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Dinesh Gajurel
University of New Brunswick, Canada

Biplob Chowdhury
University of Tasmania, Australia

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Realized Volatility, Jump and Beta: Evidence from Canadian Stock Market*

Dinesh Gajurel† and Biplob Chowdhury‡

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Abstract

Inclusion of jump component in the price process has been a long debate in finance literature. In this paper, we identify and characterize jump risks in the Canadian stock market using high-frequency data from the Toronto Stock Exchange. Our results provide a strong evidence of jump clustering - about 90% of jumps occur within first 30 minutes of market opening for trade, and about 55% of jumps are due to the overnight returns. While average intraday jump is negative, jumps induced by overnight returns bring a cancellation effect yielding average size of the jumps to zero. We show that the economic significance of jump component in volatility forecasting is very nominal. Our results further demonstrate that market jumps and overnight returns bring significant changes in systematic risk (beta) of stocks. While the average effect of market jumps on beta is not significantly different than zero, the effect of overnight returns on beta is significant. Overall, our results suggest that jump risk is non-systematic in nature.

Keywords: Financial markets, stock price process, jumps, volatility, systematic risk

JEL Classifications: C58, G12

*The authors would like to dedicat this paper to Late Professor Mardi Dungey, University of Tasmania, Australia.

†Faculty of Management, University of New Brunswick, P. O. Box # 4400, Fredericton, New Brunswick, E3B 5A3 Canada. Centre for Applied Macroeconomics Analysis Crawford School of Public Policy, Australian National University, Canberra, Australia. T: +1 506 453 5170, E: dgajurel@unb.ca; dinesh.gajurel@utas.edu.au

‡Tasmanian School of Business and Economics, University of Tasmania, Hobart, Tasmania, Australia; Australian National Institute of Management and Commerce, Hobart, Australia. Centre for Applied Macroeconomics Analysis Crawford School of Public Policy, Australian National University, Canberra, Australia. E: biplob.chowdhury@utas.edu.au

1 Introduction

Inclusion of jump component in the price process has been a long debate in finance literature. Early pioneer works in finance theories such as option pricing models do not consider the jump component (Black and Scholes, 1973; Merton, 1973). In his seminal paper, Merton (1976) suggests importance of inclusion of jump in a stochastic price process but indicates that jump risks of individual stocks are non-systematic. If jump risks are non-systematic or idiosyncratic then it may not be important because only the systematic risk should be priced (Lintner, 1965; Mossin, 1966; Sharpe, 1964). However recent literature, both theoretical and empirical, advocate for including a jump component in the stochastic price process. The advancement in financial econometrics over last decade and availability of high frequency (tick) data now allow us to test many continuous time models with nearly equivalent discrete time data enriching our understanding of stock price process and the risk-return relationship (Eraker et al., 2003; Jacod and Todorov, 2009; Huang and Tauchen, 2005). The empirical literature provides strong evidences of presence of jumps in financial assets/markets (Alexeev et al., 2017; Bollerslev et al., 2016; Lahaye et al., 2011; Todorov and Bollerslev, 2010). Andersen et al. (2007), Corsi et al. (2010) and Vortelinos and Thomakos (2012) suggest that accounting for jump in realized volatility modeling and forecasting using high-frequency data is important. Eraker et al. (2003) and Bollerslev et al. (2016) provide further evidence of significant risk premia for the jump component (Bollerslev et al., 2016; Eraker et al., 2003). Bollerslev et al. (2016), Alexeev et al. (2017) and Alexeev et al. (2019) report that individual stocks respond differently to the market jumps than the continuous counterparts suggesting different systematic risk dynamics attributed to the market jumps. Gajurel et al. (2020) further show that systemic risk and systematic jump risk are related.

While understanding jump risk in equity price process is important for examining risk-return relationship and volatility modeling, the empirical evidences are still inconclusive. Therefore it is remained an empirical question to characterize jump risk. In this paper, we provide new insights to these issues by introducing a simple yet robust econometric framework to assess the jump risk. To date, most prior research on high-frequency finance has been done in the U.S. financial market. To what extent those findings, and explanations offered in the U.S. equity market hold in other international markets have been largely unexplored. In this paper, we fill this gap by examining the realized volatlity, market jumps in the Canadian equity market and the systematic risk of Canadian firms in the 2003-2015 period. We have four main quesitons: (i) Do jump charecteristics of Canadian stock market differ from the US equity market? (ii) How sensetive are the overnight returns in jump detection in the equity price process? (iii) Does decomposed realized volatlity into continious (bipower variation) and jump compoenents improve volatility forecasting, and if so, to what extent? (iv) Does the market jumps bring changes in the systematic risk of individual firms, and if so, to what extent jump risk matters?

Using Lee and Mykland (2007), hereafter LM, jump detection methodology, we first identify jumps in the key equity indices from the Toronto Stock Exchange (TSX) and characterize the jump risk. Specifically, we show the importance of overnight returns while assessing jump intensities. We then model for the potential gains from explicitly utilizing the jump component and leverage effect in volatility modeling. Finally, we examine the effect of market jumps and overnight returns in the systematic risk of individual stocks. Therefore, our paper sheds the first light on the statistical identification and numerical characterization of jump dynamics in Canadian equities.

Our results reveal that Canadian stock market experiences significant price discontinues (jumps) and average jump arrival rate is about 0.17 jumps per day. We find that about 55% of jumps are due to the overnight returns and about 90% of jumps occur within 30 minutes of the market opening for trading – providing a strong evidence of jump clustering. While looking at the jump intensities, our results show an asymmetric distribution of positive versus negative jumps for intraday returns but such asymmetry disappears when we include overnight returns in our analysis. Berkman et al. (2012) and Lou et al. (2018) suggest that institutional investors tend to trade relatively more during the day and individual investors trade relatively more overnight. Such differences in jump charecteristics in intraday versus overnight returns potentially reflecting the corresponding clientele effects. Therefore, it is important to incorporate overnight returns in jump risk analysis.[1]

In our paper, we further show that although the effect of jump component in volatility forecasting is statistically significant, its economic significance is very nominal - large portion of realized volatility is coming from the continuous component. When we examine effect of market

[1] Many papers exludes overnight returns in jump risk analysis such as in Alexeev et al. (2017), and Zhou and Zhu (2012).

jumps on the systematic risk (beta) of the stocks, we find a strong evidence of significant changes in the beta of individual stocks, however, the directions of changes are both ways. Stocks respond aggressively to the overnight market returns leading to a significant increase in the systematic risk. Our results for jump beta are in sharp contrast to the prior empirical research that reports consistently higher jump risk response (jump beta) of individual stocks (Alexeev et al., 2017; Bollerslev et al., 2016). Theoretically, average changes in individual stock's beta due to market jumps should be zero because as market jumps do not bring changes in continious beta, the changes should be reflected in the jump beta in a way that the beta of overall market portfolio should remain to 1. However that is not the case for overnight beta. The contradictive findings on jump beta could be attributed to the parametric versus non-parametric approches of disentangling the systematic risk. While we follow a simple yet robust parametric apparoch, Bollerslev et al. (2016) and Alexeev et al. (2017) use non-parametric appraoch of Todorov and Bollerslev (2010).[2]

The remainder of the paper is organized as follows. In Second 2, we provide empirical framework and includes Lee and Mykland (2007) approach to jump detection, HAR type of model of Corsi (2009) for volatility modeling, and an econometric framework to measure systematic risk including jump beta and overnight beta. Sample and data are explained in Section 3. The results are provided in Section 4, and Section 5 concludes the paper.

2 Empirical Framework

2.1 Identifying Jumps

One of the key advances in high frequency econometrics over the last decade is the development of test proceduresfor the presence of jumps in the equity price process during a certain time interval, say in a given day or at certain point of time within a given day. Dumitru and Urga (2012) state that there are nine different jump test procedures.[3] All the jump tests rely on Centre Limit Theorem-type results based on intraday sampling frequency. The test statistics are based on realized variance and some measures of quadratic variation which are robust to jumps in the

[2]See Todorov and Bollerslev (2010) for details on non-parametric approach.

[3]See Dumitru and Urga (2012) for detail review of nonparametric jump tests.

price processes. Since we are interested in identifying exact time of a jump as well as a number of jumps within a trading day, Lee and Mykland (2007) apparoch is flexible to this end. In addition, Dumitru and Urga (2012) show that LM apparoch performs best among all other approaches. Here we briefly describe the jump detection methodology advanced by Lee and Mykland (2007).

The log-price (p_t) process of an asset at time t can be represented by a stochastic differential equation as follows

$$dp_t = \alpha_t dt + \sigma_t dW_t + \kappa_t dJ_t, \tag{1}$$

where α_t is the time-varying drift of price process, σ_t is the time-varying volatility component, W_t is standard Brownian motion, J_t is the pure jump process and κ_t is the magnitude of jump at time t. The counting process $dJ_t = 1$ if there is a jump at time t, otherwise 0.

Indra-day returns are defined as follows:

$$r_{t,s} = p_{t,s.\delta} - p_{t,(s-1).\delta} \tag{2}$$

where $r_{t,s}$ refers to s^{th} intra-day return on day t and δ is the sampling frequency within each day and $0 < s < t$. The sampling frequency is such that $s < t$. For example, δ may refer to 15 minutes.

Barndorff-Nielsen and Shephard (2006) propose two measures for the quadratic variation process - realized variance (RV) and bi-power variation (BV) which converge uniformly as $\delta \to 0$ or $s = 1/\delta \to \infty$ to different measures of the underlying jump-diffusion process,

$$RV_t \equiv \sum_{s=1}^{n} r_{t,s}^2 \to \int_{t-1}^{t} \sigma_s^2 ds + \int_{t-1}^{t} \kappa_s^2 dJ_s, \tag{3}$$

$$BV_t \equiv \mu_1^{-2} \sum_{s=1}^{n} |r_{t,s}||r_{t,(s-1)}| \to \int_{t-1}^{t} \sigma_s^2 ds, \tag{4}$$

where $\mu_1 \equiv \sqrt{2/\pi} = E(|Z|)$ denotes the mean of the absolute value of a standard normal random variable Z (Andersen et al., 2001, 2002, 2007).

Since RV is inconsistent in the presence of jumps in a return process, BV has been suggested and shown to be a consistent estimator for the integrated volatility, even when there are jumps in return processes (Barndorff-Nielsen and Shephard, 2006). The first step in applying LM procedure is to use BV to standardize the intraday returns at t_s as follows:

$$z_{t,s} = |r_s|/\sqrt{V_s} \tag{5}$$

where V_s = $BV_{t,s}/K - 2$ with K the estimation window size on which $BV_{t,s}$ is calculated. The choice of estimation window size, K, depends on the sampling frequency. Lee and Mykland (2007) suggest to take $K = \sqrt{252.n}$ where n is the number of observations per day.

Now given that $z_{t,s}$ is asymptotically normal, jumps can be identified by comparing $z_{t,s}$ with the normal distribution thresholds. Since the standard thresholds prove too permissive, LM propose using critical values from the limit distribution of the maximum of the test statistics and show that this maximum converges, for $\delta \to 0$, to a Gumbel variable:

$$(max(z_t) - C_n)/S_n \to \xi, \quad P(\xi) = exp(-e^{-x}), \tag{6}$$

$$C_n = \sqrt{\frac{2log(n)}{2/\pi}} - \frac{log(\pi) + log(log(n))}{\sqrt{(4/\pi)(2log(n))}}, \tag{7}$$

$$S_n = \frac{1}{\sqrt{(2/\pi)(2log(n))}}. \tag{8}$$

Therefore, the threshold value for $(|z_t| - C_n)/S_n$ is β^*. Since $P(\xi \leq \beta^*) = exp(-e^{-\beta^*})$, at the 1 percent level of significance $\beta^* = -log(-log(0.99)) = 4.6001$. If $(|z_t| - C_n)/S_n$ is greater than 4.6001, we reject the null hypothesis of no jumps at time t, s.

2.2 Modeling Realized Volatility

Since volatility is very important for asset pricing, portfolio and risk management (Andersen et al., 2002, 2007; Das and Uppal, 2004; Eraker et al., 2003; Merton, 1973), we capitalize the volatility measures based on high-frequency data for modeling realized volatilities. In this paper, we use Heterogeneous Autoregressive model of Realized Volatility (HAR-RV) proposed by Corsi (2009) and its variants to model realized volatilities. The main advantage of the HAR-RV class of models is that it is very simple and flexible yet incorporates some of the stylized tenets of financial time series such as multiscaling and long memory (Corsi and Reno, 2012). Andersen et al. (2004) also suggest that simple models of realized volatility outperform the GARCH type and related stochastic volatility models in out-of-sample forecasting.

The HAR-RV class of model is based on so-called "Heterogenous Market Hypothesis" presented by Corsi (2009) and a multi-component volatility model with an additive hierarchical structure of realized volatility (Muller et al., 1997). The basic idea is that investors with different investment time horizons may perceive and respond to different types of volatility components. The daily HAR-RV model can be expressed as:

$$RV_{t+1} = \alpha + \beta_D RV_{D,t} + \beta_W RV_{W,t} + \beta_M RV_{M,t} + \varepsilon_{t+1} \tag{9}$$

where $RV_{D,t}$ refers to daily measure of realized volatility as specified in Eq. (3) RV_W is the average of daily RV from day $t-4$ to day t and RV_M is the average of daily RV from day $t-21$ to day t. The Eq. (9) be easily extended to $h = 1, 2, ..., T$ days ahead forecast:

$$RV_{t,t+h} = \alpha + \beta_D RV_{D,t} + \beta_W RV_{W,t} + \beta_M RV_{M,t} + \varepsilon_{t,t+h}. \tag{10}$$

For simplicity, we refer these $h = 1$, $h = 5$ and $h = 22$ as daily, weekly, and monthly volatilities, respectively.

Considering the importance of jump component in volatility modeling, Andersen et al. (2007) extend HAR-RV model of Corsi (2009) to HAR-RV-J model by including the jump component in the right-hand side of Eq. (10) as follows:

$$RV_{t,t+h} = \alpha + \beta_D RV_t + \beta_W RV_{W,t} + \beta_M RV_{M,t} + \beta_J J_t + \varepsilon_{t,t+h} \tag{11}$$

where $J_t = Max[RV_t - BV_t, 0]$.

Andersen et al. (2007)demonstrate important gains in terms of volatility forecast accuracy by explicitly differentiating the jump and continuous sample path components of realized volatilities in the model. The extended HAR-RV-CJ model is

$$RV_{t,t+h} = \beta_0 + \beta_{CD} BV_D + \beta_{CW} BV_{W,t} + \beta_{CM} BV_{M,t} + \beta_{JD} J_D + \beta_{JW} J_{W,t} + \beta_{JM} J_{M,t} + \varepsilon_{t,t+h} \tag{12}$$

where the variables in the right-hand side of the model are daily, weekly and monthly average of bipower variation and jump components respectively.

Furthermore, Corsi and Reno (2012) suggest that accommodating leverage effect in HAR-RV class of models is very important. Therefore, by capturing the leverage effects in Eq. (11)and Eq. (12)we express respective *Leverage Heterogeneous Auto-Regressive* (LHAR) models as follows:

$$RV_{t,t+h} = \alpha + \beta_D RV_t + \beta_W RV_{W,t} + \beta_M RV_{M,t} + \beta_J J_t + \lambda r_t * I[r_t < 0] + \varepsilon_{t,t+h}, \tag{13}$$

$$\begin{aligned} RV_{t,t+h} &= \beta_0 + \beta_{CD} BV_t + \beta_{CW} BV_{W,t} + \beta_{CM} BV_{M,t} + \beta_{JD} J_t \\ &\quad + \beta_{JW} J_{W,t} + \beta_{JM} J_{M,t} + \lambda r_t * I[r_t < 0] + \varepsilon_{t,t+h}. \end{aligned} \tag{14}$$

Practical use of volatility models and forecasts often involves standard deviations (square root form) or log forms (Andersen et al., 2007; Corsi, 2009; Corsi et al., 2010; Corsi and Reno, 2012)). Therefore, we also specify Eqs. (13) and 14 for $\sqrt{RV_t}$ and for $log(RV_t)$ respectively as follows:

$$\sqrt{RV_{t,t+h}} = \alpha + \beta_D \sqrt{RV_t} + \beta_W \sqrt{RV_{W,t}} + \beta_M \sqrt{RV_{M,t}} + \beta_J \sqrt{J_t} + \lambda r_t * I[r_t < 0] + \varepsilon_{t,t+h}, \tag{15}$$

$$\begin{aligned} \sqrt{RV_{t,t+h}} &= \beta_0 + \beta_{CD} \sqrt{BV_t} + \beta_{CW} \sqrt{BV_{W,t}} + \beta_{CM} \sqrt{BV_{M,t}} + \beta_{JD} \sqrt{J_t} \\ &\quad + \beta_{JW} \sqrt{J_{W,t}} + \beta_{JM} \sqrt{J_{M,t}} + \lambda r_t * I[r_t < 0] + \varepsilon_{t,t+h}. \end{aligned} \tag{16}$$

$$log(RV_{t,t+h}) = \alpha + \beta_D log(RV_t) + \beta_W log(RV_{W,t}) + \beta_M log(RV_{M,t}) + \beta_J log(1 + J_t) + \lambda log(1 + r_t) * I[r_t < 0] + \varepsilon_{t,t+h}, \quad (17)$$

$$log(RV_{t,t+h}) = \beta_0 + \beta_{CD} log(BV_t) + \beta_{CW} log(BV_{W,t}) + \beta_{CM} log(BV_{M,t}) + \beta_{JD} log(1 + J_t) + \beta_{JW} log(1 + J_{W,t}) + \beta_{JM} log(1 + J_{M,t}) + \lambda log(1 + r_t) * I[r_t < 0] + \varepsilon_{t,t+h}. \quad (18)$$

We estimate Eqs (13-18) with $h = 1$, $h = 5$, and $h = 22$ to make one day ahead, one week ahead, and one month ahead predictions respectively, by using ordinary least squares (OLS). The error terms, $\varepsilon_{t,t+h}$, are assumed to be serially correlated up to (at least) order $h - 1$ for the forecast horizon $h > 1$. Therefore, we rely on the Newey–West/Bartlett heteroskedasticity consistent covariance matrix estimator to obtain the corresponding standard errors allowing for serial correlation of up to order 5 ($h = 1$), 10 ($h = 5$), and 44 ($h = 22$), for respective parameter estimates.

2.3 Estimating Betas - Jump Beta and Overnight Beta

In this section, we propose a simple empirical framework to estimate jump beta and overnight beta for individual stocks. In a conventional Capital Asset Pricing Model (CAPM) setting, beta of stock i can be estimated as follows:

$$r_{i,t,s} = \beta_{1,i} r_{m,t,s} + \alpha_{0,i} + e_{i,t,s}. \quad (19)$$

where r_m is market return, r_i is stock return at time t, s, and $\beta_{1,i}$ is the beta of stock i, α_0 is intercept and e is the residual.

The literature suggests that stocks respond differently to jumps in the market (Alexeev et al., 2017; Bollerslev et al., 2016; Todorov and Bollerslev, 2010). To capture potential effects of market jumps on the systematic risk of stocks, we extend Eq. (19) as follows:

$$r_{i,t,s} = \beta_{1,i} r_{m,t,s} + \beta_{2,i}(r_{m,t,s} * I^J_{m,t,s}) + \alpha_{1,i} I^J_{m,t,s} + \alpha_{0,i} + e_{i,t,s} \quad (20)$$

where I^J is an idicator function that takes value 1 when there is a market jump, otherwise 0, $\beta_{1,i}$ is the beta of the stock when there is no jumps in the market and can be approximated as a continuous beta, $\beta_{2,i}$ measures changes in beta of stock i when market experiences jumps, and $\alpha_{2,i}$ shows any structural shift due to market jumps. The sum of β_1 and β_2 above can be defined as jump beta and loosely equivalent to discontinuous beta postulated in Todorov and Bollerslev (2010).

In addition, the literature suggests that stock returns exhibit different characteristics for intraday and overnight returns (Berkman et al., 2012; Bogousslavsky, 2016; Bollerslev et al., 2016; Lou et al., 2018). To examine how systematic risk changes during the overnight returns, we further extend Eq. (20) as follows:

$$\begin{aligned} r_{i,t,s} \quad = \quad & \beta_{1,i} r_{m,t,s} + \beta_{2,i}(r_{m,t,s} * I^J_{m,t,s}) + \beta_{3,i}(r_{m,t,s} * I^{ON}_{m,t,s}) \\ & + \beta_{4,i}(r_{m,t,s} * I^{ONJ}_{m,t,s}) + a_{1,i} I^J_{m,t,s} + a_{2,i} I^{ON}_{m,t,s} + a_{0,i} + e_{i,t,s} \end{aligned} \tag{21}$$

where I^{ON} is an idicator function that takes value 1 for overnight returns and 0 for intraday returns, and $I^{ONJ} = I^{ON} * I^J$. Now, $\beta_{3,i}$ captures the changes in beta of the stock during the overnight returns, $\beta_{4,i}$ measures the changes in beta during the overnight jumps, and $\alpha_{3,i}$ shows any structural shift due to overnight returns. The sum of $\beta_1 + \beta_3$ can be defined as overnight beta. Therefore our model in Eq. (21)is flexible to capture effects of market jump and overnight returns while estimating the beta of stocks.

3 Sample and Data

We use data from Canadian stock market provided by SIRCA/Thompson Reuters. To represent the Canadian stock market we use composite index for Toronto Stock Exchange (GSPTSE). We also use two other equity portfolios, the blue-chip stock index (TSE60), and the small cap index (SPTSES). The motive behind using different indices for jump identification purpose is to explore the heterogeneity across those portfolios if there is any.

Sampling frequency has been a debatable issue in high frequency literature. Using a very high-frequency data such as 1-minute may suffer from market microstructure noise where as using lower frequency data such as sixty-minute may suffer from loss of additional information. The literature suggests that 15-minute sampling helps to maintain a balance between market microstructure noise and estimation bias (Hansen and Lunde, 2006; Lahaye et al., 2011). We, hence, use fifteen-minute frequency in this study in order to ensure minimal distortion or bias due to noise. This sampling frequency is close to the frequency chosen by Bollerslev et al. (2008), who utilize volatility signature plots for similar large-cap companies from the US to determine optimal frequency in their analysis. Furthermore, Lee (2012) confirms that using fifteen-minute data provides satisfactory power of the LM test. The significance level for the LM test is 1%, and we do not exclude the possibility of detecting jumps in overnight returns. The overnight return refers to log difference of 9:30 am price of day t and 4:00pm price of day $t-1$.

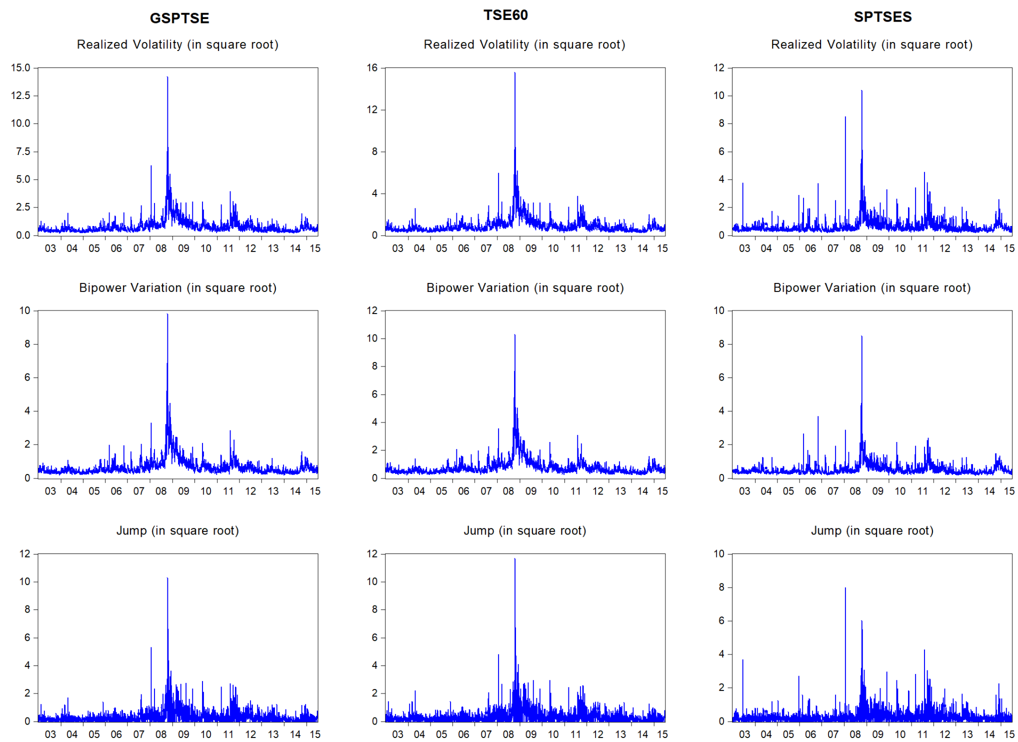
Our dataset covers a long time span for about thirteen and half-years of high-frequency data for Toronto Stock Exchange (TSX) composite index, large cap index, and small-cap index. The sample period in this paper extends from January 2, 2003, to June 30, 2015, for a total of 3,074 trading days over twelve and half years. Raw data are collected from the Thompson Reuters Tick History database, which contains tick-by-tick data. The sample is based on price data from 9:30 a.m. to 4:00 p.m., i.e., the normal trading hours on TSX. To examine the effect of market jumps in the systematic risk, we select the most actively traded Canadian large-cap stocks listed in Toronto Stock Exchange in order to maintain sufficient degrees of liquidity. Of 60 stocks, we exclude eighteen stocks because of a significant incidence of missing data or unusual name changes, either of which could create significant bias in empirical results. The name sample firms with ticker symbol and corresponding sectoral classification by TSX are provided in the Appendex of this paper.

4 Results

4.1 Identified Jumps in the Market Index(s)

Figure 1 shows the daily realized volatility, bipower variation and jumps in square root form (standard deviation) for the GSPTSE, TSE60 and SPTSES indices. The market volatilities are relatively stable before 2006 and increased during the global financial crisis period, reaching at a

Figure 1: Realized volatilities, bipower variations and jumps



peak during the collapse of the Lehman Brothers in September 2008. The bottom panels of the Figure 1 reveal although the larger portion of realized volatilities are coming from the continious compoenent (BV), many of the largest realized volatilities are associated with the jumps in the underlying price process.

The summary statistics for detected jump counts for three equity indices are presented in Table 1. Over the sample period, we find 508 jumps in the composite market index (GSPTSE) returns. Such price discontinuities are relatively less frequent in the TSE60 index returns. The number of jumps in TSE60 index is 459. However, when we look at the jump frequency for small-cap stock index, we find that the the small-cap stocks experience more frequent price discontinuities (613 jumps) than TSE60 and the composite index. Our results are consistent with the notion that small-cap stocks are more volatile than the blue-cheap stocks, therefore exhibit more price discountinuties.

In high-frequency financial econometric literature, there is no unanimous practice about inclusion of overnight returns. For example, Alexeev et al. (2017) exclude overnight returns whereas

Table 1: Descriptive statistics for jump counts and jump size

	Including overnight returns			Excluding overnight returns		
	GSPTSE	TSE60	SPTSES	GSPTSE	TSE60	SPTSES
Panel A: Descriptive statistics for jump counts						
# of jumps	508	459	613	230	214	347
# of jumps per year	40.64	36.72	49.04	18.40	17.12	27.76
# of jumps per month	3.39	3.06	4.09	1.53	1.43	2.31
# of jump per day	0.17	0.15	0.20	0.07	0.07	0.11
# of days with no jumps	2594	2642	2524	2858	2872	2755
# of days with 1 jump	453	406	488	203	190	293
# of days with 2 jumps	26	25	61	12	12	24
# of days with 3 jumps	1	1	1	1	0	2
Jump probability	0.1561	0.1405	0.1789	0.0703	0.0657	0.1038
Panel B: Descriptive statistics for jump size						
# of positive (+) jumps	244	214	312	93	85	120
proportion of (+) jumps	48.03	46.62	50.90	40.43	39.72	34.58
# of negative (-) jumps	264	245	301	137	129	227
of (-) jumps	51.97	53.28	49.10	59.57	60.28	65.42
mean of jump returns (%)	-0.0612	-0.0814	-0.0236	-0.1466	-0.1450	-0.2164
standard error of mean	(0.0584)	(0.0674)	(0.0696)	(0.0531)	(0.0622)	(0.0401)
median jump returns (%)	-0.3638	-0.4525	0.3124	0.8048	0.9100	0.7466
standard deviation (%)	1.3170	1.4441	1.1773	0.8048	0.5116	0.4291
maximum (%)	13.015	14.250	9.219	3.6474	4.3308	4.3636
minimum (%)	-7.026	-7.294	-8.322	-2.7827	-3.1091	-3.6946
average size of (+) jumps	0.9469	1.065	0.8464	0.6505	0.7822	0.6133
median (+) jumps	0.6857	0.7727	0.6081	0.4750	0.6013	0.4890
stdev of (+) jumps	0.9950	1.1435	0.7245	0.5116	0.5922	0.4795
average size of (-) jumps	-0.9929	-1.0827	-0.9254	-0.6877	-0.7560	-0.6550
median (-) jumps	-0.7714	-0.8626	-0.6675	-0.5235	-0.6027	-0.5455
stdev of (-) jumps	0.7840	0.7835	0.8249	0.4291	0.4481	0.4167

Lee (2012) includes overnight returns. We are interested how robust are the jump counts if we remove the overnight returns from our sample. To this end, we remove the overnight returns and reimplement the LM jump test procedure. The results reveal significantly less number of jumps in all three indices. More specifically, we find 230 jumps in the composite index, 214 jumps in the TSE60 index and 347 in small-cap index. These numbers translate into about 43% to 55% fewer jumps. Therefore, about half of the jumps are due to overnight returns indicating the importance of inclusion of overnight returns in the data.[4] A significant price change during the over

[4]Note that computationally the number of jumps for data excluding overnight returns is not equals to number of jumps for data including overnight returns minus number of jumps that occurred at overnight returns. See LM jump detection methodology in Section 2.

night period is very important for the investors as such price changes are information contained (Bollerslev et al., 2016; Lou et al., 2018; Patton and Verardo, 2012). Therefore, we retain overnight returns in our data for further analysis in rest of the paper.

The number of jumps per day (total number of jumps divided by number of trading days) indicates the average rate of jump arrival. It is about 17 percent for the composite index, 15 percent for the TSE60 index, and about 20 percent for the small-cap index. However, these statistics drop to about 7 percent for composite and TSE60 index and about 11 percent for small-cap index when we exclude overnight returns from the data. The rates are calculated with the assumption that the jump arrival rate is constant over time. We observe, however, that jumps do not occur on regular time space. Therefore, models with constant jump intensities may not be appropriate.

Regarding the jump probability, our results provided in Table 1 reveal that among the 3074 trading days in our sample, 2594 trading days do not experience price discontinuous in the composite index and in remaining 480 days, there are at least one jump which translate into a jump probability of 0.1561.[5] The jump probability for the TSX60 index is 0.1405 and for the small-cap index is 0.1789. Our results also show that in some cases, the jump occurs more than once in a trading day. While looking at the TSX composite index, there are 26 trading days having two jumps per day, and 1 trading day having 3 jumps. In case of the small-cap index, during the sample period, 62 trading days experience at least two jumps per day. The days with multiple jumps and jump probability statistics declines in a proportional rate when we exclude overnight returns from the tick data.

While looking at the jump intensities, the results in Table 1 Panel B reveal a very interesting insight. The jumps are not symmetrically distributed, they are left skewed. About 60 (in the composite and TSX60 indices) to 65 (in the small-cap index) percent jumps are negative jumps. The average jump size is about - 0.15 percent for the composite and TSX60 indices and about -0.22 percent for the small-cap index. The null of average jump return, $\mu \geq 0$ is rejected for all three indices. The absolute size of positive and negative jumps are similar although the biggest positive jump (price gain) was as high as 3.65 percent (in 15 mins interval) and largest negative jump (price decline) was as high as 2.78 percent (in 15 mins interval).

[5]Jump probability slightly differs from average jump arrival rate because in some cases there are more than one jumps in a single trading day.

Table 2: Timing of the jumps

Time	Including g overnight returns									Excluding overnight returns								
	GSPTSE			TSE60			SPTSES			GSPTSE			TSE60			SPTSES		
	# of jumps	Cum freq	Cum %	# of jumps	Cum freq	Cum %	# of jumps	Cum freq	Cum %	# of jumps	Cum freq	Cum %	# of jumps	Cum freq	Cum %	# of jumps	Cum freq	Cum %
9:30 AM	357	357	70.28	314	314	68.41	393	393	64.11									
9:45 AM	103	460	90.55	100	414	90.20	145	538	87.77	146	146	63.48	136	136	63.55	214	214	61.67
10:00 AM	14	474	93.31	15	429	93.46	14	552	90.05	24	170	73.91	24	160	74.77	29	243	70.03
10:15 AM	8	482	94.88	8	437	95.21	6	558	91.03	13	183	79.57	12	172	80.37	13	256	73.78
10:30 AM	5	487	95.87	4	441	96.08	3	561	91.52	8	191	83.04	7	179	83.64	7	263	75.79
10:45 AM	3	490	96.46	3	444	96.73	5	566	92.33	8	199	86.52	8	187	87.38	13	276	79.54
11:00 AM	2	492	96.85	2	446	97.17	3	569	92.82	4	203	88.26	2	189	88.32	7	283	81.56
11:15 AM	2	494	97.24	1	447	97.39	2	571	93.15	2	205	89.13	2	191	89.25	4	287	82.71
11:30 AM	0	494	97.24	0	447	97.39	0	571	93.15	1	206	89.57	1	192	89.72	3	290	83.57
11:45 AM	0	494	97.24	0	447	97.39	0	571	93.15	0	206	89.57	0	192	89.72	1	291	83.86
12:00 PM	2	496	97.64	2	449	97.82	0	571	93.15	2	208	90.43	2	194	90.65	1	292	84.15
12:15 PM	0	496	97.64	0	449	97.82	0	571	93.15	0	208	90.43	0	194	90.65	1	293	84.44
12:30 PM	0	496	97.64	0	449	97.82	1	572	93.31	0	208	90.43	0	194	90.65	1	294	84.73
12:45 PM	1	497	97.83	1	450	98.04	2	574	93.64	1	209	90.87	1	195	91.12	3	297	85.59
1:00 PM	0	497	97.83	0	450	98.04	0	574	93.64	0	209	90.87	0	195	91.12	0	297	85.59
1:15 PM	0	497	97.83	0	450	98.04	0	574	93.64	0	209	90.87	0	195	91.12	0	297	85.59
1:30 PM	0	497	97.83	0	450	98.04	0	574	93.64	0	209	90.87	0	195	91.12	0	297	85.59
1:45 PM	1	498	98.03	1	451	98.26	0	574	93.64	1	210	91.30	1	196	91.59	0	297	85.59
2:00 PM	0	498	98.03	0	451	98.26	1	575	93.80	1	211	91.74	1	197	92.06	1	298	85.88
2:15 PM	2	500	98.43	1	452	98.47	3	578	94.29	5	216	93.91	3	200	93.46	4	302	87.03
2:30 PM	3	503	99.02	2	454	98.91	3	581	94.78	4	220	95.65	5	205	95.79	3	305	87.90
2:45 PM	1	504	99.21	1	455	99.13	1	582	94.94	1	221	96.09	1	206	96.26	1	306	88.18
3:00 PM	1	505	99.41	1	456	99.35	1	583	95.11	1	222	96.52	1	207	96.73	2	308	88.76
3:15 PM	1	506	99.61	1	457	99.56	2	585	95.43	1	223	96.96	1	208	97.20	2	310	89.34
3:30 PM	0	506	99.61	0	457	99.56	1	586	95.60	1	224	97.39	1	209	97.66	1	311	89.63
3:45 PM	0	506	99.61	1	458	99.78	2	588	95.92	2	226	98.26	2	211	98.60	3	314	90.49
4:00 PM	2	508	100	1	459	100	25	613	100	4	230	100	3	214	100	33	347	100

However, when we incorporate both intraday and overnight returns in our analysis, the results show that there is a symmetric distribution of positive vs. negative jumps. For the composite index, the average size of positive jump returns is about 0.95 percent and average size of negative jump returns is about -0.99 percent. The statistics and patterns are similar in other two indices. Although the average of all jump returns is negative for all three indices, the mean is not significantly different from zero, that is, we couldn't reject the null hypothesis of mean jump return, $\mu = 0$ at 99.9% level of significance. These results imply that the stock price experiences both positive and negative jumps with a cancellation effect resulting into average jump size to zero. However, the price discontinuities occurred during the trading hours are less idiosyncratic in nature, therefore has no cancellation effect.

Our results shed some lights on contradictive empirical findings in the literature. Lou, Polk and Skouras (2018) show different risk-return dynamics of overnight versus intraday expected returns. Under different trading strategies, profits are earned entirely overnights or entirely intraday typically with profits of opposite signed across these components. Zhou and Zhu (2012) find that average jump return is positive.[6] Berkman et al. (2012) and Lou et al. (2018) find that institutional investors tend to trade relatively more during the day and individual investors trade relatively more overnight, thus indirectly suggesting that the overnight jumps could be more idiosyncratic than the intraday jumps.

At what times do jumps occur more often? Table 2 presents the timing of the jumps. It reports the percentage of detected jumps during specific time intervals (15 mins) in a trading day among all realized jumps. We find that about 60% jumps occur in the overnight returns and about 89% jumps occur within the first 30 minutes of trading hours. Even if we exclude overnight returns and assess the jump counts, about 70% of the jumps are clustered within the first 30 minutes of the trading, providing a strong evidence of jump clustering. The evidence for such a strong jump clustering suggests that the accumulated information during the overnight period, although largely reflected in first transaction, market learning keep evolving for quite sometime. The results also show that few jumps are clustered around the last 60 minutes of the trading hours (from 15:00 to 16:00). Although all three indices have some degree of closing hour jump clustering, it is more

[6]They however do not perform whether average jump return is singifiantly different than zero.

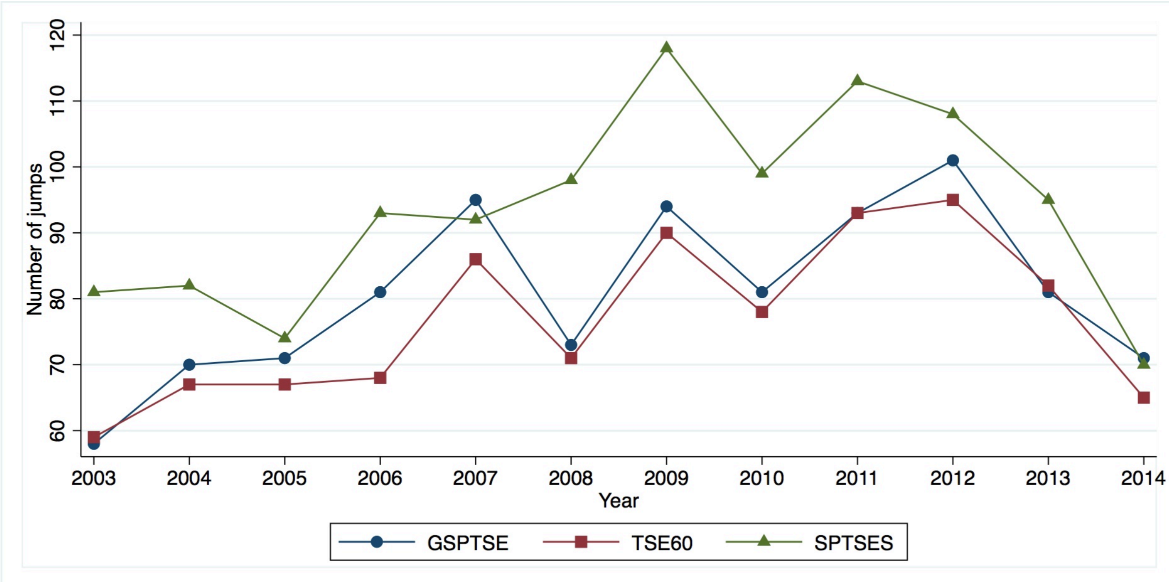
Table 3: Timing of the Jumps

	Including overnight returns			Excluding overnight returns		
	GSPTSE	TSE60	SPTSES	GSPTSE	TSE60	SPTSES
Panel A: On which day do jumps occur more often?						
Mon	0.1949	0.2004	0.2333	0.1870	0.1776	0.1931
Tue	0.2205	0.2244	0.2268	0.1522	0.1449	0.1988
Wed	0.1713	0.1590	0.1876	0.2522	0.2430	0.2536
Thu	0.2165	0.2004	0.1909	0.2435	0.2523	0.1960
Fri	0.1969	0.2157	0.1615	0.1652	0.1822	0.1585
Panel B: In which months do jumps occur more often?*						
Jan	0.0949	0.0955	0.0837	0.1198	0.1095	0.0934
Feb	0.0650	0.0586	0.0730	0.0369	0.0448	0.0633
Mar	0.0877	0.0923	0.0873	0.1244	0.1244	0.1205
Apr	0.0795	0.0793	0.0899	0.0922	0.0896	0.0843
May	0.0867	0.0782	0.0855	0.0599	0.0597	0.0964
Jun	0.0743	0.0749	0.0801	0.0553	0.0597	0.0783
Jul	0.0908	0.0923	0.0846	0.1198	0.1045	0.0843
Aug	0.0857	0.0836	0.0953	0.0645	0.0597	0.0873
Sep	0.1032	0.1010	0.0899	0.1014	0.1095	0.0994
Oct	0.0857	0.0934	0.0890	0.0922	0.1045	0.0663
Nov	0.0702	0.0749	0.0739	0.0461	0.0547	0.0572
Dec	0.0764	0.0760	0.0677	0.0876	0.0796	0.0693
Panel C: Annual jump frequency						
2003	58	59	81	27	27	34
2004	70	67	82	29	25	27
2005	71	67	74	21	19	28
2006	81	68	93	19	15	38
2007	95	86	92	19	17	28
2008	73	71	98	14	13	28
2009	94	90	118	14	12	31
2010	81	78	99	14	13	18
2011	93	93	113	14	16	26
2012	101	95	108	14	13	28
2013	81	82	95	20	20	26
2014	71	65	70	12	11	20
2015**	38	38	41	13	13	15

*Excludes jumps for 2015

**Results are for first six months (Jan-June) only.

Figure 2: Annual Jump Frequency



evident in the small-cap index which experiences about 5% (when data include overnight returns) and about 10% (when data exclude overnight returns) of the jumps during the closing hour. The evidence for jump clustering presented here can be aligned with the literature on market anomalies which provide evidence of intra-day trading patterns. Admati and Pfleiderer (1988) state that more intensive trading take place during the beginning and the end of the trading day along with higher price volatility compared to other trading hours. Harris (1986) show that prices and last trades tend to be up during the first 45 minutes of trading sessions. Gao et al. (2018) show that first half-hour returns on the market predict the last half-hour return. Coval and Shumway (2005); Haigh and List (2005); Odean (1998), all suggest that day-traders can be subject to the disposition effect. Heston et al. (2010) find a striking intraday pattern that returns on certain individual stocks tend to persist at the same half-hour intervals across trading days. Such behavioral and trading patterns can be attributed to the jump clusting in the market. Our results also align with Bollerslev et al. (2008)) and Lee (2012) who find about 70% jumps occur within 30 mins of trading hours in the S&P 500 index.

The literature on stock market anomalies suggests the day-of-week effects and the month-of-year effects (French, 1980; Solnik and Bousquet, 1990; Szakmary and Kiefer, 2004; Zhang et al., 2017). Our results reveal that often the jumps are evenly distributed among the weekdays although Tuesday experiences relatively more jumps for all three indices. However, the results from the restricted sample (excluding overnight returns) suggest that mid-week day, i.e. Wednesday experiences largest number of jumps, accounting for about 25 percent of all jumps. Regarding the month of the year pattern, often in the month of January and September, stock market experiences more jumps on an average and in the month of February, June, and November, it experiences fewer jumps. Figure 2 shows the number of jump over the sample period. As our sample ends in June 2015, we have excluded Year 2015 from the graph. During the sample period of 2003-2014, we find lowest number of jumps in 2003 and highest number of jump in 2009.

4.2 Volatility Forecasting: Realized Volatilities, Jumps and Leverage Effects

We now examine importance of jumps in volatility modelling for the Canadian equity indices in our sample by implementing HAR-RV class of models of Corsi (2009). Table 4 reports the linear and non-linear forms of HAR-RVJ regression results. Our discussion here will be more focused on the non-linear (square root form or standard deviation form). The results show that daily, weekly and monthly measures of volatility reveal that the estimates for β_D, β_W, and β_M confirm the existence of highly persistent volatility dependence. The relative importance of daily volatility decreases from daily to the weekly to the monthly regressions whereas monthly volatility tends to be relatively important for weekly and monthly regressions. The estimates for the jump component are systematically negative across all the models and all the indices, and overwhelmingly significant in daily and weekly regressions. The negative sign of the estimate for the jump component, β_J, indicates that although the realized volatilities are highly persistent, for the days in which part of the realized volatilities comes from the jump component, the increase in the volatility on the following day will be reduced. In other words, the persistency of volatility diminishes for the following day's realized volatility if the realized volatility in the given day is largely attributed to jumps.

Furthermore, our results provide a strong evidence of leverage effect. The coefficient estimate for λ is statistically significant in one-day ahead and one-week ahead forecasting indicating that daily negative returns affect not only the next day volatility but also the next week volatility. Our finding suggests that the investors might aggregate daily and weekly memories, observing

Table 4: LHAR-RVJ Regressions

	$RV_{t,t+h}$			$(RV_{t,t+h})^{1/2}$			$log(RV_{t,t+h})$		
	$h = 1$	$h = 5$	$h = 22$	$h = 1$	$h = 5$	$h = 22$	$h = 1$	$h = 5$	$h = 22$
Panel A: GSPTSE									
β_D	0.581***	0.468**	0.119	0.323***	0.235***	0.114**	0.527***	0.434***	0.140**
	(0.088)	(0.197)	(0.074)	(0.039)	(0.055)	(0.044)	(0.066)	(0.134)	(0.067)
β_W	0.345***	0.273**	0.172	0.423***	0.328***	0.110	0.352***	0.269***	0.151
	(0.093)	(0.110)	(0.132)	(0.054)	(0.061)	(0.119)	(0.073)	(0.083)	(0.129)
β_M	0.167**	0.315***	0.492***	0.228***	0.368***	0.585***	0.173***	0.325***	0.514***
	(0.083)	(0.068)	(0.109)	(0.045)	(0.056)	(0.091)	(0.062)	(0.063)	(0.109)
β_J	-0.422***	-0.422***	-0.071	-0.095***	-0.088***	-0.026	-0.322***	-0.328***	-0.069
	(0.079)	(0.153)	(0.071)	(0.013)	(0.018)	(0.021)	(0.049)	(0.089)	(0.056)
λ	-0.128***	-0.076***	-0.029	-0.068***	-0.037***	-0.008	-0.070***	-0.033	-0.005
	(0.031)	(0.027)	(0.020)	(0.008)	(0.009)	(0.008)	(0.014)	(0.021)	(0.014)
α	0.021	0.067	0.180***	0.038**	0.080***	0.162***	0.787***	0.773***	0.635***
	(0.027)	(0.046)	(0.048)	(0.016)	(0.031)	(0.047)	(0.082)	(0.129)	(0.114)
$\bar{R}^2$	0.6999	0.5677	0.3821	0.7265	0.6146	0.4703	0.7298	0.6021	0.4298
Panel B: TSE60									
β_D	0.566***	0.452**	0.093	0.320***	0.235***	0.098**	0.506***	0.418***	0.123**
	(0.087)	(0.201)	(0.058)	(0.038)	(0.057)	(0.040)	(0.062)	(0.135)	(0.051)
β_W	0.341***	0.277**	0.188	0.431***	0.335***	0.122	0.358***	0.276***	0.162
	(0.094)	(0.112)	(0.138)	(0.055)	(0.060)	(0.122)	(0.074)	(0.084)	(0.136)
β_M	0.160**	0.308***	0.484***	0.216***	0.358***	0.581***	0.167***	0.320***	0.512***
	(0.081)	(0.070)	(0.109)	(0.045)	(0.057)	(0.093)	(0.060)	(0.065)	(0.110)
β_J	-0.386***	-0.390**	-0.024	-0.083***	-0.081***	-0.010	-0.279***	-0.289***	-0.032
	(0.079)	(0.159)	(0.057)	(0.012)	(0.018)	(0.020)	(0.043)	(0.089)	(0.045)
λ	-0.136***	-0.077***	-0.030	-0.067***	-0.036***	-0.008	-0.063***	-0.022	0.002
	(0.031)	(0.025)	(0.021)	(0.008)	(0.008)	(0.007)	(0.013)	(0.021)	(0.015)
α	0.026	0.076	0.204***	0.042**	0.085**	0.173***	0.720***	0.689***	0.555***
	(0.029)	(0.053)	(0.056)	(0.017)	(0.034)	(0.052)	(0.082)	(0.138)	(0.139)
$\bar{R}^2$	0.7212	0.5876	0.3986	0.7371	0.6257	0.4787	0.7475	0.6194	0.4473
Panel C: SPTSES									
β_D	0.403***	0.326***	0.182*	0.298***	0.211***	0.115**	0.424***	0.206***	0.201*
	(0.097)	(0.113)	(0.097)	(0.041)	(0.052)	(0.050)	(0.085)	(0.068)	(0.108)
β_W	0.390***	0.216**	0.035	0.345***	0.227***	0.039	0.358***	0.242***	0.026
	(0.105)	(0.086)	(0.084)	(0.056)	(0.059)	(0.074)	(0.083)	(0.066)	(0.079)
β_M	0.225***	0.351***	0.479***	0.276***	0.379***	0.499***	0.236***	0.356***	0.480***
	(0.081)	(0.090)	(0.084)	(0.046)	(0.061)	(0.076)	(0.066)	(0.081)	(0.083)
β_J	-0.373***	-0.321***	-0.201*	-0.130***	-0.103***	-0.062*	-0.360***	-0.221***	-0.195*
	(0.087)	(0.082)	(0.114)	(0.020)	(0.021)	(0.033)	(0.072)	(0.064)	(0.109)
λ	-0.099***	-0.083**	-0.023	-0.059***	-0.036***	-0.013	-0.054***	-0.081**	-0.008
	(0.026)	(0.037)	(0.016)	(0.008)	(0.009)	(0.009)	(0.016)	(0.034)	(0.008)
α	0.054*	0.122***	0.233***	0.089***	0.161***	0.275***	0.920***	1.160***	1.166***
	(0.031)	(0.042)	(0.035)	(0.022)	(0.037)	(0.046)	(0.118)	(0.136)	(0.125)
$\bar{R}^2$	0.4174	0.2929	0.1474	0.4788	0.3430	0.2040	0.4480	0.3372	0.1705
n	3052	3048	3031	3052	3048	3031	3052	3048	3031

Table 5: LHAR-RV-BVJ Regressions

	$RV_{t,t+h}$			$(RV_{t,t+h})^{1/2}$			$log(RV_{t,t+h})$		
	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
Panel A: GSPTSE									
β_{CD}	0.435***	0.334	0.143**	0.235***	0.146***	0.099**	0.398***	0.296*	0.134**
	(0.088)	(0.216)	(0.063)	(0.039)	(0.055)	(0.041)	(0.073)	(0.153)	(0.067)
β_{CW}	0.693***	0.628***	0.119	0.756***	0.695***	0.111	0.744***	0.745***	0.110
	(0.201)	(0.213)	(0.295)	(0.087)	(0.093)	(0.200)	(0.166)	(0.162)	(0.301)
β_{CM}	-0.081	-0.053	0.505	0.113	0.165	0.729***	-0.002	-0.018	0.668*
	(0.158)	(0.172)	(0.382)	(0.083)	(0.130)	(0.279)	(0.131)	(0.168)	(0.391)
β_{JD}	-0.049	-0.116	-0.014	-0.040***	-0.033*	-0.015	-0.199***	-0.199*	-0.061
	(0.039)	(0.088)	(0.026)	(0.015)	(0.017)	(0.018)	(0.059)	(0.110)	(0.050)
β_{JW}	-0.266	-0.301**	0.106	-0.346***	-0.379***	-0.006	-0.546***	-0.657***	0.052
	(0.167)	(0.132)	(0.194)	(0.057)	(0.070)	(0.114)	(0.186)	(0.160)	(0.281)
β_{JM}	0.387***	0.648***	0.154	0.118*	0.228*	-0.181	0.267*	0.553**	-0.267
	(0.144)	(0.192)	(0.416)	(0.069)	(0.129)	(0.271)	(0.160)	(0.234)	(0.525)
λ	-0.118***	-0.067**	-0.024	-0.068***	-0.037***	-0.009	-0.068***	-0.029	-0.006
	(0.028)	(0.026)	(0.018)	(0.008)	(0.009)	(0.008)	(0.012)	(0.021)	(0.013)
α	0.011	0.069*	0.173***	0.021	0.069**	0.148***	0.938***	0.717***	0.867*
	(0.027)	(0.039)	(0.048)	(0.017)	(0.030)	(0.044)	(0.140)	(0.221)	(0.459)
$\bar{R}^2$	0.7152	0.5784	0.3849	0.7345	0.6232	0.4710	0.7364	0.6112	0.4301
Panel B: TSE60									
β_{CD}	0.445***	0.355	0.136**	0.243***	0.162***	0.085**	0.395***	0.313**	0.131**
	(0.077)	(0.225)	(0.063)	(0.038)	(0.058)	(0.040)	(0.064)	(0.157)	(0.064)
β_{CW}	0.654***	0.545**	0.122	0.717***	0.630***	0.119	0.690***	0.651***	0.111
	(0.193)	(0.216)	(0.278)	(0.089)	(0.087)	(0.197)	(0.162)	(0.156)	(0.285)
β_{CM}	-0.062	-0.037	0.440	0.132	0.197	0.722**	0.033	0.013	0.605
	(0.154)	(0.168)	(0.425)	(0.083)	(0.128)	(0.306)	(0.127)	(0.165)	(0.426)
β_{JD}	-0.034	-0.118	0.008	-0.035**	-0.036*	-0.000	-0.172***	-0.192*	-0.038
	(0.038)	(0.099)	(0.025)	(0.014)	(0.019)	(0.016)	(0.050)	(0.114)	(0.044)
β_{JW}	-0.274	-0.225	0.136	-0.306***	-0.312***	-0.003	-0.485**	-0.537***	0.069
	(0.196)	(0.145)	(0.190)	(0.062)	(0.063)	(0.108)	(0.196)	(0.153)	(0.255)
β_{JM}	0.377**	0.656***	0.233	0.089	0.187	-0.181	0.216	0.530**	-0.166
	(0.157)	(0.203)	(0.515)	(0.071)	(0.129)	(0.303)	(0.164)	(0.238)	(0.605)
λ	-0.124***	-0.067***	-0.025	-0.067***	-0.036***	-0.008	-0.060***	-0.017	0.001
	(0.027)	(0.024)	(0.018)	(0.008)	(0.008)	(0.007)	(0.012)	(0.021)	(0.013)

continue ...

Table 5: LHAR-RV-BVJ Regressions *continued*

	$RV_{t,t+h}$			$(RV_{t,t+h})^{1/2}$			$log(RV_{t,t+h})$		
	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$	$h=1$	$h=5$	$h=22$
α	0.012	0.081*	0.201***	0.025	0.075**	0.159***	0.885***	0.559**	0.678
	(0.030)	(0.042)	(0.054)	(0.018)	(0.032)	(0.046)	(0.145)	(0.265)	(0.622)
$\bar{R}^2$	0.7368	0.5962	0.4018	0.7443	0.6323	0.4794	0.7537	0.6265	0.4472
Panel C: SPTSES									
β_{CD}	0.231**	0.156	0.061*	0.207***	0.101**	0.060*	0.264***	0.015	0.080*
	(0.092)	(0.111)	(0.037)	(0.043)	(0.047)	(0.033)	(0.088)	(0.072)	(0.048)
β_{CW}	0.680***	0.535***	0.232	0.638***	0.583***	0.220	0.755***	0.678***	0.297
	(0.171)	(0.162)	(0.226)	(0.092)	(0.101)	(0.151)	(0.151)	(0.130)	(0.249)
β_{CM}	0.271**	0.475**	0.566***	0.325***	0.431***	0.523***	0.271**	0.491**	0.578***
	(0.135)	(0.240)	(0.192)	(0.086)	(0.151)	(0.161)	(0.118)	(0.206)	(0.216)
β_{JD}	-0.044	-0.033	-0.029	-0.066***	-0.026	-0.023	-0.195**	-0.023	-0.070
	(0.039)	(0.030)	(0.024)	(0.022)	(0.020)	(0.019)	(0.079)	(0.071)	(0.046)
β_{JW}	-0.110	-0.235**	-0.202	-0.305***	-0.371***	-0.188*	-0.546***	-0.605***	-0.377
	(0.081)	(0.099)	(0.153)	(0.062)	(0.077)	(0.104)	(0.139)	(0.147)	(0.281)
β_{JM}	-0.005	-0.044	0.093	-0.068	-0.074	-0.034	-0.085	-0.248	-0.177
	(0.112)	(0.222)	(0.208)	(0.078)	(0.142)	(0.159)	(0.145)	(0.269)	(0.295)
λ	-0.098***	-0.081**	-0.023	-0.059***	-0.035***	-0.012	-0.055***	-0.081**	-0.009
	(0.025)	(0.035)	(0.016)	(0.008)	(0.009)	(0.009)	(0.016)	(0.034)	(0.008)
α	0.015	0.073	0.202***	0.056**	0.122***	0.255***	1.364***	1.792***	1.579***
	(0.035)	(0.048)	(0.041)	(0.023)	(0.039)	(0.052)	(0.146)	(0.300)	(0.301)
$\bar{R}^2$	0.4312	0.3108	0.1525	0.4900	0.3593	0.2078	0.4588	0.3534	0.1766
n	3052	3048	3031	3052	3048	3031	3052	3048	3031

and reacting to negative price changes occurred in last day or week with a persistent leverage effect. However such persistency vanishes for monthly horizon. The results also indicate that negative returns make market more volatile which is consistent with literature in financial crisis and contagion. Downward pressure in market may follow some behavior pattern in stock market such as herd & sell-offs (Calvo and Mendoza, 2000; Dungey and Gajurel, 2015; Upper, 2011).

Andersen et al. (2007) suggest to separately measuring volatility forecasting from the the individual components of the realized volatility. To this end, we implement HAR-RV-CJ model where our right-hand side variables are daily, weekly and monthly measures of bipower variations and jumps. The results reported in Table 5 indicate that both the continuous and jump components predict the realized volatility mainly for the daily and weekly horizons. About the continuous component, daily continuous component is significant over all forecasting horizon where as weekly BV is significant over daily and weekly forecasting horizon. The monthly continuous component is significant only in the monthly forecasting horizon. Regarding the jump component, daily, weekly and monthly aggregated components are significant for daily and weekly forecasting horizons only. Therefore, the results suggest that the long memory or persistency in the volatility is largely coming from the continuous component of the price process. The results for λ are similar to that reported in Table 4 - consistent and persistent in relatively short horizons -one-day and one-week ahead forecasting.

In nutshell our results indicate that decomposition of realized variance in continuous and jump components enriches the volatility forecasting, and the long memory of volatility is largely coming from the continuous component and consistent with the literature (Andersen et al., 2007; Vortelinos and Thomakos, 2012).

4.3 Market Jumps and Systematic Risk of Stocks

To examine how individual stocks respond to the market jumps, we implement a conventional CAPM framework to estimate the systematic risk of constituents stocks from Toronto Stock Exchange, mainly TSX60 constituents considering the liquidity nature of these stocks. We use GSPTSE, as a proxy for the market portfolio. The results are reported in Table 6.

Our results show that, as expected, all the stocks are exposed to market risk. The estimates for

Table 6: Estimates for Different Betas

	r_m	$r_m * I^J$	$r_m * I^{ON}$	$r_m * I^{ONJ}$	I^J	I^{ON}		
Estimates	β_1	β_2	β_3	β_4	α_2	α_3	α_1	$\bar{R}^2$
Barrick Gold	1.1460***	-0.2236***	-0.2566***	-0.1581***	0.1385***	0.0371***	-0.0039***	0.179
	(0.0096)	(0.0241)	(0.0218)	(0.0612)	(0.0198)	(0.0082)	(0.0015)	
Agnico Eagle	1.3156***	-0.1776***	-0.2584***	-0.4796***	0.1334***	0.0064	-0.0017	0.170
	(0.0116)	(0.0290)	(0.0263)	(0.0737)	(0.0238)	(0.0098)	(0.0018)	
Agrium	1.3957***	-0.0471**	0.2143***	-0.3204***	-0.0380**	-0.0491***	0.0028*	0.326
	(0.0094)	(0.0234)	(0.0212)	(0.0595)	(0.0192)	(0.0079)	(0.0015)	
Brookfield Ast.	1.0638***	0.0514***	-0.0798***	-0.2752***	0.0352**	-0.0976***	0.0048***	0.276
	(0.0075)	(0.0189)	(0.0170)	(0.0478)	(0.0155)	(0.0064)	(0.0012)	
Blackberry	1.2016***	0.2020***	-0.2639***	-0.5075***	0.0075	0.0585***	-0.0017	0.113
	(0.0144)	(0.0361)	(0.0326)	(0.0916)	(0.0296)	(0.0122)	(0.0023)	
BCE	0.4538***	0.0979***	0.0124	-0.1255***	-0.0235**	0.0034	0.0009	0.135
	(0.0055)	(0.0137)	(0.0124)	(0.0349)	(0.0113)	(0.0047)	(0.0009)	
Bank of MO	0.9108***	0.0568***	0.0194*	-0.3968***	0.0393***	-0.0278***	0.0006	0.419
	(0.0049)	(0.0122)	(0.0110)	(0.0309)	(0.0100)	(0.0041)	(0.0008)	
Bank of NS	0.9919***	0.0792***	0.0053	-0.3828***	0.0302***	0.0048	-0.0003	0.476
	(0.0047)	(0.0118)	(0.0107)	(0.0300)	(0.0097)	(0.0040)	(0.0007)	
Cameco	1.4791***	0.0757***	-0.0203	-0.1700***	-0.0119	-0.0175**	0.0005	0.343
	(0.0092)	(0.0230)	(0.0208)	(0.0583)	(0.0189)	(0.0078)	(0.0014)	
CIBC	0.9146***	-0.0040	0.0426***	-0.2097***	0.0714***	-0.0562***	0.0016**	0.387
	(0.0052)	(0.0130)	(0.0117)	(0.0330)	(0.0107)	(0.0044)	(0.0008)	
C. Natural Res.	1.6151***	-0.5576***	0.2144***	0.0358	-0.0242	-0.0477***	0.0020*	0.447
	(0.0077)	(0.0193)	(0.0175)	(0.0490)	(0.0158)	(0.0065)	(0.0012)	
CN Railways	0.9533***	0.1127***	-0.2345***	-0.0972***	0.0240**	-0.0534***	0.0036***	0.316
	(0.0059)	(0.0147)	(0.0133)	(0.0374)	(0.0121)	(0.0050)	(0.0009)	
Can. Oil Sands	1.2604***	0.0319	0.4874***	-0.2161***	-0.0111	-0.0458***	0.0002	0.314
	(0.0097)	(0.0242)	(0.0219)	(0.0615)	(0.0199)	(0.0082)	(0.0015)	
CP Railways	0.9702***	0.1330***	-0.1533***	-0.1699***	0.0040	-0.0866***	0.0047***	0.280
	(0.0068)	(0.0170)	(0.0154)	(0.0431)	(0.0139)	(0.0058)	(0.0011)	
Cres. Energy	0.7292***	0.3498***	0.4298***	-0.4450***	-0.0454**	-0.0357***	0.0025	0.174
	(0.0101)	(0.0251)	(0.0227)	(0.0638)	(0.0206)	(0.0085)	(0.0016)	
Canadian Tire	0.5810***	0.0006	-0.0226	-0.0094	0.0065	-0.0943***	0.0047***	0.116
	(0.0071)	(0.0177)	(0.0160)	(0.0450)	(0.0146)	(0.0060)	(0.0011)	
Encana	1.3754***	-0.0632***	0.0775***	-0.3828***	-0.0370**	-0.0216***	-0.0003	0.432
	(0.0071)	(0.0177)	(0.0160)	(0.0449)	(0.0145)	(0.0060)	(0.0011)	
Eldorado Gold	1.2818***	-0.0800**	-0.1302***	-0.4980***	0.1879***	0.0206*	-0.0022	0.119
	(0.0147)	(0.0367)	(0.0331)	(0.0930)	(0.0301)	(0.0124)	(0.0023)	
Enbridge	0.8051***	0.1249***	-0.2450***	-0.2103***	0.0159	-0.0572**	0.0036***	0.280
	(0.0054)	(0.0134)	(0.0121)	(0.0340)	(0.0110)	(0.0045)	(0.0008)	
First Quantum	1.4510***	0.2890***	0.5373***	-0.7899***	-0.1481***	-0.0389***	0.0040*	0.244
	(0.0138)	(0.0346)	(0.0312)	(0.0877)	(0.0284)	(0.0117)	(0.0022)	
Fortis	0.3648***	0.2148***	0.0086	-0.2908***	0.0026	0.0038	0.0009	0.080
	(0.0066)	(0.0164)	(0.0148)	(0.0416)	(0.0134)	(0.0055)	(0.0010)	
Goldcorp	1.3035***	-0.2037***	-0.2194***	-0.1781***	0.1492***	0.0416***	-0.0035**	0.201
	(0.0105)	(0.0262)	(0.0237)	(0.0665)	(0.0215)	(0.0089)	(0.0016)	
Gildan	0.8023***	-0.1786***	0.1025***	0.1406*	0.0005	-0.0938***	0.0051***	0.086
	(0.0116)	(0.0290)	(0.0263)	(0.0737)	(0.0238)	(0.0098)	(0.0018)	

continue ...

Table 6 continue: Estimates for Different Betas

	r_m	$r_m * I^J$	$r_m * I^{ON}$	$r_m * I^{ONJ}$	I^J	I^{ON}		
Estimates	β_1	β_2	β_3	β_4	α_2	α_3	α_1	$\bar{R}^2$
Husky Energy	1.0918***	0.1130***	-0.0017	-0.4742***	0.0503***	-0.0124*	0.0003	0.303
	(0.0075)	(0.0188)	(0.0170)	(0.0478)	(0.0155)	(0.0064)	(0.0012)	
Emperial Oil	1.2585***	0.0216	0.0267*	-0.3118***	0.0499***	-0.0626***	0.0021**	0.426
	(0.0066)	(0.0164)	(0.0149)	(0.0417)	(0.0135)	(0.0056)	(0.0010)	
Inter Pipeline	0.2659***	0.3378***	0.1647***	-0.3847***	-0.0327**	-0.0409***	0.0034***	0.067
	(0.0078)	(0.0194)	(0.0175)	(0.0492)	(0.0159)	(0.0066)	(0.0012)	
Kinross Gold	1.3677***	-0.1267***	-0.2371***	-0.4016***	0.1058***	0.0417***	-0.0050***	0.179
	(0.0120)	(0.0299)	(0.0270)	(0.0759)	(0.0245)	(0.0101)	(0.0019)	
Loblaws	0.4298***	0.0636***	-0.0080	-0.0347	0.0022	-0.0632***	0.0021**	0.093
	(0.0062)	(0.0155)	(0.0140)	(0.0394)	(0.0127)	(0.0053)	(0.0010)	
Manulife	1.2680***	0.0415**	0.0841***	-0.4853***	0.0712***	-0.0218***	-0.0006	0.414
	(0.0069)	(0.0173)	(0.0156)	(0.0439)	(0.0142)	(0.0059)	(0.0011)	
National Bank	0.7912***	0.0840***	0.0221*	-0.2988***	0.0522***	-0.0311***	0.0013	0.313
	(0.0054)	(0.0135)	(0.0122)	(0.0343)	(0.0111)	(0.0046)	(0.0008)	
Potash Corp	1.4242***	-0.3778***	-0.3203***	0.4301***	-0.0968***	-0.0673***	0.0044***	0.242
	(0.0099)	(0.0246)	(0.0223)	(0.0625)	(0.0202)	(0.0083)	(0.0015)	
Pemb. Pipeline	0.2189***	-0.0269	0.0357**	0.0684	-0.1127***	0.0010	0.0016	0.024
	(0.0066)	(0.0165)	(0.0149)	(0.0418)	(0.0135)	(0.0056)	(0.0010)	
RBC	0.9793***	-0.0427***	0.0667***	-0.2683***	0.0681***	-0.0467***	0.0014*	0.457
	(0.0048)	(0.0120)	(0.0109)	(0.0305)	(0.0099)	(0.0041)	(0.0007)	
Saputo	0.4364***	0.2124***	-0.0748***	-0.3620***	0.0164	-0.0401***	0.0030**	0.063
	(0.0080)	(0.0200)	(0.0181)	(0.0508)	(0.0164)	(0.0068)	(0.0013)	
Sun Life	1.1376***	0.1273***	-0.0358**	-0.5918***	0.1126***	-0.0911***	0.0022**	0.368
	(0.0067)	(0.0168)	(0.0152)	(0.0427)	(0.0138)	(0.0057)	(0.0010)	
SNC-Lavalin	0.8461***	0.1544***	0.0717***	-0.1762***	0.0818***	-0.0831***	0.0034**	0.171
	(0.0090)	(0.0225)	(0.0203)	(0.0571)	(0.0185)	(0.0076)	(0.0014)	
Suncore	1.6273***	-0.0166	0.2260***	-0.5973***	0.0025	-0.0584***	0.0014	0.527
	(0.0072)	(0.0180)	(0.0162)	(0.0456)	(0.0147)	(0.0061)	(0.0011)	
Telus	0.6466***	0.0548***	0.0005	-0.2217***	0.0515***	-0.1095***	0.0051***	0.161
	(0.0067)	(0.0169)	(0.0152)	(0.0428)	(0.0138)	(0.0057)	(0.0011)	
TA	0.5670***	-0.0203	-0.0780***	-0.0459	-0.0448***	-0.0600***	0.0013	0.107
	(0.0069)	(0.0173)	(0.0156)	(0.0439)	(0.0142)	(0.0059)	(0.0011)	
TD Bank	0.9622***	-0.0065	0.0114	-0.3916***	-0.0164*	0.0013	0.0004	0.451
	(0.0047)	(0.0118)	(0.0107)	(0.0299)	(0.0097)	(0.0040)	(0.0007)	
TransCanada	0.7418***	0.1904***	-0.1669***	-0.3588***	0.0097	-0.0264***	0.0014*	0.306
	(0.0049)	(0.0122)	(0.0111)	(0.0310)	(0.0100)	(0.0041)	(0.0008)	
ValeantPharma	0.6445***	0.1071***	-0.0398	-0.1107	0.0548**	0.0410***	0.0001	0.070
	(0.0107)	(0.0268)	(0.0243)	(0.0681)	(0.0220)	(0.0091)	(0.0017)	

beta (index of systematic risk) are statistically significant and positive for all the stocks. However, 19 stocks have aggressive beta (beta greater than 1) and 23 have defensive beta (beta less than 1). When we examine the impact of market jumps on the systematic risk (beta) of individual stocks, we find that almost all the stocks (with an exception of 8 stocks) respond to the market jumps but with varying magnitudes and directions. Among 42 stocks in our sample, 12 stocks experience a decrease in beta whereas 23 stocks experience an increase in beta during the jumps in the market index. This finding contradicts with existing literature that reports consistently higher jump risk response of individual stocks (compared to continuous beta). For example, Alexeev et al. (2017) report that jump betas are 38 percent higher than continuous betas, Bollerslev et al. (2016) also find that jump betas are higher than continuous betas.

When we further look at the direction of changes in the beta of stocks, we observe an interesting pattern that most of the stocks having aggressive beta tend to exhibit a decrease in systematic risk and most of the stocks with defensive beta tend to experience an increase in systematic risk when there are jumps in the market index. Such convergence tend of individual stock's beta toward market beta (beta equals 1) is consistent with stock price comovement literature. During the stressful market conditions such as market jumps, stocks exhibit strong comovement yielding beta closer to market beta. This finding has a significant portfolio implication. In a well diversified portfolio, the systematic risk of the portfolio is less affected by the market jumps. When some stocks in the portfolio experience increased beta and some stocks experience decreased beta, the overall beta of the portfolio is less affected.

Most of the information releases/disclosures (macroeconomic as well as firm level announcements) take place outside the trading window along with the global market shocks which originates outside the time zone of trading window also affect the stock returns when trading starts, perhaps the opening of the next trading day. In this regard, the overnight returns may have different characteristics. In this regard, we examine the systematic exposure of overnight returns. Our results reveal that the market risk (beta) is somewhat different for the overnight returns. Among the 42 stocks in our sample, 32 stocks' beta changes for the overnight returns and about half of these (15) stocks' beta decreases for the overnight returns where rest experience increase in beta. However, unlike in the case of market jumps, we don't see clear evidence of increased comovement among the stocks. The direction of changes in betas during for the overnight returns do not show a convergence trend towards market beta. We also find that some stocks which do not have a significant effect of market jumps or overnight returns on their systematic risk do experience changes in systematic risk if jumps do occur in the overnight returns. The statistically significant coefficient for dummies for market jumps and overnight returns indicate that market jumps bring a shift in the average stock returns and on average, stocks exhibit significantly different pattern and size of price change for the overnight period.

From the sectoral perspective, stocks from Basic materials sector tend to have highly aggressive betas. These stocks are also very sensitive to market jumps and overnight returns. The beta of these stocks decreases during the market jumps and overnight returns. The stocks from Energy sector also exhibit aggressive betas, however, the effects of market jumps and overnight returns on the beta of these stocks are heterogeneous. Consumer products & services, Industrials, and Utilities sectors stocks are defensive. While market jumps increase the systematic risk of these stocks, overnight returns help to reduce the systematic risk. The financial firms in general have beta closer to the market beta and generally experience an increased systematic risk during the market jumps and overnight returns.

We further take a cross-sectional perspective and examine whether the changes in the systematic risk of stocks due to the market jumps and overnight returns across the firms are statistically significant. To this end, we compute the cross-sectional average of β_1 (continuous beta) and cross-sectional average of $\beta_1 + \beta_2$ (jump beta)[7] and performa a t-test whether there is a significant difference between continuous beta and jump beta. The null of no difference is not rejected at 5% level of significance. Alternatively, we also computed cross-sectional average of β_2 which simply measures the average change in beta due to the market jumps, the null of average difference is zero is not rejected at 5% level. We follow the same procedure to examine average change in beta due to overnight returns and we couldn't reject the null that the average change in overnight beta is zero. The heterogeneity across the stocks for the systematic risk and mean shift provide meaningful insight for portfolio diversification. While it has been well advocated about the systematic risk impact of market jumps and overnight returns in the literature, our simple yet robust results

[7]Note that if β_2 is not statistically significant, $\beta_1 + \beta_2 = \beta_1$

indicate that these risks are less systematic in nature and likely to be eliminated through portfolio diversification. Our results are consistent with Jarrow and Rosenfeld (1984) and Yan (2011) also suggests that jump risk is largely idiosyncratic in nature. Alexeev et al. (2016) demonstrate that the jump beta dissipates quickly through portfolio diversification.

Our results for overnight beta are consistent with asset pricing literature which suggest that stock prices behave very differently with respect to their sensitivity to market risk (beta) when markets are open for trading versus when they are closed (Heston et al., 2010; Savor and Wilson, 2016). Lou et al. (2018) show that momentum profits accrue solely overnight for U.S. stocks over 1993 to 2013. Bogousslavsky (2016) documents substantial variation in the cross-section of returns over the trading day and overnight. We thus view the overnight and intraday components of returns as potentially reflecting the specific demand by the corresponding clientele.

4.4 Robustness of the Results

We perform a battery of robustness checks. Our results are robust to sampling frequency of tick data - using 5-minute, and 30-minute. Although the jump count statistics, as in the existing literature, differ as we change the sampling frequency, the overall results, for example, the proportion of positive/native jumps, jump clustering, and proportion of daily, monthly and annual jumps are very similar to the one reported in the paper. For the robustness in Section 4.3, we also use TSE60 index as a proxy for market portfolio considering the fact that all our sample firms are TSE60 constituents. We also run the regression excluding the overnight return and restricting the parameter for overnight return interaction term to zero. Overall, our main results remain very similar.

5 Concluding remarks

In this paper, we use high-frequency data from the Canadian equity market for the first time and identify and assess the jump risk. Implementing Lee and Mykland (2007) procedure, we identify jumps in the Canadian stock market indices and provide a strong evidence of jump clustering. Our results show that jump counts and jump intensities are sensetive to inclusion/exclusion of overnight returns in the analysis. More than fifty percent jumps in the aggregate stock market index are attributed to the ovenight returns. The symetrical distribution of positive versus negative jumps can be observed only when we include overnight returns, thereby overnight jumps in the analysis - revealing idiosyncratic natue of jump returns. Therefore, jump risk analysis excluding overnight returns may lead to baised results.

Assessing the importance of jump component in volatility modeling and forecasting, we have shown that large part of the realized volatility is coming from the continious compoenent yet largest spikes in the realized volatilty is coming from the jump component. While long memory and persistency, and leverage effect are evident in our results, jump component has limited economic significance in volatility forecasting mainly in weekly and monthly forecasting.

The cross-sectional dampening effect of changes in systematic risk of individual stocks due to market jumps further support to the conclution that jump risk is non-systematic in nature. However, the effect of overnight returns on beta is less idiosyncratic in nature, therefore need to pay due attention while assess risk-return analysis using high-frequency data.

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Appendix

Table 7: List of sample firms with tickers and industry classifications

Ticker	Name	Industy classifications
ABX	Barrick Gold Corporation	Basic materials
AEM	Agnico Eagle Mines Limited	Basic materials
AGU	Agrium Inc.	Industrials
BAM.A	Brookfield Asset Management Inc	Financial services
BB	Blackbary LImited	Technology
BCE	BCE Inc.	Communicaiton services
BMO	Bank of Montreal	Financial services
BNS	Bank of Nova Scotia	Financial services
CCO	Cameco Corporation	Basic materials
CM	Canadian Imperial Bank Of Commerce	Financial services
CNQ	Canada Natural Resources Limited	Energy
CNR	Canada National Railway Company	Industrials
COS	Canadian Oil Sands Limited	Energy
CP	Canada Pacific Railway Limited	Industrials
CPG	Crescent Point Energy Corporaiton	Energy
CTC.A	Canadian Tire Corporation	Consumer products & services
ECA	Encana Corporation	Energy
ELD	Eldorado Gold Corporation	Basic materials
ENB	Enbridge Inc.	Energy
FM	First Quantum Minerals Limited	Basic materials
FTS	Fortis Inc.	Utilities
G	Goldcorp Inc.	Basic materials
GIL	Gildan Activeware Inc.	Consumer products & services
HSE	Husky Energy Inc.	Energy
IMO	Imperial Oil Limited	Energy
IPL	Inter Pipeline Limited	Energy
K	Kinross Gold Corporation	Basic materials
L	Loblaw Companies Limited	Consumer products & services
MFC	Manulife Financial Corporation	Financial services
NA	National Bank of Canada	Financial services
POT	Potash Corporation of Saskatchewan	Basic materials
PPL	Pembina Pipeline Corporation	Industrials
RY	Royal Bank of Canada	Financial services
SAP	Saputo Inc.	Consumer products & services
SLF	Sun Life Financial Inc.	Financial services
SNC	SNC-Lavalin Group Inc.	Industrials
SU	Suncore Energy Inc.	Energy
T	Telus Corporation	Telcomm
TA	TransAlta Corporation	Utilities
TD	Toronto-Dominion Bank	Financial services
TRP	TransCanada Corporation	Energy
VRX	Valeant Pharmaceuticals Inc.	Healthcare