Idiosyncratic Risk Pricing in Canada

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This paper confirms the relationship between idiosyncratic risk and excess stock returns for Canadian equities. The relationship between returns and idiosyncratic risk is examined using Fama-MacBeth two-step methodology with a modified Carhart four-factor (five-beta) model. The Fama-MacBeth tests are conducted with and without the presence of control variables for liquidity (proxied by amortized spread or the illiquidity measure of Amihud) and firm-specific information embedded in stock prices (proxied by synchronicity and the zero-return&trade metric). The conditional relation between returns and idiosyncratic risk for Canadian stocks is robust and significant. Given the model dependencies and metrics, the paper posits this to a higher competitive environment, investor under-diversification, and lower market power faced by Canadian firms as compared to US firms.

INTRODUCTION

A basic tenet of modern portfolio theory has been an assumption that, only systematic risk is priced in stock returns. However, Campbell et al. (2001) found that firm-level, idiosyncratic volatilities (*IV*s) have increased. Since that study there has been a debate on whether this effect really exists, the causal determinants for the long-term *IV* increase, and the nature of its pricing relationship with stock returns.

The first objective of this paper is to examine if *IV* is priced in the Canadian stock market for individual stocks using inferential sturdiness and after controlling for factors that are believed to affect returns and including firm-specific private information flow (Taylor 2008). The second 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.

IV has been related to a number of potential factors in the literature, including an increase in publicly traded stocks on the NASDAQ, an increase in institutional ownership and expected earnings growth (Xu and Malkiel, 2003), and an increase in smaller, riskier firms being listed through initial public offerings (Brown and Kapadia (2007). More recently Jiang et al. (2009) have attributed higher stock volatility to investor under-reaction to news due to selective corporate disclosure of negative news. An increase in momentum profits from under-reaction to firm-specific information has also been documented recently by Arena et al. (2008). On the other hand, Gasper and Massa (2006), and subsequently Irvine and Pontiff (2009), attribute an increasingly competitive environment faced by firms and consequent higher uncertainty, and lower product market power as causal factors for the rise in idiosyncratic volatility.

Recent research findings by Bekaert et al. (2010) reveal no upward trends in idiosyncratic volatilities except for short-term switching into a higher-variance regime. However, whether or not *IV* is priced and predicts future stock returns has been the subject of active research. Recent empirical findings have produced mixed results (Guo and Whitelaw, 2006) in that some of the estimated relationships between returns and various volatility measures are not robust.

Guo and Savickas (2006b) and Ang et al. (2009) have examined this issue for G7 countries (including Canada). However, their findings suffer from survivorship bias, based on limited number of existing Canadian stocks in the Datastream database. Findings by Ang et al. (2009) were weakly significant for Canada. For a more robust study, this paper used daily and monthly data of all stocks listed in the CFMRC database over the 1975-2003 period. Furthermore, the study examines various sub-samples thereof, including firms cross-listed on both the TSX and U.S. markets, non-cross listed (local) firms, big and small firms, and firms in the IT sector.

This paper makes two important contributions to the literature. The first contribution is the use of asymmetric idiosyncratic risk to confirm that there is a significant relationship between monthly excess stock returns and asymmetric idiosyncratic risk for individual stocks in Canada. This study focused on Canadian stocks, since Canada's real economy is integrated with the USA through the largest free-trade, as well as financially integrated under NAFTA, with similar opening and closing hours of TSE and NYSE, and cross-listing of Canadian stocks on US stock exchanges. On account of this integration, preliminary hypothesis would suggest a similar firm-specific risk-returns relationship. Yet, this study finds a dissimilar much stronger relationship. The relationship between monthly returns and asymmetric idiosyncratic risk is strong using *IV*s based within a 60-month moving window. Not surprisingly, the relationship is even stronger using more recent values of idiosyncratic risk (i.e., values calculated using days-within-the-month versus a 60-month moving window). The explanatory power of asymmetric idiosyncratic risk is still high for the returns of individual stocks when the *IV* value is lagged one month to correspond with the information available to a typical (uninformed) investor. This result provides evidence for the predictive power of idiosyncratic risk. This study demonstrates that this relationship is not subsumed by inclusion of various firm-specific control variables such as (il)liquidity or informational transparency, which proxy for private information flow.

The second contribution is the finding that the pricing of idiosyncratic volatility is not a small firm phenomenon (as argued for the U.S. by Brown and Ferreira, 2004). Furthermore, the premium for bearing illiquidity risk among small firms is positive and significant for most samples.

The remainder of the paper is structured as follows. Section briefly reviews the relevant literature. The samples and the data are discussed in section three. Sections four and five report on whether or not *IV*s are priced and whether or not *IV*s have any power to "predict" future stock returns in the Canadian market. Given the mixed results reported in the literature, two methodologies are employed for a robust examination of the risk-return relation. Section six concludes the paper.

IDIOSYNCRATIC VOLATILITY AND EXPECTED RETURNS

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 *IV*s are not observable, *IV* measures are dependent on the model used to price systematic risk(s). Various methodologies have been used to estimate (un)conditional *IV*s in the literature (Xu and Malkiel, 2003).

Guo and Savickas (2006c) explain that the debate on the relationship between returns and *IV*s, initiated by the stock return predictability findings of Fama (1991) continues. 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 *IV*s).

Empirical studies have produced mixed results (e.g., Guo and Whitelaw, 2006) with some such as Bali et al. (2005) finding that the *IV* measures are not robust. The reported relations for various country markets run from significantly positive (e.g., Lintner, 1965; Lehmann, 1986; French, Schwert, and Stambaugh, 1987; Campbell and Hentschel, 1992; Drew and Veeraraghaven, 2002; Goyal and Santa-Clara, 2003; Drew, Naughton and Veeraghavan, 2003; and Jiang and Lee, 2006) to insignificantly positive (e.g., Tinic and West, 1986; Xu and Malkiel , 2003; Bali et al., 2005) to negative (e.g., Breen, Glosten and Jagannathan, 1989; Longstaff, 1989; Ang et al., 2006) to significantly negative (e.g., Campbell, 1987). Xu and Malkiel (2003) 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 *IV*s. However, after controlling for numerous factors (business cycle fluctuations, liquidity, momentum, size, value, variance in analyst forecasts and volume), Ang et al. (2009) reject the notion that stocks with higher *IV*s may also have higher aggregate volatility and lower returns.

This mixed evidence suggests the need for the use of a multi-factor model (Scruggs, 1998), due to an omitted variable bias. Although some researchers argue that *IV* estimates are unable to capture time variation because of measurement errors (Fu, 2005), others (e.g., Guo and Savickas, 2003) argue that expected stock returns have risk and liquidity components that may be correlated negatively, leading to mixed results without controls. Bali et al. (2005) argue that the positive relationship between market returns and *IV*s is driven by trading on Nasdaq and the liquidity premium. Yan and Zhang (2003) find that the predictive power of *IV* is sensitive to its measure and is partly driven by the liquidity premium. Guo and Savickas (2003) conjecture that investors demand a risk premium in addition to a liquidity premium to compensate them for poorly diversified portfolios (e.g., Goetzmann and Kumar, 2003). Thus this paper adjusts for (il)liquidity using two alternative measures described below (LIQ and LIQ^{AMI}).

Early researchers found that market volatility contributed little to the prediction of returns (French, Schwert and Stambaugh, 1987). However, recent research by Guo and Savickas (2006a) confirms that market volatility in conjunction with *IV* significantly predicts a negative relationship with expected returns. Gasper and Massa (2006) posit that increased competitive conditions and lower market power result in higher uncertainty regarding firm's earnings and higher idiosyncratic volatility. Arena et al. (2008), attribute investor under-reaction to firm-specific information, and consequent increasing momentum to a rise in *IV*. Taylor (2008) has argued that incorporating proxies for private information flow, despite the positive cross-sectional association, improves the predictive relationship. Therefore, this paper uses two firm-specific metrics: the firm-specific synchronicity (*SYNC*) of Morck et al. (2000), and a zero return trade metric (*VROM*) that reflects stock informational transparency.

DATA AND METHODOLOGY

Data

The data on Canadian stocks listed on the Toronto Stock Exchange (TSX) is extracted from the CFMRC historical database. The sample for our study is from 1975-2003 and consists of 3,396 stocks classified as a group of All Firms. These are also grouped using SIC code 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, since Brown and Ferriera (2004) argue that idiosyncratic volatility is only priced for small firms. The 225 Canadian firms in the information technology, telecommunication, and consultancy sector (IT) are also examined to facilitate comparison against the findings of Domanski (2003) for this sector in the U.S. The six samples or investment opportunity (IO) sets then include, all, big, small, domestic-only listed, cross-listed in the U.S., and IT firms.

Daily and monthly stock returns, closing prices, 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 obtained from the Bank of Canada and the Federal Reserve Bank of St. Louis, respectively, are used as proxies for the respective risk-free rates to compute excess stock returns.

Monthly and daily time-series of returns are constructed for four factors for the Canadian market using a variety of sources, including the Financial Post database. These four factors are the market factor (MKT = excess market return), the size factor (SMB = Small minus Big), the growth factor (HML = High minus Low), and momentum factor (WML = Winner minus Loser = Up minus Down). The return series are subsequently used in applications of the Fama and French (1995) and Carhart (1997) models (i.e, original FF 3-factors plus momentum).

Measuring Idiosyncratic Volatility

The idiosyncratic volatility for firm *i* in sample *s* for month *t*, or $\sigma^2\left(\varepsilon_{i,s,t}^{3FF}\right)$, for the three-factor market model of Fama and French (*3FF*) is obtained in two steps. First, the following *3FF* model is estimated for each firm *i* for each month *t* using all the days within each month (i.e., $d_t = 1,...,D_t$):

$$r_{i,s,d_t} = \alpha_{i,s} + \beta_{i,s,1} \cdot MKT_{d_t} + \beta_{i,s,2} \cdot SMB_{d_t} + \beta_{i,s,3} \cdot HML_{d_t} + \varepsilon_{i,s,d_t}^{3FF} \tag{1}$$

where r_{i,s,d_t} is the return for firm *i* in sample *s* for day *d* in month *t*; MKT_d,SMB_d and HML_d are calculated as described earlier; α and β are parameters estimated; and $\varepsilon_{i,s,d_t}^{3FF}$ is the error term from the 3FF model for firm *i* in sample *s* for day *d* in month *t*, which is assumed to have the standard i.i.d. properties. Then the idiosyncratic volatility for firm *i* in sample *s* for month *t*, or $\sigma^2\left(\varepsilon_{i,s,t}^{3FF}\right)$, is obtained from:

$$\sigma^2\left(\varepsilon_{i,s,t}^{3FF}\right) = \sum_{d_t=1}^{D_t}\left(\varepsilon_{i,s,d_t}^{3FF}\right)^2 \tag{2}$$

The idiosyncratic volatility for firm *i* in sample *s* for month *t*, or $\sigma^2\left(\varepsilon_{i,s,t}^{3FF}\right)$, for the three-factor market model of Fama and French (*3FF*) combined with the model (GSC) of Goyal and Santa-Clara (2003) is also obtained in two steps, where the second step, after incorporating the autocorrelation in daily returns identified by French, Schwert and Stambaugh (1987), becomes:

$$\sigma_{adj}^2\left(\varepsilon_{i,s,t}^{3FF}\right) = \sum_{d_t=1}^{D_t}\left(\varepsilon_{i,s,d_t}^{3FF}\right)^2 + 2\sum_{d_t=2}^{D_t}\left(\varepsilon_{i,s,d_t}^{3FF}\right)\left(\varepsilon_{i,s,d_t-1}^{3FF}\right) \tag{3}$$

where all the terms are as defined earlier.

Two-Step Regression Estimation of Idiosyncratic Volatility

Testing if *IV* is priced for Canadian stocks is determined using the two-step regression approach of Fama and MacBeth (1973), which has also been used by Spiegel and Wang (2005) and Fu (2005) for US stocks. In the first step, the time series of monthly *IV*s are estimated along with estimation of the time series of each of the five betas of the 4-factor Carhart (1997) model that is modified to include up- and down-market factors. 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*.

The second step involves two robustness estimation procedures. In the first procedure, a series of realized excess returns are regressed cross-sectionally against the time series of the five betas, the *IV*s and various control variables for (il)liquidity (amortized or Amihud measures) and firm-specific information (synchronicity and zero-return metric). In the second estimation procedure, risk-adjusted returns are regressed against the time series of the *IV*s 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 *IV*s 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 *IV*s 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.

EMPIRICAL ASSET PRICING TESTS

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

$$r_{i,t}^{*} = \alpha + \beta_{i,1}^{MKT^{+}} \delta R_{m,t}^{*} + \beta_{i,2}^{MKT^{-}} (1-\delta) R_{m,t}^{*} + \beta_{i,3}\, SMB_t + \beta_{i,4} HML_t + \beta_{i,5} WML_t + \varepsilon_{i,t}^{4'FF} \tag{4}$$

where $r_{i,t}^{*}$ is the excess return on security *i* over the risk-free rate for period *t* (i.e., $R_{i,t} - R_{f,t}$); $R_{m,t}^{*}$ 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, 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 cross-sectional regressions for each month *t*:

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

where the 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 (4) (specifically, $\varepsilon_{i,t}^{4'FF}$ when (4) is estimated using monthly returns and by $\varepsilon_{i,t}^{4'FF}$ multiplied by the number of trading days in the month when (4) is estimated using daily returns). *IV* is signed in a similar fashion to *MKT* to allow for an asymmetric effect of idiosyncratic risk on stock returns, so 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 is obtained by dividing the product of the absolute difference between the trade and mid-spread prices and the traded volume by the product of the trade price times the number of shares outstanding. **(**The daily closing price is a proxy for the execution price.)

SYNC or synchronicity is the extent to which stock prices move together (Morck et al. 2000), and signifies the magnitude of firm-specific information incorporated into stock prices (Asbaugh-Skaife et al. 2006). Although different measures exist (Jin and Myers, 2006), the most popular is R^2. As in Morck et al. (2000), the logistic transformation $\gamma_j = \ln\left[R_j^2 \big/ \left(1 - R_j^2\right) \right]$ is used, since R^2 is bounded within the interval [0, 1]. The R_j^2 for each stock *j* is obtained from regression (4) using either moving monthly windows of 60 months or the days-within-each-month.

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), leading to lower idiosyncratic volatility because firm-specific information is already embedded in stock prices (Roll, 1988). However, some inconsistencies occur with synchronicity as Asbaugh-Skaife, Gassen and Lafond (2006) find that non-fundamental factors influence stock price 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 Asbaugh-Skaife, Gassen and Lafond (2006) apply to the Canadian market.

VROM is a zero-trade, zero-return measure. Asbaugh-Skaife et al. (2006) suggest that a zero-return&trade metric is a better measure of firm-specific information embedded in stock prices than R^2. Support for *VROM* 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. Asbaugh-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 natural log of the percentage of nonzero-trade&return days in a month. Thus, the expected coefficient for *VROM* is positive.

EMPIRICAL RESULTS

Results from 60-Month Rolling Windows

A series of cross-sectional regressions (5) for each month *t* based on the contemporaneous betas and *IV*s estimated from regression (4) with and without contemporaneous estimates for LIQ^{AS}, *SYNCH* and *VROM* are run for each of the six samples.

Based on the regression results reported in Table 1, the average explanatory power of the model is very high with a range of 45% to 57% for the various samples. (Median R^2 values are not materially different for the tests reported in the following section.) 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 their coefficient estimates lose some significance with the addition of the three control variables for some samples. The average coefficient estimate for positively signed *IV*s 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 *IV*s. The coefficient estimates for the various control variables are generally insignificant, except for liquidity for four of the six samples.

To determine whether the relationship between returns and *IV*s is robust to the use of *IV*s known at the beginning of each step 2 estimation period, the set of cross-sectional regressions are rerun using asymmetric *IV*s lagged one month. These results are presented in Table 2. 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 *IV*s, only the up betas are significantly priced for some of the samples. The average loadings on the *SMB*, *HML* and *WML* factor risks are generally not significantly different from zero. The 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 *IV*s 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. *LIQ*, *SYNC* and *VROM* are significant (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 *IV*s are the current period's estimates (i.e., that both follow a random walk), the initial evidence finds that both signed *IV*s are priced in the Canadian market.

Results from the Days-within-the-Month Rolling Windows

In order to compare our *IV* findings with those by Ang et al. (2006) for the U.S., the methods implemented in the previous section are repeated with daily data. The betas and signed *IV*s 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* (see regression 4). Then a series of cross-sectional regressions (5) use a rolling window of all of the trading days within month *t*, with and without contemporaneous (month *t*) estimates for LIQ^{AS}, *SYNCH* and *VROM*. (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.)

Based on the regression results reported in Table 3, 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 *IV*s based on a 60-month moving window. The intercept is negative and very significant even in the presence of the three control variables, except in the IT sample. 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. Except for the IT sample, the average loadings on the momentum factor *WML* are positive and significant.

The average loadings on the asymmetric *IV* factor risks are without exception very significant and with the expected signs, although they lose some significance with the addition of the three control variables. The average coefficient estimate for the positively signed *IV*s 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.

To examine lagged relationships, for each month *t* betas and *IV*s are again estimated from regression (4). A series of cross-sectional regressions (5) use a rolling window of all of the trading days within month *t-1*, with and without contemporaneous (month *t*) estimates for LIQ^{AS}, *SYNCH* and *VROM,* are then run. Based on the regression results reported in Table 4, the explanatory powers of the relationships decline somewhat with the use of lagged *IV*s based on trading-days-within-the-month, but remain high in the range of 0.48 to 0.57. This still exceeds the corresponding values based on lagged *IV*s from a trailing 60-month estimation window. The coefficient estimates for the *IV* factors remain highly significant, and the average coefficient estimates for the positively signed *IV*s remain significantly higher in absolute value than their negatively signed counterparts.

Using an Alternative Liquidity Measure

Robustness to our initial choice of *LIQ* measure is tested to add strength to our results. Specifically, we examine whether the relationship of returns to *IV* is robust to the approximate price impact measure of Amihud (2002) or LIQ^{AMI}, calculated as 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.

Each of the tests conducted using the amortized spread as *LIQ* is repeated using the Amihud measure of (il)liquidity LIQ^{AMI}. Tests on both moving windows of 60 months and days-within-the-month are conducted. 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. Table 5 shows the results for the days-within-the-month sample. (Results for the moving window of 60 months sample are not shown to conserve space, but the table is available from the authors.)

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 factor pricing. More specifically, the two signed *IV* factors continue to be highly significant with their correct signs for all samples.

Controlling for Measurement 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 (5). They suggest the use of risk-adjusted returns for individual stocks to avoid 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 (e.g., residual variance) through the aggregation or portfolio building process.

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

$$ar_{i,t}^* = r_{i,t}^* - R_{f,t} - (\hat{\beta}_{i,1,t}^{MKT^+} \delta R_{m,t}^* + \hat{\beta}_{i,2,t}^{MKT^-} (1-\delta) R_{m,t}^* + \hat{\beta}_{i,3,t}^{SMB} SMB_t + \hat{\beta}_{i,4,t}^{HML} HML_t + \hat{\beta}_{i,5,t}^{WML} WML_t) \qquad (6)$$

where all the terms are as previously defined, and the betas are estimated using the first-step Fama-French regressions (4). The following second-step Fama-MacBeth relationship is now estimated by a series of cross-sectional regressions given by (7) instead of (5) for each month *t*:

$$ar_{i,t}^* = \alpha + \lambda_{1,t} \phi IV_{i,t} + \lambda_{2,t} (1-\phi) IV_{i,t} + \lambda_{3,t} LIQ_{i,t} + \lambda_{4,t} SYNC_{i,t} + \lambda_{5,t} VROM_{i,t} + v_{i,t} \qquad (7)$$

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. The independent variables are liquidity (alternatively either the amortized spread *LIQ* or the Amihud measure, LIQ^{AMI}), *SYNC*, *VROM* and either contemporaneous or lagged signed *IV*s. Moving windows of 60 months or days-within-the-month are used, and the results for the latter are reported in Table 6. (Results for the moving window of 60 months sample are not shown to conserve space, but the table is available from the authors.)

Accounting for measurement error in the first-step beta estimates reduces the significance of the two *IV* variables, but 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.

CONCLUSION

This paper examines the pricing relationship of idiosyncratic volatility (*IV*) of Canadian stocks using variants of the Fama-MacBeth methodology. It uses the Fama-French (FF) model as extended by Carhart to find *IV* estimates. Using a risk-adjusted approach to overcome measurement errors, the paper confirms that, there is a significant and robust relationship between stock returns and asymmetric idiosyncratic volatility.

Unlike the findings for the U.S. (Domanski, 2003, Ang et al., 2009), this paper finds that significant risk premia for idiosyncratic volatilities are not confined to small firms in Canada. In contrast to the findings by Ang et al. (2009) on G7 countries that revealed a weak, statistically negative relationship of returns in Canada to contemporaneous and lagged *IV*, this paper finds a much stronger relationship between asymmetric *IV* and excess stock returns. This relationship is not subsumed by the presence of liquidity and information transparency factors. More recently, Brooks et al. (2011) endorse findings that idiosyncratic risk commands a risk premium that is unrelated to Size, and Book-to-Market risk factors.

The stronger relationship for Canadian equities in contrast with US findings may be explained on several bases. Canadian firms compared to US Firms are on average smaller, have lower market power, and face higher product market competition under NAFTA. This greater uncertainty is incorporated in higher unmitigated idiosyncratic volatility. Bekaert et al. (2010) have recently found that idiosyncratic volatility moves into short-term periods of higher regime change. This regime change may be reflected in our pricing relationship through the private information flow (Taylor 2008) captured by our liquidity factor and two control variables, namely synchronicity (Morck et al. 2000), and the zero return trade metric (Ashbaugh-Skaife et al. 2006).

Irvine and Pontiff (2009) attribute the upward trend in idiosyncratic volatility to increased market competition and lower power. However, Bekaert et al. (2010), observe only an increase in correlation of idiosyncratic volatilities across countries, implying that markets become increasingly integrated. Both implicitly acknowledge that cash flow shocks, lower return on assets, and consequent lower market power and short-term higher uncertainty regime changes, influence the idiosyncratic volatility pricing relationship. While, model dependencies and metrics determining non-systematic risk may influence the relationship, the Canadian industry spectrum is less atomic vis-à-vis the US, and except for some core sectors is confronted with lower market power firms, resulting in our stronger observed pricing relationship of idiosyncratic volatility and returns for Canadian stocks. The findings in this paper are reaffirmed by the investor under-diversification or poorly-diversified portfolios observed by Brockman et al. (2009) and Brooks et al. (2011). While, interesting research potential linking various volatility metrics to fundamental variables exist, this study demonstrates that the Canadian return-idiosyncratic volatility relationship is different than in the US, and that it survives after adjustment for systematic risk, liquidity, synchronicity, and firm-specific information.

TABLE 1

Time-series averages of the second-step cross-sectional regression results using contemporaneous excessreturns, betas, IVs and controls (e.g., amortized spreads) based on first-step 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: $\hat{\beta}_{i,1,t}^{MKT^+}$ and $\hat{\beta}_{i,2,t}^{MKT^-}$ for the excess market return when nonnegative and negative, respectively, for firm *i* in month *t*; $\hat{\beta}_{i,3,t}^{SMB}$ for the small minus big size factor; $\hat{\beta}_{i,4,t}^{HML}$ for the high minus low book-to-market factor; and $\hat{\beta}_{i,5,t}^{WML}$ for the momentum factor. $IV_{i,t}^{+}$ and $IV_{i,t}^{-}$ are the idiosyncratic standard deviations from the first-step Carhart 4-factor model that are signed based on the security returns using a similar method as that used to sign the market betas. The controls are $LIQ_{i,t}^{AS}$, $SYNC_{i,t}$ and $VROM_{i,t}$. 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 mid-spread prices and the traded volume by the product of the trade price times the number of shares outstanding; synchronicity, as proxies by $\gamma_j = Ln\left[R_j^2 \big/ \left(1 - R_j^2\right)\right]$, 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} 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 second-step cross sections are reported 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	**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	-0.0422^{c}	-0.0426
	(-5.11)	(-1.56)	(-5.33)	(-1.95)	(-2.62)	(0.33)	(-5.40)	(-0.62)	(-5.18)	(-1.18)	(-2.88)	(-1.03)
$\hat{\beta}_{i,1,t}^{MKT^+}$	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}	0.3111	1.0406
	(2.78)	(2.90)	(3.07)	(3.15)	(-0.39)	(-0.64)	(1.24)	(2.01)	(2.13)	(2.09)	(0.37)	(1.21)
$\hat{\beta}_{i,2,t}^{MKT^-}$	0.0113	0.0127	-0.0152	-0.0088	0.0070	0.0224	0.0309	0.0224	-0.0756	-0.0654	1.7204^{a}	0.6722
	(0.51)	(0.60)	(-0.74)	(-0.48)	(0.07)	(0.27)	(1.39)	(1.06)	(-1.33)	(-1.24)	(1.71)	(0.68)
$\hat{\beta}_{i,3,t}^{SMB}$	-0.0020	-0.0022	-0.0015	-0.0018	0.0022	0.0029	-0.0016	-0.0022^{a}	-0.0011	-0.0014	-0.0079	-0.0073
	(-1.27)	(-1.44)	(-0.93)	(-1.11)	(0.69)	(1.24)	(-1.13)	(-1.68)	(-0.72)	(-0.92)	(-1.63)	(-1.52)
$\hat{\beta}_{i,4,t}^{HML}$	0.0014	0.0014	0.0013	0.0012	0.0010	0.0014	0.0018	0.0020^{a}	0.0005	0.0004	0.0124	0.0105
	(0.77)	(0.79)	(0.68)	(0.66)	(0.44)	(0.82)	(1.56)	(1.78)	(0.21)	(0.16)	(1.43)	(1.29)
$\hat{\beta}_{i,5,t}^{WML}$	-0.0103	-0.0106	-0.0009	-0.0018	0.0078	0.0116	-0.0074	-0.0068	-0.0088	-0.0084	0.0697	0.0260
	(-0.75)	(-0.78)	(-0.07)	(-0.15)	(0.19)	(0.39)	(-0.62)	(-0.59)	(-0.67)	(-0.64)	(1.33)	(0.74)
$IV_{i,t}^{+}$	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}	1.0546^{c}	0.9707^{c}
	(23.14)	(21.58)	(22.40)	(21.05)	(13.19)	(16.60)	(28.11)	(26.87)	(20.13)	(19.12)	(8.53)	(7.69)
$IV_{i,t}^{-}$	-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}	-0.2063^{c}	-0.2842^{c}
	(-18.52)	(-18.07)	(-16.08)	(-15.93)	(-13.42)	(-15.21)	(-22.71)	(-23.29)	(-10.05)	(-10.68)	(-2.34)	(-3.09)
$LIQ_{i,t}^{AS}$		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)
$SYNC_{i,t}$		0.0016		0.0021		-0.0013		0.0000		0.0030		-0.0053
		(1.17)		(1.37)		(-0.54)		(-0.02)		(1.38)		(-0.82)
$VROM_{i,t}$		-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)
$\overline{R}^2$	0.45	0.48	0.46	0.49	0.57	0.57	0.49	0.51	0.47	0.51	0.52	0.56
# Firms	237;625		197;476		35;70		160;499		70;164		35;69	

TABLE 2

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

The variables are as detailed in Table 1 above. 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 second-step cross sections are reported 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	**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)	-0.0210 (-1.56)	-0.0572 (-1.21)
$\hat{\beta}^{MKT^+}_{i,1,t}$	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)	0.0326 (0.02)	0.7141 (0.32)
$\hat{\beta}^{MKT^-}_{i,2,t}$	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)	1.6639 (0.59)	0.9531 (0.31)
$\hat{\beta}^{SMB}_{i,3,t}$	-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)	-0.0062 (-0.96)	-0.0096 (-1.54)
$\hat{\beta}^{HML}_{i,4,t}$	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)	0.0138 (1.06)	0.0164 (1.35)
$\hat{\beta}^{WML}_{i,5,t}$	-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)	0.0479 (0.47)	0.0603 (0.59)
$IV^{+}_{i,t}$	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)	0.8835^{c} (6.85)	0.8216^{c} (5.93)
$IV^{-}_{i,t}$	-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)	-0.3322^{c} (-3.23)	-0.4513^{c} (-3.83)
$LIQ^{AS}_{i,t}$		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)
$SYNC_{i,t}$		-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)
$VROM_{i,t}$		-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)
$\overline{R}^2$	0.42	0.45	0.43	0.46	0.55	0.55	0.46	0.49	0.45	0.48	0.50	0.53
# Firms	237;614		197;468		35;70		160;493		69;161		35;68	

TABLE 3

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

The variables are as detailed in Table 1 above. 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 second-step cross sections are reported 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	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**
Intercept	-0.0141[c] (-6.29)	-0.0706[c] (-7.61)	-0.0145[c] (-5.91)	-0.0658[c] (-7.49)	-0.0129[c] (-6.20)	-0.0681[c] (-4.58)	-0.0076[c] (-4.66)	-0.0372[c] (-6.37)	-0.0397[c] (-8.25)	-0.1090[c] (-6.32)	-0.0232[c] (-2.92)	-0.0244 (-0.82)
$\hat{\beta}_{i,1,t}^{MKT^+}$	0.0009[b] (2.47)	0.0005 (1.44)	0.0008[b] (2.04)	0.0005 (1.27)	0.0017[c] (2.72)	0.0011[a] (1.72)	0.0014[c] (3.34)	0.0011[c] (2.77)	0.0004 (0.96)	0.0002 (0.43)	-0.0001 (-0.11)	-0.0006 (-0.39)
$\hat{\beta}_{i,2,t}^{MKT^-}$	-0.0006 (-1.03)	-0.0007 (-1.48)	-0.0007 (-1.12)	-0.0007 (-1.35)	-0.0001 (-0.10)	-0.0001 (-0.22)	-0.0008 (-1.46)	-0.0009[a] (-1.70)	-0.0003 (-0.50)	-0.0003 (-0.49)	0.0007 (0.38)	0.0000 (0.03)
$\hat{\beta}_{i,3,t}^{SMB}$	0.0001 (0.19)	0.0005 (0.85)	0.0002 (0.34)	0.0005 (0.77)	-0.0021[b] (-2.02)	-0.0016 (-1.46)	-0.0007 (-1.22)	-0.0006 (-1.01)	0.0004 (0.49)	0.0008 (0.91)	-0.0004 (-0.20)	0.0008 (0.39)
$\hat{\beta}_{i,4,t}^{HML}$	-0.0012 (-1.50)	-0.0012 (-1.53)	-0.0014[a] (-1.71)	-0.0015[a] (-1.79)	-0.0003 (-0.22)	0.0002 (0.20)	-0.0012[a] (-1.84)	-0.0012[a] (-1.85)	-0.0010 (-1.09)	-0.0011 (-1.19)	-0.0045 (-1.63)	-0.0040 (-1.52)
$\hat{\beta}_{i,5,t}^{WML}$	0.0071[c] (3.14)	0.0065[c] (2.88)	0.0068[c] (3.03)	0.0063[c] (2.81)	0.0066[c] (6.18)	0.0059[c] (5.83)	0.0064[c] (9.57)	0.0058[c] (9.08)	0.0056[b] (2.49)	0.0049[b] (2.21)	0.0026 (1.08)	0.0022 (0.98)
$IV_{i,t}^{+}$	0.9605[c] (53.73)	0.9628[c] (52.62)	0.9427[c] (49.08)	0.9417[c] (47.97)	1.0839[c] (43.29)	1.0919[c] (42.39)	0.9831[c] (61.65)	0.9860[c] (59.35)	0.9926[c] (35.53)	0.9905[c] (35.11)	1.0126[c] (18.28)	1.0064[c] (15.72)
$IV_{i,t}^{-}$	-0.5017[c] (-47.02)	-0.4965[c] (-42.91)	-0.4906[c] (-42.58)	-0.4875[c] (-39.37)	-0.6059[c] (-32.13)	-0.6013[c] (-28.67)	-0.6043[c] (-52.31)	-0.5990[c] (-48.05)	-0.3690[c] (-21.15)	-0.3644[c] (-19.60)	-0.5256[c] (-13.42)	-0.5390[c] (-10.41)
$LIQ_{i,t}^{AS}$		3.0382[b] (2.49)		2.8472[b] (2.15)		9.2014[b] (2.37)		3.9728[c] (2.82)		3.6424[b] (2.09)		1.9855 (0.35)
$SYNC_{i,t}$		0.0045[c] (6.56)		0.0043[c] (5.88)		0.0033[c] (3.82)		0.0030[c] (5.72)		0.0073[c] (4.40)		0.0026 (0.76)
$VROM_{i,t}$		0.0410[c] (5.94)		0.0369[c] (5.76)		0.0430[c] (3.12)		0.0187[c] (3.92)		0.0446[c] (3.78)		-0.0092 (-0.35)
$\overline{R}^2$	0.59	0.59	0.59	0.60	0.64	0.66	0.61	0.62	0.59	0.60	0.66	0.67
# Firms	247;1044		202;842		43;202		183;725		39;319		35;115	

TABLE 4

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

The variables are as detailed in Table 1 above. 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 second-step cross sections are reported 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	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**	**W/out**	**With**
Intercept	0.0007	-0.0411^{c}	0.0014	-0.0407^{c}	-0.0019	-0.0227	0.0017	-0.0192^{c}	-0.0032	-0.0677^{c}	-0.0037	-0.0038
	(0.33)	(-6.99)	(0.66)	(-6.71)	(-0.76)	(-1.40)	(0.88)	(-3.05)	(-0.72)	(-4.76)	(-0.72)	(-0.13)
$\hat{\beta}^{MKT^+}_{i,1,t}$	0.0010^{b}	0.0010^{a}	0.0005	0.0006	0.0025^{c}	0.0032^{c}	0.0017^{c}	0.0018^{c}	0.0003	0.0004	-0.0018	-0.0012
	(1.97)	(1.86)	(1.02)	(1.07)	(3.37)	(3.66)	(3.05)	(3.17)	(0.50)	(0.66)	(-1.05)	(-0.69)
$\hat{\beta}^{MKT^-}_{i,2,t}$	0.0001	-0.0001	0.0001	0.0000	0.0005	0.0003	-0.0005	-0.0006	0.0009	0.0008	0.0016	0.0026
	(0.14)	(-0.12)	(0.19)	(0.03)	(0.62)	(0.32)	(-0.86)	(-0.94)	(1.02)	(0.96)	(0.86)	(0.95)
$\hat{\beta}^{SMB}_{i,3,t}$	-0.0002	-0.0001	-0.0001	0.0000	-0.0027^{b}	-0.0027^{b}	-0.0016^{b}	-0.0017^{b}	0.0001	0.0005	0.0021	0.0009
	(-0.23)	(-0.08)	(-0.09)	(0.05)	(-2.27)	(-2.20)	(-2.09)	(-2.17)	(0.06)	(0.53)	(0.55)	(0.32)
$\hat{\beta}^{HML}_{i,4,t}$	-0.0007	-0.0006	-0.0010	-0.0008	0.0002	0.0001	-0.0004	-0.0005	-0.0003	0.0000	-0.0057	-0.0053
	(-0.67)	(-0.64)	(-0.87)	(-0.74)	(0.13)	(0.06)	(-0.55)	(-0.71)	(-0.20)	(-0.02)	(-1.50)	(-1.32)
$\hat{\beta}^{WML}_{i,5,t}$	0.0123^{c}	0.0121^{c}	0.0116^{c}	0.0116^{c}	0.0096^{c}	0.0096^{c}	0.0105^{c}	0.0103^{c}	0.0101^{c}	0.0103^{c}	0.0056^{b}	0.0058^{b}
	(5.18)	(5.06)	(4.87)	(4.84)	(8.16)	(7.80)	(12.45)	(12.49)	(4.07)	(4.12)	(2.41)	(2.07)
$IV^{+}_{i,t}$	0.7770^{c}	0.7639^{c}	0.7602^{c}	0.7475^{c}	0.8992^{c}	0.8676^{c}	0.8297^{c}	0.8181^{c}	0.7490^{c}	0.7287^{c}	0.8411^{c}	0.8031^{c}
	(47.24)	(43.60)	(43.89)	(41.48)	(34.67)	(32.04)	(41.73)	(39.84)	(29.70)	(27.88)	(22.08)	(19.47)
$IV^{-}_{i,t}$	-0.5081^{c}	-0.5177^{c}	-0.5026^{c}	-0.5111^{c}	-0.6098^{c}	-0.6383^{c}	-0.5772^{c}	-0.5846^{c}	-0.4592^{c}	-0.4671^{c}	-0.5228^{c}	-0.5489^{c}
	(-49.18)	(-45.78)	(-48.80)	(-45.22)	(-32.69)	(-31.22)	(-49.38)	(-48.16)	(-30.30)	(-28.50)	(-21.30)	(-17.51)
$LIQ^{AS}_{i,t}$		7.4526^{c}		6.7374^{c}		19.1540^{c}		8.0260^{c}		9.1468^{c}		21.1882^{b}
		(4.46)		(3.88)		(3.76)		(4.48)		(4.14)		(2.47)
$SYNC_{i,t}$		-0.0002		-0.0002		-0.0025^{c}		-0.0008		-0.0011		-0.0034
		(-0.39)		(-0.29)		(-2.65)		(-1.54)		(-0.68)		(-1.55)
$VROM_{i,t}$		0.0437^{c}		0.0440^{c}		0.0303^{b}		0.0240^{c}		0.0709^{c}		0.0084
		(7.81)		(7.63)		(1.96)		(4.09)		(5.25)		(0.29)
$\overline{R}^2$	0.48	0.49	0.48	0.49	0.55	0.57	0.50	0.51	0.49	0.50	0.54	0.56
# Firms	226;973		184;777		40;196		173;691		31;282		35;112	

TABLE 5

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

The variables are as detailed in Table 1 above. 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 second-step cross sections are reported 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**
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)
$\hat{\beta}_{i,1,t}^{MKT^+}$	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)
$\hat{\beta}_{i,2,t}^{MKT^-}$	-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)
$\hat{\beta}_{i,3,t}^{SMB}$	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)
$\hat{\beta}_{i,4,t}^{HML}$	-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)
$\hat{\beta}_{i,5,t}^{WML}$	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)
$IV_{i,t}^{+}$	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)
$IV_{i,t}^{-}$	-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)
$LIQ_{i,t}^{AMI}$	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)
$SYNC_{i,t}$	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)
$VROM_{i,t}$	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)
$\overline{R}^2$	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 6

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

The variables are as detailed in Table 1 above. 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 reported 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)
$LIQ^{AS}_{i,t}$	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)
$\bar{R}^2$	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 illiquidity												
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)
$LIQ^{AMI}_{i,t}$	-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)
$\bar{R}^2$	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

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