Essays on Corporate Risk, U.S. Business Cycles, International Spillovers of Stock Returns, and Dual Listing

Iryna Ivaschenko

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To my parents

Моим родителям

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June 2003

Iryna Ivaschenko

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CONTENTS

Introduction and Summary

The essays in this thesis investigate questions related to different areas of finance. The first essay analyzes how the systematic risk structure of the corporate sector predicts real economic activity. The second essay examines corporate vulnerability and its role in explaining business cycles. The third essay considers the international spillovers of stock price returns and volatilities. The fourth essay explores changes in the value of international listing.

Financial assets are claims on firms' future cash flows, and thus their prices reflect market expectations about future economic activity. This feature of financial data and their availability at high frequencies has spurred extensive research that tries to predict future real activity with financial variables. The empirical results to date, however, have not been robust with respect to the choice of sample and forecasting horizon. The *first essay* suggests a new variable – the systematic risk structure of the corporate sector – that exhibits strong predictive power in a parsimonious model. The variable is constructed as a systematic component of individual corporate risk structures (defined as term structures of spreads between corporate bond yields and the risk-free interest rate), using principal components analysis. It reflects the term structure of non-diversifiable economy-wide corporate risk and is thus important in predicting aggregate economic activity. The steepening of the aggregate corporate risk curve reflects expectations of higher default rates in the future and thus indicates an imminent recession.

The results show that the systematic corporate risk structure is a strong and robust predictor of industrial production 3 to 18 months into the future, even when other leading indicators are controlled for. It produces more accurate out-of-sample forecasts than the leading models, and its predictive power, unlike that of the other forecasting variables, has been robust over the last fifteen years. Finally, a regime-switching estimation shows that the systematic risk structure is successful in identifying and capturing different growth regimes of industrial production, outperforming the Index of Leading Economic Indicators. In particular, it was able to correctly predict the timing of the last slowdown in the United State – a daunting task for any model after a decade-long period of positive growth.

The *second essay* further investigates the relationship between corporate risk and business cycles in the United States. Economists have long recognized that financial conditions of the private sector exert a powerful effect on the macroeconomy. For example, the structural theory of corporate debt directly links an increase in debt with higher corporate risk and thus higher costs of external financing, which in turn could depress investment and lower output. Financial accelerator theory also suggests that the decline in the net worth of the corporate sector can make slowdowns more severe by amplifying and propagating initial adverse shocks. This paper proposes a measure of corporate vulnerability, the Corporate Vulnerability Index (CVI), and analyses whether it can explain the probability and severity of recessions. The CVI is constructed as the probability of default for the entire corporate sector using a structural debt model by Anderson, Sundaresan, and Tychon (1996).

The estimation results indicate that the CVI is able to correctly predict recessions 4 to 6 quarters ahead, even when controlling for other leading indicators widely used to predict the probability of recessions. The model using the CVI outperforms traditional specifications in predicting recessions, including the recession of 1990-1991—a common miss by the other models. In order to assess whether the CVI is related to the severity of a recession, the study proposes and constructs Severity of Recession Indices, ranking recessions both in terms of the cumulative output loss and recession duration. The estimations indicate that an increase in the CVI is associated with an increase in the probability of a more severe and lengthy recession 3 to 6 quarters ahead.

In recent years, the financial system has become an increasingly important not only for domestic economies, but also as a mechanism for transmitting and amplifying local shocks to international markets. Stock prices became particularly correlated during the so called "tech-bubble" period – a synchronous rise of technology stock prices worldwide during the period between late 1998 and early 2001, followed by an abrupt correction. The *third essay* analyzes whether transmission mechanisms differ between the technology, media and telecommunications (TMT) and non-TMT sectors, and whether there were structural breaks in their dynamics. It examines the spillovers of the conditional first and second moments of daily returns across stock markets in the United States and the Asia-Pacific region for three different periods: the period preceding the "tech bubble;" the "tech bubble" period; and the price-correction period. The analysis is based on TGARCH models, capturing the time-varying behavior of conditional means and variances of stock returns and the asymmetric effect of negative and positive returns on the conditional variance. The model for each national stock market includes the lagged return and volatility surprise from a spillover-originating foreign market, estimated as in Hamao, et al. (1990).

The study finds that U.S. stock markets have been the major source of price and volatility spillovers to stock markets in the Asia-Pacific region regardless of the sector analyzed. Hong Kong SAR, Japan, and Singapore were also important sources of spillovers within the Asia-Pacific region and, to a lesser degree, affected the United States only during the "stock market correction" period. One explanation of these findings is that prices in other markets tend to mimic those in the United States, a symptom of herding behavior abroad. Spillover patterns reveal substantially different price dynamics in the TMT and non-TMT sectors, and a pronounced "country size effect" observed in the TMT sector spillovers has not been detected in the non-TMT sector. There is also evidence of structural breaks in the stock price return and volatility dynamics induced during the "tech bubble" period. Finally, the importance of volatility spillovers compared to price return spillovers is small, and often not significant.

International spillovers have increased over time as financial markets became more integrated, including through the interlisting of national companies on foreign stock exchanges. The vast literature indicates that foreign firms listing in the United States enjoy higher equilibrium prices and lower expected returns after the listing because, among other factors, it subjects firms to U.S. corporate governance, accounting, and disclosure. Therefore, the loss of confidence in the U.S. financial reporting, auditing, and corporate governance practices that followed the failure of Enron in December 2001 and other corporate scandals could have reduced benefits of interlisting in the United States.

Accordingly, the *fourth essay* investigates whether such loss of investor confidence affected the value of listing on U.S. stock exchanges for Canadian firms. It analyzes firm-level Canadian data because Canadian firms list directly on U.S. stock exchanges and thus must comply with U.S. regulations and corporate governance requirements, and because Canada ranks high in corporate governance relative to other industrial countries. The study is limited only to firms listed in recent years (from August 1998 to November 2002) in order to keep constant the integration between Canadian and U.S. markets, as well as other time-varying effects.

The study employs the conventional event-study methodology, adjusted to include both local and global market risk factors, as well as an exchange rate risk factor. It finds that firms interlisted during the post-Enron period experienced declines in equilibrium prices, while firms interlisted during the pre-Enron period enjoyed increases in equilibrium prices after the listing—regardless of whether they listed during stock market rallies or declines. The fact that interlisitng in the United States results in a lower price is new to the literature, and the paper offers several explanations of this phenomenon.

In addition, analyzing the entire universe of Canadian firms, the paper finds that interlisted firms, regardless of their listing time, have higher betas, both global and local, compared to their domestically-listed counterparts, and these betas increased significantly during the post-Enron period. This finding suggests that interlisted companies were perceived as increasingly risky by Canadian investors after Enron's bankruptcy.

References

Anderson, Ronald, and Suresh Sundaresan, and Pierre Tychon, 1996, "Strategic Analysis of Contingent Claims," *European Economic Review* 40, pp. 871-81.

Hamao, Y., R.W. Masulis, and V. Ng, 1990, "Correlations In Price Changes and Volatility Across International Stock Markets," *Review of Financial Studies* 3, pp. 281-307.

Essay I

The Information Content of The Systematic Risk Structure of Corporate Yields for Future Real Activity: An Exploratory Empirical Investigation[1]

Iryna Ivaschenko[*]

Abstract

In this paper we construct a proxy for the systematic component of the risk structure of corporate yields (or systematic risk structure), and test how well it predicts real economic activity. We find that the systematic corporate risk structure predicts the growth rate of industrial production 3 to 18 months into the future even when other leading indicators are controlled for. It produces more accurate out-of-sample forecasts than the model using the index of leading indicators, the autoregressive model, and the random walk model over a variety of time periods. Moreover, the predictive power of the systematic risk structure, unlike that of the other forecasting variables, has been robust over the last fifteen years. Finally, a regime-switching estimation shows that the systematic risk structure is very successful in identifying and capturing different growth regimes of industrial production. It outperforms the Index of Leading Economic Indicators in doing this. In particular, it was able to correctly predict the timing of the last slowdown in the U.S. – a daunting task for any model after a decade-long period of positive growth.

Keywords: investment grade bonds, corporate spreads, risk structure of corporate spreads, principal components, regime-switching, Markov process, forecasting.

JEL Classification Numbers: E32, E37, E43, E44

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I. Introduction

Financial assets are claims on firms' future cash flows, and thus their prices should reflect market expectations about future economic activity. This feature of financial data and their availability at high frequencies has spurred extensive research that tries to predict future real activity with various financial variables. Among those variables are risk-free short-term interest rates (Bernanke and Blinder (1992)) and their term structure (see Harvey (1988), Estrella and Hardouvelis (1991), and Hamilton and Kim (2000)), stock prices and dividends (Mitchell and Burns (1932)), and default spreads (Bernanke (1983), Stock and Watson (1989), Friedman and Kuttner (1992), and Gertler and Lown (2000)).[2]

The empirical results to date, however, have not been robust with respect to the choice of sample and forecasting horizon. Moreover, several studies have documented the remarkable decline in the forecasting power of financial variables during the last fifteen years. For instance, Haubrich and Dombrosky (1986) and Dotsey (1998) found that the predictive power of the Treasury yield structure declined after 1985; Bernanke (1990) and Emery (1996) showed that the performance of the commercial paper-bill spread deteriorated during the 1980s. Fama (1981) and Stock and Watson (1989) found that the predictive power of stock prices was not robust to the inclusion of other variables.

In this paper we suggest a new variable that exhibits strong predictive power in a relatively parsimonious model – the systematic risk structure of the corporate sector. It is constructed as a first principal component of individual corporate risk structures (defined as term structures of spreads between corporate bond yields and the risk-free interest rate) and hence reflects market expectations about the future riskiness of the *aggregate* corporate sector. Although no theory is developed that would explain how the risk structure of a *universe* of corporations should behave over the different phases of a business cycle, we argue that some extension of the theory of corporate debt of an individual firm to aggregate data may be at play here.

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[2] For an excellent overview of the recent literature on the role of other financial variables as leading indicators see Stock and Watson (2001).

The theory of corporate debt for an individual firm predicts a downward-sloping or hump-shaped risk structure for low credit quality corporations and an upward-sloping structure for high credit quality corporations (see, for example, Merton (1974), Pitts and Shelby (1983), Longstaff and Shwartz (1995), Jarrow and Turnbull (1997), and Duffie and Singleton (1999)). Since it is expected that default risk of a firm with low credit quality would decline over time conditional on a firm's not defaulting until then, the downward sloping risk structure can be associated with an expected improvement in credit quality over time. By the same logic, the default risk of a corporation with high credit quality could either stay the same or decline over time, resulting in an upward sloping risk structure.[3]

Applying this theory to the aggregate corporate sector, we suggest that the long end of the aggregate corporate risk structure increases more than the short end because investors expect higher default rates in the future.[4] Since an increase in corporate defaults is a salient feature of recessions, the steepening of the corporate risk structure would thus indicate an imminent recession. Conversely, the flattening of a risk structure would signal that corporate health will be improving in the future from an initially weaker position, thus signaling a future recovery.

The main contribution of this paper to forecasting literature is that it suggests a new robust predictor of future real growth. We extract the *systematic component* of the aggregate risk structure, which allows us to filter out firm-specific or industry-specific risks reflected in bond yields. These risks are diversifiable and thus should not be important in predicting aggregate economic activity. The systematic component of the

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[3] For example, Duffie and Singleton (1999) show that if a firm's current hazard rate is above its long-run mean, the hazard rate should decline over time, resulting in the downward-sloping risk structure. Analogously, if a firm's current hazard rate is below its long-run mean, firm's risk structure should be upward-sloping.

[4] In addition to default risk, a spread between corporate bond yields and the risk-free rate also reflects liquidity risk and tax risk. While it is safe to assume that tax risk is not correlated with business cycles, and liquidity risk of the aggregate data is constant (see Anderson and Sundaresan (2000)), default risk is clearly cyclical and tends to increase before recessions (see Gertler, Hubbard, and Kashyap (1991), Duca (2000) and Kwark (2000)).

aggregate risk structure reflects the term structure of non-diversifiable economy-wide corporate risk, and thus is the only piece of information important in predicting aggregate economic activity. To extract this component we apply principal components analysis to individual risk structures for investment-grade corporate bonds rated from AAA down to Baa. We then use the first principal component as our proxy for the systematic risk structure and test its ability to predict the future growth rate of industrial production. In addition, this paper indirectly tests whether the predictions of the theory of corporate debt of an individual firm hold in the aggregate data.

The results of our study indicate that the systematic corporate risk structure predicts year-to-year growth rate of industrial production up to 18 months in the future. The risk structure retains its significance in explaining future economic activity even when other leading indicators explaining real activity are included into the equation. The choice of a proxy for the risk-free interest rate also does not change the results. When yields on Agency bonds are used as this proxy instead of yields on Treasury bonds, systematic risk structure is still significant over 3 to 18 month horizons. This suggests that the results are not driven by the movements in the U.S. Treasury yield curve. As we expected, the steepening of the corporate risk structure signals a future economic slowdown.

In out-of-sample forecasts our model outperforms an autoregressive benchmark, the Index of Leading Economic Indicators, and the simple random walk model over different time periods we experimented with. Moreover, the out-of-sample recursive analysis shows that the relationship between the systematic risk structure and future growth of industrial production has been stable for the last twenty years, which has not been the case with other financial variables.[5] Moreover, contrary to the other financial variables, the systematic corporate risk structure has not lost its forecasting power after 1985. The quality of its predictions has even improved since then.

[5] For comparison purposes we also used the Treasury yield curve, corporate yield curve and the paper-bill spread in recursive estimations. All of them exhibited significant coefficient instability during the period under consideration.

In addition, we find that the systematic risk structure is successful in capturing turning points in the growth rate of industrial production, especially in the model that allows for switches in the growth regime. In this way we allow the model to identify and capture different growth regimes present in the data. This exercise shows that the systematic corporate risk structure is very successful in identifying and capturing the "business cycle of industrial production." For example, the systematic risk structure was able to correctly predict the timing of the last slowdown – a daunting task for any model after a decade of a positive growth regime present in the U.S. data.

All in all, our results show that the systematic corporate risk structure is a strong and robust predictor of real activity, capable of capturing "business cycles of industrial production". In general, the sign of the coefficient on the systematic risk structure is consistent with the corporate debt theories for individual firms. Nevertheless, these theories may not be directly applicable to the aggregate data. For example, the shape of the aggregate risk structure may be driven by market segmentation across different maturities and time-varying quality of borrowers in different market segments. Therefore, this exploratory empirical investigation highlights a need to develop the theory linking aggregate corporate risk structure of the corporate sector with business cycles.

The rest of the paper is organized as follows. Section II describes the data and the construction of the systematic corporate risk structure. Section III describes the estimation methodology used, and presents the in-sample estimation results obtained using individual risk structures across different rating categories and the systematic risk structure. Section IV checks the stability of the coefficient on the systematic risk structure. It also presents the results of comparison of the accuracy of out-of-sample predictions produced by the systematic risk structure model and several other benchmarks. Section V analyses the ability of the systematic risk structure to correctly predict turning points in the growth rate of industrial production. It presents the results of a regime-switching estimation, which allows us to evaluate how well our model captures cycles in the industrial production data. Section VI concludes with a summary of the main findings.

II. Constructing The Systematic Corporate Risk Structure

The dependent variable in our analysis is the year-to-year growth rate of industrial production, Y_{t+k}, defined as follows:

$$Y_{t+k} = 100\ log[I_{t+k+12}/I_{t+k}]. \tag{1}$$

where k denotes the forecasting horizon in months and I_{t+k} denotes the level of the Industrial Production Index during month $t+k$. [6] Industrial production is only a part of GDP, but it is used instead of real GDP because of the availability of data on a monthly basis.[7] We use monthly data on the Industrial Production Index provided by the Office for National Statistics. The sample is from January 1973 to November 2001. The choice of the estimation period was guided by the availability of data on corporate bond yields.

The explanatory variable in our analysis is the systematic corporate risk structure, which is constructed as the systematic component of individual risk structures. Individual risk structures are constructed in the following way. First, we define a corporate spread over a riskless security of a corporate bond rated C, $SPREAD^C$, as the difference between the redemption yield on the corporate bond index corresponding to the same credit rating, R^C, and the redemption yield on the benchmark risk-free bond index of the same maturity, R^T:

$$SPREAD^C{}_t = R^C{}_t - R^T{}_t. \tag{2}$$

We use redemption yields obtained from the Lehman Brothers Investment grade indexes for the four investment grade rating categories, AAA, AA, A and Baa, as defined By Moody's. There are two indexes for each rating category: one comprising bonds with

[6] Estrella and Hardouvelis (1991) called this measure the *marginal* growth rate and we will use this term occasionally in the paper. They show that marginal growth rate is more difficult to predict, and it provides more precise indication of how far in the future the model can predict.

[7] GDP and industrial production are highly correlated. For the sample Q1:1973 – Q3:2001, the simple contemporaneous correlation between growth rates of real GDP and industrial production is 0.772. The Index of Industrial production is widely used as a Coincident Indicator of real activity (see Data Appendix).

intermediate maturities and another comprising bonds with long maturities.[8] We will call them intermediate and long maturity indexes, respectively. As in many previous empirical studies, we use U.S. Treasury bonds as a riskless benchmark security. To check the robustness of our results to the choice of a riskless benchmark security, we also use Agency bonds as an alternative risk-free asset.[9] Yield and spread variables all have conventional dating: variables dated t are aggregates for month t.

The individual risk structure of bonds rated C, STR^{C}_{t}, is then defined as a difference between the spreads of long-term ($SPREAD^{C,L}_{t}$) and intermediate-term ($SPREAD^{C,I}_{t}$) corporate bonds over a riskless security:

$$STR^{C}_{t} = SPREAD^{C,L}_{t} - SPREAD^{C,I}_{t}. \qquad (3)$$

Table 1 presents sample statistics of the main variables used in the analysis.

Since there is no theory explaining different factors governing corporate spreads in general and their term structures in particular, to construct the aggregate corporate risk structure we adopt a statistical strategy often used in empirical studies of the Arbitrage Pricing Theory (APT). This approach involves building common factors governing all asset returns from a sample set of asset returns. Since we are interested in a systematic risk structure of corporate risk, we extract a proxy for it from a sample of individual corporate risk structures constructed for different credit ratings.

There are two basic statistical techniques that have been used in the literature to extract common factors: factor analysis and principal components analysis. There is also a modification of the latter method, the asymptotic principal components analysis by

[8] Intermediate maturities are those below ten years and long maturities are those above ten years. The classification corresponds to one used in the Lehman Brothers Bond Indices used in this study. See the data appendix for mnemonics and short descriptions of the series.

[9] Agency bonds comprise those issued by government-sponsored agencies such as Fannie Mae and Freddie Mac, and are considered as almost default-free by market participants.

Connor and Korajzcyk (1986).[10] Since none of the methods offer a clear advantage in a finite sample (see Campbell et al., 1997), although all produce consistent estimates of factor loadings in large samples, we chose to employ principal components analysis to extract a systematic risk profile from individual corporate structures and use first principal component as a proxy for systematic corporate risk structure.[11]

Principal components analysis has proved very useful in the empirical study of fixed income markets, as exemplified by studies of Garbade (1986), Litterman and Scheinkman (1988), and Bertocchi et al. (2000), to name few. Garbade used this technique to identify three major models of fluctuations in U.S. Treasury securities; Litterman and Scheinkman used it to analyze bond returns; and Bertocchi et al. to model fluctuations in the yield structure of corporate bonds and derive portfolio immunization strategies.

Principal components analysis explains a set of variables with a few principal factors without losing too much information form the variables' covariance matrix. Thus, if applied to a cross-sample of individual corporate risk structures across different credit classes, it provides an effective way to extract and identify a systematic risk profile since it extracts common factors that affect individual risk profiles regardless of their credit class. Hence, by definition, these factors represent the systematic corporate risk structure. Briefly, the principal components analysis can be described as follows (for a detailed and very intuitive description of the method see Theil (1971)).

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[10] Another, non-statistical, approach involves using theoretical motivation to select factors, which is not feasible in our case due to a lack of theory on the behavior of the risk structure. In the context of APT, see Lehman and Modest (1988) on the use of factor analysis, Connor and Korajczyk (1986,1988) on the use of asymptotic principal components analysis, and Chen, Roll, and Ross (1986) on the use of the theoretical approach to the selection of common factors.

[11] We also tried estimating the systematic risk structure using principal factor analysis. Since factors can be determined uniquely only up to a non-singular transformation (see Connor and Korajchyk, 1988), we experimented with factor rotation to obtain the first factor that has economically plausible explanation, that is it affects slopes of all individual spread structures in the same direction and by the same magnitude (like the level factor). We then used the first principal factor in the estimations. The results are robust to the choice of the factor model and are consistent with those obtained when the first principal component is used.

Let m be the number of different corporate risk structures, constructed according to (2) and (3) and combined into a matrix X. We assume that every individual corporate risk structure is generated by an m-factor linear model of the form:

$$STR^{C}{}_{t} = a + b_{1t} f_1 + b_{2t} f_2 + \ldots + b_{mt} f_m + \varepsilon_t , \tag{4}$$

where a is a constant, f_i represents the i^{th} common factor, the coefficient b_{it} is referred to as the loading of the i^{th} factor, and ε_t is the error term. Principal components serve as factors. The principal components analysis extracts those linear combinations of elements of X that provide the best fit to all the columns of X. The first principal component is the linear combination of risk structures with maximum variance. Each subsequent principal component is again a linear combination of risk structures with maximum variance among all combinations that are orthogonal to the previous component. That is, the i^{th} principal component could be represented as $f_i = Xc_i$. It is not difficult to show that the weighting vectors of each principal component, c_i, correspond to the eigenvectors of the sample covariance matrix of risk structures, $\Omega = X' \times X$. For the first principal component it is the eigenvector associated with the largest eigenvalue, for the second principal component it is the eigenvector associated with the second largest eigenvalue and so on. The importance of each component in explaining the total variance of X is given by the ratio of its corresponding eigenvalue to the total sum of eigenvalues.[12]

The results presented in Table 3 indicate that the first principal component explains more than 90 percent of total variation of individual corporate risk structures, while the first two principal components explain more than 95 percent of total variation, regardless of the riskless asset used. The results also indicate that the first principal component combines individual risk structures in almost equal proportions and is thus expected to affect all of them in a similar fashion. The second principal component places positive weights on the two higher rated risk structures and negative weights on the two lower rated risk structures, with the main weight being distributed between risk structures

[12] See Amemiya (1985), Garbade (1986), or Greene (1993) for a derivation.

at the top and at the bottom of the credit spectrum. To better assess the economic meaning of these two principal components we regress individual risk structures on them. The results presented in Table 4 indicate that the first principal component is acting more like a "level" factor, affecting all risk structures in the same direction and with a similar magnitude. Thus, it represents a factor, an increase in which induces the common steepening of risk structures across the entire credit spectrum, signaling that a uniform increase in future corporate risk is expected. Thus, we might expect that this factor represents a systematic term profile of corporate risk, or the systematic risk structure, and should contain useful information about future aggregate economic activity. We will use this factor as a proxy for the systematic risk structure in this paper.

At the same time, it is more difficult to give macroeconomic interpretation to the second principal component since its increase steepens the higher rated risk structures and flattens the lower rated risk structures. Thus, it signals that the higher rated credit is expected to become relatively more risky in the future at the same time as the lower rated credit becomes less risky. Interestingly, this pattern is consistent with predictions of several theoretical models of the term structure of risk for an individual firm, outlined in the introduction. Thus, it may be that the second component captures the individual characteristics of firms within each rating category, rather than the systematic component that influences risk structures across all rating categories. Hence, the second principal component is not likely to be important in explaining aggregate economic activity.

III. Basic Linear Model: Estimation Issues

The paper assumes and evaluates the linear relationship between the future growth rate of industrial production and the systematic risk structure:

$$Y_{t+k}=\alpha + \beta_1 STR_t + \beta_2 Y_{t-12-1} + u_{t+k}, \tag{5}$$

where Y_{t+k} is the future growth rate of industrial production, defined in equation (1) Y_{t-1} is the $(k+12+1)^{th}$ lag of the dependent variable, STR_t is the systematic risk structure defined in the previous Section, and u_{t+k} is the error term. Including the lagged dependent variable is a parsimonious way to capture all economic information available at time t, and to avoid including all other variables that have been found useful in predicting real GDP.[13] The forecasting horizon k varies from 3 to 48 months. The error term, u_{t+k}, is not independently distributed because the dependent variable is temporally aggregated and, by construction, includes overlapping observations. The overlapping observations induce a moving average process of order 11 in errors. In addition, errors are likely to be autocorrelated owing to the autoregressive nature of the growth rate of industrial production.[14] These problems can be addressed by using the robust Newey and West (1987) estimators of coefficients' errors.[15]

IV. EMPIRICAL RESULTS: INDIVIDUAL RISK STRUCTURES

Before testing the forecasting ability of the systematic risk structure, we check whether individual risk structures help explaining future growth of industrial production. The correlation between the individual corporate risk structures and the growth rate of industrial production for different credit tiers and different lags is presented in Table 2. Figure 1 presents visual illustration of how individual risk structure behaves over business cycles.

We estimate model (5) for each credit rating (AAA, AA, A, and Baa), and for forecasting horizons of 3, 6, 9, 12, 18, 24, 36, and 48 months. To assure that the results are not driven entirely by the movements in the Treasury yield curve, we also experiment

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[13] Although the error term is not observed until time $t+k$, and thus even leads of the dependent variable up to $t+k-1$ should not be correlated with an error term, at time t, according to (1), the most recent observation of the dependent variable available is its $(k+12)^{th}$ lag, Y_{t-12}. The dependent variable, Y_{t+k}, is lagged $(k+12+1)$ times rather than k times to avoid endogeneity of the resulting regressor due to the temporal aggregation of the index of industrial production, I_t. However, we tried lagging the dependent variable k times, and the results did not change much.

[14] Although the corporate bond yields are related to the current business cycle variables, the endogeneity of the regressor is not a problem here because the error term is not realized until time period $t+k$, while the bond yield is already determined at time t, and hence $E_t[X_t u_{t+k}] = 0$ is satisfied.

[15] These estimation problems can also be addressed by using GMM technique which does not require the specification of the distribution of errors. All regressions reported in this paper were also estimated by GMM with Newey-West standard errors, using first and second lags of STR_t and $(k+1)^{th}$ and $(k+2)^{nd}$ lags of dependent variable as instruments. The results did not change much and all the conclusions of the paper were still valid.

with an alternative proxy for a term structure of risk-free interest rates, Agency yield curve. Since the main emphasis of this paper is on constructing the systematic risk structure and analyzing its predictive power, the estimations for individual risk structures will be reported rather briefly.

The results of in-sample estimations (over the period from January 1973 to November 2001) show that individual risk structures (spreads to Treasuries) contain information helpful for predicting the growth rate of industrial production beyond that already incorporated into the current economic conditions (as measured by the lagged growth rate of industrial production).[16] The coefficients on the AAA-rated risk structure are significant (at a 5 percent level) over 3 to 12 month horizons, and on the other credit tiers – over 3 to 18 month horizons.[17] All significant coefficients are negative, indicating that the steepening of the corporate risk structure signals a future decline in the growth rate of industrial production, which is consistent with the hypothesis outlined in the introduction.

When Agency bonds are used as an alternative proxy for a riskless asset, the results do not change much, with exception of AAA-rated bonds, where coefficients become somewhat less significant. Risk structures of AA-, A-, and Baa-rated bonds are still significant over 3 to 18 month horizons. Risk structure of AAA-rated bonds is significant over 3 to 9 months only, and over 48 months, with coefficients at 6, 9, and 48 months being only marginally significant (at a 10 percent level). The fact that the term structures of corporate spreads to an alternative proxy for a riskless security retain their predictive power is a reassuring finding indicating that our results are not driven entirely by the movements in the Treasury structure, which has been found to be a very good predictor of real GDP up to 1985.[18]

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[16] For the sake of brevity the results of individual structure estimations are not reported in the paper, but are available from the author.

[17] Lagged dependent variable is significant in the regressions using credit structures of AA and A-rated bonds over 3 and 6 month horizons; and in the regressions using AAA and Baa-rated bonds – over 3, 6, 36, and 48 month horizons.

[18] For comparison purposes, model (5) was also estimated using the slope of the term structures of yields on corporate, Treasury, and Agency bonds as the explanatory variable. In case of all three variables, a

(continued...)

The fact that the forecasting power of the risk structure of AAA-rated bonds diminishes when spreads to Agencies are used, supports our conjecture that only the systematic part of the aggregate corporate risk structure should be useful in predicting aggregate future real activity. Since Agency bonds are somewhat closer in their credit characteristics to AAA-rated bonds than Treasuries, the spread between yields on an AAA-rated bond and an Agency bond can be considered as a spread between two neighboring credit tiers.[19] And this spread turns out to be of much lesser significance than the other spreads. This finding suggests that the spread between two neighboring notches represents idiosyncratic risk associated with the riskier credit tier. Intuitively, since idiosyncratic risks can be diversified away, it should not be important in explaining aggregate economic activity.

This conjecture is supported by estimating model (5) using risk structures constructed from spreads between all possible combinations of two neighboring credit classes. As expected, the results (not reported here for the sake of brevity) indicate that these risk structures are mostly insignificant in predicting future growth of industrial production across all horizons. So, since the corporate risk structures constructed from spreads to a riskless security do contain information about future aggregate activity, it must have been a systematic component contained in them that is associated with aggregate economic activity. In the following section we test the ability of the systematic risk structure to predict future real growth rate.

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steepening of the slope of the yield structure predicted a future *increase* of industrial production growth. The fact that the slopes of the corporate, agency, and Treasury yield structures exhibit a similar cyclical behavior suggests that the term structure of corporate yields conveys little information beyond what is already contained in the U.S. Treasury yield curve. Hence, the analysis of spreads is useful for it insolates information specific to corporate bonds.

[19] Although Agency bonds bear almost zero amount of credit risk, they still trade at a small premium over Treasuries.

V. Testing the Information Content of the Systematic Risk Structure: In-Sample Estimations

This section analyses the ability of the constructed systematic risk structure to predict the future growth rate of industrial production. Further, it evaluates the stability of the relationship between the systematic risk structure and growth rate of industrial production over time and the accuracy of out-of-sample predictions. In addition, it evaluates whether the systematic risk structure contains information beyond what is in the Index of Leading Economic Indicators (LEI) and whether it improves upon the LEI in both in-sample and out-of-sample predictions.

A. Basic Model

We estimate model (5) using the systematic risk structure (see Table 5). As we expected, it is important in explaining the future growth rate of industrial production over 3 to 18 month horizons (spreads to Treasuries) and over 3 to 12 month horizons (spreads to Agencies) even when all other relevant economic information is included. All coefficients are significant at a 1 percent level and are negative indicating that a steepening of the systematic term structure signals economic slowdown in the future. As we expected, the second principal component turned out to be largely insignificant across all forecasting horizons, and thus represents some idiosyncratic factors associated with each individual rating category.[20]

These results support our decision to use only the first principal component as the proxy for the systematic risk structure, and allow us to drop other components from the further analysis. In addition, the results from the previous section indicate that very little information about individual risk structures (less than 5 percent of total variation) would be lost if the other principal components were dropped from the analysis. Moreover, since by construction the other three principal components are orthogonal to the first one, dropping them will not bias the estimation results.

[20] Results are almost uniformly insignificant, and thus we do not report them in the paper for the sake of brevity.

However, the fact that our regressor is a constructed variable may still introduce problems with estimating equation (5) because it may be an imperfect proxy for the true systematic risk structure. Using an estimated variable instead of a true one may introduce an errors-in-variables (EIV) problem. However, Connor and Korajczyk (1988) showed that when estimated factors are used in place of the true ones in testing APT, asymptotically this bias is very small compared to the estimation error of the coefficients and thus should not be a problem for inference. Chamberlain and Rotshild (1983) proved that both factor analysis and principal components analysis produce consistent estimates of the factor loadings in large samples. However, it is not clear what the properties of these estimates are in the finite sample.

Unfortunately, these results are not directly applicable in our case because we are not interested in studying how well our systematic component (or systematic factor) explains individual risk structures, but in analyzing its predictive power for future economic activity. And since there is no theory to guide us on how the true systematic risk structure should look, we assume that our proxy for systematic risk structure, PCA_t, correctly estimates the true (unobserved) systematic term structure of corporate risk, Z_t, up to a random error:

$$Z_t = w\, PCA_t + e_t, \tag{6}$$

where $E_t[PCA_t\, e_t] = 0$. Thus, all we leave out is the orthogonal noise term and the OLS estimator of w will be consistent though the OLS estimator of its standard error will be generally inconsistent (see Pagan (1984) for details). And since the hypothesis we are testing is $w < 0$, we will have to use 2SLS or 3SLS methodology to obtain correct errors. However, by construction of our variable, it is not feasible to obtain sample covariance matrix of error terms and thus implement either of approaches. Moreover, although heteroskedasticity and autocorrelation consistent estimator of standard errors is asymptotically robust, it may be biased in finite samples.[21] Therefore, we use bootstrapping to find alternative coefficients' standard errors in equation (5). One more advantage of a bootstrap method is that it allows constructing correct standard errors without imposing assumptions about the distribution of the error term.

Since, for the reasons described earlier in the paper, the regression residuals exhibit autocorrelation, we apply model-based bootstrap (see Davidson and Hinkley (1999)) to pre-whiten residuals so that they are independent and homoskedastic. In particular we first fit ARMA(5,1) to residuals, u_t, obtained from estimating equation (5) on the entire sample.[22] The residuals from the latter regression are white noise according to both Bartlett's and Portmanteau (Q) tests. Then, we resample these residuals with replacement, reconstruct u_t, and re-estimate equation (5) again, 1000 times. When doing this, we also replace the lagged dependent variable with its artificially constructed counterpart (see Davidson and MacKinnon (1993) for details on bootstrap with lagged dependent variables). The bootstrapped standard errors are presented in Table 5 in squared brackets.[23]

It is worth noting that bootstrapped errors are somewhat smaller than Newey-West errors in a majority of cases, leading to the proxy for systematic term structure being significant over the greater number of horizons. Thus, we make inferences on a case-by-case basis using the most conservative estimate of standard errors. The results of this exercise indicate that the systematic term structure still predicts the growth rate of industrial production over 3 to 18 months for spreads to Treasuries and over 3 to 12 months for spreads to Agencies.

[21] Chesher and Lewitt (1987) show that with moderate heteroskedasticity, estimates of standard errors can be biased downwards; and only with significant heteroskedasticity can they be biased upwards.

[22] Otherwise it would have been impossible to design a bootstrap test that deals both with autocorrelation and heteroskedasticity in the residuals (see Davidson and McKinnon, 1993).

[23] The bootstrap bias defined as a difference between the coefficient estimated using the entire sample and the sample average of bootstrap coefficient estimates is never greater than 7 percent of the standard error, and thus may be ignored (see Efron, 1982). Therefore, we do not report bias estimates.

B. Including the Index of Leading Economic Indicators

Although we believe that lagged growth rate of industrial production captures economic information available at time t sufficiently well, including some other variables into the vector of regressors is a good check of the robustness of the marginal explanatory power of the systematic risk structure. Including all the variables, both real and financial, that are shown to be relevant in predicting future economic activity is, however, a rather daunting task since there are many of them.[24] We avoid this problem by using the Index of Leading Economic Indicators (LEI) as an additional explanatory variable. The Index, constructed by the Conference Board, combines a wide array of variables, both financial and real, and is designed to signal peaks and troughs in the business cycle (for the detailed description of the LEI's composition, see Data Appendix). It has been especially widely regarded as a barometer of economic activity three to six months into the future. In particular, it includes the Treasury yield curve and a short-term interest rate, both well-regarded in empirical literature as predictors of economic activity. We estimate model (5) adding the change in the LEI from time t-1 to time t as another explanatory variable:[25]

$$Y_{t+k}=\alpha + \beta_1 STR_t + \beta_2 Y_{t-12-1} +\Delta LEI_t + u_{t+k}, \tag{7}$$

The results presented in Table 6 indicate that the systematic corporate risk structure retains its significance (at a 1 percent level) over 3 to 18 month horizons for spreads to Treasuries, and over 3 to 12 months horizons for spreads to Agencies. Thus, the systematic risk structure contains information about future economic activity beyond that already captured by the lagged growth rate and the Index of Leading Economic Indicators.

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[24] See Stock and Watson (2000) for an overview.

[25] By construction, changes in the index of leading indicators, not levels, are used to forecast future real activity.

C. Stability Check

To test the stability of the coefficients, model (5) was estimated over the initial period from January 1973 to December 1985, and then re-estimated recursively up to November 2001, adding one month each time.[26] The coefficients obtained this way appear to be stable over the whole estimation period.

Coefficients obtained from the static estimation over the whole sample and recursive estimations are significant across the same forecasting horizons. For the systematic risk structure constructed using spreads to Treasuries, recursive coefficients are significant for 3 to 18 month forecasting horizons over the entire recursive estimation sample. At 24 months, coefficients are marginally significant, but become more significant after 1998. Moreover, the precision of estimates almost did not change over the entire period as indicated by virtually constant standard errors. Recursive estimations show that most of the significant coefficients appear to be stable as their changes are within the one standard deviation range over the entire sample (see Figure 2). Notably, this very parsimonious model shows no statistically significant structural breaks since 1985. There are two exceptions though: coefficients at 12 and 18 month horizons changed by a little more than two standard deviations since the beginning of 1991. It is worth noting that with the exception of a 3 month horizon, trajectories of significant coefficients at all other horizons trended upwards. This fact indicates that the steepening of the risk structure would be associated with an increasingly smaller decrease in the future growth rate of industrial production. This suggests that as economic expansion progressed, investors were becoming less concerned with longer-term prospects for corporate default risk, while paying undiminished attention to the short-term creditworthiness. It is also worth noting that the situation has reversed since 2000, and all long-term coefficients have started to trend downwards (thus upwards in absolute values), suggesting that as worries about the overall health of the corporate sector were growing stronger, markets become more attentive to the credit prospects over the longer term.

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[26] Although December 1985 was chosen as a starting point for recursive estimations rather arbitrary, it represents a year after which many good predictors of real growth are documented to loose their forecasting power. We also experimented with other different starting points, including April 1991 – a start of the longest expansion period in the United States. The results did not change significantly.

For the systematic risk structure (spreads to Agencies), the recursive coefficients are significant over the same forecasting horizons as the static coefficients obtained for the whole sample. In addition, recursive coefficients for the 18 month horizon become highly significant after 1995 (see Figure 3). Naturally, this development is not picked up by the static estimation, and the coefficient obtained for the whole sample appears to be insignificant. The estimation errors are stable and very small, except for the 18 month forecasting horizon. However, the recursive coefficients are mostly unstable. Except for the 3 month coefficient, which stabilizes after 1995, coefficients at all other horizons are uniformly trending upwards, changing in the magnitude from two to four standard errors. Similarly to the systematic risk structure of spreads to Treasuries, coefficients become greater in absolute value since mid 2000.

For comparison purposes, we performed recursive estimation exercise for the model using the Index of Leading Economic Indicators as a regressor. Results presented in Figure 4 indicate that the relationship between the Index and the future growth rate of industrial production was particularly unstable until the end of 1991, with coefficient trending down to almost zero. Since then the coefficient was very stable at 3 and 6 months horizons, and trending upwards somewhat at longer horizons.

VI. Evaluating the Quality of Predictions

The accuracy of the out-of-sample predictions of the model using the systematic risk structure as a regressor was evaluated relative to the performance of a model using Index of Leading Economic Indicators as a regressor, an autoregressive model and a simple random walk model. For these models, recursive out-of-sample forecasts were estimated for the following two sets of periods: from January 1981 to December 1985 and from January 1986 to November 2001; from January 1981 to March 1991 and from April 1991 to November 2001. The first dividing point, end 1985, was selected because 1985 was shown in the literature to be the year after which many financial variables – good predictors of the GDP growth – have lost their forecasting power. The second dividing point, April 1991, is a beginning of the longest economic expansion period in the United

States, so it would be interesting to see whether this unprecedented expansion changed the forecasting power of variables. Root Mean Squared Errors (RMSE) were computed for all four periods.[27]

With regard to the systematic risk structure of spreads to Treasuries, the accuracy of the out-of-sample predictions produced by our model relative to the Index of Leading Economic Indicators improved since 1985 (see Table 7). Our model produced the same quality estimates before 1985 and more precise estimates after 1985 at 3 to 9 month forecasting horizons, and outperformed the Index of Leading Economic Indicators at longer horizons. With regard to the autoregressive model, our model produced marginally more precise forecasts at 3 and 6 month horizons and outperformed at 9 to 24 month horizons, during both periods. It should be emphasized that we compare the relative performance of our model, not the absolute one because during the pre-1985 period all models produced RMSEs ten to twenty times as large as during the post-1985 period. This striking difference could be due to much higher volatility of recursive coefficients at the beginning of the sample over which the recursive estimations are performed. When we break the recursive estimation period at April 1991, the RMSEs indicate that the predictions produced by our model relative to the Index of Leading Economic Indicators became slightly less accurate during the post-1991 period for 6 and 9 month forecasting horizons: our model outperformed the index in the earlier sample and performed as well as the index in the later one (see Table 7). Our model outperformed the autoregressive model over 6 to 24 months in both samples.

Table 7 also presents the results of the aforementioned exercise for the systematic risk structure of spreads to Agencies. The results indicate that this risk structure outperformed the Index of Leading Economic Indicators over 3 to 12 months in the before-1985 sample and at 3 to 12 months in the post-1985 sample. With respect to autoregressive model, it outperformed over 3 to 12 months in the former sample, and uderperformed in the latter sample. However, this loss of forecasting power is mainly

[27] Among other measures of forecast accuracy, RMSE is the most complete as it combines both forecasting bias and uncertainty.

confined to the 1985-1991 period, since when the 1991 dividing point is used, our model retains its forecasting power in both parts of the sample. The model outperformed both the Index of Leading Economic Indicators and the autoregressive model over 3 to 12 month forecasting horizons in the first part of the sample; outperformed the index over 3 to 12 months and performed as well as the autoregressive model in the second part of the sample.

All in all, the results of the recursive estimation show that the systematic risk structure of spreads to Treasuries preserved its forecasting power after 1985, unlike the other forecasting variables. The systematic structure of spreads to Agencies lost its forecasting power somewhat only during the 1985-1991 period.

VII. Testing the Ability of the Systematic Risk Structure to Predict Different Growth Regimes

The previous analysis in this paper presents evidence that the systematic corporate risk structure is able to predict the future growth rate of industrial production both in and out of sample. However, the metrics used to evaluate the predictive ability of the regressor in both exercises put equal weight on every correct prediction, regardless of whether the model has captured a continuing trend or has been able to identify a turning point. The ability of the model to predict turning points is intimately related to the important question of predicting future recessions, which defines whether the variable can be considered as a good forecasting indicator.

Evaluating the ability of the common factor to predict turning points in the growth rate of industrial production is complicated by the fact that there is no formal definition of turning points or business cycle for industrial production. We circumvent this problem by defining the "industrial production business cycle" as the process with two different regimes: a regime of positive and a regime of negative growth. However, we avoid imposing the zero growth level as an exact cutting point between different regimes present in the data, and let the model determine it endogenously. To perform this estimation we use the regime-switching technique developed by Hamilton (1989) and estimate the following model using EM algorithm:[28]

$$Y_{t+k} = \alpha(s_t) - \beta_1(s_t)\, STR_t + \beta_2(s_t)\, Y_{t-12-1} + \varepsilon_{t+k}, \qquad (8)$$

where STR_t is the systematic risk structure (we use both spreads to Treasuries and spreads to Agencies) and ε_{t+k} is an i.i.d. standard normal error term. Unobservable regime-defining variable s_t is assumed to follow a two-state Markov process with transition probabilities p_{ij}, $i,j = 1, 2$. k is a forecasting horizon, and $k = 3, 6, 9, 12, 18, 24, 36$, and 48 months. For comparison purposes, we also estimate model (8) using the Index of Leading Economic Indicators instead of the systematic risk structure.

Figures 5 to 7 present a visual proof of how well the systematic risk structure (spreads to Treasuries) is capturing the turning points in industrial production. Its performance is especially striking over the shortest horizon, although it performs very well at all other horizons at which the systematic risk is found to be significant: 6 to 18 months. It is worth noting that even when the model underestimated the magnitude of one peak, occurred in 1982, it captured the timing or the turning point correctly, even with a slight lead. The systematic risk structure of spreads to Agencies performs slightly worse, especially at longer horizons. The Index of Leading Economic Indicators produces forecasts that are too smooth to capture turning points even over the shortest horizons, where it is believed to perform the best.

All variables perform worse over longer forecasting horizons since the mid-point of the last expansion, although the ability of the systematic risk structure of the spreads to Treasuries to precisely capture changes in industrial production even during this period is still striking. Their predictive ability has been restored since early 2000, and all models predict imminent slowdown since then. This observation corroborates the conjecture we made at the beginning of this paper: As last economic expansion progressed, investors became more willing to take on risk and less attentive to longer-term fundamental

[28] See Demster, Laird, and Rubin (1977) for details.

prospects of the issuing firms. However, they became more concerned about fundamentals in the late stage of the expansion.

It is worth noting that the regime-switching technique significantly improves the ability of the model to predict turning points compared to its linear counterpart. To show this in a somewhat informal way we document the dates of the last turning point in the growth rate of industrial production, both observed and forecasted using the systematic risk structure (spreads to Treasuries) and the Index of Leading Economic Indicators. This exercise illustrates the ability of our model to predict slowdown in economic activity after an exceptionally long period of economic boom. Results indicate that in the linear model the systematic risk structure misses the last turning point by 6 to 8 months for 3, 6, and 18 months horizons, and only by one month for 9 and 12 month horizons. The Index of Leading Economic Indicators does not produce negative growth forecasts for the last several years at all, thus completely failing to identify the turning point and even accommodate the information on the change in the direction of growth ex post.

In the regime-switching model, the systematic risk structure exactly predicts the timing of the last turning point 3, 9, 12, and 18 months ahead, and misses it by 3 months when predicted 6 months in advance. The Index of Leading Economic Indicators also becomes a stellar performer: it predicts the last turning point exactly 3 and 6 months in advance, and misses it by one month when forecasted 9 to 18 month in advance.

To get a more precise measure of how well our model captures all changes in the industrial production growth, we estimate correlations between the actual growth rates of industrial production and its predicted counterpart produced by the two systematic risk structures (spreads to Treasuries and Agencies, respectively) and the Index of Leading Economic Indicators. Since the regime-switching estimation does not produce a standard R-squared goodness-of-fit measure, correlations provide a simple alternative to it. The results presented in Table 8 indicate that the systematic risk structure (spreads to Treasuries) produces more accurate predictions of the growth rate than the Index of Leading Economic Indicators, even at the shortest horizons, where the index is designed to perform especially well.

VIII. Conclusions

The systematic component of the risk structure of the aggregate corporate sector may represent market expectations about non-diversifiable future default risk and thus be a useful predictor of real economic activity.

The empirical results reported here support this hypothesis: in a simple linear model, our constructed proxy for the systematic corporate risk structure explains the future growth rate of industrial production over 3 to 18 month forecasting horizons. The systematic risk structure incorporates additional information about real activity beyond that already contained in the other variables that are used to explain current economic activity. In addition, it retains its forecasting power even when such a widely respected predictor of economic activity as the Index of Leading Economic Indicators is included in estimations. The results indicate that the steepening of the risk structure signals future economic slowdowns, a fact that could be associated with market expectations about higher default risk in the future.

The results are not sensitive to the choice of the proxy for a riskless security and hold with both Treasury securities and Agency bonds used as this proxy. This is a reassuring finding since it indicates that the results are not driven by the movements in the risk-free interest rate structure.

In addition, the results of recursive in-sample and out-of-sample estimates show that the relationship between the systematic risk structure and the future growth rate of industrial production has been relatively stable over the last fifteen years, and has not experienced significant structural breaks since late 1980. The relationship has been especially stable since the early 1990s. The results also show that the systematic corporate risk structure outperforms or performs as well as the Index of Leading Economic Indicators, the autoregressive model and the simple random walk model during different time periods we experimented with. Moreover, contrary to other financial variables, the corporate risk structure has not lost its forecasting power since 1985 and the quality of its predictions has even improved since then.

To assess the ability of our constructed systematic risk structure to accurately capture the turning points in the growth rate of industrial production, or the "industrial production business cycle," we estimate the model allowing for regime switches, where the unobservable regime-defining variable follows a two-state Markov process. Thus, we allow the model to identify and capture two different regimes present in the data. This exercise shows that the systematic corporate risk structure is very successful in identifying and capturing different growth regimes in the quite volatile sample data. For example, the systematic risk structure was able to correctly predict the timing of the last slowdown – a daunting task for any model after such a long period of positive growth as the last U.S. expansion.

All in all, these results show that the systematic corporate risk structure is a fairly strong and robust predictor of real activity, capable of capturing "business cycles of industrial production." However, there is no theory explaining why the systematic risk structure should contain information about future real activity, or what kind of message it should contain. And although we argue that theories of corporate debt of an individual firm may be at play here, we hope that our exploratory investigation will encourage a development of the theory linking the systematic corporate risk structure of the economy with economic business cycles.

Table 1. Series' Sample Statistics

	No. of obs.	Mean	Std. Err.
Growth rate of industrial production, year-to-year	331	2.755	0.255
Corporate Spread Curve, Spreads to Treasuries			
AAA	344	-0.036	0.022
AA	344	0.005	0.023
A	344	-0.021	0.022
Baa	344	-0.067	0.026
Corporate Spread Curve, Spreads to Agencies			
AAA	308	-0.042	0.025
AA	308	0.014	0.026
A	308	-0.007	0.025
Baa	308	-0.047	0.029

Table 2. Correlations Between the Individual Risk Structures (Spreads to Treasuries) and the Growth Rate of Industrial Production

The slope of the term structure is defined as a difference between long- and intermediate- maturity corporate spreads to Treasury securities. The slope of the tenn structure is lagged k months.

	AAA	AA	A	Baa
***k* =0**	-0.055	-0.031	-0.001	-0.003
***k* =3**	-0.175	-0.164	-0.118	-0.116
***k* =6**	-0.223	-0.221	-0.175	-0.171
***k* =9**	-0.293	-0.321	-0.280	-0.282
***k* =12**	-0.392	-0.448	-0.419	-0.401
***k* =18**	-0.343	-0.414	-0.437	-0.416
***k* =24**	-0.226	-0.250	-0.313	-0.273

Table 3. Principal Component Analysis of the Corporate Risk Structures

Principal Components are calculated using principal components analysis minimizing the covariance matrix of spread structures. The third column indicated the proportion of variance explained by each principal component, the fourth column indicated the cumulative amount of variance explained by the principal components.

					Eigenvectors			
Component	**Eigenvalue**	**Proportion of variance explained**	**Cumulative variance explained**	**Variable**	**1**	**2**	**3**	**4**
Spread Curves, Spreads to Treasuries								
1	3.603	0.901	0.901	tsaaa	0.489	0.716	0.485	0.116
2	0.209	0.052	0.953	tsaa	0.504	0.121	-0.774	0.365
3	0.124	0.031	0.984	tsa	0.513	-0.157	-0.086	-0.839
4	0.063	0.016	1.000	tsbaa	0.493	-0.670	0.399	0.387
Spread Curves, Spreads to Agencies								
1	3.648	0.912	0.912	tsaaa_ag	0.493	0.658	0.556	0.119
2	0.181	0.045	0.957	tsaa_ag	0.502	0.198	-0.758	0.367
3	0.116	0.029	0.986	tsa_ag	0.512	-0.142	-0.105	-0.841
4	0.055	0.014	1.000	tsbaa_ag	0.493	-0.712	0.324	0.380

Table 4. Explaining Individual Corporate Risk Structures Using the First Two Principal Components

The model estimated is linear regression of corporate risk structures on the first, *PCA1*, and the second, *PCA2*, principal component.

	CONST	*PCA1*	*PCA2*	*Adj. R2*
Spreads to Treasuries				
AAA	-0.036*	0.200*	0.293*	0.981
AA	0.005	0.213*	0.051*	0.978
A	-0.021*	0.212*	-0.065*	0.950
Baa	-0.067*	0.238*	-0.323*	0.970
Spreads to Agencies				
AAA	-0.042*	0.220*	0.295*	0.963
AA	0.014**	0.231*	0.091*	0.926
A	-0.007	0.222*	-0.062*	0.957
Baa	-0.047*	0.252*	-0.364*	0.98

* coefficient significant at 1 percent; ** 5 percent level.

Table 5. Explaining the Future Growth Rate of Industrial Production Using the Systematic Risk Structure: the Basic Model

The model estimated is as follows: $Y_{t+k,t+k+12}(k)=\alpha + \beta_1 PCA1_t + \beta_2 LDIP12 + u_{t+1}$, where *LDIP12* is a lagged dependent variable and *PCA1* is a systematic risk structure. Numbers in parentheses are Newey-West standard errors corrected for autocorrelation and heteroskedasticity, with 12 lags. Numbers in brackets are bootstrapped standard errors.

	Systematic Risk Curve, Spreads to Treasuries			*Systematic Risk Curve, Spreads to Agencies*		
	CONST	*PCA1*	*LDIP12*	*CONST*	*PCA1*	*LDIP12*
k = 3	0.586	-0.386*	0.766*	0.646	-1.047*	0.767*
	(0.557)	(0.153)	(0.086)	(0.433)	(0.354)	(0.059)
		[0.242]	[0.119]		[0.223]	[0.121]
	Adj. R2	*0.601*		*Adj. R2*	*0.638*	
k = 6	1.391	-0.623*	0.479*	1.424**	-1.644*	0.514*
	(0.854)	(0.202)	(0.130)	(0.696)	(0.464)	(0.095)
		[0.243]	[0.119]		[0.203]	[0.111]
	Adj. R2	*0.480*		*Adj. R2*	*0.387*	
k = 9	2.235**	-0.896*	0.188	2.272*	-2.041*	0.251***
	(0.950)	(0.210)	(0.143)	(0.889)	(0.534)	(0.134)
		[0.209]	[0.112]		[0.187]	[0.117]
	Adj. R2	0.228		Adj. R2	0.232	
k = 12	2.960*	-1.137*	-0.048	2.968*	-2.213*	0.029
	(0.882)	(0.222)	(1.347)	(0.984)	(0.597)	(0.165)
		[0.201]	[0.105]		[0.198]	[0.111]
	Adj. R2	*0.165*		*Adj. R2*	*0.185*	
k = 18	3.629*	-0.858*	-0.195	3.240*	-1.517**	-0.088
	(0.861)	(0.319)	(0.139)	(1.150)	(0.762)	(0.206)
		[0.268]	[0.109]		[0.270]	[0.127]
	Adj. R2	*0.225*		*Adj. R2*	*0.093*	
k = 24	3.645*	-0.353	-0.142	2.817*	-0.567	0.019
	(0.934)	(0.330)	(0.139)	(1.121)	(0.882)	(0.185)
		[0.277]	[0.122]		[0.300]	[0.139]
	Adj. R2	*0.071*		*Adj. R2*	*0.007*	
k = 36	3.608*	0.091	-0.182**	3.218*	1.041	-0.114
	(0.710)	(0.365)	(0.092)	(0.824)	(0.803)	(0.121)
		[0.268]	[0.128]		[0.248]	[0.134]
	Adj. R2	*0.053*		*Adj. R2*	*0.057*	
k = 48	3.419	-0.019	-0.206***	3.566*	0.473	-0.234
	(0.681)	(0.287)	(0.118)	(0.828)	(0.755)	(0.164)
		[0.239]	[0.137]		[0.227]	[0.144]
	Adj. R2	*0.061*		*Adj. R2*	*0.077*	

* coefficient significant at 1 percent; ** 5 percent; *** 10 percent level.

Table 6. Explaining the Future Growth Rate of Industrial Production Using the Systematic Risk Structure and Index of Leading Economic Indicators

The model estimated is as follows: $Y_{t+k,t+k+12}(k) = \alpha + \beta_1 PCA1_t + \beta_2 LDIP12 + \beta_3 DCLEAD_t + u_{t+1}$, where PCA1 is a systematic risk structure, *LDIP12* is a lagged dependent variable, and *DCLEAD* is a one-period change in the Index of Leading Economic Indicators. Numbers in parentheses are Newey-West standard errors, with 12 lags.

	Systematic Risk Curve, Spreads to Treasuries				***Systematic Risk Curve, Spreads to Agencies***			
	CONST	***PCA1***	***LDIP12***	***DCLEAD***	***CONST***	***PCA1***	***LDIP12***	***DCLEAD***
k = 3	0.311	-0.276**	0.791*	2.484*	0.375	-0.646*	0.790*	1.906*
	(0.450)	(0.143)	(0.072)	(0.563)	(0.332)	(0.257)	(0.047)	(0.405)
	Adj. R2	*0.675*			*Adj. R2*	*0.688*		
k = 6	1.007	-0.474*	0.514*	3.405*	1.084***	-1.017*	0.544*	2.248*
	(0.670)	(0.186)	(0.108)	(1.076)	(0.565)	(0.340)	(0.078)	(0.760)
	Adj. R2	*0.427*			*Adj. R2*	*0.457*		
k = 9	1.742**	-0.713*	0.231**	4.332**	1.800*	-1.231*	0.291*	3.084*
	(0.724)	(0.185)	(0.108)	(1.164)	(0.700)	(0.400)	(0.109)	(0.785)
	Adj. R2	*0.392*			*Adj. R2*	*0.364*		
k = 12	2.580*	-0.997*	-0.016	3.324*	2.551*	-1.407*	0.063	2.663*
	(0.721)	(0.206)	(0.111)	(0.958)	(0.854)	(0.472)	(0.149)	(0.844)
	Adj. R2	*0.364*			*Adj. R2*	*0.284*		
k = 18	3.596	-0.847*	-0.192	0.281	3.093*	-0.966***	-0.076	0.842
	(0.835)	(0.327)	(0.137)	(0.600)	(1.144)	(0.676)	(0.208)	(0.645)
	Adj. R2	*0.196*			*Adj. R2*	*0.100*		
k = 24	3.724*	-0.382	-0.149	-0.698	2.830**	-0.309	0.020	-0.154
	(0.941)	(0.329)	(0.139)	(0.643)	(1.158)	(0.757)	(0.189)	(0.548)
	Adj. R2	*0.061*			*Adj. R2*	*0.014*		
k = 36	3.583*	0.101	-0.189***	0.240	3.113*	0.460	-0.112	0.866
	(0.738)	(0.357)	(0.093)	(0.737)	(0.868)	(0.669)	(0.126)	(0.722)
	Adj. R2	*0.055*			*Adj. R2*	*0.080*		
k = 48	3.547*	-0.080	-0.222***	-1.314*	3.680*	-0.288	-0.267	-1.067***
	(0.651)	(0.273)	(0.117)	(0.467)	(0.829)	(0.578)	(0.170)	(0.589)
	Adj. R2	*0.100*			*Adj. R2*	*0.089*		

* indicates coefficient significant at 1 percent; ** at 5 percent; and *** at 10 percent level.

Table 7. Out-of-Sample Forecasting Performance of the Systematic Risk Structure in Comparison with Other Models

Figures in the table are the Root Mean Squared Errors (RMSE) for out-of-sample forecasts of the future growth rate of industrial production produced by different models. First two models are estimations of equation (4) using systematic risk structure of spreads to Treasuries (*RS_TRY*) or Agencies (*RS_AGCY*). Third model uses the Index of Leading Economic Indicators (*LEAD*) as a regressor. The last two models are AR(1) model and the random walk (RW) model of the growth rate of industrial production. Numbers in parenthesis are RMSEs' standard errors. *k* is a forecasting horizon.

	$k = 3$	$k = 6$	$k = 9$	$k = 12$	$k = 18$	$k = 24$
sample before 1991:03						
RS_TRY	8.317	13.509	14.480	13.232	15.380	14.942
	(1.306)	(2.153)	(2.435)	(1.988)	(2.769)	(2.812)
RS_AGCY	7.876	12.679	13.990	13.767	16.787	20.734
	(1.150)	(1.749)	(1.847)	(1.628)	(3.596)	(4.163)
LEAD	10.487	18.407	20.542	17.521	19.021	16.985
	(1.086)	(1.722)	(1.768)	(1.784)	(2.840)	(2.177)
AR(1)	9.013	15.985	19.135	19.078	15.919	12.724
	(1.404)	(2.462)	(2.947)	(2.598)	(2.633)	(2.159)
RW	6.946	19.237	31.703	46.668	60.490	55.077
	(1.085)	(2.886)	(5.012)	(7.497)	(9.209)	(7.421)
sample after 1991:03						
RS_TRY	2.805	5.236	7.079	8.484	9.034	9.226
	(0.353)	(0.708)	(0.784)	(0.718)	(0.809)	(1.312)
RS_AGCY	3.093	5.892	7.929	9.122	8.824	9.396
	(0.373)	(0.730)	(0.866)	(0.797)	(0.944)	(1.193)
LEAD	4.234	5.971	7.257	7.791	10.358	12.004
	(0.817)	(1.353)	(1.732)	(1.573)	(1.279)	(1.268)
AR(1)	3.131	6.068	8.222	9.134	9.317	9.527
	(0.433)	(0.954)	(1.203)	(1.146)	(1.163)	(1.358)
RW	2.220	5.730	9.681	13.519	13.540	10.900
	(0.270)	(0.845)	(1.626)	(2.341)	(2.393)	(1.932)
sample before 1985:12						
RS_TRY	15.113	25.585	26.423	20.094	27.038	33.444
	(2.405)	(4.057)	(4.862)	(3.799)	(6.358)	(6.613)
RS_AGCY	12.997	20.773	20.602	17.411	33.604	46.195
	(2.121)	(3.315)	(3.622)	(3.069)	(8.303)	(10.128)
LEAD	15.981	26.223	26.395	25.261	40.149	30.109
	(1.888)	(3.087)	(3.049)	(3.301)	(5.640)	(4.860)
AR(1)	16.353	30.130	36.468	36.547	32.127	27.062
	(2.600)	(4.609)	(5.684)	(4.911)	(5.641)	(4.979)
RW	12.668	37.141	63.938	97.543	129.100	98.819
	(2.013)	(5.268)	(9.386)	(14.320)	(18.454)	(16.663)
sample after 1985:12						
RS_TRY	2.821	5.126	6.626	7.756	8.069	8.498
	(0.313)	(0.601)	(0.647)	(0.654)	(0.634)	(0.938)
RS_AGCY	3.382	6.507	8.576	9.880	8.390	8.573
	(0.361)	(0.692)	(0.771)	(0.781)	(0.767)	(0.858)
LEAD	4.818	7.871	9.566	9.145	9.424	9.786
	(0.612)	(1.029)	(1.294)	(1.212)	(0.929)	(0.886)
AR(1)	3.056	5.859	7.967	9.059	9.290	8.956
	(0.343)	(0.702)	(0.865)	(0.865)	(0.939)	(1.007)
RW	2.069	5.325	8.739	12.100	13.587	14.051
	(0.206)	(0.622)	(1.119)	(1.578)	(1.598)	(1.475)

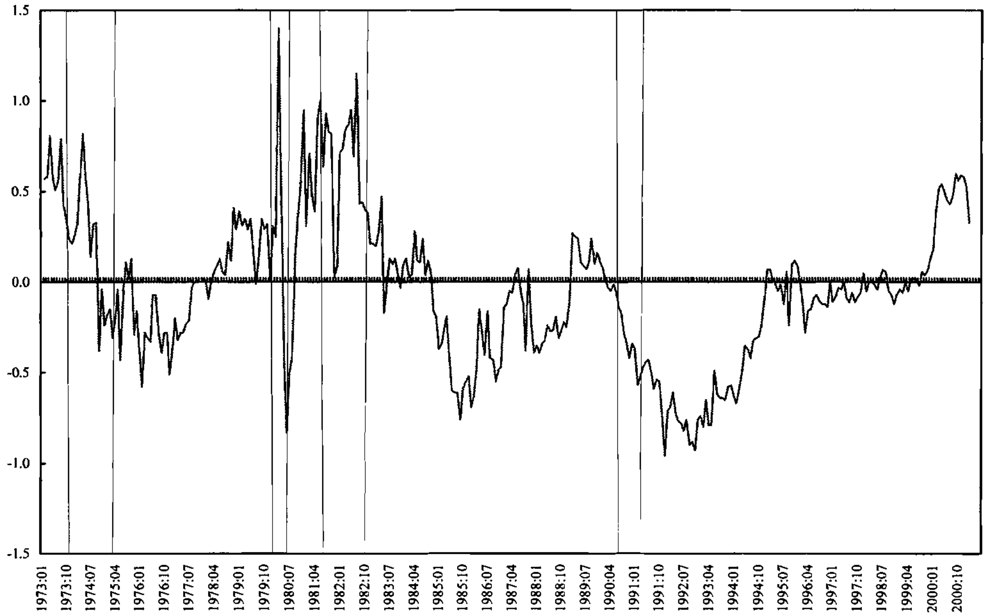
Table 8. Forecasting Performance of the Systematic Risk Structure with Regime Switches

Figures in the table are the correlations between the actual growth rate of industrial production and the predicted growth of industrial production from the regime-switching models, which use either systematic risk structure (spreads to Treasuries or spreads to Agencies) or the Index of Leading Economic Indicators (LEAD) as explanatory variables. All correlations are significant at a 1 percent level. *k* is a forecasting horizon.

	k = 3	***k = 6***	***k = 9***	***k = 12***	***k = 18***	***k = 24***	***k = 36***
Systematic Risk Curve:							
Spreads to Treasuries	0.896	0.866	0.856	0.897	0.868	0.857	0.862
Spreads to Agencies	0.933	0.874	0.879	0.871	0.872	0.853	0.855
LEAD	0.835	0.857	0.848	0.836	0.828	0.827	0.830

Figure 1.

AAA Spread Term Structure and Growth Rate of Industrial Production



Source: Chan Lau and Ivaschenko (2000)

Figure 2. Recursive Coefficients and Their Standard Errors Spreads to Treasuries

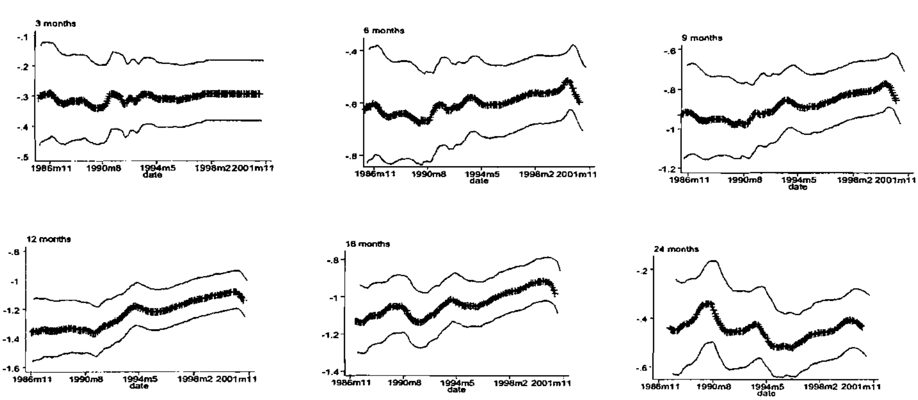


Figure 3. Recursive Coefficients and Their Standard Errors: Spreads to Agencies

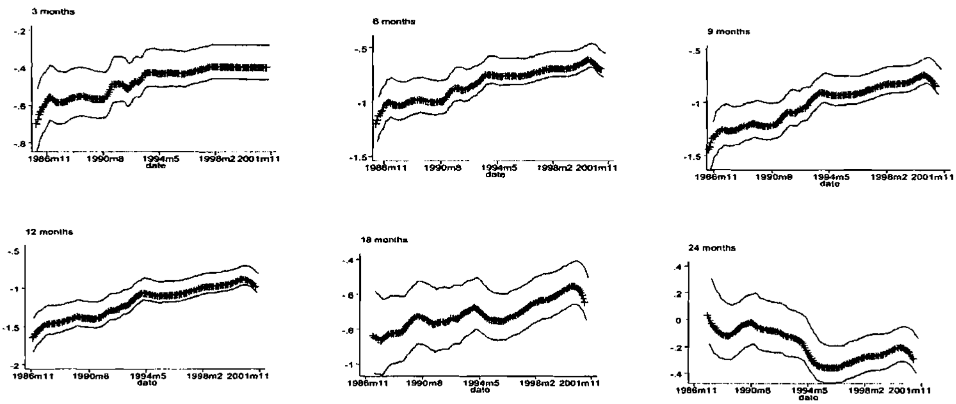


Figure 4. Recursive Coefficients and Their Standard Errors: Index of Leading Indicators

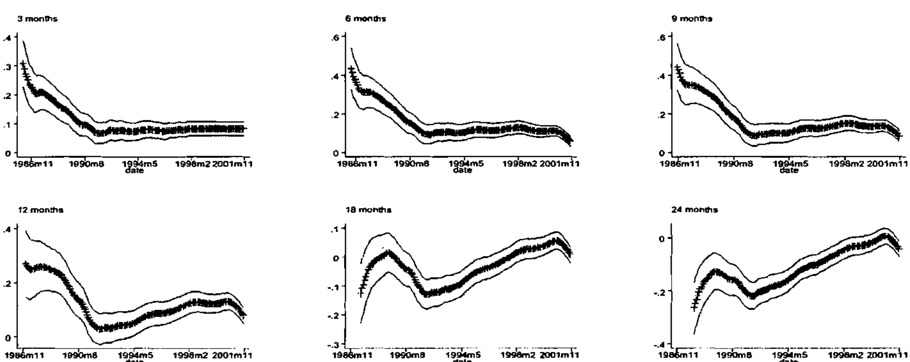


Figure 5. Actual vs. Predicted Growth Rate of IP:
Markov-Switching Model, Spreads to Treasuries

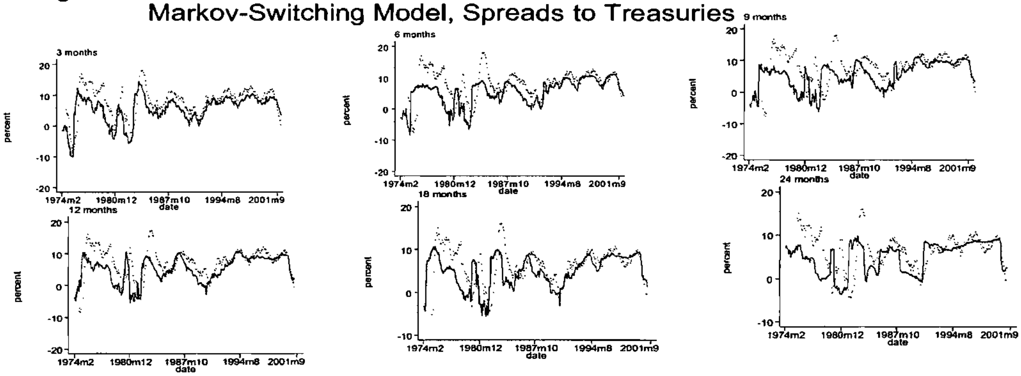


Figure 6. Actual vs. Predicted Growth Rate of IP:
Markov-Switching Model, Spreads to Agencies

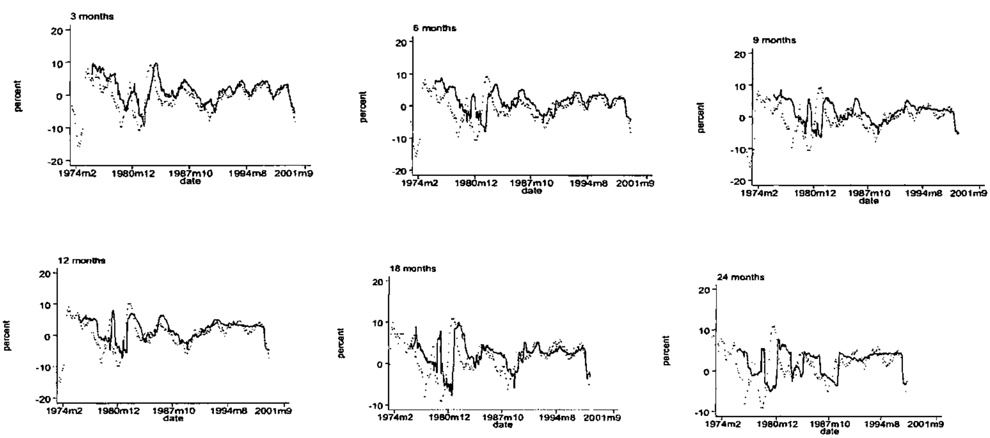
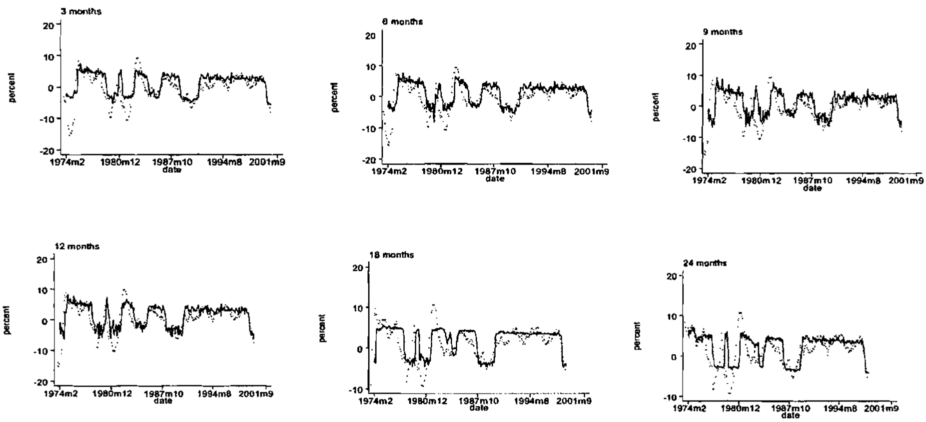


Figure 7. Actual vs. Predicted Growth Rate of IP:
Markov-Switching Model, Index of LI



REFERENCES

Amemiya, Takaheshi, 1985, *Advanced Econometrics* (Cambridge, Massachussets: Harvard University Press).

Anderson, Ronald, and Suresh Sundaresan, 2000, "A Comparative Study of Structural Models of Corporate Bond Yields: An Exploratory Investigation," *Journal of Banking and Finance* 24, pp. 255-269.

Bernanke, Ben, 1990, "On the Predictive Power of Interest Rates and Interest Rate Spreads," Federal Reserve Bank of Boston *New England Economic Review* (November-December), pp. 51-68.

Bernanke, Ben S., and Alan S. Blinder, 1992, "The Federal Funds Rate and the Channels of Monetary Transmission," *American Economic Review* 82, pp. 901-21.

Bertocchi, Marida, Rosella Giacometti, and Stavros A. Zenios, 2000, "Risk Factor Analysis and Portfolio Immunization in the Corporate Bond Market," Working Paper (Philadelphia, Pennsylvania: The Wharton Financial Institutions Center, The Wharton School, University of Pennsylvania).

Campbell, John, Andrew Lo, and Craig MacKinlay, 1997, *The Econometrics of Financial Markets* (Princeton, New Jersey: Princeton University Press).

Chan-Lau, Jorge A., and Ivaschenko, Iryna V., 2000, "The Deterioration of Credit Conditions in the United States," Mimeo (Washington D.C.: International Monetary Fund).

Chen, Nai Fu, Richard Roll, and Stephen Ross, 1986, "Economic Forces and the Stock Market," *Journal of Business* 59, pp 383-403.

Connor, Gregory and Robert Korajczyk, 1986, "Performance Measurement with the Arbitrage Pricing Theory: A New Framework for Analysis," *Journal of Financial Economics* 15, pp. 373-94.

_____, and _____, 1988, "Risk and Return in an Equilibrium APT: Application of a New Test Methodology," *Journal of Financial Economics* 21, pp. 255-90.

Chamberlain, Gary and Michael Rotshild, 1983, "Arbitrage, Factor Structure, And Mean-Variance Analysis on Large Asset Markets," *Econometrica* 51, pp. 1281-1304.

Chesher, Andrew, and Ian Jewitt, 1987, "The Bias of a Heteroskedasticity Consistent Covariance Matrix Estimator," *Econometrica* 55, pp. 1217-1222.

Davison, Anthony C. and D. V. Hinkley, 1999, *Bootstrap Methods and Their Application*, 3rd edition (Cambridge: Cambridge University Press).

Davidson, Russel and James G. MacKinnon, *Estimation and Inference in Econometrics* (Oxford: Oxford University Press).

Demster, A.P., N.M. Laird, and D. B. Rubin, 1977, "Maximum Likelihood from Incomplete Data via the EM Algorithm," *Journal of the Royal Statistical Society* Series B, 39, pp. 1-38.

Dotsey, Michael, 1998, "The Predictive Content of the Interest Rate Term Spread for Future Economic Growth," Federal Reserve Bank of Richmond *Economic Quarterly* 84 (3), pp. 31-51.

Duca John C., 2000, "What Credit Markets Tell Us", *Economic and Financial Review*, Federal Reserve Bank of Dallas, Third Quarter, pp. 2-13.

Duffie, Darrell and Kenneth J. Singleton, 1999, "Modeling Term Structure Models of Defaultable Bonds," *Review of Financial Studies* 12, pp. 687-720.

Efron, B., 1982, *The Jackknife, The Bootstrap and Other Resampling Plans* (Philadelphia: Society for Industrial and Applied Mathematics).

Emery, Kenneth, 1996, "The Information Content of The Paper-Bill Spread," *Journal of Economics and Business* 48, pp. 1-10.

Estrella, Arturo, and Gikas A. Hardouvelis, 1991, "The Term Structure as a Predictor of Real Economic Activity," *Journal of Finance* 47, pp. 555-576.

Fama, Eugene, 1981, "Stock Returns, Real Activity, Inflation and Money," *American Economic Review 71*, pp. 545-65.

Garbade, Kenneth, 1986, "Models of Fluctuations in Bond Yields: An Analysis of Principal Components," in *Topics in Money and Securities Markets* (New York: Bankers Trust). Reprinted as Chapter 16 in Kenneth D. Garbade, 1996, *Fixed Income Analytics* (Cambridge, Massachussets: MIT Press).

Gertler, Mark, and Cara S. Lown, 2000, "The Information in the High Yield Bond Spread for the Business Cycle: Evidence and Some Implications," NBER Working Paper No. 7549 (Cambridge, Massachusetts: National Bureau of Economic Research).

Gertler, Mark, Glenn Hubbard, and Anil Kashyap, 1991, "Interest Rate Spreads, Credit Constraints, and Investment Fluctuations: An Empirical Investigation," in *Financial Markets and Financial Crises*, ed. by R. Glenn Hubbard (Chicago, USA and London, UK: The University of Chicago Press), pp. 11-31.

Greene, William H., 1993, *Econometric Analysis*, 3rd edition (Englewood Cliffs, New Jersey: Prentice Hall).

Hamilton, James D., 1989, "A New Approach to the Economic Analysis of Nonstationary Time Series and Business Cycle," *Econometrica* 57, pp. 357-84.

_____, and Dong Heon Kim, 2000, "A Re-examination of the Predictability of Economic Activity Using the Yield Spread", NBER Working Paper No. 7954 (Cambridge, Massachusetts: National Bureau of Economic Research).

Haubrich, Joseph G., and Ann M. Dombrosky, 1996, "Predicting Real Growth Using the Yield Curve," Federal Reserve Bank of Cleveland *Economic Review 32*, pp. 26-34.

Jarrow, Robert and Stuart Turnbull, 1997, "A Markov Model for the Term Structure of Credit Spreads," *Review of Financial Studies* 10, pp. 481-523.

Lehman, Bruce and David Modest, 1988, "The Empirical Foundations of The Arbitrage Pricing Theory," *Journal of Financial Economics* 21, pp. 231-54.

Litterman, Robert, and José Scheinkman, 1988, "Common Factors Affecting Bond Returns," *Journal of Fixed Income* 1, pp. 54-61.

Longstaff, Francis and Eduardo Schwartz, 1995, "A Simple Approach to Valuing Risky Fixed and Floating Rate Debt," *Journal of Finance* 50, pp. 789-819.

Kwark, Noh-Sun, 2000, "Default Risk, Interest Rate Spread, and Business Cycles: Explaining the Interest Rate Spread as a Leading Indicator," *Journal of Economic Dynamics and Control* 26, pp. 271-302.

Merton, Robert, 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* 29, pp. 449-70.

Mitchell, Wesley and Arthur Burns, 1938, *Statistical Indicators of Cyclical Revivals,* NBER Bulletin 69, New York. Reprinted as chapter 6 of G.H. Moore (ed.), *Business Cycle Indicators*, Princeton: Princeton University Press, 1961.

Newey, Whitney and Kenneth West, 1987, "A Simple Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica* 55, pp. 703–708.

Pagan, Adrian, 1984, "Econometric Issues in the Analysis of Regressions with Generated Regressors," *International Economic Review* 25, pp. 221-47.

Pitts, C.G. C. and M. J. P. Selby, 1983, "The Pricing of Corporate Debt: A Further Note," *Journal of Finance* 38, pp. 1311-13.

Saito, Yoshihito, and Yoko Takeda, 2000, "Predicting the U.S. Real GDP Growth Using Yield Spread of Corporate Bonds," International Department Working Paper Series No. 00-E-3 (Tokyo: Bank of Japan)

Stock, James H. and Mark W. Watson, 1989, "New Indexes of Coincident and Leading Economic Indicators," in O. J. Blanchard and S. Fischer (eds.), *NBER Macroeconomics Manual 1989* (Cambridge, Massachusetts: National Bureau of Economic Research), pp. 352-94.

_____ and _____, 2001, "Forecasting Output and Inflation: The Role of Asset Prices," 2001, NBER Working Paper No. 8180 (Cambridge, Massachusetts: National Bureau of Economic Research).

Theil, Henri, 1971, *Principles of Econometrics*, 1st edition (John Wiley & Sons, New York, New York).

DATA APPENDIX

Bond Indices

The redemption yields used to construct the yield spreads were obtained from the following monthly series compiled by Lehman Brothers:

Corporate bonds	
LHIGAAA	AAA-rated bonds, all maturities
LHINGAA	AA-rated bonds, all maturities
LHINVGA	A-rated bonds, all maturities
LHIGBAA	BAA-rated bonds, all maturities
LHIAAAL	AAA-rated bonds, long maturities [29]
LHIGAAL	AA-rated bonds, long maturities
LHINGAL	A-rated bonds, long maturities
LHIBAAL	BAA-rated bonds, long maturities
LHIAAAI	AAA-rated bonds, intermediate maturities [30]
LHIGAAI	AA-rated bonds, intermediate maturities
LHINGAI	A-rated bonds, intermediate maturities
LHIBAAI	BAA-rated bonds, intermediate maturities
Treasury securities	
LHUSTRY	U.S. Treasury securities, all maturities
LHTRYLG	U.S. Treasury securities, long maturities
LHTRYIN	U.S. Treasury securities, intermediate maturities
Agency bonds	
LHAGNCY	Agency bonds, all maturities
LHAGLNG	Agency bonds, long maturities
LHAGINT	Agency bonds, intermediate maturities

Industrial Production data

Changes in industrial production were computed from changes in the seasonally-adjusted industrial production index, compiled by the Federal Reserve.

[29] Long maturities are those above or equal to ten years.

[30] Intermediate maturities are those below ten years.

Index of Leading Economic Indicators

The composite leading, coincident, and lagging indexes are the key elements in an analytic system designed to signal peaks and troughs in the business cycle. Because they are averages, they tend to smooth out a good part of the volatility of the individual series and thereby serve as handy summary measures of the business cycle.[31]

Leading indicators:

Average weekly hours, manufacturing
Average weekly unemployment insurance claims
Consumer expectations
Manufacturers' new orders, consumer goods and materials
Vendor performance index
Manufacturers' new orders, capital goods
Building permits for new private housing
Index of stock prices of 500 common stocks
Money supply M2
Interest rate spread between 10 year Treasury bonds and Federal Funds rate

Coincident Indicators:

Employees on non-agricultural payroll
Personal income less transfer payments
Index of industrial production
Manufacturing and trade sales

Lagging Indicators:

Average unemployment duration
Ration of manufacturing inventories to sales
Change in labor costs
Commercial and industrial loans
Average prime rate charged by banks
Ratio of consumer installment credit to personal income
Change in CPI for services

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[31] Prior to 2001, an additional adjustment was made to equalize the volatility of the composite indexes. For the U.S. leading and lagging indexes, each monthly sum (i_t) was multiplied by an index standardization factor (f) that equalizes the volatility these indexes relative to the coincident index. This factor is the ratio of the standard deviation of the percent changes for the coincident index (*vcoin*) to the standard deviation of the unadjusted percent changes for the particular composite index (*flead = vcoin/vlead, flag = vcoin/vlag*). The Conference Board decided to remove this step as it was proven not have any meaningful difference to the composite indexes' analytical value.

Essay II

How Much Leverage is Too Much, or

Does Corporate Risk Determine the Severity of a Recession?[1]

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Abstract

Several economic theories suggest that vulnerable financial conditions of the corporate sector can trigger or worsen an economy-wide recession. This paper proposes a measure of corporate vulnerability, the Corporate Vulnerability Index (CVI) and analyses whether it can explain the probability and severity of recessions.The CVI is constructed as the default probability for the entire corporate sector, using the structural model of corporate debt by Anderson, Sundaresan, and Tychon (1996). We find that the CVI is a significant predictor of the probability of a recession 4 to 6 quarters ahead, even controlling for other leading indicators. The probit model using the CVI outperforms traditional specifications in predicting recessions, including the recession of 1990-1991 – a common miss by the other models. In order to assess whether the CVI is related to the severity of a recession, Severity of Recession Indices are proposed and constructed, ranking recessions both in terms of the cumulative output loss and recession duration. The ordered probit estimations indicate that an increase in the CVI is associated with an increase in the probability of a more severe and lengthy recession 3 to 6 quarters ahead.

Key words: corporate leverage, structural models of corporate debt, default probability, probability of recession, severity of recession, ranking of recessions, probit, ordered logit, forecasting.

JEL Codes: E32, E37, E43, E44, G13

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I. INTRODUCTION

> "... moderate leverage undoubtedly boosts the capital stock and the level of output... the greater the degree of leverage in any economy, the greater its vulnerability to unexpected shortfalls in demand and mistakes."
>
> Greenspan (2002).

The rapid accumulation of corporate debt in the United States during the 1990s raised concerns that the corporate sector became more vulnerable to sudden economic shocks, such as demand fluctuations and interest rate hikes, and that the high level of corporate debt might prolong the downturn and hinder the ensuing recovery. This paper presents empirical evidence that corporate indebtedness alone does not explain the likelihood or severity of economic downturns. Rather, it is a combination of corporate leverage, future growth prospects, and current macroeconomic conditions that determines whether the economy is susceptible to a slowdown, and whether the slowdown will be severe. The Corporate Vulnerability Index, constructed in this paper as a combination of all these factors, correctly predicts U.S. economic slowdowns, including the 2001 recession, and indicates their severity.

The concerns about the rise in corporate debt are not new. Economists have long recognized that financial conditions of the private sector exert a powerful effect on the macroeconomy. For example, a structural theory of corporate debt directly links an increase in leverage with higher corporate risk and thus higher costs of external financing.[2] Higher funding costs, in turn, tend to reduce investment, depress future cash flows and output, and thus may trigger a slowdown.[3] Empirical studies corroborate this conjecture by finding that leverage, among other balance-sheet indicators, has a major

[2] See, for example, (Merton, 1974). There are a number of other theories modeling the costs of external financing as a function of the firm's balance sheet. See, for example, Kiyotaki and Moore (1997).

[3] In addition, high leverage may lead to credit rationing that limits sources of funding for corporations, thus depressing investment and output. However, with the development of alternative sources of funding for corporations, full-blown credit rationing has become less of an issue, at least for the corporate sector as a whole.

influence on investment spending, inventories and employment.[4] Moreover, financial accelerator theory as in Bernanke and Gertler (1990) and Bernanke, Gertler, and Girchrist (1996) suggests that high corporate leverage can make slowdowns more severe by amplifying and propagating initial adverse shocks and by increasing the effects of monetary policy on the real economy (Bernanke and Gertler, 1995). Finally, high debt payments may inhibit an economic recovery by creating liquidity problems that, combined with weak profits, may crowd out productive investments, push up default rates, and erode production capacity.

Financial data illustrate the connection between higher leverage and higher corporate risk. Markets indeed perceive firms with higher leverage as more risky, and demand higher premiums for the funds they borrow. In fact, corporate spreads have been increasing in tandem with debt levels and debt burdens since the mid 1990s, even though a continuing strength in equity prices pointed to optimistic expectations about future earnings growth (Figures 1 and 2). An increase in corporate leverage has also been accompanied by rising corporate defaults in both investment grade and high-yield sectors; as well as declining recovery rates.[5] The data clearly indicate that total corporate leverage – defined as a sum of the balance sheet leverage and the debt burden – tends to increase before and during recessions. On average, its level is about 35 percent higher during recessions than during expansions (Figure 3).

But how much leverage is too much? According to the structural theory of corporate debt, the cost of external funds is not very sensitive to an increase in leverage if the value of corporate assets is well above the default barrier (a firm defaults is its value falls below this threshold) which in turn depends on the condition of balance sheets, market structure, and macroeconomic variables. Moreover, an increase in leverage may not raise the probability of a corporation going bankrupt if it is offset by

[4] See, for example, Hoshi, Kashyap, and Scharfstein (1991), Gilchrist and Himmelberg (1995), Hubbard, Kashyar, and Whited (1995), Kashyap, Lamont, and Stein (1994), and Sharpe (1994). Bernanke and Gertler (1986, 1990) also argued that the strength of balance sheets determined the quality of investment projects undertaken.

[5] In 2001, the recovery rate fell to a twenty-year low of 21 percent, two times as low as an average for the same period. See Moody's (2002).

improved growth expectations, more favorable debt contract terms, and more accommodative monetary policy. This suggests that the vulnerability of the corporate sector to economic shocks and thus the probability of recessions should be related to a combination of variables, rather than corporate leverage alone. Indeed, the probit analysis performed in this paper indicates that, when other leading indicators are controlled for, the corporate leverage is not significant in predicting the probability of U.S. recessions.

Therefore, in this paper we construct a Corporate Vulnerability Index as a combination of the total corporate leverage, future growth prospects, volatility of the firm value, and current macroeconomic conditions – factors that should affect the corporate default probability and hence the vulnerability of corporate sector according to the structural theory of corporate debt. In particular, this paper uses the model by Anderson, Sundaresan, and Tychon (1996) for choosing the right combination of factors and factor loadings that govern corporate default probability. To infer how the factors might be combined, the model is fitted the model to the aggregate corporate bond yield data. The Corporate Vulnerability Index (CVI) is then constructed as the probability of default for the entire corporate sector.[6]

The probit estimation results indicate that the CVI is able to correctly predict recessions 4 to 6 quarters ahead. The CVI remains significant in predicting the recession even when other leading indicators, widely used to predict the probability of recessions, are included in the regression. The probit model using the CVI predicts the probability of recession more successfully than other forecasting models. In particular, it predicted a high probability of a recession four quarters in advance of the 1990-1991 recession, the recession episode that other widely used leading indicators failed to predict.[7] Moreover,

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[6] Although most of the models of corporate debt are developed for an individual firm, Anderson and Sundaresan (2000) showed that they can be successfully fitted to the aggregate data, yielding reasonable parameter estimates. Although the model-derived corporate default probabilities were above historical levels for short horizons and below historical levels for long horizons, overall they were comparable in magnitude to historical default rates for the aggregate corporate sector.

[7] This fact is well-documented in the literature. See, for example, Estrella and Mishkin (1997), Dotsey (1998), and Stock and Watson (2000).

adding the CVI to the probit model with other leading indicators significantly improves the model's accuracy. For example, the model using the CVI correctly predicted the timing of the recent slowdown four quarters in advance, while the model without the CVI failed to do so.

To test the hypothesis that a vulnerable corporate sector may increase the severity of slowdowns, a variable that ranks recessions with respect to their severity – the Severity of Recession Index (SRI) is constructed – since there has been no such variable in the existing literature. The SRI ranks recessions with respect to the cumulative output loss and length. The SRI is then used as a dependent variable in the ordered probit model. The estimation results indicate that an increase in the CVI is associated with an increase in the probability of having a more severe recession three to six quarters ahead, regardless of how the severity index is constructed. Moreover, an increase in the CVI also increases the probability of having a longer recession.

The rest of the paper is organized as follows. Section II describes in detail the construction of the CVI. First, it reviews structural models of corporate debt and describes the model used to construct the CVI. After describing the data and the estimation technique used to estimate unknown parameters of the model, it presents the CVI construction. Section III presents the estimation results of the probit model predicting U.S. recessions using the CVI as an explanatory variable. Section IV describes the construction of the Severity of Recession Index; and presents the results of the ordered probit estimation using the CVI as an explanatory variable to predict the severity of recessions. Section V concludes.

II. Constructing the Corporate Vulnerability Index

A. Theoretical Model

The set of factors that comprise a measure of corporate vulnerability and the way they are combined is guided by the model of corporate debt by Anderson, Sundaresan, and Tychon (1996) (AST), applied to a perpetual bond.

The AST model belongs to a class of *structural models* that are rooted in the approach of Merton (1974) who showed that firm's debt can be valued as a contingent claim on the market value of firm's assets and priced within the option-pricing framework of Black and Scholes (1973). In these models, equity has characteristics similar to a call option written on firm's assets, while the debt claim possesses features of a portfolio consisting of a discount bond and a short call option on the firm's assets. In both cases, the strike price of an option equals the face value of a debt claim. Structural modeling, therefore, links the valuation of corporate financial claims to firm-specific fundamentals, such as growth prospects (expressed in terms of current and future value of its assets) and riskiness (such as leverage and asset volatility), and economy-wide fundamentals such as the short interest rate and common factors driving stock prices.[8] This feature of structural models is supported by empirical studies showing that spreads between corporate and government bond yields are related to indicators of firm profitability and financial health (Fisher, 1959), business cycle indicators (Duffee, 1998), and economy-wide factors governing equity returns (Elton et al., 2001).

Despite its intuitive appeal, the Merton's model fit the data poorly, mostly underestimating actual corporate spreads (see Jones, et. al. (1984), Franks and Torous (1989), and Eom, et. al. (2002)). Much of the empirical mismatch comes from the model's simplifying assumptions: corporate debt structure is represented by one noncallable bond, default can occur only at maturity and when a firm exhausts its assets, the firm's asset value is independent of the short interest rate; as well as assuming strict absolute priority of claims.[9]

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[8]A number of authors took another approach, called a *reduced-form approach*, which infers prices of corporate bonds from market benchmarks, modeling default as some random process. See, for example, Litterman and Iben (1991), Jarrow and Turnbull (1995), Jarrow, Lando, ad Turnbull (1997), and Duffie and Singleton (1999). Since this approach does not shed light on the relationship between economic factors and corporate default, we chose to work with structural models.

[9] Jones, Mason, and Rosenfeld (1984), and Franks and Torous (1989) show that assuming that default can occur only when a firm exhausts its assets implied credit spreads smaller than actual credit spreads.

A number of extensions to the original model tried to rectify these shortcomings. For example, Geske (1977) models a more complex debt structure; Black and Cox (1976) allow default to occur before the firm exhausts its assets and before maturity; Logstaff and Schwartz (1995) and Ericsson and Reneby (1998) allow for deviation from the strict priority of claims and explicitly incorporate interest rate risk.[10]

However, most of these models treat the default boundary as exogenous, which seems to be an implausible assumption for analyzing the aggregate corporate sector riskiness given the dynamics of the composition of corporate financing. During the latter half of 1990s U.S. corporations increased the magnitude of equity buybacks – amounting to net $3.65 trillion by 2000 – which were largely financed through issuing debt (see Figure 4). This has been boosting equity prices while also increasing firms' leverage and thus riskiness. It has been argued that these developments are to a some extent connected to a shift in managerial incentives, resulting in favoring higher returns on equity even at the expense of the firm's riskiness.[11] These developments also suggest that corporations, aware of the trade-off between higher returns on equity and higher corporate risk, increasingly chose in favor of the former. It is therefore possible that the market value of firm's assets, leverage and thus the default barrier are not exogenous, but instead products of strategic decisions made by firm shareholders and managers.

In this respect, structural models that determine the default boundary endogenously are especially appealing for the analysis of the aggregate corporate sector. In these models, the default barrier is either determined in a game-theoretic framework of the bankruptcy process as in Anderson and Sundaresan (1996) and Anderson, Sundaresan, and Tychon (1996) or derived using variations of the real options theory of investment that treats liquidation decision as an option as in Mella-Barral and Perraudin (1997).

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[10] A number of studies show that the strict priority of claims is rarely observed in bankruptcy proceedings. See, for example, Franks and Torous (1989, 1994), Eberhart, Moore, and Roenfeldt (1990), and Weiss(1990),

[11] See Cookson (2001).

The choice to work with the AST model, applied to a corporate perpetuity, is guided by several considerations. First, the AST model explicitly allows for strategic debt service by shareholders. In addition, as many other models, it models bond market features in a realistic fashion, as it allows for costly bankruptcy, deviations from absolute claim priority. Second, modeling aggregate corporate debt as a perpetuity with time-varying coupon payments seems to be the most natural, given that individual firms continuously roll over their existing debts or issue new ones. The point at which a firm defaults – the default barrier – is not given exogenously but is derived as a result of the strategic interaction between creditors and shareholders. Finally, the model fits aggregate corporate bond data better than other structural models (see Anderson and Sundaresan, 2000).

The AST model develops the price of corporate debt in the following way. Consider a firm, whose assets value, V_t, follows a geometric Brownian motion:

$$dV = (\mu - \beta)Vdt + \sigma VdW \ , \tag{1}$$

where μ is the rate of return on firm's assets, β is the cash flow rate, σ is volatility of the asset value, and dW is a standard Wiener process. A firm's debt is modeled as a perpetual bond with the face value F and a coupon c. To accommodate the fact that the indebtness and debt burden of the U.S. corporate sector vary over time, we allow for time-varying debt level, P_t. One of the key assumptions of the model is that the bankruptcy regime allows for default which does not necessarily lead to liquidation, implying that the flow of debt service is state-dependent $S(V,c)dt$. The recovery rate given default, θ, is not restricted to equal one. In the event of liquidation, bondholders receive the assets of the firm net of non-zero liquidation costs, which are assumed to be linear $K_t + (1-\theta_t)V_t$, where K_t is the bankruptcy cost and θ_t is a debt recovery rate. This implies that the value of debt at liquidation is given by:

$$B_t^L = \max[\theta_t V_t - K_t, 0] , \tag{2}$$

In the case of perpetual bonds and under a simplifying assumption that

$$S(V_t,c) = \begin{cases} P_t c & \text{if } V_t \geq V_t^* \\ B_t^L & \text{if } V_t < V_t^* \end{cases} \tag{3}$$

the price of a perpetual bond can be expressed analytically:

$$B_t = \frac{cP_t}{r_t}(1 - P_t^d) + P_t^d \max[\theta_t V_t^* - K_t, 0], \tag{4}$$

where P_t^d is a probability of default and V_t^* is a default barrier.[12] The default barrier in the AST model is endogenously derived from the game-theoretic framework of strategic decisions by shareholders on whether to service debt obligations. Since liquidation involves a dead-weight loss for creditors (i.e., costly liquidation), shareholders might chose to underperform their debt obligations even though they have enough cash at their disposal. By underperforming debt obligations, shareholders can increase the value of equity at the expense of the bond value. In case shareholders push the debt value too low, debtholders may not agree to it and force a firm into liquidation.

Equation (4) is quite typical for asset pricing theory in general and structural models in particular, as it presents a price of a risky corporate bond as an expected value of a contract function. The value of a risky bond equals the value of a riskless (perpetual) bond, $\frac{cP_t}{r_t}$, times the probability of no default, plus the recovery value of debt at liquidation, B_t^L, times the probability of default.[13] In the AST model the probability of default is defined as follows:

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[12] Note that V_t^* is called a *default* barrier not a *liquidation* barrier meaning that default may or may not lead to the liquidation.

[13] This is a risk-neutral probability of default and thus is not directly comparable to the historical default rates. See Delianedis and Geske (1988) for a discussion.

$$P_t^d = \left(\frac{V_t}{V_t^*}\right)^{\gamma_t} , \tag{5}$$

where $\gamma_t = 0.5 - \frac{(r_t - \beta)}{\sigma_t^2} - \sqrt{\left(\left(\frac{(r_t - \beta)}{\sigma_t^2} - 0.5\right)^2 + \frac{2r_t}{\sigma_t^2}\right)} < 0 \text{ if } r_t > \beta$

Although the original AST model assumes fixed bankruptcy cost and a unity recovery ratio, we assume that bankruptcy cost as a percent of the value of assets is constant over time, and allow recovery ratio be less than unity. Thus, for the case of a perpetual bond, the default barrier is defined as:

$$V_t^* = \frac{\left(\frac{cP_t}{r_t} + K_t\right)}{\theta_t\left(1 - \frac{1}{\gamma_t}\right)}, \tag{6}$$

It is worth noting that the liquidation barrier is increasing in the dead-weight cost of bankruptcy, K_t, and declining in the recovery rate, θ. Economically, it means that the costlier the liquidation, the greater is the ability of shareholders to extract concessions from creditors. Knowing this, bondholders will demand a greater premium on corporate debt even for corporations far from default, implying higher cost of financing for corporations and resulting, according to (5), in higher default probability. The liquidation barrier is also decreasing in the risk-free interest rate, which suggests that if interest rates are high, shareholders are able to extract greater value at the expense of creditors.

From (5) and (6), the default probability can be expressed as follows:

$$P_t^d = \left(1 \Big/ \left(\frac{cP_t / V_t}{r_t\theta_t(1 - 1/\gamma_t)} + \frac{K_t / V_t}{\theta_t(1 - 1/\gamma_t)}\right)\right)^{\gamma_t} . \tag{7}$$

This is the main equation that will be used to construct the measure of corporate vulnerability in the next section. There are several noteworthy characteristics of this equation. First, the probability of default is increasing in balance sheet leverage, P_t / V_t and a coupon rate, c, indicating that both high levels of balance sheet debt and higher debt burden increase the riskiness of the company and thus should be taken into consideration when assessing total corporate leverage. Second, the probability of default is increasing in the risk-free interest rate, r_t, if $r_t > \beta$ – the condition which holds for the most of the sample period analyzed in this paper – indicating that the riskiness of the corporate sector is sensitive to macroeconomic conditions. Finally, it is increasing in the volatility of the firm's asset value above a certain level of volatility, and is nonmonotonic below this level. Thus three factors – total leverage, interest rate, and volatility – should explain changes in the corporate vulnerability over time.

B. Data and Variable Definitions

We use data on aggregate bond index yields. The aggregate bond index consists of seasoned corporate bonds – those with remaining maturities of at least 20 years – with Baa credit rating, as calculated by Moody's Investors Service. The Baa rating is chosen because an average rating of a company listed in S&P500 Composite index is Baa; and the median credit quality of all Moody's-rated North American companies (these also include Canadian firms) is approximately Baa. Quarterly data from 1969Q1 to 2001Q4 are used. The choice of frequency guided by the availability of balance sheet data. A risk-free interest rate is approximated with an average yield on Treasury bonds with effective maturities of 10 years or longer (see Data Appendix for a detailed description of the interest rate data). [14]

The measure of total corporate leverage is constructed as a sum of the balance sheet leverage and the debt burden. The balance sheet leverage is constructed from the quarterly observations on aggregate balance sheet data of non-financial corporate business from the U.S. Flow of Funds Accounts, compiled by the Board of Governors of

[14] A 30-year Treasury bond would have been the closest match to the corporate bond data we use. However, these data are available starting 1977 only (see Data Appendix).

the Federal Reserve. [15] From the debt and equity data we construct the proxy for leverage:

$$LEVER_t = \frac{DEBT_t}{DEBT_t + EQUITY_t}\ , \tag{8}$$

where $DEBT_t$ is market debt owed by the non-financial corporate business, stated at book value; and $EQUITY_t$ is a market value of outstanding equities. [16] Both values are U.S. dollar amounts outstanding at the end of period.

The balance sheet-based measure of leverage reflects only one aspect of corporate indebtedness. Practitioners and policymakers also use a flow-based measure of leverage, debt burden – debt service payments as a share of corporate profits or cash flows – to assess the financial health of corporations. Moreover, considering both balance-sheet and flow-based measure of leverage is consistent with both stock-based and flow-based definitions of financial distress discussed in Wruck (1990) and Kim, Ramaswamy, and Sundaresan (1992). Accordingly, the debt burden measure is calculated in the following way:

$$BURD_t = \frac{INTEREST_t}{PROFIT_t}, \tag{9}$$

where $INTEREST_t$ is gross debt payments, calculated as a sum of constituents of aggregate corporate liabilities, multiplied by appropriate interest rates (see Data Appendix for a detailed description); and $PROFIT_t$ is corporate profits with inventory

[15] Anderson and Sundaresan (2000) construct monthly series from the quarterly data from the Flow of Funds Accounts and the annual data from the National Income and Product Accounts (NIPA) using a set of assumptions. In contrast, raw data in the form available from the Flow of Funds and NIPA are used in this paper to make sure that the results are not driven by the way the data are constructed.

[16] Strictly speaking, since equities are neither assets nor liabilities, their value is not reflected on corporate balance sheets. Equities represent corporate capital and are stated at market values as a Memo item in the Flow of Funds. However, the net equity issuance is recorded as an increase in liabilities.

valuation and capital consumption adjustments of non-financial corporate sector.[17] All figures are available quarterly, seasonally adjusted at an annual rate.

In order to combine level-based balance sheet leverage with flow-based debt burden, we convert flows into levels at each time point t by calculating the present value of the future stream of debt payment flows. Debt payments are assumed to be constant from time t until the maturity of the bond, and are discounted with long corporate bond yield. (see Data Appendix for details).[18] Thereafter, the total leverage is computed as a sum of the balance sheet leverage and the debt burden: [19]

$$LEV_t = LEVER_t + PV_t(BURD_t), \tag{10}$$

Table 1 presents descriptive statistics of sample corporate yields and measures of leverage (see also Figure 3).

The instantaneous volatility of the asset value, v^2, is unknown. It is assumed to be time-varying, proportional to the volatility of equity returns: $v_t^2 = (A\sigma_t)^2$, where A is a constant scaling parameter. The volatility of equity returns is estimated as the square of the rolling standard deviation of quarterly returns on the S&P500 Composite index, I_t, over a 12-quarter window.[20] Returns are calculated as $R_t = lh\ I_t - ln\ I_{t-1}$,. Parameter A is estimated when the AST model is fitted to the data.

[17] Capital consumption adjustment converts depreciation and inventory valuation adjustment converts inventory withdrawal from historical to replacement costs, which is the measure used in NIPA.

[18] Another approach would be to rescale $BURD_t$ so that its mean/standard deviation ratio is comparable to that of $LEVER_t$ and to combine these measures linearly: $LEV\_AS_t = \alpha LEVER_t + \kappa \ln(\ln(BURD_t))$. Anderson and Sundaresan (2000) used this method. The results presented in this paper are not sensitive to the construction of the measure of total leverage.

[19] To be sure, any traditional measure of debt derived from the balance sheet data understates the true amount of leverage in the economy due to increasing off-balance-sheet liabilities. Nevertheless, the traditional measures of leverage calculated from the officially reported balance sheet data have proved to be useful even when measuring performance of such major derivatives players as Enron and LTCM. As pointed out by Chairman Greenspan, problems of these firms "were readily traceable to an old fashioned excess of debt, however acquired, as well as to opaque accounting of that leverage..."

[20] We also experimented with another measure of quarterly volatility – realized volatility – defined as a sum of squared daily returns, R_t^2, as in Schwert (1989). This measure is shown to be an unbiased estimator of true volatility in continuous time by Andersen et. al, (2002); and we performed Monte Carlo

(continued)

C. *Estimation*

To construct a measure of corporate vulnerability, we first fit the theoretical bond yield – calculated as $y_t = cP_t/B_t$, where B_t is a price of corporate bond, defined in (4)-(7) – to the actual yields on the corporate bond index. Since the value of corporate assets, V_t, is unknown, we normalize the model with respect to V_t, and assume that the ratio of the bankruptcy cost to the asset value, K_t/V_t, the recovery rate, θ, and the dividend rate, β, are constants. They are inferred from the data.

Given these assumptions, the structural model described in the previous Section can be implemented in the following form:

$$y_t = \alpha + y\left(\frac{P_t}{V_t}, A\sigma_t, r_t; \frac{K_t}{V_t}, \theta, \beta\right) + u_t, \tag{11}$$

where y_t is the actual yield on the Moody's long-term corporate bond index. The function $y(.)$ is the corporate spread implied by the theoretical bond value, $B(.)$, calculated using the model (4)-(7), and the formula: $y_t = c\frac{P_t}{V_t} / \frac{B_t}{V_t}$. The variable cP_t/V_t is approximated as total leverage, described in the previous Section. The additive constant, α, is included to capture corporate liquidity and tax premiums that are embedded in corporate yields, but are not captured by the AST model. Corporate bonds pay a liquidity premium over Treasuries because corporate markets are less liquid than government ones. They also pay a tax premium since interest on Treasuries is tax deductible while interest on corporate bonds is not. We assume that the sum of these

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experiments showing that sampling at a daily frequency provides a reasonably good discrete approximation to the true process governing quadratic variation of quarterly stock returns. Moreover, using nonoverlapping samples to estimate the quarterly variance avoids introducing autocorrelation into estimation error, unlike using the rolling sample standard deviation. However, we chose to work with the sample rolling volatility correcting for moving average in errors, due to ease of computation. While the model with realized volatility fitted bond yields slightly better, the results of the forecasting exercise predicting the probability and severity of recession were fairly robust to the choice of a volatility proxy.

premiums is constant over time.[21] Finally, the constant term absorbs any systematic biases in the model of $y(.)$.

We estimate the parameters a, K_t/V_t, A, θ, β by non-linear least squares. Since the model is highly non-linear, to ensure that the global maximum is found, optimization is performed in two steps. First, a generic, non-derivative, method is used to find initial values, which are then used to fit the model to the data by the modified Gauss-Newton method. The model is fitted to both nominal and real corporate bond yields.

The model is estimated in real terms as a robustness check, since in periods of high inflation firms tend to switch to different accounting methods. Theoretically, however, variable denomination is not an issue for this type of models, as long as all variables are expressed in the same terms as the models' numeraire – price (yield) of a risk-free bond. Since all balance sheet and flows data are estimated as ratios, only interest rates and bond yields are adjusted for inflation. Inflation data are derived using the implicit GDP deflator from the NIPA. Expected inflation rates are estimated by fitting an ARIMA(7,1,3) model to quarterly inflation data over the period from 1947Q2 to 2001Q4. This model fits the data well. The residuals appear to be white noise according to both Ljung-Box test and Bartlett tests. Ljung-Box (Q) statistic is 26.02, with p-value = 0.96 does not reject the null that the first forty autocorrelations are zero. Bartlett (B) statistics which is 0.45, with p-value of 0.98 also does not reject the null that residuals are white noise. Mean absolute errors are about 20 percent of the mean inflation rate.

The model fits both nominal and real yields well (Figures 5 and 6), with squared errors being less than 10 percent for nominal yield, and less than 14 percent for real yields (Table 2). While the parameters of both nominal and real models are similar, the

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[21] This simplifying assumption is mainly driven by a lack of models that explain the behavior of liquidity premium and tax differential.

cost of bankruptcy and the recovery rate are somewhat higher when expressed in real terms (Table 3).[22]

Estimated parameters are then substituted into equation (7) to obtain a measure of corporate vulnerability, which we will call a Corporate Vulnerability Index (CVI) through the rest of the paper. Figure 7 shows that the CVI increased before each recession. The CVI is a nonlinear function, increasing in leverage and the risk-free interest rate, and non-monotonic in asset volatility. The combination of these factors explained the dynamics of the CVI over the sample period. Since its dramatic peak in the early 1980s, caused by high interest rates and leverage, the CVI has generally trended down during most of the 1990s, driven by either declining leverage or lower interest rates, indicating the increased resilience of the corporate sector to adverse shocks. The CVI increased modestly at the end of the 1990s, reflecting the rise in debt levels and the increase in asset volatility, which were partially offset by lower interest rates. In general, the CVI increased before every recession, and whether it can predict economic downturns is analyzed in the next Section.

III. Predicting the Probability of Recession

As suggested by the literature reviewed in the introduction, financial conditions of the corporate sector affect the probability of recessions. To evaluate this hypothesis, we employ a probit model that uses the NBER recession index (R_t) as a dependent variable, as in many previous empirical studies.[23] The NBER index equals one if the

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[22] Derivatives of $E[y_t]$ with respect to each of the parameter estimates appear to be stationary. Thus we assume that $p\lim\left(\frac{1}{n}\right)\sum_i\left[\frac{\partial y_t(x_i\beta^0)}{\partial\beta^0}\right]\left[\frac{\partial y_t(x_i\beta^0)}{\partial\beta^{0'}}\right]=Q$, where Q is positive definite, and asymptotic properties of nonlinear least squares estimators hold (see Amemiya (1985) for a comprehensive discussion).

[23] Literature that uses binary models to evaluate the probability of recessions is vast. To name a few, Estrella and Hardovelis (1991), Stock and Watson (1993), Estrella and Mishkin (1997), Dueker (1997), and Dotsey (1998).

economy is in a recession during the given quarter, and zero otherwise.[24] To assess the marginal predictive power of the CVI, we include other leading indicators, proved to be good predictors of U.S. recessions by previous studies, such as average weekly hours worked (*AVGHRS*), Conference Board's vendor performance index (*VENDOR*), housing starts (*HOUSING*), the slope of the Treasury yield curve (*TRY_STR*), and stock returns (*SPRET*):

$$Prob\ (R_{t+k} = 1|\Omega_t) = F(c_0 + c_1 CVI_t + c_2\, AVGHRS_t + c_3\, VENDOR_t + \\ + c_4\, HOUSING_t + c_5\, TRY\_STR_t + c_6\, SPRET_t), \qquad (12)$$

where $F(.)$ is a cumulative normal distribution function and Ω_t is an information set at time t.

The estimation results indicate that the CVI is significant in predicting the probability of recession 4 to 6 quarters ahead, even controlling for other leading indicators (Table 4). For example, a ten percent increase in the CVI is associated with a 0.08 percentage point increase in the probability of recession 4 quarters ahead.[25] The fact that the CVI is significant in signaling the probability of recession at longer horizons may indicate that as markets recognize an increase in corporate vulnerability, the cost of external funding rises, and corporations are forced to work on improving their balance sheet positions. By the time the economy slips into a recession, corporate balance sheets have typically begun to improve, thereby lowering the CVI.

The model incorporating the CVI more successfully predicts the probability of a recession than traditional models. A high probability of recession was predicted four

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[24] NBER's Business Cycle Dating Committee determines whether the economy is in the recession or expansion. A recession is defined as a significant decline in activity spread across the economy, lasting more than a few months, visible in industrial production, employment, real income, and wholesale-retail sales. Expansion is a period between a trough and a peak of economic activity.

[25] The coefficients from the binary model cannot be directly interpreted as a marginal effect on the dependent variable. The marginal effect of the CVI on the conditional probability of a recession is given by: $\partial Prob(R_t = 1 | CVI_t, \beta_{CVI}) / \partial CVI_t = (-dF(-CVI_t' \beta_{CVI}) / dCVI_t)\beta_{CVI}$, where F(.) is a cumulative distribution function.

quarters in advance of the 1990-1991 recession. In contrast, other widely used leading indicators failed to predict this recession episode, as documented in Estrella and Mishkin (1997), Dotsey (1998), and Stock and Watson (2000). For example, model (9) predicted an 86 percent probability that the economy would slip into recession in 1990, while the Estrella and Hardovelis (1991) model, which uses the Treasury yield curve, implied only 20 percent probability and the Estrella and Mishkin (1997) model, which uses the Treasury yield curve and stock prices, implied only a 25 percent probability.

Adding the CVI to other leading indicators significantly improves the model's forecasting accuracy. Model (9) correctly predicted the timing of the recent recession four quarters in advance, while the same model without the vulnerability index failed to do so (Figures 8 and 9). The model with the CVI forecasted a recession with 53 percent probability in the first quarter of 2001, while the model without the CVI placed only a 6 percent probability of a recession in the first quarter of 2001. In addition, the model with the CVI did not produce false recession signals in the mid-1990s, when the economy was in the midst of an expansion, unlike the model without the CVI. Although the model with the CVI suggested a significant jump in the likelihood of a recession from virtually zero in the fourth quarter of 1994 to almost 30 percent in the second quarter of 1995, the probability was still below 50 percent. In contrast, the model without the CVI implied a 63 percent probability of a recession in the second quarter of 1995.

IV. Predicting the Severity of Recession

To assess whether the higher Corporate Vulnerability Index is associated with a more severe slowdown, as suggested by the theory outlined in the introduction, we first need to construct a variable that would rank recessions with respect to their severity. Since, to our knowledge, there is no such variable existing in the literature, we construct it in the following way. First, the magnitude of a cumulative decline of real GDP between the pre-recession quarter and the last quarter of the recession, normalized by the length of the recession, is calculated. Second, recessions are then ranked, with a higher rank representing a more severe recession or a group of more severe recessions (see Table 5 for a detailed description of ranking rules). The resulting variable is called a Severity of Recession Index (SRI). Several different rules were used for grouping the recessions according to their severity – to obtain different variations of the SRI – to check the robustness of the results. Another Severity of Recession Index was also constructed, in which recessions were ranked with respect to their length, with a higher rank representing a longer recession. Every modification of the SRI is set to zero during expansion periods.

We then estimate a model similar to model (9) with different versions of the SRI as a dependent variable:

$$Prob\ (R_{t+k} = M|\Omega_t) = N\ (c_0 + c_1 CVI_t + c_2\ AVGHRS_t + c_3\ VENDOR_t + \\ + c_4\ HOUSING_t + c_5\ TRY\_STR_t + c_6\ SPRET_t), \quad (13)$$

where M is one of the several values, taken on by the ordinal dependent variable SRI. The model is estimated by the ordered probit.

The estimation results indicate that an increase in the CVI is associated with an increase in the probability of a more severe recession three to six quarters ahead (Table 6). When recessions are ranked according to their length, the estimation results indicate that an increase in the CVI also raises the probability of having a longer recession (Table 6, bottom panel).

V. Conclusions

It has been long recognized that the financial conditions of the private sector may have significant influence on the macroeconomy. This paper shows that a combination of different factors – such as macroeconomic conditions, equity volatility, and structure of financial contracts, in addition to financial conditions – determines the health of the corporate sector, and has an impact on the entire economy. The Corporate Vulnerability Index (CVI) designed in this paper combines these factors – all of which are suggested by the structural theory of corporate debt.

The CVI is shown to predict economic recessions four to six quarters ahead. The results of the probit estimations indicate that an increase in the CVI is associated with a higher probability of a recession. The results also indicate that the model incorporating the CVI predicts recessions more successfully than other models – in fact, the timing of the 1990-1991 recession was correctly predicted four quarters in advance, the recession episode that other models fail to predict. Moreover, the model with the CVI correctly predicted the timing of the current slowdown, which was missed by the model without the CVI.

Ordered probit estimates using the Severity of Recession Index, constructed in the paper, also indicate that an increase in the CVI is associated with a higher probability of having a more severe recession, both with regard to the loss of output and the recession length.

These results shed new light on the relationship between financial conditions of corporations and the macroeconomy, indicating that higher corporate vulnerability is indeed associated with a downturn. They also provide evidence in support of the structural theory of corporate debt, which suggested the combination of factors in explaining the vulnerability of the corporate sector.

Table 1. Sample Summary Statistics: Selected Variables *

	Mean	Std. Dev.
Balance sheet leverage	53.77	9.51
Debt burden	108.76	46.30
Total leverage	147.01	50.61
Nominal corporate bond yield	10.03	2.38
Real corporate bond yield	6.92	2.73

* In percent

Table 2. Model Fit to Corporate Yields *

	Mean	Std. Dev.
Corporate yields:		
Nominal actual	10.028	2.210
Nominal fitted	10.031	2.384
Real actual	6.799	2.447
Real fitted	6.924	2.726
Root Mean Squared Error (RMSE):		
Nominal, absolute value	0.966	0.112
as percent of nominal actual mean	9.636	
Real, absolute value	0.967	0.189
as a percent of real actual mean	13.959	

* In percent

Table 3. Estimation Results of Fitting the Model to Corporate Yields

The model estimated is: $y_t = CONST + y_t(LEVER_t, r_t, A\ SIGMA_t, BCOST, THETA, BBETA) + u_t$, where y_t is the yield on a long-maturity Corporate Bond Index; $y_t(.)$ is a theoretical corporate bond yield, derived in Anderson, Sundaresan, and Tycon (1996); $LEVER_t$ is a measure of total leverage, r_t is the yield on a long-maturity Treasury Composite Bond Index, and $SIGMA_t$ is equity volatility. *CONST,* a recovery rate *THETA,* a volatility scaling factor *A,* a bankruptcy cost *BCOST,* and a dividend rate *BBETA* are constant model parameters. u_t is a residual. The model is estimated by nonlinear least squares over the sample from 1969Q1 to 2001Q4.

	Nominal Yields		Real Yields	
	Coefficient	**Standard Error**	**Coefficient**	**Standard Error**
THETA	2.004*	0.103	4.134*	0.188
BCOST	6.982*	0.414	10.699*	0.568
A	0.099*	0.000	0.178*	0.001
BBETA	27.599*	0.018	20.044*	0.037
	Adj. R-squared = 0.823		Adj. R-squared = 0.849	

* Coefficient significant at a 1 percent level.

Table 4. Predicting the Probability of Recession, Probit Estimations

The model estimated is: $Prob\ (R_{t+k} = 1) = N\,(c_0 + c_1\, CVI_t + c_2\, AVGHRS_t + c_3\, VENDOR_t + c_4\, HOUSING_t + c_5\, TRY\_STR_t + c_6\, SPRET_t)$ where R_{t+k} is the NBER recession index; the CVI_t is the Corporate Vulnerability Index; $AVGHRS_t$ is average weekly hours worked; $VENDOR_t$ is the vendor performance index; $HOUSING_t$ is housing starts; TRY_STR_t is the Treasury yield curve; and $SPRET_t$ is stock returns. $N(.)$ is a cumulative normal distribution function. k is a forecasting horizon, in quarters.

	k = 0		***k = 1***		***k = 2***		***k = 3***		***k = 4***		***k = 5***		***k = 6***	
	Coef.	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
c_1	-1.216	0.911	-1.060	1.173	0.716	1.398	1.649 ***	1.017	3.034 *	1.066	1.616 ***	0.895	2.165 **	1.022
c_2	-1.539 *	0.341	-0.900 *	0.308	0.102	0.314	0.278	0.273	0.535 *	0.289	1.609 **	0.726	0.276	0.375
c_3	-0.001	0.021	-0.005	0.020	0.022	0.022	0.027	0.017	0.034	0.021	-0.041	0.028	-0.003	0.018
c_4	-0.002 *	0.001	-0.002 *	0.001	-0.002 **	0.001	-0.001	0.001	0.001	0.001	0.000	0.001	0.003 *	0.001
c_5	0.007	0.071	-0.242 ***	0.109	-0.441 *	0.108	-0.501 *	0.125	-0.613 *	0.131	0.309 **	0.121	-0.671 *	0.137
c_6	-6.799	2.976	-17.201 *	4.545	-11.513 *	4.159	-5.796	4.093	-2.998	3.628	-2.458	2.647	3.981	3.703
c_0	63.697 *	13.537	39.099 *	12.392	-4.061	13.271	-13.74	11.118	-27.16 **	12.026	-0.443	1.151	-17.646	16.134
Pseudo R2	*0.476*		*0.602*		*0.567*		*0.478*		*0.466*		*0.208*		*0.282*	

* Coefficient significant at a 1 percent level; ** at a 5 percent level; *** at a 10 percent level.

Table 5. The Severity of Recession Indices

Recessions	Real GDP decline, cumulative,%	Length, qtr	Real GDP Decline per quarter, %	Rating: Individual *	Rating: Grouped # 1**	Rating: Grouped #2***	Rating: Recession Length
Q3 1953 - Q2 1954	2.570	4	0.643	5	3	2	3
Q4 1957 - Q2 1958	4.170	3	1.390	7	4	3	2
Q3 1960 - Q2 1961	0.710	3	0.237	2	2	1	2
Q1 1970 - Q4 1970	0.140	4	0.035	1	1	1	3
Q1 1974 - Q1 1975	2.735	5	0.547	4	3	2	4
Q2 1980 - Q3 1980	4.330	2	2.165	8	5	3	1
Q4 1981 - Q4 1982	2.244	5	0.449	3	2	2	4
Q4 1990 - Q1 1991	2.622	2	1.311	6	4	2	1
Q2 2001 - Q4 2001 (?)	0.265	3	0.088	1	1	1	2

* Rated according to a decline per quarter.

** Grouped according to a total cumulative real decline during a recession:

Rating	Cumulative decline, %
1	0-0.1
2	0.1-0.5
3	0.5-1.0
4	1.0-1.5
5	>1.5

*** Grouped according to a cumulative real decline: 1- light; 2 - average; 3 - severe.

Table 6. Predicting the Severity of Recessions, Ordered Probit Estimations

The model estimated is: $Prob\,(R_{t+k} = M) = N\,(c_0 + c_1 CVI_t + c_2\,AVGHRS_t + c_3\,VENDOR_t + c_4\,HOUSING_t + + c_5\,TRY\_STRt + c_6\,SPRET_t)$,

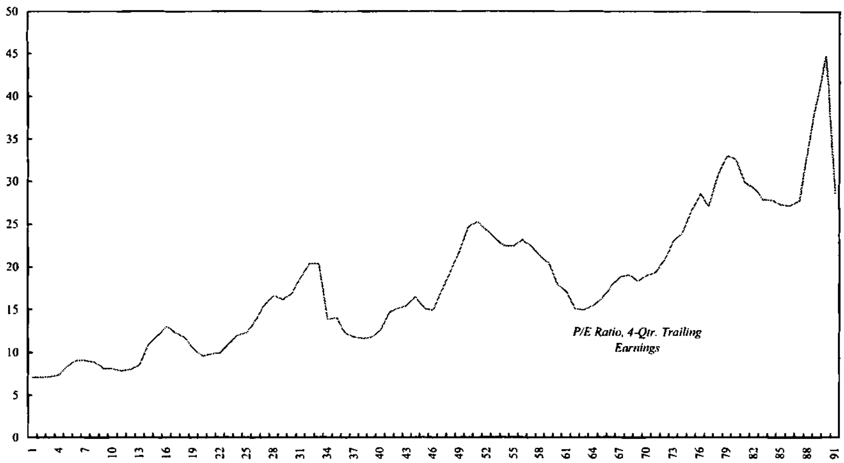
where R_{t+k} is the NBER recession index, M is one of the Severity of Recession Index (SRI) variations from Table 5; the CVI_t is the Corporate Vulnerability Index, $AVGHRS_t$ is average weekly hours worked, $VENDOR_t$ is the vendor performance index , $HOUSING_t$ is housing starts, TRY_STR_t is the Treasury yield curve, and $SPRET_t$ is stock returns. $N(.)$ is a cumulative normal distribution function. k is a forecasting horizon, in quarters.

	$k = 3$		$k = 4$		$k = 6$	
SRI, Rating: Individual						
	Coef.	*Std. Err.*	*Coef.*	*Std. Err*	*Coef.*	*Std. Err*
c_1	1.248**	0.665	1.939*	0.731	1.598*	0.696
c_2	0.122	0.223	0.160	0.255	0.170	0.293
c_3	0.015	0.014	0.022	0.017	0.000	0.016
c_4	-0.000	0.001	0.001**	0.001	0.003*	0.001
c_5	-0.447*	0.098	-0.489*	0.098	-0.571*	0.091
c_6	-4.630	3.324	-2.359	2.715	3.595	3.523
Pseudo R2	*0.282*		*0.271*		*0.236*	
SRI, Rating: Groupped # 1						
	Coef.	*Std. Err.*	*Coef.*	*Std. Err*	*Coef.*	*Std. Err*
c_1	1.323**	0.655	1.970*	0.728	1.798*	0.673
c_2	0.084	0.223	0.142	0.258	0.182	0.290
c_3	0.016	0.014	0.022	0.017	0.000	0.016
c_4	0.000	0.001	0.001*	0.001	0.003*	0.001
c_5	-0.440*	0.097	-0.482*	0.098	-0.566*	0.089
c_6	-4.485	3.278	-2.459	2.709	3.230	3.531
Pseudo R2	*0.286*		*0.271*		*0.237*	
SRI, Rating: Groupped # 2						
	Coef.	*Std. Err.*	*Coef.*	*Std. Err*	*Coef.*	*Std. Err*
c_1	1.904*	0.774	2.576*	0.833	2.223*	0.733
c_2	0.080	0.245	0.150	0.286	0.157	0.313
c_3	0.016	0.014	0.026	0.015	-0.002	0.017
c_4	0.000	0.001	0.001**	0.001	0.003*	0.001
c_5	-0.487*	0.105	-0.536*	0.113	-0.605*	0.108
c_6	-4.686	3.401	-1.813	2.720	2.778	3.670
Pseudo R2	*0.365*		*0.374*		*0.295*	
SRI, Rating: Recession Length						
	Coef.	*Std. Err.*	*Coef.*	*Std. Err*	*Coef.*	*Std. Err*
c_1	3.040*	0.932	4.516*	0.978	2.720*	1.017
c_2	0.245	0.295	0.691*	0.295	0.151	0.375
c_3	0.054*	0.017	0.056*	0.020	-0.001	0.019
c_4	0.000	0.001	0.001	0.001	0.003*	0.001
c_5	-0.492*	0.125	-0.652*	0.152	-0.694*	0.145
c_6	-5.795	4.181	-2.702	3.520	3.612	3.767
Pseudo R2	*0.416*		*0.403*		*0.308*	

* Coefficient significant at a 1 percent level; ** at a 5 percent level; *** at a 10 percent level

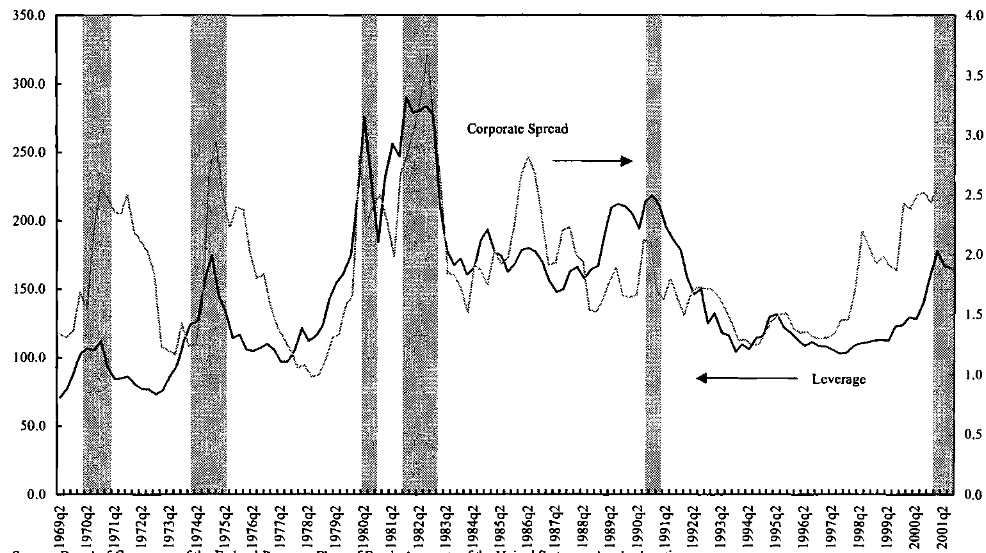
1/ k is a forecasting horizon

Figure 1. P/E Ratios of S&P 500 Composite Stock Index



Source: Haver Analytics.

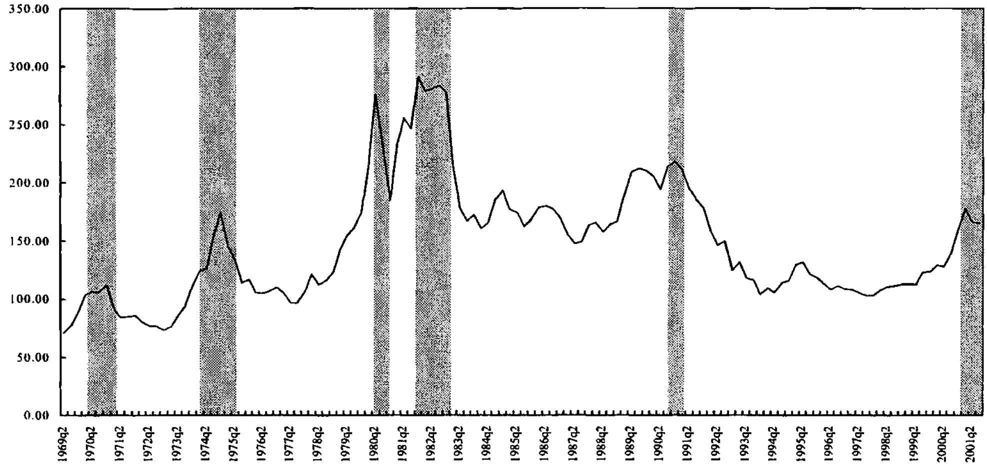
Figure 2. Corporate Sector: Total Leverage and Corporate Bond Spreads* (in percent)



Source: Board of Governors of the Federal Reserve, Flow of Funds Accounts of the United States, and author's estimates.

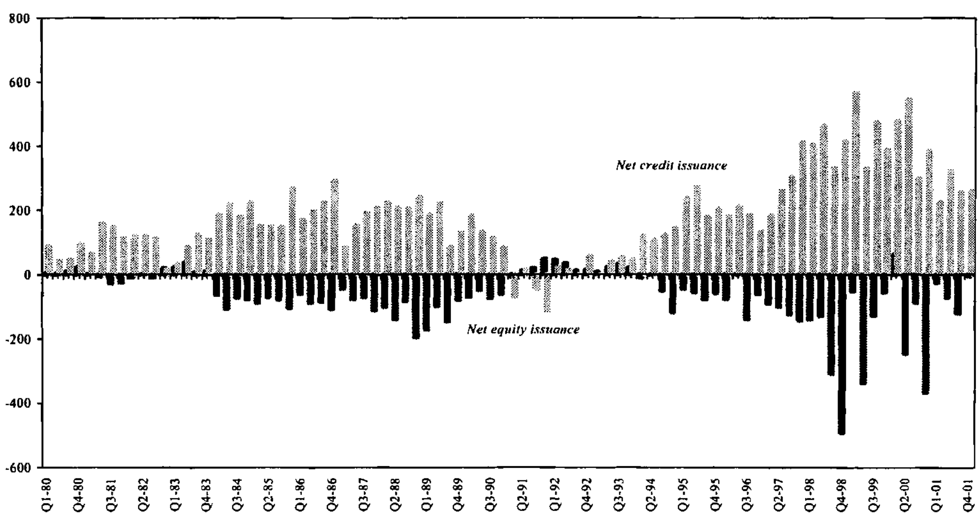
* The spread between yields on Baa-rated Corporate Bond Index and Composite Treasury Bond Index (maturitites of 10 years and above). Leverage is the total leverage, defined as a sum of the balance sheet leverage and the debt burden.

Figure 3. Corporate Sector: Total Leverage *
(In percent)



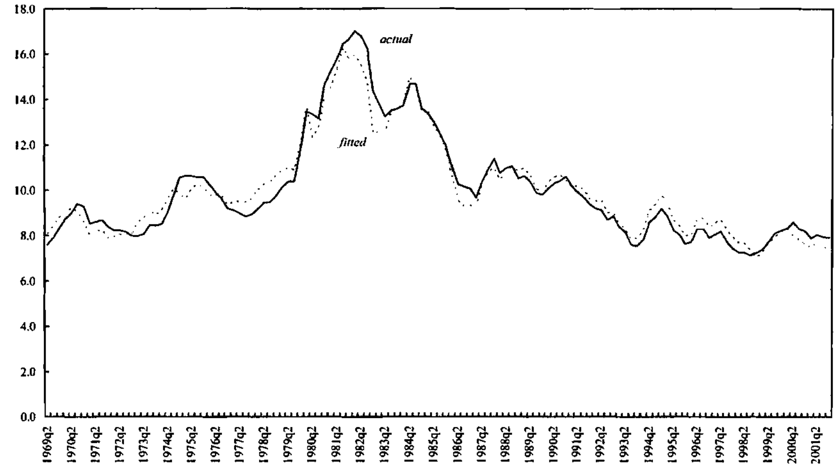
Source: Board of Governors of the Federal Reserve, Flow of Funds Accounts of the United States, and author's estimates.
* The Total Leverage is defined as a sum of balance sheet leverage and a stock of gross debt burden. Shaded areas indicate recession periods.

Figure 4. Nonfarm Nonfinancial Corporate Sector: Funds Raised, $ billions



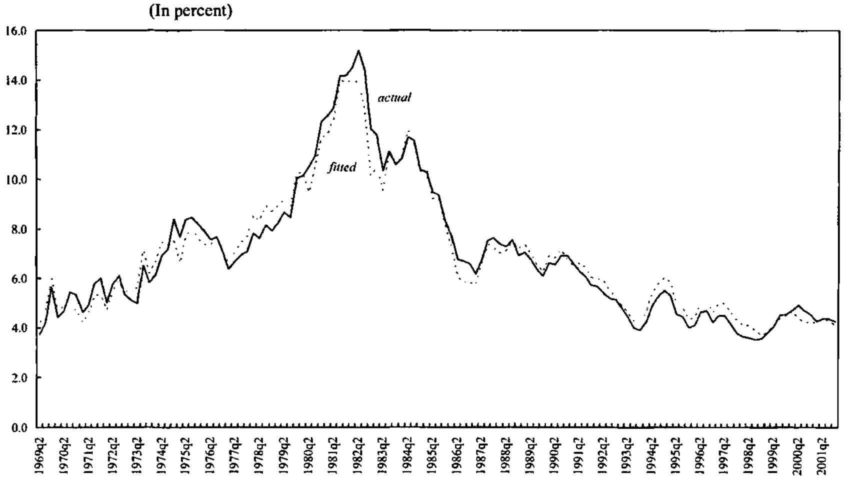
Source: Board of Governors of the Federal Reserve, Flow of Funds Accounts of the United States.

Figure 5. Nominal Corporate Bond Yields: Actual and Fitted
(In percent)



Source: Moody's Investors Service, author's estimates.

Figure 6. Real Corporate Bond Yields: Actual and Fitted
(In percent)

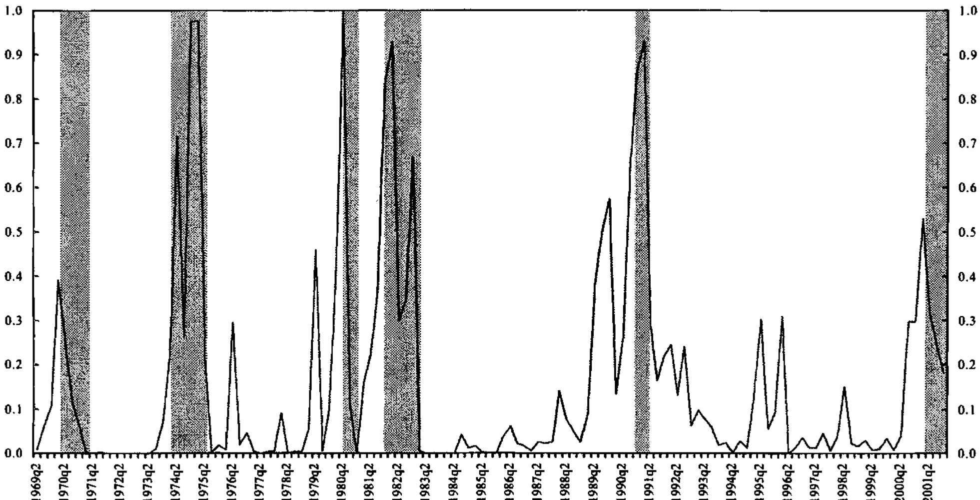


Source: Moody's Investors Service, author's estimates.

Figure 7. Corporate Vulnerability Index*

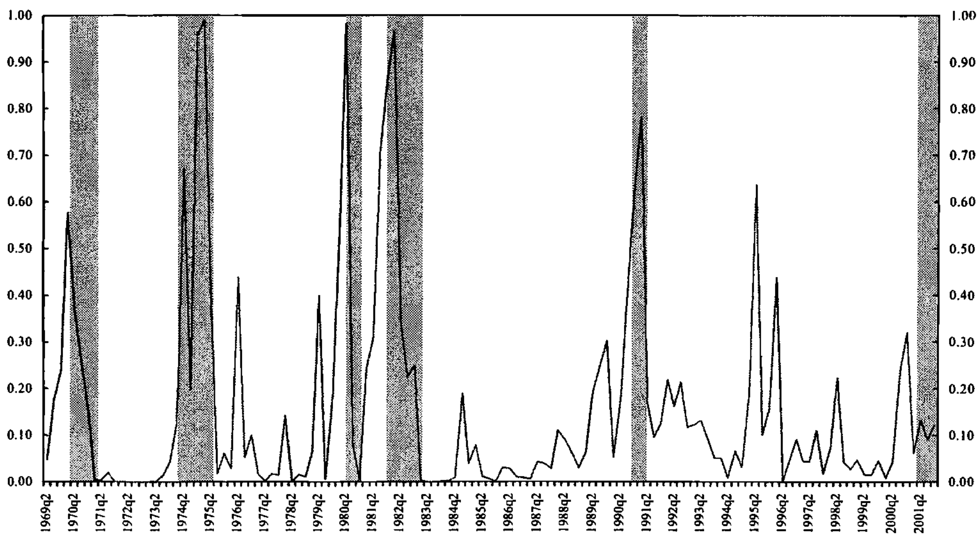
* Shaded areas indicate recession episodes.

Figure 8. Probability of Recession, Predicted with the Corporate Vulnerability Index *



* Shaded areas indicate recession episodes.

Figure 9. Probability of Recession, Predicted without the Corporate Vulnerability Index*



* Shaded areas indicate recession episodes

REFERENCES

Amemiya, Takeshi, 1985, Advanced Econometrics, (Cambridge, Massachusetts: Harvard University Press)

Andersen, Torben, Tim Bollerslev, Francis X. Diebold, and Paul Labys, 2002, "Modeling and Forecasting Realized Volatility," NBER Working Paper No. 8160 (Cambridge, Massachusetts: National Bureau of Economic Research).

Anderson, Ronald, and Suresh Sundaresan, 1996, "Design and Valuation of Debt Contracts," *Review of Financial Studies* 9, pp. 37-68.

_____, _____, and Pierre Tychon, 1996, "Strategic Analysis of Contingent Claims," *European Economic Review* 40, pp. 871-81.

_____, and _____, 2000, "A Comparative Study of Structural Models of Corporate Bond Yields: An Exploratory Investigation," *Journal of Banking And Finance* 24, pp. 255-69.

Bernanke, Ben, 1983, "Non-Monetary Effects of the Financial Crisis in the Propagation of the Great Depression." *American Economic Review* 73, pp. 257-76.

_____, and Mark Gertler, 1986, "Agency Costs, Collateral, and Business Fluctuations," NBER Working Paper No. 2015 (Cambridge, Massachusetts: National Bureau of Economic Research).

_____, and _____, 1990, "Financial Fragility and Economic Performance, "*Quarterly Journal of Economics* 105, pp. 87-114.

_____, and _____, 1995, "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives* 9, pp. 27-48.

_____, _____, and Simon Gilchrist, 1996, "The Financial Accelerator and the Flight to Quality," *Review of Economics and Statistics* 78, pp. 1-15.

_____, and Cara Lown, "The Credit Crunch," *Brookings Papers on Economics Activity* 2, pp. 205-39.

Black, Fisher, and Myers Scholes, 1973, "The Pricing of Options And Corporate Liabilities," *Journal of Political Economy* 81, pp. 637-59.

Carlstrom, Charles T. and Timothy S. Fuerst, 1997, "Agency Costs, Net Worth And Business Fluctuations: A Computable General Equilibrium Analysis," *American Economic Review* 87, pp. 893-910.

Chan-Lau, Jorge, and Iryna Ivaschenko, 2001, "Corporate Bond Risk and Real Activity: An Empirical Analysis of Yield Spreads and Their Systematic Components," Working Paper No. 01/158 (Washington D.C.: International Monetary Fund).

Cookson, Richard, 2001, "Corporate Finance," *Economist*, January 27th.

Delianedis, Gordon, and Robert Geske, 1999, "Credit Risk and Risk-Neutral Default Probabilities: Information about Rating Migrations and Defaults," Working Paper, (Los Angeles: UCLA).

Dotsey, Michael, 1998, "The Predictive Content of the Interest rate Term Spread for Future Economic Growth," Federal Reserve Bank of Richmond *Economic Quarterly* 84, pp. 31-51.

Dueker, Michael, 1997, "Strengthening the Case for the Yield Curve as a Predictor of U.S. Recessions," Federal Bank of St. Louis *Review*, March/April, pp. 41-51.

Duffee, Gregory R., 1998, "The Relation Between Treasury Yields and Corporate Yield Spreads," *Journal of Finance* 53, pp. 2225-43.

Duffie, Darrell, and Kenneth Singleton, 1999, "Modeling Term Structures of Defaultable Bonds" *Review of Financial Studies* 12, pp. 687-720.

Eberhart, Allan, William T. Moore, and Rodney L. Roenfeldt, 1990, "Security Pricing and Deviations from the Absolute Priority Rule in Bankruptcy Proceedings," Journal of Finance 45, pp. 1457-69.

Elton, Edwin J., Martin J. Gruber, Deepak Agrawal and Christopher Mann, 2001, "Explaining the Rate Spread on Corporate Bonds," *Journal of Finance* 56, pp. 247-77.

Eom, Young Ho, Jean Helwege, and Jing-zhi Huang, 2002, "Structural Models of Corporate Bond Pricing: An Empirical Analysis," Unpublished mimeo, (http://www.defaultrisk.com).

Estrella, Arturo, and Gikas Hardouvelis, 1991, "The Term Structure as a Predictor of Real Economic Activity," *Journal of Finance* 46, pp. 555-76.

_____ , and Frederic Mishkin, 1997, "Predicting U.S. Recessions: Financial Variables as Leading Indicators," *Review of Economics and Statistics* 80, pp. 45-61.

Ericsson, Jan, and Joel Reneby, (1998), "A Framework for Valuing Corporate Securities", *Applied Mathematical Finance* 5, 143-163.

Franks, Julian, and Walter Torous, 1989, "An Empirical Investigation of U.S. Firms in Reorganization," *Journal of Finance* 44, pp. 747-69.

_____, 1994, "Comparison of Financial Reconstructing in Distressed Exchanges and Chapter 11 Reorganizations," *Journal of Financial Economics* 35, pp. 349-70.

Fisher, Lawrence, 1959, "Determinants of Risk Premiums on Corporate Bonds," *Journal of Political Economy* 67, pp. 217-37.

Geske, Robert, 1977, "The Valuation of Corporate Liabilities as Compound Options," *Journal of Financial and Quantitative Analysis* 12, pp. 541-52.

Gilchrist, Simon, and Charles P. Himmelberg, 1995, "Evidence on the Role of Cash Flow for Investment," *Journal of Monetary Economics* 36, pp. 541-72.

Greenspan, Alan, 2002, Testimony of Chairman Alan Greenspan *Federal Reserve Board's Semiannual Monetary Policy Report to The Congress* Before the Committee on Financial Services, U.S. House of Representatives, February 27.

Hall, Robert, 2001, "The Stock Market and Capital Accumulation," Hoover Institution (Stanford: Stanford University).

Hoshi, Takeo, Anil Kashyar, and David Scharfstein, 1991, "Corporate Structure, Liquidity, and Investment: Evidence from Japanese Industrial Groups," *Quarterly Journal of Economics* 106, pp. 33-60.

Hubbard, Glenn, Anil Kashyar, and Toni Whited, "Internal Finance and Firm Investment," *Journal of Money, Credit, and Banking* 27, pp 683-701.

Jarrow, Robert, and Stuart Turnbull, 1995, "Pricing Derivatives on Financial Securities Subject To Credit Risk," *Journal of Finance* 39, pp. 611-25.

Jones, E. Phillip, Scott. Mason, and Eric Rosenfeld, 1984, "Contingent Claims Analysis of Corporate Capital Structure: An Empirical Investigation," *Journal of Finance* 39, pp. 611-25.

_____, David Lando, and Stuart Turnbull, 1997, "A Markov Model For The Term Structure of Credit Risk Spreads," *Review of Financial Studies* 10, pp. 481-523.

Kashyap, Anil, Owen Lamont, and Jeremy Stein, 1994, "Credit Conditions and the Cyclical Behavior of Inventories," *Quarterly Journal of Economics* 109, pp. 565-92.

Kim, In Joon, Krishna Ramaswamy, and Suresh Sundaresan, 1992, "The Valuation of Corporate Fixed Income Securities," Working Paper, (New York: New York University).

Kiyotaki, Nobuhiro and John Moore, "Credit Cycles," *Journal of Political Economy* 105, pp. 211-48.

Litterman, Robert, and Thomas Iben, 1991, "Corporate Bond Valuation and The Term Structure of Spreads," *Journal of Portfolio Management* 17, pp. 52-64.

Mella-Barral, Pierre and William Perraudin, 1997, "Strategic Debt Service," *Journal of Finance* 52, pp. 531-56.

Merton, Robert C., 1974, "On The Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* 29, pp. 449-70.

Myers, Stewart C., 1984, "The Capital Structure Puzzle," *Journal of Finance* 39, pp. 575-92.

Moody's Investors Service, 2002a, *Default & Recovery rates of Corporate Bond Issuers. A Statistical Review of Moody's Rating Performance 1970-2001*, February.

Moody's Investors Service, 2002b, *Moody's Credit Perspectives*, Volume 95, No. 3.

Schwert, William, 1989, "Why Does Stock Market Volatility Change Over Time?" *Journal of Finance* 44, pp. 1115-53.

Sharpe, Steven, 1994, "Financial Market Imperfections, Firm Leverage, and the Cyclicality of Employment," *American Economic Review* 84, pp. 1060-74.

Stock, James, and Mark Watson, 1993, "A Procedure for Predicting Recessions With Leading Indicators: Econometric Issues And Recent Performance," in James Stock and Mark Watson (eds.), Business Cycles, Indicators, and Forecasting (Chicago: University of Chicago Press).

_____, and _____, 2001, "Forecasting Output and Inflation: The Role of Asset Prices," NBER Working Paper No.WP8180 (Cambridge, Massachusetts: National Bureau of Economic Research).

Weiss, Lawrence, 1990, "Bankruptcy Resolution: Direct Costs and Violation of Priority of Claims," *Journal of Financial Economics* 27, pp. 285-314.

Wruck, Karen, 1990, "Financial Distress, Reorganization, and Organizational Efficiency," *Journal of Financial Economics* 27, pp. 419-46.

DATA APPENDIX

Calculation of Corporate Interest Payments:

Gross Interest: each subtype of corporate market debt (dealer-placed commercial paper, municipal debt, corporate bonds, bank loans n.e.c. plus other nonbank loans, mortgages) is multiplied by a respective interest rate (see description of interest rate data below).

Net Interest: gross interest after netting out receivables due to corporations. Annual data on net interest of nonfinancial corporations from the NIPA are converted to quarterly data using a cubic spline with the last observation matched to the source data. The data for 2001 are calculated assuming a constant quarterly growth rate, equal to the average growth rate in 2000.

Interest rate data:

All data are from the Federal Reserve Board (FRB), their construction is described in detail on the FRB's web-site. This Appendix only describes changes to the time-series we needed to undertake due to data limitations.

Corporate yields: Moody's average (Baa-rated) bonds, with average maturity of 25 years. Moody's attempts to construct averages derived from bonds whose remaining lifetime is such that newly issued bonds of comparable maturity would be priced off of the 30-year Treasury benchmark. Even though callable bonds are included in the index, issues that are judged susceptible to early redemption are excluded. The construction of the average yields is described in the Moody's Weekly Credit Survey, Corporate Yield Average Guidelines.

Treasury yields: 30-year constant maturity treasury bonds would have been the closest match for the corporate yield data used. However, these data are only available starting in 1977 (see table below). Therefore, average data on Treasury bonds which are neither due nor callable in less than 10 years (Treasury composite, with maturity over 10 years) are used. Since this series ends in June 2000, it is concatenated with observations calculated as an unweighted average of yields on 30, 20, and 10-year bonds. Unweighted averaging is used by the FRB in constructing the composite long-term bond. The constructed average series closely matches the Composite Fed index. For a construction of the constant maturity indexes, see Federal Reserve Board of Governors web-page: http://www.federalreserve.gov/releases/h15/data/m/tcm30y.txt

Maturity	*Availability, monthly data*
30 year	02:1977 – present
20 year	04:1953 – 12:1986 and 10:1993 – present
10 year	04:1953 – present
Composite (10 year and longer)	01:1925 – 06:2000

Mortgage rate: available only after January 1971, thus is constructed as Moody's AAA corporate bond yield plus 0.76 – an average difference between two series after 1971.

Municipal bond rates: constructed following the methodology described in Hall (2001).

Corporate Paper rate: for the sample Q1 1971 - Q2 1997 historical data on 3-Month A2/P2 Nonfinancial Commercial Paper rate is used. For the sample period 1969 Q1 - 1970 Q4 data are constructed as a sum of 3 the month T-bill yield and 0.78, an average paper-bill difference after 1971 Q1.

Bank lending rate: primary bank lending rate.

List of variables:

Variable name	Description	Source or Calculation
ASSTANG	Tangible assets*	Table B.102. Flow of Funds, Federal Reserve Board (FF, FRB)
ASSTOT	Total assets	Table B.102 (FF, FRB)
ASSFIN	Financial assets	Table F.102 (FF, FRB)
LIABTOT	Total liabilities	Table F.102 (FF, FRB)
DEBT	Liabilities: Credit market debt (Debt)	Table F.102 (FF, FRB)
EQUITY	Market value of equities outstanding (Equity)	(FF, FRB)
PROFITS	Profits with IVA and CCA	NIPA
LEVFIN	Leverage	Credit Market Debt/ Financial Assets
DBTEQTY	Balance sheet leverage	Debt/(Debt+Equity). Book value of debt and market value of equity
DBTASS	Leverage	Debt/Assets. Book value of debt and book value of assets
DBTTANG	Leverage	Debt/Tangible Assets. Book value of debt and book value of assets
DBTFIN	Leverage	Debt/ Financial Assets. Book value of debt and book value of assets
GRSINTR	Estimated gross interest, flow	Estimated as described above. Composition of liabilities: Flow of Funds, Federal Reserve Board Interest Rates: FRB data and estimation, following Hall (2001) (see above).

NETINTR	Estimated net interest, flow	Net interest of nonfinancial corporations, annual data, NIPA Converted to quarterly using cubic spline with last observation matched to the source data. The data for 2001 are calculated using assuming a constant quarterly growth rate, equal to average growth rate in 2000.
GRSBDN	Estimated Gross Interest Burden, flow	Gross interest divided by profits of nonfinancial corporate sector inventory adjustment (IVA) and capital consumption adjustment (CCA), NIPA
NETBDN	Estimated Net Interest Burden, flow	Net interest divided by profits with IVA and CCA, NIPA
GRINTSTOCK	Implied Gross Interest, stock	Estimated as present value assuming constant quarterly flows, equal to estimated gross interest, during next 25 years to maturity. Discount rate set to the current average corporate bond yield.
NETINTSTOCK	Implied Net Interest Burden Stock	Above procedure is applied to *NETINTR*
PROFSTOCK	Implied Stock of Profits	Above procedure is applied to quarterly flows of profits of nonfinancial corporations. Profits with IVA and CCA, from NIPA.
BRDGRSSTK	Stock gross interest burden	Implied stock gross interest / implied stock profits
BRDNETSTK	Stock net interest burden	Implied stock net interest / implied stock profits
TRYLONG	Estimated average yield on long treasury bonds	Unweighted average of constant maturity 10, 20, and 30 Treasury bonds, FRB
TRYCOMP	Average composite yield on Treasury bonds with 10 or more years to maturity	FRB
Y_BAA	Yield on Moody's Baa bonds	FRB
STDDEVSP	Standard deviation of S&P 500 return	Rolling standard deviation, 12-quarter window. Haver Analytics
STDEVWIL	Standard deviation, Wilshire 5000 (available from 1971 only)	Rolling standard deviation, 12-quarter window. Haver Analytics
AVRHRS	Average weekly hours, manufacturing	Haver Analytics

VENDOR	Vendor performance, slower deliveries diffusion index, percent	Haver Analytics
HOUSING	New private housing unites authorized by local building permits (thousands, SAAR)	Haver Analytics
TRY_STR	Treasury yield curve: 10-year Treasury bond less Fed Funds rates (%)	Haver Analytics
SPRET	Stock price return: S&P 500 Composite	Estimated as $R_t = lnI_t - ln\ I_{t-1}$, where I_t is the value of S&P500 Composite stock index. Haver Analytics

* All data, except for interest rates, bond yields, and stock returns, are for nonfinancial corporate business.

Essay III

Asian Flu or Wall Street Virus?

Tech and Non-Tech Spillovers in the United States and Asia[1]

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Abstract

Using TGARCH models, this paper finds that U.S. stock markets have been the major source of price and volatility spillovers to stock markets in the Asia-Pacific region during three different periods of the last decade: the pre-Long Term Capital Management crisis period, the "tech bubble" period, and the "stock market correction" period. Hong Kong SAR, Japan, and Singapore were also important sources of spillovers within the Asia-Pacific region and, to a lesser degree, affected the United States during the "stock market correction" period. There is also evidence of structural breaks in the stock price and volatility dynamics induced during the "tech bubble" period.

Keywords: Price spillovers, volatility spillovers, asymmetric GARCH models, stock markets, United States, Asia

JEL Classification Numbers: G12, G14, G15

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I. Introduction

There is a widespread belief within the business and policy-making communities that the financial system has become an increasingly important mechanism for transmitting and amplifying local shocks to the international economy, especially in recent years. This belief is supported by the fact that cross-country correlations between financial variables – in particular, equity prices – increase during periods of market stress.[2] Several arguments have been advanced to explain why stock prices across countries have become increasingly correlated, including the diversification of production across countries by multinationals, easy access to information through the Internet, increased equity issuance and securitization, and the growing importance of the telecommunications, media, and technology (TMT) sector.[3]

Empirical research has found that the importance of global factors relative to country-specific factors in determining stock returns across countries has increased significantly in recent years.[4] Both "new" and "old" economy stocks became particularly correlated during the so called "tech-bubble" period – a synchronous rise of technology stock prices across countries during the period between late 1998 and early 2001, followed by an abrupt correction – while economic fundamentals were not as synchronized.[5] This led some observers to speculate that TMT stocks may have become a new channel of transmitting shocks throughout the world financial markets.

This paper attempts to shed light on the issue by analyzing whether transmission mechanisms differ between the TMT and non-TMT sectors, and whether there were

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[2] For example, King, Sentana, and Wadhwani (1994) and King and Wadhwani (1990) found that sharp changes in one stock market transmitted quickly to other stock markets during the October 1987 crash.

[3] See *Business Week*, September 11, 2000, and the *Economist*, "Rise and Fall: A Survey of Global Equity Markets," May 5, 2001.

[4] See Baca, Garbe, and Weiss (2000), and Brooks and Catao (2000).

[5] The definition of a bubble in this paper is rather loose and refers to a period characterized by a surge in equity prices. For example, the period from the fourth quarter of 1998 to the first quarter of 2000 has been commonly referred to as the "tech bubble" period by the media. For a formal definition of a bubble, which is not used here, see Flood and Garber (1980).

structural breaks in their dynamics. It examines the transmission mechanisms of the conditional first and second moments of daily returns across stock markets in the United States and the Asia-Pacific region for three different periods. The periods under study include the period preceding the "tech bubble," the "tech bubble" period, and its aftermath or the price-correction period. We are especially interested in assessing whether price return and volatility spillovers originated mainly in the United States – the *Wall Street Virus* hypothesis – or in Asian countries – the *Asian Flu* hypothesis. The analysis is based on TGARCH models, which directly model the time-varying behavior of expected stock returns and volatility *conditioning* them on all information currently available to investors. In addition, these models are able to capture the asymmetric effect of negative and positive returns on the conditional variance of returns.[6]

The study finds that price return spillovers between the United States and the Asia-Pacific region were asymmetric. U.S. stock markets played an important role in determining the price dynamics in Asia-Pacific stock markets regardless of the sector analyzed.[7] Price spillovers from the Asia-Pacific countries had little or no effect on U.S. stock markets, especially TMT stocks. Only during the price correction period did spillovers from Japan, Hong Kong SAR, Singapore and Thailand became significant for U.S. non-TMT stock prices. These findings support the *Wall Street Virus* hypothesis over the *Asian Flu* hypothesis. One explanation of these findings is that the process of price discovery in the United States is more efficient, and hence, closely monitored and followed in other countries. Another interpretation is that prices in other markets tend to mimic those in the United States, a symptom of herding behavior abroad.[8]

The results also show that at the regional level, the importance of price spillovers from Japan and Hong Kong SAR in determining price returns in other Asia-Pacific stock markets increased during the price-correction period. Moreover, spillover patterns reveal

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[6] Bollerslev, Chou and Kroner (1992) and Bollerslev, Engle and Nelson (1994) provide two excellent surveys on the application of ARCH models in the area of financial econometrics.

[7] China was the only country not affected by the United States.

[8] This behavior is exemplified by the following quotation: "Asian shares posted broad-based gains... after Wall Street posted its biggest rise in more than six weeks." (Reuters World service, August 27, 2001).

substantially different price dynamics in the TMT and non-TMT sectors, with few markets exhibiting the same patterns across sectors. Finally, the importance of volatility spillovers compared to price return spillovers is small, and often not significant.

The structure of the rest of the paper is as follows. Section II reviews the related literature. Section III describes the data used in the study. Section IV explains the empirical methodology. Section V presents the results. Section VI concludes.

II. Related Literature

There is a substantial amount of theoretical and empirical work on documenting and analyzing how stock returns and volatility are transmitted across countries.[9] On the theoretical side, a number of explanations based on the "revision of expectations" have been advanced. For example, King and Wadhawani (1990) argue that mistakes may be transmitted between two markets since domestic traders have to infer information imperfectly from foreign prices. Kodres and Pritsker (2002) suggest that the existence of feedback traders and asymmetric information could lead to the propagation of shocks through portfolio rebalancing effects. Calvo (1999), and Calvo and Mendoza (2000) argue that co-movements in stock markets are caused by the herd behavior among portfolio managers. The importance of information asymmetries highlighted by the studies cited above is partly supported by survey studies such as Shiller, Konya, and Tsutsui (1991). Other studies – Kyle and Xiong (2001), Lagunoff and Schreft (1999), and Schinasi and Smith (2000), among others – argue that technical factors, such as margin calls and convergence trades, could lead to increased co-movements in stock markets.

In empirical studies, the simplest way to evaluate the interrelation of stock returns across markets is to compare simple correlations for different periods. Examples of this approach are numerous, for instance, Hilliard (1979), Eun and Shim (1989), Roll (1988,

[9] De Bandt and Hartmann (2000) provide a useful survey of the literature, emphasizing the relationship between increased stock market correlation and systemic risk. Jarrow (1998) provides a selected survey of multivariate GARCH models.

1989), Bertero and Mayer (1990), Baig and Goldfajn (1999), and Kumar, et. al. (2001).[10] This approach, however, has been questioned by Boyer, Gibson and Loretan (1997), Rigobón and Forbes (1998), and Rigobón (2000), among others. These authors point out that even if the data are generated from the same multivariate normal distribution, the sample correlation estimate obtained from a high volatility subsample would be higher than that corresponding to a low volatility subsample. The use of simple correlations, then, would lead to the identification of structural breaks in the transmission mechanism which are nonexistent.

Other studies have adopted a different empirical approach based on ARCH models and their variants. This approach is warranted given the fact that stock price volatility is time-varying and that high volatility episodes are usually characterized by a high correlation of stock market returns. Among these studies, our work is closely related to that of Hamao, Masulis, and Ng (1990). These authors study price changes and volatility spillovers across the New York, Tokyo, and London stock markets using various univariate GARCH models. They found volatility spillovers only for the period following the October 1987 crash and identified an asymmetry, that is Tokyo stock markets were affected by the London and New York stock markets but did not have any effect on them in turn. Lin, Engle and Ito (1994) use a signal extraction model with GARCH processes to analyze spillovers between Tokyo and New York. Once the close-to-close returns were decomposed into daytime and overnight returns, the authors were able to detect spillovers from Tokyo to New York.

The use of the ARCH methodology to study stock market interdependences has not been limited to univariate models. Booth, Martikainen and Tse (1997) analyze price and volatility spillovers across Scandinavian stock markets using a multivariate EGARCH model and find that Sweden is a major spillover source. Theodossiou (1997) estimates a multivariate GARCH model to analyze return spillovers in the United States, Japan, and the United Kingdom during the October 1987 stock market crash. In contrast

[10] The correlations can be obtained either as sample correlations, using simple OLS regressions, or using the exponential smoothing method popularized by RiskMetrics.

to Hamao, Masulis and Ng (1990), this study found that spillovers from Japan to the United Kingdom were significant.

III. DATA

The analysis in this paper uses daily close-of-day (business days) stock market prices in the United States and a number of markets of the Asia-Pacific region, including Australia, China, Hong Kong SAR, India, Japan, Korea, Malaysia, New Zealand, Philippines, Singapore, Taiwan Province of China, and Thailand. The choice of countries examined in the Asia-Pacific region has been guided by the availability of the stock market data. Stock market prices correspond to the proprietary indices compiled by Primark Datastream for two sectors: the Telecommunications, Media, and Technology (TMT) sector and the Total Stock Market Excluding the TMT (TXT, or non-TMT) sector.

The selection of Primark Datastream TMT and TXT indices is guided by the following considerations. First, the sectoral indices are constructed using the same methodology across countries, which enhances the consistency of the results. Second, these indices are available as fixed-history indices. They are not recalculated historically when constituents change, which enables the effects of "dead" stocks on the index to be seen. This feature is especially important because the analysis of this paper is concerned with evaluating the aggregate impact of one equity market on another. Finally, these data are available for a wide range of countries; since January 1996 for China and India, and since January 1990 for all other countries. All indices are expressed in local currency units, which helps disentangling stock price effects from exchange rate effects.[11]

Data limitations force us to use close-to-close price returns that are calculated as changes in log closing prices, $R_t = lnP_t - lnP_{t-1}$. The use of close-to-close returns may induce spurious cross-autocorrelation between stock markets because of asynchronous trading. However, results by Hamao, Masulis and Ng (1990) show that correcting for this

[11] Hamao, Masulis and Ng (1990) report that currency denomination of stock prices does not change results substantially.

using open-to-close returns – which are not susceptible to the spurious cross-autocorrelation problem – does not change the results significantly.

IV. Empirical Methodology

Generalized Autoregressive Conditional Heterokedastic (GARCH) models are used to analyze stock return and volatility spillovers across the different stock markets described in the previous section.[12] In particular, after some experimentation with model specifications using the likelihood ratio statistics, the TGARCH(1,1)-MA(1) model was chosen because it provided a parsimonious specification that fitted the stock return series well for all the countries analyzed.[13] The choice of an asymmetric GARCH specification, TGARCH, was motivated by the apparent asymmetry in conditional volatility responses to negative and positive shocks present in the stock return data. [14] The MA(1) term was included to capture serial correlation present in stock index returns, as in Bollerslev (1987) and French, Schwert, and Stambaugh (1987).[15] While using a single model to fit all stock markets significantly facilitates cross-country comparisons, the results are generally robust with respect to different model specifications that fit domestic stock return data well.

The following TGARCH(1,1)-MA(1) model was used to test for spillovers in conditional mean and volatility across national stock markets:

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[12] The GARCH model was first suggested by Bollerslev (1986) as a generalization of the ARCH model developed by Engle (1982).

[13] The TGARCH family of statistical models was first introduced by Zakoian (1994) and Glosten, Jaganathan and Runkle (1993), and is a special case of the Box-Cox transformation of the absolute GARCH (AGARCH) model, as shown by Hentschel (1995).

[14] Black (1976) demonstrated the existence of asymmetric effects (so called leverage effects) on the conditional variance, whereby negative equity returns are usually followed by larger increases in volatility than is the case with equally large positive returns.

[15] Scholes and Williams (1977) and Cohen et al. (1980) show that nonsynchronous trading in individual stocks, bid-ask spreads, and minimum-price changes can cause serial correlation in stock returns. Hamao et al. (1990) show that the inclusion of a MA(1) term is sufficient to extract serial correlation from the first moments of stock returns, finding no support for higher-order MA terms. We also estimate model (1)-(4) using weekly returns, less prone to noncynronous trading effects. The results are generally robust and conclusions are consistent with those obtained using daily returns.

$$R_t = \text{constant} + \beta R^f_{t-l} + \theta\varepsilon_{t-1} + \varepsilon_t, \qquad (1)$$

where the price return in the domestic stock market, R_t, is a linear function of the lagged return on the foreign stock market which is assumed to be the source of spillovers (spillover-originating market), R^f_{t-l}, and the error term, ε_t, which follows an MA(1) process.[16] The foreign return lag, l, is specified so that it accommodates the time differences between the United States and the Asia-Pacific region, and among the countries of the Asia-Pacific region. The coefficient on the foreign lagged return, β, measures price return spillovers from a spillover-originating market to a domestic market (spillover-receiving market). The conditional variance of the error term, σ^2_t, is given by:

$$\sigma^2_t = \text{constant} + \alpha\varepsilon^2_{t-1} + \gamma\varepsilon^2_{t-1}d_{t-1} + \zeta\sigma^2_{t-1} + \lambda X^f_{t-l}, \qquad (2)$$

where the dummy variable, d_t, is equal to 1 if ε_t is positive, and zero otherwise. The inclusion of the dummy variable allows for capturing the possible asymmetric effects of good news (positive ε_t) and bad news (negative ε_t). The regressors ε^2_{t-1}, $\varepsilon^2_{t-1}d_{t-1}$, and σ^2_{t-1} are commonly denominated as the GARCH, TARCH, and ARCH component, respectively. X^f_{t-l} is the volatility surprise from the same spillover-originating market which is used in equation (1), lagged l periods. The coefficient λ measures volatility spillovers from the spillover-originating market. Because the volatility surprise is an unobservable variable, it needs to be estimated. To do this, we follow the methodology first proposed by Hamao, Masulis, and Ng (1990).

Hamao, Masulis, and Ng (1990) suggest that the volatility surprise term corresponds to the squared residual derived from a GARCH model estimated for a

[16] Model (1)-(4) has also been estimated for each country including lagged domestic stock return among the regressors in mean equations (1) and (3) to capture domestically-specific factors. Lagged domestic returns are mostly insignificant across the periods and countries analyzed, and their inclusion does not significantly affect the magnitude and significance of the spillover coefficients.

spillover-originating market without including other countries' variables among the regressors. Hence, in this paper, the volatility surprise term was estimated as the squared residual derived from the following TGARCH(1,1)-MA(1) model applied to the daily close-to-close return of the stock price index in the spillover market:

$$R_t^f = \text{constant} + \alpha^f R_{t-1}^f + \theta^f \varepsilon_{ft-1} + \varepsilon_{ft}, \tag{3}$$

$$\sigma_{ft}^2 = \text{constant} + \gamma^f \varepsilon_{ft-1}^2 + \beta^f \varepsilon_{ft-1} d_{t-1} + \delta^f \sigma_{ft-1}^2 \tag{4}$$

Equation (3) indicates that for any given period the price return, R_t^f, is a function of its lag, and a moving average error term, ε_{ft}. The dynamics of the conditional variance are given by equation (4). To simplify the description of the model, equations (1)-(2) are referred to as a *spillover model*, and equations (3)-(4), as a *base model* throughout the rest of the paper.

The base model was estimated for the three different time periods, specified in the introduction: (i) the period prior to the boom in technology stock prices, from January 1, 1990 to August 31, 1998 (here called the pre-bubble period); (ii) the technology boom period from September 1, 1998 to March 27, 2000 (the tech bubble period); (iii) and the period of rapid technology stock price decline from March 28, 2000 to May 1, 2001 (the post-bubble period). The choice of periods roughly reflects stock price trends across the United States and the Asia-Pacific region.[17] Estimation was performed for the TMT and non-TMT sectors for each country assumed to be a potential source of spillovers: the United States, Japan, Hong Kong SAR, Singapore, Malaysia, and Thailand. The United States and Japan were included as possible sources of spillovers to the Asian region because of their economic importance, Hong Kong SAR and Singapore because they are important regional financial centers, and Malaysia and Thailand because they were major sources of price and volatility spillovers during the 1997 Asian financial crisis.

[17] The results are generally robust to minor changes in the period definition.

For each sector and spillover market, volatility surprise terms were estimated from the base model, and used subsequently in the estimation of the spillover models for the remaining countries in the sample, for the corresponding sector. Since generating volatility surprises from the base model (3)-(4) may introduce a generated regressor problem into model (1)-(2), we also used squared returns and residuals, generated by fitting an ARMA(1,1) model to the squared returns, as alternative volatility proxies. The results (not presented in the paper for the sake of brevity) are robust to these alternative proxies. As in the case of the base model, the spillover models were estimated for the three different time-periods described above. Wald tests were conducted to evaluate the null hypothesis that spillover coefficients between the following two pairs of time-periods are the same: (i) the tech bubble and pre-bubble periods, (ii) the post-bubble and bubble periods, and (iii) the post-bubble and pre-bubble periods. The model was estimated using maximum likelihood.[18] The main results are summarized in the next section.

V. Estimation Results

This section analyzes whether the United States, Japan, Hong Kong SAR, Singapore, Malaysia and Thailand were important sources of stock return and volatility spillovers in the Asian region, as well as whether spillovers from the above five Asian stock markets have had a significant impact on stock markets in the United States.

Overall, the main results are: (i) the U.S. stock markets have been the most important source of return spillovers to the Asia-Pacific region during the last ten years, but their relative importance during the post-bubble period has diminished as the importance of the largest stock markets in the region – Japan, Hong Kong SAR, and Singapore – has significantly increased both in the TMT and non-TMT sectors; (ii) Asia-Pacific stock markets have had only a limited impact on the stock market price dynamics experienced in the United States, as there have been neither large return nor volatility spillovers, regardless of the sector and period analyzed. In fact, for the last ten years, the United States stock market has been one of the markets least affected by developments in

[18] Since standardized residuals of model (1)-(4) exhibit excess kurtosis for almost all countries, robust Bollerslev-Wooldridge quasi-maximum likelihood standard errors are used (Bolerslev and Wooldridge, 1992).

foreign stock markets, both in the TMT and non-TMT sectors; (iii) the changes in magnitude of spillover coefficients – spillover patterns – differ between TMT and non-TMT sectors across countries; (iv) spillovers between countries in the Asia-Pacific region increased over the course of the three periods analyzed, irrespective of sector, while spillovers from the United States increased only in the TMT sector and declined in the non-TMT sector; and (v) across all periods, volatility spillovers are not as important as return spillovers, irrespective of the spillover market examined.

The results are summarized in Tables 1 to 3. Table 1 shows the three countries most affected by and the three countries least affected by price spillovers, for each spillover-originating country, sector, and period analyzed. Table 2 presents the average spillover effects for different country groupings in the region (the largest markets, the smallest countries, the countries-sources of spillovers), Japan, and the United States. Table 3 presents the spillover patterns.[19]

Price return spillovers from the ***United States*** – as measured by the impact of the previous day price returns in the United States on the price returns in Asia-Pacific stock markets – are significant in both the TMT and non-TMT sectors (Table 2). The sole exception in the Asia-Pacific region is China, which was insolated from spillovers from the United Sates during the bubble and post-bubble periods. In the TMT sector, a one percent change in stock returns in the United States translates into an average change of 0.25 percent for returns in the Asia-Pacific region during the pre-bubble period, a 0.29 percent for returns during the bubble period, and a 0.24 percent for returns during the post-bubble period (Table 2). During the bubble period, price spillover coefficients increased for 8 out of 13 countries.

Spillovers increased substantially among major markets in the region (Australia, Hong Kong SAR, Korea, Japan, and Singapore) during the time-frame examined. They jumped from an average of 0.27 percent during the pre-bubble period to 0.31 percent

[19] Due to a large number of countries analyzed, we did not include the estimation results for individual spillover markets for the sake of brevity. The detailed results are available in the working paper version (Chan-Lau and Ivaschenko, 2002).

during the bubble period, and rose further to 0.34 percent during the post-bubble period. Conversely, spillovers to the smallest markets started from a lower 0.24 percent level, remained flat during the bubble period, and dropped well below their pre-bubble level afterwards. This evidence suggests that major financial markets are better integrated.

The corresponding patterns of spillovers from the United States in the non-TMT sector are different (Tables 2 and 3).[20] Spillovers during the pre-bubble period are higher (0.30 percent), rise much more during the bubble period (to 0.39 percent), and drop more dramatically during the post-bubble period (to 0.26 percent).[21] The increase in spillover magnitudes during the bubble period is characteristic only for large countries (with the exception of Japan). By contrast, a decline in spillovers during the post-bubble period well below pre-bubble levels is observed for both larger and smaller countries. Therefore, while spillover levels were higher in the non-TMT sector before the bubble period, the magnitude of spillovers in the non-TMT sector dropped to levels comparable to those in the TMT sector after the bubble period.

There is a significant variation in the magnitude of spillovers from the United States across countries. In the TMT sector, average price spillovers in the three most affected countries are high and increase across time – 0.34 percent, 0.40 percent, and 0.43 percent for the pre-bubble, tech-bubble and post-bubble periods, respectively. In the three least affected countries they are much smaller and virtually disappear after the bubble. The same large variation in spillovers is also observed in the non-TMT sector, where the average price spillovers in the three most affected countries are 0.49, 0.59, and 0.48 percent in the pre-bubble, tech-bubble and post-bubble periods, respectively. In the three least affected countries spillovers are just about 0.05 percent for all three periods.

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[20] Wald tests were conducted to evaluate whether both price spillover and volatility spillover coefficients for each period and each country are statistically different between TMT and non-TMT sectors.

[21] This finding is somewhat surprising given the popular believe that TMT stocks were more correlated during the tech bubble period. Probably, these results suggest that during the bubble period, strong spillovers from TMT stocks to non-TMT stocks existed within national markets, thus reinforcing the ties between non-TMT markets across countries.

With respect to volatility spillovers, the results indicate that, unlike price spillovers, they are mostly insignificant across periods and sectors. Volatility spillovers became significant only after the bubble burst, and only for some countries – specifically, for four countries in TMT sector estimations, and six countries in non-TMT sector estimations. In the non-TMT sector, Korea and Japan are exceptions as volatility spillovers to these countries were insignificant only during the bubble period, increasing more than eight-fold compared to their pre-bubble levels after the bubble burst.

Spillovers from ***Japan*** have been increasingly important determinants of stock returns for countries in the Asia-Pacific region, with the exception of China, where spillovers have been insignificant. Spillovers from Japan are not very important determinants of stock returns in the United States in either sector.

In the TMT sector, average price spillovers from Japan to other countries in the region almost doubled during the bubble period and increased further the following period to a level almost three times higher than that during the pre-bubble period (Tables 2 and 3). For example, while during the pre-bubble period a one percent increase in Japanese stock returns is associated with only a 0.13 percent increase in stock returns in the region, after the bubble this effect rises to 0.34 percent. The same pattern is observed for both large and small countries in the region, although with smaller magnitudes for smaller markets. Spillovers from Japan to major markets in the region increased from 0.18 percent during the pre-bubble period to a whopping 0.41 percent after the bubble; for smaller markets spillover magnitudes increased from 0.13 to 0.27 percent, respectively. As a result, although spillovers from Japan were much smaller than those from the United States before the bubble, they became higher after the bubble burst.

Non-TMT spillovers from Japan to the rest of the region increased significantly during the bubble period, even more than those from the United States. In contrast to the United States, spillovers from Japan declined only slightly after the bubble, with a resulting two-fold increase in spillovers from the pre-bubble to the post-bubble period, that is, from 0.15 percent to 0.30 percent, respectively. This pattern is observed for most countries in the region, irrespective of size. The resulting spillovers – those in the post-bubble period – are comparable to those from the United States, with the exception of the three least affected countries, for which spillovers from Japan are more than two times higher.

Volatility spillovers from Japan are not very significant determinants of stock return volatility in the other countries. This fact is especially salient with respect to TMT stocks, where volatility spillovers are significant only after the bubble burst and in only two countries. Volatility spillovers are somewhat more important in the non-TMT sector, especially during the pre-bubble period, with coefficients being significant in five countries. However, the number of countries affected declined to two during and after the bubble. These results are similar to those obtained for U.S. spillovers and corroborate the conjecture that volatility considerations were not important determinants of stock pricing, especially across TMT markets and after the technology-related rally in stock prices began.

Patterns of ***spillovers from other countries*** in the region corroborate our conjecture that TMT stock markets in the region became more interrelated during and after the bubble period. Spillovers between countries in the region, including Japan, increased noticeably after the bubble period. There is a clear "size effect" in the magnitude of spillovers: spillover coefficients, in general, increase with the size of the country generating spillovers and decline with the size of the country receiving spillovers. For example, spillovers from Hong Kong SAR—the second largest market in the region and an important financial center—to the largest markets in the region are significantly higher than those from smaller markets.

It is worth noting that TMT spillovers from Hong Kong SAR to smaller markets declined during and after the bubble period, while spillovers from Japan increased. This suggests that smaller technology markets in the region became increasingly influenced solely by developments in Japanese markets during the bubble period, with virtually no feedback from those markets to Japan. However, spillovers from other markets to Japan did increase significantly after the bubble burst, suggesting that Japanese investors began paying greater attention not only to information from the United States, but also from regional markets.

The pattern of non-TMT market spillovers within the region is very similar to that of the TMT market. In general, intra-regional spillovers are more important during and after the bubble period, and spillovers to the United States are largely negligible.

However, there are important differences. The magnitudes of spillovers are somewhat higher in the non-TMT sector across all periods. Moreover, the "size effect" is much less pronounced. In fact, spillovers from the non-TMT sector of Hong Kong SAR to the rest of the region are much higher than corresponding spillovers from Japan, especially in the post-bubble period, and spillovers from Singapore and Malaysia are comparable to those from Japan. The apparent lack of a pronounced "size effect" suggests that specific features associated with major markets – for example, ample liquidity and broad investor recognition – may be of less importance for pricing non-TMT stocks, while company fundamentals may play a relatively more important role. This observation is worth exploring in future research.

It is worth noting that volatility spillovers from Hong Kong SAR and smaller countries in the region are, on average, much more pronounced than those from the United States and Japan. In the TMT sector, Hong Kong SAR is an especially important source of volatility spillovers to markets in the region (excluding Japan) for the post-bubble period. While there is no clear pattern in the magnitude of spillovers, the share of affected countries increases from 45 percent during the pre-bubble and bubble periods to 64 percent in the post-bubble period. Volatility spillovers from Singapore also become important after the bubble. Spillovers from Thailand are important only before the bubble period, possibly owing to the fact that Thailand was one of the countries viewed as a source of contagion during the Asian crisis. The fact that unexpected volatility surprises become much more important determinants of regional TMT stock returns after the bubble burst suggests that investors became more careful in pricing risks after stock prices began to fall.

In the non-TMT sector, volatility spillovers from Hong Kong SAR and Singapore are important for most countries (including Japan) only before the bubble period, with the number of countries affected declining significantly later on. This suggests that once investors became less concerned with volatility shocks when stock price increased during the bubble period, they maintained this pricing approach even after the bubble burst. These results, however, should be interpreted with caution, since they may be biased by such high volatility episodes as the Asian crisis and LTCM debacle.[22]

VI. Conclusions

This study contributes to the knowledge of price dynamics in the technology and non-technology sectors of the stock market in the United States and a number of Asian countries, by focusing on price and volatility spillovers across countries in both sectors prior to, during, and after the run-up in tech stock prices.

The empirical findings suggest that, so far as price return spillovers between the United States and the Asia-Pacific region are concerned, the *Wall Street virus* is a more important carrier of the "disease" than the *Asian flu*, for both TMT and non-TMT stocks. However, intra-regional spillovers are important determinants of stock returns in the Asia-Pacific region. The results also point out that spillover mechanisms have experienced structural changes during the periods analyzed, and that spillover patterns in the TMT and non-TMT sectors differ significantly. Specifically, spillovers from the United States to countries in the Asia-Pacific region increased in the TMT sector but declined in the non-TMT sector. At the same time, intra-regional spillovers increased regardless of the sector analyzed.

In sharp contrast to the results found in some earlier papers, volatility spillovers do not appear to play an important role in most of the cases. This result is likely driven by the fact that we allow for asymmetric effects in the conditional variance. Some caution is

[22] We have chosen specifications of volatility equations in model (1)-(4) so that the goodness-of-fit does not vary substantially across periods. However, a break in volatility-generating process in one of the periods might affect model's fit and influence the results.

warranted in deriving policy conclusions from the results, however, since the analysis did not look in detail into particular crisis episodes, such as the 1997 Asian financial crisis or the 1998 LTCM debacle, which took place during the time frame analyzed.

Table 1: Countries Most And Least Affected By Price Spillovers.

Panel A: Most Affected Spillover-Receiving Countries *

Spillover-receiving countries	Spillover-generating countries: United States TMT	United States Non-TMT	Japan TMT	Japan Non-TMT	Hong Kong SAR TMT	Hong Kong SAR Non-TMT	Singapore TMT	Singapore Non-TMT	Malaysia TMT	Malaysia Non-TMT	Thailand TMT	Thailand Non-TMT
Australia	1,2	1	2	1	3						1	
China												
Hong Kong	1,2,3	1,2,3	1,2,3	1,2,3			2,3	1,2,3	1	1,2,3	2,3	1,2,3
India			1		1		1		1,2		1,2	
Indonesia			3	3			3				3	
Japan	3				2,3				3			
Korea	2,3	2,3	2,3	2,3	2,3	2,3	2,3	2,3	2,3	3	2,3	2,3
Malaysia					1	1	1	1			1	1
New Zealand	1											
Philippines										3		
Singapore		2	1			1,2,3				1,2		2,3
Taiwan		1		1								1
Thailand		3		2	1,2	1,2,3	1,2	1,2,3	1,2,3	1,2		
United States												

* 1 = country affected in pre-bubble period, Jan. 2, 1990-Aug. 31, 1998; 2 = country affected in tech-bubble period, Sep. 1, 1998-Mar. 27, 2000;
3 = country affected in post-bubble period, Mar. 28, 2000-May 1, 2001.

Panel B: Least Affected Spillover-Receiving Countries **

Spillover-receiving countries	Spillover-generating countries: United States TMT	United States Non-TMT	Japan TMT	Japan Non-TMT	Hong Kong SAR TMT	Hong Kong SAR Non-TMT	Singapore TMT	Singapore Non-TMT	Malaysia TMT	Malaysia Non-TMT	Thailand TMT	Thailand Non-TMT
Australia		3		3			2	3		2		3
China	1,2,3	1,2,3	3		1,3	1,2,3	3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3
Hong Kong									3			
India	3	3		1,3	3	3			3	3	3	
Indonesia	1	1,2	1	1,2			1,2	1,2	1,3	2,3	1	2
Japan											2	
Korea	1	1	1		1	1						
Malaysia	2,3				2	2	2					
New Zealand				2	2	2	1,2		2	1	1	1
Philippines			3				3	3	3			
Singapore	2		2						2			
Taiwan		2							2,3			
Thailand			2									
United States			1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2	1,2,3	1,2,3	1,2,3	1,2,3

** 1 = country affected in pre-bubble period, Jan. 2, 1990-Aug. 31, 1998; 2 = country affected in tech-bubble period, Sep. 1, 1998-Mar. 27, 2000;
3 = country affected in post-bubble period, Mar. 28, 2000-May 1, 2001; if more than three countries are reported for any given period, spillovers were insignificant.

Table 2. Price Spillovers Across Different Countries.

Spillover-receiving countries	Period	Spillover-originating countries					
		TMT sector					
		United States	Japan	Hong Kong SAR	Singapore	Malaysia	Thailand
All countries in the region	*Pre-bubble*	0.25	0.13	0.17	0.11	0.11	0.08
	Tech-bubble	0.29	0.20	0.18	0.16	0.13	0.13
	Post-bubble	0.24	0.34	0.23	0.26	0.14	0.30
The largest regional markets**	*Pre-bubble*	0.27	0.18	0.13	0.09	0.11	0.07
	Tech-bubble	0.31	0.34	0.20	0.15	0.11	0.11
	Post-bubble	0.34	0.41	0.35	0.30	0.16	0.27
Spillover countries in the Asia-Pacific region***	*Pre-bubble*	0.23	0.18	0.19	0.16	0.14	0.08
	Tech-bubble	0.29	0.26	0.21	0.16	0.13	0.12
	Post-bubble	0.24	0.33	0.26	0.25	0.18	0.29
Smaller regional markets ♦	*Pre-bubble*	0.24	0.13	0.20	0.13	0.10	0.09
	Tech-bubble	0.24	0.17	0.17	0.16	0.11	0.13
	Post-bubble	0.15	0.27	0.16	0.20	0.09	0.28
Three most affected countries ♦	*Pre-bubble*	0.34	0.20	0.24	0.22	0.18	0.12
	Tech-bubble	0.40	0.36	0.34	0.21	0.21	0.26
	Post-bubble	0.43	0.57	0.38	0.43	0.20	0.49
Three least affected countries ♠	*Pre-bubble*	0.11	0.07	0.03	0.01	0.01	0
	Tech-bubble	0.13	0	0.02	0	0	0.02
	Post-bubble	0.04	0.03	0.04	0	0	0.08
United States	*Pre-bubble*	-	0.06	0.04	0.04	0.02	0
	Tech-bubble	-	0	0	0	0	0
	Post-bubble	-	0.14	0.12	0.04	0	0
Japan	*Pre-bubble*	0.26	-	0.15	0.07	0.07	0.05
	Tech-bubble	0.26	-	0.21	0.08	0.04	0.06
	Post-bubble	0.41	-	0.34	0.23	0.19	0.31

Table 2 (cont.). Price Spillovers Across Different Countries.

Spillover-receiving countries	Period	Spillover-originating countries					
		non-TMT sector					
		United States	Japan	Hong Kong SAR	Singapore	Malaysia	Thailand
All countries in the region	*Pre-bubble*	0.30	0.15	0.22	0.38	0.25	0.14
	Tech-bubble	0.39	0.31	0.31	0.30	0.14	0.15
	Post-bubble	0.26	0.30	0.39	0.32	0.26	0.18
The largest regional markets**	*Pre-bubble*	0.36	0.22	0.18	0.35	0.28	0.13
	Tech-bubble	0.47	0.47	0.39	0.36	0.15	0.18
	Post-bubble	0.33	0.30	0.45	0.41	0.31	0.15
Spillover countries in the Asia-Pacific region***	*Pre-bubble*	0.38	0.20	0.27	0.58	0.38	0.16
	Tech-bubble	0.42	0.51	0.38	0.41	0.20	0.18
	Post-bubble	0.31	0.30	0.39	0.37	0.33	0.18
Smaller regional markets •	*Pre-bubble*	0.32	0.11	0.25	0.40	0.23	0.15
	Tech-bubble	0.29	0.26	0.26	0.30	0.11	0.11
	Post-bubble	0.21	0.23	0.35	0.26	0.21	0.14
Three most affected countries ♠	*Pre-bubble*	0.49	0.24	0.31	0.67	0.45	0.19
	Tech-bubble	0.59	0.64	0.53	0.53	0.23	0.24
	Post-bubble	0.48	0.54	0.63	0.60	0.48	0.30
Three least affected countries ♠	*Pre-bubble*	0.05	0.04	0.07	0.07	0.03	0.03
	Tech-bubble	0.05	0.05	0.00	0.00	0.00	0.00
	Post-bubble	0.06	0.16	0.03	0.03	0.00	0.01
United States	*Pre-bubble*	-	0.05	0.05	0.07	0.04	0.03
	Tech-bubble	-	0.00	0.00	0.00	0.00	0.00
	Post-bubble	-	0.12	0.00	0.14	0.00	0.00
Japan	*Pre-bubble*	0.34	-	0.16	0.27	0.17	0.07
	Tech-bubble	0.32	-	0.28	0.22	0.12	0.12
	Post-bubble	0.17	-	0.29	0.21	0.19	0.08

* Price spillovers measured as the percentage change in price return in the spillover-receiving country corresponding to a one percent change in the price return in the spillover-originating country. Only statistically significant coefficients are taken into account; insignificant coefficients are replaced by zeroes.

** Australia, Hong Kong SAR, Japan, Korea, Singapore

*** Japan, Hong Kong SAR, Singapore, Malaysia, Thailand

• China, Indonesia, Malaysia, New Zealand, Phillipines, Taiwan POC, Thailand

♠ As measured by the average magnitude of spillover coefficients.

Table 3. Price Spillover Patterns from the United States, Japan, Hong Kong SAR, Singapore, Malaysia, and Thailand

Spillover-originating countries

Spillover-receiving countries	United States		Japan		Hong Kong	
	TMT	non-TMT	TMT	non-TMT	TMT	non-TMT
Australia	∨	↓	↑	∧	∨	↓
China	–	└	–	∧	∧	└
Hong Kong SAR	∧	∧	↑	∧		
India	∧	∧	∨	∧	↓	↓
Indonesia	↑	↑	↑	↑	↑	↑
Japan	┘	↓			↑	Γ
Korea	Γ	∧	↑	↑	↑	↑
Malaysia	∧	↓	∨	∧	∨	∨
New Zealand	↓	↓	↑	∧	∨	–
Philippines	∧	↓	↑	↑	└	↑
Singapore	∨	∧	∨	∧	∨	Γ
Taiwan POC	┘	∨	↑	∧	∨	↑
Thailand	∧	∧	↑	∧	∧	∧
United States			∨	∨	∨	└

	Singapore		Malaysia		Thailand	
	TMT	non-TMT	TMT	non-TMT	TMT	non-TMT
Australia	∨	↓	∨	∧	∨	∧
China	–	–	–	∧	–	–
Hong Kong SAR	↑	∨	¬	∨	↑	↑
India	∧	↓	∧	↓	∧	↓
Indonesia	⊥	∨	∧	∧	↑	↓
Japan	↑	↓	∨	∨	↑	∧
Korea	↑	↑	↑	↑	↑	↑
Malaysia	∨	└			↑	∨
New Zealand	∨	∨	∨	∨	↑	∧
Philippines	¬	↓	↓	∨	↑	↑
Singapore			∨	∨	↑	∧
Taiwan POC	⊥	∨	└	∨	↑	∨
Thailand	↑	∧	¬	∨		
United States	∨	∨	└	└	–	└

Spillover patterns:

Γ	upward shift in the tech-bubble period	∧	increase in the bubble period, decline afterwards*
└	downward shift in the tech-bubble period	∨	decline in the bubble period, increase afterwards*
¬	decline in the post-bubble period	↑	increasing across periods
┘	increase in the post-bubble period	↓	decreasing across periods
–	no change across periods		

* Levels in the post-bubble period do not necessarily return to levels of the pre-bubble period

REFERENCES

Baca, S.P., B. Garbe, and R.A. Weiss, 2000, The rise of sector effects in major equity markets, Financial Analysts Journal, September/October, 35-40.

Baig, T., and I. Goldfajn, 1999, Financial market contagion in the Asian crisis, IMF Staff Papers 46, 167-195.

Bertero, E., and C. Mayer, 1990, Structure and performance: global interdependence of stock markets around the crash of October 1987, European Economic Review 34, 1155-1180.

Black, F, 1976, Studies of stock price volatility changes, in: Proceedings of the 1976 Meetings of the Business and Economic Statistics Section, American Statistical Association, 177-181.

Bollerslev, T., 1986, Generalized autoregressive conditional heterosledasticity. Journal of Econometrics 31, 307-327.

_____, 1987, A conditionally heteroskedastic time series model for speculative prices and rates of return, Review of Economics and Statistics 69, 542-547.

_____, R. Chou, and K. Kroner, 1992, ARCH modeling in finance: a review of the theory and empirical evidence, Journal of Econometrics 52, 5-60.

_____, R.F. Engle, and D. Nelson, 1994, ARCH Models, in: R.F. Engle and D. McFadden, eds., Handbook of Econometrics, Chapter 49 (Elsevier, New York).

_____, and J. Wooldridge, 1992, Quasi-maximum likelihood estimation and inference in dynamic models with time-varying covariances, Econometric Reviews 11(2), 143-172.

Booth, G.G., T. Martikainen, and Y. Tse, 1997, Price and volatility spillovers in Scandinavian stock markets, Journal of Banking and Finance 21, 811-823.

Boyer, B.H., M.S. Gibson, and M. Loretan, 1997, Pitfalls in tests for changes in correlations, International Finance Discussion Paper 597, Board of Governors of the Federal Reserve, Washington, DC.

Brooks, R. and L. Catao, 2000, The new economy and global stock returns, IMF Working Paper WP/00/216, International Monetary Fund, Washington, DC.

Calvo, G.A., 1999, Contagion in emerging markets: when wall street is a carrier, Unpublished manuscript, University of Maryland, College Park, Maryland.

_____, and E.G. Mendoza, 2000, Rational contagion and the globalization of securities markets, Journal of International Economics 51, 79-113.

Chan-Lau, J. A., and I. Ivaschenko, 2002, Asian Flu or wall street virus? Price and volatility spillovers of the tech and non-tech sectors in the United States and Asia, Working paper No. 02/154, International Monetary Fund, Washington DC.

Cohen, K., G. Hawawini, S. Maler, R. Schwartz, and D. Whitcomb, 1980, Implications of microstructure theory for empirical research on stock market behavior, Journal of Finance 35, 249-257.

De Bandt, O. and P. Hartmann, 2000, Systemic risk: a survey, ECB Working Paper No. 35, European Central Bank, Frankfurt, Germany.

Engle, R., 1982, Autoregressive conditional heteroscedasticity with estimates of the variance of U.K. inflation, Econometrica 50, 987-1008.

Eun, C. and S. Shim, 1989, International transmission of stock market movements, Journal of Financial and Quantitative Analysis 24, 241-256.

French, K., G. Schwert, and R. Stambaugh, 1987, Expected stock returns and volatility, Journal of Financial Economics 19, 3-29.

Flood, R. and P. Garber, 1980, Market fundamentals versus price-level bubbles: the first tests, Journal of Political Economy 88, 745-770.

Glosten, L.R., R. Jaganathan, and D. Runkle, 1993, On the relation between the expected value and the volatility of the normal excess return on stocks, Journal of Finance 48, 1779-1801.

Hamao, Y., R.W. Masulis, and V. Ng, 1990, Correlations in price changes and volatility across international stock markets, Review of Financial Studies 3, 281-307.

Hentschel, L., 1995, All in the family: nesting symmetric and asymmetric GARCH models, Journal of Financial Economics 39, 71-104.

Hilliard, J., 1979, The relationship between equity indices on world exchanges, Journal of Finance 34, 103-114.

Jarrow, R. 1998, (editor), Volatility: new estimation techniques for pricing derivatives (Risk Books, London).

King, M. and S. Wadhwani, 1990, Transmission of volatility between stock markets, Review of Financial Studies 3, 5-33.

_____, A. Sentana, and S. Wadhwani, 1994, Volatility and links between national stock markets, Econometrica 62, 901-933.

Kodres, L.E. and M. Pritsker, 2002, A Rational expectations model of financial contagion, Journal of Finance 57(2), April, 768-799.

Kumar, M., J. A. Chan-Lau, A. Richards, and T. Sloek, 2001, Turbulence in global stock markets: trends and correlations, Unpublished manuscript, International Monetary Fund, Washington, DC.

Kyle, A.S. and W. Xiong, 2001, Contagion as a wealth effect, Journal of Finance 56, 1401-1440.

Lagunoff, R. and S.L. Schreft, 1999, Financial fragility with rational and irrational exuberance, Journal of Money, Credit and Banking 31, 531-560.

Lin, W.-L., R.F. Engle, and T. Ito, 1994, Do bulls and bears move across borders? international transmission of stock returns and volatility, Review of Financial Studies 7, 507-538.

Rigobón, R., 2000, Contagion: how to measure it, Mimeo, MIT.

_____, and K. Forbes, 1998, No contagion, only interdependence: measuring stock market comovements, Working Paper 7267, National Bureau of Economic Research, Cambridge, Massachusetts.

Roll, R., 1988, The international crash of October 1987, Financial Analysts Journal, September/October, 19-35.

_____, 1989, Price volatility, international market links, and their implications for regulatory policies, Journal of Financial Services Research 3, 211-246.

Schinasi, G.J., and R.T. Smith, 2000, Portfolio diversification, leverage, and financial contagion, *IMF Staff Papers* 47, 159-176.

Scholes, M., and J. Williams, 1977, Estimating betas from nonsynchronous data, Journal of Financial Economics 17, 197-210.

Shiller, R.J., F. Knoya, and Y. Tsutsui, 1991, Investor behavior in the October 1987 stock market crash: the case of Japan, Journal of the Japanese and International Economies 5, 1-13.

Zakoian, J.M., 1994, Threshold heteroskedastic models, Journal of Economic Dynamics and Control 18, 931-944.

Theodossiou, P., 1997, Volatility reversion and correlation structure of returns in major international stock markets, The Financial Review 32, 205-224.

Essay IV

Coping with Financial Spillovers from the United States:

The Effect of U. S. Corporate Scandals on Canadian Stock Prices[1]

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Abstract

This paper investigates the effect of U.S. corporate scandals on stock prices of Canadian firms listed in the United States. It finds that firms interlisted during the pre-Enron period enjoyed increases in equilibrium prices after the listing, while firms interlisted during the post-Enron period experienced declines in equilibrium prices, relative to a model-based benchmark. The paper offers several explanations of why firms listed post-Enron experienced negative gains from the listing. Moreover, analyzing the entire universe of Canadian firms, it finds that interlisted firms, regardless of their listing time, were perceived as increasingly risky by Canadian investors after Enron's bankruptcy.

Keywords: cross-listing, event study, IAPM, abnormal returns, investor sentiment, corporate governance, Enron, panel data.

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I. INTRODUCTION

The failure of Enron in December 2001 and other corporate accounting scandals that followed in 2002 in the United States undermined confidence worldwide in financial reporting, auditing, and corporate governance practices. Souring investor confidence induced yet another round of stock price declines in already weak markets across the world, including in Canada. Canadian stock price developments over the past two years largely matched those in the United States despite the much stronger economic performance and the lack of apparent corporate scandals in Canada (see Figure 1).[2]

The spillovers to Canada are particularly noteworthy given the absence of corporate scandals and Canada's high ranking in corporate governance relative to other industrial countries.[3] For example, survey evidence in McKinsey&Co. (2002) found that Canada had the lowest "good governance" premium—that is the least concern about governance—among a broad range of countries surveyed. Similarly, cross-country indexes measuring outside investor rights and the quality of corporate disclosure also show that Canada ranks high against a broad sample of countries (see LaPorta and Lopez-de-Silanes (1998)). Moreover, an Ontario Securities Commission review of corporate practices in 517 publicly traded Canadian companies as of early 2002 found no serious evidence of non-compliance.

Although the direct effect of spillovers from the corporate scandals in the United States on Canadian stock markets is difficult to quantify, the Canadian companies more exposed to U.S. market risks—those interlisted on U.S. stock exchanges—in general, underperformed their peers during the period when the scandals in the United States broke. The performance of interlisted companies was, however, somewhat superior before the scandals (see Table 1).

[2] The correlation between stock returns in the two markets has remained steadily above 80 percent over the past two years.

[3] See De Masi and Ivaschenko (2003) for a detailed discussion.

This paper investigates whether a loss of investor confidence affected the behavior of stock returns for Canadian firms that interlist on U.S. stock exchanges. Numerous theories and empirical studies indicate that, in general, foreign firms listing in the United States enjoy higher equilibrium prices and lower expected returns after the listing (see next section for a review of literature). It is argued that interlisting reduces informational barriers, increases liquidity, and subjects firms to U.S. corporate governance, accounting, and disclosure standards, considered among the best in the world, thus lowering the cost of capital for interlisted firms. This implies that a loss of confidence in regulatory standards could lower benefits of interlisting in the United States and the post-listing price.[4] Accordingly, this study investigates whether in recent years the price dynamics for Canadian firms changed around the time they became listed in the United States, and especially whether it changed after corporate scandals broke in the United States. The analysis of Canadian data is particularly interesting because Canadian firms list directly on U.S. stock exchanges—unlike other foreign firms that list indirectly through American Depositary Receipts (ADR)—and thus must fully comply with U.S. regulations and corporate governance requirements.[5]

Our hypothesis is that a gain in the post-listing equilibrium price should become much smaller or even turn negative for firms listed after the scandals in the United States broke—as compared to their peers that listed before the scandals—if these firms were affected by the negative investor sentiment toward U.S. markets during that time. We intentionally limit the study only to firms listed in recent years in order to keep integration between Canadian and U.S. markets and other time-varying effects constant. Specifically, the time-frame analyzed in this paper (from August 1998 to November 2002) roughly reflects the period of a dramatic increase in stock prices both in Canada and worldwide, followed by an abrupt decline—widely referred to as the "technology bubble" period—during which, it has been argued, markets became more integrated.[6]

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[4] Increasing market integration—which reduces information barriers—would also reduce benefits of listing.

[5] There are some exceptions for Canadian firms listed in the United States, provided through a bilateral agreement on the mutual recognition of disclosure systems, signed in 1991. However, several studies show that it has not been fully effective to date (for details, see footnote 25).

[6] See, for example, Chan-Lau and Ivaschenko (2003) and references therein. The "technology bubble" period roughly corresponds to the time from August 1998 to March 2000.

Employing the conventional event-study methodology, adjusted to include both local and global market risk factors, as well as exchange rate risk factor as suggested by more recent literature, the paper finds that firms that became interlisted during the *post-Enron period* (after Enron's bankruptcy on December 2, 2002) experienced stock price declines both immediately before and after the listing week. On average, risk-adjusted abnormal returns on these firms' equities are -33 percent per annum before the listing and -54 percent per annum after the listing.

Conversely, their peers that listed before the scandals still enjoyed an increase in post-listing price, although somewhat smaller than that found in earlier samples. It is worth noting that among firms listed before Enron's bankruptcy, those listed during the period of the persistent stock market decline worldwide also enjoyed gains in post-listing prices, although lower than those of firms listed during the period of the strong stock market rally. This suggests that the dismal performance of stocks that interlisted post-Enron was not due to the general stock market weakness around the time of their listing.

The fact that interlisitng in the United States results in a lower price is new to the literature, and we discuss several hypotheses that may explain this phenomenon. *First,* investor sentiment toward U.S. markets was adversely affected by corporate scandals in the United States and spurred a withdrawal of foreign capital from U.S. equities. Such souring of investor sentiment would also spur a sell-off of interlisted companies if they are perceived to be in the same category of assets as U.S. equities—a conjecture that is corroborated by notable increases in the correlation of individual stock returns with the U.S. market after the listing.

Second, the new regulatory developments in the United States may have increased the cost of capital for cross-listed firms, thus eliminating some of the gains from cross-listing.

Third, a loss of confidence in the analysts' research and recommendations in the United States may have put an additional negative premium on interlisted firms as they became covered by U.S. analysts.

Finally, relative magnitudes of risk aversion coefficients, market capitalization, and covariance of interlisted stocks with domestic and foreign markets have changed in Canadian and U.S. markets post-Enron. This could have reversed the predictions of theories arguing that, even under mild segmentation across markets, interlisting results in higher equilibrium prices and lower returns.

Since the sample of Canadian firms listed after the Enron bankruptcy is rather small—because the time that elapsed since the scandal is still relatively short—it might not have been representative enough to draw a final conclusion about whether the "U.S. listing premium" of Canadian firms was affected by corporate scandals in the United States. Therefore, we also analyzed the entire universe of large Canadian firms, to assess whether the riskiness of Canadian interlisted firms was more affected than that of the domestically-listed firms by the loss of investor confidence after the scandals in the United States. The results indicate that interlisted companies have higher betas, both global and local, compared to their domestically-listed counterparts, and these betas increase significantly during the post-Enron period. This finding suggests that interlisted companies were perceived as increasingly risky by Canadian investors after the Enron bankruptcy, and thus any firms that interlisted during that time had to pay a premium to investors.

The reminder of this paper is organized as follows. The next section describes the data. Section III is devoted to the event-study analysis of firms' returns around the listing date in the United States for firms interlisted pre- and post-Enron. It presents the methodology used, the review of literature, and the estimation results. In addition, it discusses why post-Enron interlistings resulted in lower post-listing prices. Section IV analyses changes of the relative riskiness of interlisted and domestically-listed firms across different periods. Section V concludes.

II. DATA DESCRIPTION

We use daily data for individual firms listed on the Toronto Stock Exchange (TSX) that comprise the S&P/TSX Composite Stock Index. The S&P/TSX Composite Index is compiled by Standard and Poor's (S&P) and comprises approximately 71 percent of market capitalization for Canadian-based, TSX-listed companies. The size of the index (C$913.3 billion in float market capitalization as of October, 2000) and its broad economic sector coverage has made the S&P/TSX Composite the premier indicator of market activity for Canadian equity markets since its launch on January 1, 1977.[7] Such selection criteria helps ensuring that stocks included in our sample are the most liquid and actively traded.

The dataset is constructed using daily price quotes from the Bloomberg. Bid, ask, and closing prices are selected for the period from January 2, 1997 to November 20, 2002. For the purpose of our study we divide firms into two broad groups: those listed only on the TSX (domestically-listed firms) and those listed on both the TSX and either on the New York Stock Exchange (NYSE) or National Securities Dealers' Automation Quotation (NASDAQ) system (interlisted firms). For interlisted firms, only common shares are included, eliminating subordinated voting shares, limited-voting shares, and non-voting shares. We also exclude firms for which data are not available. All in all, we collect a sample of 216 firms. Among them, 91 are interlisted: 66 on the NYSE, 25 on NASDAQ; and 125 firms are listed solely on the TSX.[8] The dates when firms became interlisted on a U.S. stock exchange are collected from the NYSE and NASDAQ web-sites.

III. ABNORMAL RETURNS AROUND LISTINGS: BEFORE AND AFTER ENRON

This section analyzes the dynamics of stock returns around the listing date for Canadian firms that became interlisted on a U.S. stock exchange during the period from August 31, 1998 to November 20, 2002. It investigates whether the behavior of returns

[7] The S&P/TSX Composite Index also serves as the benchmark for Canadian pension funds and mutual market funds. Approximately C$20 billion is indexed to the S&P/TSX Composite Index.

[8] As of November 2002.

changed across time, in particular, after the string of corporate scandals in the United States started to unfold. It presents the empirical methodology employed, analyses the results, and offers several hypotheses explaining the empirical findings.

A. Empirical Methodology

The analysis is performed for a sample of Canadian firms listed on the TSX that became interlisted on either the NYSE or NASDAQ during the time period analyzed. We intentionally limit the study only to firms listed in recent years in order to keep integration between Canadian and U.S. markets and other time variation effects constant. Specifically, the time-frame analyzed roughly reflects the period of a dramatic increase in stock prices both in Canada and worldwide, followed by an abrupt decline—widely referred to as the "technology bubble"—during which, it has been argued, markets became more integrated. This period excludes two episodes of extreme market volatility—the Asian crisis of late 1997 and the Russian crisis, immediately followed by the Long-Term Capital Management (LTCM) debacle, of mid-1998—which could have significantly affected stock price dynamics worldwide.

In total, there are 43 firms that became listed on a U.S. stock exchange during the period analyzed, of which 33 were listed on the NYSE and 10 were listed on NASDAQ. Eliminating those firms for which data are not available around the listing time, we have compiled a sample of 32 firms.

Following the literature on the effects of interlisting on stock prices, the abnormal returns—calculated as a difference between actual daily returns and benchmark returns—are calculated for three periods: before, during, and after the listing week. Benchmark returns are calculated following the methodology in Foerster and Karolyi (1998), which uses market CAPM. We will call the benchmark constructed this way a *model-based benchmark*.[9]

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[9] To check the robustness of our results to the choice of the model for calculating benchmark returns, we also calculate benchmark returns as a sample average of daily individual returns during the 150-day control period, from day -251 to day -102 before the listing date. We will call this benchmark a *constant benchmark*. The results are qualitatively similar to a *model-based benchmark* case.

Our approach differs from that of Foerster and Karolyi (1998) in two important ways. *First*, we include both local and global market factors, as well as exchange risk factor, among the regressors. The local market factor (the return on the domestic broad index) is included since Jorion and Schwartz (1986) showed that Canadian markets were not perfectly integrated with global markets and local factors were important determinants of stock returns even for interlisted firms. The global market factor (the return on the global market index) is included following a vast literature on International Asset Pricing Models (IAPM)—see Jorion and Schwartz (1986), Dumas and Solnik (1995), Ferson and Harvey (1998), and Dahlquist and Sallström (2002), to name a few—and the widespread belief that North American markets have become increasingly integrated in recent years. Finally, the exchange risk factor is included since Dumas and Solnik (1995), De Santis and Gerard (1998), and Dahlquist and Sällström (2002) show that international pricing models better explain stock returns both across the firms and over time with exchange risk among explanatory variables.[10] *Second*, the time-varying behavior of conditional expected stock returns and volatility is explicitly modeled using GARCH(1,1) model following a vast literature indicating a presence of GARCH-type effects in daily returns.[11]

We calculate abnormal returns as follows. First, we estimate a following three-factor model for each individual stock during a 150-day *control period* from day -251 to a day -102 before the listing:

$$R_{it} = \alpha_i + \beta_{CNi} R_{CNt} + \beta_{WDi} R^*_{WDt} + \beta_{ERi} R_{ERt} + u_{it} \qquad (1)$$

where R_{it} is a return on an individual stock i in period t; R_{CNt} is a Canadian market return; R^*_{WDt} is a component of the global stock market return, R_{WDt}, which is orthogonal

[10] We also estimate a one-factor CAPM version as in Foerster and Karolyi (1998), which is more closely related to other "listing" literature. The results are qualitatively similar, but the one-factor model does not explain individual stock returns as well as the three-factor model used in the paper.

[11] See Campbell, Lo, MacKinlay (1997) and references therein.

to the R_{CNt};[12] R_{ERt} is a return on a portfolio mimicking the exchange rate of the Canadian dollar vis-à-vis the U.S. dollar;[13] and u_{it} is an error term. Although the results with including R^{*}_{WDt} or R_{WDt} are qualitatively similar, we include only the orthogonal element—following the approach of Jorion and Schwartz (1985)—to avoid the possible multicollinearity problem between Canadian and global market returns. The conditional variance of u_{it} is modeled as a GARCH(1,1) process, which appeared to be the most parsimonious model that fitted most firms well. [14] Since the distribution of errors is unknown, we estimate model (1) using quasi-maximum likelihood.[15]

Second, using estimated betas, β_{CNi} and β_{WDi}, we calculate benchmark returns for each individual firm for the period from day -101 to day +101 from the listing date:

$$R^{B}{}_{it} = \alpha_i + \beta_{CNi} R_{CNt} + \beta_{WDi} R^{*}{}_{WDt} + \beta_{ERi} R_{ERt} \tag{2}$$

Finally, abnormal returns, ε_{it} , for each individual firm stock return, R_{it}, are calculated as:

$$\varepsilon_{it} = R_{it} - R_{Bit} \tag{3}$$

We estimate abnormal returns for all firms that became interlisted in the United States during the sample period analyzed. Abnormal returns are then cumulated over the *pre-listing period* (from day -101 to a day preceding the listing week), the listing weak,

[12] We use the Canadian Stock Index and World Stock Index compiled by the DataStream as domestic and global market portfolios, respectively. The World Stock Index, although including equities worldwide, is heavily dominated by U.S. stocks. In fact, using S&P500 instead of the DataStream's World Stock Index did not change results significantly.

[13] This paper only includes one exchange rate factor—the exchange rate of the Canadian dollar vis-à-vis the U.S. dollar—reflecting the fact that the United States is the main trading partner of Canada, accounting for about 80 percent of all Canadian exports.

[14] Stoll and Whaley (1990) and Muthuswamy (1990) show that infrequent trading and bid-ask spreads can cause stock index returns to follow an ARMA type process. Therefore, we also estimate model (1) using GARCH(1,1)-MA(2) residuals to account for thin trading and bid-ask spreads, and with conditional variance depending on the past returns, following Chan, Karolyi, and Stultz (1992). The results are qualitatively and quantitatively similar to ones obtained using GARCH(1,1) specification, which may be due to the fact that our sample, by construction, includes only relatively large and liquid Canadian stocks.

[15] We also estimated model (1) without GARCH effects using Newey-West heteroskedasticity and autocorrelation consistent estimators. The results are qualitatively similar.

and the *post-listing period* (from a day following the listing week to day + 101) and averaged across firms. The length of the pre- and post listing estimation periods as well as the control period chosen following Foerster and Karolyi (1999) and other event-study literature on the effects of cross-listing.

B. Results: Do Pre-Enron and Post-Enron Periods Differ?

In this section we evaluate the dynamics of abnormal returns around listing time for Canadian firms that became listed on a U.S. stock exchange, and examine whether the dynamics changed after corporate scandals broke in the United States.

Market segmentation models (see Stapleton and Subrahmanyan (1977), Errunza and Losq (1985), and Alexander et al (1987)) predict that interlisting of shares between two segmented or partially segmented markets should lead to a higher equilibrium price and a lower expected return. Interlisting can mitigate market segmentation by reducing informational barriers to foreign investors (see theoretical discussion by Merton (1987) and empirical studies by Kang and Stulz (1997), Foerster and Karolyi (1999), and Lang et al (2002)). In addition, it can increase stock prices through enhanced liquidity (see Amihud and Mendelson (1986) for theoretical model and Christie and Huang (1993), Kadlec and McConnell (1994), and Noronha et al. (1996) for empirical investigation) and better corporate governance and disclosure standards (see Cantale (1996) and Karolyi (1998)). This conjecture is supported by empirical work of Alexander et al. (1988), Mittoo (1992), and Foerster and Karolyi (1993, 1999), who show that non-U.S. companies listing in the United States earn positive abnormal returns, which do not fully dissipate immediately after the listing, and experience a reduction in their home market betas after the listing.[16] These results hold for a number of countries including Canada.

To evaluate whether abnormal returns for Canadian firms changed after the Enron bankruptcy, we group firms in accordance with the time of their listing and

[16] See Karolyi (1998) for an excellent survey of empirical evidence.

evaluate whether the means of pre-listing and post-listing returns differ across groups.[17] Specifically, the following groups of firms were formed depending on their listing time:

Group 1:	all firms that became interlisted on a U.S. exchange (NYSE or NASDAQ), from August 31, 1998 to Enron's bankruptcy, on December 2, 2001 (*pre-Enron period*)
Group 1a:	all firms that became interlisted during the period from August 31 1998 to March 24 2000—or during the period of run-up in stock prices worldwide (the *bull market pre-Enron period*)
Group 1b:	all firms listed between March 24 2000—when the persistent fallout in stock prices began—and Enron's bankruptcy on December 2, 2001 (the *bear market pre-Enron period*)
Group 2:	all firms listed during the period after the Enron's bankruptcy and until November 20, 2002 (the *post-Enron period*)

Excluding all firms for which data do not exist around listing periods, there are twenty six firms in Group 1; nineteen firms in Group 1a; seven firms in Group 1b; and seven firms in Group 2.

Results presented in Table 2 indicate that for firms that interlisted during the *pre-Enron period* (Group 1), cumulative pre-listing abnormal returns are positive, averaging to 23 percent per annum. These results are consistent with 25 percent annual return found by Foerster and Karolyi (1999) for firms listed during 1976-1992. During the post-listing period, abnormal returns for the same firms dissipate almost entirely, with cumulative annualized returns averaging -20 percent. By contrast, a post-listing decline found for earlier samples (e.g. in Foerster and Karolyi, 1999) is almost negligible, indicating that almost none of the pre-listing run-up in prices was reversed, resulting in a higher equilibrium price.[18] The fact that the post-listing gain in equilibrium price is much lower for the recent sample suggests that the segmentation between Canadian and U.S. markets has declined since 1992, which is consistent with popular beliefs and a rapid pace of globalization in recent years. Moreover, the increased degree of

[17] t-tests of equality of two sample means were performed; we do not impose an assumption that the data in two samples have equal variances.

[18] Using weekly data and defining pre- and post-listing periods to be one year, Foerster and Karolyi (1999) find that post-listing negative returns almost offset pre-listing gains for Canadian firms, but did not offset a 12 percent return earned during the listing week.

harmonization between Canadian and U.S. regulatory requirements has made the two markets better integrated.[19]

The results for firms interlisted during the *post-Enron period* are dramatically different from those for firms interlisted *pre-Enron* (Table 2). In particular, for firms interlisted during the post-Enron period (Group 2) the pre-listing abnormal returns are negative, -33 percent on average, compared to significant positive returns of Group 1 firms. Moreover, during the post-listing period, stock prices of Group 2 firms declined further, posting an average of -54 percent annualized return. These results indicate that those Canadian firms, which interlisted on a U.S. stock exchange during the period following Enron's bankruptcy, experienced significant declines in prices associated with the U.S. listing. This fact may be due to a loss of investor confidence in U.S. corporate governance and accounting standards affecting interlisted firms. The fact that results are consistent for both benchmarks is comforting since it indicates that results are robust to a model specification.

To check whether the negative experience of Group 2 firms around the listing date might be due to the fact that all these firms became interlisted during the period of persistent stock market weakness worldwide, we also compare firms listed during the post-Enron period (Group 2) with those listed during the bear market pre-Enron period (Group 1b). We intentionally limit the time-frame for selecting Group 1b firms to the period after stock prices in Canada peaked—closely following stock prices in the United States—marking a start of a prolonged bear market in Canada and worldwide, which might have influenced the dynamics of stock returns around the listing date.

Results presented in Table 2 indicate that abnormal returns for Group 2 firms are still significantly different from those of Group 1b firms. At the same time, the pattern of results for Group 1b firms is similar to that obtained for firms listed during the pre-Enron bull market (Group 1a). They enjoyed positive abnormal returns during the pre-listing period and the listing week, and negative abnormal returns during the post-listing period comparable to abnormal returns of Group 1a. Nevertheless, positive abnormal

[19] See, for example, Stymiest (2002).

returns during pre-listing and listing periods are almost two times smaller for Group 1b firms, suggesting that gains from listing are not as pronounced in times of stock market decline.

C. *Why Do Pre-Enron and Post-Enron Periods Differ?*

The fact that both pre- and post-listing abnormal returns are negative for firms that became interlisted during the post-Enron period is new to the literature and merits a further discussion. We offer four hypotheses that may explain this phenomenon.

First, investor sentiment towards U.S. markets was adversely affected by corporate scandals that transpired in the United States and spurred a withdrawal of foreign capital from U.S. equities. [20] Such souring of the investor sentiment could also spur a sell-off of interlisted Canadian stocks—even though Canadian fundamentals remained robust—if they were perceived to be in the same *category* of assets as U.S. equities (see Shleifer (2000) and Barberis et al. (2002)).[21] This may be because interlisted stocks are actually traded in the United States, together with domestic U.S. equities; they are subject to the same U.S. regulations; and their exposures to U.S. market risk tends to increase after the listing—indeed, betas with respect to the global market (global betas) of Canadian firms listed post-Enron (Group 2) increased by almost 70 percent after the listing (see Table 3).[22] At the same time, betas with respect to the Canadian market (local betas) for these firms declined by about 20 percent after the listing. These results parallel those of Barberis et al. (2002) obtained for securities added to S&P 500 Index—they find that after a stock's addition, its betas with respect to the index increase while its betas with respect to the stocks outside the index fall. Accordingly, increasing global betas and declining local betas for firms listed post-Enron corroborates our conjecture that interlisted Canadian equities could have been

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[20] On June 27, 2002, *The New York Times* wrote: "There is a unanimous agreement that the U.S. is not the best place to invest anymore..." A survey of Canadian investors also finds that in 2002, investors were much less inclined to increase their foreign asset ownerships than in 2000 (TSX, 2002)

[21] Investor sentiment here is defined as correlated judgment errors made by a substantial number of investors (see Shleifer (2000) for an excellent review of this issue).

[22] The fact that global betas of Canadian firms increase after the listing is consistent with a funding of Forester and Karolyi (1999) for a sample of firms interlisted before 1992.

broadly classified into the same *category* as domestic U.S. equities—U.S.-traded equities. Therefore, changes in investor sentiment towards U.S. equities could be a factor explaining negative pre- and post-listing returns on interlisted Canadian stocks.[23]

In addition, since domestic market betas declined after the listing for Group 2 Canadian firms, U.S. investors seeking international diversification through interlisted shares could become less willing to hold this class of assets, further exacerbating a downward pressure on prices.[24]

It is worth noting that if negative investor sentiment was driving prices of interlisted Canadian firms below their fundamental values—as suggested by the robust Canadian economy compared to a sluggish U.S. economic performance during 2001-2002—efficient market theory would suggest that such pricing errors would have been quickly corrected by arbitrageurs. However, this may not be the case during the post-Enron period because, as suggested by the literature on the limits to arbitrage, persistent stock market weakness, which depressed arbitrageurs' wealth and increased risk aversion in Canada and worldwide after Enron's bankruptcy (see IMF (2002) and TSX (2002), pages 59-61), could have significantly constrained arbitrageurs' ability and willingness to drive prices back to fundamentals.[25]

Second, it has been argued that the new regulatory developments in the United States have increased the cost of capital for cross-listed firms. As Steil (2002) shows, the cost of listing in the United States remains very high for foreign firms, both in terms of preparing the listing prospectus and subsequent compliance with U.S. regulations and reconciliation with U.S. General Accounting Principles (GAAP). Listing costs are high even in the case of Canada, which largely harmonized its accounting system with GAAP

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[23] It is worth noting that it is only Group 2 firms (listed post-Enron) that experienced a decline in local betas after the listing. Local betas of Group 1 firms (listed pre-Enron) increased after the listing, by about 60 percent.

[24] Since under the U.S. securities regulation U.S. investors can not directly buy foreign shares, equities of cross-listed companies would be a preferred asset class for investors seeking international diversification.

[25] A growing literature on the limits to arbitrage provides compelling reasons why arbitrageurs may fail to bring prices back to fundamentals, including unavailability of perfect substitutes for mispriced securities, limited wealth of arbitrageurs, and increasing risk aversion (see, for example, De Long et al. (1990), Shleifer and Vishny (1997), Gromb and Vayanos (2001), and Chen et. al.).

over the last decade and signed an agreement on mutual recognition of disclosure systems with the U.S. securities market regulator, the Securities and Exchange Commission (SEC).[26]

Moreover, the recent legislation, passed by the U.S. Congress in response to corporate scandals—the Sarbanes-Oxley Act of 2002 (SOX)—is considered by many observers and foreign companies as increasing regulatory barriers and costs of listing (and thus cost of capital) for foreign firms (as noted in WFE (2003) and Steil (2002)).[27] These costs may more than offset benefits of listing in the United States and thus push post-listing prices down, especially given that corporate scandals have dramatically reduced investor confidence in corporate governance and disclosure standards in the United States.[28] This is especially true in the case of Canada, whose governance and disclosure practices are ranked very high. In addition, many market practitioners do not believe that SOX will succeed in its goal of restoring investor confidence and thus fail to offset additional costs it levies on U.S.-listed companies.[29]

[26] The principal of mutual recognition (Multi-Jurisdictional Disclosure System or MJDS) had been a subject to unilateral revisions by the SEC and repeated threats of annulment since its inception in 1991. Jordan (1995) noted that the mutual recognition agreement was distorted by the retention of the U.S. civil liability by the SEC for the Canadian prospectus document, so that Canadian companies faced potential threat of a legal action for incomplete disclosure when using a Canadian prospectus to do a public offering in the United States. In fact, Foerster et al (1999) reported that U.S. legal considerations were a matter of concern for a majority of interlisted companies. Moreover, in 1993 the SEC amended the MJDS and reinstated the requirement to reconcile financial reports of interslisted Canadian companies with U.S. GAAP—the requirement, which Houston and Jones (1999) found to remain costly and time-consuming.

[27] In fact, there is some evidence that even U.S. public firms are considering de-listing due to increased costs of capital associated with public listing, and a number of firms that de-listed and went private increased from 35 in 1999 to 66 in 2002. Estimates of additional costs of listing stemming from the new legislation range from $1 billion to $3 billion, the liquidity premium listed firms used to enjoy declined dramatically, and issuing of new shares or trading large equity blocks are performed at a discount to a quoted price (see *Economist*, "A (Going) Private Matter," March 20, 2003).

[28] For example, *The New York Times* wrote on June 27, 2002: "... people around the world who for decades have looked to the United States as the model for openness and accountability in business have been sorely disillusioned..." At the same time, MacKinsey&Co. (2002) found that 60 percent of institutional investors are willing to pay a higher price for companies with no corporate governance concerns.

[29] For example, the latest Management Barometer survey, conducted by the PricewaterhuoseCoopers (PwC), indicated that relatively few chief finance executives (CFO) believed that SOX would do much to restore investor confidence, but would, nevertheless, notably increase compliance costs (see "Sarbanes-Oxley Increases Risks, Costs", www.CFO.com, March 25, 2003).

Third, a loss of confidence in the analysts' research and recommendations in the United States may be responsible for negative pre-listing returns. Lang et al (2002) show that U.S. analyst coverage increases after the listing and drives up the post-listing price. However, a string of revelations about analysts' conflicts of interest in the United States during the post-Enron period undermined investor's trust in analysts' recommendations.[30] Therefore, the increased analyst coverage around and after the listing would not likely result in higher prices any longer, and may even prompt investors to shy away from stocks covered by U.S. analysts or demand an extra premium for holding these stocks.

Fourth, predictions of the market segmentation models, mentioned earlier in this section, are conditional on relative magnitudes of several factors—such as aggregate risk aversion coefficients, market capitalization, and covariance of interlisted stocks with domestic and foreign markets—all of which are time-varying and may have changed so that the post-listing equilibrium price is supposed to be lower.

For example, a model by Alexander et al. (1987) suggests that the expected return on the interlisted security differs from its expected return before the listing due to two effects. First, for the interlisted security, the risk represented by its return's covariance with the global market is introduced, resulting in a premium for that risk. This result assumes that local and foreign markets are completely segmented before the listing, which is not completely realistic in our case. Nevertheless, in our case, as discussed earlier, return covariance with the global market increases after the listing, thus resulting in an *increased* premium for that risk. Second, the local covariance risk is altered by the interlisting. Before the listing, local investors alone bear local risk, while after the listing both foreign and local investors share this risk. This, in turn, changes domestic covariance risk premium, possibly downward. As a result, after the interlisting the required return on a security will change as follows:

[30] Early 2002, New York attorney general accused several investment banks in producing biased equity research. Companies, involved in a scandal, paid about $1.5 billion dollars in settlement fees. As a result, investor trust in analysts opinion was undermined. For example, TSX (2002) reports that 38 percent of surveyed Canadian investors do not trust analysts' opinions as much as they did before.

$$R^{PRE}{}_i - R^{POST}{}_i = - A^{WD}\, C_{WD}\, Cov(R^{PRE}{}_i, R^{WD}) + (A^{CN} - A^{WD})\, C_{CN}\, Cov(R^{PRE}{}_i, R^{CN}), \quad (4)$$

where $R^{PRE}{}_i$ and $R^{POST}{}_i$ are stock returns before and after the listing, respectively, A^{CN} and A^{WD} are aggregate risk-aversion coefficients, and C_{CN} and C_{WD} are market capitalizations of the Canadian and global markets, respectively. Equation (3) indicates that the resulting price of the interlisted security is determined by its covariance with the foreign market portfolio, $Cov(R^{PRE}{}_i, R^{WD})$, and a change in domestic covariance risk premium, $(A^{CN} - A^{WD})\, C_{CN}\, Cov(R^{PRE}{}_i, R^{CN})$. Thus, it can be shown that $R^{PRE}{}_i$ will be higher (lower) than $R^{POST}{}_i$ depending on whether "market gamma," $\gamma = A^{WD} C_{WD} Cov(R^{PRE}{}_i, R^{WD}) / A^{CN} C_{CN}\, Cov(R^{PRE}{}_i, R^{CN})$, is lower (higher) than unity:[31]

$$\begin{array}{ll} R^{PRE}{}_i > R^{POST}{}_i & \text{if } \gamma < 1 \\ R^{PRE}{}_i < R^{POST}{}_i & \text{if } \gamma > 1 \end{array} \quad (5)$$

Assuming that aggregate risk aversion is similar in the United States and Canada (or that $A^{WD}/A^{CN} = 1$) we calculate γ's (market gammas) for different groups of interlisted firms. The results presented in Table 4 indicate that, on average, market gammas for all firms that became interlisted before the Enron's bankruptcy (Group 1) are slightly less than unity, while market gammas for firms listed after it (Group 2) are significantly higher than unity.[32] These results imply that the post-listing equilibrium price for the latter group of firms is supposed to be lower than before the listing, which is indeed corroborated by our empirical analysis.

It is only the results for Group 1b firms (listed during the pre-Enron bear market period) that suggest that the post-listing price should be lower than before the listing,

[31] Using the following identities from Alexander et al (1987): $A^{CN} - A^{WD} = A^{CN} A^{CN} / (A^{CN} + A^{WD})$ and $A^{WD} = A^{CN} A^{WD} / (A^{CN} + A^{WD})$.

[32] Alexander et al (1987) argue that since covariance with the domestic market is likely to be higher than covariance with the foreign market, γ is likely to be less than unity, implying a lower expected return and higher equilibrium price after the listing. This argument is based on the assumption that $A^{WD}\, C_{WD} / A^{CN}\, C_{CN} = 1$, which is unrealistic in our case since the foreign market capitalization is much larger than the Canadian one. For example, market capitalization of U.S. S&P500 index is almost 19 times larger than that of Canadian TSX Composite, implying that aggregate risk aversion in Canada must be 19 times higher than that in the United States.

while our results indicate otherwise. However, since the gamma is not dramatically higher than unity, a relatively small downward deviation in the aggregate risk aversion coefficients ratio, A^{WD}/A^{CN}, can push gamma below the unity. This could happen if, for example, the immediate response to a collapse of the tech bubble manifested itself in a greater increase in risk aversion in Canada than in the United States. Although gauging relative increases in risk aversion in two countries is hard, the Canadian stock market declined much more dramatically than in the United States immediately after the tech bubble collapse, with the rate of decline slowing to that in the United States later on (see Figure 1). This suggests that an increase in risk aversion in Canada could have been more pronounced than in the United States right after the bubble collapse, affecting the listing returns for firms listed during that period (Group 1b firms).

IV. Risk and Return of Interlisted vs. Domestically-Listed Companies, Pre- and Post-Enron

Since the sample of Canadian firms listed after Enron's bankruptcy is rather small—because the time that elapsed since the scandal is still relatively short—it might not have been representative enough to draw a final conclusion about whether the "listing premium" of Canadian firms was affected by corporate scandals in the United States. Therefore, we also analyzed the entire universe of S&P/TSX Composite firms, to assess whether the riskiness of Canadian interlisted firms was more affected than that of the domestically-listed firms by the loss of investor confidence after the scandals in the United States. If interlisted companies were indeed perceived as more risky after the scandals, this finding would support our conjecture—as discussed in the previous section—that all interlisted firms, regardless of their listing date, were subject to negative investor sentiment toward all U.S. equities. To test this hypothesis, we estimate market betas with the U.S. market (global betas) and with the Canadian market (local betas) for interlisted and domestically-listed firms separately, and compare them across two periods: before and after the Enron's bankruptcy.

Accordingly, we estimate a three-factor model (1)—used to estimate benchmark returns in the previous section—for each firm in our sample, regardless of whether it is listed in the United States or not. These estimations are performed for the entire sample, and for the two periods, pre- and post-Enron. To account for the fact that price return dynamics might be different in bull and bear markets and following the analysis in the previous section, we also break the pre-Enron period into two, corresponding to a bull and bear market. The timing of periods is similar to that used in the previous section to divide interlisted firms into groups, and thus the following time dummies were formed:

D^{PRE}	the *pre-Enron period*, from July 1998 to December 2, 2001 (corresponds to the timing of Group 1)
D^{PRE1}	the *bull market pre-Enron period*, from July 1998 to March 2000 (corresponds to the timing of Group 1a)
D^{PRE2}	the *bear market pre-Enron period*, from March 2000 to December 2, 2002 (corresponds to the timing of Group 1b)
D^{ENR}	the *post-Enron period*, December 2, 2001-November 20, 2002 (corresponds to the timing of Group 2)

To analyze whether betas changed across different periods, we introduce dummy variables and interaction terms with all three factors included in equation (1). For example, for the analysis of two periods—before and after Enron's bankruptcy—the following model is estimated:

$$\begin{aligned} R_{it} = {} & \alpha^{PRE} + \beta_{CN}{}^{PRE} R_{CNt} + \beta_{WD}{}^{PRE} R_{WDt} + \beta_{ER}{}^{PRE} R_{ERt} + \\ & + \alpha^{ENR} D_t^{ENR} + \beta_{CN}{}^{ENR} R_{CNt} D_t^{ENR} + \beta_{WD}{}^{ENR} R_{WDt} D_t^{ENR} + \beta_{ER}{}^{PRE} R_{ERt} D_t^{ENR} + \varepsilon_{it} \end{aligned} \tag{6}$$

For the analysis of three periods—bull market pre-Enron, the bear market pre-Enron, and the post-Enron—the following model is estimated:

$$\begin{aligned} R_{it} = {} & \alpha^{PRE} + \beta_{CN}{}^{PRE} R_{CNt} + \beta_{WD}{}^{PRE} R_{WDt} + \beta_{ER} R_{ERt} + \\ & + \alpha^{PRE1} D_t{}^{PRE1} + \beta_{CN}{}^{PRE1} R_{CNt} D_t{}^{PRE1} + \beta_{WD}{}^{PRE1} R_{WDt} D_t{}^{PRE1} + \beta_{ER}{}^{PRE1} R_{ERt} D_t{}^{PRE1} + \\ & + \alpha^{PRE2} D_t{}^{PRE2} + \beta_{CN}{}^{PRE2} R_{CNt} D_t{}^{PRE2} + \beta_{WD}{}^{PRE2} R_{WDt} D_t{}^{PRE2} + \beta_{ER}{}^{PRE2} R_{ERt} D_t{}^{PRE2} + \\ & + \alpha^{ENR} D_t^{ENR} + \beta_{CN}{}^{ENR} R_{CNt} D_t^{ENR} + \beta_{WD}{}^{ENR} R_{WDt} D_t^{ENR} + \beta_{ER}{}^{PRE} R_{ERt} D_t^{ENR} + \varepsilon_{it} \end{aligned} \tag{7}$$

Models (5) and (6) are estimated for daily returns from August 31, 1998 to November 20, 2002; for two different groups of firms: firms interlisted on either the NYSE or NASDAQ (interlisted), and firms listed solely on the TSX (domestically-listed). There are 91 interlisted and 125 domestically-listed firms included in the estimation.

Estimation is performed using the panel data FGLS estimation, adjusting for heteroskedasticity and autocorrelations for each individual time series. The estimations are performed using the fixed-effect estimator, as guided by the decomposition of the overall variation in excess returns into the variation within individual time-series and the variation across firms at any fixed point in time. The decomposition presented in Table 5 suggests that more than 99 percent of the overall variation in excess returns is stemming from the variation of returns over time rather than from the variation across firms. Moreover, the firm-specific effects, though idiosyncratic, are likely to be correlated with explanatory variables, indicating the appropriateness of the fixed-effect model. Finally, the formal Hausman test supports the use of the fixed-effect model.[33] The results for the firms that become interlisted during the time-frame analyzed are adjusted in order to eliminate the effect of abnormal returns on the resulting coefficients.

The estimation results over the entire sample merit a separate discussion since, to our knowledge, no study has so far examined whether interlisted companies have higher global betas and lower local betas than comparable domestically listed companies (see Pagano et. al (2002)). Therefore, we first estimate model (1), without dummies, for interlisred and domestically-listed firms. The results, summarized in Table 6 indicate that interlisted companies have higher betas, both global and local, compared to their domestically-listed counterparts. The difference is especially striking for global betas—on average, global betas of interlisted companies are 2.5 times higher than global betas of their domestic peers, while local betas of interlisted companies are almost 80 percent higher than those of domestically-listed companies. The fact that interlisted companies have higher betas, both local and global, is consistent with the findings in the previous section that both betas increase after the listing for majority of firms, except for local betas for Group 2 firms. These results—as well as results presented in the previous section—suggest that interlisting did not provide significant benefits to domestic

[33] We also estimated equations (5) and (6) for each firm individually and then averaged results across firms. The results are quantitatively and qualitatively similar.

investors in terms of better sharing of local risk after the listing, particularly for the firms listed pre-Enron. This finding is contrary to studies using earlier data that found significant declines in local betas after the listing (see Foerster and Karolyi, 1999), and may be explained by higher market integration in our, more recent, sample. The exchange rate betas are not significantly different across firms.

We estimate models (5) and (6) to analyze market betas across different periods. The estimation results are presented in Table 7. The results in Panel A indicate that, post-Enron, locals betas for both interlisted and domestically-listed firms increased by more than 60 percent; global betas declined only for domestically-listed firms, by more than 70 percent; and exchange rate betas did not change. As a result, not only both local and global betas remained higher for interlisted firms, the global betas for interlisted firms became more than ten times higher than those for domestically-listed firms, indicating that interlisted firms indeed became significantly more exposed to U.S. risks than their domestically-listed counterparts during the post-Enron period. Moreover, local betas of interlisted firms became more than five times higher than their global betas and exchange rate betas, indicating that they could have been perceived by Canadian investors as increasingly risky compared to the entire universe of Canadian firms.

When the pre-Enron period was broken into the bull and bear market periods, the results did not change much compared to the previous case. For example, although global betas of interlisted firms increased almost two-fold during the bear market period compared to the bull market period, they declined back to their bull market levels after Enron's bankruptcy (see Table 7, Panel B). At the same time, local betas of interlisted firms increased dramatically during the post-Enron period, outpacing local betas of domestically-listed firms. It is worth noting that abnormal returns (α's) did not change significantly post-Enron. The results for domestically-listed firms are virtually the same.

All in all, the analysis of the entire universe of S&P/TSX Composite firms revealed that interlisted firms indeed became significantly more exposed to U.S. market risks during the post-Enron period and thus investors required higher premiums for holding these stocks. This higher covariance with U.S. risk may have been priced especially high for firms that, despite the higher premiums required by investors on U.S.-listed firms, still decided to interlist in the United States.

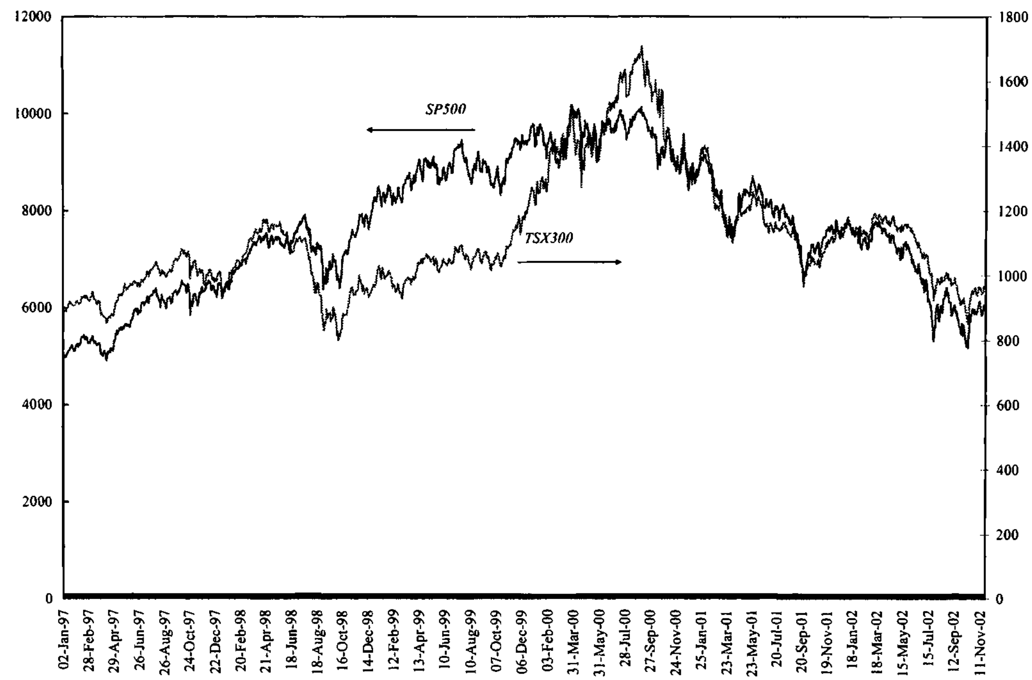
V. CONCLUSIONS

This paper investigates whether a loss of investor confidence due to corporate scandals in the United States changed the stock return dynamics for the Canadian firms listing on a U.S. stock exchange. The results indicate that firms listed during the post-Enron period experienced significant declines in prices before and after the listing. Further investigations show that these results could not be explained by the fact that the post-Enron period coincided with a period of general stock market weakness in Canada and elsewhere. Moreover, these results stand in sharp contrast with theoretical predictions on the effects of interlisitng, earlier studies, and, more importantly, with results obtained for firms listed just before Enron's bankruptcy. The latter group of firms enjoyed positive increases in prices as a result of listing, although much smaller than found in earlier samples.

We offer several explanations of why firms listed post-Enron experienced negative gains from the listing, including negative investor sentiment affecting all U.S.-listed equities; increased limits to arbitrage; higher costs of listing in the United States; loss of confidence in analysts' recommendations; and changes in relative magnitudes of aggregate risk aversion between Canadian and U.S. markets, as well as changes in correlations of individual stock returns with Canadian and U.S. markets.

Since the sample of Canadian firms that interlisted in the United States is still relatively limited to draw definite conclusions, we also analyzed the entire universe of Canadian interlisted firms, pre- and post-Enron. The results indicate that interlisted companies have higher betas, both global and local, compared to their domestically-listed counterparts, which increased significantly during the post-Enron period. This finding suggests that interlisted companies were perceived as increasingly risky by Canadian investors after Enron's bankruptcy, and thus required a premium for any firm that decided to interlist during that time.

Figure 1. Stock Prices in the United States and Canada



Source: Primark DataStream

Table 1. Excess Returns of Interlisted and Domestically-Listed Firms, Before and After Enron's Bankruptcy.

Daily excess returns for individual stocks are calculated in excess of the broad TSX Composite index and averaged across groups of firms and periods. Groups of firms are as follows: Cross-listed—Canadian firms listed both on the Toronto Stock Exchange (TSX) and on the U.S. stock exchange, either NYSE or NASDAQ; Domestically-listed—listed solely on the TSX. Time periods are as follows: Pre-Enron—from January 2, 1997 to December 2, 2001, Enron's bankruptcy; Post-Enron—from December 2, 2001 to November 20, 2002.

	INTERLISTED		*DOMESTICALLY-LISTED*	
	Mean	***Std. Err.***	***Mean***	***Std. Err.***
pre-Enron	0.068	0.037	0.060	0.030
post-Enron	-0.244	0.077	0.049	0.058

Table 2. Abnormal Returns Around Listing on U.S. Stock Exchanges.

Abnormal returns are computed as a difference between actual daily returns and a benchmark, $e_{it} = R_{it} - R_{Bit}$, where the benchmark is estimated using the following model over the control period from day -250 to day -101 before the listing:

$$R_{Bit} = \alpha_i + \beta_{CNi} R_{CNt} + \beta_{WDi} R^{*}_{WDt} + \beta_{ERi} R_{ERt} + u_{it}$$

Daily abnormal returns are cumulated across periods, annualized, and averaged across different groups of firms. The periods analysed are: *pre-listing*, from day -100 to a last day excluding the listing weak; *post-listing*, from the first day after the listing weak to day + 100 after the listing day; the *listing weak* and the *listing day*. The groups of firms are selected as follows depending on their listing time on the U.S. exchange: *Group 1:* all firms that listed during the pre-Enron period, from August 31, 1998 to Enron's bankruptcy, on December 2, 2001; *Group 1a:* all firms listed during the pre-Enron bull period, from August 31 1998 to March 24 2000; *Group 1b:* all firms listed during the bear pre-Enron period, from March 24, 2000 to Enron's bankruptcy on December 2, 2002; *Group 2:* all firms listed during the post-Enron period, after the Enron's bankruptcy and until November 20, 2002. Equality of abnormal returns for each pair of firm groups is tested using t-tests for equality of two means, numbers in brackets are p-values, numbers in parentheses are Satterthwaite's degrees of freedom.

	pre-lising period		**post-listing period**		**listing week**		**listing day**	
Group	***Mean***	***Std. Err.***	***Mean***	***Std. Err.***	***Mean***	***Std. Err.***	***Mean***	***Std. Err.***
1	0.235	0.046	-0.196	0.046	0.489	0.277	0.592	0.637
2	-0.339	0.091	-0.542	0.072	0.154	0.245	-0.110	0.510
t-statistics	5.616	[0.000]	4.051	[0.000]	0.905	[0.184]	0.859	[0.200]
		(948)		(890)		(116)		(24)
1a	0.289	0.062	-0.256	0.061	0.572	0.367	0.814	0.860
2	-0.339	0.091	-0.542	0.072	0.154	0.245	-0.110	0.510
t-statistics	3.029	[0.001]	3.029	[0.003]	0.949	[0.172]	0.924	[0.183]
		(987)		(1187)		(119)		(22)
1b	0.105	0.051	-0.042	0.051	0.275	0.306	0.050	0.689
2	-0.339	0.091	-0.542	0.072	0.154	0.245	-0.110	0.510
t-statistics	-4.255	[0.000]	-5.680	[0.000]	-0.309	[0.621]	-0.186	[0.572]
		(958)		(873)		(64)		(11)
1a	0.289	0.062	-0.256	0.061	0.572	0.367	0.814	0.860
1b	0.105	0.051	-0.042	0.051	0.275	0.306	0.050	0.689
t-statistics	2.300	[0.011]	-2.693	[0.007]	0.623	[0.535]	0.694	[0.496]
		(1982)		(2003)		(113)		(21)

Table 3. Market Betas Before and After the Listing for Different Groups of Interlisted Canadian Firms.

Market betas are estimated from regressions

$$R_{it} = \alpha_i + \beta_{CNi} R_{CNt} + \beta_{WDi} R_{WDt} + \beta_{ERi} R_{ERt} + u_t,$$

where R_{CNt} is a return on the Canadian market index, and R_{WDt} is a return on the global market index, R_{ERt} is a return on a portfolio mimicking the exchange rate of the Canadian dollar vis-à-vis the U.S. dollar, and u_t is an error term. All returns are in excess of the one-month Euro-Canadian dollar return. Market betas are estimated for the pre-listing period (from day -101 to a day preceding the listing week) and post-listing period (a day following the listing week to day + 101) and averaged across the following groups of firms, depending on their listing time on the U.S. exchange: *Group 1:* all firms that listed during the pre-Enron period, from August 31, 1998 to Enron's bankruptcy, on December 2, 2001; *Group 1a:* all firms listed during the pre-Enron bull period, from August 31 1998 to March 24 2000; *Group 1b:* all firms listed during the bear pre-Enron period, from March 24, 2000 to Enron's bankruptcy on December 2, 2002; *Group 2:* all firms listed during the post-Enron period, after the Enron's bankruptcy and until November 20, 2002.

	pre-listing				post-listing			
	β_{CN}		β_{WD}		β_{CN}		β_{WD}	
Group	***Mean***	***Std. Err.***	***Mean***	***Std. Err.***	***Mean***	***Std. Err.***	***Mean***	***Std. Err.***
Group 1	0.084	0.002	0.006	0.001	0.135	0.004	0.028	0.002
Group 1a	0.391	0.011	0.035	0.004	0.667	0.016	0.177	0.011
Group 1b	0.425	0.014	0.073	0.007	0.690	0.019	0.173	0.017
Group 2	1.255	0.017	0.112	0.011	0.985	0.028	0.187	0.021

Table 4. Market Gammas During the Pre-Listing Period for Different Groups of Interlisted Firms.

Market gammas for individual stock returns, R_{it}, are estimated as

$$\gamma_{it} = A^{WD} C_{WD} \beta_{WDi} \sigma_{CN} / A^{CN} C_{CN} \beta_{CNi} \sigma_{WD},$$

where A^{CN} and A^{WD} are aggregate risk-aversion coefficients, C_{CN} and C_{WD} are market capitalizations, β_{CNi} and β_{WDi} are market betas, and σ_{CN} and σ_{WD} are return volatilities of the Canadian and global markets, respectively. Market betas are estimated from regressions

$$R_{it} = \alpha_i + \beta_{CNi} R_{CNt} + \beta_{WDi} R'_{WDt} + \beta_{ERi} R_{ERt} + u_t,$$

where R_{CNt} is a return on the Canadian market index, and R'_{WDt} is a return on the global market index, R_{ERt} is a return on a portfolio mimicking the exchange rate of the Canadian dollar vis-à-vis the U.S. dollar, and u_t is an error term. All returns are in excess of the one-month Euro-Canadian dollar return. Market betas are estimated for the pre-listing period (from day -101 to a day preceding the listing week) and averaged across the following groups of firms, depending on their listing time on the U.S. exchange: *Group 1:* all firms that listed during the pre-Enron period, from August 31, 1998 to Enron's bankruptcy, on December 2, 2001; *Group 1a:* all firms listed during the pre-Enron bull period, from August 31 1998 to March 24 2000; *Group 1b:* all firms listed during the bear pre-Enron period, from March 24, 2000 to Enron's bankruptcy on December 2, 2002; *Group 2:* all firms listed during the post-Enron period, after the Enron's bankruptcy and until November 20, 2002.

The Ho: $\gamma_{it} > 1$ is tested using t-tests for equality of two means. Numbers in parentheses are Satterthwaite's degrees of freedom.

	β_{CN}		β_{WD}		σ_{CN}	σ_{WD}	γ^*	*t-statistics*	
Group	***Mean***	***Std. Err.***	***Mean***	***Std. Err.***				***Mean***	***p-value***
Group 1	0.084	0.002	0.006	0.001	19.096	12.492	0.918	62.009 *(13298)*	0.000
Group 1a	0.391	0.011	0.035	0.004	18.375	10.085	0.921	63.958 *(1960)*	0.000
Group 1b	0.425	0.014	0.073	0.007	24.108	13.159	1.757	6.883 *(1054)*	0.000
Group 2	1.255	0.017	0.112	0.011	11.972	15.277	2.143	12.830	0.000

* Calculated assuming $A^{CN} = A^{WD}$

Table 5. Variance Decomposition of Excess Returns.

	Mean	*Std. Dev.*	*Percent of overall variance*
INTERLISTED			
overall	0.015	11.763	100.000
between		0.253	0.046
within		11.760	99.956
DOMESTICALLY-LISTED			
overall	0.058	10.944	100.000
between		0.260	0.056
within		10.941	99.947

Table 6. Abnormal Returns and Risk Exposures of Interlisted and Domestically-Listed Canadian Firms.

Model estimated is as follows:

$$R_{ri} = \alpha^{LIST} + \beta_{CN}{}^{LIST} R_{CNt} D^{LIST} + \beta_{WD}{}^{LIST} R_{WDt} D^{LIST} + \beta_{ER}{}^{LIST} R_{ERt} D^{LIST} +$$
$$+ \alpha^{NLIST} + \beta_{CN}{}^{NLIST} R_{CNt} + \beta_{WD}{}^{NLIST} R_{WDt} + \beta_{ER}{}^{NLIST} R_{ERt} + \varepsilon_{it}$$

where D^{LIST} is a dummy variable that equals one if a firm is listed on a U.S. stock exchange and equals zero if a firm is domestically-listed. All returns are expressed in Canadian dollar terms and are in excess of one-month Euro-Canadian dollar deposit rate. Standard errors are estimated using feasible GLS correcting for heteroskedasticity and autocorrelation within panels.

	Coef.	*Std. Err.*	*P>|t|*
α	0.061	0.025	0.014
β_{CN}	0.379	0.008	0.000
β_{WD}	0.098	0.014	0.000
β_{ER}	-0.201	0.027	0.000
$\beta_{CN}{}^{LIST} D^{LIST}$	0.301	0.012	0.000
$\beta_{WD}{}^{LIST} D^{LIST}$	0.163	0.021	0.000
$\beta_{ER}{}^{LIST} D^{LIST}$	-0.060	0.040	0.136

Table 7. Abnormal Returns and Risk Exposures of Interlisted and Domestically-Listed Canadian Firms across Different Periods.

Models estimated are as follows:

Panel A:

$$R_{it} = \alpha^{PRE} + \beta_{CN}{}^{PRE} R_{CNt} + \beta_{WD}{}^{PRE} R_{WDt} + \beta_{ER}{}^{PRE} R_{ERt} + \\ + \alpha^{ENR} D_t{}^{ENR} + \beta_{CN}{}^{ENR} R_{CNt} D_t{}^{ENR} + \beta_{WD}{}^{ENR} R_{WDt} D_t{}^{ENR} + \beta_{ER}{}^{PRE} R_{ERt} D_t{}^{ENR} + \varepsilon_{it}$$

Panel B:

$$R_{it} = \alpha^{PRE} + \beta_{CN}{}^{PRE} R_{CNt} + \beta_{WD}{}^{PRE} R_{WDt} + \beta_{ER}{}^{PRE} R_{ERt} + \\ + \alpha^{PRE1} D_t{}^{PRE1} + \beta_{CN}{}^{PRE1} R_{CNt} D_t{}^{PRE1} + \beta_{WD}{}^{PRE1} R_{WDt} D_t{}^{PRE1} + \beta_{ER}{}^{PRE1} R_{ERt} D_t{}^{PRE1} + \\ + \alpha^{PRE2} D_t{}^{PRE2} + \beta_{CN}{}^{PRE2} R_{CNt} D_t{}^{PRE2} + \beta_{WD}{}^{PRE2} R_{WDt} D_t{}^{PRE2} + \beta_{ER}{}^{PRE2} R_{ERt} D_t{}^{PRE2} + \\ + \alpha^{ENR} D_t{}^{ENR} + \beta_{CN}{}^{ENR} R_{CNt} D_t{}^{ENR} + \beta_{WD}{}^{ENR} R_{WDt} D_t{}^{ENR} + \beta_{ER}{}^{PRE} R_{ERt} D_t{}^{ENR} + \varepsilon_{it}$$

where R_{CNt} is an excess return on the Canadian market, R_{WDt} is a part of the excess return on the global market orthogonal to R_{CNt}, and R_{ERt} is an excess return on the portfolio replicating exchange rate of the Canadian dollar vis-à-vis the U.S. dollar. Dummy variables define the following periods: D^{PRE} - pre-Enron period, from August 31, 1998 to December 2, 2001; D^{PRE1} - the bull market pre-Enron period, from August 31, 1998 to March 24, 2000; D^{PRE2} - the bear market pre-Enron period, from March 28, 2000 to December 2, 2002; D^{ENR} - post-Enron period, from December 2, 2001 to November 20, 2002. All returns are expressed in Canadian dollar terms and are in excess of one-month Euro-Canadian dollar deposit rate. Standard errors are estimated using feasible GLS correcting for heteroskedasticity and autocorrelation within panels. Chow tests of the structural break in the coefficients across different periods, defined by the dummy variables, is reported as an F-statistics with associated p-values in parentheses.

Panel A

	INTERLISTED				*DOMESTICALLY-LISTED*			
	Coef.	***Std. Err.***	***t***	***P>|t|***	***Coef.***	***Std. Err.***	***t***	***P>|t|***
α^{PRE}	0.085	0.045	1.880	0.060	0.063	0.036	1.720	0.086
$\beta_{CN}{}^{PRE}$	0.625	0.010	61.520	0.000	0.346	0.008	42.210	0.000
$\beta_{WD}{}^{PRE}$	0.218	0.019	11.500	0.000	0.077	0.015	5.010	0.000
$\beta_{ER}{}^{PRE}$	-0.243	0.037	-6.540	0.000	-0.155	0.030	-5.170	0.000
$\alpha^{ENR} D_t{}^{ENR}$	-0.095	0.094	-1.004	0.360	0.082	0.074	1.100	0.272
$\beta_{CN}{}^{ENR} D_t{}^{ENR}$	0.395	0.029	13.660	0.000	0.235	0.023	10.410	0.000
$\beta_{WD}{}^{ENR} D_t{}^{ENR}$	-0.065	0.041	-1.610	0.108	-0.061	0.032	-1.910	0.056
$\beta_{ER}{}^{PRE} D_t{}^{ENR}$	0.093	0.074	1.260	0.206	-0.071	0.058	-1.230	0.217
	F(4,94293) =		*51.48*	*(0.000)*	*F(4,122668) =*		*31.64*	*(0.000)*

Table 7 (cont). Abnormal Returns and Risk Exposures of Interlisted and Domestically-Listed Canadian Firms across Different Periods.

Panel B

	INTERLISTED				*DOMESTICALLY-LISTED*			
	Coef.	*Std. Err.*	*t*	*P>|t|*	*Coef.*	*Std. Err.*	*t*	*P>|t|*
α^{PRE}	0.003	0.065	0.040	0.969	-0.029	0.054	-0.540	0.586
$\beta_{CN}{}^{PRE}$	0.680	0.016	41.430	0.000	0.393	0.013	29.200	0.000
$\beta_{WD}{}^{PRE}$	0.117	0.030	3.930	0.000	0.073	0.024	2.980	0.003
$\beta_{ER}{}^{PRE}$	-0.183	0.053	-3.440	0.001	-0.184	0.044	-4.210	0.000
$\alpha^{PRE2} D_t{}^{PRE2}$	0.149	0.091	1.630	0.102	0.143	0.074	1.940	0.053
$\beta_{CN}{}^{PRE2} D_t{}^{PRE2}$	-0.088	0.021	-4.200	0.000	-0.074	0.017	-4.380	0.000
$\beta_{WD}{}^{PRE2} D_t{}^{PRE2}$	0.173	0.039	4.470	0.000	0.011	0.031	0.340	0.736
$\beta_{ER}{}^{PRE2} D_t{}^{PRE2}$	-0.043	0.076	-0.570	0.571	0.087	0.061	1.430	0.153
$\alpha^{ENR} D_t{}^{ENR}$	-0.012	0.106	-0.110	0.908	0.175	0.084	2.070	0.039
$\beta_{CN}{}^{ENR} D_t{}^{ENR}$	0.339	0.032	10.710	0.000	0.188	0.025	7.540	0.000
$\beta_{WD}{}^{ENR} D_t{}^{ENR}$	0.036	0.047	0.760	0.444	-0.057	0.027	-2.107	0.024
$\beta_{ER}{}^{PRE} D_t{}^{ENR}$	0.033	0.083	0.400	0.689	-0.042	0.066	-0.640	0.520
	F(90, 94289) =		*0.6*	*(0.991)*	*F(124, 122664) =*		0.61	*(0.998)*

REFERENCES

Alexander, Gordon, Cheol Eun, and S, Janakiramanan, 1987, "Asset Pricing and Dual Listing on Foreign Capital Markets: A Note," *Journal of Finance* 42, pp. 151-158.

_____, 1988, "International Listings and Stock Returns: Some Empirical Evidence," *Journal of Financial and Quantitative Analysis* 23, pp. 135-151.

Amihud, Yakov, and Haim Mendelson, 1986, "Asset-Pricing and the Bid-Ask Spread," *Journal of Financial Economics* 17, pp. 223-249.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, "Comovement," Unpublished manuscript.

Campbell, John, Adrew Lo, and Craig MacKinlay, 1997, *The Econometrics of Financial Markets, Princeton University Press* (New Jersey: Princeton).

Cantale, Salvatore, 1996, "The Choice of A Foreign Market as a Signal," INSEAD Working Paper.

Chan, K. C., Andrew Karolyi, and Rene Stultz, 1992, "Global Financial Markets and the Risk Premium on U.S. Equity," Journal of Financial Economics, p. 137-168.

Chan-Lau, Jorge A., and Iryna Ivaschenko, 2003, "Asian Flu or Wall Street Virus? Tech and Non-Tech Spillovers in the United States and Asia," *Journal of Multintional Financial Management*, forthcoming.

Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2001, "Breadth of Ownership and Stock Returns" *Journal of Financial Economics*, forthcoming.

Dahlquist, Magnus, and Torbjörn Sallström, 2002, "An Evaluation of International Asset Pricing Models," Duke University Working Paper.

Dumas, Bernard, and Bruno Solnik, 1995, "The World Price of Foreign Exchange Risk," *Journal of Finance* 50, pp. 445-479.

De Masi, Paula, and Iryna Ivaschenko, 2003, "Corporate Governance in Canada: Coping with Financial and Regulatory Spillovers from the United States," in *Canada—Selected Issues Paper,* IMF Country Report, January.

De Santis, Giorgio, and Bruno Gerard, 1997, "International Asset Pricing and Portfolio Diversification with Time-Varying Risk," *Journal of Finance* 52, pp. 1881-1912.

Errunza, Vihang, and Etienne Losq, 1985, "International Asset Pricing Under Mild Segmentation: Theory and Test," *Journal of Finance* 50, pp. 1547-1574.

Ferson, Wayne, and Campbell Harvey, 1998, "Fundamental Determinants of National Equity Market Returns: A Perspective on Conditional Asset Pricing," *Journal of Banking and Finance* 21, pp. 1625-1665.

Foerster, Stephen, and Andrew Karolyi, 1993, "International Listings of Stocks: The Case of Canada and the U.S.," *Journal of International Business Studies* 24, pp. 763-784.

_____, 1999, "The Effects of Market Segmentation and Investor Recognition on Asset Prices: Evidence From Foreign Stocks Listing in the United States," *Journal of Finance* 54, pp. 981-103.

_____, and D. Weiner, 1999, "Capital Rewards: The Lure of U.S. Exchanges," *Ivey Business Journal*, May/June, pp. 63-66.

Gromb, Dennis, and Dimitri Vayanos, 2001, "Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs," CERP Discussion Paper No. 3049 (Centre for Economic Policy Research).

Harvey, Campbell, 1991, "The World Price of Covariance Risk," *Journal of Finance* 46, pp. 11-157.

Houston, C., and R. Jones, 1999, "The Multijurisdictional Disclosure System: Model for Future Cooperation?" *Journal of International Financial Management and Accounting* 10, pp. 227-248.

International Monetary Fund, 2002, *Global Financial Stability Report*, various issues.

Jordan, C., 1995, "Regulation in Canadian Capital Markets in the 1990s: The United States in the Driver's Seat," *Pacific Rim Law and Policy Journal* 4, pp. 577-632.

Jorion, Philippe, and Eduardo Schwartz, 1986, "Integration vs. Segmentation in the Canadian Stock Market," *Journal of Finance* 41, pp 603-614.

Kadlec, Gregory, and John McConnell, 1994, "The Effect of Market Segmentation and Illiquidity on Asset Prices: Evidence from Exchange Listings," *Journal of Finance* 49, pp. 611-636.

Kang, Jun-Koo, and Rene Stulz, 1997, "Why is There Home Bias? An Analysis of Foreign Portfolio Equity Ownership in Japan, " *Journal of Financial Economics* 46, pp. 3-28.

Karolyi, Andrew, 1998, "Why Do Companies List Shares Abroad? A Survey of the Evidence and its Managerial Implications," *Financial Markets, Institutions, and Instruments* 7, New York University Salomon Center.

_____, and Rene Stulz, 2002, "Are Financial Asset Prices Priced Locally or Globally," NBER Working Paper 8994.

Lakonishok, Joseph, Andrei Shleifer, Robert Vishny, 1994, "Contrarian Investment, Extrapolation, and Risk," *Journal of Finance* 49, pp. 1541-78.

Lang, Mark, Karl V. Lins, and Darius Miller, 2002, "ADRs, Analysts, and Accuracy: Does Cross Listing in the U.S. Improve a Firm's Information Environment and Increase Market Value?" NYSE Working Paper.

LaPorta, R., and F. Lopez-de-Silanes, 1998, "Law and Finance," *Journal of Political Economy*, vol. 106.

Merton, Robert, 1987, "Presidential Address: A Simple Model of Capital Market Equilibrium with Incomplete Information," *Journal of Finance* 42, pp. 483-510.

Mittoo, Usha, 1992, "Additional Evidence on Integration in the Canadian Stock Market," *Journal of Finance* 47, pp. 2035-2054.

Muthuswamy, Jayaram, 1990, "Non-Syncronous Trading and the Index Autocorrelation Problem," Ph.D. dissertation, Graduate School of Business, University of Chicago.

Noronha, Gregory, Atulya Sarin, and Sharokh Saudaragan, 1996, "Testing for Microstructure Effects of International Dual Listings Using Intraday Data," *Journal of Banking and Finance* 20, pp. 965-983.

Pagano, Marco, Alisa Roell, and Josef Zechner, 2002, "The Geography of Equity Listing: Why Do Companies List Abroad?" *Journal of Finance* 107, pp. 2651-2694.

Shleifer, Andrei, 2000, *Inefficient Markets. An Introduction to Behavioral Finance*, Clarendon Lectures in Economics, Oxford University Press.

_____, and Robert Vishny, 1997, "The Limits of Arbitrage," *Journal of Finance* 52, pp. 35-55.

Solnik, Bruno, 1974, "An Equilibrium Model of the International Capital Market," *Journal of Economic Theory* 8, pp. 500-524.

Stapleton, R. C., and M. G. Subrahmanyan, 1977, "Market Imperfections, Capital Market Equilibrium, and Corporation Finance," *Journal of Finance* 32, pp. 307-319.

Steil, Benn, 2002, "Building a Transatlantic Securities Market," International Securities Market Association.

Stoll, Hans, and Robert Whaley, 1990, "The Dynamics of Stock Index and Stock Index Futures Returns," *Journal of Financial and Quantitative Analysis* 25, pp. 441-468.

Stymiest, Barbara, 2002, Letter to Mr. David Brown, Chair, Ontario Securities Commission, September 17.

Toronto Stock Exchange, 2002, *Canadian Shareowners Study*, July.

World Federation of Exchanges, 2003, *Focus*, Monthly Newsletter, February.

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Center for Management and Organization 50 (1951-2001).
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