-15818.6	15.73	0.8947	8.4023	8.5112	8.4410
8	-15812.5	12.17	0.8960	8.4038	8.5276	8.4478

Note: LogL, LR, FPE, AIC, SIC, and HQIC equal the log likelihood value, the likelihood ratio, the final prediction error, the Akaike information criterion, the Schwartz information criterion, and the Hannan-Quinn information criterion.

Table 6: Johansen Tests of Cointegration -- Model 1

		Trace Statistic for Cointegrating Rank		
H_0:	**H_A:**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
$r = 0$	$r \geq 1$	0.0039	24.5335	34.9100
$r \leq 1$	$r \geq 2$	0.0018	9.7345	19.9600
$r \leq 2$	$r = 3$	0.0008	2.9302	9.2400
		Maximum Eigenvalue Statistic for Cointegrating Rank		
H_0:	**H_A:**	**Eigenvalue**	**Maximum Eigenvalue**	**5% Critical Value**
$r = 0$	$r = 1$	0.0039	14.7990	22.0000
$r \leq 1$	$r = 2$	0.0018	6.8043	15.6700
$r \leq 2$	$r = 3$	0.0008	2.9302	9.2400

Note: H_0 and H_A equal the null and alternative hypotheses. In Model 1, the series exclude deterministic trends and the cointegrating equations include intercepts.

Table 7: Johansen Tests of Cointegration -- Model 2

		Trace Statistic for Cointegrating Rank		
H_0:	**H_A:**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
$r = 0$	$r \geq 1$	0.0035	16.6024	29.7900
$r \leq 1$	$r \geq 2$	0.0008	3.1710	15.4900
$r \leq 2$	$r = 3$	0.0000	0.0077	3.8400
		Maximum Eigenvalue Statistic for Cointegrating Rank		
H_0:	**H_A:**	**Eigenvalue**	**Maximum Eigenvalue**	**5% Critical Value**
$r = 0$	$r = 1$	0.0035	13.4314	21.1316
$r \leq 1$	$r = 2$	0.0008	3.1633	14.2646
$r \leq 2$	$r = 3$	0.0000	0.0077	3.8415

Note: See Table 6. In Model 2, the series include deterministic trends, but the cointegrating equations only include intercepts.

Table 8: Johansen Tests of Cointegration -- Model 3

		Trace Statistic for Cointegrating Rank		
H_0:	**H_A:**	**Eigenvalue**	**Trace Statistic**	**5% Critical Value**
$r = 0$	$r \geq 1$	0.0050	27.2579	42.9152
$r \leq 1$	$r \geq 2$	0.0014	8.3383	25.8721
$r \leq 2$	$r = 3$	0.0008	3.1625	12.5179
		Maximum Eigenvalue Statistic for Cointegrating Rank		
H_0:	**H_A:**	**Eigenvalue**	**Maximum Eigenvalue**	**5% Critical Value**
$r = 0$	$r = 1$	0.0050	18.9196	25.8232
$r \leq 1$	$r = 2$	0.0014	5.1759	19.3870
$r \leq 2$	$r = 3$	0.0008	3.1625	12.5179

Note: See Table 6. In Model 3, the series and the cointegrating equations include deterministic trends.

Table 9: Generalized Impulse Response of US Returns:

	One Standard Deviation in		
Period	**US Market**	**Canadian Market**	**Mexican Market**
1	1.034037	0.723898	0.553128
	(0.01169)	(0.01389)	(0.01522)
2	-0.027797	-0.021308	-0.024413
	(0.01682)	(0.01684)	(0.01686)
3	-0.044758	-0.028887	-0.021987
	(0.01663)	(0.01679)	(0.01673)
4	0.010966	0.001436	0.013743
	(0.01622)	(0.01670)	(0.01632)
5	6.11E-05	-0.000301	0.000643
	(0.00391)	(0.00288)	(0.00309)
6	-0.000984	-0.000333	-0.001335
	(0.00194)	(0.00162)	(0.00183)
7	-4.55E-05	0.000171	-0.000165
	(0.00103)	(0.00084)	(0.00091)
8	0.000106	9.72E-05	7.90E-05
	(0.00025)	(0.00022)	(0.00021)
9	5.37E-06	-1.57E-05	1.91E-05
	(0.00015)	(0.00012)	(0.00014)
10	2.06E-06	-6.03E-06	6.58E-06
	(4.8E-05)	(4.1E-05)	(4.4E-05)

Note: Period equals the number of days since the innovation. Numbers in parentheses equal standard errors calculated through a Monte Carlo simulation with 1,000 repetitions.

Table 10: Generalized Impulse Response of Canadian Returns:

Period	One Standard Deviation in		
	US Market	**Canadian Market**	**Mexican Market**
1	0.642031	0.917095	0.435253
	(0.01235)	(0.01048)	(0.01421)
2	0.100003	0.079624	0.048547
	(0.01514)	(0.01504)	(0.01492)
3	-0.005393	-0.019550	0.021343
	(0.01524)	(0.01529)	(0.01521)
4	0.037463	0.014930	0.034610
	(0.01531)	(0.01561)	(0.01480)
5	-0.002220	-0.002699	-0.000688
	(0.00371)	(0.00385)	(0.00388)
6	-0.002773	-0.000985	-0.002715
	(0.00189)	(0.00151)	(0.00179)
7	0.000259	0.000476	1.78E-05
	(0.00113)	(0.00106)	(0.00114)
8	0.000151	0.000141	0.000119
	(0.00032)	(0.00028)	(0.00025)
9	1.43E-05	-1.97E-05	2.65E-05
	(0.00016)	(0.00013)	(0.00014)
10	8.02E-06	-5.95E-06	1.38E-05
	(5.8E-05)	(5.4E-05)	(5.7E-05)

Note: See Table 9.

Table 11: Generalized Impulse Response of Mexican Returns:

Period	One Standard Deviation in		
	US market	**Canadian market**	**Mexican market**
1	0.890224	0.789836	1.664216
	(0.02518)	(0.02619)	(0.01954)
2	0.095020	0.070445	0.166250
	(0.02691)	(0.02647)	(0.02670)
3	-0.034335	-0.049562	-0.034957
	(0.02695)	(0.02663)	(0.02777)
4	0.053834	0.048747	0.031622
	(0.02672)	(0.02657)	(0.02629)
5	0.007165	0.007756	0.003003
	(0.00621)	(0.00643)	(0.00684)
6	-0.004174	-0.002791	-0.002314
	(0.00327)	(0.00248)	(0.00305)
7	0.001318	0.000381	0.001458
	(0.00194)	(0.00162)	(0.00182)
8	0.000299	7.14E-05	0.000325
	(0.00050)	(0.00051)	(0.00051)
9	-0.000146	-7.58E-05	-0.000141
	(0.00025)	(0.00020)	(0.00024)
10	-1.66E-05	7.22E-06	-2.65E-05
	(9.5E-05)	(8.6E-05)	(0.00010)

Note: See Table 9.

Table 12: Estimates of VAR(3)-BEKK-GARCH(1,1) 1992-2007

Panel 1. The VAR(3) Model : The Mean Equations

Variable	Normal Distribution		*t*-Distribution	
	Symmetric	Asymmetric	Symmetric	Asymmetric
		US Stock Market		
constant	0.0612	0.0391	0.0658	0.0517
	(3.3963)	(4.4454)	(5.6895)	(5.3687)
r_{t-1}^{US}	-0.0224	-0.0173	-0.0391	-0.0311
	(1.2379)	(2.0634)	(2.4541)	(2.5083)
r_{t-2}^{US}	-0.0299	-0.0275	-0.0360	-0.0369
	(1.6643)	(2.1814)	(2.2056)	(3.5259)
r_{t-3}^{US}	-0.0034	-0.0016	-0.0207	-0.0123
	(0.1839)	(0.2185)	(1.3882)	(1.0758)
r_{t-1}^{MEX}	0.0046	0.0051	0.0080	0.0057
	(0.5633)	(0.9635)	(1.0256)	(0.9703)
r_{t-2}^{MEX}	-0.0028	-0.0003	0.0007	0.0021
	(0.3658)	(0.0495)	(0.0959)	(0.3275)
r_{t-3}^{MEX}	0.0078	0.0115	0.0021	0.0047
	(0.7731)	(2.0971)	(0.2701)	(0.7642)
r_{t-1}^{CAN}	0.0296	0.0228	0.0335	0.0275
	(1.3647)	(2.7614)	(2.0084)	(2.0917)
r_{t-2}^{CAN}	-0.0013	-0.0014	-0.0280	-0.0221
	(0.0597)	(0.1120)	(1.5459)	(1.8252)
r_{t-3}^{CAN}	-0.0136	-0.0153	0.0027	-0.0045
	(0.6044)	(1.6424)	(0.1656)	(0.3646)
		Mexican Stock Market		
constant	0.1305	0.0877	0.1272	0.0989
	(4.6172)	(4.6300)	(6.4951)	(6.1046)
r_{t-1}^{MEX}	0.1097	0.1169	0.1135	0.1143
	(4.8006)	(10.2507)	(6.9250)	(10.1196)
r_{t-2}^{MEX}	-0.0359	-0.0204	-0.0357	-0.0262
	(1.7162)	(1.6493)	(2.2639)	(2.1753)
r_{t-3}^{MEX}	-0.0033	0.0089	-0.0102	-0.0029
	(0.1571)	(0.6836)	(0.6476)	(0.2477)
r_{t-1}^{US}	0.0111	0.0096	0.0085	0.0126
	(0.3118)	(0.6512)	(0.3264)	(0.6944)
r_{t-2}^{US}	0.0048	0.0000	-0.0036	-0.0061
	(0.1449)	(0.0011)	(0.1316)	(0.3550)
r_{t-3}^{US}	0.0470	0.0395	0.0222	0.0284

	(1.1517)	(2.2688)	(0.8486)	(1.6042)
r_{t-1}^{CAN}	0.0547	0.0534	0.0384	0.0385
	(1.3322)	(3.8479)	(1.3288)	(1.8086)
r_{t-2}^{CAN}	0.0017	-0.0191	-0.0377	-0.0385
	(0.0443)	(1.0601)	(1.2125)	(1.7519)
r_{t-3}^{CAN}	0.0137	0.0174	0.0246	0.0216
	(0.3015)	(0.9612)	(0.8149)	(1.0732)
Canadian Stock Market				
constant	0.0554	0.0411	0.0644	0.0559
	(3.4761)	(4.0530)	(6.2808)	(6.5967)
r_{t-1}^{CAN}	0.0594	0.0638	0.0520	0.0552
	(3.0157)	(6.0731)	(3.2990)	(4.4573)
r_{t-2}^{CAN}	-0.0327	-0.0278	-0.0448	-0.0414
	(1.8861)	(2.3505)	(2.7502)	(3.8917)
r_{t-3}^{CAN}	-0.0364	-0.0325	-0.0223	-0.0243
	(1.9121)	(3.4403)	(1.4836)	(2.1751)
r_{t-1}^{US}	0.0722	0.0749	0.0709	0.0734
	(4.4425)	(9.2269)	(5.1388)	(6.9300)
r_{t-2}^{US}	0.0109	0.0105	-0.0003	0.0009
	(0.5772)	(0.9985)	(0.0210)	(0.0911)
r_{t-3}^{US}	0.0513	0.0459	0.0339	0.0359
	(2.8510)	(5.8329)	(2.5637)	(3.7102)
r_{t-1}^{MEX}	0.0114	0.0113	0.0104	0.0092
	(1.1931)	(1.9777)	(1.4096)	(1.7097)
r_{t-2}^{MEX}	0.0151	0.0176	0.0160	0.0163
	(1.8699)	(3.1404)	(2.3488)	(2.9157)
r_{t-3}^{MEX}	0.0098	0.0122	0.0041	0.0061
	(1.2318)	(2.3114)	(0.5612)	(1.1525)

Panel 2. The BEKK-GARCH(1,1) Model : The Variance-Covariance Equations

Parameter Estimate	**Normal Distribution**		***t*-Distribution**	
	Symmetric	**Asymmetric**	**Symmetric**	**Asymmetric**
c_{11}	0.0741	0.0839	-0.0440	0.0541
	(4.6375)	(5.6855)	3.4516	(4.3695)
c_{21}	0.1265	0.0905	-0.0992	0.0586
	(3.6008)	(3.4166)	2.6015	(2.1608)
c_{22}	0.1614	0.1761	0.1423	0.1746
	(4.0133)	(10.7620)	(6.3501)	(10.2424)
c_{31}	0.0540	0.0395	-0.0411	0.0148
	(3.0602)	(3.0052)	2.8563	(0.9307)

c_{32}	0.0122	0.0199	0.0052	0.0156
	(1.1813)	(1.9856)	(0.4863)	(1.4267)
c_{33}	0.0447	0.0505	0.0511	0.0539
	(3.0040)	(4.0375)	(5.5876)	(5.4162)
a_{11}	0.1850	0.0873	0.1449	0.0775
	(5.5379)	(3.0564)	(8.5845)	(3.6122)
a_{12}	-0.0447	-0.1286	-0.0906	-0.1293
	(0.8756)	(3.9561)	(3.2977)	(4.1822)
a_{13}	0.0307	-0.0324	-0.0081	-0.0389
	0.8519	(1.4093)	(0.5124)	(2.4181)
a_{21}	0.0134	0.0014	0.0100	0.0011
	(1.5194)	(0.2859)	(1.7861)	(0.1628)
a_{22}	0.2943	0.1710	0.2579	0.1677
	(6.0293)	(12.7758)	(11.9926)	(10.8424)
a_{23}	0.0074	-0.0069	0.0020	-0.0033
	0.6728	(1.3085)	(0.3213)	(0.4744)
a_{31}	0.0530	0.0903	0.0596	0.0895
	(0.0530)	(0.0903)	(0.0596)	(0.0895)
a_{32}	0.0642	0.1863	0.0980	0.1816
	(0.0642)	(0.1863)	(0.0980)	(0.1816)
a_{33}	0.1969	0.2772	0.2121	0.2629
	(4.6661)	(6.4586)	(11.6884)	(12.9770)
b_{11}	0.9800	0.9760	0.9891	0.9830
	(126.4601)	(122.1161)	(294.6741)	(222.5317)
b_{12}	0.0103	0.0145	0.0172	0.0185
	(0.7339)	(1.6027)	(2.9121)	(2.4392)
b_{13}	-0.0060	-0.0041	0.0021	0.0008
	0.7869	(0.5767)	(0.6462)	(0.2043)
b_{21}	-0.0046	-0.0048	-0.0029	-0.0033
	(1.7867)	(2.6696)	(2.0689)	(2.0507)
b_{22}	0.9478	0.9470	0.9588	0.9512
	(53.0703)	(291.6405)	(142.0247)	(207.9020)
b_{23}	-0.0032	-0.0053	-0.0011	-0.0032
	(1.0400)	(3.2185)	(0.7006)	(1.7769)
b_{31}	-0.0081	-0.0095	-0.0104	-0.0101
	(0.9790)	(0.9217)	(2.6446)	(1.7049)
b_{32}	-0.0088	-0.0246	-0.0161	-0.0225
	(0.5205)	(1.5894)	(1.9645)	(1.9937)
b_{33}	0.9786	0.9642	0.9745	0.9661
	(89.8161)	(80.6899)	(221.9527)	(167.0360)

g_{11}	0.2901		0.2646
	(9.4779)		(8.6955)
g_{12}	0.0841		0.0575
	(1.4530)		(1.0722)
g_{13}	0.1771		0.1439
	(3.6749)		(4.9775)
g_{21}	0.0216		0.0150
	(2.1952)		(1.7777)
g_{22}	0.3642		0.3389
	(17.0682)		(15.3678)
g_{23}	0.0372		0.0202
	(2.7956)		(2.3013)
g_{31}	-0.0714		-0.0816
	(1.3396)		(2.4720)
g_{32}	-0.1838		-0.1914
	(1.7085)		(3.0486)
g_{33}	-0.0723		-0.0574
	(0.8876)		(1.6681)
υ		8.6801	9.5725
		(16.0696)	(29.6186)

Note: Numbers in parentheses under coefficient estimates equal *t*-statistics.

Table 13: Multivariate Diagnostics

Statistic	Normal Distribution		*t*-Distribution	
	Symmetric	**Asymmetric**	**Symmetric**	**Asymmetric**
Log of the Likelihood	-14409	-14292	-14162	-14092
Akaike Information Criterion (AIC)	28927	28711	28435	28313
Schwarz Information Criterion (BIC)	29264	29104	28778	28712
Multivariate Q(12)[a]	115.05	109.31	114.77	110.45
	[0.3032]	[0.4466]	[0.3095]	[0.4165]
Multivariate Q(24)[a]	228.82	223.58	229.49	224.71
	[0.2620]	[0.3473]	[0.2521]	[0.3280]
Multivariate $Q^2(12)$[a]	162.85	116.34	201.05	108.99
	[0.0005]	[0.2747]	[0.0065]	[0.4549]
Multivariate $Q^2(24)$[a]	273.00	243.00	254.89	230.36
	[0.0052]	[0.0975]	[0.0359]	[0.2394]
Multivariate Normality[b]	895	755	1076	874
	[0.0000]	[0.0000]	[0.0000]	[0.0000]

Note: Numbers in brackets equal p-values. Numbers in parentheses equal lags.

a. Hosking (1980) multivariate tests for autocorrelation in standardized and squared standardized residuals.

b. Doornik-Hansen (1994) multivariate normality test.

Table 14: Alternative Conditional Volatility Models

Model	AIC	BIC	Log-likelihood
Normal Distribution			
Diagonal VECH	28893	29193	-14399
CCC	29218	29480	-14567
CCC VARMA-GARCH	29169	29506	-14531
CCC VARMA -AGARCH	29016	29409	-14445
DCC	28858	29114	-14388
DCC VARMA-GARCH	28853	29184	-14374
DCC VARMA-AGARCH	28733	29119	-14304
t-Distribution			
DIAG VECH	28406	28712	-14154
CCC	28676	28944	-14295
CCC VARMA-GARCH	28642	28985	-14266
CC VARMA-AGARCH	28549	28948	-14211
DCC	28394	28656	-14155
DCC VARMA-GARCH	28390	28727	-14141
DCC VARMA-AGARCH	28316	28709	-14095

Note: The various conditional volatility models that we compare with the BEKK specification include the Diagonal VECH model of Bollerslev et al. (1988), the CCC model of Bollerslev (1990), the DCC model of Engle (2002), the VARMA-GARCH model of Ling and McAleer (2003), and the VARMA-AGARCH model of Chan et al. (2002). We estimate the latter two models using both the CCC specification and the DCC specification.

Table 15: Linearized Parameter Estimates of the *t*-distributed asymmetric BEKK model.

Panel 1: Estimates of the Variance Equations

Variable	h_{11} (S&P500)	h_{22} (IPC)	h_{33} (S&P500/TSX)
Constant	0.0368	0.0307	0.0029
	(5.7821)	(5.1952)	(2.7081)
$\varepsilon_{1,t-1}^2$	0.0060	0.0167	0.0015
	(1.8061)	(2.0911)	(1.2090)
$\varepsilon_{2,t-1}^2$	0.0000	0.0281	0.0000
	(0.0814)	(5.4212)	(0.2372)
$\varepsilon_{3,t-1}^2$	0.0080	0.0330	0.0691
	(2.0553)	(2.3184)	(6.4885)
$\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	0.0002	0.0609	-0.0018
	(0.1652)	(3.6000)	(0.4864)
$\varepsilon_{1,t-1}\varepsilon_{3,t-1}$	0.0139	-0.0470	-0.0205
	(4.4817)	(2.4759)	(2.1815)
$\varepsilon_{2,t-1}\varepsilon_{3,t-1}$	0.0002	0.0609	-0.0018
	(0.1628)	(4.5562)	(0.4699)
$h_{11,t-1}$	0.9663	0.0003	0.0000
	(111.2659)	(1.2196)	(0.1022)
$h_{22,t-1}$	0.0000	0.9048	0.0000
	(1.0253)	(103.9510)	(0.8884)
$h_{33,t-1}$	0.0001	0.0005	0.9334
	(0.8524)	(0.9969)	(83.5180)
$h_{12,t-1}$	-0.0064	0.0352	0.0000
	(2.0453)	(2.4511)	(0.1899)
$h_{13,t-1}$	-0.0198	-0.0428	0.0016
	(1.6957)	(1.9931)	(0.2045)
$h_{23,t-1}$	0.0001	-0.0428	-0.0062
	(1.3317)	(1.9931)	(1.7757)
$\eta_{1,t-1}^2$	0.0700	0.0033	0.0207
	(4.3477)	(0.5361)	(2.4887)
$\eta_{2,t-1}^2$	0.0002	0.1148	0.0004
	(0.8888)	(7.6839)	(1.1507)
$\eta_{3,t-1}^2$	0.0067	0.0366	0.0033
	(1.2360)	(1.5243)	(0.8341)
$\eta_{1,t-1}\eta_{2,t-1}$	0.0079	0.0390	0.0058

	(1.8047)	(1.0940)	(2.2594)
$\eta_{1,t-1}\eta_{3,t-1}$	-0.0432	-0.0220	-0.0165
	(2.0000)	(0.8319)	(1.3141)
$\eta_{2,t-1}\eta_{3,t-1}$	-0.0024	-0.1297	-0.0023
	(1.4064)	(2.9789)	(1.2777)

Panel 2: Estimates of the Covariance Equations

Variable	h_{12} (S&P500 and IPC)	h_{13} (S&P500 and S&P500/TSX)	h_{23} (IPC and S&P500/TSX)
Constant	0.0105	0.0008	0.0008
	(2.2352)	(0.8769)	(1.3477)
$\varepsilon^2_{1,t-1}$	-0.0100	-0.0030	0.0050
	(4.4107)	(3.0649)	(1.7363)
$\varepsilon^2_{2,t-1}$	0.0002	0.0000	-0.0006
	(0.1623)	(0.1672)	(0.4768)
$\varepsilon^2_{3,t-1}$	0.0163	0.0235	0.0477
	(2.3280)	(3.2653)	(3.6607)
$\varepsilon_{1,t-1}\varepsilon_{2,t-1}$	0.0152	0.0000	0.0435
	(3.1911)	(0.5681)	(1.9351)
$\varepsilon_{1,t-1}\varepsilon_{3,t-1}$	0.0025	0.0169	-0.0411
	(0.3914)	(2.6124)	(3.3080)
$\varepsilon_{2,t-1}\varepsilon_{3,t-1}$	0.0152	0.0000	0.0435
	(3.7464)	(0.0090)	(8.3048)
$h_{11,t-1}$	0.0182	0.0008	0.0003
	(2.4199)	(0.2042)	(1.2196)
$h_{22,t-1}$	-0.0031	0.0000	-0.0031
	(2.0529)	(1.1554)	(1.7779)
$h_{33,t-1}$	0.0002	-0.0097	-0.0218
	(0.9796)	(1.7192)	(2.0109)
$h_{12,t-1}$	0.9350	-0.0032	0.0007
	(159.4208)	(1.7733)	(0.1899)
$h_{13,t-1}$	-0.0223	0.9497	0.0147
	(1.9766)	(196.9415)	(2.0380)
$h_{23,t-1}$	-0.0095	-0.0031	0.9191
	(1.7009)	(2.0365)	(130.5956)
$\eta^2_{1,t-1}$	0.0152	0.0381	0.0083
	(0.9765)	(3.3697)	(0.9240)
$\eta^2_{2,t-1}$	0.0051	0.0003	0.0068
	(1.7402)	(1.1928)	(2.2689)

$\eta_{3,t-1}^2$	0.0156	0.0047	0.0110
	(1.4299)	(1.0587)	(1.1487)
$\eta_{1,t-1}\eta_{2,t-1}$	0.0905	0.0075	0.0499
	(7.8369)	(2.4718)	(4.5962)
$\eta_{1,t-1}\eta_{3,t-1}$	-0.0424	-0.0269	-0.0308
	(2.9821)	(1.6586)	(1.7717)
$\eta_{2,t-1}\eta_{3,t-1}$	-0.0305	-0.0025	-0.0233
	(2.5262)	(1.6149)	(1.8083)

Note: Numbers in parentheses under coefficient estimates equal *t*-statistics.

Table 16: Parameter Estimates of Negative Shocks

Panel 1: The Variance Equations

	h_{11}	h_{22}	h_{33}
$\varepsilon^2_{1,t-1} < 0$	0.0760	0.0200	0.0222
	(4.8692)	(1.7955)	(2.6056)
$\varepsilon^2_{2,t-1} < 0$	0.0002	0.1429	0.0004
	(0.8933)	(9.0194)	(1.1607)
$\varepsilon^2_{3,t-1} < 0$	0.0147	0.0696	0.0724
	(1.9036)	(2.1526)	(5.9771)
$\varepsilon_{1,t-1}\varepsilon_{2,t-1} < 0$	-0.0022	-0.0688	-0.0041
	(1.8148)	(0.1255)	(2.2711)
$\varepsilon_{1,t-1}\varepsilon_{3,t-1} < 0$	-0.0293	-0.0690	-0.0370
	(1.3386)	(1.8713)	(2.2151)
$\varepsilon_{2,t-1}\varepsilon_{3,t-1} < 0$	-0.0022	-0.0688	-0.0041
	(1.0520)	(1.7237)	(0.9570)

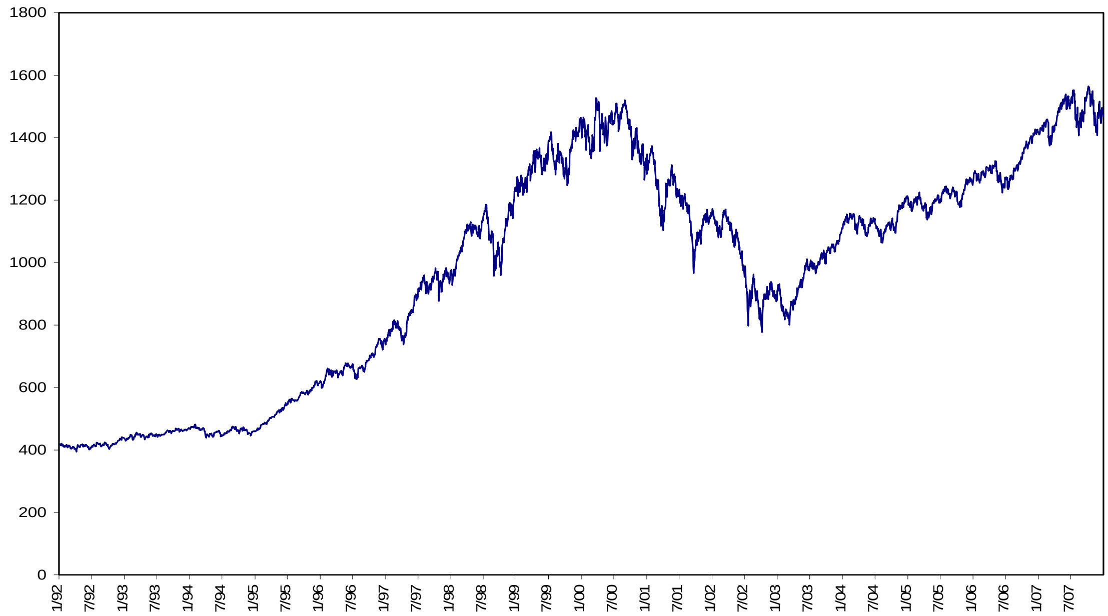
Panel 2: The Covariance Equations

	h_{12}	h_{13}	h_{23}
$\varepsilon^2_{1,t-1} < 0$	0.0052	0.0351	0.0133
	(0.3309)	(3.1248)	(1.3261)
$\varepsilon^2_{2,t-1} < 0$	0.0052	0.0003	0.0063
	(1.7025)	(1.1815)	(1.9852)
$\varepsilon^2_{3,t-1} < 0$	0.0319	0.0282	0.0587
	(2.0953)	(2.9525)	(3.1186)
$\varepsilon_{1,t-1}\varepsilon_{2,t-1} < 0$	-0.0153	-0.0025	0.0202
	(9.1143)	(2.3621)	(4.0146)
$\varepsilon_{1,t-1}\varepsilon_{3,t-1} < 0$	0.0930	-0.0100	-0.0719
	(8.2781)	(0.5420)	(2.9203)
$\varepsilon_{2,t-1}\varepsilon_{3,t-1} < 0$	-0.0153	-0.0025	0.0202
	(1.3411)	(1.0045)	(1.5279)

Note: Numbers in parentheses under coefficient estimates equal *t*-statistics.

Figure 1: Stock Price Indices 1992-2007

a) S&P500



b) IPC

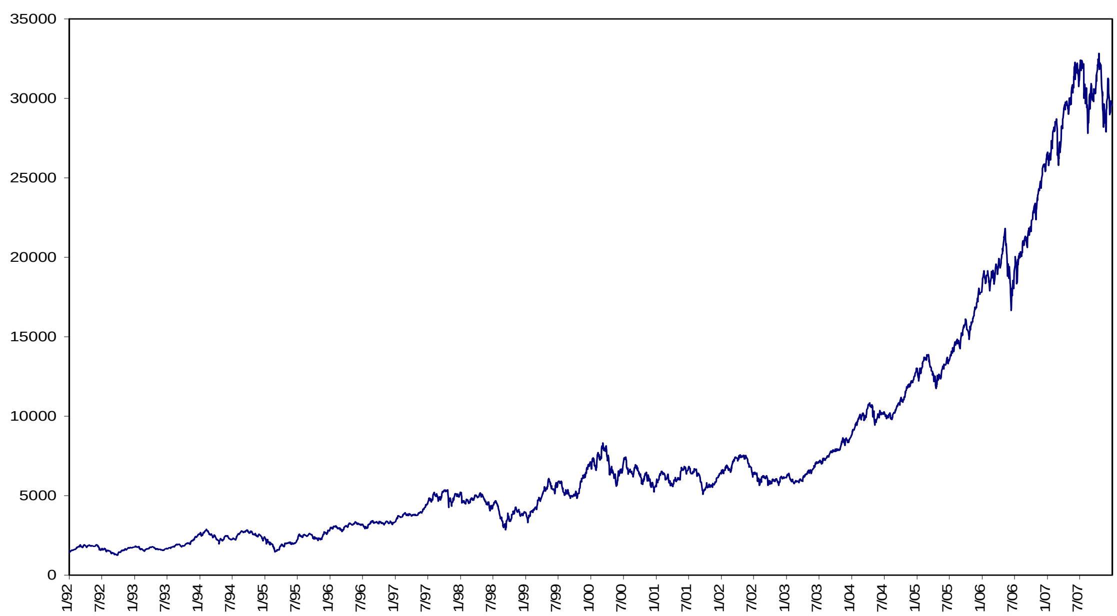


Figure 1: Stock Price Indices 1992-2007 (continued)

c) S&P TSX

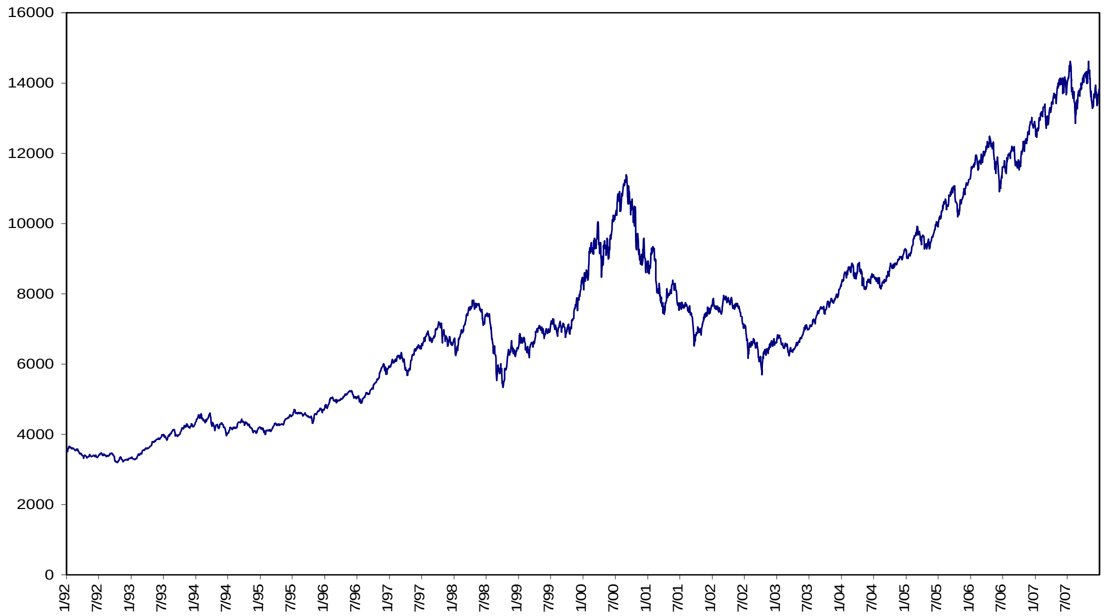
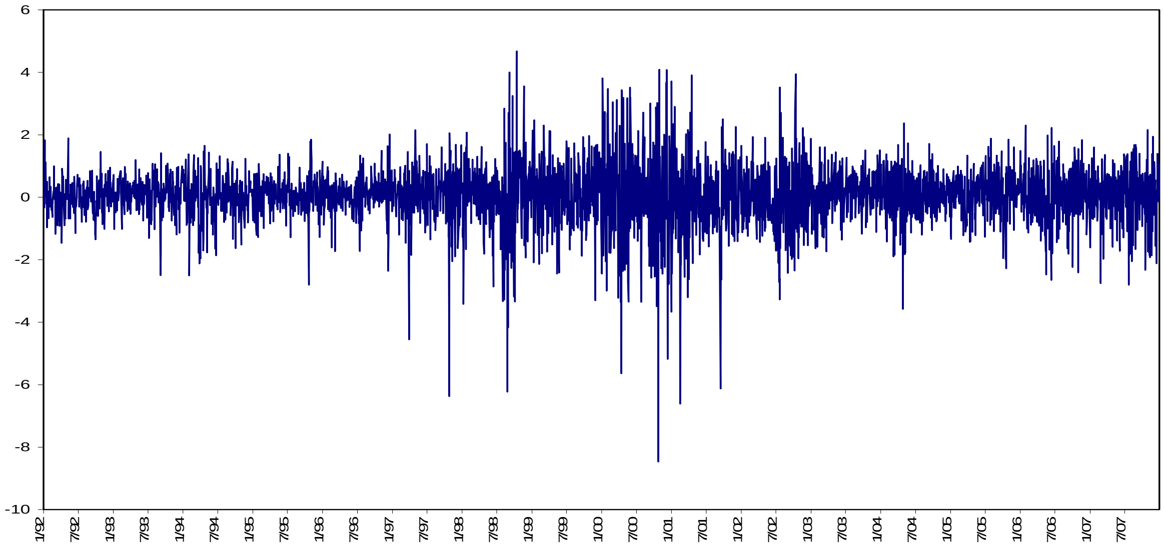


Figure 2: Stock Price Returns 1992-2007

a) S&P 500



b) IPC

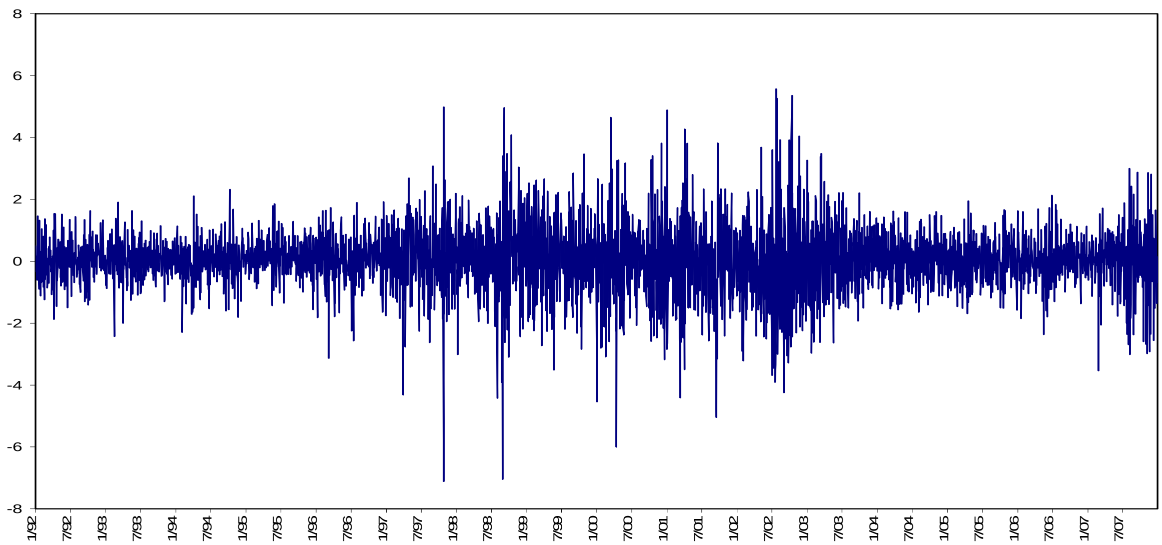


Figure 2: Stock Price Returns 1992-2007 (continued)

c) S&P TSX

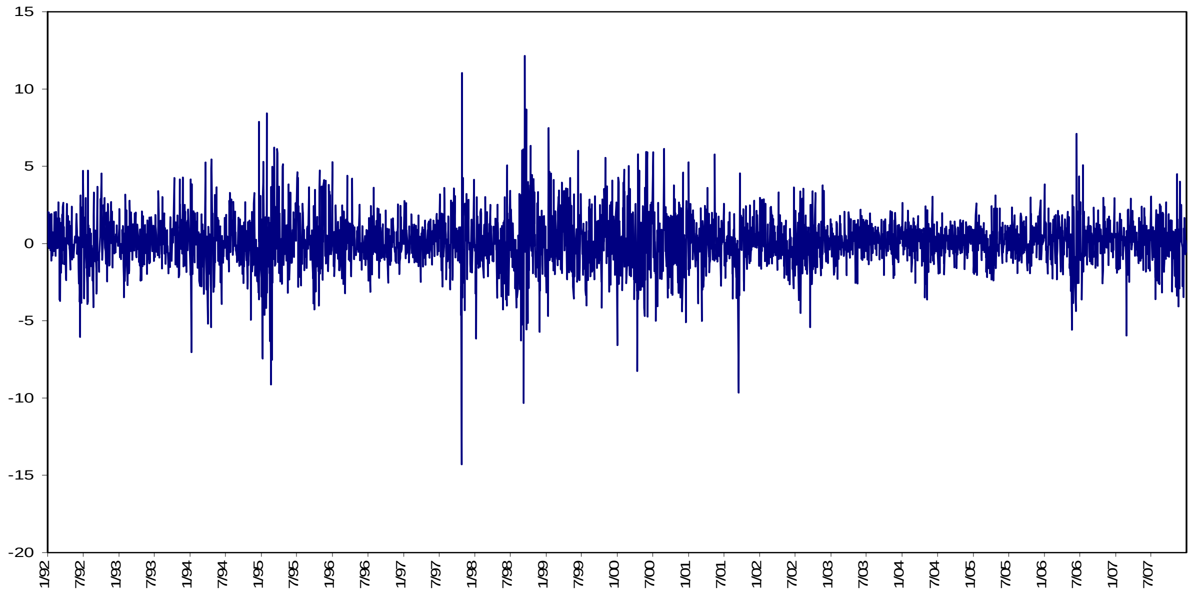
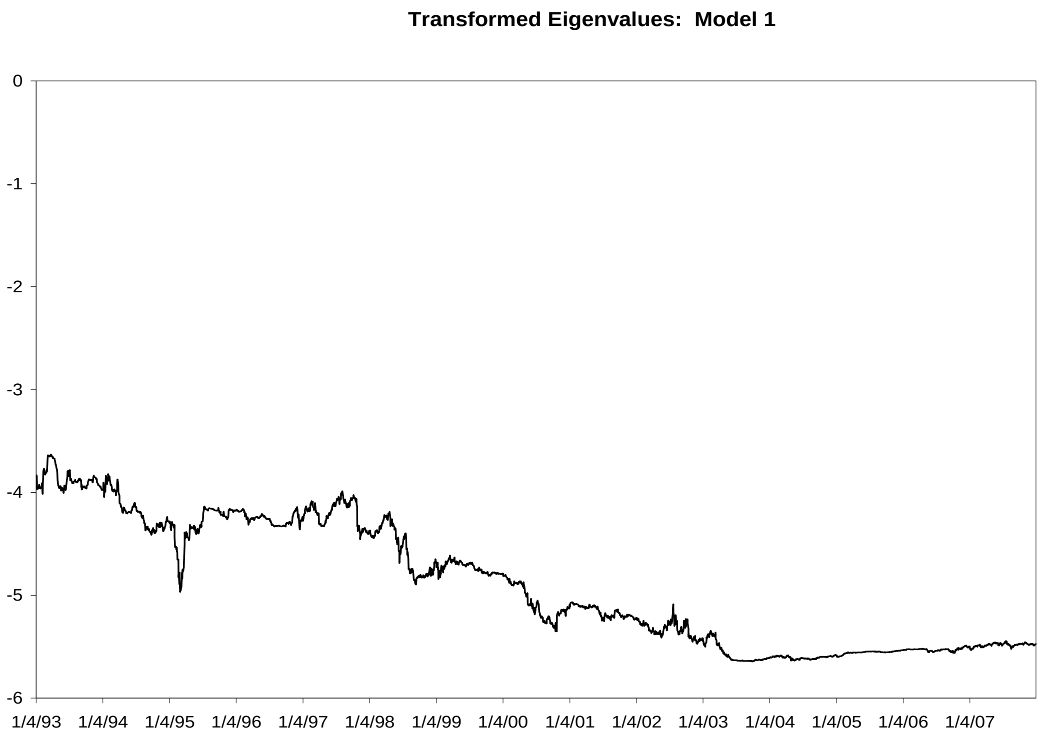


Figure 3: **Time Path of the Transformed Eigenvalue $\xi_1 = ln(\lambda_1 / 1 - \lambda_1)$.**



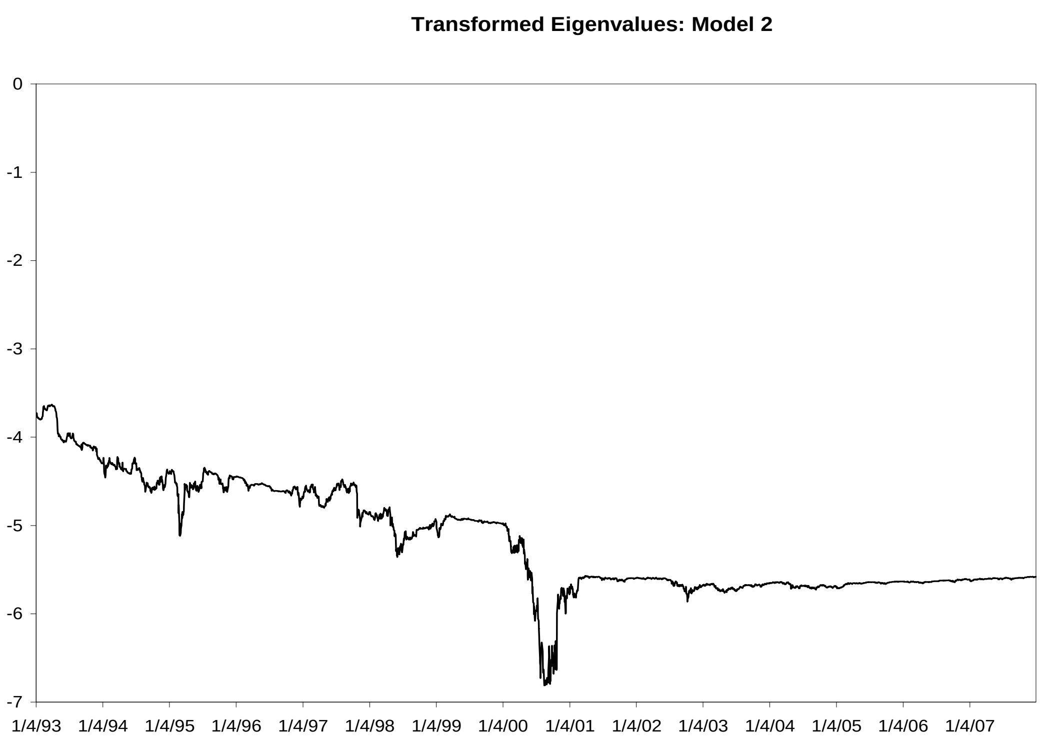


Figure 3: Time Path of the Transformed Eigenvalue $\xi_1 = ln(\lambda_1 / 1 - \lambda_1)$ (continued).

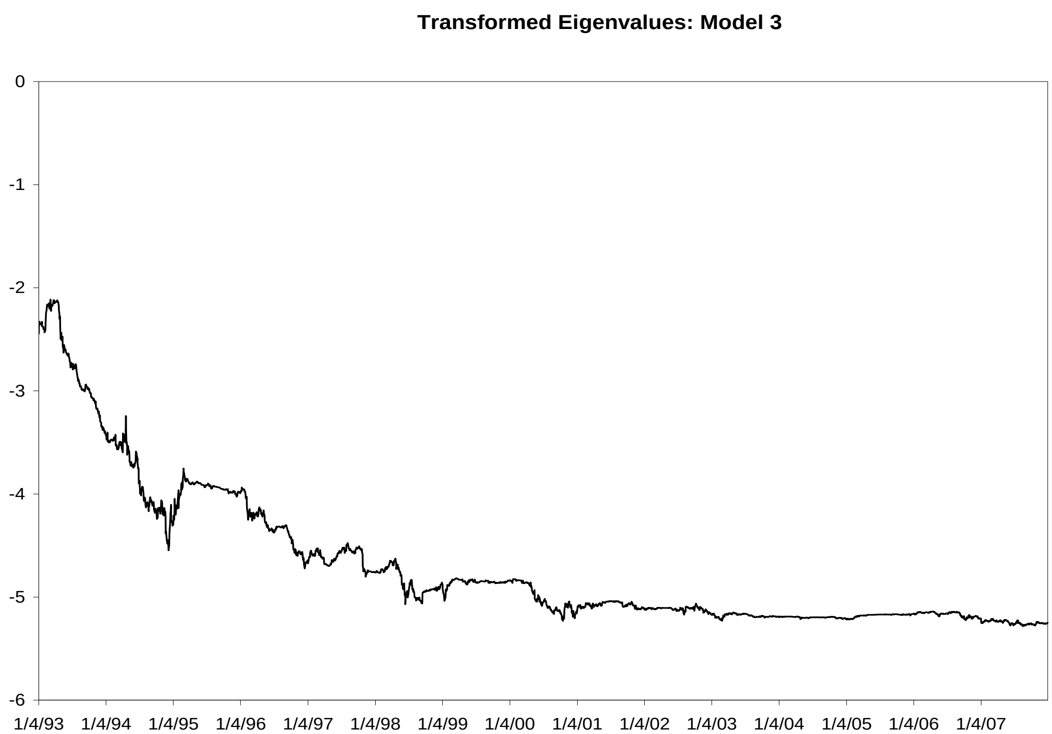
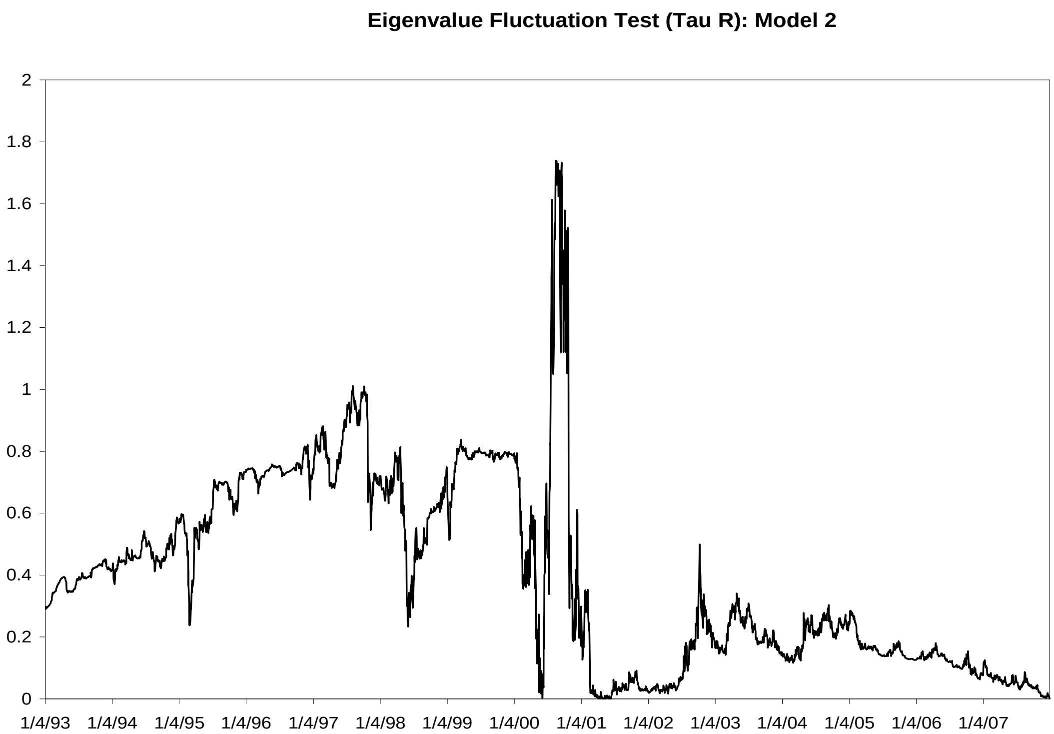


Figure 4: Fluctuation Tests of the Transformed First Eigenvalue -- Model 1

Eigenvalue Fluctuation Test (Tau R): Model 1

Eigenvalue Fluctuation Test (Tau X): Model 1

Figure 5: Fluctuation Tests of the Transformed Largest Eigenvalue -- Model 2



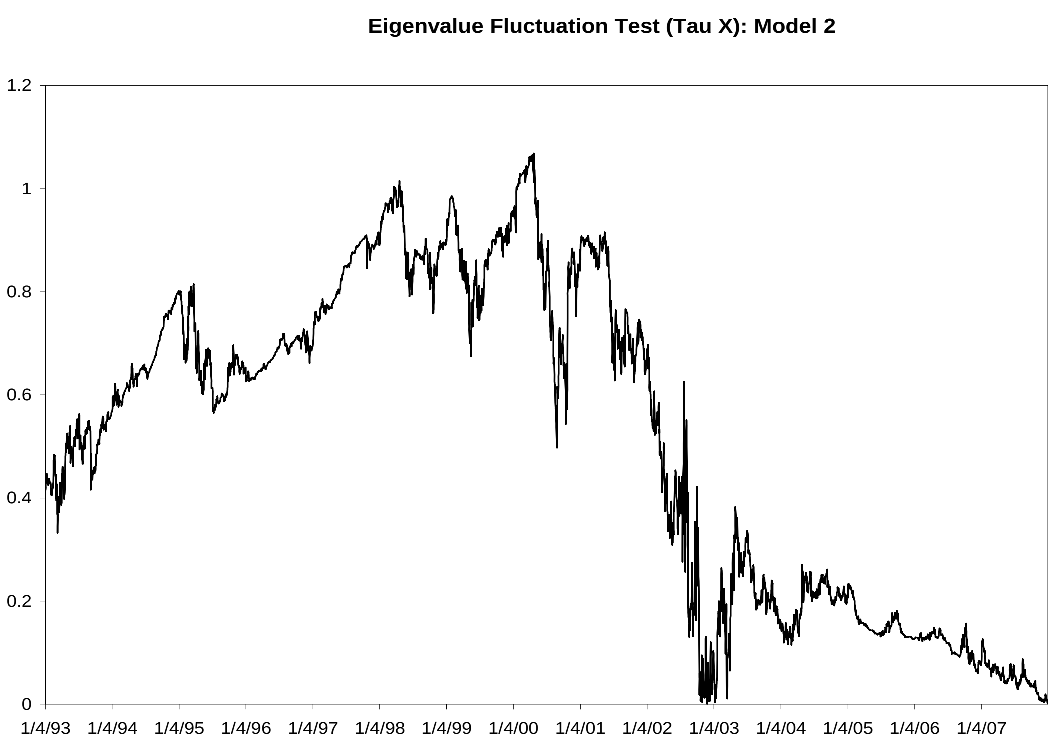
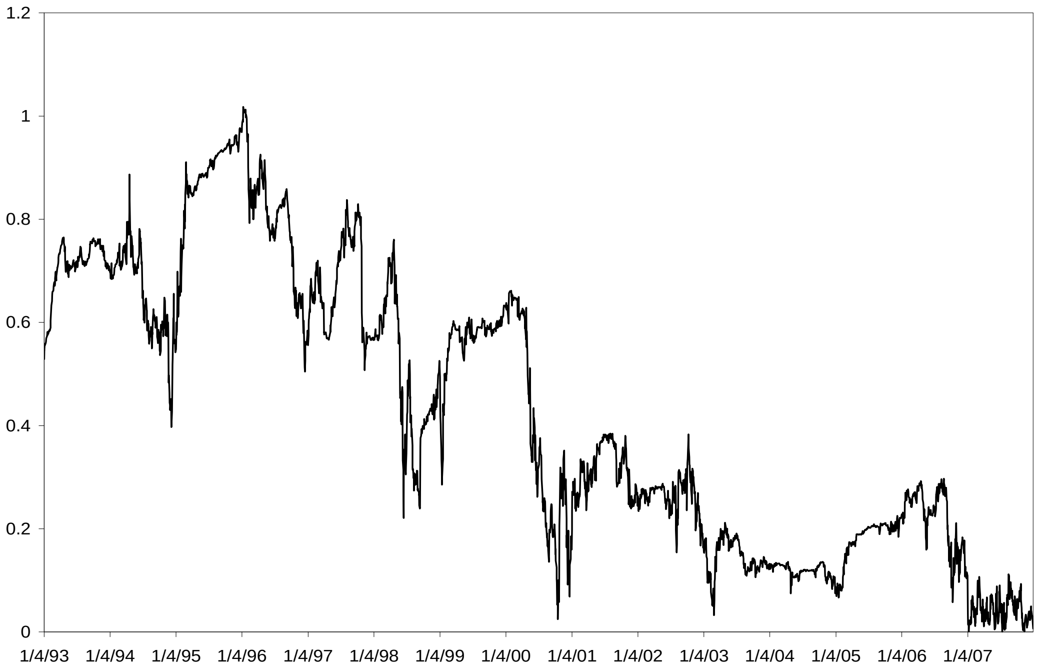


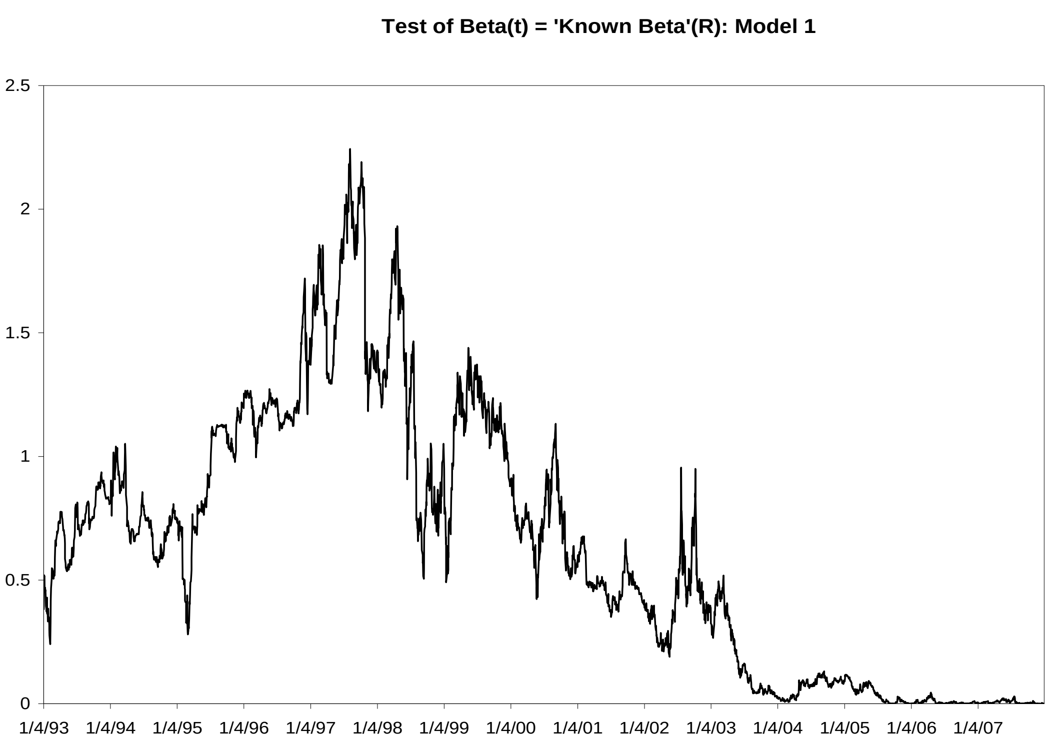
Figure 6: Fluctuation Tests of the Transformed Largest Eigenvalue -- Model 3

Eigenvalue Fluctuation Test (Tau R): Model 3



Eigenvalue Fluctuation Test (Tau X): Model 3

Figure 7: Time Path of the Tests for $\beta_0 \in \text{Span}\left\{\hat{\beta}^{(t_1)}\right\}$ -- Model 1



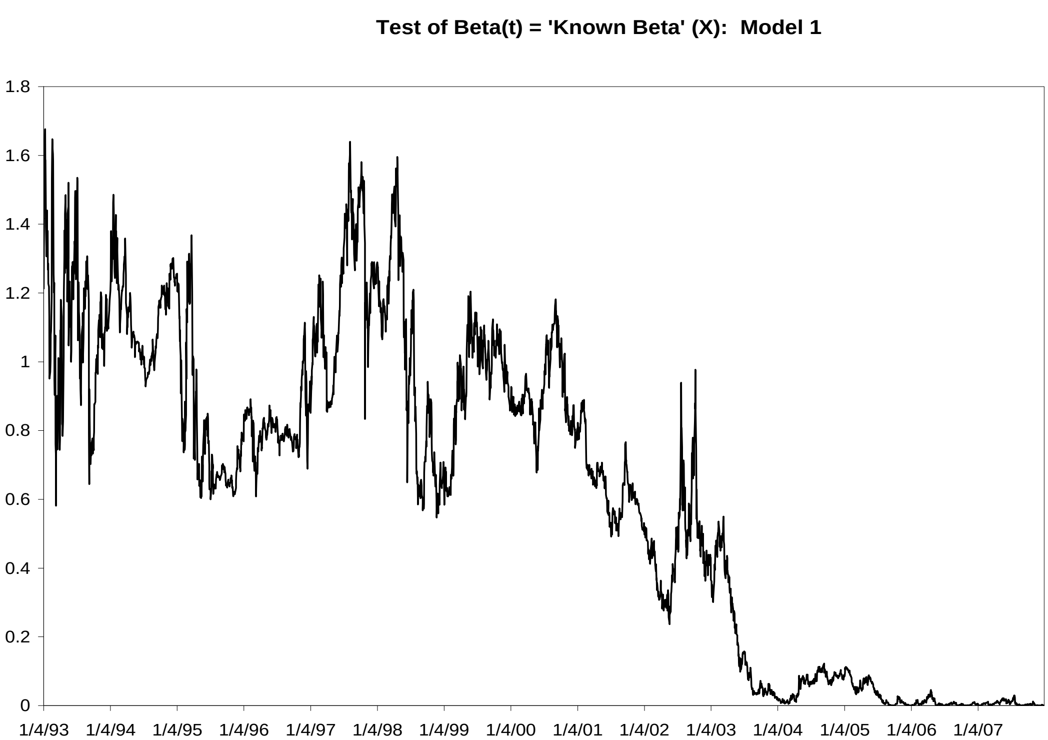
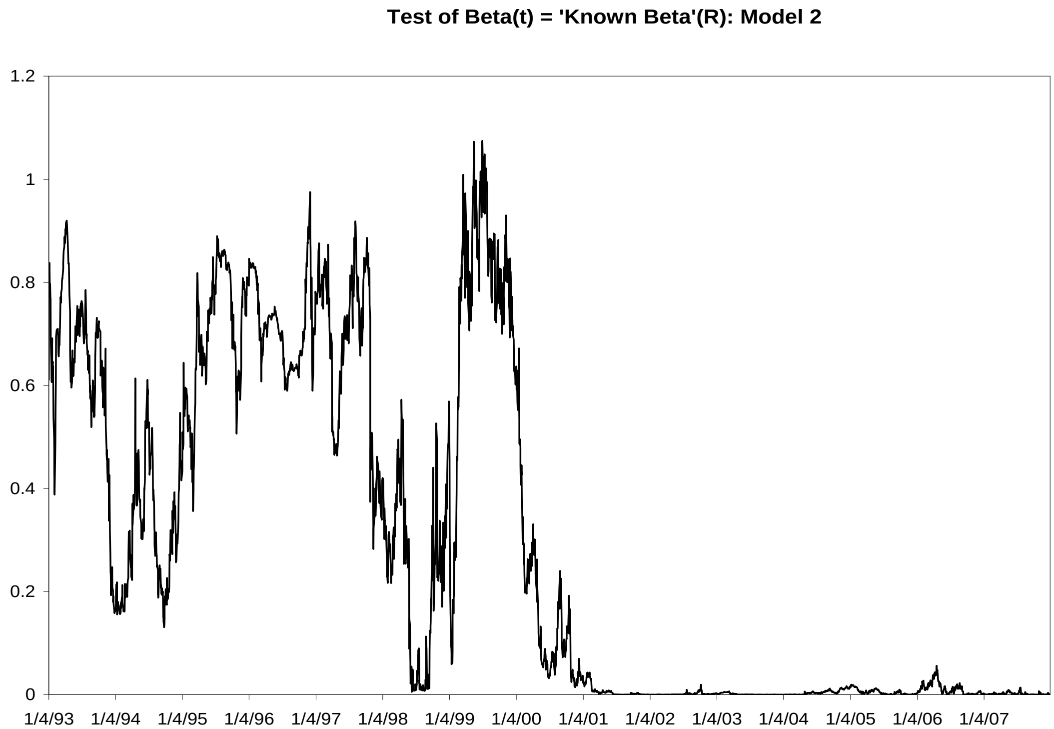


Figure 8: Time Path of the Tests for $\beta_0 \in \text{Span}\left\{\hat{\beta}^{(t_1)}\right\}$ -- Model 2



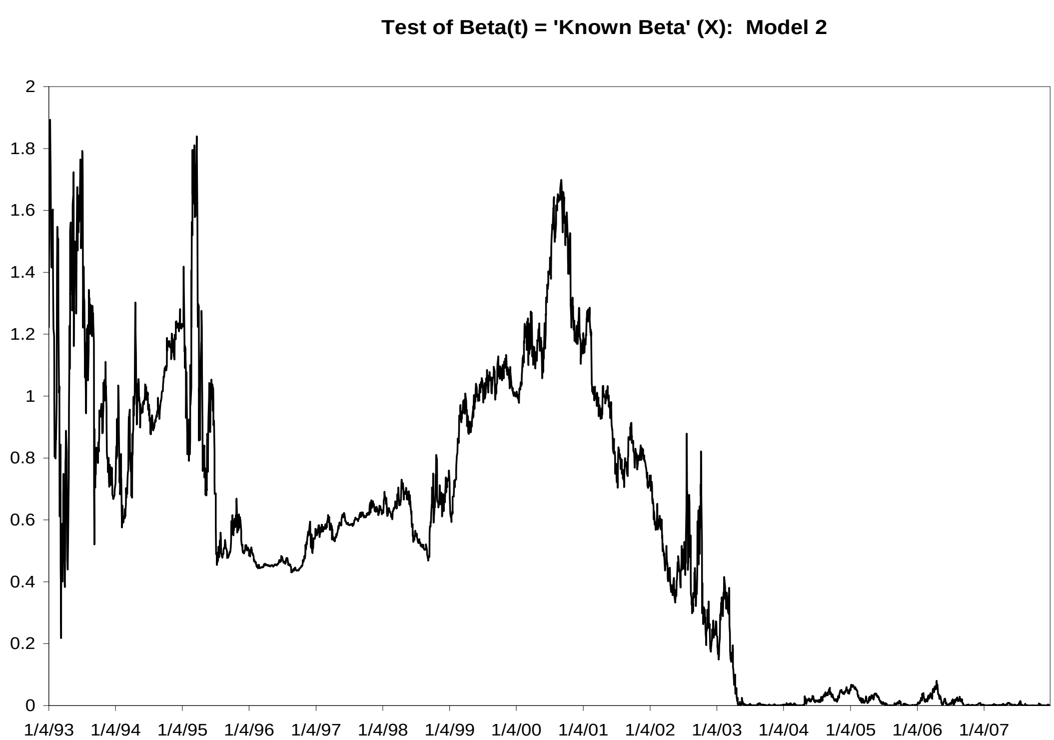
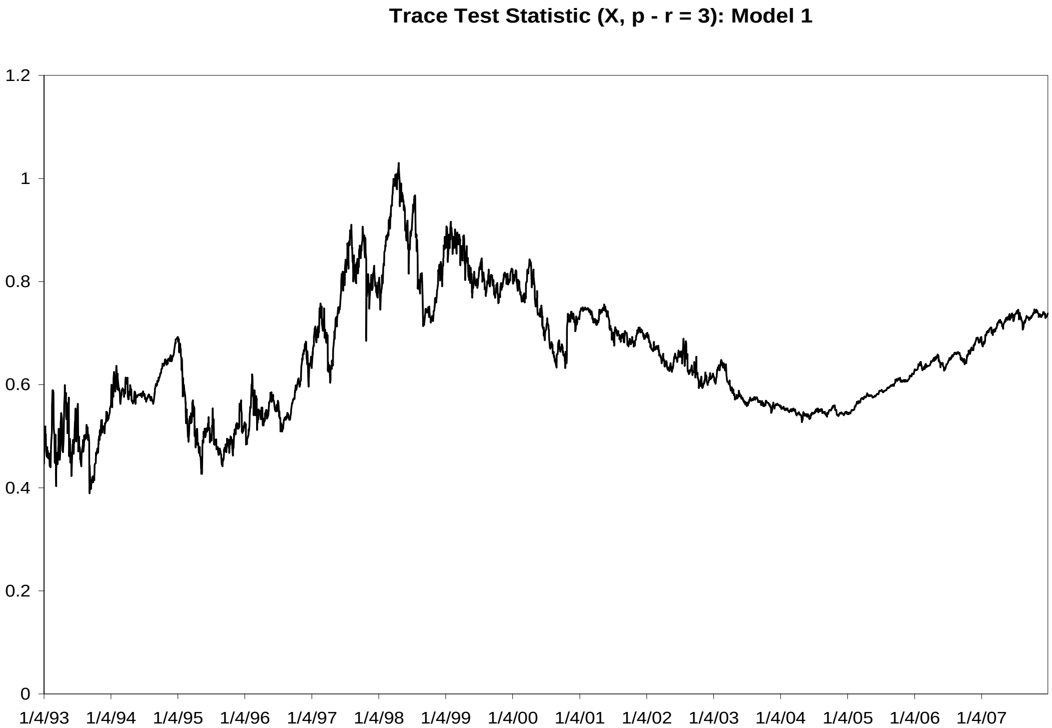


Figure 9: Time Path of the Tests for $\beta_0 \in \text{Span}\left\{\hat{\beta}^{(t_1)}\right\}$ -- Model 3

Test of Beta(t) = 'Known Beta'(R): Model 3

Test of Beta(t) = 'Known Beta' (X): Model 3

Figure 10: The Recursively Calculated Trace Test Statistics -- Model 1



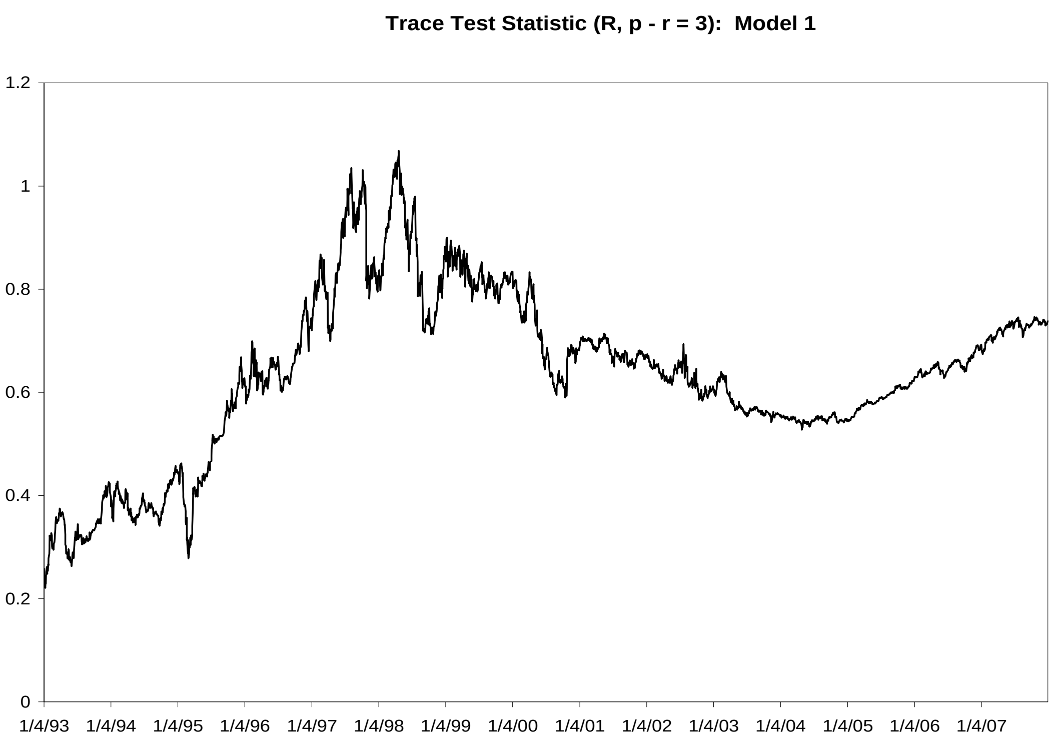
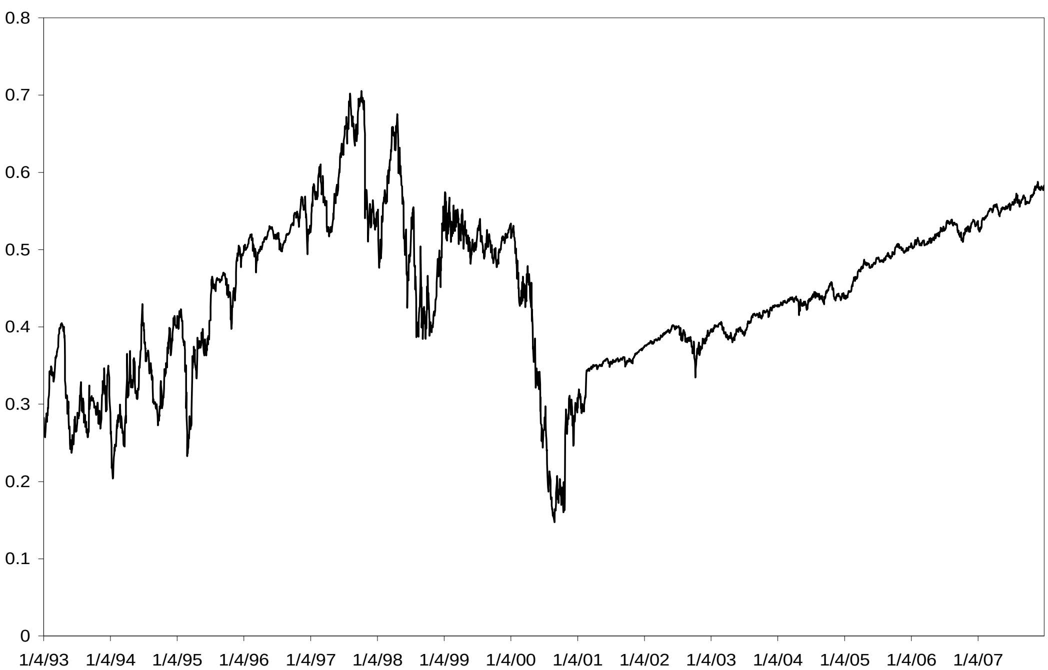


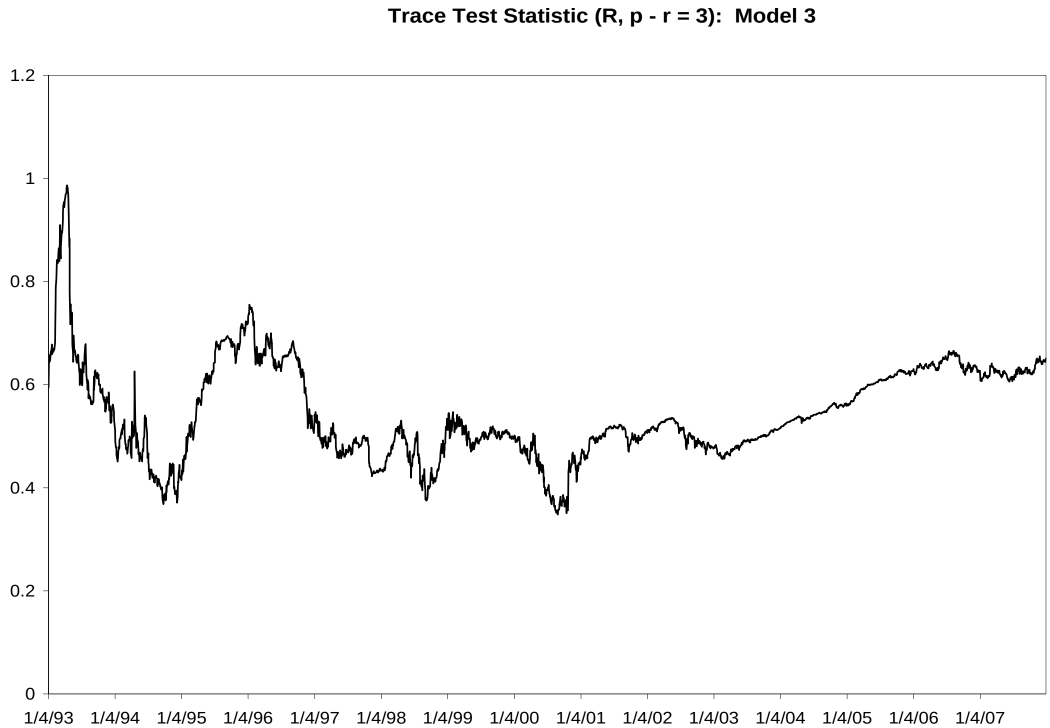
Figure 11: The Recursively Calculated Trace Test Statistics -- Model 2

Trace Test Statistic (R, p - r = 3): Model 2



Trace Test Statistic (X, p - r = 3): Model 2

Figure 12: The Recursively Calculated Trace Test Statistics -- Model 3



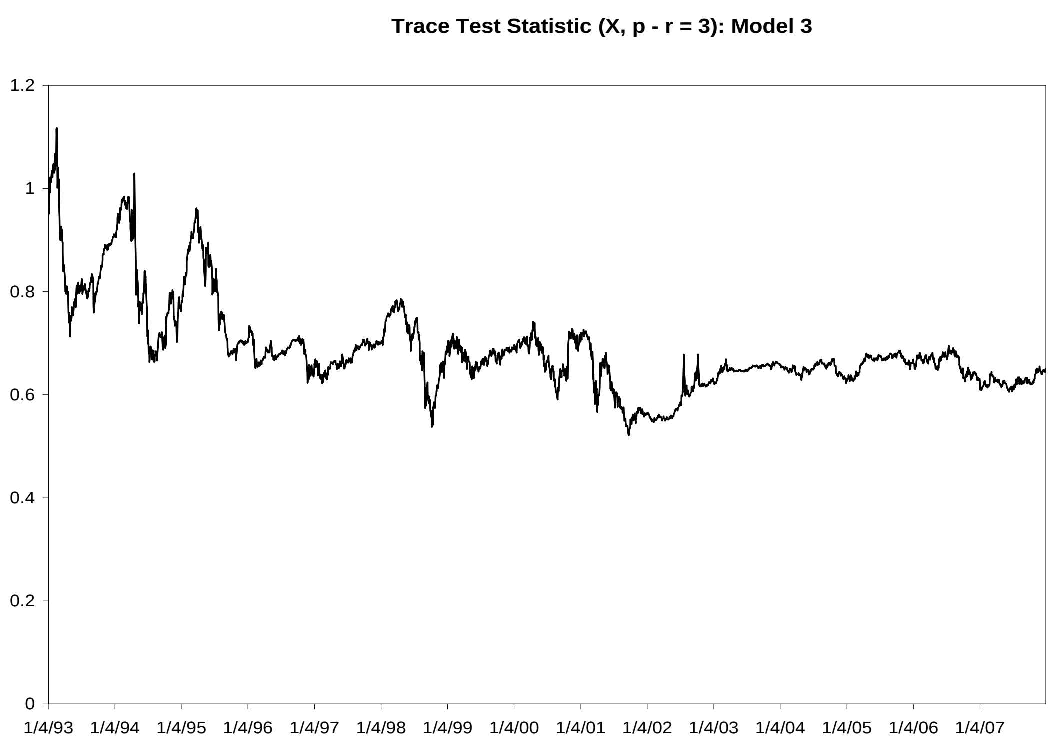


Figure 13: Generalized Impulse Response Functions to 1 SD in Stock Market Returns

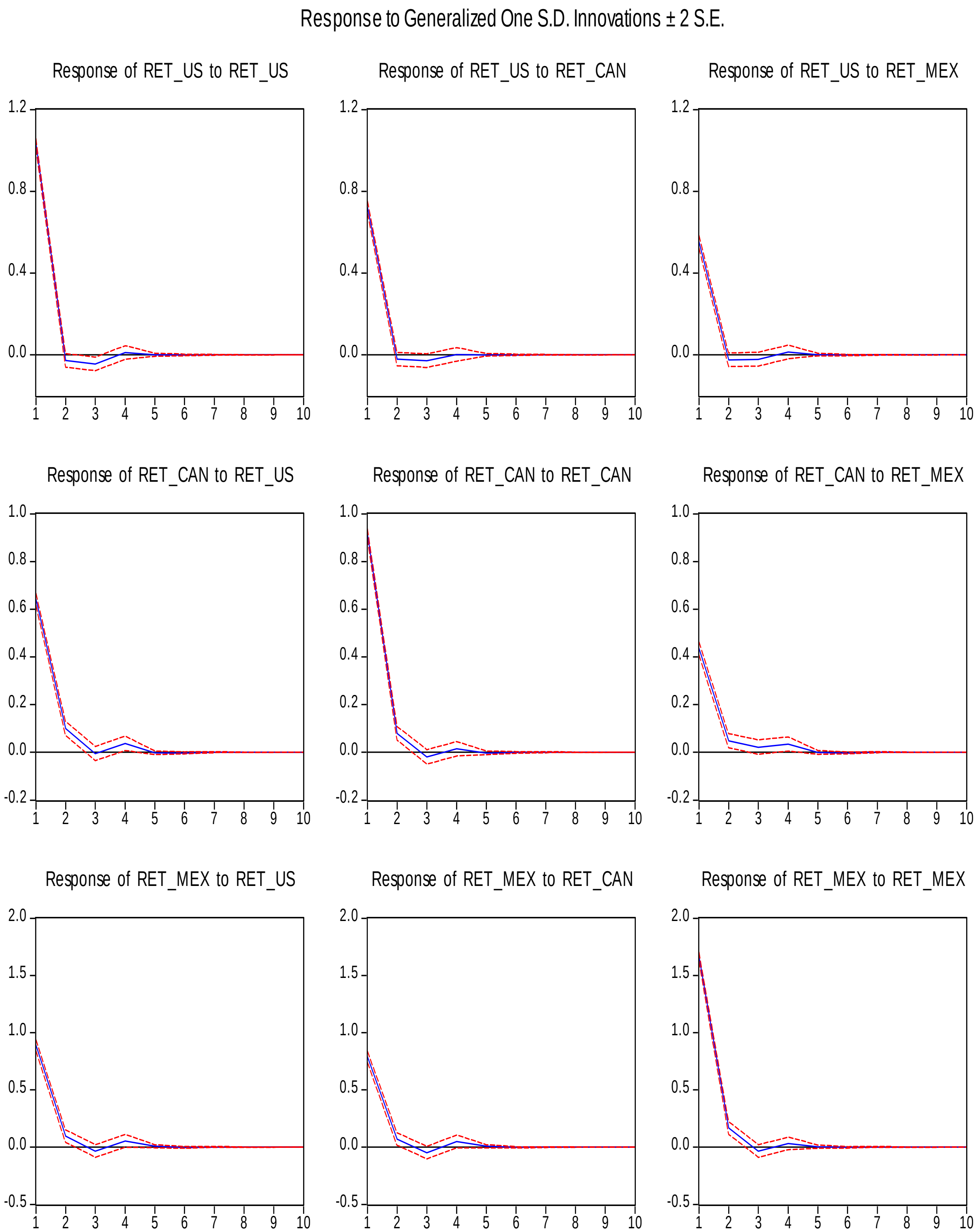
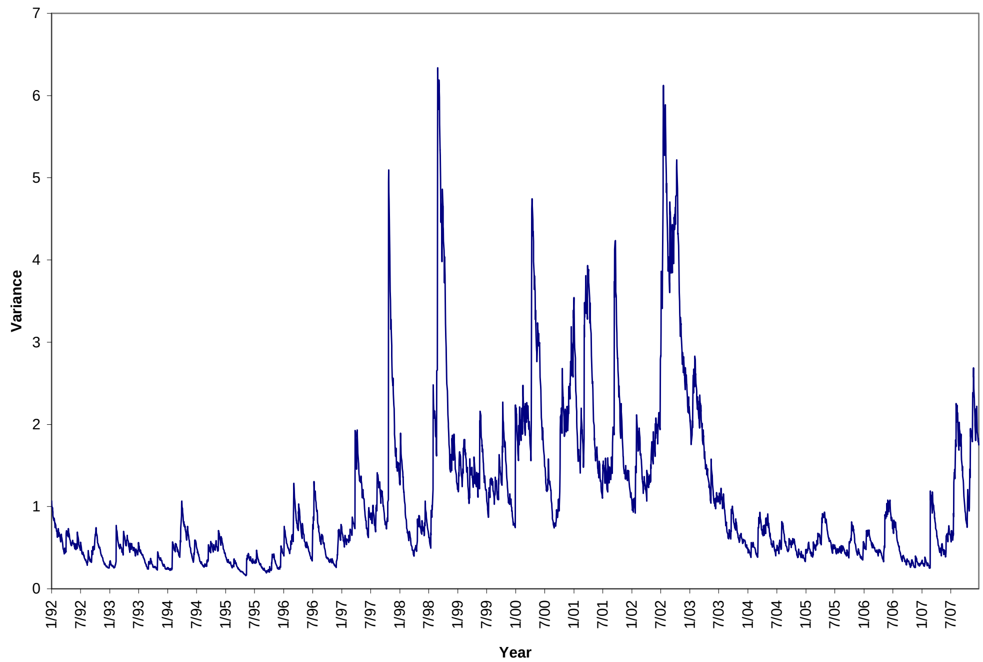


Figure 14: Conditional Variances

Conditional Variance S&P500 1992 -2007



Conditional Variance IPC 1992 -2007

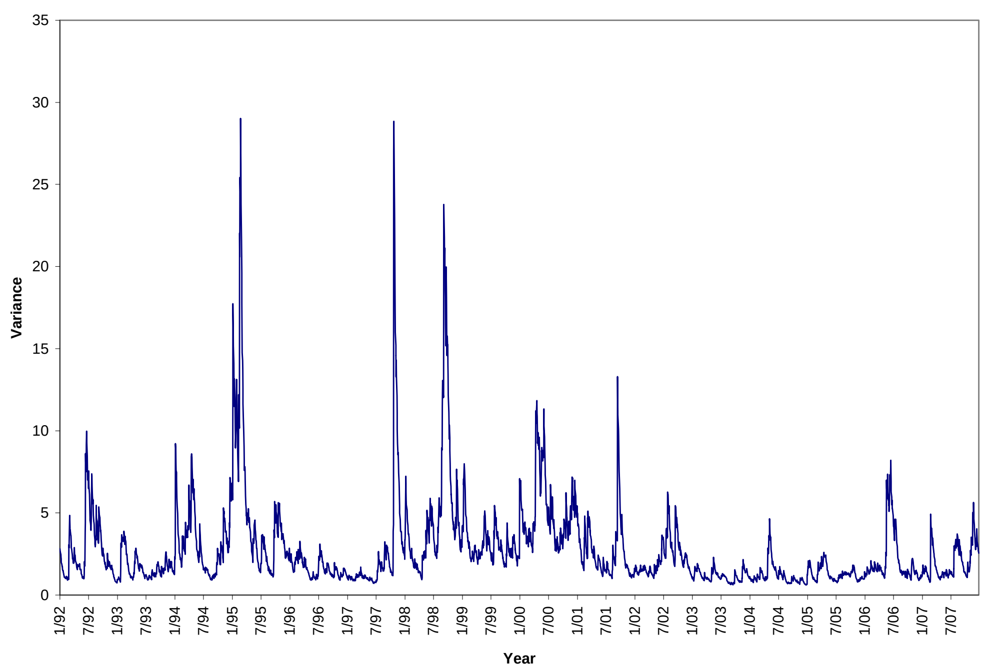


Figure 14: Conditional Variances (continued)

Conditional Variance S&P/TSX 1992 -2007

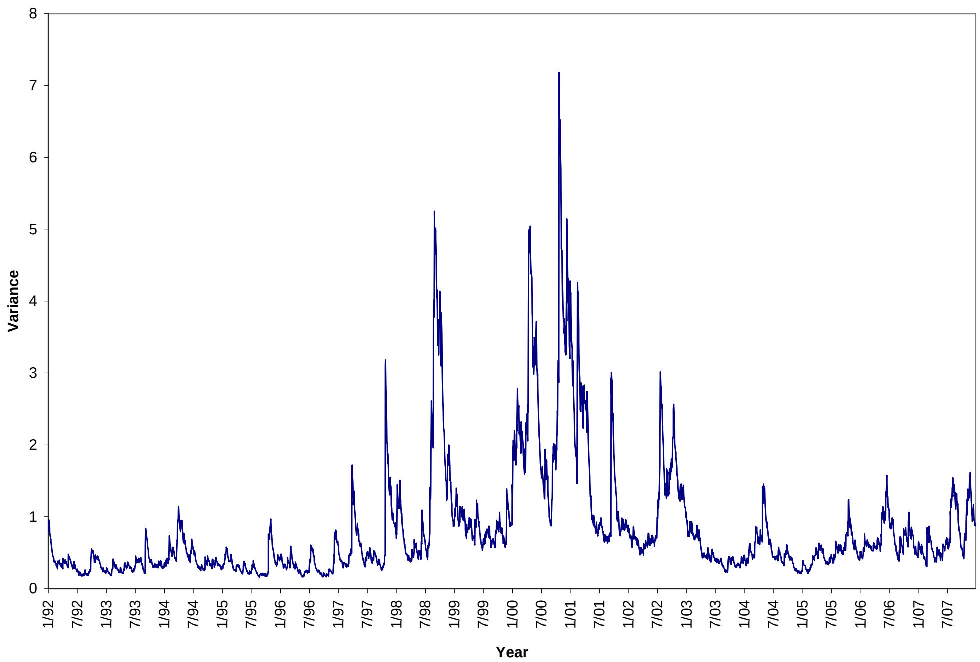
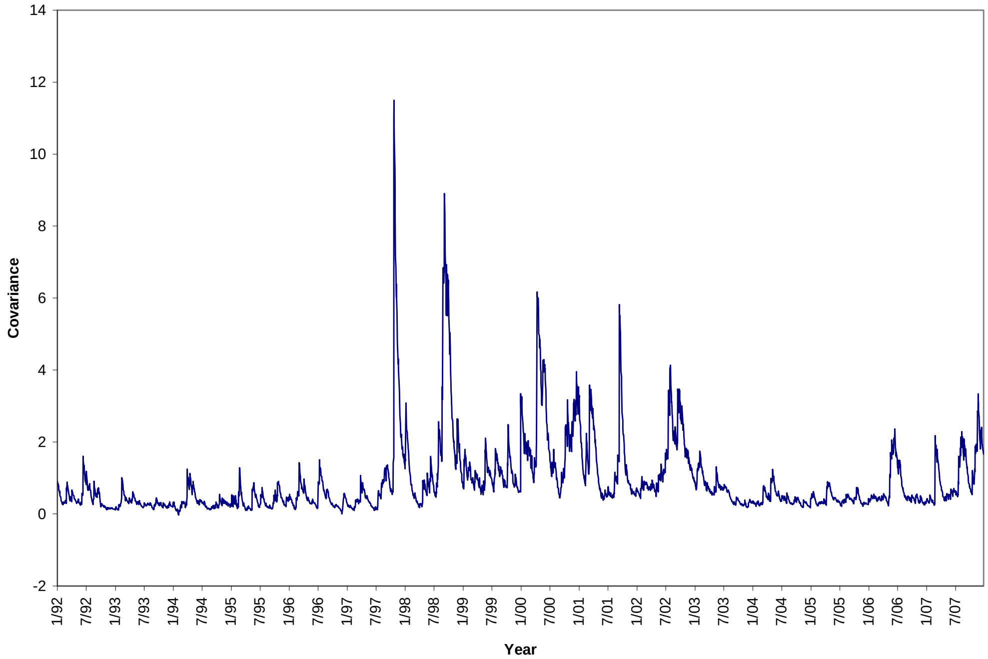


Figure 15: Conditional Covariances

Conditional Covariance S&P 500 and IPC 1992 -2007



Conditional Covariance S&P 500 and S&P/TSX 1992 -2007

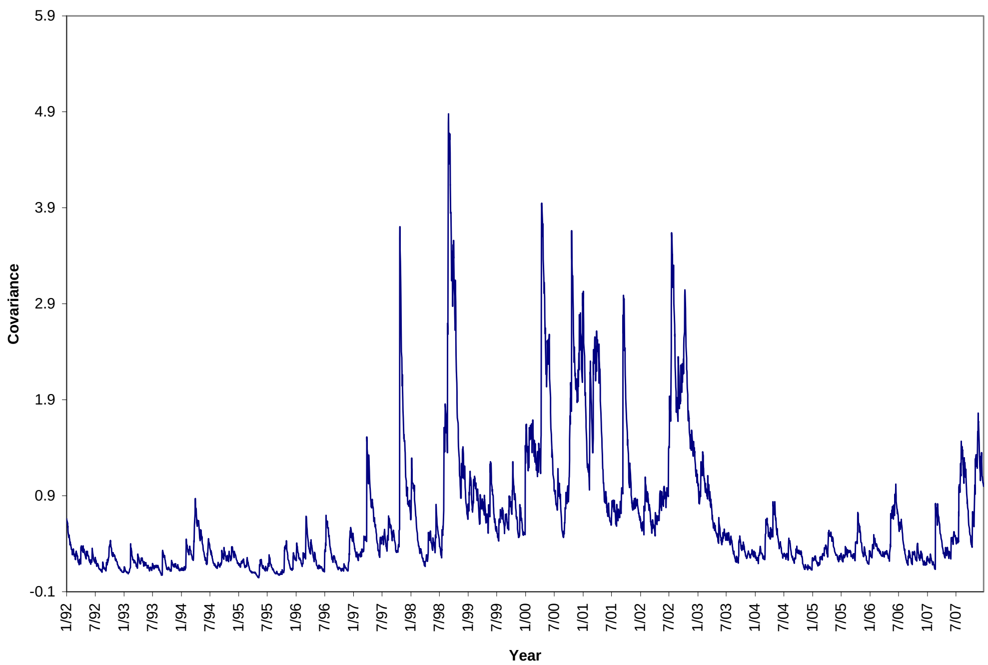


Figure 15: Conditional Covariances (continued)

Conditional Covariance IPC and SP/TSX 1992 -2007

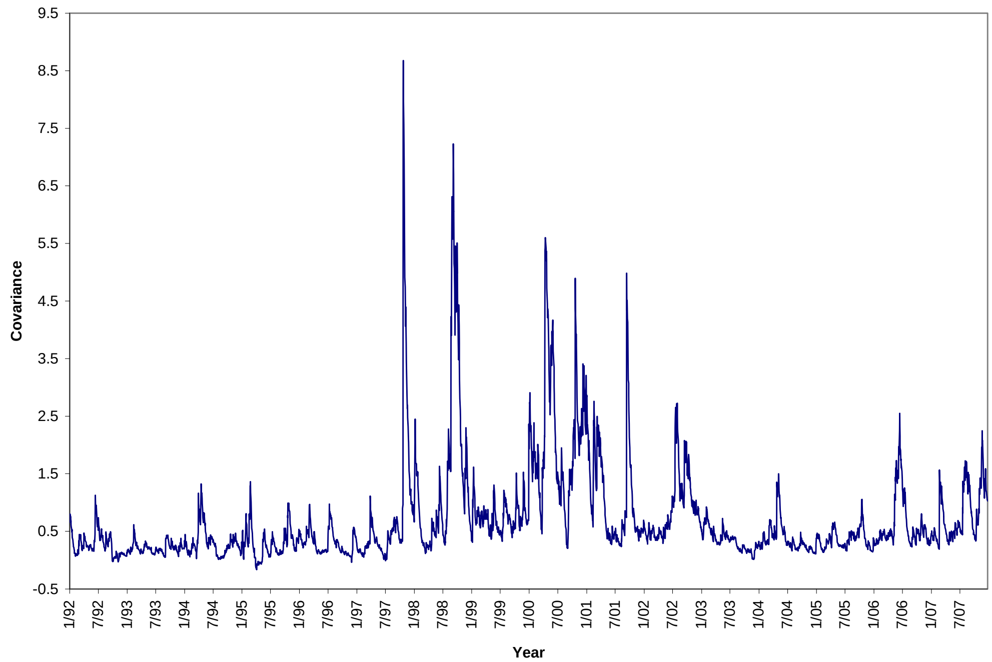
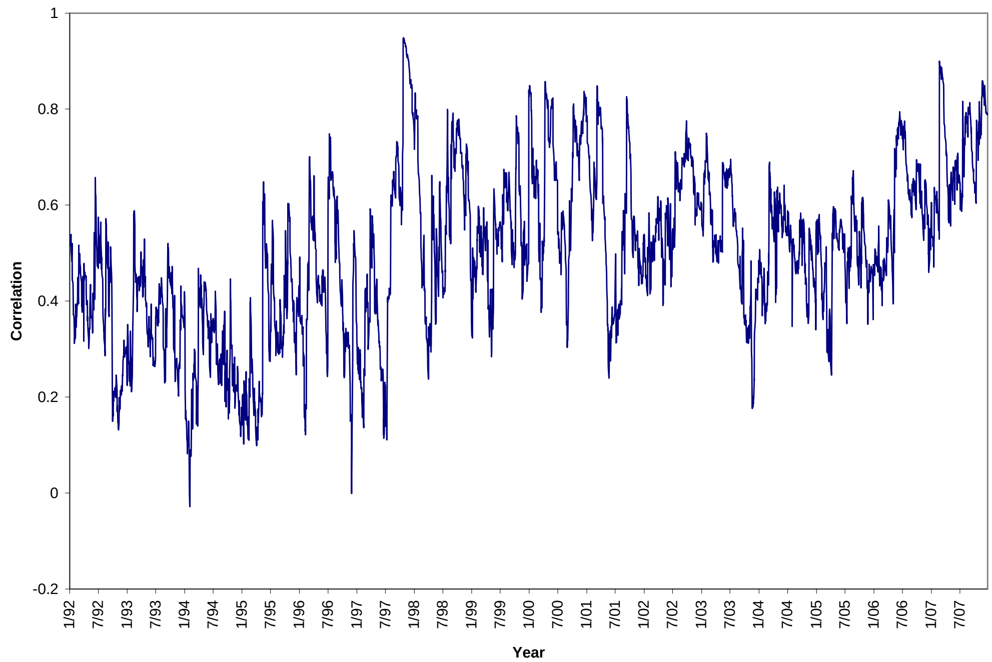


Figure 16: Conditional Correlations

Conditional Correlations: S&P500 and IPC 1992 -2007



Correlations: S&P 500 and S&P/TSX 1992 -2007

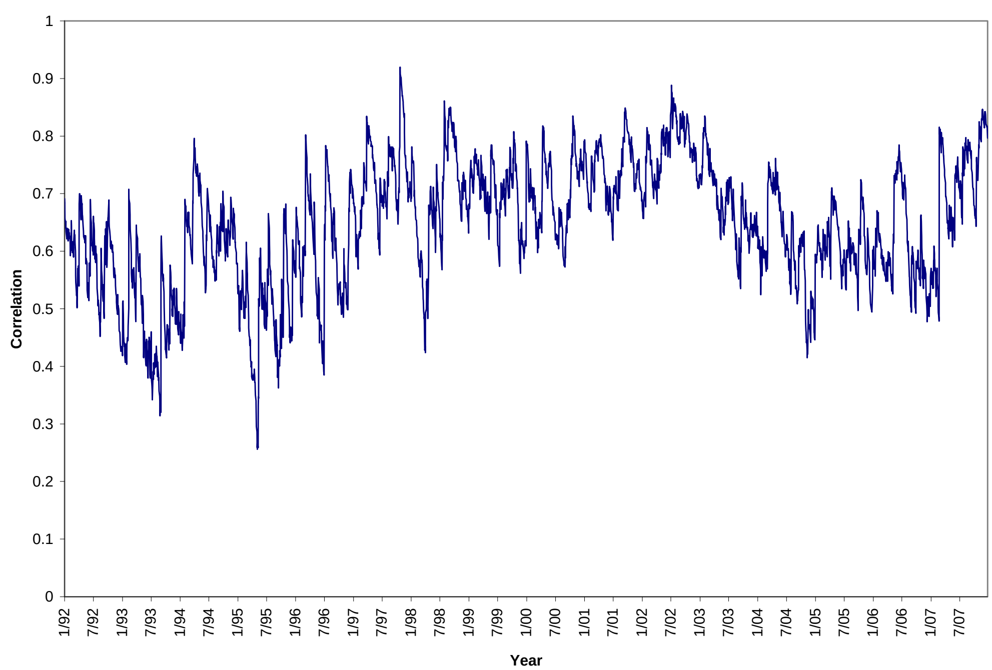


Figure 16: Conditional Correlations (continued)

Correlations: IPC and S&P/TSX 1992 -2007