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Oil and US stock market shocks: implications for Canadian equities

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Abstract

Oil and US stock market shocks are expected to be relevant for Canadian equities, as Canada is an oil-exporter adjacent to the US. We evaluate how the relationship between Canadian stock market indices and such external shocks change under extraordinary events. To do this, we subject statistically identified oil and S&P 500 market shocks to a surprise filter, which detects shocks with the greatest magnitude occurring over a given lookback period; and an outlier filter, which detects extrema shocks that exceed a normal range. Then, we examine how the dependence structure between shocks and Canadian equities change under the extreme surprise and outlier episodes through various co-moment spillover tests. Our results show that co-moments beyond correlation are important in reflecting the changes occurring in the relationships between external shocks and Canadian equities in extreme events. Additionally, the differences in findings under extreme positive and negative shocks provide evidence for asymmetric spillover effects from the oil and US stock markets to Canadian equities. Moreover, the observed heterogeneity in the relationships between disaggregated Canadian equities and shocks in the crude oil and S&P 500 markets are useful to policymakers for revealing sector-specific vulnerabilities, and provide portfolio diversification opportunities for investors to exploit.

Keywords: Canada; oil market; spillover; stock market

JEL classification: C32; G15; Q43

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1. Introduction

Canada is a top energy producer, with its position shifting between fourth and fifth in the global rankings over the last 40 years[1]. Along with being in close geographic proximity to each other, the US is unquestionably Canada's principal trading partner. Moreover, the vast majority of Canada's petroleum and natural gas exports are destined for the US market (EIA, 2019). Thus, oil and the US are arguably two of the most important external markets for Canada. Hence, our study analyses the channels through which extreme spillover shocks from both the oil and US stock markets can affect Canadian equities. As stock market activity is a leading indicator of business cycles and particularly so in the trough (Bosworth et al., 1975), it can be useful for policymakers to understand the impending real sector ramifications of exogenous developments on a recipient country through the performance of the stock market when unexpected events occur. Additionally, investors trading in either hard commodities and/or holding a portfolio of assets which consists of interests in both the US and Canada can benefit from this line of research.

In this paper, we first apply the strategy of Herwartz and Plödt (2016) and Herwartz (2018) to statistically identify international crude oil market supply and demand shocks and other shocks to the US stock market proposed in the

[1]Data accessed from eia.gov/international/rankings in January 2021.

theoretical model of Kilian and Park (2009). The advantages of using this statistical identification strategy is that the structural shocks are orthogonal and the higher order moment dependencies between shocks are also minimised. Moreover, much has changed with the increasing financialisation of oil in recent times (Creti et al., 2013; Zhang and Broadstock, 2020). Therefore, it becomes important to examine the plausibility of delay restrictions based on economic theory when labelling meaningful shocks in the crude oil and financial markets suggested in Kilian and Park (2009) in more recent datasets by using a statistically motivated identification approach. We show that these structural shocks identified through independent components are consistent with those derived from the recursive structure implied by Kilian and Park (2009). Furthermore, from the impulse response analysis we document additional evidence that the two estimation approaches closely align.

We then propose filtering the identified shocks into relatively quiet and extreme episodes to inform our understanding of how market relationships change in extraordinary times. Hamilton (1996) argues that it is the surprise increases in oil prices over the preceding year which is of consequence to the economy, while Akram (2004) suggests that it is outlier oil prices exceeding a normal range which matters most. Such premises sit well with the finance literature, which posits that unprecedented events arising from a stable environment is a hallmark of the contagion phenomenon (Kaminsky et al., 2003). As such, we build on the work of Mahadeo et al. (2019b) who augment such established non-linear oil price measures for sorting oil market shocks into quiet and extreme episodes. Hence, we are able to empirically timestamp extraordinary *surprise* and *outlier* scenarios in both the international crude oil and US stock markets.

Using these quiet and extreme episodes as discrete subsamples, we evaluate whether correlations between Canadian equities and structural oil and US stock market shocks change under extreme shocks across various co-moment spillover channels. This step further consolidates approaches employed in two empirical oil-finance studies. One, based on Broadstock and Filis (2014), is to explicitly estimate the relationship between structural oil market shocks suggested in Kilian (2009) and stock market returns. In the context of our analysis of Canadian equities, we extend this idea to the SVAR model of Kilian and Park (2009) to also acquire other shocks to the US stock market. The other study we build on is Mahadeo et al. (2019a), who use recently introduced co-moment contagion tests in Fry et al. (2010) and Fry-McKibbin et al. (2014) to analyse how the relationship between oil and financial markets change in a small oil-exporter under extreme conditions in the oil market. We include an additional co-moment contagion channel (i.e, co-kurtosis) introduced in Fry-McKibbin and Hsiao (2018), and instead of oil returns as the source market variable we use shocks from the crude oil and US stock markets. A principal advantage of the various co-moment tests we employ is that they do not involve the specification of complex economic models, requiring large datasets on trade and economic fundamentals, in order to gain valuable insights into the linkages between a source and recipient market in the wake of a shock (Fry-McKibbin et al., 2018). By incorporating the aforementioned modifications to these previous studies, we aim to contribute valuable insights into the relationship between shocks from the international crude oil and US stock markets and the Canadian stock returns.

In addition to assessing the spillover effects from shocks in these relevant external markets on Canada's headline equity index - the Toronto Stock Exchange (TSX) Composite, we also consider the relationship between such shocks and the sector level equities of this index. In so doing, we can determine the winners and losers when extreme shocks occur, and gain further insights into market resilience and vulnerabilities. Instead of a focus of the relationship between crude oil market shocks and the headline stock market index in multiple countries (see, *inter alia*, Jones and Kaul, 1996; Filis et al., 2011; Kang and Ratti, 2013; Kang et al., 2015b; Boldanov et al., 2016; Antonakakis et al., 2017; Heinlein et al., 2020), another strand of the literature examines the impact of oil price shocks on sector equities and certain sectors of the economy. With specific reference to the Canadian housing market, Kilian and Zhou (2018) demonstrate that oil price shocks raise real estate demand and real house prices not only in oil-rich provinces but in oil-poor regions as well. Some recent studies on the impact of structural crude oil market shocks on disaggregated stock returns include Sakaki (2019) for the US and Mishra and Mishra (2020) for India. The former study modifies the Kilian and Park (2009) SVAR model for identifying shocks from the crude oil market and other shocks to the US stock market, by substituting the returns of the composite US stock index with the returns of US sectoral stock indices. Their impulse response analyses illustrate that oil supply and aggregate demand shocks have a positive effect on sector level stock returns, while oil-specific demand shocks adversely affects stock returns for all sector equities except energy and utilities. On the other hand, the latter study uses an alternative SVAR model to Kilian and Park (2009) suggested by Ready (2018), and estimate the time varying relationship between these shocks and sector equities in India. Their results show oil demand shocks have positive effects on all sector equities.

Our analysis on how the relationship between Canadian equities and structural oil and US stock market shocks change, in extreme shock episodes compared to quiet periods, across various co-moment spillover channels is subsequently summarised. First, while there is a weak correlation between oil supply shocks and the real TSX composite returns, which is consistent with the diminished role of oil supply shocks documented in the literature, we observe that supply shocks affect these returns through co-skewness and co-kurtosis channels. Second, there are contagion effects from global aggregate demand shocks to Canadian equities illustrated by the rise in correlations and several statistically significant spillover channels during negative extreme global aggregate demand shocks, while this relationship is relatively unremarkable in periods of positive extreme global aggregate demand shocks. Third, both positive and negative extreme oil-specific demand shocks exhibit contagion effects on Canadian equities. Penultimately, the strongest market relationships are noted between shocks to the US stock market and Canadian equities, and changes in this relationship manifest in higher co-moments beyond the linear correlation channel. Lastly, the relationship between disaggregated Canadian equities and the oil and US stock market shocks are heterogeneous across the various sectors of this recipient market. Our spillover test results are found to be robust to alternative specifications, in both the duration of the surprise filter and the bandwidth of the outlier filter, for identifying discrete quiet and extreme shock episodes. This line of work is useful to policymakers for identifying systemic and sectoral vulnerabilities to shocks from external markets, and for investors in formulating portfolio diversification strategies.

The rest of the paper is organised as follows. In Section 2, we provide coverage of the literature on the role of commodity markets and the US on Canadian equities. Subsequently, we explain our empirical steps and describe the data used in Section 3. We then present, analyse, and discuss our findings in Section 4. Section 5 concludes the paper.

2. Literature on the effects of oil and US stock markets on Canadian equities

In this section, we consolidate some of the salient literature covering the influence of the crude oil and US markets on Canadian equities. Many researchers have highlighted the impact of US developments on the Canadian real and financial sectors. Canadian and US economies are highly integrated, and the structure and regulation of stock markets in the two countries are similar. The stock markets share the same trading hours and some companies listed on Canadian stock markets are inter-listed on US markets. A strand of literature has studied the extent to which these two markets are financially integrated (see, for example, Jorion and Schwartz, 1986, and Mittoo, 1992). Such studies employ CAPM and APT frameworks, whereby findings suggest a move from segmentation to integration of markets over time.

In Karolyi (1995), bi-variate GARCH models are used to study the dynamics of returns and volatility of the S&P 500 and the TSE 300[2] markets. In the BEKK specification of the model no statistically significant spillovers from lagged TSE 300 returns to future S&P 500 returns cannot be rejected, while lagged S&P 500 returns are relevant for future TSE 300 returns. In all model specifications, the authors find a strong response of Canadian equity returns to S&P 500 shocks.

A further study applying M-GARCH models in the context of US/Canadian stock markets is Racine and Ackert (2000). They find significant cross-market volatility dependencies, with a correlation in volatility for the S&P 500 and Toronto 35 stock index of 0.679. Interestingly, when they split their sample, January 1988 to March 1993, in half, the second part of the sample shows a lower correlation between markets compared to the first part. They state a declining correlation in their conclusion, although the total sample considered is short.

From a forecasting perspective, Rapach et al. (2013) show that lagged US stock returns help to predict returns of major international markets. Working with monthly data from 1980:02 to 2010:12 and Granger causality tests, they give in-sample and out-of-sample evidence of the predictive power of lagged US returns on Canadian returns, among other markets. Wang et al. (2018) show that US stock volatility can predict volatility of other markets. Their proposed model is superior in forecasting 1-day ahead of the Canadian S&P TSX Composite index volatility compared to benchmark models.

We turn the emphasis now from the relationship between US and Canadian equities towards the influence of the oil market on Canada. Elder and Serletis (2009), Rahman and Serletis (2012), and Bashar et al. (2013) all examine oil price uncertainty in Canada. The first study employs a SVAR with multivariate GARCH-in-Mean; while the second uses a VARMA, GARCH-in-Mean, asymmetric BEKK model; and the third uses alternative SVAR models. Across all studies, it is consistently illustrated that rising oil price uncertainty leads to a reduction in Canadian economic

[2]The TSE 300 has been replaced by the S&P TSX Composite Index on May 1^{st}, 2002.

activity.

Another strand of literature has exploited big data approaches to evaluate the impact of international shocks on the Canadian economy. For instance, Vasishtha and Maier (2013) employ a factor-augmented VAR model, using monthly data from January 1985 to May 2008 and across 261 series, to examine how the sources of global shocks influence Canada. Their results show that Canada is vulnerable to foreign economic activity and commodity prices but is comparatively more isolated to global inflation and interest rates. In another example, using a combination of structural dynamic factor and VAR models, Charnavoki and Dolado (2014) estimate the dynamic responses of Canadian macroeconomic indicators to global commodity market shocks. Their analysis utilises a quarterly dataset which spans 1975 to 2010 and makes use of 281 variables. They show that positive global demand and negative commodity supply shocks lead to commodity price increases, and generate favourable external balances and commodity currency effects. These authors also find a Dutch disease effect[3] in response to commodity price increases resulting from negative commodity supply shocks.

There are also insightful papers on the relationship between oil and the stock market that cover multiple countries, which includes Canada. In the remainder of this section, we place the spotlight on the results relating to Canada from such studies. One such study by Jones and Kaul (1996) find that the Canadian stock market reaction to oil price shocks, which is similar to the US but dissimilar to Japan and the UK, is rational - oil price shocks influence on the stock market is entirely explained through current and expected future real cash flows. In another study, Kang and Ratti (2013) use an extension of the SVAR model introduced by Kilian (2009) to disentangle the international crude oil market disturbances into supply and demand shocks. They do so by appending two additional variables to the bottom of the recursive identification structure in the contemporaneous matrix of the SVAR, i.e. economic policy uncertainty and stock returns. Their results show that oil price shocks and economic policy uncertainty are interrelated, and that a rise in economic policy uncertainty leads to a significant reduction in real Canadian stock returns. Their results for Canada are in line with the US, but are much less pronounced than their findings for Europe. In yet another study, Kang et al. (2015b) use a mixture innovation time-varying parameter VAR model to examine structural oil market shocks on stock returns. Their results demonstrate that in Canada (and Europe), oil supply and oil-specific demand shocks are a greater source of volatility than in the US. However, global aggregate demand shocks are the main source of stock market volatility in Canada, and this finding is consistent for the US and Europe as well.

Filis et al. (2011), Boldanov et al. (2016), and Antonakakis et al. (2017) all investigate the relationship between oil and stock markets of multiple oil-exporting and importing countries using different approaches, and all include Canada in their analyses. In the first study, a dynamic conditional correlations (DCC) model is used to examine the changes in the oil-stock market relationship during key events in the international crude oil market. They document that correlations do not differ between oil-exporters and importers. A BEKK model is used in the second study, which contrastingly finds heterogeneity in correlations between oil-exporters and oil-importers. Their specific results

[3]The Dutch disease characterises the adverse effects a booming tradeable resource sector has on the non-boom tradeable sector, particularly through the appreciation of the real exchange rate. See, *inter alia*, Corden (1984, 2012) for further context.

for Canada (and Norway) suggests that time varying correlations between the volatilities of oil prices and the stock market are negatively correlated, which is a contrast to the positive correlations reported in the case of oil-importers. The third study utilises an extension of the Diebold and Yilmaz (2014) dynamic connectedness measure based on structural forecast error variance decompositions, and reports both between and within country differences in both the strength and direction of the relationship between oil and stock markets for oil-exporters and oil-importers. Their specific analysis for Canada imply that in turbulent conditions, the transmission of shocks to the stock market are primarily driven by global aggregate demand shocks, but this source of transmission becomes much less pertinent in tranquil conditions.

In a recent study, Heinlein et al. (2020) assess the relationship between oil and stock markets for a heterogeneous selection of oil-exporters and importers in the onset of the COVID-19 pandemic. They use local Gaussian correlations with high frequency intraday data to determine whether market connections increase between crude oil and stock returns in the wake of the crisis. Their results show that, even with such high frequency data, oil-exporting countries experience comparatively stronger oil-stock market correlations compared to importers in both pre-crisis and crisis periods. Among the other oil-exporters in the analysis (i.e., Norway and Russia), the relationship between oil and stock returns for Canada is relatively lower in the wake of the global pandemic.

3. Methods and data

Our empirical procedure consists of four steps. The first step documents how we disentangle shocks in the international crude oil and US stock markets. In the second step, we outline two approaches for filtering these shocks into discrete quiet and extreme episodes. For the third step, we explain the regressions used to adjust the returns of the Canadian equity indices for market fundamentals and describe the resulting data series. Finally, the fourth step illustrates various co-moment tests for evaluating whether the relationship between the identified shocks and the various returns of Canadian equity indices change during extreme episodes compared to relatively quiet conditions.

Monthly data are used for all empirical steps, as this is the highest frequency at which the identifying assumptions made about demand and supply shocks in the crude oil market are valid (see, e.g., Kilian, 2009; Kilian and Park, 2009). Our period of investigation is January 1988 to April 2020, which is dictated by the availability of the Canadian equity indices for the third step of our analysis. Combined, the first and second steps of identifying oil and US stock market shocks, as well as filtering the data into quite and extreme episodes require approximately three preceding years of data to prime these procedures. We further describe the data attributes below.

3.1. Identifying structural oil and S&P 500 market shocks through independent components

We estimate a structural vector autoregression model (SVAR) based on monthly data, from 1985:1 to 2020:4, for the global oil and US stock market following Kilian and Park (2009), which is represented in Eq. (1):

$$\boldsymbol{y}_t = \boldsymbol{\nu} + \sum_{i=1}^{24} \boldsymbol{A}_i \boldsymbol{y}_{t-i} + \boldsymbol{B}\boldsymbol{\varepsilon}_t, \qquad t = 1, \ldots, T \tag{1}$$

where the vector $\boldsymbol{y}_t = (\Delta q_t, x_t, \Delta p_t, r_t)'$ includes the change in global crude oil production[4], Δq_t; a measure of world demand for commodities, x_t, for which we use the global index of real economic activity in industrial commodity markets suggested in Kilian (2009, 2019)[5]; the change of the real price of oil, Δp_t, for which we use the US crude oil imported acquisition cost by refiners, expressed in constant 2015 prices [6]; and the real stock returns of the US stock market, r_t, for which we use the S&P 500 market index returns also deflated with 2015 prices[7]. Figure 1 shows the raw data for these four series. We take a moment to justify the use of these variables in the context of our application to Canada. Although in 2018 Canada was the world's fourth largest producer of petroleum, other related downstream liquids, and natural gas (EIA, 2019), the international crude oil market activity is considered sufficient to capture the information content across these hydrocarbon commodity markets. This is because natural gas prices and contracts are commonly indexed to crude oil prices (Zhang and Broadstock, 2020). In addition, the S&P 500 market index is considered to be the most appropriate indicator for assessing the influence of the US stock market on Canadian equities, due to its size and prominence on global financial markets (see, e.g., Phillips and Shi, 2020).

Furthermore, the structural shocks, $\boldsymbol{\varepsilon}_t$, in Eq. (1) are uncorrelated across equations and over time with mean zero and unit covariance matrix, $\boldsymbol{\Sigma}_\varepsilon$. The reduced form residuals, $\boldsymbol{u}_t = \boldsymbol{B}\boldsymbol{\varepsilon}_t$, are linear functions of the structural innovations and $Cov(\boldsymbol{u}_t) = \boldsymbol{\Sigma}_u = \boldsymbol{B}\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t^{'}\boldsymbol{B}^{'} = \boldsymbol{B}\boldsymbol{\Sigma}_\varepsilon\boldsymbol{B}^{'} = \boldsymbol{B}\boldsymbol{B}^{'}$. Up to 24 lags are included in the estimation of Eq. 1, as is conventional with specification of SVAR models for capturing the dynamics in the international crude oil market (see, e.g., Kilian, 2009; Kilian and Park, 2009; Kilian and Murphy, 2014; Kang et al., 2015a; Baumeister and Kilian, 2016a,b).

The model of the global crude oil market comprises four types of structural shocks, which are labelled as oil supply shock (ε_s), aggregate demand shock (ε_{ad}), oil-specific demand shock (ε_{osd}), and other shocks to stock returns (ε_r). To identify the impact of the structural shocks on the variables in the system, Kilian and Park (2009) have applied economic theory to justify the use of a recursive form in the $\boldsymbol{B}$ matrix. Some of the main premises of their SVAR model is a vertical short run oil supply curve, whereby demand-side shocks do not contemporaneously affect the global oil supply as it is generally costly for oil producers to respond to high frequency demand innovations; due to the sluggishness in global real economic activity, this variable does not respond to oil-specific demand shocks in the same month; and that developments in the international crude oil market are treated as predetermined for the US stock market within the same month (for further details, see Kilian, 2009; Kilian and Park, 2009). In recent times,

[4] World crude oil production in thousands of barrels per day is obtained from the US Energy Information Administration (EIA), available from eia.gov/opendata, and accessed in September 2020.

[5] The global measure of real economic activity is obtained from Lutz Kilian's website, available at sites.google.com/site/lkilian2019/research/data-sets, and accessed in September 2020.

[6] Refiners acquisitions cost per barrel of imported crude oil, accessed in September 2020, is also obtained from the US EIA at eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=r1300_3&f=m. The oil price data is expressed in constant 2015 prices using the US CPI obtained from fred.stlouisfed.org/series/CPIAUCSL, also accessed in September 2020, and converted into percent changes.

[7] S&P 500 index is obtained from Yahoo Finance, available at finance.yahoo.com/quote, and accessed in September 2020. Like oil prices, this series is adjusted for inflation using the US CPI with a 2015 base year. Returns are subsequently computed as the logarithmic-differencing of the real stock market index times 100.

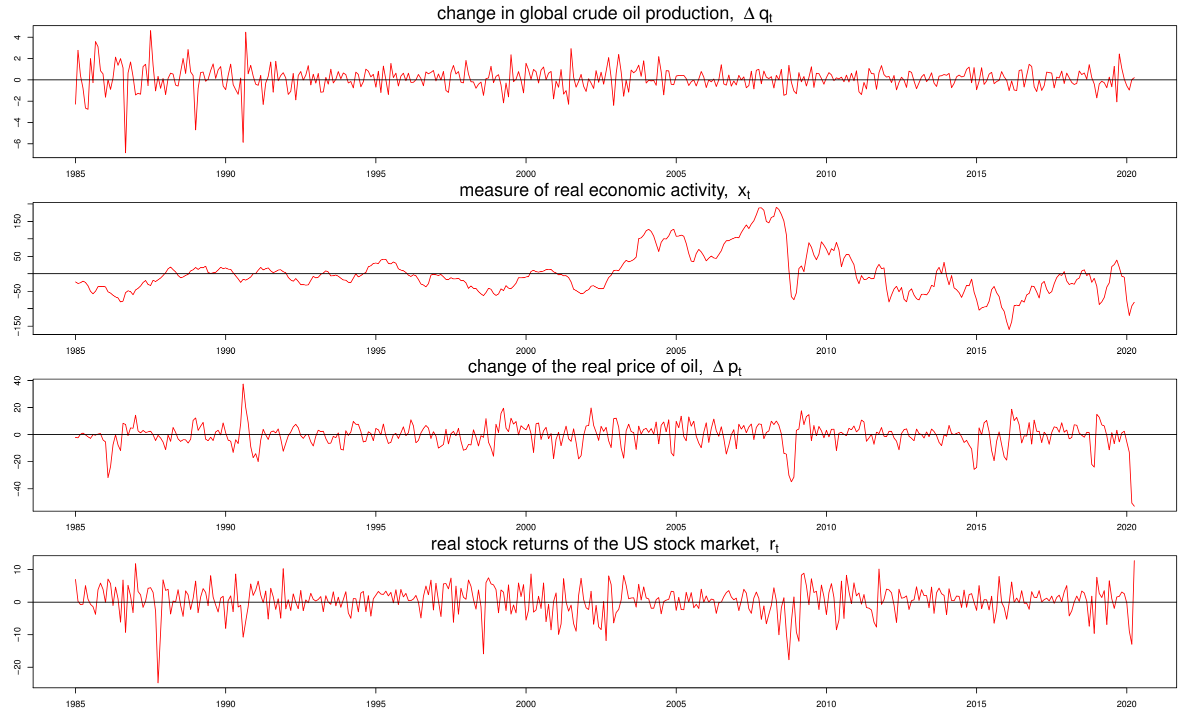

Figure 1: The four time series of the SVAR model: the change in global crude oil production, Δq_t; a measure of real economic activity, x_t; the change of the real price of oil, Δp_t; and the real stock returns of the US stock market, r_t.

the financialisation process in which commodity prices are not determined entirely on supply and demand but also by several financial factors and investors' behaviour in derivative markets (see, for example, Creti et al., 2013; Zhang and Broadstock, 2020). Consequentially, it becomes important to carefully scrutinize the validity and relevance of an identification strategy implied by economic theory. Hence, in this paper, we follow the statistical identification strategy of Herwartz and Plödt (2016) and Herwartz (2018).

Under normality, the decomposition of the reduced form covariance matrix $\boldsymbol{\Sigma}_u = \boldsymbol{B}\boldsymbol{B}'$ is not unique such that the space spanned by $\boldsymbol{B}$ and its rotations can be considered as observationally equivalent. Comon (1994) shows that if the components of $\boldsymbol{\varepsilon}_t$ are non-Gaussian (i.e., not more than one marginal structural shock process is Gaussian), the independence of the ε_{it} can be used to identify the matrix $\boldsymbol{B}$. Lanne et al. (2017) prove uniqueness of $\boldsymbol{B}$ for non-Gaussian models, except for the ordering and sign of its columns. Herwartz (2018) introduces identification via least dependent structural innovations, using the copula-based Cramér-von Mises statistics (CVM) as a nonparametric independence test to measure the degree of dependence.[8] The matrix $\hat{\boldsymbol{B}}$ is chosen as such that the CVM dependence criterion for the structural shocks is minimised (for details, see Herwartz, 2018).

The lower triangular Choleski factor $\boldsymbol{D}$ is a possible solution to the decomposition of $\boldsymbol{\Sigma}_u = \boldsymbol{D}\boldsymbol{D}'$, hence linking the structural errors to the reduced-form errors, $\boldsymbol{\varepsilon}_t = \boldsymbol{D}^{-1}\boldsymbol{u}_t$. More candidate structural shocks can be computed $\tilde{\boldsymbol{\varepsilon}}_t = \boldsymbol{Q}\boldsymbol{\varepsilon}_t = \boldsymbol{Q}\boldsymbol{D}^{-1}\boldsymbol{u}_t$, when multiplying with a rotation matrix $\boldsymbol{Q}$ with $\boldsymbol{Q} \neq \boldsymbol{I}_4$ and $\boldsymbol{Q}\boldsymbol{Q}' = \boldsymbol{I}_4$. As we are working with

[8] A parametric non-Gaussian structural error approach is suggested by Lanne et al. (2017) based on Maximum Likelihood estimation.

a $K = 4$ dimensional system, the rotation matrix can be parameterised as the product of 6 orthogonal Givens rotation matrices, $K(K-1)/2$, leading to the optimisation of a 6-dimensional vector of rotation angles. This identification via least dependent innovations is capable to identify the link matrix $\boldsymbol{B}$ except for column permutations and column signs. If needed, we switch the columns of the matrix $\boldsymbol{B}$ by comparing and aligning the resulting impulse responses with those impulse responses achieved by using the lower triangular Choleski factor $\boldsymbol{D}$. This way we achieve an economic meaningful labelling of the structural shocks in a statistical identification procedure.

3.2. Filtering shocks into discrete quiet and extreme episodes

We adopt two alternative measures to sort the statistically identified shocks into discrete outcomes of extreme and quiet episodes. One measure is based on the idea suggested by Hamilton (1996), who argues that it is actually surprise oil price increases over the preceding year which are of consequence to the economy rather than increases which are simply corrections for previous price declines. It becomes straightforward to use this measure to also obtain surprise oil price decreases, especially in analyses involving oil-exporters such as Canada. Furthermore, capturing unexpected events arising from a stable oil market environment integrates comfortably with the literature on the causes of spillovers. For instance, Kaminsky et al. (2003) characterise surprise shocks in a source market as one of the unholy trinities of a contagion phenomenon. Therefore, it is also simple to extend the filter posited by Hamilton (1996) to acquire relatively quiet and extreme surprise shock episodes, across all four identified shocks ($\varepsilon_s, \varepsilon_{ad}, \varepsilon_{osd}$, and ε_r), such that:

$$surprise^+_{i,t} = \begin{cases} 1, & \text{if } \varepsilon_{i,t} > \max(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ..., \varepsilon_{i,t-12}) \\ 0, & \text{if } 0 \leq \varepsilon_{i,t} \leq \max(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ..., \varepsilon_{i,t-12}) \end{cases} \quad , \qquad i = s, ad, osd, r, \tag{2}$$

$$surprise^-_{i,t} = \begin{cases} 1, & \text{if } \varepsilon_{i,t} < \min(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ..., \varepsilon_{i,t-12}) \\ 0, & \text{if } 0 \geq \varepsilon_{i,t} \geq \min(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ..., \varepsilon_{i,t-12}) \end{cases} \quad , \qquad i = s, ad, osd, r, \tag{3}$$

where $surprise^+_{i,t}$ ($surprise^-_{i,t}$) is an indicator variable with 0 and 1 in Eq. (2) (Eq. (3)) representing the relatively quiet and extreme positive (negative) surprise shock episodes, respectively. The periods which are found to be consistently quiet (0) across all the four structural shocks, such that there exists no extreme positive or negative outlier shock episodes, forms a *mutually quiet sample*. This mutually quiet sample will provide the basis of how we will evaluate whether market relationships change in the presence of extreme shocks. In particular, we test whether various co-moments between external shocks and Canadian equity returns differ under shock episodes classified as extreme positive (negative) surprises compared to all other relatively quieter positive (negative) shock periods.

The second measure we use to sort the identified shocks into categories of extreme and quiet episodes is motivated by Akram (2004) that it is the extreme oil prices outside a normal range which are of consequence to the economy. It is also straightforward to apply this idea to the four identified structural shocks to obtain extreme outlier episodes in the oil and US financial markets. However, the band of stable oil prices, of USD 14 to USD 20, used in Akram (2004) is a feature of oil markets prior to the 21^{st} century. Hence, we use the standard deviation (σ_i) of the structural shocks (ε_i) to provide context of what is considered quiet and extreme. Using σ is appealing because it does not require imposing priors about the typical range of values of the different structural shocks, which can be difficult to establish. As testing for asymmetric responses to positive and negative shocks is a cornerstone of applied macroeconomics, especially oil empirics, we can further disaggregate extreme outlier shocks to also evaluate these cases. Given that $\sigma_i = 1$ for all ε_i, the filters in Eqs. (4) and (5) are applied to each of the four identified shocks to sort values into relatively quiet and extreme outlier episodes:

$$outlier^{+}_{i,t} = \begin{cases} 1, & \text{if } \varepsilon_{i,t} > 1 \\ 0, & 0 \leq \varepsilon_{i,t} \leq 1 \end{cases} , \quad i = s, ad, osd, r, \tag{4}$$

$$outlier^{-}_{i,t} = \begin{cases} 1, & \text{if } \varepsilon_{i,t} < -1 \\ 0, & 0 \geq \varepsilon_{i,t} \geq -1 \end{cases} , \quad i = s, ad, osd, r, \tag{5}$$

where $outlier^{+}_{i,t}$ ($outlier^{-}_{i,t}$) takes the form of an indicator variable with 0 and 1 in Eq. (4) (Eq. 5) representing the relatively quiet and extreme positive (negative) outlier shock episodes, respectively. Once again, values which are found to be consistently 0 for all four shocks will form a mutually quiet sample to determine if linkages vary under extreme scenarios. In this instance, we test whether co-moments between external shocks and Canadian equity returns change under shock episodes classified as extreme positive (negative) outliers compared to all other relatively quieter positive (negative) periods.

3.3. Estimating returns net of market fundamentals for Canadian equity indices

We work with the residuals, $\epsilon_{k,t}$, from the generic regression in Eq. (6) to represent the returns of the real Canadian equity indices adjusted for the macroeconomic environment:

$$r^{CAN}_{k,t} = \alpha_k + \Sigma^{n}_{j=1}\beta_{k,j}r^{CAN}_{k,t-j} + \Sigma^{n}_{j=1}\gamma_j IR^{CAN}_{t-j} + \Sigma^{n}_{j=1}\lambda_j IR^{US}_{t-j} + \epsilon_{k,t} \tag{6}$$

where k denotes a given real Canadian equity index so that the returns, $r^{CAN}_{k,t}$, are the logarithmic difference of a particular index times 100. The regressors used to control for lead-lag effects follow the contagion literature, which include lags of the returns of a given real Canadian equity index, $r^{CAN}_{k,t-j}$; Canadian short term interest rates, IR^{CAN}_{t-j}, for which we use Canada's interbank rate[9]; and US interest rates, IR^{US}_{t-j}, for which we use the US effective federal

[9]Canadian 3-month rates and yields are obtained from the FRED database, available at fred.stlouisfed.org/series/IR3TIB01CAM156N, and accessed in September 2020.

funds rate[10]. Interest rates are commonly used to account for market fundamentals, as they reflect information about both macroeconomic developments and the policy environment (Forbes and Rigobon, 2002). We include lags of both Canadian and US interest rates, to respectively control for domestic and foreign activity. An optimal lag length, n, for these single equation regression models are selected by the Schwarz information criterion (SIC).

We estimate the returns net of market fundamentals as described in Eq. 6 for twelve Canadian equity market indices. These include the S&P Toronto Stock Exchange (TSX) Composite, the headline Canadian equity market index, as well as the eleven sector indices. The sector equities are defined along the Global Industrial Classification Standard (GICS) Level 1 taxonomy, which are a subset of the constituents comprised in the parent S&P TSX Composite, and consists of equities on the Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, Telecommunication, and Utilities Sectors. SIC suggests an optimal lag length of 2 months across all twelve regressions for adjusting the Candian equity returns.

Canadian equity indices data are obtained from the Bloomberg terminal and deflated using Canada's CPI[11]. As previously discussed, our period of analysis is 1988:1 to 2020:4, determined by the Canadian equity indices data availability. This therefore implies that data for priming the surprise shock filters in the second step are needed 12 months in advance, i.e. January 1987. As a consequence, the first step of statistically identifying structural shocks requires data from December 1984, i.e. 25 months which include: 1 month for the computing the percentage changes in world crude oil supply, oil prices, and the stock market; as well as a lag length of 24 months in estimating oil and US stock market shocks.

Figure 2 illustrates the returns, net of market fundamentals, for the real S&P TSX Composite and its 11 GICS Level 1 real S&P TSX sector equities. Firstly, the returns of the real TSX Composite is punctuated with spikes during the key contemporary global financial crises such as the Asian financial crisis (late 1990s), the dotcom crash (early 2000s), the 2008 Global Financial Crisis (GFC), and the COVID-19 pandemic (2020). Secondly, the returns of the real TSX Consumer Discretionary index shows higher volatility in the wake of global financial crises. On the other hand, the real TSX Consumer Staples returns appears to be relatively more stable as might be expected. The real equity returns of the TSX Energy, Finance, Materials, Real Estate, and Utilities Sectors all convey larger fluctuations for international events like the Asian financial crisis, the GFC, and COVID-19. However, as anticipated, the real equity returns of the IT and Telecommunications Sectors were particularly hard hit when the dotcom bubble burst but perhaps more resilient in the COVID-19 pandemic in comparison to spikes observed in other sectors, due to working from home and lock-down polices which rely on such technologies. The salient features of the real returns of the TSX Industrial Sector index resembles that of the Composite Index, while the real Health Sector equity returns experienced larger swings in the latter half of the 2010s.

[10]The US federal funds rate data are also obtained from the FRED database, available at fred.stlouisfed.org/series/DFF, and accessed in September 2020.

[11]Canadian stock market data are expressed in constant 2015 prices obtained from fred.stlouisfed.org/series/CPALCY01CAM661N, and both sets of data were accessed in September 2020.

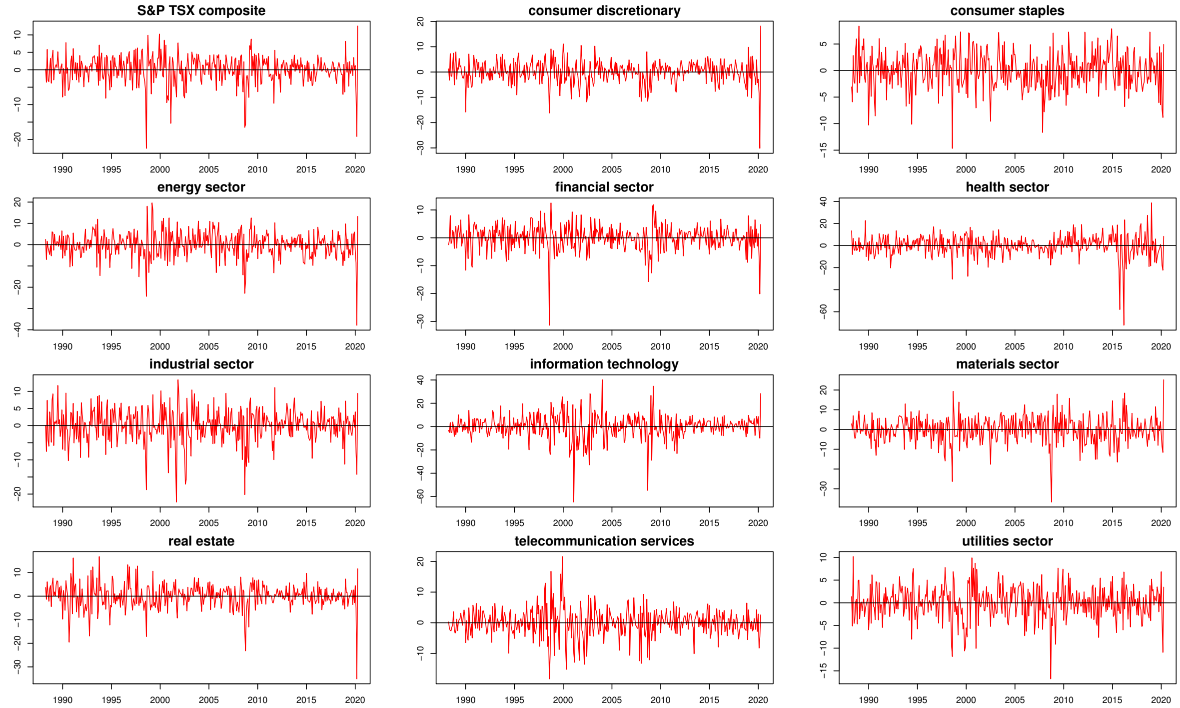

Figure 2: Returns net of market fundamentals for the real S&P TSX Composite and the corresponding real Level 1 GICS sector equities.

3.4. Spillover channels from oil and the S&P 500 market shocks to Canadian equities

To analyse whether the relationship between Canadian equities, and oil and S&P 500 market shocks change under extreme episodes, we adopt linear, asymmetric, and extremal dependence tests employed in Fry-McKibbin and Hsiao (2018)[12]. The following notation are used in the specification of the dependence tests: z_i is the standardised scaling of ε_i, which are the statistically identified structural residuals, where i denotes the various source of the shocks: oil supply, aggregate demand, oil-specific demand, or other shocks to the US stock market (hereafter called S&P 500 market shocks). z_k is the standardised scaling of ϵ_k, which are the residuals of Eq. (6) representing the returns adjusted for market fundamentals, where k is a given real Canadian equity index. T_x and T_y are the sample sizes, such that x_t are the time periods of quiet shocks which come from the aforementioned mutually quiet sample (0) defined by either the surprise filters (i.e., Eqs. 2 and 3) or outlier filters (i.e., Eqs. 4 and 5); and y_t are the time periods of surprise or outlier shock episodes, which can be positive or negative. $\hat{\mu}_{ix}$ ($\hat{\mu}_{kx}$) and $\hat{\mu}_{iy}$ ($\hat{\mu}_{ky}$) are the sample means of ε_{i,x_t} (ϵ_{k,x_t}) and ε_{i,y_t} (ϵ_{k,y_t}), respectively; and $\hat{\sigma}_{ix}$ ($\hat{\sigma}_{kx}$) and $\hat{\sigma}_{iy}$ ($\hat{\sigma}_{ky}$) are the corresponding sample standard deviations. Finally, as correlation coefficients are widely known to become spuriously over-inflated in the presence of heteroskedasticity, a correction is used in all dependence tests to scale the volatility in extreme shock episodes conditional of the volatility experienced in quiet shocks given by:

[12] Fry-McKibbin and Hsiao (2018) put forward the co-kurtosis channels of extremal dependence and also consolidates into their analysis the linear and asymmetric dependence contagion tests introduced in Fry et al. (2010), as well as the co-volatility channel of extremal dependence proposed in Fry-McKibbin et al. (2014).

$$\hat{\rho}_{y|x_i} = \frac{\hat{\rho}_y}{\sqrt{1 + ((\sigma^2_{i,y} - \sigma^2_{i,x})/\sigma^2_{i,x})(1 - \hat{\rho}^2_y)}} \tag{7}$$

where $\sigma^2_{i,x}$ ($\sigma^2_{i,y}$) is the variance of a given shock in quiet (extreme) episodes and $\hat{\rho}_y$ is the Pearson correlation coefficient between a given shock and the returns of a Canadian equity index in extreme shock episodes.

3.4.1. Linear dependence

To evaluate whether there is a change in correlation between a given external shock and a Canadian equity index, during quiet and extreme shock episodes, we employ a two-sided version of the Forbes and Rigobon (2002) significance test suggested in Fry et al. (2010):

$$CR_{11}(i \to k) = \left(\frac{\hat{\rho}_{y|x_i} - \hat{\rho}_x}{\sqrt{Var(\hat{\rho}_{y|x_i} - \hat{\rho}_x)}} \right)^2 \tag{8}$$

where $\hat{\rho}_{y|x_i}$ is the heteroskedasticity corrected correlation coefficient between an external shock and Canadian equities during extreme episodes; $\hat{\rho}_x$ is the Pearson correlation in the quiet sample.

3.4.2. Asymmetric dependence

We employ the co-skewness contagion tests introduced in Fry et al. (2010), to analyse whether there is a statistically significant difference between quiet and extreme shock episodes about how the (i) mean of extreme shocks (denoted as z^1_i) affect the volatility of real Canadian equity returns (denoted as z^2_k), as specified in Eq. (9); and (ii) volatility of extreme shocks (denoted as z^2_i) affect the mean of real Canadian equity returns (denoted as z^1_k), as specified in Eq. (10):

$$CS_{12}(i \to k; z^1_i, z^2_k) = \left(\frac{\hat{\psi}_y(z^1_i, z^2_k) - \hat{\psi}_x(z^1_i, z^2_k)}{\sqrt{(4\hat{\rho}^2_{y|x_i} + 2)/T_y + (4\hat{\rho}^2_x + 2)/T_x}} \right)^2 \tag{9}$$

$$CS_{21}(i \to k; z^2_i, z^1_k) = \left(\frac{\hat{\psi}_y(z^2_i, z^1_k) - \hat{\psi}_x(z^2_i, z^1_k)}{\sqrt{(4\hat{\rho}^2_{y|x_i} + 2)/T_y + (4\hat{\rho}^2_x + 2)/T_x}} \right)^2 \tag{10}$$

where the parameters $\hat{\psi}_x(z^m_i, z^n_k)$ and $\hat{\psi}_y(z^m_i, z^n_k)$ are defined as:

$$\hat{\psi}_x(z^m_i, z^n_k) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{\varepsilon_{i,x_t} - \hat{\mu}_{ix}}{\hat{\sigma}_{ix}} \right)^m \left(\frac{\epsilon_{k,x_t} - \hat{\mu}_{kx}}{\hat{\sigma}_{kx}} \right)^n \tag{11}$$

$$\hat{\psi}_y(z^m_i, z^n_k) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{\varepsilon_{i,y_t} - \hat{\mu}_{iy}}{\hat{\sigma}_{iy}} \right)^m \left(\frac{\epsilon_{k,y_t} - \hat{\mu}_{ky}}{\hat{\sigma}_{ky}} \right)^n \tag{12}$$

where z^m (z^n) is the standardised returns for market i (k) in the CS_{12} (CS_{21}) test version and squared standardised returns in the CS_{21} (CS_{12}) test version.

3.4.3. Extremal dependence

In order to examine whether the volatility of external market shocks (denoted as z_i^2) affect the volatility of real Canadian equity returns (denoted as z_k^2) differently during episodes of quiet and extreme shocks, we make use of the co-volatility contagion test suggested in Fry-McKibbin et al. (2014), as described in Eq. (13):

$$CV_{22}(i \to k; z_i^2, z_k^2) = \left(\frac{\hat{\xi}_y(z_i^2, z_k^2) - \hat{\xi}_x(z_i^2, z_k^2)}{\sqrt{(4\hat{\rho}^4_{y|x_i} + 16\hat{\rho}^2_{y|x_i} + 4)/T_y + (4\hat{\rho}^4_x + 16\hat{\rho}^2_x + 4)/T_x}} \right)^2 \tag{13}$$

where the standardisation parameters $\hat{\xi}_x(z_i^2, z_k^2)$ and $\hat{\xi}_y(z_i^2, z_k^2)$ are respectively defined in Eq. (14) and (15):

$$\hat{\xi}_x(z_i^2, z_k^2) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{\varepsilon_{i,x_t} - \hat{\mu}_{ix}}{\hat{\sigma}_{ix}} \right)^2 \left(\frac{\epsilon_{k,x_t} - \hat{\mu}_{kx}}{\hat{\sigma}_{kx}} \right)^2 - (1 + 2\hat{\rho}^2_x) \tag{14}$$

$$\hat{\xi}_y(z_i^2, z_k^2) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{\varepsilon_{i,y_t} - \hat{\mu}_{iy}}{\hat{\sigma}_{iy}} \right)^2 \left(\frac{\epsilon_{k,y_t} - \hat{\mu}_{ky}}{\hat{\sigma}_{ky}} \right)^2 - (1 + 2\hat{\rho}^2_{y|x_i}) \tag{15}$$

We utilise the co-kurtosis contagion tests, introduced in Fry-McKibbin and Hsiao (2018), to analyse whether there is a statistically significant difference between quiet and extreme shock episodes about how the (i) mean of extreme shocks (denoted as z_i^1) affect the cubed returns of real Canadian equities (denoted as z_k^3), as specified in Eq. (16); (ii) cubed values of extreme shocks (denoted as z_i^3) affect the mean of real Canadian equity returns (denoted as z_k^1), as specified in Eq. (17):

$$CK_{13}(i \to k; z_i^1, z_k^3) = \left(\frac{\hat{\zeta}_y(z_i^1, z_k^3) - \hat{\zeta}_x(z_i^1, z_k^3)}{\sqrt{(18\hat{\rho}^2_{y|x_i} + 6)/T_y + (18\hat{\rho}^2_x + 6)/T_x}} \right)^2 \tag{16}$$

$$CK_{31}(i \to k; z_i^3, z_k^1) = \left(\frac{\hat{\zeta}_y(z_i^3, z_k^1) - \hat{\zeta}_x(z_i^3, z_k^1)}{\sqrt{(18\hat{\rho}^2_{y|x_i} + 6)/T_y + (18\hat{\rho}^2_x + 6)/T_x}} \right)^2 \tag{17}$$

where cubed returns are a proxy for skewness, and the parameters $\hat{\zeta}_x(z_i^m, z_k^n)$ and $\hat{\zeta}_y(z_i^m, z_k^n)$ are defined as:

$$\hat{\zeta}_x(z_i^m, z_k^n) = \frac{1}{T_x} \sum_{t=1}^{T_x} \left(\frac{\varepsilon_{i,x_t} - \hat{\mu}_{ix}}{\hat{\sigma}_{ix}} \right)^m \left(\frac{\epsilon_{k,x_t} - \hat{\mu}_{kx}}{\hat{\sigma}_{kx}} \right)^n - (3\hat{\rho}_x) \tag{18}$$

$$\hat{\zeta}_y(z_i^m, z_k^n) = \frac{1}{T_y} \sum_{t=1}^{T_y} \left(\frac{\varepsilon_{i,y_t} - \hat{\mu}_{iy}}{\hat{\sigma}_{iy}} \right)^m \left(\frac{\epsilon_{k,y_t} - \hat{\mu}_{ky}}{\hat{\sigma}_{ky}} \right)^n - (3\hat{\rho}_{y|x_i}) \tag{19}$$

where z^m (z^n) is the standardised returns for market i (k) in the CK_{13} (CK_{31}) test version and cubed standardised returns in the CK_{31} (CK_{13}) test version.

3.4.4. Evaluating the null hypothesis of the dependence tests

The linear, asymmetric, and extremal dependence tests, under their respective null hypotheses of no changes in the correlation, co-skewness, co-volatility, and co-kurtosis during quiet and extreme shock episodes, are asymptotically distributed as:

$$CR_{11}, CS_{12}, CS_{21}, CV_{22}, CK_{13}, CK_{31}(i \to k) \xrightarrow{d} \chi_1^2.$$

As our sample sizes in the dependence tests are relatively small and the splits between extreme and calm periods are unequal, it is not optimal to use the asymptotic critical values. In the case of short crisis periods, the linear test, CR_{11}, tends to be oversized while the higher moment tests, CS_{12}, CV_{22} and CK_{13}, tend to be undersized, see Fry-McKibbin et al. (2019). On these grounds we simulate critical values. When conducting simulating exercises, under the null hypothesis, we use sample sizes for the extreme and quiet shock periods identical to our applications, as implied by the surprise and outlier filters. The results of the critical values obtained from the simulation exercises, based on 50,000 replications, are presented in Table A.3 for the conventional levels of statistical significance (i.e., 1%, 5%, and 10% levels).

4. Results and discussion

4.1. Comparison of identification strategies of the oil and S&P 500 market shocks

Jarque–Bera tests for normality on the reduced-form residuals of the VAR show that there is strong evidence against the null hypothesis of normality for all four components of the model, see Table 1. Hence, identification through independent components is an adequate identification technique.[13]

Table 1: Jarque–Bera normality tests.

Component	Skewness	Kurtosis	JB statistic	p-value
u_{1t}	-0.476	8.176	461.610	0.000
u_{2t}	-0.632	6.608	243.650	0.000
u_{3t}	-0.219	4.701	51.459	0.000
u_{4t}	-0.533	3.720	27.553	0.000

[13] We use the R package 'svars' of Lange et al. (2019).

The estimated impact matrices of the recursive-Cholesky approach $\hat{\boldsymbol{D}}$ and of the identification-through-independent-components approach $\hat{\boldsymbol{B}}_{cvm}$ reads as:

$$\hat{\boldsymbol{D}} = \begin{bmatrix} 0.764 & 0 & 0 & 0 \\ 0.466 & 13.268 & 0 & 0 \\ -0.908 & 0.886 & 6.659 & 0 \\ -0.008 & 0.199 & 0.244 & 3.695 \end{bmatrix}$$

$$\hat{\boldsymbol{B}}_{cvm} = \begin{bmatrix} 0.735 & -0.028 & 0.175 & -0.113 \\ 1.542 & 12.964 & -2.411 & -0.030 \\ -2.345 & 2.254 & 5.926 & -0.504 \\ 0.399 & 0.287 & 0.662 & 3.616 \end{bmatrix}.$$

We compare the structural shocks obtained from the statistical identification strategy of Herwartz and Plödt (2016) and Herwartz (2018), with the theoretical approach suggested in Kilian and Park (2009), in Figure 3, and note that the results are qualitatively consistent. We further investigate the impulse response functions of these two identification strategies, in Figure 4, and observe a close alignment in the dynamics between the approaches across a forecast horizon of 15 months. The similarity in dynamics shows that the correct column permutation has been chosen in the statistical approach.

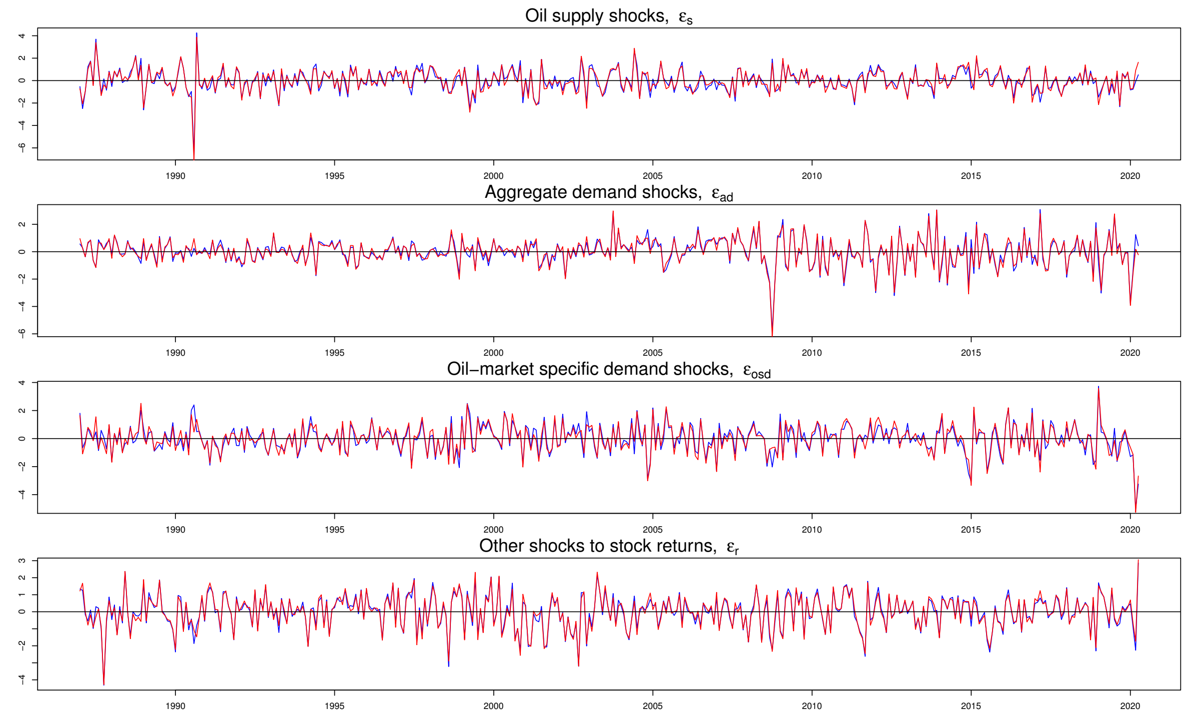

Figure 3: Structural shocks comparison of different identification approaches. Blue line: shocks of a model identified as a recursive structure. Red line: shocks computed from a model which has been identified through independent components.

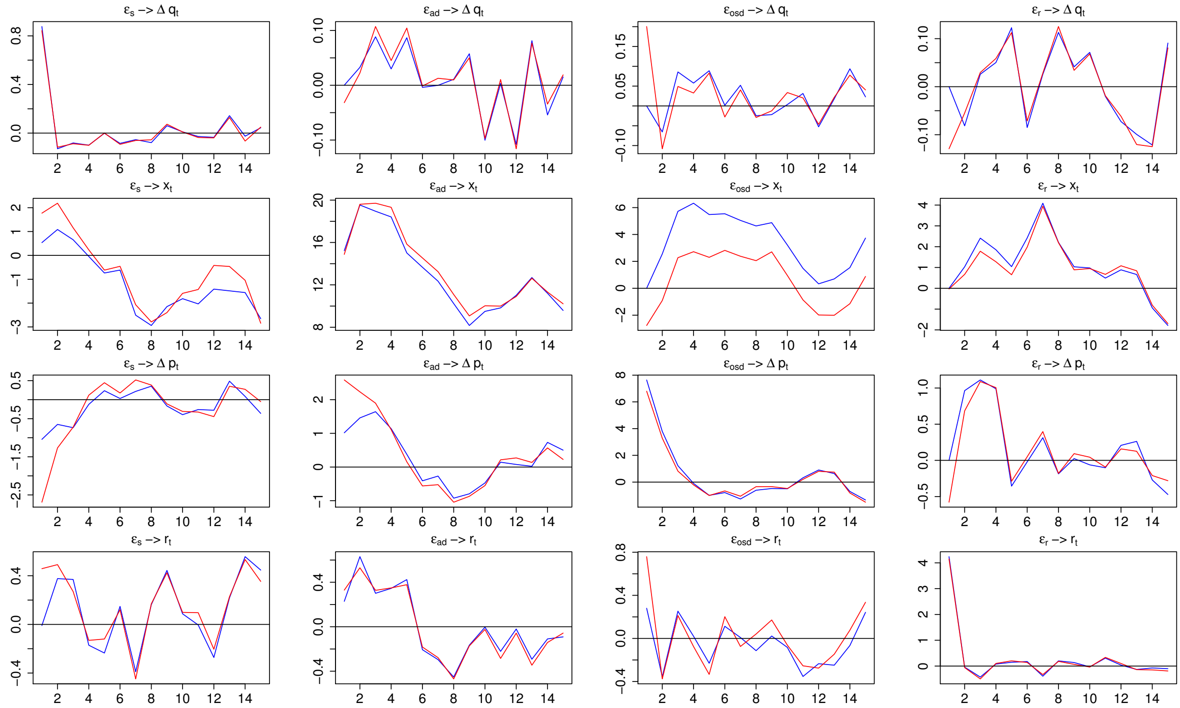

Figure 4: Impulse response comparison of different identification approaches. Blue line: responses of a model identified as a recursive structure. Red line: responses computed from a model which has been identified through independent components.

We prefer using the statistical identification strategy, because it does not rely on strict zero restrictions derived from economic theory. Further, under the statistical identification strategy the structural shocks are not just orthogonal but the higher order moment dependencies between shocks are also minimised.

4.2. Evidence of spillover effects from oil and S&P 500 market shocks to Canadian equities

We now turn to our main research question of this paper - do various co-moments between real Canadian equity returns and shocks from the crude oil and US stock markets differ under extreme shock episodes compared to quiet periods? Due to the variations in quiet and extreme sample sizes produced by the positive and negative surprise and outlier shock filters in Eqs. (2), (3) (4), and (5), we use simulated critical values to evaluate the null hypothesis of "no contagion" across the various co-moment channels.

For both the surprise and outlier shock filters, T_x and T_y in Table 2 show the sample sizes of the amount of months distributed between quiet and extreme shocks, respectively. Out of the overall sample of 375 months (i.e., 1988:4 - 2020:4), the sum of positive and negative T_x samples in the case of each of the four shocks are equal to 206 (115) mutually quiet months under the surprise (outlier) filter. The remainder 169 (260) extreme episodes are distributed across positive and negative oil supply (os), global aggregate demand (gd), oil-specific demand (od), and S&P 500 market (sp) shocks, denoted in months by T_y, with the possibility of overlaps where some months experience multiple types of extreme shocks.

4.2.1. Implications for the S&P TSX Composite Index

Table 2 shows that, over all periods of time, the highest positive (lowest negative) returns in the real S&P TSX Composite are experienced when the S&P 500 market exhibits extreme positive (negative) shocks. These findings are similar for both the surprise and outlier shock filters, and illustrates the synchronisation between the financial markets of Canada and the US. Additionally, the return volatility of the real TSX Composite Index is typically higher under extreme shock episodes in the crude oil and S&P 500 markets relative to quiet shock episodes [14]. Furthermore, for each of the four identified shocks, returns volatility of the TSX Composite is higher under negative episodes compared to positive episodes. As stock return volatility is a proxy for market uncertainty (see, e.g., Bloom et al., 2007), higher volatility in extreme shock episodes reflect the fear associated with such events in the TSX market. The largest return volatility values in the real TSX Composite occur under negative oil supply and demand shocks. These aforementioned findings, regarding the return volatility of the real TSX Composite, are the same across both surprise and outlier filters.

From the spillover test results produced with the surprise and outlier filters, a general consistency is also observed in Table 2. However, there is a tendency for the outlier filter to provide additional spillover channels from the oil and S&P 500 markets to the TSX Composite relative to the surprise filter. Furthermore, the results are in line with the contagion literature, that co-moments beyond the correlation channel are important in reflecting the changes occurring between market relationships in times of extreme events (see, e.g., Fry et al., 2010; Fry-McKibbin and Hsiao, 2018). There is also strong evidence to support asymmetric spillover effects from oil and US financial market shocks to Canadian equities, as noted by difference in findings under extreme positive and negative shocks.

We find a weak and (for the most part) negative correlation between oil supply shocks and the TSX composite under quiet/extreme, positive/negative, and surprise/outlier oil supply shock episodes. Although oil supply shocks are thought to become irrelevant in the recent literature (see, e.g., Broadstock and Filis, 2014 and references within), asymmetric and extremal dependence channels detect changes in the relationship between oil supply shocks and the TSX Composite in extreme episodes.

Turning to the relationship between global aggregate demand side shocks and the TSX Composite, contagion effects are noted under extreme negative episodes, while extreme positive global aggregate demand side shocks appear comparatively inconsequential. This is evidenced by a generally weak relationship between global aggregate demand shocks and the TSX Composite, which becomes stronger and positive under extreme negative episodes, in both surprise and outlier shocks. Our results align with Antonakakis et al. (2017), who also document that global aggregate demand shocks only matter in Canada during turbulent periods but the effects of such shocks are muted in tranquil conditions. However, the correlation coefficient corrected for heteroskedasticity underscores the upward bias in the linear correlation coefficient during the high volatility associated with extreme episodes. Nevertheless, even after

[14] The one exception where return volatility in the real TSX Composite is higher in the quiet episodes is observed under positive oil-specific demand shocks using the surprise filter.

Table 2: Spillover tests from shocks in the crude oil and S&P 500 markets to the adjusted returns of real S&P TSX Composite Index based on the surprise and outlier shock filter.

Surprise shock filter

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
T_x	107	99	111	95	107	99	113	93
T_y	34	29	27	39	34	32	29	29
$\hat{\mu}_x$	0.721	-0.411	0.577	-0.290	0.669	-0.354	1.623	-1.580
$\hat{\mu}_y$	-1.072	-0.771	0.045	-0.807	1.373	-1.275	3.704	-5.203
$\hat{\sigma}_x$	3.248	3.605	3.543	3.324	3.550	3.302	3.044	3.122
$\hat{\sigma}_y$	5.694	6.814	3.728	4.582	2.871	5.989	3.103	5.857
$\hat{\rho}_x$	-0.109	-0.065	0.027	0.003	0.166	-0.157	0.314	0.457
$\hat{\rho}_y$	-0.049	0.009	-0.030	0.366	0.406	0.423	0.495	0.636
$\hat{\rho}_{y\|x_i}$	-0.031	0.003	-0.017	0.158	0.275	0.234	0.457	0.543
CR_{11}	0.295	0.336	0.095	1.614	0.617	8.521^{**}	0.888	0.464
CS_{12}	0.661	0.042	0.379	21.620^{***}	1.375	7.944^{***}	1.652	0.512
CS_{21}	0.735	1.709	0.041	18.312^{***}	2.555^{*}	24.596^{***}	2.591^{*}	0.340
CV_{22}	1.664	0.000	0.228	91.016^{***}	6.064^{***}	52.590^{***}	4.036^{**}	0.001
CK_{13}	4.944^{**}	2.115^{*}	0.327	62.485^{***}	0.551	44.276^{***}	1.777^{*}	0.769
CK_{31}	4.014^{**}	22.799^{***}	0.858	100.552^{***}	11.567^{***}	102.444^{***}	4.477^{**}	0.122

Outlier shock filter

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
T_x	54	61	61	54	57	58	70	45
T_y	57	48	43	48	55	58	54	65
$\hat{\mu}_x$	0.613	0.321	0.889	-0.029	0.873	0.051	1.164	-0.640
$\hat{\mu}_y$	-0.135	-1.232	0.310	-0.698	1.296	-0.519	3.382	-4.996
$\hat{\sigma}_x$	2.677	3.342	2.836	3.208	3.178	2.863	2.911	2.932
$\hat{\sigma}_y$	4.591	5.480	3.648	4.270	3.290	5.391	3.161	4.750
$\hat{\rho}_x$	-0.112	-0.236	0.132	0.046	0.021	-0.283	0.149	0.251
$\hat{\rho}_y$	-0.138	-0.066	-0.128	0.374	0.318	0.294	0.469	0.461
$\hat{\rho}_{y\|x_i}$	-0.083	-0.018	-0.064	0.109	0.202	0.124	0.364	0.310
CR_{11}	0.034	2.960	1.766	0.196	1.363	9.140^{***}	2.180	0.146
CS_{12}	1.276	0.008	3.355^{**}	26.992^{***}	0.813	21.284^{***}	6.164^{***}	8.348^{***}
CS_{21}	3.401^{*}	3.590^{**}	0.259	33.529^{***}	13.248^{***}	23.760^{***}	8.510^{***}	3.028^{*}
CV_{22}	0.027	0.000	0.002	176.352^{***}	5.843^{**}	146.538^{***}	16.419^{***}	6.841^{***}
CK_{13}	0.209	3.002^{**}	1.600	104.609^{***}	1.982	49.867^{***}	4.945^{**}	7.965^{***}
CK_{31}	23.764^{***}	45.658^{***}	2.461^{*}	248.299^{***}	42.118^{***}	235.226^{***}	26.297^{***}	6.489^{***}

Notes: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.

We apply simulated critical values, see Table A.3.

correcting for this over-inflation, all co-moment spillover channels, with the sole exception of the linear correlation channel, indicate that the dependence structure between the source shock and the recipient market change.

For the relationship between oil demand shocks and the TSX Composite, a weak positive correlation in quiet periods becomes relatively stronger under extreme positive shocks in the cases of both surprise and outlier filters. Co-skewness, co-kurtosis, and co-volatility dependence tests provide evidence of spillover effects in the extreme positive oil demand episodes. Under negative oil demand shocks, the correlation between the TSX composite and oil demand shocks switches from negative in quiet periods to positive in extreme episodes. All spillover channels detect changes in this relationship between quiet and extreme episodes during both negative oil demand surprise and outlier shocks. The results from demand side shocks (both global aggregate demand and oil demand) are in line with the findings of Kilian and Park (2009) on the impact of oil price shocks on the US stock market that it is demand side shocks which have a greater consequence for markets compared to supply side shocks.

With regards to the relationship between the S&P 500 market shocks and the TSX Composite, a relatively moderate and positive interdependence becomes stronger under extreme conditions. This is consistent for both positive and negative S&P 500 market shocks, as well as for both surprise and outlier approaches. The various co-moment dependence test results suggest that the outlier shock filter provide stronger evidence of spillover effects than the surprise shock filter. Again, it is the channels beyond linear correlation which are significant and once more underscores the importance of asymmetric and extremal dependence tests in analysing the relationship between markets under stress.

4.2.2. Implications for the sector equities of the S&P TSX Composite Index

Similar to the results of the parent composite index, the findings for the sector equities obtained using the surprise and outlier shocks are generally consistent with the tendency to convey additional spillover channels across the various co-moments. We subsequently highlight the main results obtained from the sectoral analysis using the surprise and outlier shock filters, respectively presented in Tables A.4 and A.5.

Of all extreme episodes, the 11 real TSX Composite GISC Level 1 Sectors all experienced the lowest returns during the negative S&P 500 market shocks. The real TSX Consumer Discretionary, Consumer Staples, Energy, and Financial Sectors all experienced the highest return volatility under negative oil-specific demand shocks. However, for the real TSX Industrial, IT, Telecommunications, and Utilities Sectors, the highest return volatility are recorded under negative oil supply shocks. These observations about the summary statistics are consistent across both the surprise and outlier filters. However, the real TSX Health, Materials, and Real Estate Sector equities conveyed differences between surprise and outlier filters for periods where the highest return volatility occurred.

Out of the four main types of shocks, the TSX Consumer Discretionary Sector is more correlated with oil-specific demand and S&P 500 market shocks; and the TSX Consumer Staples Sector is more correlated with S&P 500 market shocks. The TSX Consumer Discretionary Sector shows more spillover channels detected in comparison to the TSX Consumer Staples Sector across samples obtained using the surprise and outlier shock filters. Such results are theoretically consistent with the idea that the Consumer Discretionary Sector is sensitive to extreme market conditions whereas the Consumer Staples Sector is relatively more stable (unchanged) in the wake of an extreme shock compared to quiet periods. This is particularly evident during negative global aggregate and positive oil-specific demand shocks.

The results for the TSX Energy Sector equities show, as one might expect, that changes in the co-moments between shocks and this sector index primarily relate to extreme negative global aggregate and oil-specific demand side shocks. For the relationship between TSX Financial Sector equities and shocks from the crude oil and US stock markets, correlations are strongest under extreme positive and negative oil demand shocks, as well as under extreme negative S&P 500 market shocks. Turning to the TSX Health, Industrial, IT, Materials, and Telecommunications Sectors, the correlation between each of these sector indices and S&P 500 market shocks are stronger when compared to relationship between these indices and crude oil market shocks. In the case of the TSX Real Estate Sector equities, with the exception of positive global aggregate demand shocks, the crude oil market is found to be the source of spillovers for this sector market. From the TSX Utilities Sector results, most spillover activity occurs in the relationship between this sector index and oil demand shocks under negative episodes.

4.2.3. Robustness analysis

We test the sensitivity of the results from the various dependence tests to alternative specifications in the filters for identifying discrete quiet and extreme shocks. For instance, in the case of the definition of surprise shocks corresponding to major increases or decreases in a shock over the preceding 12 months, we also consider the cases 9 months and 15 months. With respect to the outlier shocks for classifying extreme episodes as values exceeding 1 SD band, we also consider the cases of 1.2 and 1.5 SD bands. The overall results from both filters for identifying surprise and outlier shocks are robust to such alternative specifications in these rules[15].

5. Conclusion

Our paper contributes to the literature by consolidating various empirical procedures into an original approach to investigate the channels through which Canadian equities are affected by extreme spillover shocks from two of the most important external markets of this country - the international crude oil and S&P 500 markets. To do this, we first disentangle structural shocks from these external markets through independent components. Comparisons of the structural shocks and impulse response functions implied by the statistically identified strategy and a theoretical SVAR are found to closely align, yet pursuing the former strategy has advantages of orthogonality and a minimisation of higher order moment dependencies between the estimated shocks.

Subsequently, we filter the statistically identified oil and S&P 500 market shocks into discrete quiet and extreme episodes. This is achieved using two different approaches: a surprise filter, which detects major shocks occurring

[15] The results from the robustness analysis can be made available upon request to the authors.

over the preceding year; and an outlier filter, to detect extreme shocks outside a normal range of values. These discrete filters fit well with the contagion literature, which advocates that it is the unprecedented shocks from a stable environmental that gives rise to an increase in cross-market linkages. We then use the periods of quiet and extreme shocks to construct sub-samples for constructing spillover tests through multiple co-moment channels. These tests evaluate whether correlation, co-skewness, co-volatility, and co-skewness between Canadian equity returns and shocks from the crude oil and S&P 500 markets change during quiet and extreme shock episodes.

We show that although oil supply shocks and Canadian equities are weakly correlated, the former can influence the latter through certain higher co-moment channels. We also find contagion effects between global aggregate demand shocks and Canadian equities, since only negative extreme shocks lead to a rise in correlation and the detection of many statistically significant spillover channels. Regarding the relationship between oil-specific demand shocks and Canadian equities, episodes of positive and negative extreme values in such shocks exhibit contagion effects. Moreover, we observe that compared to all shocks, market correlations are highest in the relationship between S&P 500 market and Canadian equities. Additionally, from the relationship between oil and S&P 500 market shocks and disaggregated Canadian equities, our results suggest heterogeneity across various sectors. This type of research can benefit Canadian policymakers interested in both systemic and sector vulnerability and resilience to external shocks. It is also useful to stock market participants with interests in US, Canadian, international commodity markets seeking to optimise their portfolio choice.

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Appendix A.

Table A.3: Simulated critical values, 50,000 repetitions.

T_x		107	99	111	95	107	99	113	93
T_y		34	29	27	39	34	32	29	29
	10%	3.201	3.320	3.421	3.065	3.201	3.223	3.341	3.312
CR_{11}	5%	4.739	4.952	5.162	4.503	4.739	4.797	5.024	4.883
	1%	8.930	9.576	10.241	8.308	8.930	9.102	9.886	9.312
	10%	2.272	2.218	2.150	2.347	2.272	2.273	2.168	2.219
CS_{12}	5%	3.268	3.181	3.088	3.356	3.268	3.217	3.126	3.140
	1%	5.800	5.514	5.541	5.821	5.800	5.602	5.551	5.482
	10%	1.887	1.808	1.774	1.941	1.887	1.857	1.814	1.771
CV_{22}	5%	2.725	2.588	2.540	2.825	2.725	2.699	2.585	2.606
	1%	5.345	4.955	4.771	5.582	5.345	5.165	5.002	4.994
	10%	1.839	1.716	1.672	1.900	1.839	1.789	1.715	1.722
CK_{13}	5%	2.770	2.569	2.497	2.852	2.770	2.708	2.594	2.571
	1%	5.624	5.404	5.137	5.960	5.624	5.621	5.431	5.383

T_x		54	61	61	54	57	58	70	45
T_y		57	48	43	48	55	58	54	65
	10%	2.926	2.985	3.042	2.967	2.960	2.933	2.942	2.944
CR_{11}	5%	4.236	4.324	4.375	4.326	4.232	4.212	4.236	4.219
	1%	7.500	7.633	7.689	7.612	7.478	7.468	7.436	7.531
	10%	2.364	2.353	2.320	2.331	2.374	2.380	2.358	2.360
CS_{12}	5%	3.411	3.350	3.337	3.383	3.411	3.439	3.379	3.373
	1%	5.971	5.858	5.811	5.837	5.999	6.022	5.898	5.845
	10%	1.965	1.962	1.925	1.915	1.960	1.999	2.037	1.971
CV_{22}	5%	2.963	2.926	2.865	2.898	2.987	3.041	3.036	2.960
	1%	6.050	5.995	5.817	5.934	6.049	6.065	6.147	6.061
	10%	1.999	1.966	1.928	1.947	2.020	2.025	2.057	1.966
CK_{13}	5%	3.016	2.968	2.914	2.914	3.010	3.019	3.095	2.975
	1%	6.060	6.084	6.054	6.061	6.121	6.162	6.202	6.019

Notes: We simulated critical values 10% (weak), 5% (moderate), and 1%(strong) levels of statistical significance, respectively, which corresponds to asymptotic χ^2_1 critical values of 2.706, 3.841 and 6.635. The top panel replicates the sample sizes for the Surprise shock filter and the bottom panel the sample sizes for the Outlier shock filter.

Table A.4: Spillover tests from shocks in the crude oil and S&P 500 markets to the adjusted returns of real S&P TSX GICS Sector indices based on the surprise shock filter.

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
S&P TSX consumer discretionary sector index								
$\hat{\mu}_x$	0.489	-0.545	0.653	-0.780	0.214	-0.247	1.303	-1.600
$\hat{\mu}_y$	-0.895	0.114	-0.291	0.070	0.754	-0.682	3.778	-5.762
$\hat{\sigma}_x$	3.777	3.851	3.659	3.918	3.790	3.896	3.211	3.951
$\hat{\sigma}_y$	7.080	5.516	3.910	4.107	4.227	7.792	4.836	6.965
$\hat{\rho}_x$	-0.014	-0.020	0.000	0.141	-0.013	-0.070	0.174	0.386
$\hat{\rho}_y$	0.117	0.086	0.208	0.283	0.425	0.479	0.352	0.458
$\hat{\rho}_{y\|x_i}$	0.075	0.028	0.118	0.119	0.290	0.271	0.322	0.375
CR_{11}	0.374	0.170	0.681	0.033	4.545*	6.418**	0.728	0.006
CS_{12}	0.441	0.004	1.652	2.430*	3.006*	20.402***	14.587***	0.473
CS_{21}	1.413	6.714***	1.326	7.665***	2.890*	41.432***	10.930***	0.327
CV_{22}	0.363	0.416	0.093	9.562***	2.029*	172.023***	20.836***	1.127
CK_{13}	13.421***	1.450	1.121	3.195**	1.160	122.489***	7.749***	0.502
CK_{31}	4.753**	56.781***	2.115*	41.217***	6.442***	161.253***	22.707***	0.029
S&P TSX consumer staples sector index								
$\hat{\mu}_x$	0.024	-0.265	0.145	-0.418	0.181	-0.434	0.280	-0.594
$\hat{\mu}_y$	-0.353	-0.425	0.053	0.295	0.225	0.036	1.790	-2.572
$\hat{\sigma}_x$	3.079	3.506	3.345	3.207	3.217	3.347	3.175	3.372
$\hat{\sigma}_y$	4.410	4.278	2.864	3.957	2.637	5.073	2.975	4.558
$\hat{\rho}_x$	0.036	-0.093	0.073	0.144	-0.081	-0.116	0.189	0.172
$\hat{\rho}_y$	-0.029	0.163	0.131	-0.074	0.234	0.127	0.420	0.273
$\hat{\rho}_{y\|x_i}$	-0.018	0.054	0.074	-0.030	0.153	0.066	0.386	0.218
CR_{11}	0.141	1.568	0.000	2.123	2.593	1.815	1.419	0.071
CS_{12}	2.934*	0.416	0.200	0.004	0.247	0.843	0.570	0.691
CS_{21}	4.864**	7.258***	0.229	0.139	0.071	10.705***	4.467**	0.000
CV_{22}	3.344**	1.292	0.348	2.389*	0.126	3.886**	0.694	0.280
CK_{13}	0.575	2.130*	0.357	0.025	0.029	1.224	0.487	0.430
CK_{31}	22.640***	44.490***	0.005	6.547***	1.376	42.041***	3.043**	0.632
S&P TSX energy sector index								
$\hat{\mu}_x$	0.282	-0.597	0.465	-0.848	0.352	-0.673	1.300	-1.891
$\hat{\mu}_y$	-0.922	1.820	1.628	-1.623	3.697	-3.448	1.782	-4.730
$\hat{\sigma}_x$	4.982	5.534	5.170	5.302	5.276	5.216	5.277	4.702
$\hat{\sigma}_y$	8.912	9.118	5.841	6.813	5.245	9.376	5.341	9.350
$\hat{\rho}_x$	0.000	-0.096	0.041	0.014	0.156	0.014	0.130	0.172
$\hat{\rho}_y$	0.047	-0.206	-0.234	0.230	0.570	0.435	0.466	0.354
$\hat{\rho}_{y\|x_i}$	0.030	-0.069	-0.133	0.096	0.409	0.241	0.430	0.285
CR_{11}	0.042	0.054	1.486	0.453	3.590*	2.874	3.463*	0.459
CS_{12}	3.140*	0.021	0.023	5.524**	1.633	35.207***	0.973	0.709
CS_{21}	0.582	0.146	0.072	12.190***	0.531	27.953***	1.512	0.084
CV_{22}	2.011*	1.157	3.223**	22.072***	0.352	176.408***	0.916	0.005
CK_{13}	13.569***	0.578	1.702*	13.817***	0.793	121.443***	0.000	0.024
CK_{31}	2.029*	0.956	0.134	57.692***	1.334	157.567***	1.378	0.024

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Table A.4 – *Continued from previous page*

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
S&P TSX financial sector index								
$\hat{\mu}_x$	0.805	-0.574	0.545	-0.328	0.419	-0.156	1.401	-1.386
$\hat{\mu}_y$	-2.024	-0.194	-0.110	-0.619	1.453	-1.416	3.868	-5.229
$\hat{\sigma}_x$	3.898	3.363	3.678	3.704	3.760	3.644	3.529	3.339
$\hat{\sigma}_y$	5.784	7.532	4.455	4.533	3.769	7.887	3.608	7.374
$\hat{\rho}_x$	0.052	0.038	-0.062	-0.069	0.102	0.034	0.263	0.305
$\hat{\rho}_y$	-0.125	0.075	-0.051	0.377	0.361	0.440	-0.018	0.579
$\hat{\rho}_{y\|x_i}$	-0.080	0.025	-0.028	0.163	0.243	0.245	-0.016	0.488
CR_{11}	0.821	0.013	0.055	3.602*	0.981	2.467	2.165	1.640
CS_{12}	0.270	0.296	0.928	5.656**	0.531	0.460	0.055	2.954*
CS_{21}	3.335**	6.676***	0.385	19.582***	1.516	19.533***	0.425	0.021
CV_{22}	0.091	0.130	0.039	84.957***	1.069	6.645***	0.000	0.679
CK_{13}	0.727	6.308***	0.100	66.094***	0.001	14.943***	5.850***	6.881***
CK_{31}	13.714***	65.085***	0.095	95.819***	3.707**	73.974***	0.463	0.042
S&P TSX health sector index								
$\hat{\mu}_x$	1.275	-0.536	1.269	-0.606	1.329	-0.594	2.196	-1.772
$\hat{\mu}_y$	1.443	0.528	-4.628	0.387	-0.081	-0.724	1.438	-5.815
$\hat{\sigma}_x$	9.316	8.822	8.886	9.299	10.013	7.938	9.358	8.329
$\hat{\sigma}_y$	9.384	12.538	8.760	7.344	16.591	10.897	16.745	10.955
$\hat{\rho}_x$	0.013	-0.020	0.013	0.081	-0.165	0.104	-0.055	0.182
$\hat{\rho}_y$	-0.024	0.220	-0.065	-0.037	0.113	0.330	0.285	0.461
$\hat{\rho}_{y\|x_i}$	-0.015	0.074	-0.036	-0.015	0.073	0.177	0.259	0.378
CR_{11}	0.038	0.631	0.117	0.638	2.692	0.301	2.993	1.524
CS_{12}	0.392	0.123	0.008	0.787	2.686*	2.647*	4.250**	0.085
CS_{21}	7.088***	2.861*	0.810	0.355	2.880*	5.375**	0.567	0.044
CV_{22}	0.009	0.058	0.314	3.326**	11.008***	16.612***	4.882**	0.076
CK_{13}	14.493***	0.468	0.026	10.633***	0.835	5.161**	5.170**	0.115
CK_{31}	8.294***	31.169***	0.035	1.135	10.015***	39.826***	1.138	0.058
S&P TSX industrial sector index								
$\hat{\mu}_x$	0.450	-0.628	0.671	-0.932	0.431	-0.608	1.647	-2.152
$\hat{\mu}_y$	-0.583	-0.403	-0.021	-0.695	0.405	-0.007	4.332	-5.665
$\hat{\sigma}_x$	3.874	5.081	3.810	5.108	4.342	4.659	3.566	4.686
$\hat{\sigma}_y$	5.359	6.873	5.694	5.249	4.427	5.968	4.370	5.776
$\hat{\rho}_x$	0.017	0.157	0.116	-0.046	-0.017	0.016	0.166	0.399
$\hat{\rho}_y$	0.008	0.112	0.070	0.162	0.325	0.381	0.222	0.733
$\hat{\rho}_{y\|x_i}$	0.005	0.037	0.039	0.067	0.217	0.207	0.201	0.646
CR_{11}	0.006	1.078	0.292	0.857	2.639	2.026	0.036	4.495*
CS_{12}	0.042	0.037	2.023	0.394	0.272	4.023**	0.019	0.000
CS_{21}	1.371	4.729**	0.006	0.098	0.999	17.125***	2.951*	0.030
CV_{22}	0.341	3.314**	1.407	2.350*	0.779	26.991***	0.065	1.586
CK_{13}	0.077	4.216**	1.696*	6.930***	0.029	7.315***	0.140	4.743**
CK_{31}	3.705**	72.814***	1.323	1.025	4.746**	70.337***	7.178***	0.223

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Table A.4 – *Continued from previous page*

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
S&P TSX information technology sector index								
$\hat{\mu}_x$	1.709	-0.291	0.998	0.456	1.749	-0.334	3.458	-2.545
$\hat{\mu}_y$	0.460	-6.735	-3.471	-0.875	1.479	0.472	6.813	-7.692
$\hat{\sigma}_x$	8.680	9.089	9.340	8.428	9.356	8.322	8.629	8.150
$\hat{\sigma}_y$	10.988	18.115	10.516	12.636	8.825	8.071	8.597	11.194
$\hat{\rho}_x$	-0.019	-0.086	-0.142	-0.077	0.113	-0.158	0.181	0.437
$\hat{\rho}_y$	0.043	0.063	0.314	0.052	-0.106	0.222	0.435	0.579
$\hat{\rho}_{y\|x_i}$	0.027	0.021	0.181	0.021	-0.068	0.116	0.400	0.487
CR_{11}	0.100	0.830	5.210**	0.654	1.549	4.176*	1.785	0.139
CS_{12}	2.862*	0.405	0.127	0.356	0.036	0.857	0.113	0.010
CS_{21}	0.010	0.194	0.186	0.332	0.954	6.397***	3.070*	0.089
CV_{22}	3.815**	1.001	0.685	4.307**	0.492	0.023	3.222**	0.117
CK_{13}	1.484	2.326*	4.350**	31.615***	0.740	9.174***	0.003	0.077
CK_{31}	0.959	4.104**	0.440	1.593	4.559**	21.068***	3.596**	0.028
S&P TSX materials sector index								
$\hat{\mu}_x$	0.092	-0.183	0.258	-0.389	-0.053	-0.027	1.573	-2.000
$\hat{\mu}_y$	-0.630	0.501	1.093	-1.392	1.345	-0.659	3.155	-4.543
$\hat{\sigma}_x$	6.423	6.547	6.555	6.383	6.626	6.328	6.128	6.360
$\hat{\sigma}_y$	9.666	9.460	6.864	8.301	4.574	7.427	5.747	10.102
$\hat{\rho}_x$	-0.159	-0.135	0.143	0.037	0.134	-0.237	0.107	0.142
$\hat{\rho}_y$	-0.131	-0.010	-0.125	0.516	0.101	0.036	0.546	0.316
$\hat{\rho}_{y\|x_i}$	-0.084	-0.003	-0.070	0.238	0.066	0.019	0.508	0.253
CR_{11}	0.279	1.282	2.252	2.699	0.218	3.778*	7.011**	0.436
CS_{12}	0.077	0.022	0.029	48.862***	0.012	3.105*	16.792***	2.423*
CS_{21}	0.082	1.317	0.023	32.461***	1.164	2.647*	11.662***	0.094
CV_{22}	4.248**	0.017	3.426**	306.002***	0.109	5.766***	47.961***	0.001
CK_{13}	0.830	0.607	3.310**	248.748***	0.024	0.042	56.868***	4.619**
CK_{31}	0.776	10.861***	0.906	188.805***	5.669***	19.834***	16.892***	0.010
S&P TSX real estate sector index								
$\hat{\mu}_x$	-0.088	-0.198	0.013	-0.320	0.271	-0.586	0.798	-1.282
$\hat{\mu}_y$	-1.607	-0.865	0.934	-0.338	0.508	-0.249	3.726	-4.738
$\hat{\sigma}_x$	4.631	3.960	4.161	4.496	4.351	4.245	4.384	3.952
$\hat{\sigma}_y$	9.274	5.732	5.072	6.332	3.526	8.661	5.554	8.253
$\hat{\rho}_x$	0.123	-0.006	-0.073	0.125	0.016	0.017	0.154	0.105
$\hat{\rho}_y$	-0.249	-0.075	-0.018	0.407	0.434	0.480	0.256	0.280
$\hat{\rho}_{y\|x_i}$	-0.161	-0.025	-0.010	0.179	0.297	0.271	0.233	0.224
CR_{11}	3.895*	0.026	0.197	0.199	3.944*	3.619*	0.189	0.473
CS_{12}	0.798	0.946	0.554	16.781***	0.243	54.764***	2.608*	0.077
CS_{21}	9.429***	5.184**	0.093	19.984***	2.578*	34.479***	0.556	0.008
CV_{22}	6.469***	0.596	0.111	151.688***	6.648***	272.979***	0.021	2.348*
CK_{13}	1.145	0.682	0.438	97.595***	0.404	194.356***	0.786	0.210
CK_{31}	19.737***	48.254***	0.016	118.896***	7.598***	176.472***	0.822	0.089

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Table A.4 – *Continued from previous page*

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
S&P TSX telecommunication services sector index								
$\hat{\mu}_x$	0.606	-0.175	0.591	-0.190	0.702	-0.278	1.218	-0.968
$\hat{\mu}_y$	-1.792	-1.296	-0.495	-0.065	0.029	0.774	2.728	-2.458
$\hat{\sigma}_x$	4.502	5.093	4.899	4.672	4.651	4.928	4.729	4.632
$\hat{\sigma}_y$	3.774	5.808	3.417	4.035	4.538	5.477	3.447	5.372
$\hat{\rho}_x$	-0.197	0.137	-0.042	0.106	0.022	-0.160	0.369	0.353
$\hat{\rho}_y$	-0.250	-0.100	-0.083	-0.114	-0.008	0.044	0.071	0.368
$\hat{\rho}_{y\|x_i}$	-0.161	-0.033	-0.047	-0.047	-0.005	0.023	0.064	0.297
CR_{11}	0.064	2.142	0.001	1.601	0.034	1.869	2.717	0.122
CS_{12}	0.516	2.026	1.020	0.246	0.084	1.680	3.528**	0.015
CS_{21}	0.338	0.287	0.619	9.116***	3.084*	8.300***	3.489**	2.015
CV_{22}	0.439	2.414*	0.200	8.512***	0.985	3.470**	17.898***	0.459
CK_{13}	4.073**	2.644**	6.664***	0.000	2.064*	4.812**	20.405***	1.306
CK_{31}	6.989***	0.051	0.655	30.026***	6.082***	17.911***	5.658***	1.100
S&P TSX utilities sector index								
$\hat{\mu}_x$	-0.128	-0.373	-0.313	-0.167	-0.548	0.082	0.219	-0.810
$\hat{\mu}_y$	-0.446	0.360	0.739	-0.269	0.309	-0.201	1.997	-1.904
$\hat{\sigma}_x$	3.293	3.644	3.589	3.320	3.826	2.999	3.357	3.516
$\hat{\sigma}_y$	3.568	5.357	2.686	4.597	3.353	4.566	4.111	3.836
$\hat{\rho}_x$	0.175	-0.015	0.122	0.068	-0.030	-0.279	0.155	-0.040
$\hat{\rho}_y$	-0.140	-0.056	0.106	0.061	0.230	0.179	0.145	0.281
$\hat{\rho}_{y\|x_i}$	-0.089	-0.018	0.059	0.025	0.151	0.093	0.131	0.224
CR_{11}	3.398*	0.001	0.193	0.128	1.538	8.087***	0.016	2.313
CS_{12}	0.019	0.087	0.219	0.395	0.896	5.833***	3.873**	0.724
CS_{21}	2.159	0.494	0.163	0.028	1.557	18.897***	1.383	0.014
CV_{22}	0.498	1.228	1.569	0.398	0.049	22.398***	2.724**	0.549
CK_{13}	1.036	1.105	0.750	3.644**	0.009	1.866*	1.595	2.634**
CK_{31}	3.805**	5.251**	0.001	0.167	0.456	62.184***	1.596	0.010

Notes: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.
We apply simulated critical values, see Table A.3.

Table A.5: Spillover tests from shocks in the crude oil and S&P 500 markets to the adjusted returns of real S&P TSX GICS Sector indices based on the outlier shock filter.

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
S&P TSX consumer discretionary sector index								
$\hat{\mu}_x$	0.603	0.449	1.054	-0.081	0.832	0.216	1.168	-0.485
$\hat{\mu}_y$	0.328	-0.604	-0.004	-0.348	0.604	0.266	3.054	-4.987
$\hat{\sigma}_x$	3.731	3.122	3.299	3.457	3.645	3.158	3.182	3.534
$\hat{\sigma}_y$	4.597	4.892	4.015	4.270	4.217	6.794	4.090	5.460
$\hat{\rho}_x$	0.015	-0.085	0.020	0.220	-0.164	-0.225	0.142	0.161
$\hat{\rho}_y$	-0.039	-0.038	0.042	0.258	0.370	0.343	0.322	0.364
$\hat{\rho}_{y\vert x_i}$	-0.023	-0.010	0.021	0.072	0.238	0.146	0.243	0.238
CR_{11}	0.060	0.317	0.000	1.211	6.753**	7.246**	0.454	0.228
CS_{12}	0.623	0.010	0.388	1.538	3.771**	64.305***	34.436***	0.001
CS_{21}	2.396*	7.951***	1.290	8.095***	11.207***	55.021***	10.982***	2.609*
CV_{22}	0.534	1.079	0.298	6.237***	7.189***	511.143***	93.914***	0.383
CK_{13}	0.305	1.608	2.646*	2.432*	3.684**	216.313***	31.605***	10.656***
CK_{31}	30.555***	88.798***	3.064**	78.826***	40.569***	436.525***	57.429***	4.035**
S&P TSX consumer staples sector index								
$\hat{\mu}_x$	-0.073	0.172	0.155	-0.054	0.215	-0.099	0.129	-0.055
$\hat{\mu}_y$	0.104	-0.094	0.351	0.286	-0.026	0.345	1.437	-2.213
$\hat{\sigma}_x$	3.412	2.828	2.958	3.286	3.361	2.850	3.123	3.106
$\hat{\sigma}_y$	3.808	3.790	2.846	4.262	3.092	4.477	3.275	4.446
$\hat{\rho}_x$	0.169	-0.028	-0.216	0.146	-0.141	-0.135	0.160	0.206
$\hat{\rho}_y$	-0.085	0.135	0.024	-0.054	0.137	0.032	0.347	0.090
$\hat{\rho}_{y\vert x_i}$	-0.051	0.037	0.012	-0.015	0.085	0.013	0.263	0.057
CR_{11}	2.026	0.236	2.501	1.339	2.136	1.126	0.474	0.852
CS_{12}	3.614**	0.769	0.447	0.000	0.785	2.685*	2.904*	0.453
CS_{21}	7.833***	16.078***	4.044**	0.006	1.622	9.411***	3.030*	0.225
CV_{22}	16.195***	4.046**	0.124	1.294	1.112	12.246***	0.600	1.211
CK_{13}	1.532	2.982**	0.050	0.137	0.176	1.128	1.010	2.560*
CK_{31}	76.325***	147.419***	0.437	5.319**	2.720*	95.028***	6.819***	2.289*
S&P TSX energy sector index								
$\hat{\mu}_x$	-0.215	-0.006	0.712	-1.026	0.290	-0.492	0.651	-1.279
$\hat{\mu}_y$	-0.157	0.972	1.160	-1.112	3.386	-2.543	2.791	-3.462
$\hat{\sigma}_x$	5.087	5.616	4.765	5.854	5.518	5.201	5.491	4.960
$\hat{\sigma}_y$	5.718	7.888	6.307	5.950	5.815	8.113	5.483	7.635
$\hat{\rho}_x$	-0.007	-0.239	0.206	0.135	0.078	-0.204	0.045	0.246
$\hat{\rho}_y$	-0.009	-0.225	-0.114	0.304	0.378	0.347	0.196	0.185
$\hat{\rho}_{y\vert x_i}$	-0.005	-0.062	-0.057	0.086	0.243	0.148	0.145	0.117
CR_{11}	0.000	1.981	3.307*	0.121	1.155	6.436**	0.424	0.656
CS_{12}	0.241	0.000	0.013	16.775***	1.991	54.359***	0.279	3.365*
CS_{21}	0.025	1.266	0.041	22.318***	9.654***	37.879***	6.636***	0.321
CV_{22}	1.704	0.506	0.520	64.427***	0.348	439.863***	1.486	2.853*
CK_{13}	0.028	0.833	0.181	28.873***	0.131	236.933***	0.463	4.868**
CK_{31}	6.339***	16.698***	0.354	175.946***	12.540***	407.281***	13.459***	2.033*

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Table A.5 – *Continued from previous page*

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
S&P TSX financial sector index								
$\hat{\mu}_x$	0.671	0.209	0.853	-0.056	0.624	0.232	1.202	-0.781
$\hat{\mu}_y$	-0.163	-1.126	-0.314	-0.191	0.910	-0.839	3.529	-4.481
$\hat{\sigma}_x$	3.583	3.127	3.198	3.464	3.603	3.082	3.264	3.126
$\hat{\sigma}_y$	5.062	6.171	4.299	4.397	3.903	6.660	3.928	5.695
$\hat{\rho}_x$	-0.007	-0.044	-0.154	-0.033	0.045	0.047	0.151	0.090
$\hat{\rho}_y$	-0.241	-0.033	-0.071	0.427	0.351	0.350	0.040	0.428
$\hat{\rho}_{y\|x_i}$	-0.147	-0.009	-0.036	0.127	0.224	0.150	0.029	0.285
CR_{11}	0.792	0.068	0.657	1.258	1.340	0.522	0.630	1.392
CS_{12}	0.841	0.012	0.688	11.026***	0.033	4.958**	0.001	13.888***
CS_{21}	6.142***	6.610***	1.515	29.778***	12.737***	30.321***	0.292	6.674***
CV_{22}	9.946***	1.697	0.031	162.751***	3.715**	53.735***	0.189	27.122***
CK_{13}	4.275**	4.742**	0.487	62.550***	0.884	17.732***	0.001	62.542***
CK_{31}	66.964***	136.794***	1.166	231.419***	27.344***	217.174***	0.567	9.113***
S&P TSX health sector index								
$\hat{\mu}_x$	1.964	0.615	1.772	0.657	1.648	0.855	2.610	-0.869
$\hat{\mu}_y$	2.521	-1.478	-3.245	0.530	-0.234	-1.116	3.716	-5.112
$\hat{\sigma}_x$	6.627	8.278	8.420	6.446	8.580	6.423	7.319	7.483
$\hat{\sigma}_y$	7.872	10.831	13.774	8.562	16.089	9.170	9.266	10.004
$\hat{\rho}_x$	-0.042	-0.096	-0.120	0.145	-0.385	-0.111	-0.089	0.073
$\hat{\rho}_y$	-0.185	0.065	-0.044	0.008	0.114	0.145	0.021	0.368
$\hat{\rho}_{y\|x_i}$	-0.112	0.018	-0.022	0.002	0.071	0.059	0.015	0.241
CR_{11}	0.203	0.733	0.438	1.056	10.407***	1.458	0.450	1.014
CS_{12}	0.038	0.238	7.670***	1.864	0.785	4.768**	2.593*	0.047
CS_{21}	6.730***	3.995**	0.014	0.885	9.609***	8.171***	0.080	2.445*
CV_{22}	0.392	0.001	0.016	9.258***	27.892***	50.839***	0.013	0.656
CK_{13}	1.844	7.106***	33.316***	7.096***	0.521	7.451***	2.119*	0.001
CK_{31}	42.510***	69.215***	0.041	1.084	33.688***	98.455***	0.048	4.584**
S&P TSX industrial sector index								
$\hat{\mu}_x$	0.713	0.887	1.214	0.345	1.272	0.347	1.620	-0.462
$\hat{\mu}_y$	0.293	-1.695	0.188	-0.841	0.527	-0.333	3.464	-5.437
$\hat{\sigma}_x$	3.836	3.903	3.764	3.941	4.000	3.685	3.689	3.805
$\hat{\sigma}_y$	4.802	6.701	5.028	4.860	4.379	5.681	4.356	5.546
$\hat{\rho}_x$	-0.004	-0.067	0.211	0.000	-0.164	-0.049	0.174	0.221
$\hat{\rho}_y$	-0.054	-0.024	-0.045	0.158	0.214	0.178	0.289	0.480
$\hat{\rho}_{y\|x_i}$	-0.032	-0.006	-0.023	0.043	0.134	0.073	0.217	0.325
CR_{11}	0.031	0.204	2.617	0.092	3.714*	0.742	0.080	0.434
CS_{12}	1.865	0.088	0.008	2.689*	0.070	4.066**	0.839	5.913***
CS_{21}	2.104	7.598***	0.160	2.066	6.279***	18.149***	0.740	5.293**
CV_{22}	0.065	2.249*	0.014	0.050	1.244	43.758***	1.137	7.043***
CK_{13}	1.250	0.956	1.239	6.234***	1.719	12.612***	0.122	1.582
CK_{31}	17.137***	124.912***	2.853*	16.283***	18.804***	153.157***	9.407***	11.595***

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	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
S&P TSX information technology sector index								
$\hat{\mu}_x$	1.982	0.467	1.996	0.255	2.486	-0.106	2.840	-1.405
$\hat{\mu}_y$	1.028	-5.541	-1.706	0.634	1.446	0.589	6.324	-9.974
$\hat{\sigma}_x$	7.373	9.262	9.456	7.061	7.531	9.104	8.176	8.240
$\hat{\sigma}_y$	10.704	15.352	10.469	12.361	9.925	9.754	9.756	14.097
$\hat{\rho}_x$	0.016	-0.186	-0.064	0.022	-0.043	-0.155	0.043	0.327
$\hat{\rho}_y$	0.031	0.037	0.008	0.084	-0.028	0.018	0.302	0.349
$\hat{\rho}_{y\|x_i}$	0.018	0.010	0.004	0.023	-0.017	0.007	0.227	0.228
CR_{11}	0.000	2.279	0.209	0.000	0.026	1.370	1.449	0.440
CS_{12}	14.628***	0.621	0.676	4.556**	0.163	0.276	0.022	0.250
CS_{21}	0.000	1.328	0.787	0.356	0.788	1.671	7.749***	0.744
CV_{22}	1.523	0.954	1.345	2.563*	0.166	0.236	12.988***	0.263
CK_{13}	2.354*	2.521*	0.010	14.764***	0.036	13.794***	0.006	0.086
CK_{31}	2.079*	17.765***	0.663	6.978***	7.469***	24.207***	23.278***	5.157**
S&P TSX materials sector index								
$\hat{\mu}_x$	-0.303	0.813	0.923	-0.426	0.282	0.296	0.971	-0.772
$\hat{\mu}_y$	-0.672	-0.308	1.264	-2.566	1.499	0.316	2.609	-4.616
$\hat{\sigma}_x$	6.017	6.685	6.257	6.493	6.686	6.116	6.236	6.517
$\hat{\sigma}_y$	8.871	7.897	6.829	7.537	5.479	7.862	5.804	8.520
$\hat{\rho}_x$	-0.121	-0.241	0.203	-0.143	0.188	-0.215	-0.014	-0.160
$\hat{\rho}_y$	-0.126	-0.038	-0.132	0.420	0.057	0.032	0.425	0.123
$\hat{\rho}_{y\|x_i}$	-0.076	-0.010	-0.066	0.125	0.035	0.013	0.327	0.078
CR_{11}	0.086	3.329*	3.429*	3.615*	1.011	2.811	5.071**	2.062
CS_{12}	0.843	0.717	1.115	47.560***	1.933	3.110*	8.958***	5.192**
CS_{21}	2.535*	3.059*	0.202	63.324***	2.855*	0.377	17.988***	4.225**
CV_{22}	2.208*	0.262	0.284	512.601***	1.482	9.567***	74.995***	6.702***
CK_{13}	1.044	1.912	0.641	333.663***	2.743*	0.606	57.619***	10.501***
CK_{31}	5.296**	27.305***	1.201	425.974***	11.362***	26.920***	49.607***	2.123*
S&P TSX real estate sector index								
$\hat{\mu}_x$	0.070	0.069	-0.165	0.334	0.001	0.137	0.482	-0.572
$\hat{\mu}_y$	0.039	-0.487	0.417	-0.431	0.434	-0.492	2.459	-3.724
$\hat{\sigma}_x$	5.619	4.333	4.432	5.519	5.605	4.271	5.066	4.763
$\hat{\sigma}_y$	5.804	4.837	4.709	5.394	4.614	7.166	4.710	7.064
$\hat{\rho}_x$	0.106	-0.185	-0.117	0.082	0.025	-0.140	0.102	0.131
$\hat{\rho}_y$	-0.426	-0.038	-0.023	0.439	0.195	0.316	0.437	0.202
$\hat{\rho}_{y\|x_i}$	-0.271	-0.010	-0.012	0.132	0.121	0.134	0.337	0.128
CR_{11}	5.768**	1.812	0.509	0.125	0.379	3.769*	2.501	0.000
CS_{12}	17.072***	2.538*	0.491	28.028***	0.780	65.831***	2.806*	2.924*
CS_{21}	29.483***	7.730***	1.275	44.484***	7.797***	55.917***	2.167	0.025
CV_{22}	119.571***	5.790**	1.251	391.582***	3.152**	720.941***	0.416	0.325
CK_{13}	33.084***	1.132	0.057	229.257***	0.032	379.969***	0.403	1.305
CK_{31}	168.235***	135.486***	0.365	352.623***	22.857***	529.841***	8.066***	0.114

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Table A.5 – *Continued from previous page*

	os_{pos}	os_{neg}	gd_{pos}	gd_{neg}	od_{pos}	od_{neg}	sp_{pos}	sp_{neg}
S&P TSX telecommunication services sector index								
$\hat{\mu}_x$	0.741	0.359	0.640	0.424	1.229	-0.140	0.409	0.740
$\hat{\mu}_y$	-1.448	-1.226	0.397	-0.121	-0.611	1.478	2.888	-3.311
$\hat{\sigma}_x$	3.774	3.522	3.589	3.710	3.708	3.453	3.978	3.048
$\hat{\sigma}_y$	4.222	5.371	3.899	4.421	4.942	5.360	4.825	5.238
$\hat{\rho}_x$	-0.105	0.075	-0.108	-0.106	0.166	0.090	0.251	0.108
$\hat{\rho}_y$	-0.129	-0.132	-0.276	-0.026	0.065	0.044	0.217	0.236
$\hat{\rho}_{y\|x_i}$	-0.077	-0.036	-0.142	-0.007	0.040	0.018	0.161	0.151
CR_{11}	0.032	0.687	0.052	0.499	0.684	0.265	0.373	0.068
CS_{12}	0.812	0.001	0.259	2.115	0.022	0.090	0.846	0.285
CS_{21}	0.611	0.133	0.106	4.584**	2.626*	3.655**	0.004	1.322
CV_{22}	1.044	3.525**	2.672*	0.711	0.327	0.001	0.035	2.130*
CK_{13}	4.291**	0.508	11.437***	1.451	9.657***	0.267	0.714	3.667**
CK_{31}	16.317***	1.496	0.087	23.994***	13.069***	35.749***	0.072	1.985*

S&P TSX utilities sector index								
$\hat{\mu}_x$	-1.083	0.304	-0.461	-0.219	-0.535	-0.163	-0.170	-0.622
$\hat{\mu}_y$	0.435	0.239	0.520	-0.272	-0.312	0.687	1.595	-1.614
$\hat{\sigma}_x$	3.081	3.682	3.420	3.550	3.781	3.154	3.307	3.728
$\hat{\sigma}_y$	3.292	4.291	3.346	4.061	3.999	3.934	3.942	4.178
$\hat{\rho}_x$	0.335	-0.032	-0.008	0.015	-0.013	-0.064	0.128	-0.032
$\hat{\rho}_y$	-0.232	-0.068	0.070	0.070	0.318	0.198	0.160	0.036
$\hat{\rho}_{y\|x_i}$	-0.141	-0.018	0.035	0.019	0.202	0.082	0.118	0.023
CR_{11}	10.491***	0.011	0.085	0.001	1.906	1.057	0.004	0.104
CS_{12}	2.405*	0.325	0.303	3.901**	0.405	12.778***	1.222	0.382
CS_{21}	4.815**	0.441	1.814	0.786	8.382***	20.542***	0.154	0.644
CV_{22}	0.102	5.206**	0.167	0.034	0.356	85.526***	0.371	0.018
CK_{13}	0.090	1.642	1.216	5.292**	2.667*	24.949***	2.006	0.876
CK_{31}	17.889***	7.935***	1.689	6.147***	13.454***	199.002***	2.963*	1.011

Notes: * significant at 10% level, ** significant at 5% level, *** significant at 1% level.
We apply simulated critical values, see Table A.3.