RETURN, RISK AND DIVERSIFICATION OF CANADIAN STOCKS

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ABSTRACT

Return, Risk and Diversification of Canadian Stocks

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This thesis examines three major issues dealing with the risk of Canadian stocks. The first issue is what are the differences in various measures of idiosyncratic volatility (IV) and is this risk priced. To this end, various measures of realized, conditional and idiosyncratic volatility are examined for Canadian stocks for the 1975-2003 period. As for other markets, smaller firms exhibit higher total and idiosyncratic risks than their larger counterparts, and IV accounts for almost three-quarters of total volatility for the six studied samples. Unlike other markets, Canadian IT firms exhibit considerably lower volatilities. The relationship between returns and IV is examined using various approaches with(out) the presence of control variables for liquidity and firm-specific information embedded in stock prices. The conditional relation between returns and asymmetric IV is highly significant, robust and as expected (i.e., positive and negative for correspondingly signed excess returns).

The second issue is whether a minimum portfolio size (PS) should be prescribed to achieve a naively but sufficiently well-diversified portfolio for investment opportunity sets (un)differentiated by cross-listing status and market capitalization. To this end, various (un)conditional metrics are used to measure diversification benefits for stocks listed on the TSX for 1975-2003. The minimum PS is found to depend upon the chosen investment opportunity set, the metric(s) for measuring diversification benefits, and the criterion for determining when the portfolio is sufficiently well diversified.

The third (final) issue is to re-examine volatility transmission for stocks cross-listed in synchronous markets. To this end, four bi-variate GARCH models are used to examine contemporaneous co-movement, asymmetry and volatility transmission effects for equal-(value-)weighted daily returns for Canadian stocks cross-listed on the TSX and U.S. markets for 1975-2003. Contemporaneous and asymmetric comovements decrease during the 1990s and increase thereafter, mostly due to the entrance of new (and smaller) stocks into both national markets. Conclusions about the directional change of asymmetric volatility spillovers depend upon the choice of GARCH model. Thus, a researcher should use more than one multivariate GARCH model in order to draw robust inferences on cross-market volatility dynamics.

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Any errors in the thesis are of course, my sole responsibility.

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CHAPTER 1

INTRODUCTION

Common definitions of volatility include a direction-less statistical measure of dispersion (Investopedia) or the standard deviation of a financial asset (Wikipedia). Various measures of volatility are often used to quantify the risk of a financial asset over a specific time period. Higher volatility (uncertainty or risk) is undesirable from an investor's viewpoint as higher volatility implies that asset prices or returns can change dramatically in either direction. Stock volatility is decomposable into a systematic (non-diversifiable) component and an unobserved unsystematic (diversifiable) component, where the latter is theoretically equal to the standard deviation of innovations beyond what investors expect given market or factor returns. However, there is considerable debate not only on how expectations are generated by investors but also on the choice of the empirical model to determine innovations and on whether or not these innovations are priced. This thesis addresses this debate by examining risk, risk diversification and risk pricing for Canadian publicly traded equities.

Thus, the main objective of this thesis is to examine three major risk-related issues for Canadian equities. The first issue is centered on the academic debate on what is an exact measure of risk and what risk is priced in the market. To address this issue, this thesis compares various measures of realized, conditional and idiosyncratic risk, and tests whether idiosyncratic risk is priced in its relationship with expected returns. The second issue deals with whether or not a minimum portfolio size can be prescribed for investors by examining the extent of risk diversification achieved as measured by various metrics for various portfolio sizes for six investment opportunity sets. The third issue relates to co-movement, volatility transmission and asymmetric response to negative shocks for Canadian stocks cross-listed on both the TSX and US markets.

The second chapter (first essay) addresses the debate on an exact measure of risk by comparing various measures of realized, conditional, idiosyncratic and downside risk for different portfolio groups, including all stocks, non-cross-listed, cross-listed, big firms, small firms, and IT firms. This chapter is grounded in the ongoing debate about the irrelevance of idiosyncratic risk in the pricing of equities. While Fama and MacBeth (1973) argue for the irrelevance of idiosyncratic risk since it can be diversified away by holding a diversified portfolio of stocks, other authors (Brennan, 1975; Fu, 2005) note that the majority of investors are under-diversified given transaction and information costs, and intuitively need to be compensated for holding stocks with high idiosyncratic risk. Hence, under incomplete information (Merton 1987), idiosyncratic risk is expected to be priced in the cross-section of expected returns. Using cross-sections of stocks or portfolios of stocks, recent studies report mixed results of either a weak positive relation (Malkiel and Xu, 2002), or a negative relation (Ang et al., 2006), or a significant positive relation (Fu, 2005). Arguments presented to explain these puzzling findings include an 'error-in-variables' problem caused by the unobservability of both expected returns and idiosyncratic volatility; realized returns are a poor proxy for expected returns (Chua, Goh and Zhang, 2006); models of idiosyncratic volatility used in the extant literature do not capture substantial time variation (Fu, 2005); data frequency, the weighting scheme, as well as controls for size and liquidity play a critical role (Bali and Cakici, 2006); and that expected returns include a liquidity component as well as a risk component (Guo and Savickas, 2005).

The second chapter examines whether or not firm-level volatilities or IVs have increased over time, and whether idiosyncratic volatility is priced in its relationship with expected returns. The risk-return relationship is examined using two robust empirical procedures. The first empirical procedure sorts idiosyncratic volatilities into quintiles and then examines the differences in the expected returns between the first and fifth quintiles. The second method uses the Carhart four-factor model in a two-step Fama-MacBeth methodology to examine the relationship between expected returns and idiosyncratic volatility in the presence of control variables for liquidity and firm-specific information. The chapter finds a substantial increase in idiosyncratic volatility for Canadian stocks consistent with findings reported for other markets in the recent literature. A positive and significant relationship between expected returns and idiosyncratic volatility is found using quintiles as well as the multiple regressions. The multiple regression results are robust to the choice of liquidity measure, controlling for measurement error resulting from the first-step regressions and controlling for structural breaks in the returns for each of the investment opportunity sets. The existence of a positive relationship between expected returns and asymmetric idiosyncratic risk reveals that idiosyncratic volatility is priced and is not completely diversified away.

The third chapter (second essay) examines the extent of diversification achieved, on average, for portfolio sizes ranging from two stocks to 100 stocks for six investment opportunity sets using various diversification metrics. The background to this inquiry stems from findings by various studies that at least 15 to 20 securities are needed to obtain approximately 90 percent of the benefits of diversification for US equity markets, and about twice that number is needed for Canadian equity markets. Consequently, an average individual investor is advised that portfolios of about 20 and 30 stocks are sufficient to achieve about 90% of the risk-reduction benefits from increasing portfolio size in the U.S. and Canadian equity markets, respectively. However, an average investor is found to hold two to four stocks depending upon the sample, even during periods of relatively stable overall market risk and rising firm-specific risk.

The metrics used to assess diversification benefits in the third chapter fit into four categories; namely, those that measure risk reduction, those that measure the impact on higher-order return moments, those that measure the impact on reward-to-risk, and those that examine the impact on the probabilities of underachieving various target or lower-bound rates of return. A clinical approach is implemented to obtain the minimum portfolio size to achieve, on average, an acceptable level of risk diversification. When combined with the increase in firm-level idiosyncratic volatility for the TSX documented in the second chapter, the decline in average correlations identified in this chapter substantiates the intuition that an increasing number of stocks is required to achieve a reasonably well diversified portfolio in Canada. This minimum portfolio size depends on the chosen metric used to measure diversification benefits, chosen investment opportunity sets, and the criteria for sufficient diversification. The minimum portfolio size for Canada is higher than is reported in the literature for US markets, probably due to the less distributed nature of Canadian industries.

The fourth chapter (third essay) examines contemporaneous asymmetry, co-movement, and volatility transmission between Canadian stocks cross-listed on TSX and

US markets having synchronous trading hours. The background to this inquiry stems from two empirical observations. The first observation is that few studies examine inter-market volatility dynamics for the same group of stocks that trade on two different national markets with synchronous trading hours, as these would provide a cleaner test of the nature of information flows between the two financial markets, their level of integration and the nature of their interdependence (Niarchos et al., 1999). The second observation is that the number of Canadian stocks cross-listed on the TSX and U.S. markets now accounts for the single largest share of foreign stocks cross-listed on U.S. markets, and thus is an ideal group to study inter-market volatility dynamics.

Four bi-variate GARCH models are used to test for the robustness of any relations between the fluctuations in returns for two financial markets in terms of integration, asymmetric shock transmission and persistence. The chapter finds US markets transmit volatility and the direction of volatility transmission is mainly from US to Canadian markets with Canadian stocks traded on the TSX having higher asymmetry than for their trades on US markets. Asymmetric co-movement and volatility spillovers have increased more recently due to increased financial integration and increases in the numbers of smaller and newer stocks.

The fifth chapter summarizes the principal findings of the three essays in this thesis and provides avenues for further research on, for example, idiosyncratic volatility (IV). This further work on IV involves the assessment of causal factors, predictive pricing relationships, and international diversification using other synchronous markets.

CHAPTER 2

MEASUREMENT AND PRICING OF IDIOSYNCRATIC RISK FOR CANADIAN EQUITIES

2.1 INTRODUCTION

The finance literature includes an ongoing debate on three related issues (see the next section for greater details). The first issue deals with what is an exact measure of risk (Bali et al., 2005), and is reflected in the various metrics used to measure the idiosyncratic variance (or standard deviation) or volatility or risk (henceforth IV) of stocks. Early researchers measure stock risk by the covariance between the stock's return and other variables, such as market return (Black, Jensen, and Scholes, 1972; Fama and MacBeth, 1973), macroeconomic variables (Chen, Roll, and Ross, 1986), and extracted factors from multivariate time series (Roll and Ross, 1980). More recently, researchers focus on realized volatility measures that include aggregate market volatility (Schwert, 1989) and various equal- and value-weighted average firm-level variance (or standard deviation) measures or IVs (e.g., Goyal and Santa-Clara, 2003).[1]

The second issue deals with whether or not firm-level volatilities or IVs have increased, and what are the causal determinants for such changes. An IV increase is related to a number of potential factors in the literature, including an increase in publicly traded stocks on the NASDAQ (Campbell et al., 2001) and an increase in institutional ownership and expected earnings growth (Xu and Malkiel, 2003).

[1] This measure incorporates the autocorrelation term due to non-synchronous trading, as identified by Fama, French and Stambaugh (1987) and Schwert and Seguin (1990).

The third issue deals with the nature of the return-risk relation (Guo and Savickas, 2003b) and whether or not IV is priced and is a predictor of future stock returns. Recent empirical findings produce mixed results (Guo and Whitelaw, 2006) in that some of the estimated relationships between returns and various volatility measures are not robust.[2] While some researchers argue that some IV estimates are measured with error and are unable to capture time-varying properties (Fu, 2005), other researchers argue that the mixed results reported in the literature may be caused by not controlling for either the liquidity component in expected stock returns (Guo and Savickas, 2003) or other stock return determinants such as the relative extent of firm- and market-level information available in the market (Roll, 1988; Morck et al., 2000).

Thus, this chapter has three objectives. The first is to compare various measures of IV for the Canadian market, and to determine if IVs have increased significantly recently. The second objective is to examine if IV is priced in the Canadian stock market for individual stocks using various methodological testing approaches to ensure inferential sturdiness and after controlling for other factors that are believed to affect returns. Although Guo and Savickas (2004) and Ang, Hodrick, Xing and Zhang (2006b) examine this issue for G7 countries (which include Canada), their findings suffer from survivorship bias since they are based on the Datastream database, which has only a limited number of existing stocks. Our study overcomes these limitations by using all stocks listed in the CFMRC database over the 1975-2003 period. Furthermore, our study examines various subsamples thereof, including noncross-listed (local) firms, firms cross-listed on both the TSX and U.S. markets, big and small firms, and firms in the IT sector.

[2] Bali et al. (2005) find that the significance of the equal-weighted average stock variance in the return-risk relationship identified by Goyal and Santa-Clara (2003) is not robust across portfolios and sample periods.

The third and final objective is to examine the relation between contemporaneous returns for individual stocks and lagged IV values, which provides a weak test of the predictive power of idiosyncratic risk.

This chapter makes two major contributions to the literature. The first is to illustrate the differences in the various measures of idiosyncratic volatility that are extant in the literature, and the time-series and cross-sectional differences in IVs for various subsets of Canadian firms. This chapter confirms recent findings by Brown and Ferreira (2005) that smaller firms have higher average total and firm-specific risks (whether measured by variance or lower partial moments) than larger firms, and that smaller firms are major contributors to peaks in market volatility.

The second major contribution of this chapter is the use of asymmetric idiosyncratic risk to confirm that there is a significant relation between monthly returns and asymmetric idiosyncratic risk for individual stocks, and to demonstrate that this relation is not subsumed by the addition of various firm-specific variables such as (il) liquidity or informational transparency. By using an approach other than the traditional approach of forming portfolios to deal with the measurement errors in the beta estimates from the first step of the Fama-MacBeth approach, we find that the significant relation between returns and asymmetric idiosyncratic risk remains after controlling for the so-called regressor problem using the approach of Brennan et al (1998). The major advantage of this approach is that it provides for a "fairer" test because it does not diversify away the impact of firm-specific characteristics by forming portfolios. While the relation between monthly returns and asymmetric idiosyncratic risk is stronger using more recent values of idiosyncratic risk (i.e., values calculated using days-within-the-month versus a 60-month moving window), we also find that the explanatory power of asymmetric idiosyncratic risk is still very high for the returns of individual stocks when the value is lagged one month to correspond with the information available to a typical (uninformed) investor.

The remainder of the chapter is structured as follows. Section two briefly reviews the relevant literature. Section three provides various estimates of risk at the market, industry and firm levels using various estimation methods for various samples of Canadian stocks in order to determine if they are similar and have increased more recently. Section four reports on whether or not IVs are priced and whether or not IVs have any power to "predict" further stock returns in the Canadian market. Section five concludes the chapter.

2.2. BRIEF LITERATURE REVIEW

Idiosyncratic variance or its square root, volatility or risk (henceforth IV) represents firm-specific information (Fu, 2005), and is captured by the innovations not explained by expected returns (Spiegel and Wang, 2005). Since expected returns and expected IVs are not observable, IV measures are dependent on the model used to price systematic risk(s). Various estimation methodologies are used to estimate (un)conditional IVs in the literature (Xu and Malkiel, 2003).

The disaggregated indirect approach of Campbell et al. (2001) uses a market- (industry-) return-adjusted disaggregated method to avoid the estimation of industry and firm-specific betas in order to estimate aggregate market, industry and average firm-level risks. The indirect decomposition approach of Malkiel and Xu (2000) computes aggregate IVs as the differences between conditional aggregated value-weighted firm-level and market-level variances. The direct decomposition method uses the monthly standard deviations of either CAPM innovations (Guo and Savickas, 2005) or innovations from the three-factor FF model (Fama and French, 1973) in the average stock variance model of Goyal and Santa-Clara (2003) that incorporates autocorrelations using lagged terms.

Other IV proxies include the product of the standard deviation and the square root of the number of observations (Fu, 2005), and the absolute and squared innovations from cross-sectional regressions incorporating contemporaneous and lagged market, industry and firm returns to incorporate autocorrelations (Duffee, 2000). Although Xu and Malkiel (2003) argue for the use of a GARCH estimation model to capture time variation, they use a Monte Carlo derived optimum rolling window with declining geometric weights to model persistence in conditional IVs. Given a lack of robustness, Spiegel and Wang (2005) use nine EGARCH models on the innovations from the 3-factor FF model to derive conditional IVs.

In summary, this literature finds that the various IV estimates are somewhat different, and that IVs comprise about 85% of total risk (e.g., Goyal and Santa-Clara, 2003).

2.2.1 Time-series Behavior of Idiosyncratic Risk

Campbell et al. (2001) report that firm-level IVs have a large and significant positive trend in the U.S. during the period 1962-1997, while market and industry variances are without any significant trend (as found earlier by Schwartz, 1989). Most studies of other country markets report similar results.[3] Exceptions include no trend in the U.K. (Frazzini and Marsh, 2003), and a decline in Japan (Hamao, Mei, and Xu, 2003).

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[3] These include: Guo and Savickas (2004) for equal-(not value-)weighted average realized variances for some G7 countries; Kearney and Poti (2004) for Europe; Domanski (2003) for IT firms in Europe; and

2.2.2 Idiosyncratic Risk Determinants

Idiosyncratic volatility is related to a number of factors. These include an increase in publicly traded stocks on NASDAQ (Campbell et al., 2001), and especially small firms (Bali et al., 2005); an increase in institutional ownership and expected earnings growth (Xu and Malkiel, 2003); an increase in less diversified and more levered firms (Dennis and Strickland, 2005); an increase in the number of smaller firms (Brown and Ferreira, 2005), and those issuing IPO's (Fink et al., 2005); product markets becoming more competitive (Irvine and Pontiff, 2005); increase in the dispersion of firm's fundamentals (Wei and Zhang, 2006); a decline in quality of earnings (Diether et al., 2002); an increase in dispersion of analyst's forecasts of earnings (Rajgopal and Venkatachalam, 2006); and an increase in the accrual anomaly of cash flows (Mashruwala et al., 2006). Idiosyncratic volatility is also related to past, current and future earnings (respectively, Wei and Zhang, 2006; Chang and Dong, 2005; and Jiang, Xu and Yao, 2005) and positively related (as is total risk) to the variation of earnings (Pastor and Veronesi, 2002; Wei and Zhang, 2006).

While some researchers interpret this as evidence that information risk is not priced (Johnson, 2004) or priced only for smaller firms (Brown and Kapadia, 2006), others report that the return of IVs to their pre-1990s level in the U.S. signifies a speculative episode (Brandt, Brav and Graham, 2005). Pastor and Varonesi (2005) argue that new and small firms (particularly IT firms) have largely idiosyncratic risk, and that this component is transformed into systematic risk as the firms become bigger or as their technology becomes mature and widely accepted.

Maukonen (2004) for Finland. While Guo and Savickas (and others) examine the Canadian market, their sample has survivorship bias since it is derived from the limited number of existing stocks reported in Datastream.

2.2.3 Relationship between Idiosyncratic Risk and Returns[4]

The debate on the relationship between returns and IVs, which was initiated by the stock return predictability findings of Fama (1991), continues (Guo and Savickas, 2006c). Under the intertemporal CAPM of Merton (1973) with time-varying expected returns, Campbell (1993) argues that stock returns are determined not only by their covariances with market returns but also with their covariances with variables that forecast market returns (such as IVs).

Not only do the empirical studies produce mixed results (e.g., Guo and Whitelaw, 2006) but some find that the IV measures are not robust.[5] The reported relations for various country markets run from positive and significant (e.g., Lintner, 1965; Campbell and Hentschel, 1992; French, Schwert, and Stambaugh, 1987; Lehmann, 1990; Drew and Veeraraghaven, 2002, for Hong Kong, India, Malaysia and Philippines; Goyal and Santa-Clara, 2003; Drew, Naughton and Veeraraghavan, 2003, for China; and Jiang and Lee, 2004) to positive and insignificant (e.g., Tinic and West, 1986; Malkiel and Xu, 2002; Bali, Cakici, Yan and Zhang, 2005) to negative and insignificant (e.g., Breen, Glosten, and Jagannathan, 1989; Longstaff, 1989; Ang et al., 2006a) to negative and significant (e.g., Campbell, 1987). To illustrate this rapidly growing literature, Malkiel and Xu (2002a) find that IV is positively related to stock returns after controlling for size, book-to-market ratios and liquidity, and that stock fundamentals partially explain increases in aggregate IVs. Similarly, after controlling for numerous factors (such as business cycle

[4] Since stock returns reflect both market- and firm-level information (Morck et al., 2000), other firm-specific factors are examined in the literature. These include synchronicity (Morck et al., 2000), fundamentals such as dividend yield (Pastor and Varonesi, 2003) and non-fundamentals that focus on heterogeneous beliefs (Levy et al., 2006).

[5] For example, Bali et al. (2005) find that equal-weighted average stock variances used by Goyal and Santa-Clara (2003) are not robust across portfolios and sample periods.

fluctuations, liquidity, momentum, size, value, variance in analyst forecasts and volume), Ang, Hodrick, Xing, and Zhang (2006a) reject the notion that stocks with higher IVs may also have higher aggregate volatility, and therefore lower returns.

However, this mixed evidence suggests a need for using a multi-factor model with other risk factors (Scruggs, 1998) due to misspecification or an omitted variable bias. While some researchers argue that IV estimates are unable to capture time variation because of measurement errors (Fu, 2005), other researchers (e.g., Guo and Savickas, 2003) argue that expected stock returns have risk and liquidity components that may be correlated negatively. This would lead to mixed results unless the liquidity component is controlled for.[6] While Bali et al. (2005) argue that the positive relationship between market returns and IVs is driven partly by trading on Nasdaq and partly due to the liquidity premium, Guo and Savickas (2006) conjecture that investors demand a risk premium in addition to a liquidity premium to compensate them for their not well diversified portfolios (the latter is documented by, e.g., Goetzmann and Kumar, 2003).

2.2.4 Power of Idiosyncratic Risk to Predict Returns

While early researchers in finance found market volatility contributed little to the prediction of returns (French, Schwert and Stambaugh, 1987), recent research by Guo and Savickas (2006) and Guo (2006) confirms that market volatility in conjunction with IV significantly predicts a negative relation with expected returns, although market volatility and IV are positively correlated (Guo and Higbee, 2006). Furthermore, Yan and

[6] This is supported by findings of a relation between stock returns and both the level and variability of liquidity (Chordia, Subrahmanyam, and Anshuman, 2001; Pastor and Stambaugh, 2003).

Zhang (2003) find that the predictive power of IV is sensitive to its measure and is partly driven by the liquidity premium.

2.3 SAMPLES AND DATA

The sample of all-firms consists of the 3,396 stocks listed on the Toronto Stock Exchange (TSX) that are included in the December 2003 edition of the CFMRC historical database for which a SIC code could be assigned for industry classification. This sample is subdivided into those firms that are (not) cross-listed in U.S. markets based on various issues of the *TSE Monthly Review*. This results in samples of 3,072 that are not cross-listed (TSX only – local control group) and 324 that are cross-listed (treatment group) in both TSX and U.S. markets (NYSE, AMEX, or NASDAQ). The all-firm sample is also subdivided by the median market capitalization each year into a sample of big and small firms, given that some authors argue that idiosyncratic volatility is only priced for small firms (Brown and Ferriera, 2005). The 225 Canadian firms in the IT sector (i.e., information technology, telecommunication, and consultancy) are also examined to facilitate comparison against the findings of Domanski (2003) for this sector in the U.S.

Daily and monthly stock returns, closing prices, closing bids and asks, traded share volume and numbers of shares outstanding over the period from 1975-2003 are extracted from the CFMRC. The 30-day Canadian and U.S. T-Bill rates are obtained from the Bank of Canada and the Federal Reserve Bank of St. Louis, respectively, and are used as proxies for the respective risk-free rates to compute excess stock returns. The SIC code classifications by Fama and French (1997) are used to group stocks into 47 industry groups (industry group 20, Fabricated Products, was empty).

Following the approach of Fama and French (1992, 1995), monthly and daily time-series of returns are constructed for five factors for the Canadian market using a variety of sources, including the Financial Post database. These five factors are the market factor (excess market return), the size factor (Small minus Big), the growth factor (High minus Low), momentum factor (Up minus Down), and the value at risk factor (High VAR minus low VAR). These return series are subsequently used in various applications of the Fama-French three factor model, the Carhart model (i.e., original FF 3-factors plus momentum) and a five-factor model (i.e., Carthart 4 factors plus VAR).

2.4 REALIZED VOLATILITIES AT THE MARKET, INDUSTRY, AND FIRM LEVELS

In this section, volatilities (primarily variances) of various samples of Canadian stocks are computed at the market, industry and firm levels using both equal- and value-weighting schemes. Various computation methods are employed to examine the robustness of the alternatives available in the literature for calculating such volatilities.

2.4.1 Cross-sectional Average Stock Market Variance

Two measures of the cross-sectional average realized variance of the total stock market are examined first. The first measure, which is based on Schwert (1990), is the equal- or value-weighted average of the monthly variances for all the firms in sample s for month t. This measure is given by:

$$\overline{V}_{1,s,t} = \sum_{j=1}^{N_t} w_{j,t,s} \sum_{d_t=1}^{D_t} \left(r_{j,d_t,s} - \overline{r}_{t,s} \right)^2 \tag{2.1}$$

where $w_{j,t,s}$ is the equal weight or the beginning-of-the-month relative market value of firm j in sample s for month t; $r_{j,d_t,s}$ is the return for stock j for day d of month t for sample s, and $\overline{r}_{t,s}$ is the average daily return for month t for sample s based on the daily returns for the N_t stocks for the D_t in month t.

The second measure, which is used by Goyal and Santa-Clara (2003) and Bali et al. (2005), incorporates the autocorrelation in daily returns identified by French et al. (1987). Thus, the equal- or value-weighted average of the monthly variances with the autocorrelation correction for daily returns for all the firms in sample s for month t is given by:

$$\overline{V}_{2,s,t} = \sum_{j=1}^{N_t} w_{j,t,s} \left[\sum_{d_t=1}^{D_t} r_{j,d_t,s}^2 + 2 \sum_{d_t=2}^{D_t} r_{j,d_t,s} r_{j,d_t-1,s} \right] \tag{2.2}$$

where $w_{j,s}$ is either the equal weight (i.e., $1/N_t$) or value weight based on the previous month's relative market value for stock j for month t for sample s; and all the other terms are as defined earlier.

To facilitate comparisons with the conditional idiosyncratic volatilities later derived from the Fama-French model, the equal- or value-weighted average of the monthly variances for each month t is also calculated for sample s using:[7]

$$\overline{V}_{3,t,s} = \sum_{j=1}^{N_t} w_{j,t,s} r_{j,t,s}^2 - \left(\sum_{j=1}^{N_t} w_{j,t,s} r_{j,t,s} \right)^2 \tag{2.3}$$

where all the terms are as defined previously.

[7] No correction is made for autocorrelation given its insignificance in monthly returns.

Summary statistics for the distributions of estimates for all these measures are summarized in Table 2.1. Based on panels A and B of Table 2.1, small firms have the highest average volatilities over the entire period, and exhibit more variation in these conditional volatilities. Not only are the average volatilities of the IT firms lower than those for all firms but so are the variations in the volatilities over the studied time period. This differs from the findings of Domanski (2003) for U.S. IT firms. The time-series distributions for each measure for the seven samples are right skewed and are highly peaked with positive excess kurtosis.[8] The only exception is the cross-listed firms based on U.S. trades, whose volatility distributions exhibit negative skewness and negative excess kurtosis.

[Please place Table 2.1 about here.]

2.4.2 Lower Partial Moments

Lower partial moments (LPMs) measure higher-order moments below a target rate. The main advantages of using LPMs as an alternative risk measure are that they do not assume that return distributions are normal (Stevenson, 2001) or symmetric (Estrada, 2003). LPMs are also more plausible measures of the risk of asymmetric returns as they incorporate information on variance and skewness in a single measure. The lower partial second moment (LPSM) is given by:

$$LPSM_t^h = \frac{1}{(N_t - 1)} \sum_{d_t} \left[\left(R_{j,d} - R_{j,d}^h \right)^- \right]^2 \qquad (2.4)$$

[8] Excess kurtosis is a useful measure obtained by subtracting 3 (i.e., the kurtosis of a normal distribution) from the kurtosis measure. Positive excess kurtosis indicates a "peaked" distribution and negative excess kurtosis indicates a "flat" distribution.

where $R_{j,d}$ is the rate of return for firm *j* in day *d*; $R^h_{j,d}$ is the target rate of return for firm *j* in day *d*; and N_t is the number of firms in the sample for month *t*. Three target rates are examined herein; namely, $\overline{R}_d$ (cross-sectional sample mean), R_0 (zero return) and $R_{f,t}$ (risk-free rate).

Summary statistics for the distributions of estimates for the LPSM for seven samples for the three target returns are summarized in Table 2.2. As reported in the previous section, small firms have the highest average LPSMs over the entire period, and exhibit more variation in these conditional LPSMs. The average LSPM is not much lower and the coefficient of variation is much higher for the IT firms compared to all firms over the studied time period. This reinforces our earlier findings based on variances. The time-series distributions for each measure for the seven samples are right skewed for all seven samples and are highly peaked with positive excess kurtosis except for cross-listed firms based on U.S. trades for all three target returns and small firms for the zero and risk-free rate of return targets.

[Please place Table 2.2 about here.]

2.4.3 Three-level Variance Decompositions

2.4.3.1 Indirect three-level variance decomposition

The main advantage of the indirect volatility decomposition method proposed by Campbell et al. (2001) is that neither covariances nor betas need to be estimated. Value-weighted returns are first aggregated across each firm j in industry i, and then across each industry *i* to obtain excess market returns $R_{m,t}$ for month *t*. More formally:

$$R_{i,t} = \sum_{j\in i} w_{j,i,t} \cdot R_{j,i,t} \text{, and} \tag{2.5}$$

$$R_{m,t} = \sum_{i} w_{i,t} R_{i,t} = \sum_{i} w_{i,t} \cdot \sum_{j\in i} w_{j,i,t} R_{j,i,t}, \tag{2.6}$$

where $R_{j,i,t}$ and $R_{i,t}$ are the monthly excess stock returns for stock j in industry i and for industry i, respectively, for month t; $w_{j,i,t}$ and $w_{i,t}$ are the proportional beginning-of-the-month t market capitalization weights for stock j in industry i and for industry i in the market m, respectively.[9]

The market variance for month t is computed in two ways using:

$$\sigma^2_{1,m,t} = \sum_{d\in t} \left(R_{m,d} - \bar{R}_m\right)^2 \text{, and} \tag{2.7}$$

$$\sigma^2_{2,m,t} = \sum_{d\in t} \left(R_{m,d} - \bar{R}_{m,d}\right)^2, \tag{2.8}$$

where $R_{m,d}$ is the value-weighted excess return for all stocks for day t; $\bar{R}_m$ is the mean of the time-series of monthly averages of the $R_{m,d}$ over the entire estimation period; and $\bar{R}_{m,d}$ is the cross-sectional average (i.e., equal-weighted) return across all stocks for day d.

The industry-level variance is calculated using the residuals from a modified CAPM model that relates industry returns with market returns without an intercept and with industry-specific betas that are implicitly assumed to be 1. Specifically, the equal- or value-weighted industry variance for a representative industry I for month t (i.e., $\sigma^{2,EWorVW}_{I,t}$) is given by:

$$\sigma^{2,EWorVW}_{I,t} = \sum_{i} w_{i,t} \cdot \sigma^2_{\varepsilon_{i,t}} \tag{2.9}$$

[9] As in Campbell et al. (2001), the closing numbers of outstanding shares for the previous month are used to compute all market capitalization weights.

where $\sigma^2_{\varepsilon_{i,t}} = \sum_{d \in t} \varepsilon^2_{i,d,t}$ is the aggregation of the daily squared excess returns for industry i over those of the market over the days d in month t; $\varepsilon_{i,d,t} = R_{i,d,t} - R_{m,d,t}$ is the excess return for industry i over that of the market for day d in month t.

The equal- or value-weighted variance for a typical firm J for month t (i.e., $\sigma^{2,EWorVW}_{J,t}$), which is derived in a similar fashion as that at the industry level, is given by:

$$\sigma^{2,EWorVW}_{J,t} = \sum_{i} w_{i,t} \left(\sum_{j \in i} w_{j,i,t} \cdot \sigma^2_{\eta_{j,i,t}} \right) \tag{2.10}$$

where $\sigma^2_{\eta_{j,i,t}} = \sum_{d \in t} \eta^2_{j,i,d,t}$ is the aggregation of the daily squared excess returns for firm j over those of it industry i over the days d in month t; $\eta_{j,i,d,t} = R_{j,i,d,t} - R_{i,d,t}$ is the excess return for firm j over that of its industry i for day d in month t.

Summary statistics for the distributions of the variance estimates for the three levels using the indirect decomposition method are summarized in Table 2.3. In contrast to the findings of Campbell et al. (2001), the monthly market variance is not only higher on average but also is more volatile when measured against a time-varying cross-sectional mean return. Variances at the industry and firm levels are higher on average using equal-weights, since the use of equal weights places relatively more weight on smaller firms. This also applies to the variances of the variances, except for the value-weighted variance at the firm level for all firms in the sample. Based on the average variances, firm-level variance accounts for at least 69% (and up to 86%) of total variance (i.e., the sum of market, industry and firm-level variances) for the four examined cases.

[Please place Table 2.3 about here.]

2.4.3.2 Direct three-level variance decomposition

Since the direct method accounts for variations in risk across industries, it results in different estimates of industry- and firm-level variances. The variance for industry *i* is given by:

$$Var_D\left(R_{i,t}\right)=\beta_{i,m}^2\cdot Var\left(R_{m,t}\right)+Var\left(\tilde{\varepsilon}_{i,t}\right) \tag{2.11}$$

where $\beta_{i,m}$ is the beta for industry *i*; $Var\left(R_{m,t}\right)$ is the variance of the market return for month *t*; $\tilde{\varepsilon}_{i,t}$ is the error term or innovation for the relationship between the excess returns on industry *i* and the market *m* for month *t*;[10] $Var\left(\tilde{\varepsilon}_{i,t}\right)=\sum\varepsilon_{i,d}^2$ over each month *t*. Similarly, the firm-specific variance for firm *i* is given by:

$$\begin{aligned}\overline{var}_D\left(R_{j,i,t}\right)&=\sum_{j\in i}w_{j,i,t}\cdot Var\left(R_{j,i,t}\right)=\beta_{i,m}^2\cdot Var\left(R_{m,t}\right)+Var\left(\tilde{\varepsilon}_{i,t}\right)+Var\left(\eta_{j,i,t}\right)\\&=\beta_{i,m}^2\cdot Var\left(R_{m,t}\right)+\tilde{\sigma}_{i,t}^2+\sigma_{\eta_{i,t}}^2\end{aligned} \tag{2.12}$$

where $\sigma_{\eta_{i,t}}^2=\sum_{j\in i}w_{j,i,t}\cdot Var\left(\eta_{j,i,t}\right)$ is obtained by weighting the summed daily firm-specific residuals over each month, and all the other terms are as defined earlier. [11]

Since the market variances are the same for the direct and indirect decomposition methods, only the industry- and firm level variances are reported in Table 2.4. If only industries with at least five firms are considered, the five industries with the highest

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[10] The industry-specific betas and innovations are obtained from CAPM-based regressions of daily excess industry returns against daily excess market returns when the intercept α is constrained to zero, or: $R_{i,d}=\beta_{i,m}\cdot R_{m,d}+\varepsilon_{i,d}$.

[11] The firm-specific betas and innovations are obtained from CAPM-based regressions of daily excess firm returns against daily excess industry returns when the intercept α is constrained to zero, or: $R_{j,i,d}=\beta_{i,m}\cdot R_{m,d}+\varepsilon_{i,d}+\eta_{j,i,d}$. Thus, firm-specific innovations can be obtained as the difference between excess daily firm-specific returns and the estimated excess daily industry returns (from the first step regression) as: $R_{j,i,d}-R_{i,d}=\eta_{j,i,d}$.

industry betas in descending order are electronic equipment (1.4157), computers (1.4002), automobiles and trucks (1.0906), electrical equipment (1.0677) and steel works (0.8785), and the five industries with the lowest betas in ascending order are apparel (0.2059), food products (0.2759), textiles (0.3238), consumer goods (0.3431) and utilities (0.3531). Using the same industry inclusion criterion, the five industries with the highest average industry-level variances in descending order are printing & publishing (0.0224), coal (0.0222), aircraft (0.0150), healthcare (0.0150), and measure & control equipment (0.0132), and those with the lowest average industry-level variances in ascending order are rubber & plastic (0.0016), computers (0.0029), miscellaneous (0.0036), steel works, etc (0.0041) and construction (0.0045). These industries also tend to be those with the highest and lowest time-series variations in their industry-level variances.

[Please place Table 2.4 about here.]

Using the same industry inclusion criterion, the five industries with the highest average firm-level variances in descending order are business services (0.4418), printing & publishing (0.3731), utilities (0.2287), coal (0.0264), and recreational products (0.0239) , and those with the lowest average firm-level variances in ascending order are rubber & plastic (0.0051), insurance (0.0056), miscellaneous (0.0070), steel works, etc. (0.0087) and business supplies (0.0111). Printing & publishing and coal are in the most risky top five and rubber & plastic, miscellaneous, and steel works are in the least risky top five at both the industry and firm levels.

Only the ratio of average firm-level variance to industry-level variance for insurance is below one. Using the same industry inclusion criterion, the five industries with the highest ratios in descending order are business services (40.91), utilities (23.10), printing

& publishing (16.66), computers (5.97) and construction (3.87), and those with the lowest ratios in ascending order are insurance (0.47), coal (1.19), textiles (1.26), banking (1.27) and candy & soda (1.31).

2.4.3.3 Regression-based variance decomposition

As in Duffee (2000), industry- and firm-specific innovations are obtained respectively from the following variants of the market model that includes lagged returns:

$$r_{i,t} = \alpha_i + \beta^i_{1,t} \cdot r_{m,t} + \beta^i_{2,t} \cdot r_{m,t-1} + \beta^i_{3,t} \cdot r_{i,t-1} + \varepsilon_{i,t} \tag{2.13}$$

$$r^i_{j,t} = \alpha_j + \beta^j_{1,t} \cdot r_{m,t} + \beta^j_{2,t} \cdot r_{m,t-1} + \beta^j_{3,t} \cdot r_{i,t} + \beta^j_{4,t} \cdot r_{i,t-1} + \beta^j_{5,t} \cdot r^i_{j,t-1} + \varepsilon_{j,t} \tag{2.14}$$

where $r_{i,t}$ and $r^i_{j,t}$ are industry and corresponding stock returns in that industry, obtained by market weighting the daily stock returns with market capitalizations from period *t-1* so that these results are comparable with those presented earlier. While Duffee (2000) argues for the use of absolute over squared residuals due to the fat-tailed distribution of daily returns and sensitivity of squared residuals (used in Fama-French, 1993) to outliers (Schwert and Seguin, 1990), both types of residuals are used herein as a test of robustness.

Thus, four variances are calculated monthly for both the industry and firms levels. The industry variances are cross-sectional averages (i.e., across the 47 industries) of the equal- and value-weighted absolute and squared error terms from (13). Similarly, the firm-level variances for each month t are cross-sectional averages (i.e., across all N_t stocks in month t) of the equal- and value-weighted absolute and squared error terms from (2.14).

Summary statistics for the various industry- and firm-level variances using this decomposition method for all the firms and those that only trade on the TSX are summarized in Table 2.5. While the value-weighted variances are higher at the industry level, they are lower at the firm level. Furthermore, the variances exhibit considerably higher volatility over time for the value versus equal-weighted errors, except for the variances at the firm level based on squared errors. While the variances are higher using absolute instead of squared errors at the industry level, the orderings are mixed at the firm level. The ratio of the variance at the firm level to that at the industry level is above 1, except for the TSX-only listed firms based on value-weighted absolute errors. This is consistent with the results presented earlier in this section.

[Please place Table 2.5 about here.]

2.4.3.4 Multi-factor regression-based variance decomposition

In this section, firm-specific innovations are obtained respectively from the following five-factor market model and more parsimonious versions thereof:

$$r_{i,t} = \alpha + \beta_{i,1} \cdot MKT_t + \beta_{i,2} \cdot SMB_t + \beta_{i,3} \cdot HML_t + \beta_{i,4} \cdot WML_t + \beta_{i,5} \cdot VAR_t + \varepsilon_{i,t}^{5FF} \qquad (2.15)$$

where $MKT_t = R_{m,t} - R_{f,t}$, SMB is the small minus big cap factor, HML is the high minus low book-to-market factor, *WML* is the momentum factor and *VAR* is the high minus low variance factor. The first three factors are from the model of Fama and French (1992, 1995), the fourth and fifth factors are added by Carhart (1997) and Bali and Cakici (2004), respectively. The average firm-level or idiosyncratic variance is obtained by equal- and value-weighting the squared residuals of (2.15) in an analogous fashion to that used in the indirect decomposition method.

Since the idiosyncratic variances derived from the three, four and five factor models are not significantly different, only the variances from the three-factor model for seven samples are reported in Table 2.6. As reported earlier, the mean of the average firm-level variances is highest for the small firm sample, which also exhibits the highest intertemporal volatility in its average firm-level variance. The lowest mean and standard deviations of the average firm-level variances are for cross-listed firms based on their U.S. trades. Interestingly, the IT firms exhibit lower means and standard deviations of their average firm-level variances than the samples of all firms and TSX-only listed firms over the studied period.

[Please place Table 2.6 about here.]

2.5 RELATIONSHIP BETWEEN RETURNS AND RISK

In this section of the chapter, the relationship between returns and idiosyncratic risk (i.e., idiosyncratic volatility or IV) in the presence of various control variables is examined. Given the mixed results reported in the literature that were reviewed earlier, two methodologies are employed for a robust examination of the risk-return relation.

2.5.1 Risk-Return Results Based on Extreme Quintile Portfolios

The first test is based on the approach used recently by Ang et al. (2006a) and Bali et al. (2006), where stocks are first sorted into quintiles based on their idiosyncratic volatilities as derived from the three-factor model of Fama and French (1993) or this model combined with the model (GSC) of Goyal-Santa Clara (2003). Then, the differences in the average equal- or value-weighed returns between the first and fifth quintiles are measured for sign, size and significance.

The average percentage monthly returns for the five quintiles for the seven samples using the four types of estimates of the IVs are presented in Table 2.7. All of the differences in the average returns between the quintiles with the highest and lowest IVs (i.e., 5-1 returns) are positive. The differences are consistently significant for all equal-weighted samples, and for the samples of all firms, TSX-only listed firms, cross-listed firms using U.S. trades and small firms. For the other three samples, the 5-1 returns generally lose significance when the IVs are value- and not equal-weighted.

[Please place Table 2.7 about here.]

2.5.2 Risk-Return Results Based on a Two-Step Regression Approach

The second method for testing if IV is priced is the use of the two-step regression approach of Fama and Macbeth (1973), which is used by Spiegel and Wang (2005) and Fu (2005). In the first step, the time series of monthly IVs are estimated. The IV for month t is based on the standard deviations of the innovations from a conditional 4-factor Carhart model using a rolling window of 60 months ending with month t or $t-1$, or by using all of the trading days within month t or $t-1$. This step also involves the estimation of the time series of each of the five betas of the 4-factor Carhart model that is modified to include up- and down-market factors.

The second step involves two estimation procedures as a test of robustness. In the first estimation procedure for the second step, a series of cross-sectional regressions are run where realized excess returns are regressed against the time series of the five betas, the IVs and various control variables for (il)liquidity (amortized spread or Amihud) and firm-specific information (synchronicity and zero-return metric). In the second estimation procedure for the second step, risk-adjusted returns are regressed against the time series of the IVs and the same three control variables. The use of risk-adjusted (excess) returns for individual securities avoids the measurement error problem that occurs when using estimated betas as independent variables (Brennan et al, 1998) without diversifying away the potential pricing information implicit in IVs that occurs with the use of the common portfolio approach for dealing with measurement error. The risk-adjusted returns for each firm are calculated by subtracting the product of each of the five estimated factor coefficients from step 1 times its associated factor realization from the realized excess return for each time period t. For both second-step estimation procedures, the resulting time-series of parameter estimates for the IVs and the three control variables are then tested for significance, as in the original Fama-MacBeth (1973) procedure. Robust standard errors are used in the regression-based tests for testing the time-series of coefficient estimates when structural breaks in raw and risk-adjusted returns for the various IO sets are accounted for.

2.5.2.1 Empirical Test Procedure

In the first step, the 4-factor FF (Carhart) model that is modified to incorporate the two market beta approach examined by Pettengill, Sundaram and Mathur (1995), amongst others, is run for each month t.[12] He and Kryzanowski (2006) find that a model with conditional (up and down) market betas provides a better description of the pricing relation in Canadian markets. The specific model is given by:

$$r_{i,t}^{*} = \alpha + \beta_{i,1}^{MKT^{+}} \delta R_{m,t}^{*} + \beta_{i,2}^{MKT^{-}} (1-\delta) R_{m,t}^{*} + \beta_{i,3} SMB_{t} + \beta_{i,4} HML_{t} + \beta_{i,5} WML_{t} + \varepsilon_{i,t}^{4'FF} \quad (2.16)$$

[12] Pettengill et al. argue that when using *realized* returns to test the CAPM, beta should be positively related to returns when the excess market returns are positive, but a negative relation should be expected when the excess market returns are negative.

where $r^*_{i,t}$ is the excess return on security i over the risk-free rate for period t (i.e., $R_{m,t} - R_{f,t}$); $R^*_{m,t}$ is the excess market return over the risk-free rate for period t; δ is a dummy variable that is equal to 1 if $(R_{m,t} - R_{f,t}) > 0$ & is equal to 0 otherwise; and all the other terms are as defined earlier. Subsequently, we refer to $\delta R^*_{m,t}$ and $(1-\delta)R^*_{m,t}$ as MKT^+_t and MKT^-_t or as up- and down-market excess returns, respectively. To reduce the impact of infrequent trading on the various estimates, a stock is considered in month t if it has a minimum of either 45 months over the 60-month rolling window for which monthly returns and non-zero trading volumes are reported in CFMRC or 15 days in the month t or t-1 for which daily returns and non-zero trading volumes are reported in CFMRC (the latter is as in Fu, 2005).

In the second step, the following cross-sectional relationship is estimated by a series of cross-sectional regressions for each month t:

$$\begin{aligned} r^*_{i,t} = \alpha + \lambda_{1,t}\delta\hat{\beta}^{MKT^+}_{i,1,t} + \lambda_{2,t}(1-\delta)\hat{\beta}^{MKT^-}_{i,2,t} + \lambda_{3,t}\hat{\beta}^{SMB}_{i,3,t} + \lambda_{4,t}\hat{\beta}^{HML}_{i,4,t} + \lambda_{5,t}\hat{\beta}^{WML}_{i,5,t} \\ + \lambda_{6,t}\phi IV_{i,t} + \lambda_{7,t}(1-\phi)IV_{i,t} + \lambda_{8,t}LIQ_{i,t} + \lambda_{9,t}SYNC_{i,t} + \lambda_{10,t}VROM_{i,t} + \zeta_{i,t} \end{aligned} \quad (2.17)$$

where the five betas are the respective estimates from the first-step regressions; δ, SMB, HML and WML are as described earlier; ϕ is a dummy variable that is equal to 1 if $(R_{i,t} - R_{f,t}) > 0$ and is equal to 0 otherwise; and IV is the standard deviation of the residuals from regression (2.16) (specifically, $\varepsilon^{4'FF}_{i,t}$ when (2.16) is estimated using monthly returns and by $\varepsilon^{4'FF}_{i,t}$ multiplied by the number of trading days in the month when (2.16) is estimated using daily returns). Since IV is signed in a similar fashion to MKT to allow for an asymmetric effect of idiosyncratic risk on stock returns, we subsequently refer to $\phi IV_{i,t}$ and $(1-\phi)IV_{i,t}$ as $IV_{i,t}^{+}$ and $IV_{i,t}^{-}$ or as idiosyncratic risk for up- and down-stock excess returns, respectively.

LIQ is initially proxied by the amortized spread measure of Chalmers and Kadlec (1998) or LIQ^{AS}. The amortized spread measure intuitively is a product of effective spread and share turnover, and is obtained by dividing the product of the absolute difference between the trade and midspread prices and the traded volume by the product of the trade price times the number of shares outstanding.[13]

SYNC or synchronicity is the extent to which stock prices move together (Morck, Yeung, and Yi, 2000), and signifies the magnitude of firm-specific information incorporated into stock prices (Asbaugh-Skaife et al., 2006). Although different measures of synchronicity exist in the literature (Li et al., 2003), the most popular is R^2. As in Morck et al. (2000), the logistic transformation $\gamma_j = \ln\left[R_j^2/\left(1-R_j^2\right)\right]$ is used herein since R^2 is bounded within the interval [0,1]. The R_j^2 for each stock j is obtained from regression (2.16) using either the 60-month moving monthly windows or the days-within-each-month moving monthly windows.

Higher values of R^2 imply an increase in co-movement of the stock with the market, and thus an increase in synchronicity (Durnev et al., 2003). Also, higher R^2 may imply a decline in firm-specific variation or noise (Jin and Myers, 2006), which leads to lower idiosyncratic volatility because firm-specific information is already embedded in stock prices (Roll, 1988). However, some inconsistencies occur with synchronicity as Ashbaugh-Skaife et al. (2006) find that non-fundamental factors influence stock price

[13] The daily closing price is taken as a proxy for the execution price, and the closing mid-spread is used in its absence.

synchronicity but the variation in firm-specific information flows or fundamentals is not consistently captured by R^2. Thus, the expected coefficient for *SYNC* is indeterminate if the findings of Ashbaugh-Skaife et al. (2006) apply to the Canadian market.

VROM is a zero-trade, zero-return measure. Given the inconsistent results regarding R^2 and synchronicity in being able to capture firm-specific information, Ashbaugh-Skaife et al. (2006) suggest that a zero-return&trade metric is a better measure of firm-specific information embedded in stock prices. The argument for this metric is based on Lesmond et al. (1999), who argue that no information-based trades will occur as long as the transaction costs of trading exceed the value of the information signal. Ashbaugh-Skaife et al. (2006) propose that the smaller the proportion of zero returns in a given period, the greater the firm-specific information impounded in stock prices. The monthly measure of the zero-return&trade metric used herein is the ln of the percentage of nonzero-trade&return days in a month. Thus, the expected coefficient for *VROM* is positive.

2.5.2.2 Empirical Results

2.5.2.2.1 Based on 60-month Rolling Windows

A series of cross-sectional regressions (2.17) for each month t based on the contemporaneous betas and IVs estimated from regression (2.16) with and without contemporaneous estimates for LIQ^{AS}, *SYNCH* and *VROM* are run for each of the six samples. A cross-sectional regression is run for month t if at least 30 observations are available for that month. This reduces the number of cross-sectional regressions from 288 only for the IT sample (to 106).

Based on the regression results reported in Table 2.8, the average explanatory power of the model is very high with a range of 45% to 57% for the various samples.[14] The intercept is negative and very significant in the absence of the three control variables, and remains significant at the 0.05 level with the addition of the three control variables for only the TSX-only listed sample. This is in contrast to the positive and significant values reported for tests of the CAPM. While the down market betas are not priced, the up market betas are significantly priced for the full sample and the TSX-only listed and small firm samples. The average loadings on the SMB, HML and WML factor risks are not significantly different from zero. Most interestingly, the average loadings on the asymmetric IV factor risks are without exception very significant and with their expected signs. Although the coefficient estimates for the IV factors lose some significance with the addition of the three control variables for some samples, they remain highly significant. The average coefficient estimate for positively signed IVs is always significantly higher in absolute value than its negatively signed counterpart. These results are most surprising given that the Fama-MacBeth estimation procedure implicitly assumes that the estimates from the past 60 months of data are good proxies for the conditional beta and conditional idiosyncratic risk in the current month, which Fu (2005) argues is not the case for IVs. The coefficient estimates for the various control variables are generally insignificant, except for liquidity for four of the six samples.

[Please place Table 2.8 about here.]

To examine if the relationship between returns and IVs is robust to the use of IVs known at the beginning of each step 2 estimation period, the set of cross-sectional

[14] Median R^2 values are not materially different for the tests reported in this and following sections.

regressions are rerun using asymmetric IVs lagged one month. These results are presented in table 2.9. As expected, the average explanatory power of the model is weakened but only marginally for the various samples. As for the results based on contemporaneous IVs, only the up betas are significantly priced for some of the samples (and with their expected positive sign). The average loadings on the SMB, HML and WML factor risks are generally not significantly different from zero. The average coefficient estimates for the asymmetric IV factor risks continue without exception to be very significant and with the expected signs. The average coefficient estimates for positively signed IVs continue to be always significantly higher in absolute value than their negatively signed counterparts. Unlike the results above for the use of contemporaneous IV estimates, more of the average coefficient estimates for the three control variables are now significant. For example, LIQ, SYNC and VROM are significant (and with their expected signs) for the samples of all firms, and LIQ and VROM are significant for TSX-only listed, big and small firms. Thus, even if one makes the strong assumption that the best predictor of next period's signed IVs are the current period's estimates (i.e., that both follow a random walk), the initial evidence finds that both signed IVs appear to be priced in the Canadian market.

[Please place Table 2.9 about here.]

2.5.2.2.2 Based on the Days-within-the-month Rolling Windows

In order to compare our IV findings with those by Ang et al. (2006a, b) for the U.S. and given the conclusion of Fu (2005) that idiosyncratic risk is best measured over a short contemporaneous window, the methodologies implemented in the previous section are repeated where the betas and signed IVs for the second-step regressions are estimated in the first step for a conditional 4-factor (i.e., 5-beta) Carhart model using a rolling window of all of the trading days within month *t* or *t-1*.

A series of cross-sectional regressions (2.17) for each month *t* based on the betas and signed IVs estimated from regression (2.16) using a rolling window of all of the trading days within month *t*, and with and without contemporaneous (month *t*) estimates for LIQ^{AS}, *SYNCH* and *VROM* are then run for each of the six samples.[15] Based on the regression results reported in Table 2.10, the average explanatory power of the model increases and is very high with a range of 59% to 67% for the various samples. Not unexpectedly, these average R^2-values exceed their counterparts for the models estimated using contemporaneous IVs based on a 60-month moving window. The intercept is negative and very significant even in the presence of the three control variables, except for the IT sample. This is in contrast to the positive and significant values reported for tests of the CAPM. The risk premia on the up market betas are positive as expected for the full sample, the TSX-only listed sample, the cross-listed sample and big firm sample, but only in the absence of the control variables for the first three of these samples. With a few exceptions, the average loadings on the down market, *SMB* and *HML* factor risks are not significantly different from zero. With the exception of the IT sample, the average loading on the momentum factor *WML* is positive and significant.

[Please place Table 2.10 about here.]

As reported earlier, the average loadings on the asymmetric IV factor risks are without exception very significant and with the expected signs. The coefficient estimates

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[15] A cross-sectional regression is run for month *t* only if at least 30 observations are available for that month. This only affected the IT sample, and reduced the number of cross-sectional regressions from 288 to 106.

for the signed IV factors lose some significance with the addition of the three control variables but remain highly significant. The average coefficient estimate for the positively signed IVs is always significantly higher in absolute value than its negatively signed counterpart. The coefficient estimates for all three control variables are positive and highly significant for all but the IT sample.

A series of cross-sectional regressions (2.17) for each month *t* based on the betas and IVs estimated from regression (2.16) using a rolling window of all of the trading days within month *t-1*, and with and without contemporaneous (month *t*) estimates for LIQ^{AS}, *SYNCH* and *VROM* are then run for each of the six samples. Based on the regression results reported in Table 2.11, the explanatory power of the relationships declines with the use of lagged IVs based on trading-days-within-the-month but remains high in the range of 0.48 to 0.57, which exceeds the corresponding values based on lagged IVs from a trailing 60-month estimation window. Furthermore, the coefficient estimates for the IV factors remain highly significant, and the average coefficient estimates for the positively signed IVs remain significantly higher in absolute value than their negatively signed counterparts.

[Please place Table 2.11 about here.]

2.5.3 Test of Robustness using an Alternative Liquidity Measure

In this section, the robustness of the relation between realized returns and IVs to our initial choice of *LIQ* measure is tested. Specifically, we examine if the relation is robust to the use of the approximate price impact measure of Amihud (2002) or LIQ^{AMI}, which is given by the absolute market return to traded dollar share volume over a monthly frequency. If greater illiquidity is priced, then the expected coefficient for LIQ^{AMI} is positive.

Thus, each of the tests conducted using the amortized spread as a measure of liquidity is repeated using the Amihud measure of illiquidity. The time-series averages of the second-step cross-sectional regression results where the dependent variable is contemporaneous excess returns and the independent variables are the five estimated betas, LIQ^{AMI}, SYNC, VROM and either contemporaneous or lagged asymmetric IVs based on 60-month moving windows and days-within-the-month moving windows are reported in Tables 2.12 and 2.13, respectively. Although the average explanatory power of the model remains very high in all cases, it is generally lower (marginally) when the Amihud measure is used instead of amortized spread to measure (il)liquidity. Otherwise, the results are qualitatively similar in terms of what factor risks are priced. More specifically, the two signed IV factors continue to be highly significant with their correct signs for all samples.

[Please place Tables 2.12 and 2.13 about here.]

2.5.4 Controlling for Measurement Error

Because the betas in equation (2.16) are estimated with error, Brennan et al. (1998) recommend that risk-adjusted excess returns be used instead of raw excess returns as the dependent variable in the cross-sectional regression (2.17). The reason is that the use of risk-adjusted returns for individual stocks avoids the measurement problem that occurs when first-step beta estimates are used as independent variables in the second-step cross-sectional regressions in the Fama-MacBeth procedure. This avoids the use of the portfolio approach to minimize measurement error, which tends to average-out the importance of firm-specific characteristics through the aggregation or portfolio building process.

The risk-adjusted excess returns for firm i for period t, or ar_{it}^{*}, are given by:

$$ar_{i,t}^{*} = r_{i,t}^{*} - R_{f,t} - \left(\hat{\beta}_{i,1,t}^{MKT^{+}} \cdot \delta R_{m,t}^{*} + \hat{\beta}_{i,2,t}^{MKT^{-}} (1-\delta) R_{m,t}^{*} + \hat{\beta}_{i,3,t}^{SMB} SMB_{t} + \hat{\beta}_{i,4,t}^{HML} HML_{t} + \hat{\beta}_{i,5,t}^{WML} WML_{t}\right) \quad (2.18)$$

where all the terms are as previously defined, and the betas are estimated using the first-step Fama-French regressions (2.16). The following second-step Fama-MacBeth relationship is now estimated by a series of cross-sectional regressions given by (2.19) instead of (2.17) for each month t:

$$ar_{i,t}^{*} = \alpha + \lambda_{1,t}\phi IV_{i,t} + \lambda_{2,t}(1-\phi)IV_{i,t} + \lambda_{3,t}LIQ_{i,t} + \lambda_{4,t}SYNC_{i,t} + \lambda_{5,t}VROM_{i,t} + v_{i,t} \quad (2.19)$$

where all the terms are as previously defined.

The time-series averages of the second-step cross-sectional regression results where the dependent variable is contemporaneous risk-adjusted excess returns and the independent variables are LIQ (alternatively, either the amortized spread or the Amihud measure), SYNC, VROM and either contemporaneous or lagged signed IVs based on 60-month or days-within-the-month moving windows are reported in Tables 2.14 and 2.15, respectively. While accounting for measurement error in the first-step beta estimates reduces the significance of the two IV variables, their average estimated coefficients retain their expected signs and remain highly significant in all cases. Thus, the importance of asymmetric idiosyncratic risk for the pricing of individual securities is robust to not only the choice of metric for measuring (il)liquidity but also to accounting for measurement error in the coefficient estimates from the first-step regressions in the Fama-MacBeth empirical procedure.

[Please place Tables 2.14 and 2.15 about here.]

2.5.5 Impact of Structural Breaks in the Return Series

The tests of the time-series of cross-sectional coefficient estimates for each of the IO sets conducted in earlier parts of section five of this chapter implicitly assume that the coefficients are drawn from the same underlying distribution (i.e., the same underlying regime). In this section of the chapter, we examine the impact of accounting for structural breaks in the series of raw and risk-adjusted returns in tests of the time-series of the cross-sectional estimates of the IV and AS coefficients for each IO set.

2.5.5.1 Tests for structural breaks

Two types of tests are conducted for structural breaks in the equal-weighted series of raw and risk-adjusted returns for each IO set. The risk-adjusted returns are adjusted using the modified (5-beta) Carhart four-factor model described earlier in this chapter. The first type of test, which is implemented using the unit roots test of Zivot and Andrews (1992), allows for the presence of a single structural break in the intercept and/or the trend of the series. The second type of test, which is implemented using the test of Clemente, Montañés and Reyes (1998) (henceforth CMR) allows for two events or structural breaks within the observed history of a time series. Specifically, the CMR tests allow for either an additive outlier that captures a sudden change in a series (the AO model) or an innovational outlier that allows for a gradual shift in the mean of the series (the IO model). The test statistic for both types of tests is the minimum t-statistic below the critical value of the coefficient of the lagged endogenous variable from a recursive regression. Our preferred test is the AO model of CMR because it not only tests for two structural breaks but it also captures a sudden change in a return series.

The optimal breakpoints for the six IO sets are identified whenever the t-statistic on the (rho-1) coefficient exceeds the 5% critical value (Baum 2004). The t-values for the various tests for structural breaks that are significant at the 0.05 level and their corresponding breakpoints (represented by "year.month") for the six IO sets are summarized in Table 2.16. For tests for one structural break, the structural break in the raw returns occurs more recently in time for all six IO sets based on the CMR tests. While the structural breaks identified by the two CMR tests occur in 1987 for cross-listed and big firms and in 1996 for all firms, TSX-only listed and small firms, the ZA test identifies structural breaks for months in 1980 for all of these IO sets. In contrast, both the ZA and CMR tests identify the single structural breaks as occurring in the 1996-2000 period for all the IO sets. For tests for two structural breaks, the structural breaks occur in both the 1980s and 1990s for the raw monthly returns and in the 1993-2000 period for the risk-adjusted returns. With a few exceptions, the month and year of the structural break identified by the CMR AO or IO tests are within a month of each other, and are never more than three months apart.

[Please place Table 2.16 about here.]

Unlike the raw returns, the risk-adjusted returns undergo structural breaks only during the turbulent 1996-2000 period during which e-commerce and IT firms greatly affected equity returns. Given the strong tendency of the CMR tests to detect structural breaks in close proximity but prior to their actual occurrence, the October '87 crash is identified as a structural break in 1987.08 or 1987.09 by the CMR tests for all firms, TSX-only listed firms, cross-listed firms and big firms. Not surprisingly, the October '87 crash is not identified as a structural break for IT firms and for small firms given that most IT firms are in the small firm IO set.

2.5.5.2 Price of idiosyncratic risk and liquidity accounting for structural breaks

In this section, the impact of accounting for two structural breaks in the raw and risk-adjusted returns that are identified using the CMR AO model on the price of asymmetric idiosyncratic risk and liquidity as measured by the amortized spread are examined for each of the six IO sets. To implement this test, the following two regressions are run:

$$\bar{\hat{\beta}}_{k,t} = \alpha_0 D_{1,t} + \alpha_1 D_{2,t} + \alpha_2 D_{3,t} + \xi_{k,t} \qquad (2.20)$$

$$\bar{\hat{\beta}}_{k,t} = \alpha_0^* + \alpha_1^* D_{2,t} + \alpha_2^* D_{3,t} + \zeta_{k,t} \qquad (2.21)$$

where $\bar{\hat{\beta}}_{k,t}$ is the cross-sectional average coefficient estimate for $IV_{k,t}^{+}$, $IV_{k,t}^{+}$ and $AS_{k,t}$, respectively, for IO set k for month t based on second-step Fama-MacBeth type regressions using either raw or risk-adjusted returns as the dependent variable;[16]

D_1, D_2 and D_3 are dummy variables that are equal to one for each month in the period up to but not including the month of the first structural break, in the period from and including the month of the first structural break and up to but not including the month of the second structural break, and in the period after

[16] The time-series of cross-sectional average prices or rewards for each of these return determinants are obtained from Fama-MacBeth second-step cross-sectional regressions between contemporaneous raw excess returns and contemporaneous betas, IVs and controls (e.g., amortized spreads), where the first-step estimations of the modified Carhart model are based on contemporaneous days-within-the-month moving windows. They also are obtained from Fama-MacBeth second-step cross-sectional regressions between contemporaneous risk-adjusted excess returns and contemporaneous IVs and controls where the excess returns are risk-adjusted using the beta estimates from first-step time-series regressions between contemporaneous raw returns and the four factors in the modified Carhart model based on contemporaneous days-within-the-month moving windows.

and including the month of the second structural break, respectively, and are equal to zero otherwise; and

$\xi_{k,t}$ and $\zeta_{k,t}$ are error terms with the commonly assumed properties.

An examination of the significance of the three alpha estimates (i.e., $\hat{\alpha}_0$, $\hat{\alpha}_1$ and $\hat{\alpha}_2$) generated by regression (2.20) allows for a test of whether or not the price of risk is significant for each of the three determinants of raw and risk-adjusted returns for each of the three periods identified by the two structural breaks using the CMR AO model for each of the six IO sets. Similarly, an examination of the significance of $\hat{\alpha}_1^*$ [$\hat{\alpha}_2^*$] generated by regression (2.21) allows for a test of whether or not the change in the price of risk for IV_{kt}^+, $IV_{k,t}^+$ or $AS_{k,t}$ from the first structural break point and up to the second structural break point [from the second structural break point] is significant for each of the three determinants of raw and risk-adjusted returns for each of the three periods identified by the two structural breaks for each of the six IO sets.

Based on the results summarized in panel A of Table 2.17, all of the estimated coefficients of the signed IVs are significant and have the correct sign for all three periods delineated by the two structural breaks in the raw monthly return series for the six IO sets. While all of the estimated coefficients of the amortized spread have the correct sign, they are significant in all three periods for only three IO sets (all, TSX-only-listed and small firms). The changes in the coefficient estimates in the second and third periods versus their estimated values in the first period are generally not significant for the positively signed IV and the amortized spread, but are significant for seven of the 16 changes for the negatively signed IV (six of which are positive). This suggests that the risk premiums for bearing these risks exhibit some time-variation, especially for bearing negatively signed idiosyncratic risk.

[Please place Table 2.17 about here.]

Based on the results summarized in panel B of Table 2.17, all of the estimated coefficients of the signed IVs have the correct sign for all three periods delineated by the two structural breaks in the risk-adjusted monthly return series for the six IO sets, and all but two are significant. While all of the significant estimated coefficients for the amortized spread have the correct sign, they are significant in all three periods for only four IO sets (all, TSX-only-listed, big and small firms). In contrast, all of the estimated coefficients for the amortized spread are not significant for cross-listed and IT firms. The changes in the coefficient estimates in the second and third periods versus their estimated values in the first period are not significant for the negatively signed IV and the amortized spread, and are significant for five of the 16 changes for the positively signed IV. This suggests that, after correcting for measurement error in the first-step Fama-MacBeth estimates, the risk premiums for bearing these risks exhibit some time-variation only for bearing negatively signed idiosyncratic risk.

2.6 CONCLUSION

This chapter makes two contributions to the literature. The first contribution is an assessment of various measures of idiosyncratic volatility that are extant in the literature. This chapter confirms recent findings by Brown and Ferreira (2005) that smaller firms have higher average stock variances and idiosyncratic volatilities than larger firms. This chapter also interestingly finds that IT firms have relatively low volatilities and downside risks (lower partial moments) during the studied period.

The second contribution of this chapter is an analysis of the relationship between returns and idiosyncratic volatilities for Canadian stocks using quintiles, and various variants of the Fama-MacBeth methodology. This result confirms that there is a significant and robust relationship between returns and asymmetric idiosyncratic volatility.

There is scope for further research on two related aspects. The first is an examination of the prediction of expected returns using idiosyncratic volatility in the presence of the consumption-wealth ratio (cay / tay), as has recently been undertaken for U.S. markets by Guo and Whitelaw (2006). The second is an examination of the relationship between idiosyncratic volatility and various possible determinants, such as the volatility of liquidity, for Canadian stocks.

CHAPTER 3

SHOULD MINIMUM PORTFOLIO SIZES BE PRESCRIBED FOR ACHIEVING SUFFICIENTLY WELL-DIVERSIFIED EQUITY PORTFOLIOS

3.1 INTRODUCTION

One of the most troubling implications of the basic CAPM is that the optimal portfolio of risky assets for all investors consists of the market portfolio. Given constant or increasing marginal costs as reported by Bloomfield, Leftwich and Long (1977) and decreasing marginal benefits associated with increasing portfolio size (henceforth, PS), Mao (1971), Levy (1978), Kryzanowski and To (1982) and Merton (1987) develop so-called clinical versions of the CAPM for friction-related, constrained investment opportunity sets. [17] Various studies specifically examine the marginal benefits associated with increasing portfolio size. These studies generally find that at least 15 to 20 securities are needed to obtain approximately 90 percent of the benefits of diversification for US equity markets, and about twice that number is needed for Canadian equity markets. As a result, the average individual investor is advised that portfolios of about 20 and 30 stocks are sufficient to achieve about 90% of the risk-reduction benefits from increasing portfolio size in the US and Canadian equity markets, respectively (Xu, 2003; BMO, 2001). However, the majority of individual investors only hold one to three stocks in their equity portfolios (Goetzmann and Kumar, 2005).[18] The average investor holds two to four stocks depending upon the sample (Goetzmann and Kumar, 2005; Statman 2004; Xu

[17] Brennan (1975) shows that a perfectly diversified portfolio is not necessarily optimal for individual investors given transaction costs.

[18] Using other sources of data for US households, Kelly (1995) and Polkovnichenko (2006) report similar results.

2003), even during periods of relatively stable overall market risk and rising firm-specific risk (Campbell et al., 2001; Malkiel and Xu, 2003).

Thus, the major objective of this chapter is to answer the following question: Should minimum portfolio sizes be prescribed for achieving sufficiently well-diversified equity portfolios? To this end, the chapter examines the impact of increasing portfolio size for portfolios drawn from various investment opportunity (IO) sets using monthly data for Canadian stocks listed on the TSX over the period, 1975-2003 inclusive. The IO sets consist of some of the common mandates of investment managers, such as all firms, (non-)cross listed firms on US trade venues, big/small firms, and IT firms. For each portfolio size and IO set, 5000 portfolios are formed using a naïve diversification strategy of randomly selecting and equally weighting the selected stocks. The metrics chosen to assess diversification benefits fit into four categories; namely, those that measure risk reduction, those that measure the impact on higher-order return moments, those that measure the impact on reward-to-risk, and those that examine the impact on the probabilities of underachieving various target or lower-bound rates of return. The specific rationales for the choice of these metrics and their implementation are described in section four of this chapter.

We make several contributions to the literature. The first contribution is a negative answer to the question: Should minimum portfolio sizes be prescribed for achieving sufficiently well-diversified portfolios? We find that the minimum portfolio size (PS) depends upon the chosen investment opportunity (IO) set, the metric(s) used to measure the benefits of diversification, and the criterion chosen to determine when the portfolio is sufficiently well diversified. The minimums for a fixed investment opportunity set differ both within and across the categories of metrics used for measuring diversification benefits.

The second contribution is that we revisit the portfolio size issue for Canadian stocks for a more recent time period and using a number of recently developed measures of the relative benefits of diversification. We show that the use of these "new" measures introduces considerable ambiguity into the common prescriptions on what constitutes a minimum portfolio size for achieving a sufficiently well-diversified portfolio of domestic equities.

The third and final contribution is that we nevertheless find that the minimum portfolio sizes for various measures and implementations of the benefits of achieving greater portfolio diversification by increasing portfolio size are considerably higher for Canadian equities than the values reported in the literature for US equities. We attribute these differences to the less granular nature of both inter- and intra-industrial sector weights in the Canadian equity market.

The remainder of the chapter is organized as follows. A brief review of the relevant literature is presented in the next section. In section three, the sample and data are described. Section four focuses on test results for the various performance metrics that are used to determine the number of stocks needed to naively achieve a specific level of the potential benefits through diversification. Section five concludes the chapter.

3.2 BRIEF LITERATURE REVIEW

Markowitz (1952) provides a theoretical foundation for portfolio diversification by examining the trade-offs between the means and variances of returns for financial assets.

Sharpe (1964), Lintner (1965) and Mossin (1966) use the effect of increasing portfolio size on the diversification of portfolios to derive their versions of the Capital Asset Pricing Model (CAPM). For example, Lintner (1965) capitalizes on the finding of Markowitz (1959) that the total risk of a portfolio is not only less than the weighted sum of the own risks of individual assets, but converges to systematic or market or nonidiosyncratic risk as the portfolio size tends to infinity.

While researchers agree in principle that the firm-specific risk component of total portfolio risk can be reduced to just systematic risk through diversification, researchers report conflicting evidence on how many assets are needed to achieve a "well-diversified" portfolio. The most distant literature includes the often-cited article by Evans and Archer (1968) who observe that most of the economic benefits of diversification are captured with a PS of eight to ten securities. While Elton and Gruber (1977) find that a PS of eight stocks yields about eighty percent of the benefits from diversification, other studies report that a larger PS is required. According to Latane and Young (1969), a PS of eight only provides 25 percent of potential benefits from diversification. Jennings (1971) and Fama (1965) report PS of 15 and at least 100 to nearly exhaust potential diversification benefits. Kryzanowski and Rahman (1986) find that a PS of 15 securities produces 95 and 98 percent of the benefits of diversification in terms of the mean and variance of time-varying (MINQUE-estimated) variances, respectively. According to Statman (1987), a PS of at least 30 and 40 stocks is required for borrowers and lenders, respectively, to achieve sufficient portfolio diversification. Wagner and Lau (1971) argue that an investor is better off as measured by the Sharpe ratio by holding a larger number of low quality stocks than a smaller number of high quality stocks. According to

Kryzanowski, Rahman, and Sim (1985), the minimum PS is 15 and 30 for the US and Canadian equity markets, respectively.[19]

More recent studies find that the benefits of increasing PS are more complex than previously thought and provide weaker improvements in diversification benefits (e.g., Surz and Price, 2000; Bennett and Sias, 2005). Due to increases in idiosyncratic volatility, the optimal PS is now 50 stocks (Malkiel and Xu, 2006) or exceeds 300 stocks (Statman, 2004).

The same level of portfolio diversification also is more difficult to achieve in a bearish market as average conditional correlations (Silvapulle and Granger, 2001) and firm-level return dispersions (Demier and Lien, 2004) are higher when market returns are largely negative. Nieuwerburgh and Veldkamp (2005) attempt to explain the diversification puzzle by arguing that investors hold more specialized and less diversified portfolios because they acquire informational scale economies about a set of highly correlated assets. Bennett and Sias (2005) argue that idiosyncratic risk may be priced because increasing PS results in a decline of the impact of systematic shocks on the time-series variance of a portfolio but not on the cross-sectional portfolio variances. As a result, they argue that the cross-sectional standard deviation of returns is a more intuitive measure of the benefits of diversification.

International risk diversification benefits exist because the correlations across markets tend to be lower than those within a national market (Solnik et al., 1996). However, the benefits of international diversification have declined as higher correlations are reported

[19] Cleary and Copp (1999) find that PS of 50 and 90 stocks achieve total risk reduction benefits of 90% and 95%, respectively, for a sample of Canadian stocks with complete return information for the time period being examined. Due to the introduction of this "look-ahead" bias into their results, their findings may not be useful for making ex ante decisions on the required portfolio size to achieve what the investor considers to be a sufficiently well-diversified portfolio.

between, for example, US and international stocks (Goetzman, Li and Rouwenhorst, 2001).

3.3 SAMPLES AND DATA

The sample consists of all TSX-listed firms. The primary source of data is the CFMRC for TSX monthly returns over the period 1975-2003. The risk-free rate is proxied by the 30-day Canadian T-Bills rate, which is obtained from the Bank of Canada.[20]

Portfolios are formed for IOs consisting of all firms, TSX-only listed firms, TSX firms cross-listed in US markets, big/small firms (with firm capitalizations above and below the median, respectively, each year), and IT firms. Using a Monte Carlo approach, 5000 equal-weighted portfolios are formed for portfolio sizes (PSs) of two, five through 100 in increments of five and all stocks for each of the six IO sets.[21]

Care should be exercised when comparing portfolio sizes across the six IOs since the IO sets differ in the numbers of stocks included in each IO set population (henceforth IOSP). For example, based on the weighted average number of stocks in each IO set over the studied time period, a portfolio size of 100 represents 13.3% of the IOSP for all firms, 15.9% of the IOSP for TSX-only listed firms, 20.7% of the IOSP for big firms, 37.3% of the IOSP for small firms, 61.0% of the IOSP for cross-listed firms and 91.7% of the IOSP for IT firms. While we follow conventional academic and practitioner practice of defining portfolio sizes in terms of the number of stocks, we also provide the percentage

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[20] The results using US trade data drawn from CRSP for TSX-listed firms that are cross-listed in the US are similar, and thus are not presented herein.

[21] Checks using 25000 portfolios of some randomly chosen PS/IO combinations suggest that the results reported herein are robust.

that a specific portfolio size represents of the IOSP to facilitate comparisons across IO sets.

3.4 DIVERSIFICATION BENEFITS MEASURED USING VARIOUS METRICS

Various metrics for measuring portfolio diversification are examined in this section of the chapter. The primary purpose for doing so is to identify the minimum number of stocks (so-called portfolio size or PS) needed, for example, on average to naively diversify a specific percentage of nonsystematic (or idiosyncratic or firm-specific) risk or to capture a specific percentage on average of the reward from bearing risk.

3.4.1 Correlations of Stock Returns

Correlations among stocks and between the various investment opportunity (IO) sets are now examined. The average correlation coefficient is used as a standardized measure of the rate and the level of maximum naive risk reduction (Dirk and Wit, 1998). While the average covariance represents the minimum risk level of a portfolio, it is unbounded and needs to be standardized. For the US markets during 1962-1997, Campbell et al. (2001) find stable market volatility, increasing firm-level volatility, and declining average correlations among individual stock returns. This implies that an increasing PS is needed to diversify firm-specific risk. As in Campbell et al. (2001), the monthly correlations are calculated herein using the previous 60 months of returns (i.e., moving window τ).

Summary statistics for the time-series of conditional mean cross-sectional correlations of returns for the six IO sets of TSX-listed stocks are reported in panel A of Table 3.1. To obtain these values, the mean is first calculated for the correlations between every unique pair of stocks in IO set j for moving window τ. Repeating the previous step for each moving window τ for each IO set j generates a time-series of mean conditional cross-sectional correlations for each IO set j. The mean, median and standard deviation of these time-series are highest for the all-firm IO set and lowest for the small firm IO set, which suggests that whatever diversification is possible is achievable quicker for small firms all else held equal. The conditional mean cross-sectional monthly correlations appear to trend downwards after the 1987 market crash. This is illustrated for big and small firms in Figure 3.1.

[Please insert Table 3.1 and Figure 3.1 about here.]

The correlations between these time-series of conditional mean cross-sectional correlations of returns for the six IO sets of TSX-listed stocks are reported in panel B of Table 3.1. Sample pairs with negative mean conditional correlations include big firms with all the other IO sets except for small firms, and those with positive mean conditional correlations below 0.5 include IT firms with all firms and TSX-only-listed firms, and small firms with each of the other five IO sets. The low positive and negative correlations between the time-series of conditional mean cross-sectional correlations of returns for some of the IO sets of TSX-listed stocks provide the greatest risk-reduction options for portfolio construction.

3.4.2 Dispersion of Stock Return Metrics[22]

Dispersion metrics are superior to the correlation metric as a measure of diversification benefits since the dispersion metrics do not depend upon correlations being persistent (Solnik and Roulet, 2000), and they incorporate the effects of both correlations and standard deviations (Statman and Scheid, 2004).[23] Lower levels of stock return dispersion are typically associated with lower levels of risk.

The first "dispersion" metric examined in this section of the chapter is referred to as the mean derived dispersion (MDD) or excess standard deviation (Campbell et al., 2001). The MDD for a fixed portfolio size s and IO set j is given by:

$$MDD_{j,s} = \bar{\sigma}_{j,s} - \sigma_j \tag{3.1}$$

where $\bar{\sigma}_{j,s}$ is the mean of the standard deviations for the 5000 randomly selected portfolios with a portfolio size or PS of s for IO set j over the whole time period, and σ_j is the average standard deviation of all the stocks in IO set j.

The mean derived dispersion should be positive and converge monotonically to zero with increasing PS for each investment opportunity (IO) set. The MDD are computed herein and reported in table 3.2 for 22 portfolio sizes (PS) for each of six IO sets using monthly returns for the period, 1975-2003. The MDD decrease monotonically from a positive value for a PS of 2 to a value of zero for a PS of all for each IO set. The MDDs for PSs of 2 and all also are significantly different at conventional levels for each IO set. If the decision criterion is to achieve at least 90 percent of the potential decline in the MDD by moving from a PS of 2 to all, then the required PS is about 40 (IOSP of 15.1%)

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22 For expositional ease, the term is used herein also for time-series measures of variability and semi-variability.

23 An inverse relationship is expected between correlations and dispersion (Solnik and Roulet, 2000).

for cross-listed firms, 45 (IOSP of 9.3%) for big firms, 95 (IOSP of 15.1%) for TSX-only listed firms and over 100 for the remaining three IO sets. Thus, although the minimum number of stocks is lower for cross-listed firms than for big firms (40 versus 45), it represents a larger percentage of the stocks available for investment in that IO set (15.1% versus 9.3%). If the threshold is increased to 95 percent, then the required PS is about 75 for cross-listed firms, 100 for big firms and over 100 for the remaining four IO sets. Nevertheless, the MDDs for the small-firm IOs are substantially higher for PSs through 100. This is consistent with the finding reported by Bennet and Sias (2005) that smaller firms have relatively higher risk in the US. In addition, about 90 percent of the reduction in the standard deviation of the MDD measures across the 5000 portfolios for each PS and IO set occurs with a PS of between 25 and 40 stocks, where the lower value occurs for big firms and the higher value for all firms.

[Please insert Table 3.2 about here.]

The second dispersion metric examined in this section is referred to as the mean realized dispersion or MRD (de Silva et al., 2001; Ankrim and Ding, 2002). The MRD for a fixed portfolio size *s* and IO set *j* is given by:

$$MRD_{j,s} = \frac{1}{N}\sum_{\tau=1}^{N}\sigma_{j,s,\tau} , \tag{3.2}$$

where $\sigma_{j,s,\tau}$ is the cross-sectional standard deviation for the 5000 randomly selected portfolios for IO set j with a portfolio size of s for month τ; and N is the number of cross-sections. To obtain the MRD for a portfolio of all stocks, we bootstrap using 5000 samples of N-1 firms.

The time-series of conditional MRD are computed herein for 22 portfolio sizes (PS) for the six IO sets and are reported in table 3.3. According to expectations, the MRD decrease monotonically with increasing PS for each of the IO sets. The MRD metric emits different inferences than those reported above for the MDD metric. For example, the required PS to achieve at least 90 percent of the potential improvement in the MRD by moving from a PS of 2 to all is under 100 for only two IO sets. The two PSs below 100 are 70 (IOSP of 42.7%) for cross-listed firms and 60 (IOSP of 55.0%) for IT firms. The decrease in the cross-sectional standard deviation of returns of individual firms with increasing portfolio size may help to explain the findings of MacDonald and Shawky (1995) that using this measure instead of a time-series measure reduces market volatility by about 50%, and results in a significantly positive relation between risk and return. This time-varying measure should be superior in capturing the impact of a changing investment opportunity set on conditional risk.

However, the MRD inferences implicitly assume that the cross-sectional distribution of portfolio standard deviations across the 5000 randomly selected portfolios for each unique combination of PS and IO set is relatively normal. If the distributions are highly positively skewed with high positive kurtosis at low PSs and these higher-order moments become more like those of a normal distribution as the PS increases (as is subsequently shown), then the required PS for an investor who dislikes both positive variance and kurtosis and likes positive skewness is likely to be lower than the over 100 stocks based on a consideration of the MRD metric in isolation. The MRD also is consistently higher for the small-firm IO set relative to the other IO sets for all PSs.

[Please insert Table 3.3 about here.]

The third "dispersion" metric examined in this section is referred to as the normalized portfolio variance (NPV) in the literature (e.g., Goetzmann and Kumar, 2005). This measure is based on the law of average covariances by Markowitz (1976), which states that the variance of a portfolio approaches the average covariance among the stock returns as the PS increases. This measure is developed from the following simplified expression for the variance of a portfolio drawn from IO set j for a PS of s (Bodie et al., 2003):

$$\sigma_{j,s}^2 = \sum_{i=1}^{s} w_i^2 \ \sigma_i^2 + \sum_{j=1}^{s}\sum_{i=1}^{s} w_i w_k \ cov(r_i, r_k) \quad \text{for } k \neq i \tag{3.3}$$

Since the weights for stocks i and k in an equal-weighted portfolio of s stocks are $w_i = w_k = 1/s$, the variance of the portfolio can be re-written as:

$$\sigma_{j,s}^2 = \frac{1}{s} \sum_{i=1}^{s} \frac{1}{s} \ \sigma_i^2 + \sum_{k=1}^{s}\sum_{i=1}^{s} \frac{1}{s^2} \ Cov(r_i, r_k) \quad \text{for } k \neq i \tag{3.4}$$

Defining average variance and covariance as $\bar{\sigma}_{j,s}^2 = \frac{1}{s} \sum_{i=1}^{s} \sigma_i^2$ and $\overline{cov}_{j,s} = \frac{1}{s(s-1)} \sum_{k=1}^{s}\sum_{i=1}^{s} cov(r_i, r_k)$, respectively, and substituting these expressions into equation (3.4) yields:

$$\sigma_{j,s}^2 = \left(\bar{\sigma}_{j,s}^2 / s\right) + (s-1)\overline{Cov}_{j,s} \tag{3.5}$$

Normalizing both sides of the above expression by the average variance yields the following normalized variance for the i-th randomly selected and equal-weighted portfolio of size s for IO set j:

$$NPV_{j,s,i} = \sigma_{j,s,i}^2 / \bar{\sigma}_J^2 = (1/s) + \left[(s-1)/s\right] \left(\overline{cov}_{j,s,i} / \bar{\sigma}_J^2\right) = (1/s) + \left[(s-1)/s\right] \overline{corr}_{j,s,i}, \tag{3.6}$$

where $\sigma^2_{j,s,i}$ is the variance of returns for the i-th randomly selected portfolio of size s for IO set j over the full period; $\bar{\sigma}^2_j$ is the average cross-sectional variance of returns for all the stocks in IO set j over the full period; $\overline{\text{cov}}_{j,s,i}$ is the average cross-sectional covariance of returns for the i-th randomly selected portfolio of size s for IO set j over the full period; $\overline{corr}_{j,s,i}$ is the average cross-sectional correlation of returns for the i-th randomly selected portfolio of size s for IO set j over the full period; and $I = 1, \ldots, 5000$.

Cross-sectional mean NPV values for 22 portfolio sizes for six IO sets using monthly returns over the period, 1975-2003, are reported in table 3.4 and are depicted in Figure 3.2. The means of the NPV display a gradual asymptotic decline as the PS increases and the mean NPVs are significantly different for portfolio sizes of 2 and all. If the decision criterion is to achieve at least 90 percent of the potential reduction of moving from a PS of 2 to all, then the required PS is about 20 to 25 stocks for the six IO sets. This represents an IOSP that ranges from a low of 2.7% for all firms to a high of 18.3% for IT firms. If the threshold is increased to 95 percent, then the required PSs are higher at about 40 for all IO sets. Furthermore, 90 and 95 percent of the convergence towards the steady-state standard deviation of the NPVs is obtained with approximately 20 and 30 stocks, respectively, for the six IO sets. These findings differ from those presented above for the MDD metric but are similar to those reported for an earlier period for Canadian markets by Kryzanowski et al. (1985) and Kryzanowski and Rahman (1986).

[Please insert Table 3.4 and Figure 3.2 about here.]

The last measure of stock diversification benefits examined in this section is the semi-variance. Cross-sectional mean values of the semi-variance measured in reference to the risk-free rate and the market return for 22 portfolio sizes for each of the six IO sets using monthly returns over the period, 1975-2003, are reported in Table 3.5. As for the NPVs, both measures of semi-variance decline asymptotically as the PS increases and all their means are significantly different for portfolio sizes of 2 and all. For a risk-reduction threshold of 90% percent, the required PS is marginally higher than for the NPVs at approximately 25 for all IO sets, which represents an IOSP range of 3.3% (big firms) to 22.9% (IT firms). For a risk-reduction threshold of 95%, the required PSs are also higher than for the NPVs and range between about 45 and 55 stocks. Thus, the required PS is higher for all IO sets when risk is measured by semi-variance instead of variance. Also, as shown earlier, while adequate diversification may require the same number of stocks, for example, for the all firm and IT IO sets, it requires a much greater proportion of the stocks in the IT versus the all-firm IO set.

[Please insert Table 3.5 about here.]

3.4.3 Higher-order Moments of Stock Return Metrics

Since the higher-order moments of stock returns are priced,[24] this section examines the impact of increasing portfolio size on the third (skewness) and fourth (kurtosis) moments of stock returns. The time-series mean of the cross-sectional *Skew* and *Kurt* for a fixed portfolio size *s* and IO set *j* are given by:

$$\mu_{Skew_{j,s}} = \frac{1}{N}\sum_{\tau=1}^{N} Skew_{j,s,\tau} \text{ and } \mu_{Kurt_{j,s}} = \frac{1}{N}\sum_{\tau=1}^{N} Kurt_{j,s,\tau} \tag{3.7}$$

[24] Kraus and Litzenberger (1976) and Harvey and Siddique (1999) find that unconditional and conditional skewness in returns, respectively, are priced. Fang and Lai (1997) find that the expected excess rate of return is related not only to the systematic variance but also to the systematic skewness and systematic kurtosis with a positive, negative and positive premium, respectively, for each.

where $Skew_{j,s,\tau}$ and $Kurt_{j,s,\tau}$ are respectively the cross-sectional skewness and kurtosis for the 5000 randomly selected portfolios for IO set j with a portfolio size of s for month τ; and N is the number of cross-sections.

The time-series means of the conditional skewness estimates for the cross-sectional distributions of portfolio returns are computed herein for 22 portfolio sizes (PS) for each of the six IO sets and are reported in panel A of Table 3.6. Our expectation is that the skewness of the cross-sectional distribution of returns across the 5000 randomly generated portfolios for each unique combination of PS and IO set should, on average, be highly right skewed at a PS of 2, and should decrease with increasing portfolio size. As expected, the mean cross-sectional skewness is highly positive at a PS of 2 and decreases monotonically as the PS increases from 2 to all stocks for all IO sets. Furthermore, between 35 to 40% of the cross-sectional right skewness is foregone when the PS increases from 2 to 5. Since skewness is positively priced by investors, this suggests that the required PS to not lose over 10% of the benefits of right cross-sectional skewness is about 2 stocks (i.e., a highly concentrated portfolio). This is consistent with the lower PSs of portfolio managers (such as hedge funds) who aggressively attempt to achieve high returns.

[Please insert Table 3.6 about here.]

The time-series means of the conditional kurtosis of the cross-sectional distributions of portfolio returns are computed herein for 22 PSs for each of the six IO sets and are reported in panel B of Table 3.6. Our expectation is that the kurtosis of the cross-sectional distribution of portfolio returns for the 5000 randomly generated portfolios for each unique combination of PS and IO set should, on average, be highly peaked at a PS of two, and that the excess kurtosis should decline with increasing portfolio size.[25] As expected, the time-series means of the cross-sectional kurtosis begin with their largest positive values at a PS of two for the six IO sets and decrease monotonically in value towards 3 but still remain positive for a PS of all for all six IO sets. This suggests that the cross-sectional distributions of portfolio returns are quite peaked for low PSs, and become increasing less peaked (i.e., flatter) as the PS increases and have almost the same peakedness as a normal distribution when all stocks in each IO set are considered. Since kurtosis is negatively priced by investors, this suggests that the required PS to achieve at least 90 percent of the potential reduction in the mean cross-sectional kurtosis by moving from a PS of 2 to a PS of all is, on average, about 20 to 25 for all six IO sets.

3.4.4 Composite Return and Risk Metrics

This section examines metrics that capture the various types of tradeoffs between the first (mean) and second (standard deviation or semi-standard deviation) moments of return distributions. The first and second composite metrics examined in this section of the chapter are the Sharpe-ratio-adjusted excess-return measure (ER) and the relative return measure (θ) used by Xu (2003), which are respectively given by:[26]

$$ER_{j,s} = \overline{R}_{j,s} - \left(\sigma_{j,s}/\sigma_J\right)\overline{R}_J \tag{3.8}$$

$$\theta_{j,s} = \frac{\overline{R}_{j,s}}{\left|\overline{R}_J\right|} - \frac{\sigma_{j,s}}{\sigma_J}\frac{\overline{R}_J}{\left|\overline{R}_J\right|} \tag{3.9}$$

[25] Excess kurtosis is a useful measure obtained by subtracting 3 (i.e., the kurtosis of a normal distribution) from the kurtosis measure. Positive excess kurtosis indicates a "peaked" distribution and negative excess kurtosis indicates a "flat" distribution.

[26] The ER metric becomes the M^2 metric of Modigliani and Modigliani (1997) if excess returns are used for the portfolio and the market, respectively.

where $\bar{R}_{j,s}$ and $\sigma_{j,s}$ are the average return and standard deviation of returns for IO set j for a PS of s, and $\bar{R}_J$, $|\bar{R}_J|$ and σ_J are the average return, average absolute return and standard deviation of returns for the equal-weighted portfolio of all the stocks in IO set j.

The mean values are reported in Table 3.7 for these two measures for 5000 randomly generated portfolios for each unique combination of j and s. As expected given the theoretical efficiency of holding the "market", both ER and θ are negative at a PS of two and move monotonically towards zero with increasing portfolio size. If the decision criterion is to achieve at least 90 percent of the potential reduction in the shortfalls in Sharpe-ratio-adjusted excess returns and relative returns of moving from a PS of 2 to all, then the required PS is about 40 for IO sets consisting of cross-listed firms (IOSP of 24.4%) and of big firms (IOSP of 8.3%), about 55 (IOSP of 50.5%) for the IO set of IT firms and over a hundred for the other three IO sets. Only the IO set of cross-listed firms has a PS less than 100 (i.e., 75) if the threshold is increased to 95 percent. Furthermore, 90 percent of the convergence towards the steady-state standard deviation of zero for both of these measures is obtained with approximately 40, 40 and 45 stocks for the IO sets of cross-listed, big and IT firms, respectively.

[Please insert Table 3.7 about here.]

The third and fourth measures of diversification benefits examined in this section are the Sharpe (Sharpe, 1994) and the Sortino (Sortino and Price, 1994) ratios. While the previous two measures, ER and θ, are total-risk- and market-adjusted measures, the Sharpe ratio is an excess return to total risk measure given by $Sh_{j,s} = (\bar{r}_{j,s} - r_f)/\sigma_{j,s}$, and the Sortino ratio is an excess return to semi-standard deviation risk measure given by

$Sor_{j,s} = (\bar{r}_{j,s} - r_f) / \sigma^-_{j,s}$. Thus, while the Sharpe ratio accounts for any volatility in the return of an asset, the Sortino ratio only accounts for deviations below the mean since deviations above the mean are not considered to be a component of risk.

The mean values of the Sharpe and Sortino ratios are reported in Table 3.8 for 5000 randomly generated portfolios for each unique combination of j and s. As expected given the theoretical efficiency of holding the "market", both *Sh* and *Sor* increase with increasing portfolio size. If the decision criterion is to achieve on average at least 90 percent of the potential increase in the Sharpe ratio from moving from a PS of 2 to all, then the required PS is about 75 (IOSP of 45.7%) for cross-listed firms, 85 (IOSP of 17.6%) for big firms, and over a hundred for the other four IO sets. None of the IO sets has a PS less than 100 for the Sharpe ratio if the threshold is increased to 95 percent. In contrast and as expected given the positive skewness identified earlier, the required PSs are much lower for all IO sets based on the Sortino metric in order to achieve at least 90 percent of the potential increase in the Sortino ratio from moving from a PS of 2 to all (also see figure 3.3). Specifically, the required PSs on average are about 50 for cross-listed firms (IOSP of 30.5%) and IT firms (IOSP of 45.9%), 55 for big firms (IOSP of 11.4%), 60 for TSX-only listed firms (IOSP of 9.5%) and all firms (IOSP of 8.0%), and 75 for small firms (IOSP of 28.0%). This once again illustrates the greater risk inherent in the small firm and IT sectors.

[Please insert Table 3.8 and Figure 3.3 about here.]

3.4.5 Probability of Underperforming a Target or Lower-bound Rate of Return

The metrics examined in this section of the chapter are based on the intuition of reducing the relative importance of idiosyncratic volatility with respect to total portfolio variance. Based on the approach by Xu (2003), these measures deal with determining the number of stocks required for the probability (likelihood) to underperform a target or lower-bound return over various investment holding periods. Three target or lower-bound rates of return are used herein; namely, the market return (as proxied by an equal-weighted average of all the stocks available for investment in each IO set in each month over the studied period), a zero return and a lower-bound return of -25%.

The mean values of the average probabilities over implicit holding periods of one month, one year and three years of not achieving these three target or lower-bound rates of return criteria are reported in Tables 3.9, 3.10 and 3.11, respectively, for 5000 randomly generated portfolios for various unique combinations of j and s. The results for the shortest holding period of one month should capture the trading behavior of an active noise trader, and the successively longer one and three year holding periods should capture the trading behavior of progressively more value-oriented investors.

[Please insert Tables 3.9, 3.10 and 3.11 about here.]

The Table 3.9 results, which report the average probabilities of obtaining (compound) returns that are inferior to the all-firm ("market") returns for each IO set over the three holding periods, are examined first. The average probabilities for the least diversified portfolios consisting of two stocks are always above 0.5 (ranging between 0.543 for cross-listed firms for the one-month holding periods to 0.683 for TSX-only listed firms for the three-year holding periods), and the average probabilities decline monotonically with movement towards the most diversified portfolios consisting of all stocks in each IO set for all three holding periods. The reduction in the average probabilities from a PS of two to a PS of all is significant for all IO sets for the three holding periods. The average probabilities for the IO set of small firms are higher than for the other five IO sets for the less diversified PSs for all three holding periods. For a fixed PS and IO set, most of the average probabilities decline as the holding period gets longer. The major exceptions are the slightly higher average probabilities for big firms and IT firms for more diversified portfolios when the holding period goes from one to three years. These results strongly show that holding portfolios that tend to mimic the market will be favored if the investor is concerned about the probability of underperforming the market. This may explain the behavior of many managed funds (such as mutual funds) to behave as if they were closet-indexers.

The Table 3.10 results, which report the average probabilities of obtaining negative (compound) returns over the three holding periods, are examined next. All but one of the average probabilities for the least diversified portfolios consisting of two stocks is below 0.5, and average probabilities decline monotonically as one moves to the most diversified portfolios consisting of all stocks in each IO set for all three holding periods. The reduction in the average probabilities from a PS of two to a PS of all is significant for all IO sets for the three holding periods. Not surprisingly, the average probabilities for the IO set of small firms are higher than for the other five IO sets for all PSs for all three holding periods. For a fixed PS and IO set, the average probabilities also decline as the holding period gets longer. If the decision criterion is to achieve on average at least 90 percent of the potential decrease in the average probabilities from moving from a PS of 2 to all, then the required PS is dependent on both the IO set being examined and the length of the holding period. Specifically, the required PSs at 90% are approximately 70 stocks for cross-listed and IT firms, 60 for big firms and over 100 for the other three IO sets for the one-month holding periods. The required PSs at 90% are approximately 55 stocks for the all-firm IO set, 60 for the TSX-only listed and big firm IO sets, about 75 stocks for cross-listed firms, about 95 for IT firms and over 100 for small firms for a one-year holding period. The required PSs at 90% are 50 for big firms, 70 for IT firms and over 100 for the other four IO sets for the three-year holding periods.

The Table 3.11 results, which report the average probabilities of obtaining (compound) returns that are more than 25% over the three holding periods, are examined next. For the least diversified portfolio size of 2, the average probabilities of achieving a loss of more than -25% is lowest for big firms and highest for small firms for all three holding periods. For PSs of 5 or less, this probability generally increases with an increase in the holding period for each of the six IO sets. For PSs of 10 or greater, this probability generally increases from a one month to a one year holding period and then generally decreases from a one year to a three year holding period. If the decision criterion is to achieve on average at least 90 percent of the potential decrease in the average probabilities from moving from a PS of 2 to all, then the required PS is dependent on both the IO set being examined and the length of the holding period. Specifically, the required PSs at 90% are approximately 5 stocks for big firms, 10 stocks for all, TSX-listed only and small firms, 15 for cross-listed firms and 20 for the IT firms for the one-month holding periods. The required PSs at 90% are approximately 25 stocks for the IT IO set, about 35 for the All, TSX-only listed and cross-listed firm IO sets, about 40 for big firms, and over 100 for small firms for a one-year holding period. The required PSs at 90% are about 15 for big firms, about 25 for cross-listed and IT firms, about 30 for all and TSX-only listed firms and about 85 for small firms for the three-year holding periods. Thus, with the exception of portfolios drawn from the small or IT IO sets, a portfolio of 40 stocks will have, on average, a probability of up to about 6% of obtaining a compound return of more than -25% for holding periods of 1 month, 1 year or 3 years.

These findings provide mixed evidence for the refutation by various authors (e.g., Samuelson, 1963, 1989; Kritzman, 1994, 1997; Fisher and Statman, 1999) that investors suffer from the cognitive error that losses are reduced over longer holding periods. Specifically, while the probability of not earning a positive return is reduced with a longer holding period, the probability of not earning the market return is increased with a longer holding period. Thus, the existence of cognitive error depends upon the choice of anchor or benchmark return.

3.5 CONCLUDING COMMENTS

This chapter used various metrics to determine the minimum portfolio size required to achieve a sufficiently well diversified portfolio that is chosen naively for various investment opportunity sets. Based on a summary of these results for the achievement, on average, of 90% of the benefits of diversification presented in Table 3.12, we found that this minimum portfolio size is very sensitive to the performance metric used to measure such benefits and is somewhat less sensitive to the investment opportunity set from which the portfolio selection is made. Whether or not these findings are applicable to future periods depends upon whether or not the investment opportunities represented by the period studied herein are applicable to future time periods.

Thus, if the conventional measures of risk (such as the time-series variance, semi-variance and NPV) are used, then about 20 to 25 stocks are required on average to achieve about 90% of the potential benefits from diversification. If average time-series measures of the excess standard deviation of nonmarket portfolios over that of the market portfolio (such as the MDD) are used, then the number of stocks required to achieve about 90% of the potential benefits from diversification is about 40 and 45 stocks for cross-listed and big firms, respectively, and about 95 or greater for the other four investment opportunity sets. As noted repeatedly in the text, a similar portfolio size in number represents quite different proportions of the total number of stocks available in each investment opportunity set (24.4% and 9.3% for cross-listed and big firms in this case). If instead time-series averages of the standard deviations of the cross section of portfolio returns (such as the MRD) are used, then the required number of stocks on average is about 70 for cross-listed firms, 60 for IT firms and over 100 for the other four IO sets. However, this inference must be tempered since it ignores higher-order moments of the cross-sectional distributions of portfolio returns, especially for investors who prefer positive skewness and dislike positive kurtosis. If skewness and kurtosis are considered in isolation, then the minimum number of stocks required to achieve about 90% of the potential benefits from diversification (or not diversifying in the case of skewness) is about 2 stocks for skewness and about 20 to 25 stocks for kurtosis.

If the investor is concerned about the impact of diversification on reward for bearing risk (as measured by ER, θ, Sharpe ratio or Sortino ratio), then the minimum number of stocks required to achieve about 90% of the potential benefits from diversification ranges from 40 to over 100 stocks depending upon the performance metric used and the investment opportunity set considered. To illustrate, most likely due to the skewness and kurtosis in the various return distributions considered, such diversification benefits are achieved with from about 50 stocks to about 75 stocks depending upon the investment opportunity set based on the Sortino ratio that uses downside risk. And finally, if the investor is interested in achieving about 90% of the potential benefits from diversification in meeting three rates of return targets or lower bounds over holding periods of one month, one year or three years, then portfolio sizes of over 100 are required for a market rate of return target, portfolio sizes of 55 to over 100 are required for a zero rate of return target, and portfolio sizes of 5 to 40 (up to 100 for small firms) are required for a lower-bound return target of more than -25%.

Despite this ambiguity in what is the optimal portfolio size to obtain a fixed percentage of the benefits from diversification, the chapter finds that the minimum portfolio sizes for specific performance metrics are higher for Canadian equities than the values reported in the literature for US equities. This is probably due to the higher concentration of Canadian stocks within a few industries (sectors), which makes it more difficult to diversify away firm-specific risk.

The ambiguity in what is the optimal portfolio size also illustrates the need for financial advisors to carefully implement the "know your client" rules. Specifically, it raises the standard of care required in assessing the tolerance and attractiveness of various moments of the return distributions of various potential portfolio sizes for investors.

Much scope exists for further research on this theme. This includes an examination of other investment opportunity sets that are consistent with the objectives of open-end mutual funds or the mandates of pension fund managers such as value and growth, industry-specific and multi-asset classes. It also includes the consideration of the costs associated with increasing portfolio size, particularly trade costs, and the lack of liquidity. Other interesting avenues of research include an examination of potentially asymmetric benefits of diversification in up and down markets or in expansionary or recessionary economies, and an examination of whether the ambiguity in the minimum portfolio size extends to other asset classes and markets.

CHAPTER 4

ASYMMETRIC VOLATILITY TRANSMISSION, CO-MOVEMENT AND PERSISTENCE FOR CANADIAN CROSS-LISTED STOCK

4.1 INTRODUCTION

Asymmetric volatility is induced by overreaction to negative news (Crouchy and Rockinger, 1997) when contemporaneous returns and conditional return volatility are negatively correlated (Wu, 2001). The existence of this relationship across financial markets can lead to volatility spillover. Volatility spillover research focuses on inter-market returns (Eun and Shim, 1989; Aggarwal and Park, 1994), and on inter-market volatility shocks (King and Wadhwani, 1990; Karolyi, 1995; Koutmos, 1996). Since much of the research on inter-market volatility transmission examines the spillover effects among markets with non-synchronous trading hours (Brooks and Henry, 2000), their results are not robust (Gannon and Choi, 1998). Also, the robustness of such tests can only be verified for a time period that covers several business and market cycles (Longin and Solnik, 1995).

The topic of inter-market volatility dynamics needs to be revisited by examining co-movements and volatility spillovers for the same group of stocks that trade on two different national markets with synchronous trading hours in order to provide a cleaner test of the nature of information flows between the two financial markets, their level of integration and the nature of their interdependence (Niarchos et al., 1999). Cross-listed Canadian stocks appear to be a good choice for such a study since the number of Canadian stocks cross-listed on the TSX and U.S. markets has increased from 133 in

1990 (Karolyi, 1995) to 324 in 2003. These stocks now account for the single largest share of foreign stocks cross-listed on the U.S. markets.

Thus, the main objective of this chapter is to examine co-movements, asymmetries and volatility spillovers for the 324 Canadian stocks cross-listed on the TSX and U.S. markets over the 1975-2003 period. To ensure inferential sturdiness, the chapter uses four bi-variate versions of the popular GARCH(1,1) model (namely, the GJR-, E-, DCC-, and BEKK) to examine asymmetry, comovement and volatility transmission for the equal- and value-weighted daily and monthly returns for this sample of cross-listed firms.

The remainder of this chapter is structured as follows. A brief literature review is presented in the next section. In section three, the sample and data are described. In section four, variance asymmetry is examined for the sample of cross-listed firms in each market using various univariate models. In section five, variance asymmetry, spillover and persistence are examined for the cross-listed samples using four bivariate GARCH models. Section six concludes the chapter.

4.2 BRIEF LITERATURE REVIEW

4.2.1 Asymmetry and Volatility Spillovers

Some stylized facts exist about the properties of stock returns. These include leptokurtic distributions (Nelson, 1991; Booth et al., 1997), presence of autocorrelation (Lo and MacKinlay, 1990), volatility clustering where large changes follow large changes of either sign and small changes follow small changes (Engle, 1982; Bollerslev et al., 1994), and asymmetry in volatility, which implies a negative correlation between past returns with current volatility (Bekaert and Wu, 2000). Two hypotheses exist to explain this asymmetry in volatility; namely, the leverage effect (Black, 1976; Christie, 1982), and the volatility feedback effect due to a time-varying risk premium (French, Schwert and Stambaugh, 1987). According to the leverage effect hypothesis, a decrease in stock price lowers returns, and increases the proportion of debt and consequently financial leverage and return volatility. According to the time-varying risk premium hypothesis, a rise in equity volatility raises the required return on equity by increasing the risk premium, which lowers equity prices (Chan et al., 2005). Thus, required returns on equity are related to a time-varying risk proxy (expected volatility). The two theories provide contradictory predictions on causality with return shocks leading to [following] changes in conditional volatility according to the leverage [volatility feedback] hypothesis.

Empirical findings suggest that both theories only partially explain asymmetric volatility (Schwert, 1989), and that the two effects interact simultaneously in that the leverage effect reinforces the volatility feedback effect (Bekaert and Wu, 2000). This is consistent with a partial-adjustment price model (Koutmos, 1998) where positive returns are incorporated faster into market prices because they are more persistent than negative returns. This leads some researchers to interpret the evidence as providing more support for the volatility feedback over the leverage hypothesis (Bekaert and Wu, 2000). In sum, the debate of whether the asymmetric volatility phenomenon is due to a firm-level leverage effect or a market-wide volatility feedback effect continues (Dennis, Mayhew, and Stivers, 2004).

A debate also exists regarding the sign of the relationship between returns and volatility (Li et al., 2004). A size or threshold effect also affects the asymmetric impact of negative and positive returns on volatility (Crouchy and Rockinger, 1997). Negative returns below a threshold level strongly increase volatility due to 'leverage' and the 'feedback mechanism', while positive returns seem to have a negligible effect on volatility. In a similar manner, a long-term trend of either negative or positive shocks has a cumulative effect on crossing a certain threshold.

Despite low correlations between markets that indicate market segmentation (Niarchos et al., 1999), some studies report increasing interdependences among stock markets (Eun and Shim, 1989; Arshanapalli and Doukas, 1993). Progressive globalization and increasing integration of financial markets following the market crash of October 1987 led several studies to examine the nature of the mechanisms influencing information flows between various capital markets (Liu and Pan, 1997). Information transmission occurs through both a mean spillover effect as well as volatility transmission (King and Wadhwani, 1990; Theodossiou and Lee, 1993). Financial researchers find supporting evidence (Yang and Doong, 2004) for price (first-moment) and volatility (second-moment) spillovers and reciprocity in terms of their interdependencies (Hamao et al., 1990). Research on understanding how volatility spillovers and transmissions occur (Kearney and Patton, 2000) has caused some debate about the duration and size of their magnitudes. For example, some authors find that their magnitudes are small and of short duration (Susmel and Engle, 1994).

While some of these studies have shortcomings due to potentially misleading spillover tests in nonsynchronous markets where one market is closed while the other is still trading (Gannon and Choi, 1998), the empirical evidence on the role of the U.S. stock market is mixed. While some researchers find that mean and/or volatility spillovers originate significantly from the U.S. market (Hamao, Masulis, and Ng, 1990; Theodossiou and Lee, 1993), others find nonsupportive evidence (Lin, Engle, and Ito, 1994). Furthermore, some researcher find significant spillovers in both directions (Koutmos and Booth, 1995; Bae and Karolyi, 1994).

Researchers also report that causalities and volatility spillovers change over time (Wu and Su, 1998). Current research on asymmetry and volatility transmission finds an increase in correlations in down markets (Longin and Solnik, 2001), time-variation in conditional skewness (Harvey and Siddique, 2000), no spillovers in unrelated markets (Niarchos et al., 1999), no asymmetric conditional volatilities for bonds (Cappiello et al., 2003), and intra-day unidirectional effects (Gannon, 1994) in contemporaneous markets. Since volatility spillover tends to increase non-systematic (idiosyncratic) risk, it reduces the gains from international portfolio diversification (Kanas, 2000). The covariance structure between markets also changes since the volatilities of markets and the interdependences across markets evolve (Longin and Solnik, 1995), although some researchers consider such changes as being transitory (King, Sentana, and Wadhwani, 1992).

As further evidence of how actively researchers are pursuing the examination of asymmetries and volatility spillovers in various markets, we list the following studies as an incomplete list: Yang and Doong (2004) for the G-7 countries; Kearney and Patton (2000) for the countries in the European Monetary System; Booth et al. (1997) for the countries in the Scandinavian stock markets; In et al. (2001) for Asian stock markets

(Hong Kong, Korea and Thailand); Liu and Pan (1997) for the U.S. and Pacific-Basin stock markets; Niarchos et al. (1999) for U.S. and Greece; Brooks and Henry (2000) for U.S., Japan and Australia; Gannon and Choi (1998) and Koutmos and Booth (1995) for the New York, Tokyo and London stock markets; Karolyi (1995) for U.S. and Canada; Koutmos (1998) for the value-weighted stock indices of nine industrialized countries; Gannon (1996) for East Asian currencies; Laopodis (1998) for the German mark versus three EMS currencies (French franc, Dutch guilder, and Belgian franc) and three non-EMS currencies (Canadian dollar, U.S. dollar, and Japanese Yen); Arago et al. (2003) for spot and index futures; Kanas (2000) for stock returns and exchange rates for six industrialized countries; So (2001) for interest rates and U.S. dollar; Tse (1999) for the DJIA index and the futures market; and Chan et al. (1991) for the S&P 500 and the futures market.

4.2.2 Autoregressive Conditional Heteroskedasticity

Engle (1982) developed the autoregressive conditional heteroskedasticity (ARCH) model to capture volatility clustering and persistence in financial time series. Bollerslev (1986) subsequently generalized the ARCH to the GARCH model. These models have the ability to capture volatility persistence and clustering, thick-tailed distributions, and even an infinite unconditional variance. Unfortunately, the simple GARCH models are indifferent to both positive and negative innovations, and they underpredict volatility due to negative shocks (Crouchy and Rockinger, 1997). Based on an examination of the causality of autocorrelations towards the conditional volatility of returns under a GARCH process (Diebold and Nerlove, 1989; Lamoureux and Lastraps, 1990), researchers model volatility in terms of information arrival (Engle and Ng, 1993; Bollerslev and Melvin, 1994; and Hogan and Melvin, 1994). The research methodology used to study the transmission of movements include the dynamic simultaneous model (Koch and Koch, 1991), VAR (Eun and Shim, 1989), uni-variate GARCH (Hamao et al., 1990), multi-variate GARCH models (Theodossiou and Lee, 1993), the GJR-GARCH that is less sensitive to outliers (Glosten, Jagannathan, and Runkle, 1993) and the EGARCH or Exponential GARCH that ensures that the variance is positive (Nelson, 1991). The last two models enable empirical researchers to test for asymmetric volatility (Koutmos, 1998) and volatility spillover.[27]

Multivariate GARCH models include the Vech and Diagonal Vech models (Bollerslev, Engle and Woolridge, 1988), Constant Correlation model (Bollerslev, 1990), BEKK model (Engle and Kroner, 1995), and the Dynamic Conditional Correlation model (Engle and Sheppard, 2001). The main problems associated with the multivariate GARCH models are the strong restrictions on the number of parameters to be estimated that hinder convergence (Baur, 2002) and the optimization of the maximum likelihood function to a global maximum (Engle, 2002), and the restrictions on positive definiteness of the covariance matrix (Kash-Haroutounian, 2005). The Conditional Correlation models of Bollerslev (1990) overcome these limitations with the estimation of volatility using a univariate GARCH model, followed by the use of a conditional correlation matrix using standardized residuals. Nevertheless, the assumption of a constant conditional correlation is restrictive (Tsui and Yu, 1999; Tse, 2000) since it does not reflect a dynamic response to innovations (Chiang and Tan, 2005) and it results in covariances of

[27] The asymmetric volatility hypothesis incorporates both the 'heat wave' hypothesis reflecting country-specific volatility and the 'meteor shower' hypothesis of volatility spillover from one market to another (Niarchos et al., 1999).

assets being determined solely by their respective variances (Harris, Stoja, and Tucker, 2004). The latter limitation is overcome by the Dynamic Conditional Correlation (DCC-MVGARCH) model of Engle (2001) and Engle and Sheppard (2001). This model estimates the conditional correlation coefficients and variance-covariance matrix simultaneously after estimating the univariate GARCH parameters in the first stage and the DCC parameters in the second stage.

4.3 SAMPLE AND DATA

Using the TSX Monthly Review, 324 Canadian firms cross-listed on the TSX and U.S. markets are identified in December 2003. Using daily returns extracted from the CFMRC and the CRSP historical database, both equal- and value-weighted portfolio returns are computed for these 324 cross-listed Canadian stocks.

The basic statistics for these respective return series, which are presented in Table 4.1, confirm the stylized facts reported in the literature. The kurtosis measure and Jarque-Bera statistics indicate that the distributions of returns are leptokurtic and 'fat-tailed' (not normal). The results for all five tests (F-test, Siegel-Tukey, Bartlett, Levene, and Brown-Forsythe) that are reported in Table 4.2 reject the equality of inter-market variances, except for the monthly returns for the equal-weighted portfolio. Based on Table 4.3, the correlations between the return variances are lower for equal- versus corresponding value-weighted portfolios, and the correlations are lower using daily than monthly returns.

[Please place Tables 4.1, 4.2 and 4.3 about here.]

Based on the unit root tests reported in Table 4.4, the null hypothesis of a unit root is rejected for the series of return variances for both the equal- and value-weighted portfolios of daily and monthly returns based on both the Adjusted Dickey-Fuller and Phillips-Perron tests. Based on the critical values for the Johansen co-integration test (Cavaliere, Fanelli and Paruolo, 2001), the null hypothesis of co-integration between two series of rank 0 and 1 is rejected by both the Johansen's trace test (λ_T) and the lambda-max test (λ_M) for all the tested return variance series that are reported in Table 5. These findings reinforce the subsequent decision to use the simple mean model without ARMA terms in the first moment equations of the two GARCH models, as our focus is on analyzing components of the time-varying covariance matrix (Bauer, 2002). Preliminary modeling of an AR(1) term in the mean equation also confirms that the error terms associated with this formulatiion are white noise (i.e., likely to contain only "non-priced risk"). In addition, it is not necessary to model returns herein as an autoregressive process since this chapter models synchronous markets (as in Gannon and Au-Yeung, 2004).

[Please place Tables 4.4 and 4.5 about here.]

4.4 UNIVARIATE MODELS AND CROSS-LISTED VOLATILITY ASYMMETRY

The first test for asymmetry in the variances of the various return series uses squared returns as the variance measure and dummy variables in the following regression (Brooks and Henry, 2000; Engle and Ng, 1993):

$$R_{i,t}^2 = \alpha_{i,0} + \beta_{i,1} \cdot N_{i,t-1} + \beta_{i,2} \cdot \left(N_{i,t-1} \cdot R_{i,t-1}\right) + \beta_{i,3} \cdot \left(P_{i,t-1} \cdot R_{i,t-1}\right) + \varepsilon_{i,t} \qquad (4.1)$$

where $N_{i,t-1} = 1$ if $R_{i,t-1} < 0$ and zero otherwise, and $P_{i,t-1} = 1 - N_{i,t-1}$. In (4.1), the sign bias is given by the estimated coefficient of $\beta_{i,1}$ and the size biases by the estimated coefficients of $\beta_{i,2}$ and $\beta_{i,3}$ that capture the magnitude of innovations in $R_{i,t-1}$. Based on the results reported in Table 4.6, estimates of coefficient $\beta_{i,1}$ reveal a sign bias in three of the four daily series of return variances (the exception is the value-weighted portfolio of U.S. trades) and only one of the four series of monthly variances (i.e., for the value-weighted portfolio for TSX trades). The estimated coefficients for the size bias $(\beta_{i,2}, \beta_{i,3})$ are of opposite signs, as expected, except for the return variances for the value-weighted portfolio for TSX trades. However, the size-bias estimates are significant for the same variance series as for the sign-bias estimates.

[Please place Table 4.6 about here.]

The next test for asymmetry in the return volatilities of the daily and monthly equal- and value-weighted series uses two univariate GARCH models; namely, the GJR-TGARCH of Glosten, Jaganathan, and Runkle (1993), and EGARCH of Nelson (1991). Two models are used because the choice of volatility model can lead to different inferences (Kroner and Ng, 1998).

The variance term of the univariate GJR-GARCH model can be expressed as:

$$\sigma_t^2 = \alpha_0 + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \varepsilon_{t-1}^2 I_{\varepsilon<0}(\varepsilon_{t-1}) + \beta_3 \sigma_{t-1}^2 \qquad (4.2)$$

where persistence is measured by the coefficient β_3 and the indicator variable I for $\varepsilon < 0$ captures asymmetry in the estimate of coefficient β_2. A negative value of $\hat{\beta}_2$ implies that negative residuals increase the variance more than positive residuals.

Based on the results reported in Table 4.7 for the univariate GJR-GARCH model, the return variances for both equal- and value-weighted portfolios exhibit stronger asymmetry for trades on the TSX versus those in the U.S. for daily returns. This indicates that negative shocks increase volatility more on the TSX than in the U.S. for the same cross-listed shares. In contrast, the equal-weighted monthly portfolios of U.S. trades exhibit stronger asymmetry than the TSX trades. Also, positive shocks lead to volatility for the value-weighted monthly portfolios, with TSX trades exhibiting higher sensitivity.

[Please place Table 4.7 about here.]

The variance term of the univariate E-GARCH model can be expressed as:

$$Ln\left(\sigma_t^2\right) = \alpha_0 + \beta_1\left(\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}}\right) + \beta_2\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \beta_3\, Ln\left(\sigma_{t-1}^2\right) \tag{4.3}$$

where persistence is captured by the coefficient β_3, and significant negative values of $\hat{\beta}_2$ indicate that negative residuals lead to higher variances (i.e., asymmetry).

Based on the results reported for the univariate E-GARCH model in Table 4.7, variances based on TSX trades exhibit stronger asymmetries than those based on their U.S. counterparts for both equal- and value-weighted daily returns. In contrast and consistent with the GJR-GARCH findings discussed above, equal-weighted monthly portfolios of U.S. trades exhibit stronger asymmetry than the TSX trades, and positive shocks lead to greater volatility for value-weighted monthly portfolios, with greater sensitivity for TSX versus U.S. trades.

[Please place Table 4.8 about here.]

4.5. VARIANCE ASYMMETRY, COMOVEMENT, SPILLOVER AND PERSISTENCE

Variance asymmetry, spillover and persistence are examined in this section using a multivariate GARCH framework, which allows for a conditional or time-varying covariance matrix. Once again to ensure inferential sturdiness, four bi-variate GARCH models (the GJR-, E-, DCC-, and BEKK) are used herein. The GARCH(1,1) specification is retained for all four bi-variate models, since research in finance finds that this model is the most robust and parsimonious (Engle, 2001), avoids over-fitting, and is less likely to violate non-negativity constraints (Brooks, Burke, and Persand, 2003). Furthermore, the GARCH(1,1) is not inferior to other models (Hansen and Lunde, 2005), except when other models include a leverage effect (as is done herein). For consistency, the four models have the same mean equations (first-moment condition) but differ only in their conditional variance expressions (second-moment condition). When univariate models are extended to a multivariate framework, an additional constraint must be imposed to ensure that the likelihood function is defined. This constraint is that the conditional covariance matrix is positive definite. Furthermore, the results based on the monthly return series are not reported in the interests of compactness due to their similarity with the results reported herein for the daily return series.

The first bivariate model considered herein is the GJR-GARCH, which is also called the threshold GARCH or T-GARCH. It is simpler and less sensitive to outliers than other GARCH models (Arago et al., 2003). While the mean equations in GJR-GARCH are modeled by Niarchos et al. (1999) with MA(1) terms using their own past residuals as well as those of the other series, our Johansen cointegration tests rejected the null hypothesis of cointegrating vectors in both daily and monthly equal- and value-weighted return series. Hence, past innovations are not included in our mean equations and the returns are regressed only on a constant (intercept).

The conditional return variances $\sigma^2_{cd,t} = Var\left(\varepsilon_{cd,t} / \Omega_{t-1}\right)$ and $\sigma^2_{us,t} = Var\left(\varepsilon_{us,t} / \Omega_{t-1}\right)$ for the trades for the same securities in the two markets are expressed as:

$$\sigma^2_{cd,t} = \alpha_{cd,1} + \beta_{cd,1} \cdot \varepsilon^2_{cd,t-1} + \beta_{cd,2} \cdot \sigma^2_{cd,t-1} + \beta_{cd,3} \cdot \varepsilon^2_{us,t-1} + \beta_{cd,4} \cdot I_{cd} \cdot \varepsilon^2_{cd,t-1} + \beta_{cd,5} \cdot I_{us} \cdot \varepsilon^2_{us,t-1} \quad (4.4)$$

$$\sigma^2_{us,t} = \alpha_{us,1} + \beta_{us,1} \cdot \varepsilon^2_{us,t-1} + \beta_{us,2} \cdot \sigma^2_{us,t-1} + \beta_{us,3} \cdot \varepsilon^2_{cd,t-1} + \beta_{us,4} \cdot I_{us} \cdot \varepsilon^2_{us,t-1} + \beta_{us,5} \cdot I_{cd} \cdot \varepsilon^2_{cd,t-1} \quad (4.5)$$

Persistence in the conditional volatilities is captured by the coefficients $\left(\beta_{cd,2}, \beta_{us,2}\right)$ for the Canadian and U.S. markets, respectively. Asymmetries in the Canadian (cd) and U.S. (us) markets are captured by the coefficients $\beta_{cd,4}$ and $\beta_{cd,5}$, respectively, where $I_{cd} = 1$ if $\varepsilon_{cd,t-1} < 0$ and $I_{us} = 1$ if $\varepsilon_{us,t-1} < 0$. Volatility spillover from the U.S. market to the Canadian market is captured by the coefficient $\beta_{cd,3}$, and by $\beta_{us,3}$ for spillovers in the reverse direction. These estimates reflect the effect of the two squared cross-innovation terms $\left(\varepsilon^2_{us,t-1}, \varepsilon^2_{cd,t-1}\right)$.

The results for the bivariate GJR-GARCH estimations for the portfolios of daily equal- and value-weighted returns are presented in panels A and B of table 8. All the estimated coefficients (including pair-wise coefficients) are very significant. Negative [positive] persistence exists in the TSX [U.S.] trades for the equal-weighted series for all the time periods. In contrast, negative persistence exists in the TSX trades (except during 1990-1999) and in the U.S. trades for the value-weighted series for all the time periods. Volatility spillover from the U.S. to the Canadian market increases during 1975-1999 and turns negative during the most recent 2000-2003 period for both the equal- and value-weighted series. Volatility spillover from the Canadian to the U.S. market increases over time for the equal-weighted series and is only significant for the value-weighted series for the period 1990-1999. Thus, the direction of volatility spillover is mainly from the U.S. to the Canadian market for the value-weighted series. The asymmetric response of TSX trades to negative shocks in the U.S. market (and vice versa) for the equal-weighted series decreases after October 1987 but has subsequently increased during 2000-2003.

The second bivariate model considered is the exponential GARCH (E-GARCH), which ensures that the logarithmic conditional variances are always positive (Niarchos et al., 1999). The model is given by:

$$Ln\left(\sigma_{cd,t}^{2}\right)=\alpha_{cd,1}+\beta_{cd,1}\cdot Ln\left(\sigma_{cd,t-1}^{2}\right)+\beta_{cd,2}\cdot G_{cd,t-1}+\beta_{cd,3}\cdot G_{us,t-1} \tag{4.6}$$

$$Ln\left(\sigma_{us,t}^{2}\right)=\alpha_{us,1}+\beta_{us,1}\cdot Ln\left(\sigma_{us,t-1}^{2}\right)+\beta_{us,2}\cdot G_{us,t-1}+\beta_{us,3}\cdot G_{cd,t-1} \tag{4.7}$$

where

$$G_{cd,t-1}=\left(\left|\frac{\varepsilon_{cd,t-1}}{\sigma_{cd,t-1}}\right|-\sqrt{\frac{2}{\pi}}\right)+\theta_{cd}\frac{\varepsilon_{cd,t-1}}{\sigma_{cd,t-1}}, \text{ and} \tag{4.8}$$

$$G_{us,t-1}=\left(\left|\frac{\varepsilon_{us,t-1}}{\sigma_{us,t-1}}\right|-\sqrt{\frac{2}{\pi}}\right)+\theta_{us}\frac{\varepsilon_{us,t-1}}{\sigma_{us,t-1}}. \tag{4.9}$$

In this model, the asymmetric response in the two markets is captured by the coefficients $(\theta_{cd},\theta_{us})$ where $\theta_{cd}=1$ if $\varepsilon_{cd,t-1}<0$ and $\theta_{us}=1$ if $\varepsilon_{us,t-1}<0$. The coefficients $\beta_{cd,3}$ and $\beta_{us,3}$ capture volatility spillover from the U.S. to the Canadian market and vice versa, respectively, after reflecting the effect of the two cross-innovation terms $(G_{cd,t-1},G_{us,t-1})$. The persistence in the conditional volatilities in the two markets is captured by the coefficients $(\beta_{cd,1},\beta_{us,1})$ (Yang and Doong, 2004). The terms

$(G_{cd,t-1}, G_{us,t-1})$ are an asymmetric function of past standardized innovations, and measure the magnitude and sign effect (In et al., 2001).

The results for the bivariate E-GARCH estimations for the portfolio pairings of daily equal- and value-weighted returns are presented in panels A and B of Table 4.9. In contrast with the estimates from the GJR-GARCH for both the equal- and value-weighted series, the estimated volatility spillovers from both markets remain virtually unchanged for all the time periods. The asymmetric responses to negative shocks in both markets for both types of return series increase for all the time periods, with the exception of the asymmetric response for the U.S. trades to negative shocks from the Canadian market for the equal-weighted series. This response declines during 1990-1999 and then increases during 2000-2003.

[Please place Table 4.9 about here.]

The third bi-variate model used herein is the Dynamic Conditional Correlation (DCC-) GARCH model of Engle (2001), which estimates the conditional correlation coefficients and the variance-covariance matrix simultaneously. The univariate GARCH parameters are estimated in the first stage and the DCC parameters in the second stage. For the bi-variate case, the conditional variance-covariance matrix (H_t) in the DCC model may be expressed as:

$$H_t = D_t R_t D_t \quad = \left(\rho_{ij,t}\sqrt{h_{ii,t}\, h_{jj,t}}\right) \tag{4.10}$$

where $R_t = \{\rho_{ij}\}_t$ is the conditional correlation matrix, and D_t is the diagonal matrix of time-varying standard deviations from univariate GARCH models such that:

$$[H_t]_{i,j} = h_{i,j,t} \quad [D_t]_{i,j} = \sqrt{h_{ij}}\ \forall\ i = j\ \&\ 0\ \forall\ i \neq j \tag{4.11}$$

The elements of D_t follow a univariate GARCH(1,1), and for the bivariate Canada-U.S. case can be expressed as:

$$\begin{aligned} h_{cn,t} &= \omega_{cn} + \alpha_{cn,1}\,\varepsilon^2_{cn,t-1} + \beta_{cn,1}\,h_{cn,t-1} \\ h_{us,t} &= \omega_{us} + \alpha_{us,1}\,\varepsilon^2_{us,t-1} + \beta_{us,1}\,h_{us,t-1} \end{aligned} \tag{4.12}$$

The volatility co-movements and spillovers are incorporated into the conditional variance equations (h_{it}) as in Balasubramanyan (2004) as follows:

$$\begin{aligned} h_{cn,t} &= \omega_{cn} + \alpha_{cn}\,\varepsilon^2_{cn,t-1} + \beta_{cn}\,h_{cn,t-1} + \gamma_{cn}\,\varepsilon^2_{us,t} + \theta_{cn}\,\varepsilon^2_{us,t-1} \\ h_{us,t} &= \omega_{us} + \alpha_{us}\,\varepsilon^2_{us,t-1} + \beta_{us}\,h_{us,t-1} + \gamma_{us}\,\varepsilon^2_{cn,t} + \theta_{us}\,\varepsilon^2_{cn,t-1} \end{aligned} \tag{4.13}$$

where β_{cn}, β_{us} are coefficients that reflect persistence, γ_{cn}, γ_{us} are coefficients that reflect contemporaneous co-movement, and the coefficients θ_{cn}, θ_{us} reflect volatility spillover (U.S. to the Canadian market and vice versa, respectively).

The results from estimating the DCC-GARCH with co-movements and spillovers for the daily equal- and value-weighted series are reported in panels A and B of Table 10. All the estimated coefficients are very significant. Contemporaneous comovements increase during 1975-1989, decline during 1990-1999 and rise during 2000-2003 for both the equal- and value-weighted series. The volatility spillover from the U.S. into the Canadian market increases for both the equal- and value-weighted series during 1980-2003 although it declines for 1975-1989. Volatility spillover from the Canadian to the U.S. market is high during 1990-1999 and declines during 2000-2003 for the equal-weighted series. The negative coefficient for the value-weighted series indicates that volatility spillover has been mainly from the U.S. market to the Canadian market, and that this spillover effect increased during 2000-2003.

[Please place Table 4.10 about here.]

Incorporating asymmetry into the measures of co-movement and spillover in the DCC-GARCH model yields:

$$\begin{aligned} h_{cn,t} &= \omega_{cn} + \alpha_{cn}\varepsilon^2_{cn,t-1} + \beta_{cn}h_{cn,t-1} + \gamma_{cn}\varepsilon^2_{us,t} + \theta_{cn}\varepsilon^2_{us,t-1} + \eta_{cn}\varepsilon^2_{us,t}I_{\varepsilon_{us,t}<0} + \psi_{cn}\varepsilon^2_{us,t-1}I_{\varepsilon_{us,t-1}<0} \\ h_{us,t} &= \omega_{us} + \alpha_{us}\varepsilon^2_{us,t-1} + \beta_{us}h_{us,t-1} + \gamma_{us}\varepsilon^2_{cn,t} + \theta_{us}\varepsilon^2_{cn,t-1} + \eta_{us}\varepsilon^2_{cn,t}I_{\varepsilon_{cn,t}<0} + \psi_{us}\varepsilon^2_{cn,t-1}I_{\varepsilon_{cn,t-1}<0} \end{aligned} \tag{4.14}$$

where asymmetric co-movements are reflected in the coefficients η_{cn}, η_{us} such that the indicator dummy variables $I_{\varepsilon_{us,t}<0}, I_{\varepsilon_{cns,t}<0}$ each take the value of 1 whenever $\varepsilon_{us,t} < 0$ & $\varepsilon_{cn,t} < 0$ and zero otherwise. The asymmetric volatility spillovers are reflected in the coefficients ψ_{cn}, ψ_{us} such that the indicator dummy variables $I_{\varepsilon_{us,t-1}<0}, I_{\varepsilon_{cn,t-1}<0}$ each take the value of 1 whenever $\varepsilon_{us,t-1} < 0$ & $\varepsilon_{cn,t-1} < 0$ and zero otherwise.

The results from estimating the asymmetric DCC-GARCH model with co-movements and volatility spillovers for the daily equal- and value-weighted series are reported in panels A and B of Table 4.11. Compared to the DCC model results discussed above, the effects are split into their (a)symmetric co-movements as well as their (a)symmetric volatility spillovers. Contemporaneous co-movements for equal-weighted TSX trades increase (except immediately after the October 1987 crash), and those for the equal-weighted U.S. trades decline during 2000-2003. While co-movements of value-weighted TSX trades remain fairly stationary over the period, those for U.S trades decline only during 1990-1999. Asymmetric co-movements due to negative shocks in both markets increase for both the equal- and value-weighted series after the October 1987 crash. The direction of volatility spillovers for both the equal- and value-weighted series is from the U.S. into the Canadian market, although it is more moderate during 2000-2003. This is confirmed by the negative coefficient for U.S. trades, which reveals the opposite direction of information flow. The measure of asymmetric volatility spillover reveals that negative shocks in the Canadian market lead to a much higher impact on U.S. trades for the equal- versus value-weighted portfolio during 2000-2003.

[Please place Table 4.11 about here.]

The final bi-variate model examined herein is the Baba, Engle, Kroner, and Kraft or BEKK model, which is a variant of the multivariate GARCH process proposed by Engle and Kroner (1995). The BEKK model overcomes the numerous parameters problem associated with the VECH (Bollerslev, Engle, and Wooldridge, 1988) model by ensuring that the variance-covariance matrix is always positive definite (Gannon and Au-Yeung, 2004). Unlike the VECH and other models, the parameters of the BEKK model cannot be interpreted on an individual basis (Worthington and Higgs, 2003), instead functions of these parameters are of interest (Kearney and Patton, 2000).

The variance-covariance matrix of the asymmetric version of the BEKK-GARCH (1,1) model can be expressed as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B + D'\eta_{t-1}\eta'_{t-1}D \tag{4.15}$$

where asymmetric negative shocks are modeled as $\eta_{1,t-1} = \varepsilon_{1,t-1} \cdot 1\{if\ \varepsilon_{1,t-1} < 0\}$ and $\eta_{2,t-1} = \varepsilon_{2,t-1} \cdot 1\{if\ \varepsilon_{2,t-1} < 0\}$ for the bi-variate case, and the matrices C (lower triangular), A, B, and D are of dimension $2 \otimes 2$ (Baele, 2004). Alternatively, the BEKK can be represented as:

$$\begin{aligned} H_t = C'C &+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} & \varepsilon_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \\ &+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} \sigma_{1,t-1}^2 & \sigma_{12,t-1} \\ \sigma_{21,t-1} & \sigma_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}' \begin{bmatrix} \eta_{1,t-1}^2 & \eta_{1,t-1}\eta_{2,t-1} \\ \eta_{1,t-1}\eta_{2,t-1} & \eta_{2,t-1}^2 \end{bmatrix} \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix} \end{aligned} \tag{4.16}$$

The variance-covariance matrix depends on squares and cross products of lagged innovations ε_{t-1} and lagged volatility H_{t-1} (Worthington et al., 2002). The combination of various parameter estimates presents some inference difficulties. Coefficients a_{11} and a_{22} represent the effect of shocks on the future uncertainty of TSX and U.S. returns, respectively, while coefficients a_{12} and a_{21} represent the cross effects of the TSX on U.S. markets and vice versa, respectively. In addition, if coefficients a_{11} and a_{21} have different signs, then shocks with opposite signs in the two series tend to increase future risk in the TSX market, while if coefficients a_{12} and a_{22} have different signs, then shocks with opposite signs in the two series tend to increase future risk in the U.S. market.

The source of volatility spillovers as in Dark et al. (2006) is tested more formally as follows:

Hypothesis A:

$H_0 : a_{21} = b_{21} = 0$ {No Volatility Spillover from U.S. to TSX}

$H_1 : a_{21} \neq 0 \quad or \quad b_{21} \neq 0$ {Volatility Spillover from U.S. to TSX}

Hypothesis B:

$H_0 : a_{12} = b_{12} = 0$ {No Volatility Spillover from TSX to U.S.}

$H_1 : a_{12} \neq 0 \quad or \quad b_{12} \neq 0$ {Volatility Spillover from TSX to U.S.}

Based on volatility values for the equal-weighted returns reported in Table 4.12, risk in the TSX market increases during the overall period of 1975-2003, as well as for time periods of 1975-1979, 1990-1999, and 2000-2003, and risk in U.S. markets increases during the time periods of 1975-1979, 1980-1989, and 2000-2003. The only difference when the volatility values are based on the value-weighted returns is that risk in the U.S. markets did not increase during the time period of 1975-1979.

Based on tests of the above hypotheses for volatility spillovers for the bi-variate BEKK models for various time periods, the estimates of a_{21} are insignificant for time periods of 1975-2003, 1975-1979 and 1980-1989 based on the equal-weighted return series, and the estimate of a_{21} is insignificant for the time period of 1990-1999 based on the value-weighted return series. Since the estimates of b_{21} are significant for both the equal and value-weighted return series for all time periods, this implies a volatility spillover from U.S. markets to the TSX. In a similar manner, volatility spillover is implied from the TSX market to U.S. markets since the estimates of a_{12} are significant for all but one time period (i.e, the 1990-1999 time period for the equal-weighted return series), and the estimates of b_{12} are significant for all time periods for both types of return series. Asymmetric negative shocks as captured by the estimates of d_{11} and d_{22} are insignificant only during the time period 1990-1999 for the equal-weighted U.S. and TSX returns, and for the equal-weighted TSX returns and value-weighted U.S. returns during 2000-2003.

[Please place Table 4.12 about here.]

4.6. CONCLUDING COMMENTS

This chapter examined the time-series behavior in the contemporaneous comovement and asymmetric volatility transmissions between U.S. and Canadian markets that have synchronous trading hours, using daily equal- and value-weighted returns for Canadian stocks that are cross-listed on the TSX and U.S. markets. Both the uni-variate GJR-GARCH and E-GARCH models confirm that TSX trades have higher asymmetries compared to the U.S. trades for both equal- and value-weighted daily returns for the same set of stocks. In contrast, the inferences for volatility transmission depend upon the model and return series studied. This is consistent with the debate on the choice of the appropriate model in the recent comprehensive survey of the literature on multivariate GARCH models by Bauwens, Laurent, and Rombouts (2006).

Based on the findings from the multivariate GARCH models, contemporaneous and asymmetric comovements declined during the 1990s but have increased more recently due to the effect of newer and smaller stocks. The symmetric volatility spillovers in both markets similarly declined after increasing during the 1990s, with the exception of the increase in volatility spillover from the U.S. into the Canadian market, as reflected in the equal-weighted returns based on TSX-trades. The asymmetric volatility spillovers due to negative shocks increased [decreased] in both markets based on the E- and DCC- [GJR-] GARCH results. Based on the DCC model results, the asymmetric volatility spillovers due to negative shocks in the Canadian market lead to a much higher impact on U.S. trades for the equal- versus value-weighted return series during 2000-2003. Estimates for the BEKK model also confirm the bi-directional nature of volatility spillovers. While multi-variate GARCH modeling poses the dilemma between flexibility and parsimony, and few researchers compare results from different MGARCH models, the BEKK models are not suitable for examining volatility transmission, while factor models like DCC allow for more persistence between variances and correlations. Thus, it is advisable to use more than one multivariate GARCH model before drawing robust inferences when one is examining the dynamics of cross-market volatility.

CHAPTER 5

CONCLUSION

This thesis examined a number of issues related to the risk or volatility of Canadian stocks. It focused on three major issues regarding idiosyncratic volatility. The first major issue is whether idiosyncratic volatility is priced in its relationship with expected returns. The second major issue is the rate at which idiosyncratic risk is diversifiable, on average, as portfolio size increases and the minimum number of stocks or portfolio size needed, on average, to achieve a target level of risk reduction through naïve diversification. The third major issue is the extent and nature of asymmetric volatility transmission between stocks trading on two synchronous financial markets, as proxied by Canadian stocks cross-listed on the TSX and the US markets.

Since no widely accepted definition of risk exists, the second chapter (first essay) examined various measures of realized, conditional and idiosyncratic volatility for Canadian stocks for the period 1975–2003. The chapter also examined downside risk using three plausible downside benchmarks; namely, the market-return, risk-free rate, and zero returns. The finding of increasing idiosyncratic volatility is consistent with recent findings in other markets (e.g., US). Furthermore, firm-level (idiosyncratic) volatility was almost 75% of total stock volatility as compared to almost 85% for US stocks (Goyal and Santa-Clara, 2003). This lower unsystematic and higher systematic volatility components for Canadian stocks imply that less overall risk reduction is achievable in Canada. Smaller firms have a higher average stock variance, idiosyncratic volatility and downside risk as compared to bigger firms. Also, since smaller IT firms have the highest idiosyncratic volatility and downside risk, they contributed relatively more given their size to market peaks.

An examination of the relationship between idiosyncratic volatility and expected returns for Canadian stocks using quintiles found positive and significant differences in the expected returns between the first and fifth quintiles of stocks sorted by idiosyncratic volatility. Using the Carhart four-factor model in a two-step Fama-MacBeth methodology, a robust and significant positive relationship was found between expected returns and asymmetric idiosyncratic volatility in the presence of control variables for liquidity and firm-specific information. This latter result was robust to the choice of liquidity measure and adjusting for measurement error in the factor coefficient beta estimates from the first-step Fama-MacBeth regressions.

The third chapter (second essay) investigated the nature of risk diversification. Earlier studies found that at least 15 to 20 securities are needed to obtain approximately 90 percent of the benefits of diversification for US equity markets, and about twice that number for Canadian equity markets. The methodology in this chapter utilized a variety of metrics that assess diversification benefits. These metrics fit into four categories; namely, those that measure risk reduction, those that measure the impact on higher-order return moments, those that measure the impact on reward-to-risk, and those that examine the impact on the probabilities of underachieving various target or lower-bound rates of return. A major finding of this chapter is that average daily and monthly correlations for various investment opportunity sets have declined over time, which is consistent with the findings reported by Campbell et al. (2001) for the US market. However, this is more than offset by the increase in firm-level risk and number of equities identified in the previous chapter, which together imply that more stocks are now needed to diversify an equivalent quantity of risk. Using portfolio sizes from 2 to 100 stocks and six investment opportunity sets, the minimum portfolio size required to achieve a sufficiently well diversified portfolio is found to be very sensitive to the performance metric used to measure such benefits and is somewhat less sensitive to the investment opportunity set from which the portfolio selection is made. Despite this ambiguity in what is the minimum portfolio size to obtain a fixed percentage of the overall benefits, on average, from naive diversification, the chapter finds that the minimum portfolio sizes for specific performance metrics are higher for Canadian equities than the values reported in the literature for US equities. This is probably due to the higher concentration of Canadian stocks within a few industries (sectors), which makes it more difficult to diversify away firm-specific risk.

The fourth chapter (third essay) dealt with the nature of contemporaneous asymmetry, co-movement, and volatility transmission between Canadian stocks cross-listed on the TSX and US markets having synchronous trading hours. Both equal- and value-weighted series of Canadian stocks that comprise the largest share of cross-listed stocks on the US markets were examined in a bi-variate GARCH framework using four models to achieve a robust analysis. The findings confirm previous findings that the direction of volatility spillover is from the US markets to the TSX market. The findings revealed that while TSX trades have higher asymmetry as compared to US trades, asymmetric volatility spillover due to negative shocks increased in both markets as did contemporaneous and asymmetric co-movements due to increases in newer and smaller stocks as well as closer integration of these synchronous markets. Furthermore, robust inferences on cross-market dynamics are found to depend on using more than one multivariate GARCH model.

There is considerable scope for further research in this domain. First, causal factors that lead to an increase in idiosyncratic risk in the US market can be used to determine if idiosyncratic risk continues to be priced in the presence of these controls. Such causal factors include institutional ownership, expected earnings growth, issue of IPOs by newer and smaller firms, and the dispersion of analyst's forecasts of earnings. Since the pricing of idiosyncratic risk also suggests that priced systematic factors may be missing from the underlying model used to price risk (specifically, the four-factor model of Carhart herein), tests using other asset pricing models such as the APT should be considered in future research. With regard to the diversification of risk, an examination of the minimum portfolio size to achieve a sufficient level of diversification for a mix of international IO sets that includes US stocks would be of interest. Other optimization metrics such as time-varying (MINQUE-estimated) variances could be explored to determine the minimum portfolio size to achieve a sufficient level of risk diversification. Further analysis using holiday dummies for the two markets could be undertaken to determine what effect asymmetric holidays have on asymmetric volatility dynamics. In addition, bi-variate GARCH modeling before and after structural breaks in return volatilities that involve regime shifts could lead to further insights into the transmission of volatility shocks between markets.

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Table 2.1 Summary Statistics for Aggregate Total Stock Return Variances for Canadian Stocks

This table reports summary distributional statistics for aggregate total stock return variances for Canadian stocks. The average stock volatility is as in Schwert (1990). The average stock variability is as in Goyal and Santa-Clara (2003) and Bali et al. (2005). CL_{TSX} and CL_{US} refer to the TSX and U.S. trades, respectively, of TSX-listed stocks cross-listed on U.S. trade venues. "Avg.", "Stdev.", "CV", "Skew", "Kur.", "EW" and "VW" refer to average, standard deviation, coefficient of variation, skewness, kurtosis, equal-weighted and value-weighted, respectively.

	Avg.		Stdev.		CV		Skew.		Kur.	
Sample	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**
Panel A: Stock volatility with no autocorrelation correction at monthly frequency based on daily returns										
All Firms	0.0381	0.0288	0.4658	0.2895	12.2407	10.0520	16.0529	17.4980	272.7236	316.6624
TSX only	0.0369	0.0351	0.5522	0.4887	14.9783	13.9326	18.2286	18.6421	336.5143	347.6815
CL_{TSX}	0.0034	0.0236	0.0234	0.1817	6.8675	7.6879	14.5714	14.0319	223.0155	209.0182
CL_{US}	0.0020	0.0099	0.0021	0.0085	1.0512	0.8627	2.5565	3.9234	8.2095	21.2475
Big Firms	0.0132	0.0133	0.2142	0.0628	16.2343	4.7355	18.6453	12.9236	347.7622	171.0911
Small Firms	0.0904	0.9354	1.3681	16.6689	15.1395	17.8192	18.1400	18.6535	334.0224	347.9680
IT Firms	0.0024	0.0106	0.0026	0.0210	1.1097	1.9842	3.1520	7.3976	13.7322	72.1529
Panel B: Stock volatility with autocorrelation correction at monthly frequency based on daily returns										
All Firms	0.0394	0.0295	0.4891	0.3042	12.4057	10.3042	16.0727	17.5107	273.4132	316.9785
TSX only	0.0382	0.0357	0.5804	0.5135	15.1891	14.3883	18.2145	18.6496	336.1201	347.8708
CL_{TSX}	0.0033	0.0241	0.0231	0.1790	6.9870	7.4385	14.2448	13.9884	212.0364	205.0192
CL_{US}	0.0010	0.0169	0.0031	0.0589	3.1278	3.4773	-0.6929	-0.4504	2.6049	2.8778
Big Firms	0.0135	0.0133	0.2230	0.0656	16.4936	4.9294	18.6452	13.0812	347.7587	174.0060
Small Firms	0.0940	0.9754	1.4382	17.5162	15.3006	17.9577	18.1233	18.6535	333.5490	347.9672
IT Firms	0.0025	0.0105	0.0059	0.0176	2.4025	1.6858	13.5546	5.6882	220.0583	46.0267
Panel C: Stock volatility with no autocorrelation correction based on monthly returns										
All Firms	0.3873	0.0217	5.9023	0.2046	15.2392	9.4112	18.5862	17.5378	346.2457	316.7635
TSX only	0.4642	0.0267	7.2359	0.3451	15.5876	12.9210	18.5895	18.6395	346.3323	347.6190
CL_{TSX}	0.0447	0.0157	0.2499	0.0982	5.5954	6.2631	17.8698	18.0616	327.4367	332.7336
CL_{US}	0.0264	0.0114	0.0217	0.0133	0.8228	1.1649	2.2229	4.2946	6.4021	26.7163
Big Firms	0.0304	0.0107	0.0799	0.0447	2.6288	4.1923	13.2067	17.6980	201.7497	323.7775
Small Firms	0.1482	0.0423	0.7971	0.1398	5.3765	3.3043	14.5311	10.6958	235.6411	125.0297
IT Firms	0.1070	0.0102	0.9145	0.0190	8.5445	1.8694	14.7579	5.1209	230.7454	34.4443

Table 2.2 Summary Statistics for Aggregate Total Lower Partial Second Moment for Canadian Stocks

This table reports summary distributional statistics for aggregate total lower partial second moments (LPSMs) for Canadian stocks. CL_{TSX} and CL_{US} refer to the TSX and U.S. trades, respectively, of TSX-listed stocks cross-listed on U.S. trade venues. "h" refers to the market return and is taken as the mean, a zero return or the risk-free rate. "Avg.", "Stdev.", "CV", "Skew" and "Kur." refer to average, standard deviation, coefficient of variation, skewness and kurtosis, respectively.

Sample	h = mean					h = zero return					h = risk-free rate				
	Avg.	Stdev.	CV	Skew.	Kurt.	Avg.	Stdev.	CV	Skew.	Kurt.	Avg.	Stdev.	CV	Skew.	Kurt.
All Firms	0.0021	0.0012	0.6007	6.1291	65.3912	0.0017	0.0008	0.4506	1.5499	3.8420	0.0017	0.0008	0.4487	1.5513	3.8564
TSX only	0.0022	0.0016	0.7154	10.1970	150.3628	0.0018	0.0008	0.4434	1.4291	3.0573	0.0018	0.0008	0.4416	1.4306	3.0689
CL_{TSX}	0.0012	0.0008	0.6534	2.5537	14.0422	0.0011	0.0007	0.6670	1.8889	5.3595	0.0011	0.0007	0.6632	1.8898	5.3796
CL_{US}	0.0013	0.0011	0.8033	1.2958	1.7311	0.0011	0.0009	0.8027	1.2794	1.6499	0.0011	0.0009	0.8020	1.2751	1.6315
Big	0.0011	0.0009	0.8024	9.1364	126.5462	0.0009	0.0005	0.6019	2.2309	7.9268	0.0009	0.0005	0.5980	2.2339	7.9691
Small	0.0046	0.0083	1.7963	16.3703	290.2835	0.0034	0.0017	0.4924	1.0587	0.3751	0.0034	0.0017	0.4909	1.0602	0.3797
IT Firms	0.0016	0.0014	0.8287	1.8068	3.7678	0.0014	0.0012	0.8541	1.8377	3.6599	0.0014	0.0012	0.8501	1.8377	3.6596

Table 2.3 Summary statistics for variances at the market, industry and firm levels based on the indirect three-level decomposition method

Summary statistics are reported in this table for the variances at the market, industry and firm levels obtained using the indirect decomposition method of Campbell et al. (2001). Market variances are computed using value-weighted daily excess returns of all stocks minus either the overall mean of the market over the entire time period (Constant Mean) or the daily cross-sectional average (Conditional Mean) across all firms. Industry- and firm-level variances are computed using both equal weights (EW) and value weights (VW). "Avg.", "Stdev.", "CV", "Skew" and "Kur." refer to average, standard deviation, coefficient of variation, skewness and kurtosis, respectively.

	Constant Mean					**Conditional Mean**				
	Avg.	Stdev.	CV	Skew.	Kur.	Avg.	Stdev.	CV	Skew.	Kur.
Panel A: Market-Level Volatility										
All Firms	0.0015	0.0029	1.9451	8.3744	89.5816	0.0018	0.0102	5.6131	15.8408	272.3804
TSX-only	0.0014	0.0033	2.3115	12.2109	176.9950	0.0023	0.0153	6.7353	17.0189	304.0869
	Equal-Weighted					**Value-Weighted**				
Panel B: Industry-Level Volatility										
All Firms	0.0108	0.0488	4.5352	11.0977	126.7972	0.0032	0.0084	2.5954	12.1857	174.5353
TSX-only	0.0099	0.0400	4.0564	13.5157	195.3952	0.0029	0.0053	1.8447	9.2995	102.6114
Panel C: Firm-Level Volatility										
All Firms	0.0272	0.2321	8.5181	11.6263	139.0183	0.0254	0.3026	11.9004	17.6760	321.5012
TSX-only	0.0626	1.0403	16.6259	18.6542	347.9851	0.0324	0.5100	15.7296	18.6507	347.8972

Table 2.4 Summary statistics for variances at the industry and firm levels based on the direct three-level decomposition method

This table reports industry betas and summary statistics for the variances at the industry- and firm-levels using the direct decomposition method of Campbell et al (2001). The 47 industry groups, which are arranged in alphabetical order, are those used by Fama and French (1997). "Ratio", "Avg.", Stdev." and "CV" refer to the ratio of the mean at the firm-level to that at the industry level, mean, standard deviation and coefficient of variation, respectively.

		#		Firm Variance			Industry Variance		
Industry	**Betas**	**Firms**	**Ratio**	**Avg**	**Stdev**	**CV**	**Avg**	**Stdev**	**CV**
Agriculture	1.3580	3	1.06	0.0115	0.1176	0.0980	0.0108	0.1172	0.0920
Aircraft	0.7370	17	1.37	0.0205	0.0874	0.2349	0.0150	0.0877	0.1709
Alcoholic Beverages	0.4275	26	1.43	0.0139	0.0512	0.2723	0.0097	0.0504	0.1931
Apparel	0.2059	22	1.59	0.0210	0.0586	0.3580	0.0132	0.0572	0.2307
Automobiles & Trucks	1.0906	50	1.32	0.0119	0.0684	0.1735	0.0090	0.0658	0.1372
Banking	0.6006	98	1.27	0.0116	0.0456	0.2541	0.0091	0.0452	0.2014
Business Services	0.6756	218	40.91	0.4418	7.8949	0.0560	0.0108	0.0595	0.1823
Business Supplies	0.6155	52	1.98	0.0111	0.0560	0.1978	0.0056	0.0554	0.1008
Candy and Soda	0.7965	6	1.31	0.0118	0.0799	0.1477	0.0090	0.0797	0.1130
Chemicals	0.5776	44	1.79	0.0175	0.0620	0.2820	0.0098	0.0590	0.1652
Coal	0.5954	9	1.19	0.0264	0.1738	0.1518	0.0222	0.1719	0.1290
Computers	1.4002	48	5.97	0.0173	0.0902	0.1915	0.0029	0.0826	0.0353
Construction	0.4427	23	3.87	0.0174	0.0738	0.2352	0.0045	0.0770	0.0579
Construction Materials	0.5531	42	2.02	0.0117	0.0668	0.1755	0.0058	0.0666	0.0870
Consumer Goods	0.3431	24	1.84	0.0145	0.0508	0.2848	0.0079	0.0506	0.1564
Defense	0.9405	1	1.00	0.0182	0.1198	0.1518	0.0182	0.1198	0.1518
Electrical Equipment	1.0677	21	1.77	0.0170	0.1093	0.1553	0.0096	0.1074	0.0890
Electronic Equipment	1.4157	73	1.67	0.0177	0.1011	0.1748	0.0106	0.0998	0.1066
Entertainment	0.8196	45	1.34	0.0141	0.0645	0.2191	0.0105	0.0644	0.1637
Food Products	0.2759	34	1.62	0.0147	0.0521	0.2820	0.0091	0.0514	0.1774
Healthcare	0.5288	16	1.44	0.0216	0.0789	0.2740	0.0150	0.0796	0.1886
Insurance	0.4728	41	0.47	0.0056	0.0040	1.4000	0.0118	0.0474	0.2501
Machinery	0.4605	91	2.52	0.0161	0.0503	0.3193	0.0064	0.0505	0.1270
Measure & Control Equip.	0.8249	11	1.62	0.0214	0.1449	0.1479	0.0132	0.1429	0.0926
Medical Equipment	0.5974	13	2.11	0.0179	0.1254	0.1430	0.0085	0.1224	0.0691
Miscellaneous	0.4621	11	1.94	0.0070	0.0606	0.1149	0.0036	0.0608	0.0589
Nonmetallic Mining	0.8224	240	2.59	0.0166	0.0718	0.2312	0.0064	0.0707	0.0906
Personal Services	0.4158	13	1.54	0.0160	0.0980	0.1635	0.0104	0.0966	0.1075
Petrol & Natural Gas	0.6436	656	1.78	0.0167	0.0586	0.2850	0.0094	0.0584	0.1618
Pharmaceutical	0.6749	59	3.44	0.0220	0.0851	0.2582	0.0064	0.0837	0.0769
Precious Metals	0.5570	366	2.20	0.0222	0.0942	0.2361	0.0101	0.0942	0.1075
Printing & Publishing	0.6771	26	16.66	0.3731	6.7408	0.0554	0.0224	0.2775	0.0806
Real Estate	0.4763	90	1.81	0.0114	0.0084	1.3571	0.0063	0.0595	0.1060
Recreational Products	0.5726	15	1.87	0.0239	0.0983	0.2431	0.0128	0.0952	0.1339
Restaurants, Hotel, Motel	0.4799	34	1.57	0.0163	0.0538	0.3034	0.0104	0.0535	0.1952
Retail	0.3981	117	1.85	0.0144	0.0430	0.3362	0.0078	0.0434	0.1793
Rubber & Plastic	0.5719	13	3.19	0.0051	0.0647	0.0788	0.0016	0.0651	0.0253
Shipbuilding, Railroad	0.5225	3	1.00	0.0250	0.2637	0.0947	0.0250	0.2637	0.0947
Shipping Containers	0.3941	4	1.60	0.0193	0.1276	0.1513	0.0121	0.1265	0.0959
Steel Works, Etc.	0.8785	43	2.12	0.0087	0.0648	0.1344	0.0041	0.0652	0.0633
Telecommunications	0.6411	93	1.54	0.0129	0.0518	0.2486	0.0084	0.0556	0.1507
Textiles	0.3238	15	1.26	0.0160	0.0875	0.1830	0.0127	0.0867	0.1458
Tobacco Products	0.0116	1	1.00	0.0289	0.2401	0.1202	0.0289	0.2401	0.1202
Trading	0.6596	331	1.59	0.0121	0.0506	0.2391	0.0076	0.0529	0.1428
Transportation	0.7179	66	1.54	0.0114	0.0517	0.2202	0.0074	0.0519	0.1429
Utilities	0.3531	52	23.10	0.2287	3.9692	0.0576	0.0099	0.0405	0.2457
Wholesale	0.5089	120	2.23	0.0178	0.0555	0.3206	0.0080	0.0545	0.1463

Table 2.5 Summary statistics for variances at the industry and firm levels based on the Duffee decomposition method

This table reports summary statistics for the variances at the industry- and firm-levels using the decomposition method of Duffee (2000). "Avg.", "Stdev.", "CV", "Skew" and "Kur." refer to average, standard deviation, coefficient of variation, skewness and kurtosis, respectively.

	Equal-Weighted					Value-Weighted				
Sample	**Avg.**	**Stdev.**	**CV**	**Skew.**	**Kur.**	**Avg.**	**Stdev.**	**CV**	**Skew.**	**Kur.**
Panel A: Industry Volatility - Absolute Errors										
All Firms	0.0102	0.0032	0.3152	2.1344	0.0102	0.1777	0.0676	0.3802	1.7828	4.3691
TSX-only	0.0101	0.0031	0.3067	2.1248	0.0101	0.1746	0.0631	0.3612	1.6810	4.9518
Panel B: Industry Volatility - Squared Errors										
All Firms	0.0005	0.0023	4.7895	13.0245	171.2439	0.0043	0.0094	2.2053	10.4206	126.1386
TSX-only	0.0004	0.0018	4.1858	17.4009	314.8446	0.0040	0.0074	1.8647	10.7481	141.6660
Panel C: Firm Volatility - Absolute Errors										
All Firms	0.0259	0.0062	0.2381	1.4758	3.4587	0.2027	0.0789	0.3891	1.2451	1.830654
TSX-only	0.0285	0.0059	0.2078	1.0468	1.2052	0.1315	0.0622	0.4728	1.2345	1.69336
Panel D: Firm Volatility - Squared Errors										
All Firms	0.0520	0.6673	12.8409	16.1721	276.5395	0.0260	0.3028	11.6461	17.9933	329.9109
TSX-only	0.0091	0.0819	8.9744	18.5058	344.2405	0.0065	0.0150	2.3214	8.5854	84.86412

Table 2.6 Summary statistics for variances at the firm level based on the three-factor model

Firm-level variances are computed using both equal weights (EW) and value weights (VW) on the residuals from the three-factor model of Fama and French. "Avg.", "Stdev.", "CV", "Skew" and "Kur." refer to average, standard deviation, coefficient of variation, skewness and kurtosis, respectively.

	Avg.		Stdev.		CV		Skew.		Kur.	
Sample	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**
All Firms	0.3344	0.0192	4.9117	0.1907	14.6860	9.9470	18.5810	17.5320	346.1150	316.5160
TSX only	0.3954	0.0243	5.9280	0.3216	14.9910	13.2400	18.5840	18.6400	346.1780	347.6210
CL_{TSX}	0.0520	0.0125	0.4614	0.0924	8.8700	7.3700	18.4590	18.2360	342.9570	337.0860
CL_{US}	0.0218	0.0082	0.0163	0.0075	0.7490	0.9120	1.9740	4.2390	4.6810	27.2750
Big Firms	0.0260	0.0085	0.0721	0.0417	2.7770	4.9290	13.7000	18.1920	212.9330	336.2890
Small Firms	0.9424	0.6665	14.5815	10.9703	15.4740	16.4590	18.5910	18.6310	346.3740	347.4040
IT Firms	0.0957	0.0076	0.8251	0.0137	8.6250	1.7960	14.8010	5.6330	231.5790	42.2650

Table 2.7 Relationship between average returns and idiosyncratic risk based on extreme quintile portfolios

This table reports the average equal- and value-weighted returns for the five quintiles for 6 samples of Canadian stocks sorted by their idiosyncratic variances derived from the Fama-French three-factor (3FF) model and this model combined with the model (GSC) of Goyal-Santa Clara (2003). Quintiles 1 and 5 are composed of the stocks with the lowest and highest idiosyncratic variances, respectively. EW and VW refer to equal and value weights, respectively. CL_{TSX} and CL_{US} refer to TSX and U.S. trades, respectively, of TSX-listed stocks cross-listed on U.S. trade venues. "a", "b" and "c" indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Average Returns (x 100)						
Quintile	**All Firms**	**TSX-only**	**CL_{TSX}**	**CL_{US}**	**Big Firms**	**Small Firms**	**IT Firms**
Panel A: 3FF & EW							
1	0.0328	0.0409	-0.0219	0.4462	0.0214	0.0712	0.3384
2	0.1053	0.1018	0.0895	0.4086	0.1465	-0.0051	0.0130
3	-0.0591	-0.0293	-0.2834	0.7641	0.1695	-0.2589	-0.2059
4	0.5011	0.3747	1.6011	0.6930	0.5381	0.4234	0.0053
5	6.6598	6.0377	11.5390	1.9688	6.0033	7.6246	6.8183
5 - 1	6.6271[c]	5.9968[c]	11.5609[b]	0.0152[c]	5.9819[c]	7.5534[c]	6.4799[c]
T-stat	7.6400	8.60000	2.4400	3.3100	8.1100	5.8700	4.6700
P-value	0.0000	0.00000	0.0150	0.0010	0.0000	0.0000	0.0000
Panel B: 3FF & VW							
1	0.0000	-0.0000	0.0000	-0.1670	0.0000	-0.0000	0.0000
2	0.0000	0.0000	-0.0000	0.0825	0.0000	0.0000	0.0000
3	0.0001	0.0001	0.0001	0.5889	0.0001	0.0000	0.0002
4	0.0003	0.0002	0.0004	1.1170	0.0002	0.0003	0.0003
5	0.0030	0.0024	0.0105	2.6007	0.0041	0.0022	0.0169
5 - 1	0.0030[b]	0.0024[b]	0.0105	0.0277[c]	0.0041[a]	0.0022[b]	0.01692
T-stat	2.1300	2.0500	1.6500	8.0900	1.9200	2.0100	1.22000
P-value	0.0340	0.0420	0.1010	0.0000	0.0550	0.0450	0.2220
Panel C: 3FF & GSC & EW							
1	-0.4042	-0.3806	-0.3945	0.6283	-0.3298	-0.4231	-0.0150
2	-0.4486	-0.4593	-0.5596	0.4311	-0.4675	-0.5351	-0.0740
3	-0.5286	-0.5265	-0.4439	0.6003	-0.4225	-0.5860	-0.4700
4	-0.0518	-0.0224	-0.0757	0.5313	0.1435	-0.2940	-0.2663
5	7.3088	6.5820	12.6410	2.0766	6.8202	8.0754	6.5806
5 – 1	7.7130[c]	6.9626[c]	13.0355[c]	0.0145[c]	7.1500[c]	8.4985[c]	0.0660[c]
T-stat	9.280000	10.180000	3.2800	3.080000	9.4000	7.1600	5.1400
P-value	0.000000	0.000000	0.0010	0.002000	0.0000	0.0000	0.0000
Panel D: 3FF & GSC & VW							
1	-0.0000	-0.0000	-0.0001	-0.1468	-0.0000	-0.0000	0.0001
2	-0.0001	-0.0000	-0.0001	0.1376	-0.0001	-0.0000	-0.0002
3	-0.0000	-0.0000	-0.0000	0.3552	0.0000	-0.0001	0.0000
4	0.0002	0.0002	0.0004	1.2524	0.0002	0.0001	0.0003
5	0.0030	0.0024	0.0100	2.6684	0.0040	0.0023	0.0168
5 - 1	0.0031[b]	0.0025[b]	0.0100[a]	0.0282[c]	0.0040[b]	0.0024[b]	0.0002
T-stat	2.2800	2.2100	1.6900	8.1300	2.0200	2.2700	1.3700
P-value	0.0230	0.0280	0.0920	0.0000	0.0440	0.0240	0.1710

Table 2.8 Time-series averages of the second-step cross-sectional regression results with contemporaneous excess returns, betas, IVs and controls (e.g., amortized spreads) based on first-stage 60-month moving windows

Time-series averages of the parameter estimates for the series of second-step cross-sectional regressions with and without the control variables (designated "with" and "w/out" below) for six samples of Canadian stocks are reported in this table. The regressions use contemporaneous betas derived from the Carhart 4-factor model using a 60-month moving window, and contemporaneous estimates for *IV*, *LIQ*, *SYNCH* and *VROM*. First-step beta estimates from the Carhart model are: $\hat{\beta}_{i1t}^{MKT^+}$ and $\hat{\beta}_{i2t}^{MKT^-}$ for the excess market return when nonnegative and negative, respectively, for firm *i* in month *t*; $\hat{\beta}_{i3t}^{SMB}$ for the small minus big size factor; $\hat{\beta}_{i4t}^{HML}$ for the high minus low book-to-market factor; and $\hat{\beta}_{i5t}^{WML}$ for the momentum factor. IV_{it}^{+} and IV_{it}^{-} are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed based on the security return. The controls are LIQ_{it}^{AS}, $SYNC_{it}$ and $VROM_{it}$. They are respectively liquidity as proxied by the amortized spread of Chalmers and Kadlec (1998), which is obtained by dividing the product of the absolute difference between the trade and midspread prices and the traded volume by the product of the trade price times the number of shares outstanding); synchronicity as proxied by $\gamma_j = \ln\left[R_j^2/\left(1 - R_j^2\right)\right]$ where the R^2 values are from the first-step regressions; and the zero-trade, zero-return measure, which is given by the ln of the percentage of nonzero-trade&return days in a month. CL_{TSX} refer to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. T-values based on robust standard errors are reported in the parentheses. "a", "**b**" and "**c**" indicate statistical significance at the 10%, 5% and 1% levels, respectively. The minimum and maximum number of firms in the various cross sections are report under "#Firms". The average R^2 value is reported in the table.

Sample	All Firms		TSX-only		CL_{TSX}		Big		Small		IT	
Variable	W/out	With	W/out	With	W/out	With	W/out	With	W/out	With	W/out	With
Intercept	-0.0192[c]	-0.0186	-0.0212[c]	-0.0231[b]	-0.0160[c]	0.0113	-0.0146[c]	-0.0053	-0.0362[c]	-0.0181		-0.0426
	(-5.11)	(-1.56)	(-5.33)	(-1.95)	(-2.62)	(0.33)	(-5.40)	(-0.62)	(-5.18)	(-1.18)		(-1.03)
$\hat{\beta}_{i1t}^{MKT^+}$	0.0468[c]	0.0448[c]	0.0484[c]	0.0452[c]	-0.0318	-0.0398	0.0136	0.0204[b]	0.1410[b]	0.1284[b]		1.0406
	(2.78)	(2.90)	(3.07)	(3.15)	(-0.39)	(-0.64)	(1.24)	(2.01)	(2.13)	(2.09)		(1.21)
$\hat{\beta}_{i2t}^{MKT^-}$	0.0113	0.0127	-0.0152	-0.0088	0.0070	0.0224	0.0309	0.0224	-0.0756	-0.0654		0.6722
	(0.51)	(0.60)	(-0.74)	(-0.48)	(0.07)	(0.27)	(1.39)	(1.06)	(-1.33)	(-1.24)		(0.68)
$\hat{\beta}_{i3t}^{SMB}$	-0.0020	-0.0022	-0.0015	-0.0018	0.0022	0.0029	-0.0016	-0.0022[a]	-0.0011	-0.0014		-0.0073
	(-1.27)	(-1.44)	(-0.93)	(-1.11)	(0.69)	(1.24)	(-1.13)	(-1.68)	(-0.72)	(-0.92)		(-1.52)
$\hat{\beta}_{i4t}^{HML}$	0.0014	0.0014	0.0013	0.0012	0.0010	0.0014	0.0018	0.0020[a]	0.0005	0.0004		0.0105
	(0.77)	(0.79)	(0.68)	(0.66)	(0.44)	(0.82)	(1.56)	(1.78)	(0.21)	(0.16)		(1.29)
$\hat{\beta}_{i5t}^{WML}$	-0.0103	-0.0106	-0.0009	-0.0018	0.0078	0.0116	-0.0074	-0.0068	-0.0088	-0.0084		0.0260
	(-0.75)	(-0.78)	(-0.07)	(-0.15)	(0.19)	(0.39)	(-0.62)	(-0.59)	(-0.67)	(-0.64)		(0.74)
IV_{it}^{+}	0.8736[c]	0.8296[c]	0.8988[c]	0.8579[c]	0.9485[c]	0.9350[c]	0.8871[c]	0.8383[c]	0.9584[c]	0.9041[c]		0.9707[c]
	(23.14)	(21.58)	(22.40)	(21.05)	(13.19)	(16.60)	(28.11)	(26.87)	(20.13)	(19.12)		(7.69)
IV_{it}^{-}	-0.3725[c]	-0.3979[c]	-0.3611[c]	-0.3831[c]	-0.4906[c]	-0.4880[c]	-0.4702[c]	-0.4924[c]	-0.3089[c]	-0.3343[c]		-0.2842[c]
	(-18.52)	(-18.07)	(-16.08)	(-15.93)	(-13.42)	(-15.21)	(-22.71)	(-23.29)	(-10.05)	(-10.68)		(-3.09)
LIQ_{it}^{AS}		13.6474[c]		12.3875[c]		2.5959		13.9812[c]		15.6545[c]		5.0081
		(7.33)		(6.50)		(0.90)		(5.96)		(6.61)		(0.84)
$SYNC_{it}$		0.0016		0.0021		-0.0013		0.0000		0.0030		-0.0053
		(1.17)		(1.37)		(-0.54)		(-0.02)		(1.38)		(-0.82)
$VROM_{it}$		-0.0049		-0.0038		-0.0237		-0.0082		-0.0309[b]		0.0157
		(-0.64)		(-0.51)		(-0.74)		(-1.32)		(-2.18)		(0.39)
$\bar{R}^2$	0.45	0.48	0.46	0.49	0.57	0.57	0.49	0.51	0.47	0.51		0.56
# Firms	237;625		197;476		35;70		160;499		70;164		35;69	

Table 2.9 Time-series averages of the second-step cross-sectional regression results with contemporaneous excess returns, betas and controls (e.g., amortized spreads) and lagged IVs based on first-stage 60-month moving windows

Time-series averages of the parameter estimates for the series of second-step cross-sectional regressions with and without the control variables (designated "with" and "w/out" below) for six samples of Canadian stocks are reported in this table. The regressions use contemporaneous betas derived from the Carhart 4-factor model using a 60-month moving window, contemporaneous estimates for *LIQ*, *SYNCH* and *VROM*, and one-period-lagged estimates for *IV*. First-step beta estimates from the Carhart model are: $\hat{\beta}_{i1t}^{MKT^+}$ and $\hat{\beta}_{i2t}^{MKT^-}$ for the excess market return when nonnegative and negative, respectively, for firm *i* in month *t*; $\hat{\beta}_{i3t}^{SMB}$ for the small minus big size factor; $\hat{\beta}_{i4t}^{HML}$ for the high minus low book-to-market factor; and $\hat{\beta}_{i5t}^{WML}$ for the momentum factor. IV_{it}^{+} and IV_{it}^{-} are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed similarly to the excess market return. The controls are LIQ_{it}^{AS}, $SYNC_{it}$ and $VROM_{it}$. They are respectively liquidity as proxied by the amortized spread of Chalmers and Kadlec (1998), which is obtained by dividing the product of the absolute difference between the trade and midspread prices and the traded volume by the product of the trade price times the number of shares outstanding); synchronicity as proxied by $\gamma_j = \ln\left[R_j^2/\left(1 - R_j^2\right)\right]$ where the R^2 values are from the first-step regressions; and the zero-trade, zero-return measure, which is given by the ln of the percentage of nonzero-trade&return days in a month. CL_{TSX} refer to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. T-values based on robust standard errors are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 10%, 5% and 1% levels, respectively. The minimum and maximum number of firms in the various cross sections are report under "#Firms". The average R^2 value is reported in the table.

Sample	**All Firms**		**TSX-only**		**CL_{TSX}**		**Big**		**Small**		**IT**	
Variable	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**
Intercept	-0.0075^{b} (-2.43)	0.0270^{c} (3.01)	-0.0094^{c} (-2.80)	0.0220^{b} (2.26)	-0.0087 (-1.59)	0.0753^{b} (2.16)	-0.0073^{c} (-3.12)	0.0183^{b} (2.36)	-0.0114^{b} (-2.04)	0.0418^{b} (2.22)	-0.0422^{c} (-2.88)	-0.0572 (-1.21)
$\hat{\beta}_{i1t}^{MKT^+}$	0.0577^{c} (2.78)	0.0698^{c} (3.50)	0.0580^{c} (2.81)	0.0671^{c} (3.45)	0.0121 (0.15)	0.0275 (0.51)	0.0181 (1.54)	0.0284^{c} (2.60)	0.2663^{c} (3.10)	0.2848^{c} (3.43)	0.3111 (0.37)	0.7141 (0.32)
$\hat{\beta}_{i2t}^{MKT^-}$	0.0318 1.26)	0.0207 (0.87)	-0.0177 (-0.60)	-0.0199 (-0.71)	-0.0281 (-0.26)	-0.0312 (-0.43)	0.0391 (1.60)	0.0289 (1.27)	-0.0914 (-1.27)	-0.1219^{a} (-1.77)	1.7204^{a} (1.71)	0.9531 (0.31)
$\hat{\beta}_{i3t}^{SMB}$	-0.0012 (-0.53)	-0.0015 (-0.70)	-0.0006 (-0.25)	-0.0010 (-0.43)	0.0023 (0.68)	0.0031 (1.48)	-0.0029 (-1.32)	-0.0035^{a} (-1.73)	0.0025 (1.15)	0.0019 (0.86)	-0.0079 (-1.63)	-0.0096 (-1.54)
$\hat{\beta}_{i4t}^{HML}$	0.0043 (1.58)	0.0044^{a} (1.67)	0.0046 (1.60)	0.0045 (1.63)	0.0020 (0.76)	0.0022 (1.37)	0.0025^{a} (1.85)	0.0027^{b} (1.97)	0.0033 (1.00)	0.0031 (0.99)	0.0124 (1.43)	0.0164 (1.35)
$\hat{\beta}_{i5t}^{WML}$	-0.0168 (-1.23)	-0.0188 (-1.41)	-0.0128 (-0.90)	-0.0151 (-1.09)	0.0102 (0.24)	0.0103 (0.40)	-0.0072 (-0.53)	-0.0050 (-0.40)	-0.0209 (-1.32)	-0.0163 (-1.03)	0.0697 (1.33)	0.0603 (0.59)
IV_{it}^{+}	0.7411^{c} (32.10)	0.6773^{c} (30.28)	0.7690^{c} (30.66)	0.7080^{c} (29.18)	0.8811^{c} (13.89)	0.8529^{c} (20.47)	0.7925^{c} (32.65)	0.7323^{c} (31.34)	0.7912^{c} (25.60)	0.7225^{c} (23.95)	1.0546^{c} (8.53)	0.8216^{c} (5.93)
IV_{it}^{-}	-0.4308^{c} (-24.57)	-0.4751^{c} (-26.21)	-0.4211^{c} (-20.39)	-0.4619^{c} (-22.25)	-0.5291^{c} (-15.60)	-0.5412^{c} (-21.43)	-0.5146^{c} (-29.03)	-0.5500^{c} (-32.40)	-0.4152^{c} (-14.67)	-0.4486^{c} (-15.70)	-0.2063^{b} (-2.34)	-0.4513^{c} (-3.83)
LIQ_{it}^{AS}		17.2281^{c} (8.29)		15.9791^{c} (7.48)		0.4780 (0.19)		17.2921^{c} (6.83)		19.0524^{c} (6.89)		0.0015 (1.34)
$SYNC_{it}$		-0.0028^{b} (-2.12)		-0.0021 (-1.52)		-0.0041^{a} (-1.84)		-0.0021^{a} (-1.85)		-0.0035 (-1.38)		-0.0126 (-1.15)
$VROM_{it}$		-0.0268 ^{c} (-3.75)		-0.0259^{c} (-3.45)		-0.0718^{b} (-2.18)		-0.0184^{c} (-2.79)		-0.0526^{c} (-3.02)		0.0751^{a} (1.83)
$\bar{R}^2$	0.42	0.45	0.43	0.46	0.55	0.55	0.46	0.49	0.45	0.48	0.52	0.53
# Firms	237;614		197;468		35;70		160;493		69;161		35;68	

Table 2.10 Time-series averages of the second-step cross-sectional regression results with contemporaneous excess returns, betas, IVs and controls (e.g., amortized spreads) based on first-stage contemporaneous days-within-the-month moving windows

Time-series averages of the parameter estimates for the series of second-step cross-sectional regressions with and without the control variables (designated "with" and "w/out" below) for six samples of Canadian stocks are reported in this table. The regressions use contemporaneous betas derived from the Carhart 4-factor model using a contemporaneous days-within-the-month moving window, and contemporaneous estimates for *IV*, *LIQ*, *SYNCH* and *VROM*. First-step beta estimates from the Carhart model are: $\hat{\beta}_{i1t}^{MKT^+}$ and $\hat{\beta}_{i2t}^{MKT^-}$ for the excess market return when nonnegative and negative, respectively, for firm *i* in month *t*; $\hat{\beta}_{i3t}^{SMB}$ for the small minus big size factor; $\hat{\beta}_{i4t}^{HML}$ for the high minus low book-to-market factor; and $\hat{\beta}_{i5t}^{WML}$ for the momentum factor. IV_{it}^{+} and IV_{it}^{-} are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed based on the security return. The controls are LIQ_{it}^{AS}, $SYNC_{it}$ and $VROM_{it}$. They are respectively liquidity as proxied by the amortized spread of Chalmers and Kadlec, 1998), which is obtained by dividing the product of the absolute difference between the trade and midspread prices and the traded volume by the product of the trade price times the number of shares outstanding); synchronicity as proxied by $\gamma_j = \ln\left[R_j^2/\left(1-R_j^2\right)\right]$ where the R^2 values are from the first-step regressions; and the zero-trade, zero-return measure, which is given by the ln of the percentage of nonzero-trade&return days in a month. CL_{TSX} refer to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. T-values based on robust standard errors are reported in the parentheses. "a", "b" and "c" indicate statistical significance at the 10%, 5% and 1% levels, respectively. The minimum and maximum number of firms in the various cross sections are report under "#Firms". The average R^2 value is reported in the table.

Sample	All Firms		TSX-only		CL_{TSX}		Big		Small		IT	
Variable	W/out	With	W/out	With	W/out	With	W/out	With	W/out	With	W/out	With
Intercept		-0.0706^{c}		-0.0658^{c}		-0.0681^{c}		-0.0372^{c}		-0.1090^{c}		-0.0244
		(-7.61)		(-7.49)		(-4.58)		(-6.37)		(-6.32)		(-0.82)
$\hat{\beta}_{i1t}^{MKT^+}$		0.0005		0.0005		0.0011^{a}		0.0011^{c}		0.0002		-0.0006
		(1.44)		(1.27)		(1.72)		(2.77)		(0.43)		(-0.39)
$\hat{\beta}_{i2t}^{MKT^-}$		-0.0007		-0.0007		-0.0001		-0.0009^{a}		-0.0003		0.0000
		(-1.48)		(-1.35)		(-0.22)		(-1.70)		(-0.49)		(0.03)
$\hat{\beta}_{i3t}^{SMB}$		0.0005		0.0005		-0.0016		-0.0006		0.0008		0.0008
		(0.85)		(0.77)		(-1.46)		(-1.01)		(0.91)		(0.39)
$\hat{\beta}_{i4t}^{HML}$		-0.0012		-0.0015^{a}		0.0002		-0.0012^{a}		-0.0011		-0.0040
		(-1.53)		(-1.79)		(0.20)		(-1.85)		(-1.19)		(-1.52)
$\hat{\beta}_{i5t}^{WML}$		0.0065^{c}		0.0063^{c}		0.0059^{c}		0.0058^{c}		0.0049^{b}		0.0022
		(2.88)		(2.81)		(5.83)		(9.08)		(2.21)		(0.98)
IV_{it}^{+}		0.9628^{c}		0.9417^{c}		1.0919^{c}		0.9860^{c}		0.9905^{c}		1.0064^{c}
		(52.62)		(47.97)		(42.39)		(59.35)		(35.11)		(15.72)
IV_{it}^{-}		-0.4965^{c}		-0.4875^{c}		-0.6013^{c}		-0.5990^{c}		-0.3644^{c}		-0.5390^{c}
		(-42.91)		(-39.37)		(-28.67)		(-48.05)		(-19.60)		(-10.41)
LIQ_{it}^{AS}		3.0382^{b}		2.8472^{b}		9.2014^{b}		3.9728^{c}		3.6424^{b}		1.9855
		(2.49)		(2.15)		(2.37)		(2.82)		(2.09)		(0.35)
$SYNC_{it}$		0.0045^{c}		0.0043^{c}		0.0033^{c}		0.0030^{c}		0.0073^{c}		0.0026
		(6.56)		(5.88)		(3.82)		(5.72)		(4.40)		(0.76)
$VROM_{it}$		0.0410^{c}		0.0369^{c}		0.0430^{c}		0.0187^{c}		0.0446^{c}		-0.0092
		(5.94)		(5.76)		(3.12)		(3.92)		(3.78)		(-0.35)
$\bar{R}^2$		0.59		0.60		0.66		0.62		0.60		0.67
# Firms		247;1044		202;842		43;202		183;725		39;319		35;115

Table 2.11 Time-series averages of the second-step cross-sectional regression results with contemporaneous excess returns, betas and controls (e.g., amortized spreads) and lagged IVs based on first-stage contemporaneous days-within-the-month moving windows

Time-series averages of the parameter estimates for the series of second-step cross-sectional regressions with and without the control variables (designated "with" and "w/out" below) for six samples of Canadian stocks are reported in this table. The regressions use contemporaneous betas derived from the Carhart 4-factor model using a contemporaneous days-within-the-month moving window, contemporaneous estimates for *LIQ*, *SYNCH* and *VROM*, and one-month lagged IV. First-step beta estimates from the Carhart model are: $\hat{\beta}_{i1t}^{MKT^+}$ and $\hat{\beta}_{i2t}^{MKT^-}$ for the excess market return when nonnegative and negative, respectively, for firm *i* in month *t*; $\hat{\beta}_{i3t}^{SMB}$ for the small minus big size factor; $\hat{\beta}_{i4t}^{HML}$ for the high minus low book-to-market factor; and $\hat{\beta}_{i5t}^{WML}$ for the momentum factor. IV_{it}^{+} and IV_{it}^{-} are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed based on the security return. The controls are LIQ_{it}^{AS}, $SYNC_{it}$ and $VROM_{it}$. They are respectively liquidity as proxied by the amortized spread of Chalmers and Kadlec, 1998), which is obtained by dividing the product of the absolute difference between the trade and midspread prices and the traded volume by the product of the trade price times the number of shares outstanding; synchronicity as proxied by $\gamma_j = \ln\left[R_j^2/\left(1 - R_j^2\right)\right]$ where the R^2 values are from the first-step regressions; and the zero-trade, zero-return measure, which is given by the ln of the percentage of nonzero-trade&return days in a month. CL_{TSX} refer to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. T-values based on robust standard errors are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 10%, 5% and 1% levels, respectively. The minimum and maximum number of firms in the various cross sections are report under "#Firms". The average R^2 value is reported in the table.

Sample	**All Firms**		**TSX-only**		**CL_{TSX}**		**Big**		**Small**		**IT**	
Variable	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**
Intercept		-0.0411[c]		-0.0407[c]		-0.0227		-0.0192[c]		-0.0677[c]		0.0101
		(-6.99)		(-6.71)		(-1.40)		(-3.05)		(-4.76)		(0.26)
$\hat{\beta}_{i1t}^{MKT^+}$		0.0010[a]		0.0006		0.0032[c]		0.0018[c]		0.0004		0.0044
		(1.86)		(1.07)		(3.66)		(3.17)		(0.66)		(0.89)
$\hat{\beta}_{i2t}^{MKT^-}$		-0.0001		0.0000		0.0003		-0.0006		0.0008		0.0051
		(-0.12)		(0.03)		(0.32)		(-0.94)		(0.96)		(1.19)
$\hat{\beta}_{i3t}^{SMB}$		-0.0001		0.0000		-0.0027[b]		-0.0017[b]		0.0005		-0.0071
		(-0.08)		(0.05)		(-2.20)		(-2.17)		(0.53)		(-1.07)
$\hat{\beta}_{i4t}^{HML}$		-0.0006		-0.0008		0.0001		-0.0005		0.0000		-0.0102
		(-0.64)		(-0.74)		(0.06)		(-0.71)		(-0.02)		(-1.50)
$\hat{\beta}_{i5t}^{WML}$		0.0121[c]		0.0116[c]		0.0096[c]		0.0103[c]		0.0103[c]		0.0030
		(5.06)		(4.84)		(7.80)		(12.49)		(4.12)		(1.03)
IV_{it}^{+}		0.7639[c]		0.7475[c]		0.8676[c]		0.8181[c]		0.7287[c]		1.0689[c]
		(43.60)		(41.48)		(32.04)		(39.84)		(27.88)		(13.90)
IV_{it}^{-}		-0.5177[c]		-0.5111[c]		-0.6383[c]		-0.5846[c]		-0.4671[c]		-0.5614[c]
		(-45.78)		(-45.22)		(-31.22)		(-48.16)		(-28.50)		(-10.82)
LIQ_{it}^{AS}		7.4526[c]		6.7374[c]		19.1540[c]		8.0260[c]		9.1468[c]		0.0005
		(4.46)		(3.88)		(3.76)		(4.48)		(4.14)		(0.64)
$SYNC_{it}$		-0.0002		-0.0002		-0.0025[c]		-0.0008		-0.0011		-0.0009
		(-0.39)		(-0.29)		(-2.65)		(-1.54)		(-0.68)		(-0.28)
$VROM_{it}$		0.0437[c]		0.0440[c]		0.0303[b]		0.0240[c]		0.0709[c]		-0.0380
		(7.81)		(7.63)		(1.96)		(4.09)		(5.25)		(-0.95)
$\bar{R}^2$		0.49		0.49		0.57		0.51		0.50		0.66
# Firms		226;973		184;777		40;196		173;691		31;282		35;115

Table 2.12 Time-series averages of the second-step cross-sectional regression results with contemporaneous excess returns, betas, and controls (e.g., Amihud liquidity) and contemporaneous/lagged IVs based on first-stage 60-month moving windows

Time-series averages of the parameter estimates for the series of second-step cross-sectional regressions with the control variables for six samples of Canadian stocks are reported in this table. The regressions use contemporaneous betas derived from the Carhart 4-factor model using a 60-month moving window, contemporaneous estimates of *LIQ*, *SYNCH* and *VROM* and contemporaneous ("cont.") or lagged ("lagged") estimates for *IV*. First-step beta estimates from the Carhart model are: $\hat{\beta}_{i1t}^{MKT^+}$ and $\hat{\beta}_{i2t}^{MKT^-}$ for the excess market return when nonnegative and negative, respectively, for firm *i* in month *t*; $\hat{\beta}_{i3t}^{SMB}$ for the small minus big size factor; $\hat{\beta}_{i4t}^{HML}$ for the high minus low book-to-market factor; and $\hat{\beta}_{i5t}^{WML}$ for the momentum factor. IV_{it}^+ and IV_{it}^- are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed based on the security return. The controls are LIQ_{it}^{AMI} , $SYNC_{it}$ and $VROM_{it}$. They are respectively liquidity as proxied by the approximate price impact measure of Amihud, 2002), which is given by the absolute return for the month divided by the traded dollar share volume for the month; synchronicity as proxied by $\gamma_j = \ln\left[R_j^2/\left(1-R_j^2\right)\right]$ where the R^2 values are from the first-step regressions; and the zero-trade, zero-return measure, which is given by the ln of the percentage of nonzero-trade&return days in a month. CL_{TSX} refer to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. T-values based on robust standard errors are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 10%, 5% and 1% levels, respectively. The minimum and maximum number of firms in the various cross sections are report under "#Firms". The average R^2 value is reported in the table.

Sample	**All Firms**		**TSX-only**		**CL_{TSX}**		**Big**		**Small**		**IT**	
Variable	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**
Intercept	-0.0189[a]	0.0232[c]	-0.0225[b]	0.0176[a]	0.0020	0.0233	-0.0089	0.0078	-0.0148	0.0417[a]	-0.0431	-0.0572
	(-1.87)	(2.76)	(-2.24)	(1.83)	(0.12)	(1.24)	(-1.04)	(0.97)	(-0.90)	(1.90)	(-0.97)	(-1.21)
$\hat{\beta}_{i1t}^{MKT^+}$	0.0395[b]	0.061[c]	0.0392[b]	0.0555[b]	-0.0740	-0.0205	0.0172	0.0271[b]	0.1140[a]	0.2596[c]	0.4610	0.7141
	(2.42)	(2.87)	(2.51)	(2.46)	(-1.18)	(-0.31)	(1.68)	(2.43)	(1.65	(2.98)	(0.54)	(0.32)
$\hat{\beta}_{i2t}^{MKT^-}$	0.0078	0.0280	-0.0027	0.0140	0.0310	0.0127	0.0264	0.0307	-0.0785	-0.0209	1.6559	0.9531
	(0.36)	(1.08)	(-0.13)	(0.31)	(0.36)	(0.14)	(1.24)	(1.31)	(-1.33)	(-0.17)	(1.55)	(0.31)
$\hat{\beta}_{i3t}^{SMB}$	-0.0033	-0.0015	-0.0030	-0.0011	-0.0010	-0.0009	-0.0012	-0.0028	-0.0032	0.0013	-0.0082[a]	-0.0096
	(-1.60)	(-0.65)	(-1.35)	(-0.46)	(-0.81)	(-0.73)	(-0.90)	(-1.30)	(-1.37)	(0.58)	(-1.71)	(-1.54)
$\hat{\beta}_{i4t}^{HML}$	0.0001	0.0040	-0.0002	0.0039	0.0027[b]	0.0034[c]	0.0017	0.0026[a]	-0.0008	0.0023	0.0116[a]	0.0164
	(0.03)	(1.45)	(-0.08)	(1.32)	(2.39)	(2.79)	(1.44)	(1.82)	(-0.31)	(0.68)	(1.69)	(1.35)
$\hat{\beta}_{i5t}^{WML}$	-0.0015	-0.0112	0.0092	-0.0041	-0.0102	-0.0086	-0.0074	-0.0087	0.0047	-0.0063	0.0886[a]	0.0603
	(-0.10)	(-0.78)	(0.67)	(-0.27)	(-0.68)	(-0.55)	(-0.62)	(-0.64)	(0.32)	(-0.36)	(1.79)	(0.59)
IV_{it}^+	0.8813[c]	0.7115[c]	0.9113[c]	0.7471[c]	0.8261[c]	0.7259[c]	0.8548[c]	0.7405[c]	0.9697[c]	0.7781[c]	1.0905[c]	0.8216[c]
	(20.68)	(31.24)	(20.26)	(29.47)	(23.59)	(24.55)	(25.48)	(30.92)	(18.89)	(23.74)	(8.04)	(5.93)
IV_{it}^-	-0.3654[c]	-0.4600[c]	-0.3465[c]	-0.4389[c]	-0.5663[c]	-0.6325[c]	-0.4864[c]	-0.5537[c]	-0.2939[c]	-0.4223[c]	-0.2325[b]	-0.4513[c]
	(-14.15)	(-22.98)	(-11.88)	(-18.79)	(-20.21)	(-24.25)	(-20.19)	(-29.71)	(-7.98)	(-13.44)	(-2.30)	(-3.83)
LIQ_{it}^{AMI}	0.0001	0.0003[c]	0.0000	0.0002[c]	0.0008[b]	0.0014[c]	0.0001	0.0005[c]	-0.0001	0.0001	-0.0007	0.0015
	(1.02)	(3.31)	(0.51)	(2.74)	(2.16)	(3.30)	(0.99)	(2.87)	(-1.01)	(0.90)	(-0.51)	(1.34)
$SYNC_{it}$	0.0018	-0.0037[b]	0.0020	-0.0036[b]	-0.0008	-0.0027[c]	-0.0001	-0.0021	0.0030	-0.0059[a]	-0.0022	-0.0126
	(1.26)	(-2.41)	(1.31)	(-2.02)	(-0.53)	(-1.83)	(-0.07)	(-1.84)	(1.26)	(-1.76)	(-0.38)	(-1.15)
$VROM_{it}$	-0.0061	-0.0184[c]	-0.0056	-0.0162[b]	-0.0083	-0.0161	-0.0036	-0.0059	-0.0334[b]	-0.0393	0.0060	0.0751[a]
	(-0.91)	(-2.63)	(-0.83)	(-1.99)	(-0.55)	(-0.92)	(-0.55)	(-0.84)	(-2.20)	(-1.64)	(0.12)	(1.83)
$\bar{R}^2$	0.47	0.44	0.47	0.44	0.56	0.55	0.50	0.48	0.49	0.46	0.55	0.53
# Firms	299; 625	297; 614	251; 476	248; 468	46; 152	46; 150	208; 499	206; 493	70; 164	69; 161	35; 69	34; 68

Table 2.13 Time-series averages of the second-step cross-sectional regression results with contemporaneous excess returns, betas and controls (e.g., Amihud liquidity) and contemporaneous/lagged IVs based on first-stage contemporaneous days-within-the-month moving windows

Time-series averages of the parameter estimates for the series of second-step cross-sectional regressions with the control variables for six samples of Canadian stocks are reported in this table. The regressions use contemporaneous betas derived from the Carhart 4-factor model using a contemporaneous days-within-the-month moving window, and contemporaneous estimates for *LIQ*, *SYNCH* and *VROM* and contemporaneous ("cont.") or lagged ("lagged") estimates for *IV*. First-step beta estimates from the Carhart model are: $\hat{\beta}_{i1t}^{MKT^+}$ and $\hat{\beta}_{i2t}^{MKT^-}$ for the excess market return when nonnegative and negative, respectively, for firm i in month t; $\hat{\beta}_{i3t}^{SMB}$ for the small minus big size factor; $\hat{\beta}_{i4t}^{HML}$ for the high minus low book-to-market factor; and $\hat{\beta}_{i5t}^{WML}$ for the momentum factor. IV_{it}^{+} and IV_{it}^{-} are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed based on the security return. The controls are LIQ_{it}^{AMI}, $SYNC_{it}$ and $VROM_{it}$. They are respectively liquidity as proxied by the approximate price impact measure of Amihud, 2002), which is given by the absolute return for the month divided by the traded dollar share volume for the month; synchronicity as proxied by $\gamma_j = \ln\left[R_j^2/\left(1-R_j^2\right)\right]$ where the R^2 values are from the first-step regressions; and the zero-trade, zero-return measure, which is given by the ln of the percentage of nonzero-trade&return days in a month. CL_{TSX} refer to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. T-values based on robust standard errors are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 10%, 5% and 1% levels, respectively. The minimum and maximum number of firms in the various cross sections are report under "#Firms". The average R^2 value is reported in the table.

Sample	**All Firms**		**TSX-only**		**CL_{TSX}**		**Big**		**Small**		**IT**	
Variable	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**
Intercept	-0.0737^{c}	-0.0418^{c}	-0.0697^{c}	-0.0410^{c}	-0.0751^{c}	-0.0379^{b}	-0.0359^{c}	-0.0206^{c}	-0.1223^{c}	-0.0807^{c}	0.0101	0.0191
	(-7.97)	(-6.67)	(-7.81)	(-6.29)	(-4.91)	(-2.18)	(-6.21)	(-3.37)	(-6.38)	(-4.66)	(0.26)	(0.35)
$\hat{\beta}_{i1t}^{MKT^+}$	0.0006	0.0010^{a}	0.0006	0.0006	0.0010	0.0028^{c}	0.0011^{c}	0.0018^{c}	0.0004	0.0004	0.0044	0.0029
	(1.63)	(1.92)	(1.42)	(1.10)	(1.50)	(3.29)	(2.86)	(3.18)	(0.84)	(0.54)	(0.89)	(0.62)
$\hat{\beta}_{i2t}^{MKT^-}$	-0.0006	0.0003	-0.0006	0.0004	0.0000	0.0004	-0.0008	-0.0005	0.0000	0.0014	0.0051	0.0070
	(-1.06)	(0.34)	(-1.05)	(0.49)	(-0.06)	(0.44)	(-1.48)	(-0.79)	(0.08)	(1.50)	(1.19)	(1.24)
$\hat{\beta}_{i3t}^{SMB}$	0.0005	-0.0001	0.0005	0.0001	-0.0018^{a}	-0.0029^{b}	-0.0004	-0.0017^{b}	0.0007	0.0007	-0.0071	-0.0052
	(0.80)	(-0.07)	(0.80)	(0.09)	(-1.67)	(-2.22)	(-0.79)	(-2.09)	(0.84)	(0.69)	(-1.07)	(-0.63)
$\hat{\beta}_{i4t}^{HML}$	-0.0011	-0.0007	-0.0013	-0.0009	0.0000	-0.0001	-0.0012^{a}	-0.0005	-0.0009	0.0003	-0.0102	-0.0125^{a}
	(-1.32)	(-0.63)	(-1.53)	(-0.75)	(-0.04)	(-0.05)	(-1.78)	(-0.62)	(-0.84)	(0.19)	(-1.50)	(-1.71)
$\hat{\beta}_{i5t}^{WML}$	0.0065^{c}	0.0122^{c}	0.0062^{b}	0.0114^{c}	0.0065^{c}	0.0103^{c}	0.0058^{c}	0.0104^{c}	0.0048^{b}	0.0098^{c}	0.0030	0.0087^{b}
	(2.87)	(5.06)	(2.75)	(4.75)	(6.35)	(8.33)	(9.10)	(12.22)	(2.16)	(3.89)	(1.03)	(2.31)
IV_{it}^{+}	0.9664^{c}	0.7722^{c}	0.9460^{c}	0.7535^{c}	1.1088^{c}	0.8915^{c}	0.9818^{c}	0.8142^{c}	0.9982^{c}	0.7553^{c}	1.0689^{c}	0.8632^{c}
	(51.23)	(44.32)	(46.96)	(41.55)	(39.56)	(33.11)	(58.93)	(39.52)	(34.10)	(28.28)	(13.90)	(20.45)
IV_{it}^{-}	-0.4946^{c}	-0.5120^{c}	-0.4868^{c}	-0.5091^{c}	-0.5918^{c}	-0.6265^{c}	-0.6002^{c}	-0.5879^{c}	-0.3660^{c}	-0.4603^{c}	-0.5614^{c}	-0.5588^{c}
	(-40.65)	(-48.36)	(-37.35)	(-47.90)	(-26.57)	(-29.62)	(-47.83)	(-47.99)	(-17.94)	(-29.11)	(-10.82)	(-14.00)
LIQ_{it}^{AMI}	0.0001^{b}	0.0003^{c}	0.0001^{b}	0.0003^{c}	0.0001	0.0004	0.0001^{a}	0.0005^{c}	0.0001^{a}	0.0002^{a}	0.0005	0.0018^{b}
	(2.15)	(3.39)	(2.10)	(3.64)	(0.51)	(1.60)	(1.88)	(4.26)	(1.68)	(1.73)	(0.64)	(2.01)
$SYNC_{it}$	0.0047^{c}	-0.0003	0.0046^{c}	-0.0002	0.0034^{c}	-0.0026^{c}	0.0029^{c}	-0.0009^{a}	0.0079^{c}	-0.0004	-0.0009	-0.0069^{a}
	(6.31)	(-0.50)	(5.62)	(-0.34)	(3.74)	(-2.59)	(5.54)	(-1.65)	(3.74)	(-0.22)	(-0.28)	(-1.88)
$VROM_{it}$	0.0440^{c}	0.0450^{c}	0.0405^{c}	0.0449^{c}	0.0496^{c}	0.0465^{c}	0.0183^{c}	0.0266^{c}	0.0592^{c}	0.0833^{c}	-0.0380	-0.0031
	(6.49)	(7.45)	(6.32)	(7.15)	(3.54)	(2.82)	(3.84)	(4.56)	(4.49)	(5.13)	(-0.95)	(-0.06)
$\bar{R}^2$	0.58	0.47	0.59	0.48	0.65	0.56	0.61	0.50	0.59	0.49	0.66	0.55
# Firms	256; 1044	233; 973	211; 842	186; 777	44; 202	40; 196	189; 725	177; 691	39; 319	35; 282	35; 115	35; 112

Table 2.14 Time-series averages of the second-step cross-sectional regression results with contemporaneous risk-adjusted excess returns and controls and contemporaneous/lagged IVs based on first-stage 60-month moving windows

Time-series averages of the parameter estimates for the series of second-step cross-sectional regressions with the control variables for six samples of Canadian stocks are reported in this table. The regressions use contemporaneous risk-adjusted excess returns based on estimates derived from the Carhart 4-factor model using a 60-month moving window, contemporaneous estimates of *LIQ*, *SYNCH* and *VROM* and contemporaneous ("cont.") or lagged ("lagged") estimates for *IV*. IV_{it}^{+} and IV_{it}^{-} are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed based on the security return. The controls are LIQ_{it}, $SYNC_{it}$ and $VROM_{it}$. They are respectively liquidity LIQ_{it}^{AS} as proxied by the amortized spread of Chalmers and Kadlec, 1998, which is obtained by dividing the product of the absolute difference between the trade and midspread prices and the traded volume by the product of the trade price times the number of shares outstanding; LIQ_{it}^{AMI} as proxied by the approximate price impact measure of Amihud, 2002, which is given by the absolute return for the month divided by the traded dollar share volume for the month; synchronicity $SYNC_{it}$ as proxied by $\gamma_j = \ln\left[R_j^2/\left(1 - R_j^2\right)\right]$ where the R^2 values are from the first-step regressions; and the zero-trade, zero-return measure $VROM_{it}$, which is given by the ln of the percentage of nonzero-trade&return days in a month. CL_{TSX} refer to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. T-values based on robust standard errors are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 10%, 5% and 1% levels, respectively. The minimum and maximum number of firms in the various cross sections are report under "#Firms". The average R^2 value is reported in the table.

Sample	**All Firms**		**TSX-only**		**CL_{TSX}**		**Big**		**Small**		**IT**	
Variable	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**
Panel A: Using the amortized spread proxy for liquidity												
Intercept	-0.0100	-0.0033	-0.0075	-0.0134	-0.0181	0.0335	-0.0163	0.0060	-0.0005	-0.1041	-0.0636	0.0233
	(-0.70)	(-0.10)	(-0.51)	(-0.30)	(-0.37)	(0.59)	(-1.48)	(0.57)	(-0.03)	(-0.72)	(-1.12)	(0.41)
IV_{it}^{+}	0.6072^{c}	0.5266^{c}	0.6515^{c}	0.6075^{c}	0.7776^{c}	0.7139^{c}	0.6392^{c}	0.5470^{c}	0.6569^{c}	0.5968^{c}	0.7361^{c}	0.5339^{c}
	(12.97)	(8.98)	(13.64)	(7.01)	(10.19)	(10.22)	(15.35)	(17.20)	(12.08)	(5.46)	(6.31)	(5.84)
IV_{it}^{-}	-0.4574^{c}	-0.4969^{c}	-0.4682^{c}	-0.5043^{c}	-0.4950^{c}	-0.5414^{c}	-0.5306^{c}	-0.5820^{c}	-0.4631^{c}	-0.5424^{c}	-0.3989^{c}	-0.5113^{c}
	(-16.88)	(-18.79)	(-16.29)	(-16.38)	(-11.13)	(-12.35)	(-16.93)	(-21.34)	(-13.52)	(-16.70)	(-7.32)	(-9.17)
LIQ_{it}^{AS}	18.7534^{c}	21.3962^{c}	17.2284^{c}	19.0219^{c}	0.6763	-1.9978	20.9643^{c}	24.7385^{c}	19.4422^{c}	19.2510^{c}	16.4466^{b}	37.6123^{a}
	(9.53)	(9.23)	(8.53)	(6.70)	(0.17)	(-0.46)	(8.54)	(9.06)	(7.89)	(4.56)	(2.52)	(1.71)
$SYNC_{it}$	-0.0010	-0.0031^{b}	-0.0011	-0.0025	-0.0029	-0.0047	-0.0019	-0.0035^{c}	0.0013	0.0039	-0.0005	-0.0102^{b}
	(-0.67)	(-1.94)	(-0.68)	(-1.19)	(-0.89)	(-1.38)	(-1.56)	(-3.00)	(0.56)	(0.57)	(-0.08)	(-1.98)
$VROM_{it}$	0.0018	0.0108	-0.0004	0.0170	0.0076	-0.0305	0.0125^{a}	0.0026	-0.0174	0.1156	0.0449	-0.0001
	(0.20)	(0.36)	(-0.04)	(0.44)	(0.17)	(-0.58)	(1.86)	(0.30)	(-1.36)	(0.83)	(1.00)	(0.00)
$\bar{R}^2$	0.49	0.46	0.50	0.48	0.46	0.45	0.42	0.40	0.52	0.50	0.45	0.43
# Firms	237;625	237;614	197;476	197;468	35;70	35;70	160;499	160;493	70;164	69;161	35;69	35;68
Panel B: Using the Amihud proxy for liquidity												
Intercept	-0.0095	-0.0134	-0.0057	-0.0217	-0.0338^{a}	0.0022	-0.0224^{b}	-0.0067	0.0082	-0.1185	-0.0503	-0.0843
	(-0.75)	(-0.36)	(-0.44)	(-0.46)	(-1.89)	(0.12)	(-2.21)	(-0.71)	(0.47)	(-0.75)	(-1.03)	(-0.84)
IV_{it}^{+}	0.6383^{c}	0.5423^{c}	0.6850^{c}	0.6227^{c}	0.6096^{c}	0.8261^{c}	0.6583^{c}	0.5630^{c}	0.6918^{c}	0.6096^{c}	0.8661^{c}	0.4330^{c}
	(13.31)	(10.76)	(13.98)	(8.44)	(13.67)	(17.82)	(15.21)	(16.97)	(12.81)	(7.25)	(5.88)	(3.91)
IV_{it}^{-}	-0.4428^{c}	-0.5053^{c}	-0.4575^{c}	-0.5164^{c}	-0.6399^{c}	-0.5929^{c}	-0.5291^{c}	-0.5876^{c}	-0.4635^{c}	-0.5696^{c}	-0.3541^{c}	-0.7026^{c}
	(-15.56)	(-21.19)	(-14.61)	(-19.45)	(-17.87)	(-17.10)	(-15.99)	(-20.67)	(-12.94)	(-17.90)	(-4.02)	(-6.10)
LIQ_{it}^{AMI}	0.0003^{c}	0.0006^{c}	0.0002^{b}	0.0005^{c}	0.0013^{c}	0.0008^{b}	0.0005^{b}	0.0007^{c}	0.0001	0.0004^{b}	-0.0008	0.0093^{b}
	(2.75)	(3.98)	(2.46)	(3.84)	(3.47)	(2.02)	(2.49)	(3.67)	(1.28)	(1.99)	(-0.38)	(2.06)
$SYNC_{it}$	-0.0024	-0.0048^{c}	-0.0029	-0.0047^{a}	-0.0025	-0.0014	-0.0019^{a}	-0.0035^{c}	-0.0019	-0.0004	-0.0016	-0.0394^{a}
	(-1.37)	(-2.57)	(-1.39)	(-1.93)	(-1.64)	(-0.80)	(-1.72)	(-3.06)	(-0.49)	(-0.06)	(-0.36)	(-1.72)
$VROM_{it}$	0.0073	0.0301	0.0051	0.0361	0.0410^{c}	-0.0064	0.0211^{c}	0.0186^{b}	-0.0084	0.1532	0.0284	0.2188^{a}
	(0.93)	(0.86)	(0.64)	(0.85)	(2.73)	(-0.42)	(3.22)	(2.33)	(-0.48)	(0.98)	(0.52)	(1.65)
$\bar{R}^2$	0.47	0.44	0.49	0.46	0.49	0.51	0.42	0.39	0.50	0.47	0.45	0.42
# Firms	299;625	297;614	251;476	248;468	46;152	46;152	208;499	206;493	70;164	69;161	35;69	35;68

Table 2.15 Time-series averages of the second-step cross-sectional regression results using contemporaneous risk-adjusted excess returns and controls and contemporaneous/lagged IVs based on first-step contemporaneous days-within-the-month moving windows

Time-series averages of the parameter estimates for the series of second-step cross-sectional regressions with the control variables for six samples of Canadian stocks are reported in this table. The regressions use contemporaneous risk-adjusted excess returns based on estimates derived from the Carhart 4-factor model using a contemporaneous days-within-the-month moving window, contemporaneous estimates of *LIQ*, *SYNCH* and *VROM* and contemporaneous ("cont.") or lagged ("lagged") estimates for *IV*. $IV_{i,t}^{+}$ and $IV_{i,t}^{-}$ are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed based on the security return. The controls are $LIQ_{i,t}$, $SYNC_{i,t}$ and $VROM_{i,t}$. They are respectively $LIQ_{i,t}^{AS}$ as proxied by the amortized spread of Chalmers and Kadlec (1998), which is obtained by dividing the product of the absolute difference between the trade and midspread prices and the traded volume by the product of the trade price times the number of shares outstanding; $LIQ_{i,t}^{AMI}$ as proxied by the approximate price impact measure of Amihud (2002), which is given by the absolute return for the month divided by the traded dollar share volume for the month; synchronicity $SYNC_{i,t}$ as proxied by $\gamma_j = \ln\left[R_j^2/\left(1 - R_j^2\right)\right]$ where the R^2 values are from the first-step regressions; and the zero-trade, zero-return measure $VROM_{i,t}$, which is given by the ln of the percentage of nonzero-trade&return days in a month. CL_{TSX} refers to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. T-values are reported in the parentheses. "**a**", "**b**" and "**c**" indicate statistical significance at the 10%, 5% and 1% levels, respectively. The minimum and maximum number of firms in the various cross sections are report under "#Firms". The average second-step R^2 values are reported in the table.

Sample	**All Firms**		**TSX-only**		**CL_{TSX}**		**Big**		**Small**		**IT**	
Variable	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**	**Cont.**	**Lagged**
Panel A: Using the amortized spread proxy for liquidity												
Intercept	-0.1169[a]	-0.1485	-0.1372[b]	-0.2039[a]	0.0450	0.0899	-0.0453	-0.0299	-0.1767[a]	-0.3400	-0.1837[b]	-0.1310
	(-1.94)	(-1.62)	(-2.43)	(-1.82)	(0.31)	(0.73)	(-1.59)	(-0.71)	(-1.85)	(-1.38)	(-1.98)	(-1.31)
$IV_{i,t}^{+}$	1.0305[c]	0.8319[c]	1.0776[c]	0.8557[c]	0.7686[c]	0.6165[b]	0.9464[c]	0.8315[c]	1.0752[c]	0.7814[c]	1.1004[c]	0.7907[c]
	(6.15)	(9.69)	(6.41)	(8.46)	(3.06)	(2.10)	(13.60)	(10.16)	(5.94)	(7.36)	(8.99)	(11.41)
$IV_{i,t}^{-}$	-0.4287[c]	-0.4494[c]	-0.3947[c]	-0.4411[c]	-0.8498[c]	-0.8019[c]	-0.4893[c]	-0.5135[c]	-0.3112[b]	-0.4490[c]	-0.1769	-0.3816[c]
	(-4.60)	(-12.90)	(-4.24)	(-11.63)	(-2.91)	(-3.46)	(-7.11)	(-18.00)	(-2.23)	(-10.50)	(-0.85)	(-2.84)
$LIQ_{i,t}^{AS}$	3.6606	8.2168[b]	3.3299	6.2975	9.8623	21.5342[b]	7.0527	16.8707[b]	5.0452	5.5970	9.3295	41.0736[c]
	(1.05)	(1.95)	(0.89)	(1.33)	(1.17)	(2.20)	(1.07)	(2.29)	(1.28)	(0.93)	(0.85)	(3.54)
$SYNC_{i,t}$	0.0053	0.0121	0.0064	0.0202	0.0031	-0.0102	0.0013	-0.0034	0.0080	0.0474	0.0177[b]	0.0062
	(0.82)	(0.79)	(0.98)	(1.05)	(0.57)	(-1.20)	(0.30)	(-0.64)	(0.70)	(1.02)	(2.19)	(1.06)
$VROM_{i,t}$	0.0739[b]	0.1025[b]	0.0854[c]	0.1329[c]	-0.0496	-0.0471	0.0297[a]	0.0395	0.0900[a]	0.1842[a]	0.0922	0.1179
	(2.40)	(2.51)	(3.09)	(2.77)	(-0.44)	(-0.51)	(1.66)	(1.37)	(1.87)	(1.66)	(1.17)	(1.29)
$\overline{R}^2$	0.33	0.23	0.32	0.23	0.39	0.30	0.35	0.26	0.32	0.22	0.41	0.29
# Firms	247;1047	226;973	202;842	184;777	43;202	40;196	183;725	173;691	39;319	31;282	35;115	35;112
Panel B: Using the Amihud proxy for liquidity												
Intercept	-0.1191[b]	-0.1445	-0.1425[b]	-0.1979[a]	0.0218	0.0504	-0.0439	-0.0315	-0.1997[b]	-0.3358	-0.1744[b]	-0.1036
	(-2.03)	(-1.59)	(-2.55)	(-1.78)	(0.16)	(0.45)	(-1.55)	(-0.76)	(-2.14)	(-1.39)	(-2.17)	(-1.04)
$IV_{i,t}^{+}$	1.0357[c]	0.8408[c]	1.0908[c]	0.8663[c]	0.8448[c]	0.7417[c]	0.9455[c]	0.8260[c]	1.0740[c]	0.7866[c]	1.1216[c]	0.8986[c]
	(6.14)	(10.01)	(6.43)	(8.67)	(4.44)	(3.81)	(12.00)	(7.99)	(5.84)	(7.22)	(9.81)	(10.75)
$IV_{i,t}^{-}$	-0.3952[c]	-0.4383[c]	-0.3533[c]	-0.4328[c]	-0.7737[c]	-0.6915[c]	-0.4795[c]	-0.5179[c]	-0.2955[b]	-0.4462[c]	-0.1729	-0.2702
	(-4.33)	(-13.23)	(-3.76)	(-11.66)	(-3.41)	(-4.63)	(-7.44)	(-12.35)	(-2.16)	(-8.68)	(-0.83)	(-1.44)
$LIQ_{i,t}^{AMI}$	-0.0001	0.0003	-0.0001	0.0003	-0.0014	-0.0025	-0.0003	0.0003	0.0002	0.0004	-0.0006	0.0017
	(-0.55)	(1.29)	(-0.72)	(1.47)	(-0.70)	(-0.83)	(-1.55)	(1.12)	(1.02)	(1.59)	(-0.46)	(1.10)
$SYNC_{i,t}$	0.0054	0.0112	0.0068	0.0191	0.0034	-0.0105	0.0010	-0.0037	0.0091	0.0456	0.0152[a]	0.0044
	(0.84)	(0.71)	(1.06)	(0.98)	(0.68)	(-1.22)	(0.20)	(-0.69)	(0.82)	(0.99)	(1.95)	(0.75)
$VROM_{i,t}$	0.0759[b]	0.1026[c]	0.0886[c]	0.131[c]	-0.0307	-0.0098	0.0304[a]	0.0446	0.1132[b]	0.1893[a]	0.0981	0.1003
	(2.52)	(2.59)	(3.21)	(2.83)	(-0.28)	(-0.11)	(1.85)	(1.64)	(2.37)	(1.79)	(1.44)	(1.12)
$\overline{R}^2$	0.32	0.22	0.31	0.23	0.39	0.29	0.34	0.25	0.31	0.22	0.39	0.27
# Firms	256;1044	233;973	211;842	186;777	44;202	40;196	189;725	177;691	39;319	35;282	35;115	35;112

Table 2.16 Structural breaks in the raw and risk-adjusted return series

This table reports t-statistics in the first row and the break dates (year.month) in the second row for each IO set for the Zivot-Andrews or ZA (1992) test for the presence of one structural break in the intercept or trend and for the Clemente-Montañés-Reyes or CMR (1998) tests that allow for one (two) structural breaks in the presence of Additive (AO) or Innovative (IO) outliers. CL_{TSX} refer to the TSX trades of TSX-listed stocks cross-listed on U.S. trade venues. All reported t-values are significant at the 0.05 level. The critical t-values at the 0.05 level are: -5.08 (ZA); -3.56 (CMR for 1 structural break AO); -4.27 (CMR for 1 structural break IO); and -5.49 (CMR for 2 structural break A/IO).

	One Structural Break			Two Structural Breaks	
	Zivot-Andrews	Clemente-Montañés-Reyes		Clemente-Montañés-Reyes	
IO set	Intercept or Trend	Additive Outlier	Innovative Outlier	Additive Outlier	Innovative Outlier
Panel A: Raw monthly returns					
All Firms	-15.699 1980.12	-12.592 1996.09	-16.068 1996.10	-13.204 1987.08 1996.09	-16.801 1987.09 1996.10
TSX only	-15.675 1980.12	-12.788 1996.09	-16.409 1996.10	-13.347 1981.07 1996.09	-17.131 1987.09 1996.10
CL_{TSX}	-16.698 1980.12	-13.312 1987.08	-17.275 1987.09	-13.984 1987.08 1998.06	-17.911 1987.09 1998.07
Big Firms	-16.589 1980.12	-13.363 1987.08	-17.208 1987.09	-14.125 1987.08 1998.06	-17.965 1987.09 1998.07
Small Firms	-15.558 1980.03	-9.823 1996.09	-17.891 1996.10	-9.892 1996.09 1999.12	-18.755 1996.10 2000.01
IT Firms	-11.554 1999.03	-5.637 1999.11	-12.381 1999.12	-8.916 1999.10 1999.12	-14.199 1999.09 2000.01
Panel B: Risk-adjusted monthly returns					
All Firms	-18.410 1997.01	-8.055 1996.09	-10.159 1996.10	-7.420 1996.09 1999.03	-11.425 1996.10 1998.12
TSX only	-18.768 1997.01	-8.139 1996.09	-11.301 1996.10	-7.382 1996.09 1999.03	-12.341 1996.10 1999.04
CL_{TSX}	-16.953 1994.04	-6.505 1999.10	-13.858 1999.11	-7.684 1994.05 1999.10	-14.645 1994.02 1999.11
Big Firms	-17.150 1999.02	-8.750 2000.12	-8.525 1999.12	-7.859 1993.03 2000.02	-9.440 1993.04 1999.12
Small Firms	-19.085 1997.01	-7.742 1996.09	-13.032 1996.10	-8.239 1996.09 1999.03	-14.131 1996.10 1999.04
IT Firms	-12.107 1999.03	-6.513 1999.03	-8.731 1999.04	-7.004 1999.03 1999.11	-11.779 1999.04 1999.12

Table 2.17 Tests of the significance of the price of asymmetric idiosyncratic risk and liquidity reflecting two structural breaks for raw and risk-adjusted excess returns

This table reports the mean of the time-series of cross-sectional prices or rewards for bearing asymmetric idiosyncratic risk (IV^{+} and IV^{-}) and (il)liquidity (as measured by *AS* or amortized spread) based on raw and risk-adjusted returns for each of the three periods as identified by the two structural breaks using the CMR AO model for each of the six IO sets. The table also presents the changes in the means for the second and third periods relative to the first period. The time-series of cross-sectional average prices or rewards for each of these return determinants are obtained from Fama-MacBeth second-step cross-sectional regressions between contemporaneous raw excess returns and contemporaneous betas, IVs and controls (e.g., amortized spreads), where the first-step estimations of the Carhart model are based on contemporaneous days-within-the-month moving windows. They also are obtained from Fama-MacBeth second-step cross-sectional regressions between contemporaneous risk-adjusted excess returns and contemporaneous IVs and controls where the excess returns are risk-adjusted using the beta estimates from first-step time-series regressions between contemporaneous raw returns and the four factors in the Carhart model based on contemporaneous days-within-the-month moving windows. The first period is up to the first structural break month as identified by the CMR AO model. Period 2 is from the month of the first structural break and up to the second structural break month. Period 3 is from the second structural break month and onwards. The structural break months are reported in table 2.16. The statistical significance of the mean value for each period or for the change in the mean values for the second and third periods relative to the first period are examined by running regressions of the cross-sectional rewards for each of the three return determinants against various dummy variable formulations for each period. T-values based on robust standard errors are reported in the parentheses. "a", "b" and "c" indicate statistical significance at the 10%, 5% and 1% levels, respectively.

		Mean			Change in Mean	
IO Set	**Factor**	**Period 1**	**Period 2**	**Period 3**	**Period 2**	**Period 3**
Panel A: Raw monthly returns						
All Firms	$IV^{+}_{i,t}$	0.8806^{c} (17.00)	0.8659^{c} (9.48)	0.7301^{c} (11.09)	-0.0147 (-0.14)	-0.1504^{a} (-1.80)
	$IV^{-}_{i,t}$	-0.4917^{c} (-11.83)	-0.3599^{c} (-9.83)	-0.3463^{c} (-10.17)	0.1318^{b} (2.36)	0.1454^{c} (2.71)
	$LIQ^{AS}_{i,t}$	12.2853^{c} (3.19)	16.4660^{c} (4.01)	11.5565^{c} (3.25)	4.1807 (0.74)	-0.7289 (-0.14)
TSX only	$IV^{+}_{i,t}$	0.7409^{c} (12.95)	0.9121^{c} (14.08)	0.7700^{c} (10.74)	0.1713^{b} (1.97)	0.0291 (0.32)
	$IV^{-}_{i,t}$	-0.5862^{c} (-16.06)	-0.3791^{c} (-11.86)	-0.3470^{c} (-8.17)	0.2071^{c} (4.29)	0.2391^{c} (4.27)
	$LIQ^{AS}_{i,t}$	22.8799^{c} (4.32)	12.5662^{c} (4.18)	9.7220^{b} (2.46)	-10.3136^{a} (-1.76)	-13.1579^{b} (-1.99)
CL_{TSX}	$IV^{+}_{i,t}$	0.7988^{c} (10.10)	0.7259^{c} (13.17)	1.0595^{c} (10.73)	-0.0729 (-0.76)	0.2607^{b} (2.06)
	$IV^{-}_{i,t}$	-0.6362^{c} (-8.71)	-0.5686^{c} (-15.78)	-0.4644^{c} (-10.91)	0.0676 (0.83)	0.1718^{b} (2.03)
	$LIQ^{AS}_{i,t}$	0.0008 (1.30)	0.0009^{b} (2.05)	0.0004 (0.74)	0.0000 (0.05)	-0.0004 (-0.46)
Big Firms	$IV^{+}_{i,t}$	0.8846^{c} (15.42)	0.7551^{c} (11.76)	0.9376^{c} (9.03)	-0.1295 (-1.57)	0.0529 (0.45)
	$IV^{-}_{i,t}$	-0.5597^{c} (-9.89)	-0.4716^{c} (-15.00)	-0.4396^{c} (-9.40)	0.0881 (1.38)	0.1202 (1.64)
	$LIQ^{AS}_{i,t}$	12.3345^{b} (2.10)	18.9746^{c} (4.30)	6.4412^{a} (1.83)	6.6401 (0.90)	-5.8933 (-0.86)
Small Firms	$IV^{+}_{i,t}$	0.9403^{c} (13.80)	0.9809^{c} (8.38)	0.6904^{c} (6.59)	0.0406 (0.30)	-0.2499^{b} (-2.00)
	$IV^{-}_{i,t}$	-0.3496^{c} (-10.04)	-0.3380^{c} (-3.91)	-0.2668^{c} (-5.06)	0.0117 (0.13)	0.0828 (1.31)
	$LIQ^{AS}_{i,t}$	15.8363^{c} (4.25)	21.5059^{c} (2.69)	10.1394^{b} (2.54)	5.6696 (0.64)	-5.6968 (-1.04)
IT Firms	$IV^{+}_{i,t}$	1.1067^{c} (5.09)	3.7306^{c} (52.71)	0.7509^{c} (5.36)	2.6239^{c} (11.28)	-0.3558 (-1.37)
	$IV^{-}_{i,t}$	-0.3053^{b} (-2.04)	1.515^{c} (39.09)	-0.342^{c} (-3.61)	1.515^{c} (39.09)	-0.342^{c} (-3.61)
	$LIQ^{AS}_{i,t}$	6.7061 (0.65)	-16.8501^{c} (-6.24)	4.6101 (0.97)	-23.5561 (-2.18)	-2.0960 (-0.18)

Table 2.17 Cont'd.

IO Set	Factor	Mean			Change in Mean	
		Period 1	Period 2	Period 3	Period 2	Period 3
Panel B: Risk-adjusted monthly returns						
All Firms	$IV^{+}_{i,t}$	0.6877[c] (10.70)	0.5434[b] (2.38)	0.3568[c] (5.85)	-0.1442 (-0.60)	-0.3309[c] (-3.73)
	$IV^{-}_{i,t}$	-0.4884[c] (-14.02)	-0.4319[c] (-4.73)	-0.3611[c] (-5.38)	0.0565 (0.58)	0.1274[a] (1.69)
	$LIQ^{AS}_{i,t}$	19.3703[c] (7.28)	18.6904[b] (2.29)	16.6109[c] (3.55)	-0.6800 (-0.08)	-2.7594 (-0.51)
TSX only	$IV^{+}_{i,t}$	0.7141[c] (10.27)	0.6269[c] (3.88)	0.4438[c] (6.10)	-0.0873 (-0.49)	-0.2703[c] (-2.69)
	$IV^{-}_{i,t}$	-0.4673[c] (-13.00)	-0.5523[c] (-5.02)	-0.4272[c] (-4.90)	-0.0850 (-0.73)	0.0401 (0.43)
	$LIQ^{AS}_{i,t}$	17.9779[c] (6.90)	16.6416[b] (2.10)	14.8943[c] (2.72)	-1.3362 (-0.16)	-3.0836 (-0.51)
CL_{TSX}	$IV^{+}_{i,t}$	0.8228[c] (4.13)	0.6265[c] (6.65)	0.9641[c] (9.81)	-0.1964 (-0.91)	0.1413 (0.64)
	$IV^{-}_{i,t}$	-0.3191[b] (-2.21)	-0.5906[c] (-11.09)	-0.4095[c] (-9.92)	-0.2715[a] (-1.78)	-0.0903 (-0.60)
	$LIQ^{AS}_{i,t}$	1.5201 (0.24)	2.4883 (0.86)	-1.8650 (-0.38)	0.9682 (0.14)	-3.3851 (-0.43)
Big Firms	$IV^{+}_{i,t}$	0.7599[c] (12.84)	0.4737[c] (4.96)	0.5203[c] (7.28)	-0.2862[b] (-2.54)	-0.2396[b] (-2.58)
	$IV^{-}_{i,t}$	-0.5173[c] (-9.72)	-0.5877[c] (-8.78)	-0.4740[c] (-10.32)	-0.0705 (-0.83)	0.0433 (0.62)
	$LIQ^{AS}_{i,t}$	20.4164[c] (4.65)	25.6393[c] (4.99)	14.4230[c] (3.21)	5.2229 (0.77)	-5.9934 (-0.95)
Small Firms	$IV^{+}_{i,t}$	0.7250[c] (9.14)	0.6449[c] (4.09)	0.4233[c] (4.91)	-0.0801 (-0.45)	-0.3017[b] (-2.58)
	$IV^{-}_{i,t}$	-0.4600[c] (-11.78)	-0.5681[c] (-4.74)	-0.4186[c] (-4.69)	-0.1080 (-0.86)	0.0414 (0.43)
	$LIQ^{AS}_{i,t}$	19.4706[c] (5.55)	18.8668[b] (2.27)	19.6451[c] (3.63)	-0.6038 (-0.07)	0.1745 (0.03)
IT Firms	$IV^{+}_{i,t}$	0.6319[c] (5.21)	0.7753 (1.33)	0.4346[c] (4.01)	0.1434 (0.23)	-0.1973 (-1.21)
	$IV^{-}_{i,t}$	-0.5638[c] (-8.15)	-0.6292 (-1.60)	-0.4600[c] (-6.10)	-0.0654 (-0.16)	0.1038 (1.01)
	$LIQ^{AS}_{i,t}$	10.9592 (0.82)	78.9297 (1.58)	47.1848 (1.28)	67.9705 (1.30)	36.2256 (0.92)

Table 3.1 Summary statistics for the time-series of conditional mean cross-sectional correlations differentiated by investment opportunity set for TSX-listed stocks

This table reports various summary statistics and the correlations between the time-series of mean cross-sectional conditional correlations of returns for six investment opportunity (IO) sets of TSX-listed stocks for monthly returns. A time-series of conditional mean cross-sectional correlations for IO set j is generated by calculating the mean of the correlations between every unique pair of stocks in IO set j for each moving window τ. The correlations between the time-series of conditional mean cross-sectional correlations for all the unique combinations of IO set j and k are then computed and reported herein. Monthly correlations are computed based on the past 60 months, which corresponds to a moving window of 5 years. The 288 moving windows for the monthly returns are from the first month of 1980 through the last month of 2003. "IT" refers to information technology firms.

Panel A: Summary statistics for the time-series of conditional mean cross-sectional correlations of returns					
IO Set *j* Firms	**Mean**	**Median**	**Std Dev**	**Minimum**	**Maximum**
All	0.3823	0.3764	0.1353	0.1721	0.5879
TSX-only Listed	0.3669	0.3700	0.1288	0.1642	0.5719
Cross-listed	0.1620	0.1525	0.0712	0.0636	0.3710
Big	0.0487	0.0489	0.0106	0.0258	0.0787
Small	0.0341	0.0334	0.0050	0.0251	0.0517
IT	0.1268	0.1255	0.0440	0.0517	0.2502
Panel B: Correlations between the time-series of conditional mean cross-sectional correlations of returns					
IO Set *j* Firms	**All**	**TSX-only Listed**	**Crosslisted**	**Big**	**Small**
TSX-only Listed	0.992				
Cross-listed	0.814	0.819			
Big	-0.002	-0.042	-0.301		
Small	0.381	0.350	0.349	0.433	
IT	0.456	0.438	0.558	-0.270	0.126

Table 3.2 Mean derived dispersions differentiated by portfolio size and investment opportunity set

This table reports the mean derived dispersions (MDDs) or excess standard deviations for 22 portfolio sizes (PS) for six investment opportunity (IO) sets using returns for the 348 months in the period, 1975-2003. The mean excess standard deviation for a fixed portfolio size s and IO set j is given by $MDD_{j,s} = \bar{\sigma}_{j,s} - \sigma_J$, where $\bar{\sigma}_{j,s}$ is the mean of the standard deviations for the 5000 randomly selected portfolios with a portfolio size of s for IO set j, and σ_J is the standard deviation of the equal-weighted portfolio of all the stocks in IO set j. [a] indicates that the means for a s of 2 and "All" are significantly different at the 0.05 level. [b] and [c] refer to the lowest s that captures at least 90% and 95% of the reduction in MDD from moving from a s of 2 to a s of "All" provided that the difference in the means for a s of 2 and "All" are significantly different at the 0.05 level.

	Portfolio Size (PS or s)										
IO Set j Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
All	0.120[a]	0.074	0.060	0.051	0.048	0.040	0.038	0.040	0.034	0.034	0.034
TSX-only Listed	0.114[a]	0.060	0.043	0.033	0.031	0.025	0.022	0.021	0.020	0.018	0.016
Cross-listed	0.069[a]	0.035	0.021	0.015	0.011	0.010	0.008	0.007	0.006[b]	0.006	0.005
Big	0.070[a]	0.036	0.022	0.016	0.013	0.011	0.009	0.008	0.007	0.007[b]	0.006
Small	0.198[a]	0.125	0.088	0.081	0.073	0.060	0.059	0.054	0.051	0.050	0.046
IT	0.119[a]	0.074	0.051	0.039	0.034	0.029	0.026	0.023	0.022	0.020	0.020

	Portfolio Size (PS or s)										
IO Set j Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
All	0.032	0.031	0.029	0.028	0.029	0.028	0.026	0.026	0.025	0.024	0.000
TSX-only Listed	0.015	0.014	0.014	0.013	0.012	0.012	0.011	0.012	0.010[b]	0.011	0.000
Cross-listed	0.005	0.004	0.004	0.004	0.003[c]	0.003	0.003	0.003	0.003	0.003	0.000
Big	0.006	0.005	0.005	0.005	0.004	0.004	0.004	0.004	0.004	0.003[c]	0.000
Small	0.043	0.043	0.040	0.038	0.038	0.036	0.035	0.035	0.034	0.033	0.000
IT	0.018	0.018	0.017	0.016	0.016	0.015	0.015	0.014	0.014	0.013	0.000

Table 3.3 Mean realized dispersions differentiated by portfolio size and investment opportunity set

This table reports the means of the time-series of conditional cross-sectional mean realized dispersions (MRD) or standard deviations of returns for 22 portfolio sizes (PS) for six investment opportunity (IO) sets using returns for the 348 months in the period, 1975-2003. The MRD for a fixed portfolio size s and IO set j is given by $MRD_{j,s} = \frac{1}{N}\sum_{\tau=1}^{N}\sigma_{j,s,\tau}$, where $\sigma_{j,s,\tau}$ is the cross-sectional standard deviation across the 5000 randomly selected portfolios for IO set j with a portfolio size of s for month τ; and N is the number of cross-sections. [a] indicates that the means for a s of 2 and "All" are significantly different at the 0.05 level. [b] and [c] refer to the lowest s that captures at least 90% and 95% of the decrease in the MRD from moving from a s of 2 to a s of "All". "All" is proxied by the MRD for a PS of N-1 for all the IO sets.

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
All	0.164[a]	0.103	0.075	0.061	0.053	0.047	0.043	0.040	0.037	0.035	0.033
TSX-only Listed	0.163[a]	0.098	0.072	0.058	0.051	0.045	0.041	0.039	0.036	0.034	0.032
Cross-listed	0.108[a]	0.068	0.048	0.039	0.034	0.030	0.028	0.026	0.024	0.023	0.021
Big	0.103[a]	0.065	0.046	0.037	0.032	0.029	0.026	0.024	0.023	0.022	0.020
Small	0.225[a]	0.139	0.098	0.081	0.070	0.062	0.057	0.052	0.049	0.046	0.044
IT	0.126[a]	0.080	0.056	0.046	0.040	0.035	0.032	0.030	0.028	0.026	0.025
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
All	0.032	0.031	0.029	0.028	0.027	0.026	0.025	0.025	0.024	0.024	0.004
TSX-only Listed	0.031	0.029	0.028	0.027	0.026	0.025	0.025	0.024	0.023	0.023	0.004
Cross-listed	0.020	0.020	0.019	0.018[b]	0.018	0.017	0.016	0.016	0.016	0.015	0.008
Big	0.020	0.019	0.018	0.017	0.017	0.016	0.016	0.015	0.015	0.014	0.004
Small	0.042	0.040	0.039	0.037	0.036	0.035	0.034	0.033	0.032	0.031	0.008
IT	0.024	0.023[b]	0.022	0.021	0.020	0.020	0.019	0.019	0.018	0.018	0.012

Table 3.4 Normalized portfolio variances (NPV) differentiated by portfolio size and investment opportunity set

This table reports mean values of the normalized portfolio variance (NPV) metric for 22 portfolio sizes for 6 investment opportunity (IO) sets using returns for the 348 months in the period, 1975-2003. The mean NPV for investment opportunity (IO) set j and portfolio size s is given by: $\mu_{NPV_{j,s}} = (1/5000)\sum_{i=1}^{5000} \sigma_{j,s,i}^2 / \bar{\sigma}_j^2 = (1/5000)\sum_{i=1}^{5000} (1/s) + [(s-1)/s] (\overline{\text{cov}}_{j,s,i} / \bar{\sigma}_j^2)$, where $\sigma_{j,s,i}^2$ is the standard deviation of returns for the i-th randomly selected portfolio of size s for IO set j over the full period; $\bar{\sigma}_j^2$ is the average cross-sectional standard deviation of returns for all the stocks in IO set j over the full period; and $\overline{\text{cov}}_{j,s,i}$ is the average cross-sectional covariance of returns for the i-th randomly selected portfolio of size s for IO set j over the full period. [a] in the s =2 column indicates that the means for a s of 2 and "All" are significantly different at the 0.05 level. [b] and [c] refer to the lowest s that captures at least 90% and 95% of the reduction in the mean NPV from moving from a s of 2 to a s of "All" provided that the means for a s of 2 and "All" are significantly different at the 0.05 level.

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
All	0.503[a]	0.206	0.107	0.072	0.056[b]	0.048	0.040	0.036	0.031[c]	0.031	0.027
TSX-only Listed	0.505[a]	0.215	0.117	0.082	0.062[b]	0.053	0.047	0.042	0.037[c]	0.036	0.035
Cross-listed	0.550[a]	0.285	0.195	0.165	0.150[b]	0.140	0.135	0.130	0.129	0.125[c]	0.124
Big	0.540[a]	0.270	0.177	0.149	0.133	0.123[b]	0.119	0.114	0.109[c]	0.106	0.105
Small	0.503[a]	0.204	0.110	0.074	0.058[b]	0.048	0.041	0.037	0.033[c]	0.031	0.028
IT	0.523[a]	0.240	0.143	0.111	0.095[b]	0.086	0.080	0.075	0.071[c]	0.069	0.067
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
All	0.026	0.024	0.023	0.022	0.020	0.020	0.019	0.019	0.018	0.018	0.007
TSX-only Listed	0.033	0.030	0.029	0.028	0.027	0.026	0.026	0.024	0.024	0.023	0.014
Cross-listed	0.123	0.121	0.119	0.119	0.117	0.117	0.116	0.116	0.114	0.114	0.105
Big	0.103	0.101	0.101	0.100	0.099	0.098	0.098	0.097	0.097	0.097	0.087
Small	0.027	0.025	0.024	0.022	0.022	0.021	0.020	0.020	0.019	0.018	0.009
IT	0.066	0.064	0.062	0.062	0.060	0.060	0.059	0.059	0.058	0.058	0.048

Table 3.5 Semi-variance measures differentiated by portfolio size and investment opportunity set

This table reports the semi-variances measured relative to the risk-free rate and the portfolio's mean return based on 5000 random drawings for each unique combination of the 22 PS and six IO sets using monthly returns over the period, 1975-2003. [a] in the s =2 column indicates that the means for a *s* of 2 and "All" are significantly different at the 0.05 level. [b] and [c] refer to the lowest *s* that captures at least 90% and 95% of the reduction in the semi-variance from moving from a *s* of 2 to a *s* of "All".

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
Panel A: Semi-variance measured relative to the risk-free rate multiplied by 100											
All	0.590[a]	0.330	0.241	0.211	0.196	0.187[b]	0.181	0.176	0.173	0.170[c]	0.169
TSX-only Listed	0.602[a]	0.336	0.245	0.213	0.198	0.188[b]	0.182	0.177	0.174	0.171[c]	0.169
Cross-listed	0.526[a]	0.312	0.243	0.219	0.207	0.199[b]	0.195	0.191	0.188	0.187	0.185
Big	0.420[a]	0.241	0.182	0.162	0.152	0.146[b]	0.142	0.139	0.137	0.136[c]	0.134
Small	0.924[a]	0.521	0.379	0.328	0.303	0.288[b]	0.278	0.271	0.265	0.260	0.257
IT	0.570[a]	0.337	0.258	0.230	0.217	0.208[b]	0.202	0.198	0.196	0.193[c]	0.191

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
Panel A cont'd: Semi-variance measured relative to the risk-free rate multiplied by 100											
All	0.167	0.165	0.164	0.163	0.162	0.161	0.161	0.160	0.159	0.159	0.149
TSX-only Listed	0.167	0.166	0.164	0.163	0.162	0.161	0.161	0.160	0.160	0.159	0.149
Cross-listed	0.184[c]	0.182	0.182	0.181	0.180	0.179	0.179	0.179	0.178	0.178	0.166
Big	0.133	0.132	0.132	0.131	0.131	0.130	0.129	0.129	0.129	0.128	0.122
Small	0.255[c]	0.252	0.250	0.248	0.246	0.245	0.244	0.243	0.242	0.241	0.221
IT	0.189	0.189	0.188	0.186	0.186	0.185	0.184	0.184	0.184	0.183	0.175

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
Panel B: Semi-variance measured relative to the mean return for the portfolio multiplied by 100											
All	0.767[a]	0.433	0.324	0.283	0.263	0.249[b]	0.241	0.236	0.230	0.227	0.225
TSX-only Listed	0.756[a]	0.420	0.315	0.276	0.258	0.245[b]	0.236	0.231	0.227	0.223	0.220[c]
Cross-listed	0.617[a]	0.380	0.302	0.273	0.259	0.250[b]	0.245	0.241	0.237	0.235	0.232[c]
Big	0.499[a]	0.299	0.230	0.207	0.195	0.188[b]	0.183	0.179	0.177	0.174	0.173[c]
Small	1.290[a]	0.719	0.521	0.459	0.425	0.398[b]	0.386	0.375	0.368	0.363	0.357
IT	0.702[a]	0.431	0.338	0.303	0.287	0.276[b]	0.269	0.264	0.261	0.258	0.256

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
Panel B cont'd: Semi-variance measured relative to the mean return for the portfolio multiplied by 100											
All	0.222[c]	0.220	0.218	0.217	0.216	0.215	0.213	0.213	0.212	0.211	0.195
TSX-only Listed	0.217	0.216	0.214	0.213	0.212	0.210	0.209	0.209	0.208	0.207	0.195
Cross-listed	0.231	0.229	0.229	0.228	0.227	0.226	0.226	0.225	0.224	0.224	0.213
Big	0.171	0.170	0.169	0.169	0.168	0.167	0.167	0.166	0.166	0.165	0.156
Small	0.353[c]	0.350	0.346	0.344	0.342	0.340	0.339	0.337	0.336	0.335	0.306
IT	0.253[c]	0.253	0.251	0.250	0.249	0.248	0.247	0.247	0.246	0.245	0.230

Table 3.6 Skewness and kurtosis measures differentiated by portfolio size and investment opportunity set

This table reports the time-series means of the cross-sectional skewness and kurtosis for each unique combination of the 22 PS and six IO sets using monthly returns over the period, 1975-2003. The time-series mean of the cross-sectional *Skew* and *Kurt* for a fixed portfolio size s and IO set j are given by $\mu_{Skew_{j,s}} = \frac{1}{N}\sum_{\tau=1}^{N} Skew_{j,s,\tau}$ and $\mu_{Kurt_{j,s}} = \frac{1}{N}\sum_{\tau=1}^{N} Kurt_{j,s,\tau}$, where $Skew_{j,s,\tau}$ and $Kurt_{j,s,\tau}$ are respectively the cross-sectional skewness and kurtosis for the 5000 randomly selected portfolios for IO set j with a portfolio size of s for month τ ; and N is the number of cross-sections. [a] in the s =2 column indicates that the means for a s of 2 and "All" are significantly different at the 0.05 level. [b] and [c] refer to the lowest s that avoids foregoing respectively more than 10% and 5% of the skewness and the lowest s that captures respectively 90% and 95% of the reduction in positive kurtosis from moving from a s of 2 to a s of "All". "All" is proxied by the skewness or kurtosis for a PS of N-1 for all the IO sets.

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
Panel A: Skewness											
All	2.605[a,c]	1.642	1.175	0.949	0.818	0.736	0.668	0.621	0.585	0.549	0.519
TSX-only Listed	2.402[a,c]	1.527	1.082	0.878	0.750	0.673	0.616	0.571	0.531	0.504	0.482
Cross-listed	0.989[a,c]	0.629	0.445	0.364	0.317	0.280	0.261	0.239	0.219	0.210	0.197
Big	1.486[a,c]	0.931	0.664	0.544	0.469	0.417	0.389	0.358	0.334	0.313	0.295
Small	1.902[a,c]	1.209	0.860	0.699	0.602	0.540	0.498	0.461	0.431	0.406	0.381
IT	0.742[a,c]	0.470	0.330	0.265	0.229	0.211	0.186	0.175	0.163	0.152	0.145
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
Panel A cont'd: Skewness											
All	0.502	0.474	0.459	0.439	0.422	0.412	0.397	0.388	0.378	0.370	0.064
TSX-only Listed	0.456	0.433	0.418	0.407	0.390	0.372	0.365	0.357	0.346	0.339	0.059
Cross-listed	0.192	0.181	0.175	0.169	0.163	0.162	0.151	0.152	0.144	0.142	0.077
Big	0.282	0.269	0.261	0.252	0.244	0.234	0.232	0.221	0.218	0.213	0.054
Small	0.365	0.351	0.336	0.320	0.312	0.305	0.294	0.286	0.281	0.270	0.069
IT	0.144	0.133	0.129	0.130	0.122	0.117	0.110	0.108	0.105	0.106	0.068
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
Panel B: Kurtosis											
All	35.400[a]	15.307	9.915	7.296	6.064[b]	5.567	5.060	4.791	4.638	4.440[c]	4.277
TSX-only Listed	28.545[a]	13.791	8.191	6.413	5.417[b]	4.959	4.681	4.427	4.224[c]	4.136	4.030
Cross-listed	7.691[a]	4.905	3.971	3.635	3.492	3.367[b]	3.336	3.286	3.232[c]	3.204	3.180
Big	14.055[a]	7.368	5.226	4.514	4.119	3.883[b]	3.765	3.665	3.561[c]	3.489	3.446
Small	16.352[a]	8.487	5.884	4.793	4.348	4.096[b]	3.933	3.780	3.698	3.623[c]	3.535
IT	5.912[a]	4.181	3.585	3.361	3.288[b]	3.233	3.189	3.162[c]	3.139	3.121	3.104
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
Panel B cont'd: Kurtosis											
All	4.199	4.028	3.990	3.908	3.838	3.823	3.743	3.712	3.687	3.646	3.015
TSX-only Listed	3.940	3.816	3.752	3.729	3.680	3.582	3.573	3.556	3.515	3.497	3.023
Cross-listed	3.189	3.157	3.157	3.133	3.128	3.136	3.112	3.105	3.100	3.099	3.026
Big	3.404	3.363	3.344	3.319	3.301	3.269	3.271	3.240	3.248	3.214	3.014
Small	3.502	3.470	3.423	3.387	3.362	3.357	3.334	3.299	3.290	3.282	3.013
IT	3.100	3.094	3.088	3.092	3.072	3.064	3.070	3.066	3.059	3.062	3.028

Table 3.7 Sharpe-ratio-adjusted excess-return (ER) and relative-return (θ) measures differentiated by portfolio size and investment opportunity set

This table reports the Sharpe-ratio-adjusted excess-return measure (ER) and the relative return measure (θ) based on 5000 random drawings for each unique combination of the 22 PS and six IO sets using monthly returns over the period, 1975-2003. The measures are respectively given by $ER_{j,s} = \bar{R}_{j,s} - (\sigma_{j,s}/\sigma_J)\bar{R}_J$ and $\theta_{j,s} = (\bar{R}_{j,s}/|\bar{R}_J|) - [(\sigma_{j,s}/\sigma_J)(\bar{R}_J/|\bar{R}_J|)]$, where $\bar{R}_{j,s}$ and $\sigma_{j,s}$ are the average return and standard deviation of returns for IO set j for a PS of s, and $\bar{R}_J$, $|\bar{R}_J|$ and σ_J are the average return, average absolute return and standard deviation of returns for the equal-weighted portfolio of all the stocks in IO set j. [a] in the s =2 column indicates that the means for a s of 2 and "All" are significantly different at the 0.05 level. [b] and [c] refer to the lowest s that avoids at least 90% and 95% of the negative mean ER or θ from moving from a s of 2 to an s of "All".

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
Panel A: ER measure											
All	-0.032[a]	-0.019	-0.015	-0.013	-0.012	-0.010	-0.009	-0.009	-0.008	-0.008	-0.008
TSX-only Listed	-0.034[a]	-0.019	-0.013	-0.011	-0.010	-0.008	-0.007	-0.007	-0.007	-0.006	-0.005
Cross-listed	-0.019[a]	-0.010	-0.006	-0.004	-0.003	-0.003	-0.002	-0.002	-0.002[b]	-0.002	-0.001
Big	-0.022[a]	-0.011	-0.007	-0.005	-0.004	-0.003	-0.003	-0.002	-0.002[b]	-0.002	-0.002
Small	-0.044[a]	-0.028	-0.020	-0.017	-0.016	-0.013	-0.012	-0.011	-0.011	-0.010	-0.010
IT	-0.026[a]	-0.016	-0.010	-0.008	-0.006	-0.005	-0.004	-0.004	-0.004	-0.003	-0.003
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
Panel A cont'd: ER measure											
All	-0.007	-0.007	-0.007	-0.006	-0.007	-0.006	-0.006	-0.006	-0.005	-0.005	0.000
TSX-only Listed	-0.005	-0.005	-0.005	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004	0.000
Cross-listed	-0.001	-0.001	-0.001	-0.001	-0.001[c]	-0.001	-0.001	-0.001	-0.001	-0.001	0.000
Big	-0.002	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000
Small	-0.009	-0.009	-0.008	-0.008	-0.008	-0.007	-0.007	-0.007	-0.007	-0.007	0.000
IT	-0.003[b]	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	0.000
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
Panel B: θ measure											
All	-1.665[a]	-0.995	-0.795	-0.656	-0.620	-0.506	-0.476	-0.497	-0.415	-0.415	-0.406
TSX-only Listed	-1.854[a]	-0.999	-0.720	-0.570	-0.527	-0.435	-0.383	-0.376	-0.360	-0.333	-0.292
Cross-listed	-1.112[a]	-0.557	-0.330	-0.234	-0.183	-0.153	-0.127	-0.113	-0.095[b]	-0.088	-0.078
Big	-1.272[a]	-0.658	-0.394	-0.277	-0.219	-0.182	-0.151	-0.132	-0.120[b]	-0.108	-0.096
Small	-1.977[a]	-1.202	-0.837	-0.768	-0.687	-0.554	-0.541	-0.493	-0.464	-0.454	-0.420
IT	-1.378[a]	-0.806	-0.537	-0.388	-0.323	-0.263	-0.231	-0.195	-0.181	-0.163	-0.157
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**55**	**60**	**65**	**70**	**75**	**80**	**85**	**90**	**95**	**100**	**All**
Panel B cont'd: θ measure											
All	-0.377	-0.366	-0.345	-0.328	-0.345	-0.319	-0.292	-0.298	-0.284	-0.267	0.000
TSX-only Listed	-0.274	-0.266	-0.257	-0.239	-0.234	-0.231	-0.212	-0.229	-0.202	-0.207	0.000
Cross-listed	-0.072	-0.065	-0.062	-0.057	-0.054[c]	-0.050	-0.048	-0.045	-0.043	-0.041	0.000
Big	-0.089	-0.082	-0.075	-0.070	-0.067	-0.062	-0.058	-0.056	-0.052	-0.049	0.000
Small	-0.384	-0.386	-0.354	-0.332	-0.337	-0.321	-0.311	-0.309	-0.298	-0.287	0.000
IT	-0.131[b]	-0.129	-0.120	-0.111	-0.106	-0.095	-0.095	-0.089	-0.079	-0.077	0.000

Table 3.8 Sharpe and Sortino ratios differentiated by portfolio size and investment opportunity set

This table reports the mean Sharpe and Sortino ratios based on 5000 random drawings for each unique combination of the 22 PS and six IO sets using monthly returns over the period, 1975-2003. The Sharpe ratio is a mean excess return to total risk measure given by $Sh_{j,s} = (\bar{r}_{j,s} - r_f)/\sigma_{j,s}$, and the Sortino ratio is a mean excess return to semi-standard deviation risk measure given by $Sor_{j,s} = (\bar{r}_{j,s} - r_f)/\sigma^{-}_{j,s}$. [a] in the s =2 column indicates that the means for a *s* of 2 and "All" are significantly different at the 0.05 level. [b] and [c] refer to the lowest *s* that captures at least 90% and 95% of the increase in the Sharpe or Sortino ratio from moving from a *s* of 2 to an *s* of "All".

Panel A: Sharpe ratios (Portfolio Size (PS or *s*))

IO Set *j* Firms	2	5	10	15	20	25	30	35	40	45	50
All	0.069[a]	0.091	0.104	0.112	0.117	0.123	0.126	0.126	0.130	0.132	0.133
TSX-only Listed	0.069[a]	0.093	0.111	0.122	0.127	0.134	0.138	0.140	0.142	0.144	0.148
Cross-listed	0.085[a]	0.113	0.133	0.144	0.149	0.154	0.157	0.159	0.161	0.163	0.164
Big	0.088[a]	0.120	0.143	0.155	0.163	0.169	0.172	0.176	0.178	0.180	0.182
Small	0.059[a]	0.076	0.089	0.096	0.101	0.106	0.109	0.111	0.114	0.115	0.118
IT	0.068[a]	0.087	0.104	0.113	0.119	0.125	0.128	0.131	0.134	0.136	0.137

Panel A cont'd: Sharpe ratios (Portfolio Size (PS or *s*))

IO Set *j* Firms	55	60	65	70	75	80	85	90	95	100	All
All	0.135	0.137	0.139	0.140	0.139	0.141	0.143	0.144	0.145	0.146	0.186
TSX-only Listed	0.149	0.152	0.153	0.155	0.156	0.156	0.158	0.157	0.159	0.159	0.192
Cross-listed	0.165	0.166	0.166	0.167	0.168[b]	0.168	0.169	0.169	0.170	0.170	0.177
Big	0.183	0.184	0.185	0.186	0.187	0.188	0.188[b]	0.189	0.189	0.190	0.199
Small	0.120	0.120	0.123	0.125	0.124	0.126	0.127	0.128	0.129	0.130	0.166
IT	0.139	0.140	0.141	0.142	0.143	0.144	0.145	0.145	0.146	0.146	0.158

Panel B: Sortino ratios (Portfolio Size (PS or *s*))

IO Set *j* Firms	2	5	10	15	20	25	30	35	40	45	50
All	0.150[a]	0.195	0.231	0.244	0.257	0.258	0.263	0.269	0.267	0.271	0.274
TSX-only Listed	0.146[a]	0.183	0.216	0.230	0.241	0.245	0.247	0.253	0.255	0.257	0.258
Cross-listed	0.143[a]	0.180	0.203	0.214	0.218	0.223	0.225	0.227	0.228	0.229	0.230[b]
Big	0.155[a]	0.199	0.226	0.237	0.245	0.250	0.252	0.256	0.258	0.259	0.261
Small	0.163[a]	0.204	0.231	0.254	0.264	0.265	0.272	0.273	0.277	0.281	0.282
IT	0.160[a]	0.200	0.228	0.238	0.245	0.249	0.252	0.254	0.256	0.257	0.260[b]

Panel B cont'd: Sortino ratios (Portfolio Size (PS or *s*))

IO Set *j* Firms	55	60	65	70	75	80	85	90	95	100	All
All	0.274	0.276[b]	0.276	0.276	0.279	0.278	0.277	0.280	0.279	0.279	0.290
TSX-only Listed	0.257	0.260[b]	0.262	0.261	0.263	0.264	0.264	0.266	0.265	0.266	0.275
Cross-listed	0.231	0.231	0.232	0.232	0.233	0.233	0.234	0.234	0.235	0.235[c]	0.240
Big	0.262[b]	0.262	0.263	0.264	0.264	0.265	0.265	0.266	0.266	0.266	0.272
Small	0.282	0.284	0.284	0.285	0.287[b]	0.287	0.288	0.290	0.290	0.292	0.301
IT	0.259	0.261	0.261	0.261	0.263	0.263	0.264	0.264	0.263	0.263	0.270

Table 3.9 Probability of observing market underperformance differentiated by portfolio size and investment opportunity set for three holding periods

This table reports the mean probabilities that a portfolio of size *s* that is randomly drawn from investment opportunity (IO) set *j* will, on average, underperform the market return over holding periods of one month, one year and three years. A PS of all is an equal-weighted average of all (i.e., N-1) stocks available for investment for each IO set. The approach is based on Xu (2003). [a] in the *s* =2 column indicates that the means for a *s* of 2 and All are significantly different at the 0.05 level. [b] and [c] refer to the lowest *s* that captures at least 90% and 95%, respectively, of the decrease in the mean probabilities from moving from a *s* of 2 to a *s* of All, and is not indicated if *s* exceeds 100. If the lowest *s* occurs for one of the studied *s* that is not reported herein to conserve space, the significance indicator is reported for the two adjacent reported *s*.

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel A: Probability of market return underperformance over a one-month holding period											
All	0.560[a]	0.554	0.549	0.546	0.544	0.542	0.540	0.538	0.535	0.532	0.000
TSX-only Listed	0.560[a]	0.554	0.549	0.545	0.543	0.539	0.536	0.535	0.530	0.528	0.000
Cross-listed	0.547[a]	0.541	0.535	0.532	0.531	0.527	0.526	0.524	0.523	0.524	0.000
Big	0.543[a]	0.537	0.532	0.529	0.526	0.523	0.520	0.517	0.514	0.511	0.000
Small	0.574[a]	0.563	0.555	0.550	0.546	0.542	0.539	0.536	0.532	0.528	0.000
IT	0.550[a]	0.541	0.529	0.523	0.519	0.514	0.512	0.510	0.508	0.507	0.000
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel B: Probability of market return underperformance over a one-year holding period											
All	0.617[a]	0.596	0.583	0.577	0.572	0.567	0.565	0.559	0.556	0.550	0.000
TSX-only Listed	0.615[a]	0.595	0.584	0.580	0.577	0.571	0.568	0.564	0.557	0.554	0.000
Cross-listed	0.583[a]	0.560	0.548	0.540	0.540	0.534	0.530	0.529	0.525	0.520	0.000
Big	0.580[a]	0.562	0.553	0.549	0.544	0.540	0.534	0.532	0.528	0.525	0.000
Small	0.645[a]	0.619	0.603	0.590	0.582	0.571	0.567	0.557	0.548	0.537	0.000
IT	0.596[a]	0.572	0.552	0.543	0.537	0.528	0.525	0.522	0.518	0.516	0.000
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel C: Probability of market return underperformance over a three-year holding period											
All	0.681[a]	0.649	0.635	0.631	0.626	0.622	0.625	0.619	0.616	0.612	0.000
TSX-only Listed	0.683[a]	0.653	0.634	0.629	0.625	0.618	0.614	0.610	0.598	0.595	0.000
Cross-listed	0.643[a]	0.615	0.604	0.598	0.604	0.605	0.605	0.610	0.616	0.621	0.000
Big	0.615[a]	0.578	0.555	0.546	0.535	0.524	0.512	0.506	0.493	0.480	0.000
Small	0.731[a]	0.690	0.671	0.651	0.642	0.629	0.622	0.608	0.596	0.577	0.000
IT	0.643[a]	0.605	0.570	0.554	0.542	0.524	0.513	0.503	0.490	0.481	0.000

Table 3.10 Probability of observing negative returns differentiated by portfolio size and investment opportunity set for various holding periods

This table reports the mean probabilities that a portfolio of size *s* that is randomly drawn from investment opportunity (IO) set *j* will, on average, have a negative return over holding periods of one month, one year and three years. A PS of all is an equal-weighted average of all (i.e., N-1) stocks available for investment for each IO set. The approach is based on Xu (2003). [a] in the *s* =2 column indicates that the means for a *s* of 2 and All are significantly different at the 0.05 level. [b] and [c] refer to the lowest *s* that captures at least 90% and 95%, respectively, of the decrease in the mean probabilities from moving from a *s* of 2 to a *s* of All, and is not indicated if *s* exceeds 100. If the lowest *s* occurs for one of the studied *s* that is not reported herein to conserve space, the significance indicator is reported for the two adjacent reported *s*. In panel A, at least 90% is achieved for an unreported *s* of 60 for Big and of 70 for Cross-listed and IT. In panel B, at least 90% is achieved for an unreported *s* of 55 for All, 60 for TSX-only and Big, and 95 for IT. In panel C, at least 90% is achieved for an unreported *s* of 70 for IT; and at least 95% is achieved for an unreported *s* of 95 for Big.

	Portfolio Size (PS or *s*)									
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel A: Probability of observing negative returns over a one-month holding period											
All	0.482[a]	0.457	0.432	0.418	0.409	0.398	0.392	0.388	0.382	0.378	0.366
TSX-only Listed	0.485[a]	0.459	0.436	0.422	0.413	0.402	0.395	0.390	0.383	0.380	0.367
Cross-listed	0.464[a]	0.437	0.416	0.405	0.398	0.389	0.385	0.382[b]	0.378[b]	0.375	0.369
Big	0.455[a]	0.426	0.403	0.391	0.382	0.373	0.367	0.364[b]	0.360[b]	0.357[c]	0.352
Small	0.517[a]	0.491	0.468	0.456	0.447	0.437	0.431	0.427	0.421	0.417	0.403
IT	0.472[a]	0.448	0.425	0.413	0.406	0.397	0.392	0.387[b]	0.382[b]	0.379	0.373
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel B: Probability of observing negative returns over a one-year holding period											
All	0.429[a]	0.362	0.323	0.306	0.294	0.283	0.277	0.272[b]	0.265[b]	0.262[c]	0.253
TSX-only Listed	0.435[a]	0.370	0.331	0.315	0.303	0.293	0.286	0.280[b]	0.274[b]	0.269	0.259
Cross-listed	0.386[a]	0.322	0.285	0.268	0.258	0.247	0.240	0.235	0.228[b]	0.224	0.211
Big	0.366[a]	0.298	0.259	0.242	0.231	0.220	0.211	0.207[b]	0.201[b]	0.198	0.188
Small	0.491[a]	0.428	0.394	0.377	0.367	0.355	0.348	0.342	0.334	0.327	0.307
IT	0.393[a]	0.338	0.311	0.300	0.296	0.289	0.286	0.283	0.279	0.277[b]	0.265
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel C: Probability of observing negative returns over a three-year holding period											
All	0.386[a]	0.281	0.219	0.191	0.171	0.151	0.138	0.129	0.116	0.107	0.064
TSX-only Listed	0.398[a]	0.296	0.231	0.202	0.182	0.162	0.149	0.138	0.124	0.115	0.080
Cross-listed	0.318[a]	0.222	0.169	0.143	0.128	0.109	0.097	0.089	0.077	0.070	0.035
Big	0.290[a]	0.183	0.123	0.097	0.082	0.063	0.052	0.045[b]	0.037[c]	0.031[c]	0.019
Small	0.494[a]	0.398	0.348	0.317	0.300	0.276	0.263	0.252	0.238	0.227	0.192
IT	0.332[a]	0.246	0.195	0.173	0.161	0.147	0.141	0.136[b]	0.131[b]	0.128	0.109

Table 3.11 Probability of observing a loss of more than 25 percent differentiated by portfolio size and investment opportunity set for three holding periods

This table reports the mean probabilities that a portfolio of size *s* that is randomly drawn from investment opportunity (IO) set *j* will, on average, achieve a loss of more than 25% over holding periods of one month, one year and three years. A PS of all is an equal-weighted average of all (i.e., N-1) stocks available for investment for each IO set. The approach is based on Xu (2003). [a] in the *s* =2 column indicates that the means for a *s* of 2 and All are significantly different at the 0.05 level. [b] and [c] refer to the lowest *s* that captures at least 90% and 95%, respectively, of the decrease in the mean probabilities from moving from a *s* of 2 to a *s* of All, and is not indicated if *s* exceeds 100. If the lowest *s* occurs for one of the studied *s* that is not reported herein to conserve space, the significance indicator is reported for the two adjacent reported *s*. In panel B, at least 90% is achieved for an unreported *s* of 35 for All, TSX-only & Cross-listed and for an unreported *s* of 25 for IT; and at least 95% is achieved for an unreported *s* of 90 for All, 65 for Cross-listed, 95 for Big and 35 for IT. In panel C, at least 90% is achieved for an unreported *s* of 25 for Cross-listed and IT and 85 for Small; and at least 95% is achieved for an unreported *s* of 25 for Big, 45 for Cross-listed and IT and 60 for TSX-only.

	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel A: Probability of a loss of at least 25% over a one-month holding period											
All	0.015[a]	0.005	0.003[b,c]	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
TSX-only Listed	0.016[a]	0.004	0.003[b,c]	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Cross-listed	0.013[a]	0.005	0.004	0.004[b]	0.004	0.004	0.004	0.003[c]	0.003	0.003	0.003
Big	0.009[a]	0.003[b,c]	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.003
Small	0.030[a]	0.009	0.005[b]	0.004	0.004[c]	0.004	0.004	0.003	0.003	0.003	0.003
IT	0.017[a]	0.006	0.003	0.002	0.001[b]	0.001[c]	0.001	0.000	0.000	0.000	0.000
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel B: Probability of a loss of at least 25% over a one-year holding period											
All	0.209[a]	0.130	0.092	0.079	0.071	0.064	0.061[b]	0.058	0.056[c]	0.054[c]	0.047
TSX-only Listed	0.216[a]	0.136	0.096	0.081	0.074	0.067[b]	0.063[b]	0.060	0.057[c]	0.055	0.049
Cross-listed	0.169[a]	0.104	0.077	0.066	0.061	0.054[b]	0.051[b]	0.049[c]	0.045[c]	0.043	0.040
Big	0.140[a]	0.077	0.051	0.042	0.037	0.033	0.030[b]	0.028	0.026[c]	0.025[c]	0.019
Small	0.308[a]	0.221	0.177	0.157	0.146	0.132	0.125	0.120	0.112	0.106[b]	0.085
IT	0.195[a]	0.139	0.113	0.103	0.099[b]	0.093[b,c]	0.091[c]	0.090	0.088	0.087	0.087
	Portfolio Size (PS or *s*)										
IO Set *j* Firms	**2**	**5**	**10**	**15**	**20**	**30**	**40**	**50**	**75**	**100**	**All**
Panel C: Probability of a loss of at least 25% over a three-year holding period											
All	0.260[a]	0.145	0.086	0.063	0.049	0.036[b]	0.031	0.026[c]	0.022	0.020	0.015
TSX-only Listed	0.272[a]	0.156	0.094	0.070	0.055	0.042[b]	0.036	0.031[c]	0.026[c]	0.024	0.017
Cross-listed	0.197[a]	0.100	0.054	0.036	0.026[b]	0.016[b]	0.012[c]	0.009[c]	0.006	0.004	0.001
Big	0.162[a]	0.067	0.027	0.014[b]	0.008[c]	0.003[c]	0.002	0.001	0.000	0.000	0.000
Small	0.391[a]	0.271	0.206	0.171	0.152	0.129	0.118	0.108	0.097[b]	0.089[b]	0.062
IT	0.229[a]	0.142	0.098	0.082	0.075[b]	0.067[b]	0.064[c]	0.062[c]	0.060	0.058	0.055

Table 3.12 Summary of the minimum portfolio size required to achieve 90% of the benefits of diversification based on the various performance metrics

This table reports the minimum portfolio sizes (PS or *s*) that are indicated by each of the tests reported earlier to achieve 90% of the benefits of diversification achieved from moving from a PS of 2 to a PS of all for each of the six IO sets examined herein. $\overline{R}_{j,s}$ is the average return for investment opportunity set *j* for a portfolio size (PS) of *s*, and $\overline{R}_J$ is the mean return on the market as proxied by the equal-weighted average return of all the stocks available for investment during each month in IO set *j*. The values in the brackets represent the proportion of the time-series weighted average population of stocks in each IO set *j* represented by the indicated portfolio size.

	IO Set *j* For Firms					
Performance Metric	**All**	**TSX-only Listed**	**Cross-listed**	**Big**	**Small**	**IT**
Panel A: Dispersion of stock returns						
Mean derived dispersions (MDD)	>100 [>13.3%]	95 [15.1%]	40 [24.4%]	45 [9.3%]	>100 [>37.3%]	>100 [>91.7%]
Mean realized dispersions (MRD)	>100 [>13.3%]	>100 [>15.9%]	70 [42.7%]	>100 [20.7%]	>100 [>37.3%]	60 [55.0%]
Normalized portfolio variances (NPV)	20 [2.7%]	20 [3.2%]	20 [12.2%]	25 [5.2%]	20 [7.5%]	20 [18.3%]
Semi-variance (risk-free or mean return as target)	25[3.3%]	25 [4.0%]	25 [15.2%]	25 [5.2%]	25 [9.3%]	25 [22.9%]
Panel B: Higher-order moments of stock returns						
Skewness	2 [0.3%]	2 [0.3%]	2 [1.2%]	2 [0.4%]	2 [0.7%]	2 [1.8%]
Kurtosis	20 [2.7%]	20 [3.2%]	25 [15.2%]	25 [5.2%]	25 [9.3%]	20 [18.3%]
Panel C: Composite return and risk						
Sharpe-ratio-adjusted excess-(relative) return (ER & θ)	>100 [>13.3%]	>100 [>15.9%]	40 [24.4%]	40 [8.3%]	>100 [37.3%]	55 [50.5%]
Sharpe ratio	>100 [>13.3%]	>100 [>15.9%]	75 [45.7%]	85 [17.6%]	>100 [37.3%]	>100 [91.7%]
Sortino ratio	60 [8.0%]	60 [9.5%]	50 [30.5%]	55 [11.4%]	75 [28.0%]	50 [45.9%]
Panel D: Probability of underperforming a target return						
Prob. [$\overline{R}_{j,s} < 0$], 1-month holding period	>100 [>13.3%]	>100 [>15.9%]	70 [42.7%]	60 [12.4%]	>100 [>37.3%]	70 [64.2%]
Prob. [$\overline{R}_{j,s} < 0$], 1-year holding period	55 [7.3%]	60 [9.5%]	75 [45.7%]	60 [12.4%]	>100 [>37.3%]	95 [87.2%]
Prob. [$\overline{R}_{j,s} < 0$], 3-year holding period	>100 [>13.3%]	>100 [>15.9%]	>100 [>61.0%]	50 [10.4%]	>100 [>37.3%]	70 [64.2%]
Prob. [($\overline{R}_{j,s} - \overline{R}_J$)< 0], **all 3** holding periods	>100 [>13.3%]	>100 [>15.9%]	>100 [>61.0%]	>100 [>20.7%]	>100 [>37.3%]	>100 [>91.7%]
Prob. [$\overline{R}_{j,s} \leq$ -25%], 1-month holding period	10 [1.3%]	10 [1.6%]	15 [9.1%]	5 [1.0%]	10 [3.7%]	20 [18.3%]
Prob. [$\overline{R}_{j,s} \leq$ -25%], 1-year holding period	35 [4.7%]	35 [5.6%]	35 [21.3%]	40 [8.3%]	100 [37.3%]	25 [22.9%]
Prob. [$\overline{R}_{j,s} \leq$ -25%], 3-year holding period	30 [4.0%]	30 [4.8%]	25 [15.2%]	15 [0.31%]	85 [31.7%]	25 [22.9%]

Table 4.1 Basic Summary Statistics for Daily and Monthly Returns

This table reports various distribution statistics for the daily and monthly returns for equal-weighted (EW) and value-weighted (VW) portfolios of the Canadian stocks cross-listed on the TSX and in the U.S. for trades on each respective trade venue.

	Daily Returns				Monthly Returns			
	TSX Trades		U.S. Trades		TSX Trades		U.S. Trades	
Statistic	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**	**EW**	**VW**
Mean	0.0013	0.0008	0.0010	0.0008	0.0181	0.0177	0.0137	0.0172
Std. Dev	0.0098	0.0095	0.0095	0.0106	0.0628	0.0504	0.0648	0.0596
Skewness	1.1564	0.1280	-0.5182	-0.1380	-0.4777	-0.2565	-0.4097	-0.1190
Kurtosis	47.8321	16.9339	17.0685	14.0162	5.5185	5.4735	5.3802	5.2912
Jarque-Bera	625403.80	60272.88	61755.49	37684.91	105.21	92.53	91.8850	76.9411

Table 4.2 Tests of the Equality of Variances for Trades on the TSX and U.S. Trade Venues for Canadian Stocks Cross-listed on the TSX and U.S. Trade Venues

This table reports on various tests of the equality of variances for daily and monthly returns for equal-weighted (EW) and value-weighted (VW) portfolios of the Canadian stocks cross-listed on the TSX and in the U.S. for trades on each respective trade venue. The null hypothesis tested is that the variances of returns are equal inter-market. ^{a}, ^{b} and ^{c} indicate significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Daily Returns				Monthly Returns			
	Equal-Weighted		Value-Weighted		Equal-Weighted		Value-Weighted	
Statistic	**Statistic**	**P-value**	**Statistic**	**P-value**	**Statistic**	**P-value**	**Statistic**	**P-value**
F-test	1.0511	0.0316^{b}	1.2500	0.0000^{c}	1.0657	0.5536	1.3953	0.0020^{c}
Siegel-Tukey	2.7268	0.0064^{c}	6.1358	0.0000^{c}	0.2223	0.8241	2.1296	0.0332^{b}
Bartlett	4.6193	0.0316^{b}	92.4997	0.0000^{c}	0.3510	0.5536	9.5679	0.0020^{c}
Levene	3.4274	0.0641^{a}	40.0586	0.0000^{c}	0.1119	0.7380	5.5155	0.0191^{b}
Brown-Forsythe	3.4226	0.0643^{a}	40.0439	0.0000^{c}	0.1033	0.7480	5.4832	0.0195^{b}

Table 4.3 Correlations between the Various Return Series for Trades on the Various Trade Venues

This table reports the correlations between the return series for portfolios with the same return frequency and portfolio weighting of the Canadian stocks cross-listed on the TSX and in the U.S. for trades on each respective trade venue. The return frequencies are daily and monthly returns, and the portfolio weightings are equal-weighted (EW) and value-weighted (VW).

Return Frequency	Portfolio Weighting	Correlation
Daily	EW	0.7575
Daily	VW	0.8753
Monthly	EW	0.9305
Monthly	VW	0.9620

Table 4.4 Unit Root Tests for the Return Series for the Equal- and Value-weighted Portfolios

This table reports the results of two tests for unit roots in the daily and monthly series of return variances for the equal-weighted (EW) and value-weighted (VW) portfolios of the Canadian stocks cross-listed on the TSX and in the U.S. for trades on each respective trade venue. Both the Augmented Dickey-Fuller and Phillips-Perron tests are used to examine the null hypothesis of no unit root. The critical values at the 5% and 10% level are respectively |2.8697| and |2.5712| for the Augmented Dickey-Fuller test and respectively |3.4228| and |3.1343| for the Phillips-Perron test. [b] indicates significance at the 0.05 level.

Return Series			Augmented Dickey-Fuller		Phillips-Perron	
			With(out) Trend			
Frequency	Portfolio Weights	Trades from:	Without	With	Without	With
Monthly	EW	TSX	16.502[b]	16.477[b]	16.502[b]	16.477[b]
Monthly	VW	TSX	18.335[b]	18.323[b]	18.370[b]	18.356[b]
Monthly	EW	U.S.	17.036[b]	17.023[b]	17.030[b]	17.018[b]
Monthly	VW	U.S.	18.437[b]	18.423[b]	18.452[b]	18.438[b]
Daily	EW	TSX	14.439[b]	14.448[b]	75.612[b]	75.603[b]
Daily	VW	TSX	18.007[b]	18.021[b]	75.604[b]	75.602[b]
Daily	EW	U.S.	14.020[b]	14.029[b]	76.423[b]	76.414[b]
Daily	VW	U.S.	74.159[b]	74.156[b]	74.106[b]	74.103[b]

Table 4.5 Summary of the Results for the Johansen Cointegration Tests

This table reports the results of the Johansen Cointegration tests for the daily and monthly series of return variances for the equal-weighted (EW) and value-weighted (VW) portfolios of the Canadian stocks cross-listed on the TSX and in the U.S. for trades on each respective trade venue. "CV" refers to the critical value at the 0.05 level. [b] indicates that the test statistic (Test-Stat) is significant at the 0.05 level. R is the number of cointegration relations.

		Daily Returns				Monthly Returns			
		Equal-Weighted		Value-Weighted		Equal-Weighted		Value-Weighted	
λ	R =	Test-Stat	CV	Test-Stat	CV	Test-Stat	CV	Test-Stat	CV
λ_T	0	2405.8440[b]	15.4947	2891.8860[b]	15.4947	104.3787[b]	15.4947	94.1805[b]	15.4947
	1	1002.5340[b]	3.8415	1280.5820[b]	3.8415	49.4403[b]	3.8415	41.6239[b]	3.8415
λ_{max}	0	1403.3100[b]	14.2646	1611.3040[b]	14.2646	54.9384[b]	14.2646	52.5565[b]	14.2646
	1	1002.5340[b]	3.8415	1280.5820[b]	3.8415	49.4403[b]	3.8415	41.6239[b]	3.8415

Table 4.6 Test of Asymmetry

This table tests for the presence of sign and size biases. If the sign bias is significant, it indicates that negative innovations in returns affect future volatility. Significance of the size bias indicates that the magnitudes of innovations also are important. [a], [b] and [c] indicate significance at the 0.10, 0.05 and 0.01 percent levels, respectively.

	Daily				Monthly			
	Equal-Weighted		Value-Weighted		Equal-Weighted		Value-Weighted	
Coefficient	TSX Trades	U.S. Trades	TSX Trades	U.S. Trades	TSX Trades	U.S. Trades	TSX Trades	U.S. Trades
$\alpha_{I,0}$	0.0000[c]	0.0000[c]	0.0000[c]	0.0000	0.0040[c]	0.0040[c]	0.0020[c]	0.0030[c]
$\beta_{I,1}$ (Sign Bias)	0.0000[c]	0.0000[c]	0.0000[c]	0.0000	0.0010	0.0000	0.0020[c]	0.0010
$\beta_{I,2}$ (Size Bias)	-0.0450[c]	-0.0280[c]	-0.0190[c]	-0.0210	-0.0030	-0.0200	0.0100[c]	-0.0110
$\beta_{I,3}$ (Size Bias)	0.0050[c]	0.0040[c]	0.0060[c]	0.0060	0.0040	0.0020	0.0160[c]	0.0190

Table 4.7 Test of Asymmetry in the Variances of Returns Using the Univariate GJR-GARCH and EGARCH Models

This table reports the results from univariate GJR-GARCH and E-GARCH models for equal- and value-weighted portfolios of TSX and U.S. daily returns. Significant values of the coefficient β_3 indicate an asymmetric response to negative innovations. [a], [b] and [c] indicate significance at the 0.10, 0.05 and 0.01 levels, respectively.

	Daily				Monthly			
	Equal-Weighted		Value-Weighted		Equal-Weighted		Value-Weighted	
Coefficient	**TSX Trades**	**U.S. Trades**	**TSX Trades**	**U.S. Trades**	**TSX Trades**	**U.S. Trades**	**TSX Trades**	**U.S. Trades**
Panel A: **Univariate GJR-GARCH model**								
α (Mean Eqn)	0.0013[c]	0.0010[c]	0.0008[c]	0.0008[c]	0.0193[c]	0.0141[c]	0.0174[c]	0.0164[c]
α_1 (Variance Eqn)	0.0000[c]	0.0000[c]	0.0000[c]	0.0000[c]	0.0020[c]	0.0033[c]	0.0000[b]	0.0001[a]
β_1	0.2163[c]	0.1562[c]	0.1041[c]	0.1009[c]	0.2879	0.3122[a]	-0.0098	0.0136
β_2	0.7318[c]	0.8139[c]	0.9064[c]	0.9048[c]	0.2998	0.0722	0.9360[c]	0.9080[c]
β_3(Asymmetry)	-0.1020[c]	-0.0566[c]	-0.0426[c]	-0.0337[c]	-0.1827	-0.3516[b]	0.1160[c]	0.0977[c]
Panel B: **Univariate EGARCH model**								
α(Mean Eqn)	0.0013[c]	0.0010[c]	0.0008[c]	0.0008[c]	0.0194[c]	0.0128[c]	0.0180[c]	0.0167[c]
α_1(Variance Eqn)	-1.0372[c]	-0.6986[c]	-0.2757[c]	-0.2532[c]	-2.6678[c]	-2.7524[b]	-0.1300[c]	-0.2861[b]
β_1	0.2827[c]	0.2459[c]	0.1777[c]	0.1741[c]	0.3108[c]	0.2687[c]	0.0344	0.1411[b]
β_2	0.9128[c]	0.9462[c]	0.9851[c]	0.9870[c]	0.5659[c]	0.5394[b]	0.9829[c]	0.9689[c]
β_3 (Asymmetry)	-0.0584[c]	-0.0352[c]	-0.0309[c]	-0.0283[c]	-0.0946	-0.1034	0.0968[c]	0.0540[a]

Table 4.8 Results Based on the Bivariate GJR-GARCH Model

This table reports the estimates of Persistence, Volatility Spillover and Asymmetric responses to negative innovations using a bivariate GJR-GARCH for equal- and value-weighted portfolios of daily TSX and U.S. returns. [a], [b] and [c] indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficient is not different from zero. [d], [e] and [f] indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficients for the portfolio pairing is not different for the TSX versus the U.S. trades.

GJR-GARCH Coefficient	1975-2003		1975-1979		1980-1989		1990-1999		2000-2003	
	TSX	U.S.	TSX	U.S.	TSX	U.S.	TSX	U.S.	TSX	U.S.
Panel A: Equal-weighted										
α(MeanEqn)	0.0047[c,f]	0.0044[c,f]	0.0046[c,f]	0.0043[c,f]	0.0050[c,f]	0.0045[c,f]	-0.0029[c,f]	-0.0025[c,f]	0.0000[c,f]	-0.0004[c,f]
α_1(Var Eqn)	0.0048[c,f]	0.0043[c,f]	0.0046[c,f]	0.0041[c,f]	0.0046[c,f]	0.0041[c,f]	0.0042[c,f]	0.0038[c,f]	0.0029[c,f]	0.0033[c,f]
β_1	0.2134[c,f]	0.1042[c,f]	0.1924[c,f]	0.1028[c,f]	0.1910[c,f]	0.1078[c,f]	0.1417[c,f]	0.1945[c,f]	0.1493[c,f]	0.1239[c,f]
Persistence	-0.0012[c,f]	0.0042[c,f]	-0.0012[c,f]	0.0041[c,f]	-0.0014[c,f]	0.0037[c,f]	-0.0022[c,f]	0.0026[c,f]	-0.0916[c,f]	0.0178[c,f]
VolSpillover	0.1177[c,f]	0.2014[c,f]	0.1092[c,f]	0.2520[c,f]	0.1131[c,f]	0.2405[c,f]	0.1809[c,f]	0.4746[c,f]	-0.0831[c,f]	0.3199[c,f]
Asymmetry	-0.1253[c,f]	-0.0373[c,f]	-0.1335[c,f]	-0.0370[c,f]	-0.1404[c,f]	-0.0391[c,f]	-0.0189[c,f]	0.0088[c,f]	-0.1792[c,f]	0.0556[c,f]
Panel A: Value-weighted										
α(MeanEqn)	0.0000[c,f]	-0.0001[c,f]	0.0002[b,f]	0.0000[c,f]	-0.0016[c,f]	-0.0019[c,f]	-0.0022[c,f]	-0.0026[c,f]	0.0000[c,f]	0.0006[c,f]
α_1(Var Eqn)	0.0036[c,f]	0.0050[c,f]	0.0036[c,f]	0.0049[c,f]	0.0035[c,f]	0.0048[c,f]	0.0035[c,f]	0.0046[c,f]	0.0027[c,f]	0.0041[c,f]
β_1	-0.0270[c,f]	-0.0738[c,f]	0.1998[c,f]	0.0427[c,f]	0.2004[c,f]	0.0330[c,f]	0.1076[c,f]	-0.0877[c,f]	0.3490[c,f]	-0.0263[c,f]
Persistence	-0.0003[c,f]	-0.0098[c,f]	-0.0149[c,f]	-0.0468[c,f]	-0.0134[c,f]	-0.0454[c,f]	0.0048[c,f]	-0.0869[c,f]	-0.0354[c,f]	-0.0601[c,f]
VolSpillover	0.1553[c,f]	0.2966[c,f]	0.0553[c,f]	-0.0334[b,f]	0.0807[c,f]	-0.0843[c,f]	0.1928[c,f]	0.0833[c,f]	0.0910[c,f]	-0.1238[c,f]
Asymmetry	-0.0258[c,f]	-0.0021[a,f]	-0.0320[c,f]	-0.0215[c,f]	-0.0091[c,f]	0.0088[c,f]	-0.0108[c,f]	0.0056[c,f]	-0.1195[c,f]	0.0070[c,f]

Table 4.9 Results Based on the Bivariate Exponential-GARCH Model

This table reports the estimates of Persistence, Volatility Spillover and Asymmetric responses to negative innovations using a bivariate E-GARCH model for equal- and value-weighted portfolios of daily TSX and U.S. returns. [a], [b] and [c] indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficient is not different from zero. [d], [e] and [f] indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficients for the portfolio pairing is not different for the TSX versus the U.S. trades.

E-GARCH	1975-2003		1975-1979		1980-1989		1990-1999		2000-2003	
Coefficient	TSX	U.S.	TSX	U.S.	TSX	U.S.	TSX	U.S.	TSX	U.S.
Panel A: Equal-weighted										
α_0 (MeanEqn)	$0.0064^{c,f}$	$0.0015^{c,f}$	$-0.0035^{c,f}$	$0.0018^{c,f}$	$-0.0005^{c,f}$	$0.0005^{c,f}$	$0.0009^{c,f}$	$0.0004^{c,f}$	$0.0055^{c,f}$	$0.0045^{c,f}$
α_1 (Var Eqn)	$0.0049^{c,f}$	$0.0047^{c,f}$	$0.0046^{c,f}$	$0.0047^{c,f}$	$0.0046^{c,f}$	$0.0047^{c,f}$	$0.0046^{c,f}$	$0.0047^{c,f}$	0.0046^{c}	0.0046^{c}
β_1	$0.0046^{c,f}$	$0.0044^{c,f}$	$0.0045^{c,f}$	$0.0040^{c,f}$	$0.0045^{c,f}$	$0.0040^{c,f}$	$0.0045^{c,f}$	$0.0040^{c,f}$	$0.0044^{c,f}$	$0.0039^{c,f}$
Persistence	0.0025	0.0025	0.0016^{c}	0.0016^{c}	$0.0003^{c,f}$	$0.0000^{,f}$	$0.0003^{c,f}$	-0.0001^{f}	$-0.0010^{c,f}$	$-0.0011^{c,f}$
VolSpillover	$0.0048^{c,f}$	$0.0047^{c,f}$	$0.0046^{c,f}$	$0.0044^{c,f}$	$0.0045^{c,f}$	$0.0044^{c,f}$	$0.0045^{c,f}$	$0.0044^{c,f}$	$0.0045^{c,f}$	$0.0041^{c,f}$
Asymmetry	$0.0963^{c,f}$	$0.0797^{c,f}$	$0.1376^{c,f}$	$0.1427^{c,f}$	$0.3050^{c,f}$	$0.3815^{c,f}$	$0.3167^{c,f}$	$0.2555^{c,f}$	$0.9037^{c,f}$	$1.1326^{c,f}$
Panel A: Value-weighted										
α(MeanEqn)	$-0.0004^{c,f}$	$-0.0001^{c,f}$	$0.0034^{c,f}$	$0.0019^{c,f}$	$0.0024^{c,f}$	$0.0032^{c,f}$	$0.0023^{c,f}$	$0.0019^{c,f}$	$-0.0015^{c,f}$	$-0.0001^{c,f}$
α_1 (Var Eqn)	$0.0048^{c,f}$	$0.0046^{c,f}$	$0.0047^{c,f}$	$0.0045^{c,f}$	$0.0046^{c,f}$	$0.0044^{c,f}$	$0.0045^{c,f}$	$0.0043^{c,f}$	$0.0045^{c,f}$	$0.0042^{c,f}$
β_1	$0.0045^{c,f}$	$0.0041^{c,f}$	$0.0044^{c,f}$	$0.0040^{c,f}$	$0.0042^{c,f}$	$0.0038^{c,f}$	$0.0041^{c,f}$	$0.0037^{c,f}$	$0.0040^{c,f}$	$0.0036^{c,f}$
Persistence	$0.0045^{c,f}$	$0.0061^{c,f}$	$0.0030^{c,f}$	$0.0051^{c,f}$	$0.0031^{c,f}$	$0.0019^{c,f}$	$0.0029^{c,f}$	$0.0018^{c,f}$	$0.0008^{c,f}$	0.0000^{f}
VolSpillover	0.0047^{c}	0.0047^{c}	$0.0044^{c,f}$	$0.0045^{c,f}$	$0.0044^{c,f}$	$0.0045^{c,f}$	$0.0045^{c,f}$	$0.0046^{c,f}$	$0.0044^{c,f}$	$0.0046^{c,f}$
Asymmetry	$0.0755^{c,f}$	$0.0767^{c,f}$	$0.1828^{c,f}$	$0.1802^{c,f}$	$0.2094^{c,f}$	$0.3421^{c,f}$	$0.2337^{c,f}$	$0.3984^{c,f}$	$0.8726^{c,f}$	$1.0363^{c,f}$

Table 4.10 Results Based on the Bivariate DCC-GARCH (Symmetric) Model

This table reports the estimates of Persistence, Volatility Spillover and Asymmetric responses to negative innovations using a bivariate symmetric DCC-GARCH for equal- and value-weighted portfolios of daily TSX and U.S. returns. [a], [b] and [c] indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficient is not different from zero. [d], [e] and [f] indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficients for the portfolio pairing is not different for the TSX versus the U.S. trades.

Symmetric DCC Coefficient	1975-2003		1975-1979		1980-1989		1990-1999		2000-2003	
	TSX	U.S.	TSX	U.S.	TSX	U.S.	TSX	U.S.	TSX	U.S.
Panel A: Equal-weighted										
α(MeanEqn)	$0.0013^{c,f}$	$0.0010^{c,f}$	$0.0017^{c,f}$	$0.0014^{c,f}$	$0.0010^{c,f}$	$0.0004^{c,f}$	$0.0014^{c,f}$	$0.0019^{c,f}$	0.0023^{f}	0.0020^{f}
α_1(Var Eqn)	0.0001^{c}	0.0001^{f}	$0.0001^{c,f}$	$0.0000^{c,f}$	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}
β_1	$0.1044^{c,f}$	$0.0881^{c,f}$	$0.0352^{c,f}$	$0.0411^{c,f}$	$0.0412^{c,f}$	$0.1662^{c,f}$	$0.1014^{c,f}$	$0.1263^{c,f}$	$0.2751^{c,f}$	$0.1062^{c,f}$
Persistence	$0.0124^{c,f}$	$-0.0478^{c,f}$	$-0.1523^{c,f}$	$0.6451^{c,f}$	$0.3651^{c,f}$	$0.4915^{c,f}$	$0.4317^{c,f}$	$0.5140^{c,f}$	$-0.0283^{c,f}$	$0.2297^{c,f}$
Comovement	$0.0998^{c,f}$	$0.1507^{c,f}$	$0.0882^{c,f}$	$0.1069^{c,f}$	$0.2048^{c,f}$	$0.1621^{c,f}$	$0.0412^{c,f}$	$0.0845^{c,f}$	$0.3468^{c,f}$	$0.3430^{c,f}$
Vol Spillover	$0.1040^{c,f}$	$0.0521^{c,f}$	$0.1074^{c,f}$	-0.0230^{f}	$0.0980^{c,f}$	$-0.0594^{c,f}$	$0.1564^{c,f}$	$0.1045^{c,f}$	$0.3193^{c,f}$	$0.0269^{c,f}$
DCC α	0.0125^{c}		0.0491^{c}		0.0445^{c}		0.3973^{c}		0.0037^{c}	
DCC β	-0.0360^{c}		-0.7736^{c}		-0.6396^{c}		0.2500^{c}		0.5784^{c}	
Panel B: Value-weighted										
α(MeanEqn)	0.0009^{c}	0.0009^{c}	$0.0011^{c,f}$	$0.0009^{c,f}$	$0.0004^{c,f}$	$0.0005^{c,f}$	$0.0010^{c,f}$	$0.0012^{c,f}$	$0.0008^{c,f}$	$0.0011^{c,f}$
α_1(Var Eqn)	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{a}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	$0.0001^{c,f}$	$0.0000^{c,f}$
β_1	$0.0618^{c,f}$	$0.1108^{c,f}$	$0.0435^{a,f}$	$0.0693^{c,f}$	$0.0735^{c,f}$	$0.0948^{c,f}$	-0.0068^{f}	$0.2421^{c,f}$	0.0201^{f}	$0.1760^{c,f}$
Persistence	$0.8215^{c,f}$	$0.8387^{c,f}$	$0.9288^{c,f}$	$0.9092^{c,f}$	$0.4102^{c,f}$	$0.6126^{c,f}$	$0.6045^{c,f}$	$0.5681^{c,f}$	$0.2784^{c,f}$	$0.7285^{c,f}$
Comovement	$0.0586^{c,f}$	$0.0937^{c,f}$	$0.0519^{c,f}$	$0.1269^{c,f}$	$0.2551^{c,f}$	$0.3327^{c,f}$	$0.0604^{c,f}$	$0.1148^{c,f}$	$0.0674^{c,f}$	$0.1336^{c,f}$
Vol Spillover	$0.0151^{c,f}$	$-0.0501^{c,f}$	$-0.0454^{c,f}$	$-0.1297^{c,f}$	$-0.0093^{c,f}$	$-0.0740^{c,f}$	$0.1968^{c,f}$	$-0.0290^{b,f}$	$0.2150^{c,f}$	$-0.1288^{c,f}$
DCC α	0.0926^{c}		0.0445^{a}		0.2886^{c}		0.2673^{c}		0.0191^{b}	
DCC β	0.8201^{c}		0.9529^{c}		-0.4273^{c}		-0.3718^{c}		-0.1903^{c}	

Table 4.11 Bivariate DCC-GARCH (Asymmetric) Estimates of Persistence, Symmetric and Asymmetric Comovements and Volatility Spillovers

This table reports the estimates of Persistence, Contemporaneous and Asymmetric Comovements and Volatility Spillovers using a bivariate asymmetric DCC-GARCH model for equal- and value-weighted portfolios of daily TSX and U.S. returns. ^{a}, ^{b} and ^{c} indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficient is not different from zero. ^{d}, ^{e} and ^{f} indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficients for the portfolio pairing is not different for the TSX versus the U.S. trades.

Asymmetric DCC Coefficient	1975-2003		1975-1979		1980-1989		1990-1999		2000-2003	
	TSX	U.S.	TSX	U.S.	TSX	U.S.	TSX	U.S.	TSX	U.S.
Panel A: Equal-weighted										
α(MeanEqn)	$0.0014^{c,f}$	$0.0010^{c,f}$	$0.0017^{c,f}$	$0.0013^{c,f}$	$0.0011^{c,f}$	$0.0006^{c,f}$	$0.0012^{c,f}$	$0.0015^{c,f}$	0.0009^{c}	0.0009^{c}
α_1(Var Eqn)	$0.0001^{c,f}$	$0.0000^{c,f}$	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}
β_1	$0.0787^{c,f}$	$0.0757^{c,f}$	$0.0700^{b,f}$	0.0225^{f}	$0.0675^{c,f}$	$0.0852^{c,f}$	$0.0910^{c,f}$	$0.1669^{c,f}$	$0.1400^{c,f}$	$0.0841^{c,f}$
Persistence	$0.0684^{c,f}$	$0.7877^{c,f}$	0.0457^{f}	$0.8208^{c,f}$	$0.7042^{c,f}$	$0.7128^{c,f}$	$0.7206^{c,f}$	$0.7730^{c,f}$	$0.7279^{c,f}$	$0.5441^{c,f}$
Comovement	$0.1117^{c,f}$	$0.1665^{c,f}$	0.0416^{f}	$0.1004^{c,f}$	$0.1613^{c,f}$	$0.1972^{c,f}$	$0.1395^{c,f}$	$0.2050^{c,f}$	$0.1946^{c,f}$	$0.1459^{c,f}$
Vol Spillover	$0.0876^{c,f}$	$-0.1341^{c,f}$	0.0381^{f}	-0.0150^{f}	$-0.0371^{c,f}$	$-0.1125^{c,f}$	$-0.0106^{c,f}$	$-0.0657^{c,f}$	$0.0396^{c,f}$	0.0036^{f}
AsymmComov	$0.0555^{c,f}$	-0.0015^{f}	$0.0620^{a,f}$	0.0223^{f}	$0.0528^{c,f}$	$-0.0296^{c,f}$	$0.0736^{c,f}$	$0.0105^{c,f}$	$0.1462^{c,f}$	$0.0600^{c,f}$
Asymm VolSpill	$0.0227^{c,f}$	0.0010^{f}	0.0244^{f}	$-0.0780^{c,f}$	$-0.0566^{c,f}$	$0.0160^{c,f}$	$-0.0044^{c,f}$	$-0.0917^{c,f}$	$0.0601^{c,f}$	$0.3252^{c,f}$
DCC α	0.0090^{c}		0.0208		0.0739^{c}		0.2011^{c}		-0.0008^{c}	
DCC β	-0.0965^{c}		-0.7925^{c}		0.4658^{c}		0.7688^{c}		0.4099^{c}	
Panel B: Value-weighted										
α(MeanEqn)	0.0011^{c}	0.0011^{c}	$0.0011^{c,f}$	$0.0009^{c,f}$	0.0007^{c}	0.0007^{c}	0.0010^{c}	0.0010^{c}	$0.0010^{c,f}$	$0.0011^{c,f}$
α_1(Var Eqn)	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}	0.0000^{c}
β_1	$0.0557^{c,f}$	$0.1108^{c,f}$	$0.0699^{c,f}$	$0.0591^{c,f}$	$0.0386^{c,f}$	$0.0614^{c,f}$	$0.0361^{c,f}$	$0.1087^{c,f}$	$0.0546^{c,f}$	$0.0750^{c,f}$
Persistence	$0.8319^{c,f}$	$0.8449^{c,f}$	$0.8522^{c,f}$	$0.8542^{c,f}$	$0.8280^{c,f}$	$0.8437^{c,f}$	$0.8377^{c,f}$	$0.8644^{c,f}$	$0.7733^{c,f}$	$0.8447^{c,f}$
Comovement	$0.0306^{c,f}$	$0.0759^{c,f}$	$0.0379^{c,f}$	$0.1234^{c,f}$	$0.0727^{c,f}$	$0.1326^{c,f}$	$0.0740^{c,f}$	$0.0866^{c,f}$	$0.0737^{c,f}$	$0.1049^{c,f}$
Vol Spillover	$0.0206^{c,f}$	$-0.0625^{c,f}$	$-0.0309^{c,f}$	$-0.0512^{c,f}$	$-0.0066^{b,f}$	$-0.0495^{c,f}$	$-0.0026^{c,f}$	$-0.0832^{c,f}$	$0.0079^{c,f}$	$-0.0790^{c,f}$
Asymm Comov	$0.0678^{c,f}$	$0.0573^{c,f}$	$0.0226^{a,f}$	$-0.0500^{b,f}$	$0.0076^{c,f}$	$-0.0296^{c,f}$	$0.0231^{c,f}$	$0.0283^{c,f}$	$0.0661^{c,f}$	$0.1065^{c,f}$
Asymm VolSpill	$-0.0276^{c,f}$	$-0.0135^{b,f}$	-0.0112^{f}	0.0058^{f}	$-0.0200^{c,f}$	$0.0227^{c,f}$	$-0.0263^{c,f}$	$-0.0333^{c,f}$	$0.0195^{c,f}$	$0.0089^{b,f}$
DCC α	0.0928^{c}		0.0786^{c}		0.0595^{c}		0.1176^{c}		0.0516^{c}	
DCC β	0.8285^{c}		0.8986^{c}		0.8138^{c}		0.6589^{c}		0.9090^{c}	

Table 4.12 Bivariate BEKK (Equal- and Value-Weighted) estimates of Asymmetry and Volatility Spillovers

This table reports the estimates of asymmetry and volatility spillover using a bivariate asymmetric BEKK-GARCH model for equal-weighted portfolios of daily TSX and U.S. returns. [a], [b] and [c] indicate significance at the 0.10, 0.05 and 0.01 levels, respectively, for a t-test of the null that the estimated coefficient is not different from zero.

Asymmetric BEKK	1975-2003		1975-1979		1980-1989		1990-1999		2000-2003	
Coefficient	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
α_{CN} (*mean eqn*)	0.0013[c]	0.0008[c]	0.0018[c]	0.0008[c]	0.0010[c]	0.0007[c]	0.0011[c]	0.0008[c]	0.0013[c]	0.0006[b]
α_{US} (*mean eqn*)	0.0012[c]	0.0008[c]	0.0015[c]	0.0007[c]	0.0005[c]	0.0008[c]	0.0016[c]	0.0007[c]	0.0010[c]	0.0010[c]
c_{11}	-0.0016[c]	0.0007[c]	0.0005[c]	0.0019[c]	-0.0011[c]	0.0021[c]	0.0043[c]	0.0013[c]	0.0036[b]	-0.0016[c]
c_{21}	0.0018[c]	-0.0011[c]	-0.0034[c]	-0.0001	-0.0018[c]	0.0011[c]	0.0006	0.0003	0.0018	0.0009[b]
c_{22}	0.0000	0.0002	0.0000	0.0000	-0.0001	0.0000	0.0021[c]	0.0000	0.0026[c]	0.0000
a_{11}	0.3920[c]	-0.2097[c]	0.3207[c]	0.4177[c]	0.3661[c]	0.1986[c]	-0.7805[c]	0.3219[c]	-0.0071	-0.2177[c]
a_{12}	0.0828[c]	0.1705[c]	0.4430[c]	0.2040[c]	0.1707[c]	0.4882[c]	0.0049	0.1462[c]	0.0173	0.3166[c]
a_{21}	-0.0315	0.4306[c]	0.0856	-0.1367[c]	-0.0557	0.1231[c]	0.3961[c]	-0.0527	0.1524[b]	0.1241[c]
a_{22}	0.3022[c]	0.0935[c]	-0.0255	0.0797[b]	0.1501[c]	-0.1689[c]	-0.2751[c]	0.1632[c]	-0.1674[b]	-0.4124[c]
b_{11}	0.9731[c]	0.6401[c]	1.1940[c]	-0.7465[c]	0.1295	0.2148	-0.2994[c]	1.5347[c]	1.2399[c]	-0.0310
b_{12}	1.3022[c]	-0.2331[c]	1.0642[c]	0.0943[b]	1.0356[c]	1.2808[c]	0.0997[b]	1.8823[c]	1.4651[c]	-0.9021[c]
b_{21}	-1.2788[c]	-1.2975[c]	-0.9781[c]	-0.1649[c]	0.8202[c]	0.6025[c]	-0.4118[c]	-0.8301[c]	-1.4139[c]	-0.8295[c]
b_{22}	-1.0223[c]	-0.7710[c]	-0.3822[c]	-1.0327[c]	-0.1879	-0.2004	-0.9578[c]	-1.5814[c]	-1.1486[c]	-0.1793
d_{11}	-0.2498[c]	-0.2596[c]	-0.3845[c]	0.0914	-0.3992[c]	-0.3815[c]	0.1348	-0.6140[c]	0.0400	-0.1244[a]
d_{12}	-0.4732[c]	-0.3353[c]	-0.3569[c]	0.1597	-0.4422[c]	-0.3304[c]	0.3861[c]	-0.6741[c]	-0.3422[c]	-0.2080[b]
d_{21}	0.5654[c]	0.1585[c]	0.6808[c]	-0.1681	0.6324[c]	0.5077[c]	0.2739[c]	0.8180[c]	0.4031[c]	-0.2301[c]
d_{22}	0.5106[c]	0.3757[c]	0.6502[c]	-0.1940[a]	0.5780[c]	0.5613[c]	-0.0179	0.8129[c]	0.5554[c]	0.0117

Figure 3.1 Time-series of mean cross-sectional conditional correlations for big and small firms, 1980-2003

This figure depicts the time-series of mean cross-sectional conditional correlations of returns for two investment opportunity (IO) sets of TSX-listed stocks for monthly returns. Each time-series of mean cross-sectional conditional correlations is generated by calculating the mean of the correlations between every unique pair of stocks in IO set j (big firms and small firms) for each moving window τ, which consists of the past 60 months and begins from the first month of 1980 through the last month of 2003.

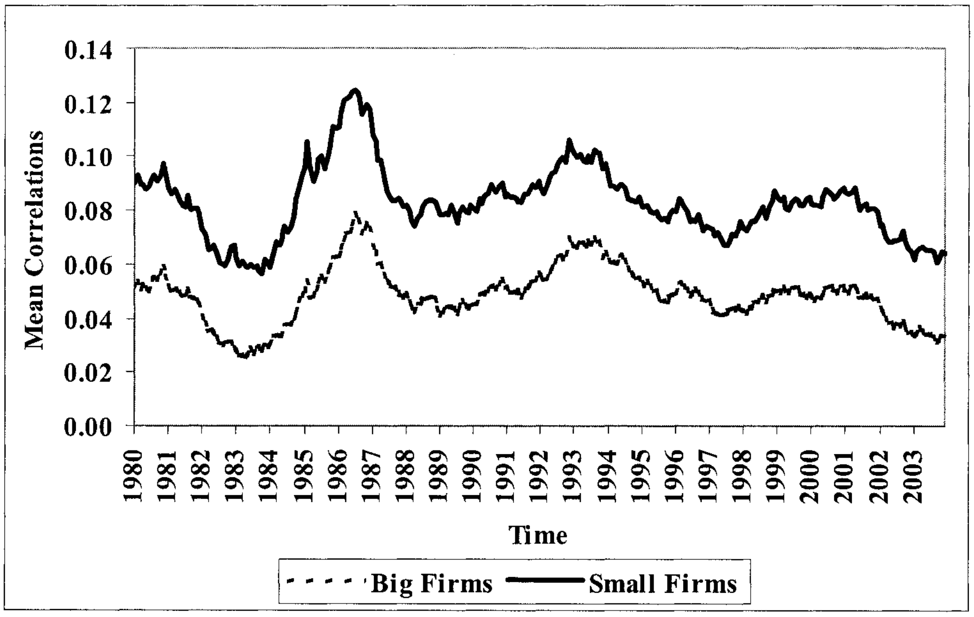

Figure 3.2 Mean normalized portfolio variances (NPV) for twenty portfolio sizes for six investment opportunity sets using monthly returns

This figure depicts the mean normalized portfolio variance (NPV) values based on 5000 randomly generated portfolios for each unique combination of the 20 PS and six IO sets using monthly returns over the period, 1975-2003.
The mean NPV for investment opportunity (IO) set j and portfolio size s is given by:
$\mu_{NPV_{j,s}} = \sum_{i=1}^{5000} \sigma_{j,s,i}^2 / \bar{\sigma}_J^2 = \sum_{i=1}^{5000} (1/s) + (s-1)\left(\overline{\text{cov}}_{j,s,i} / \bar{\sigma}_J^2\right)$, where $\sigma_{j,s,i}^2$ is the standard deviation of returns for the i-th randomly selected portfolio of size s for IO set j over the full period; $\bar{\sigma}_J^2$ is the average cross-sectional standard deviation of returns for all the stocks in IO set j over the full period; and $\overline{\text{cov}}_{j,s,i}$ is the average cross-sectional covariance of returns for the i-th randomly selected portfolio of size s for IO set j over the full period.

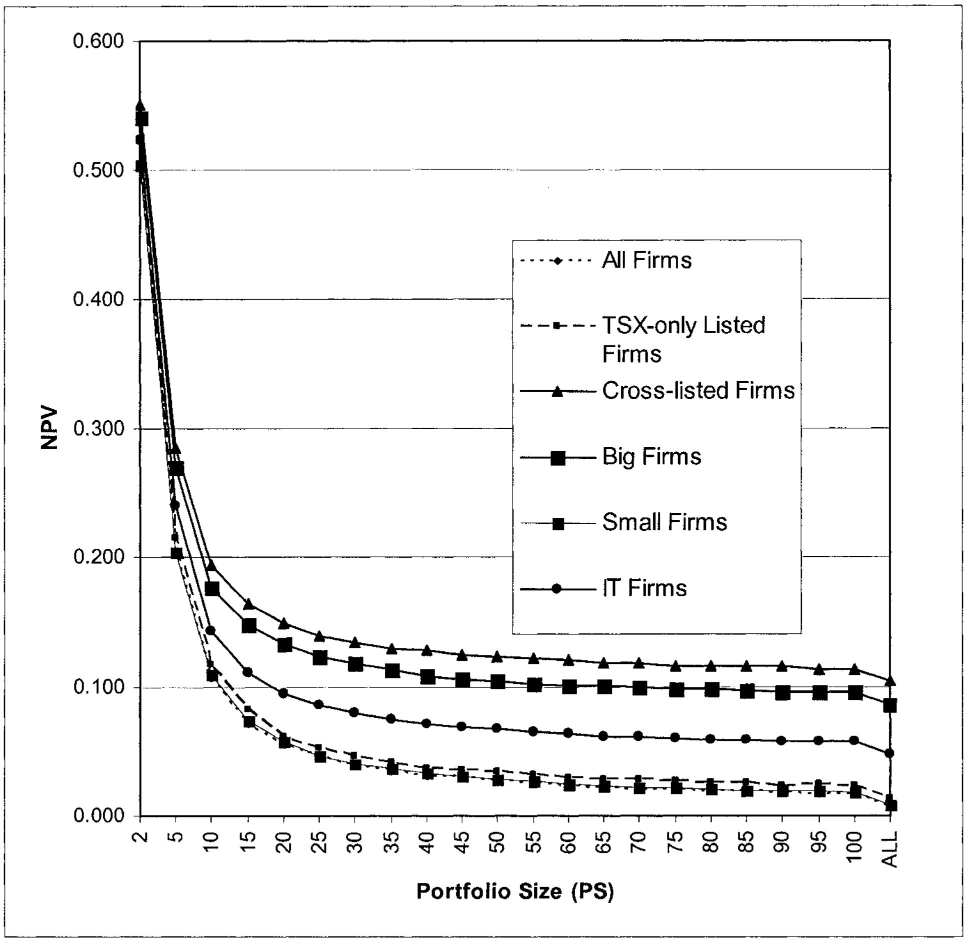

Figure 3.3 Mean Sortino ratios (*Sor*) for twenty portfolio sizes for six investment opportunity sets

This figure depicts the mean Sortino ratios based on 5000 randomly generated portfolios for each unique combination of the 20 PS and six IO sets using monthly returns over the period, 1975-2003. The Sortino ratio is a mean excess return to semi-standard deviation risk measure given by $Sor_{j,s} = (\bar{r}_{j,s} - r_f)/\sigma^-_{j,s}$.