Stochastic Analysis and Applications

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/lsaa20

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To cite this article: Milan Stehlík, Danilo Leal, Jozef Kiseľák, Joshua Leers, Luboš Střelec & Felix Fuders (2024) Stochastic approach to heterogeneity in short-time announcement effects on the Chilean stock market indexes within 2016-2019, Stochastic Analysis and Applications, 42:1, 1-19, DOI: 10.1080/07362994.2022.2164508

To link to this article: https://doi.org/10.1080/07362994.2022.2164508

STOCHASTIC ANALYSIS AND APPLICATIONS
2024, VOL. 42, NO. 1, 1–19
https://doi.org/10.1080/07362994.2022.2164508

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Stochastic approach to heterogeneity in short-time announcement effects on the Chilean stock market indexes within 2016-2019

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ABSTRACT

We aim to examine stock market returns before and after key events in the U.S. Sino trades between 2016 and 2019. The study tracks Cumulative Abnormal Returns (CAR) of the Índice de Precio Selectivo de Acciones (IPSA or S&P/CLX IPSA is a Chilean stock market index) for 26 important events throughout this time period. By testing for both directions and significance of market reaction to said events this study aims to clarify if these events and policy announcements were sufficient to influence local equity markets, and in which direction. A simple analysis of CAR showed 16 negative reactions and 10 Positive reactions. An estimated 13 billion USD in market capitalization was lost as a result. Of the 26 events studied 18 were found to produce statistically significant reactions and 8 did not. The IPSA's reaction to the significant events was mixed with 11 negative reactions and 7 positive reactions. We also checked for the normality of the distribution by robust normality tests and expected returns possess significant asymmetry and above-normal kurtosis. As such on aggregate it can be concluded that Chilean capital markets reacted negatively to the U.S. Sino trade war. We model IPSA in the period 2016–2022, where we can observe qualitative differences before and after 2019. To the best knowledge of the authors, the model of IPSA in this article is the first attempt in this direction.

ARTICLE HISTORY
Received 7 September 2022
Accepted 21 December 2022

KEYWORDS
Cumulative abnormal returns; Chilean capital markets; stock market data; event studies; stochastic model of interest rate

SUBJECT CLASSIFICATION CODES
Primary 60H10; Secondary 60H30

JEL CLASSIFICATION
G14; G100; F130

1. Introduction

The United States of America (US) and the Peoples' Republic of China (PRC) are the world's two largest economies, with 2018 Gross Domestic Products (GDP) of 20.5 and 13.6 trillion United States dollars (USD) respectively, according to a study done by the World Bank [1]. The afore-mentioned values represent 39.7% of the total global GDP.

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According to the Office of United States Trade Representative [2], exchange of goods and services between the two countries had a 2018 value of 737.1 billion USD which represents nearly 1% of total global GDP. As of 2018, the trade deficit between the two nations sits at 419.2 billion USD in favor of the PRC. Considering the size and the importance of this trade relationship, economic cooperation between the two powers is of vital importance to overall global prosperity, however in recent years relations home come to an impasse. In addition to the damage being done to US-SINO relations, the "trade war" has strong implications for all world economies as the sum of these two nations represents nearly 40% of the world GDP, and as such, it is implicit that any damage done to their economic growth significantly affects world growth.

As the dispute intensifies it is important to consider the economic "collateral damage" done to third parties, who have little or no interest or in or ability to effect outcomes of this dispute yet suffer a large portion of the brunt of this ordeal. To date, a multitude of studies have been carried out to assess the damage to both the US and Chinese economies, yet little or no time has been spent assessing the implications and or impacts on small third-party economies.

In the context of a vast and highly interconnected globalized world economy, governments should carefully consider the implications of their policy decisions weighing not only the direct impacts but also the magnitude of the indirect consequences. As such this study will attempt to assess the impact of the trade war to date on Chile is an ideal candidate considering its strong trade ties to both the US and PRC, and its percentage of trade to GDP which sits very close to the world average, (55.7%) according to a study carried out by the OECD [3] as well as having strong market ties to both of these countries, making it a good proxy for understanding the effects of the trade war on other regions.

The main goal of this article is to analyze how a third country is indirectly affected by the problems that the two main economies of the world may have. Here we are using the main stock market indicator of the Chilean Stock Exchange as a variable of such analysis. The manuscript is organized as follows: In the next Subsections 1.1 and 1.2, we discuss studies on the effects of economic protectionism and some previous methodologies applied to measuring the impacts of trade wars. In Section 2, we introduce the data set and methodologies. In Section 3, we analyze the CAR value events, we test also for normality by utilizing a robust class of tests. In Section 4, we introduce a novel model for changes in trade volumes.

1.1. Effects of economic protectionism

Protectionism or the act of seeking to positively influence domestic production and economic performance through the use of government, or other regulations to restrict imports has been around for several centuries at a minimum [4]. These policies have their most recent and more informal origins in 1800s French and English mercantilism. Notwithstanding, to this day there is still significant debate as to whether protectionism is a driver of economic welfare loss, and in the case that it is, to what extent. Another area of debate is who ultimately pays the price of tariffs and other measures.

[5] suggested that the costs of economic protectionism are not as severe as generally agreed upon. This article suggests that some of the economic turbulence generally attributed to protectionism such as the depressions of the 1930s and 1980 can actually

be traced to financial instability and credit difficulties. It is the view of this article that the idea of protectionism as a driver of major economic instability is essentially a myth.

[6], however, took a much more severe stance on the effect of protectionism citing a rise in protectionist measures as one of the principal motors driving the great depression. [7] examined trade tendencies and protectionism in the between-war period of the 1930s and concluded that protectionist measures resulted in a dramatic drop in overall trade, a drastic shortening of average route length, and the strengthening of politico-economic trade blocks. This work seems to agree that protectionism has dramatic economic consequences, as well as driving the intensification of political tensions.

[8] examined the specific historical effect of sanctions from a U.S. standpoint analyzing their effect on the rest of the world. It was concluded that U.S. sanctions can be very damaging to foreign economies, specifically considering that they tend to be targeted on specific countries and industries, and as such are capable of causing serious consequences. This article also concludes that free trade associations tend to promote trade within themselves, while also having the consequence of dampening trade between unaffiliated regions. [4] examined protectionism from 4 distinct viewpoints, and ultimately concludes that these practices are quite beneficial to the specific sector of the economy to which imports are restricted, however, they are a significant driver of overall welfare loss.

As would be expected, non-entry trade measures seem to be more effective than tariffs which allow goods to be imported with a specific tax on the item, making them less competitive in the market. [9] studied the effect of inefficient entry on local production costs and found that both average production costs and price charges increased in the industry are protected. There was a general loss of welfare and consumers paid the costs.

Considering the sheer volume of literature supporting the idea that protectionism is either a driver or a major driver of overall welfare and value loss it seems necessary to conclude that this may be the case.

1.2. Previous methodologies applied to measuring the impacts of trade wars and other policy shocks on economies and markets

Addressing the specific consequences of the current trade war [10] used a descriptive methodology comparing the preparedness of the U.S. and China to handle a trade war and then examine existing economic data to assess impacts. It was concluded that the U.S. is better prepared to confront this challenge as far less of its economy relies on Chinese trade both in terms of USD value and % of GDP. It also concluded that the U.S. has seen far less economic hardship as a result and it is well positioned to continue and leverage its position for a good outcome.

The preferred method of estimating the economic and welfare loss created by the trade war appears to be via computed general equilibrium models or (CGE). Over the short course of the trade war, a considerable amount of the literature estimating its effects using CGE models has been created. [11] attempted to apply one such model to estimate impact on U.S., Chinese, Australian, and overall world economies. This work used the Global Trade Analysis Project (GTAP) CGE model with some modifications and found that the joint effect of trade tariffs (U.S. and Chinese) had an overall negative effect on GDP, employment and consumption in both China and the U.S. but surprisingly had an overall positive effect on Australian GDP and consumption while employment figures remained unchanged. It is questionable whether GDP is really a good indicator of welfare. For further references see [12] or [13]. The authors suggest a new index for measuring welfare based on the human-scale-development approach [12] quantifying the subjective perception of the satisfaction of fundamental human needs.

[14] also used a CGE model, in this case, a static CGE model to estimate the level of welfare loss caused. His finding was consistent with the majority of studies cited in this literature review, as it concluded that both countries suffered significant welfare losses with China losing significantly more than the U.S. [15] also attempts to estimate welfare loss using a CGE model with data from the GTAP 9.0 database, and had similar findings, that is to say considerable welfare loss to both economies with a more significant decline in China.

[16] used a novel partial equilibrium model to estimate the future effects of the trade war on both Chinese and east Asian economies in general. His paper focused on identifying products that could potentially be substituted by competing economies in the region. He concluded that considering tariff levels at the time of publishing there would be a 0.3% drop in Chinese GDP. This article also estimates that the impact on GDP in many potential substitute markets which would look to replace Chinese production could be significant, with Vietnam, The Philippines, and Cambodia leading the way. In total eight countries in the region could experience GDP growth of over 1% as a result of continued tensions.

Shifting this examination to the subject of market impacts [17] examined the market value of firms in relation to their exposure to global value chains involving the U.S. and Chinese firms. Their work analyzed the immediate impact on stock prices of firms in a reduced time frame, and then compared real-world results to estimated results based on the idea that firms with greater exposure to global value changes would incorporate these policy shocks into their market valuation. The finding of their paper was that real-world results closely followed expected results and that U.S. firms with elevated exposure to Chinese supply chains were the most severely affected.

Many authors such as [18–21] have applied methodologies of data analytics involving abnormal returns and cumulative abnormal returns in a specific event window on capital markets in order to assess the impact of policy shocks and other types of events to make judgments on the type and magnitude of the market's reaction; see Figures 1 and 2 for cumulative abnormal returns of specific events. This methodology is particularly useful in assessing such impacts as it can track the outcome of multiple events or announcements and make a cumulative judgment on the overall outcome. This type of work makes use of portfolio theory first developed by [22] which calculates an expected rate of return for a financial instrument based in its systematic and nonsystematic rate of risk. Real-world returns are then compared with expected returns within a specific event window in order to assess the impact of events within that event window.

2. Materials and methods

2.1. Data Description

An initial review of the principal events that composed the trade war revealed 29 significant dates between its origins in June of 2016 when US President announced he would apply tariffs under sections 201 and 301 of the 1974 Trade Act, through October

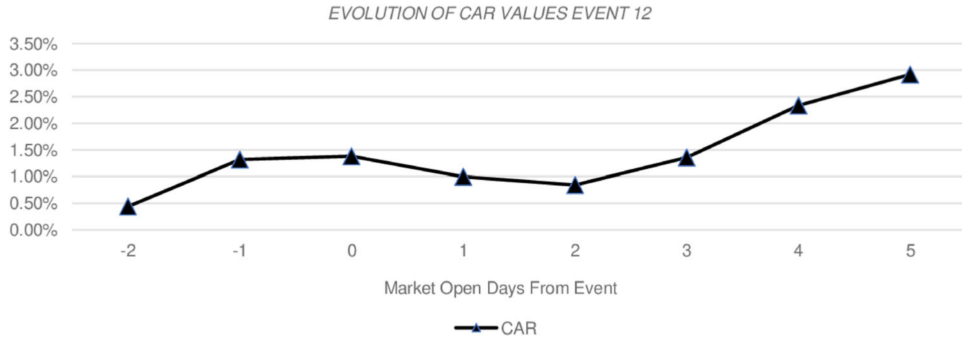


Figure 1. Cumulative abnormal returns for event 12, Source: Santiago Stock Exchange, Authors' Calculations.

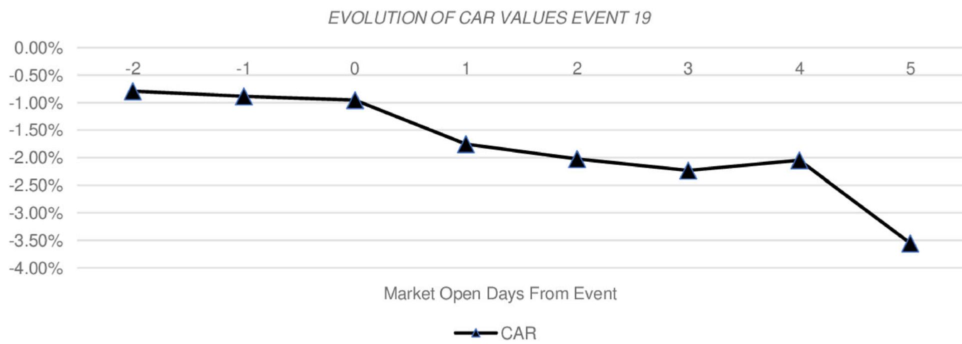


Figure 2. Cumulative abnormal returns for event 19, Source: Santiago Stock Exchange, Authors' Calculations.

of 2019 when phase one of the trade deal would suspend further tariffs. These events were determined by [23]. As a matter of judgment, this study has suspended all events with a date after September 10^{th} of 2019 due to significant unrelated market volatility connected to local protests, leaving a total of 26 (3 events were discarded as a result of this decision) events through August 2019.

Having chosen a finite number of events this study compiled data for market performance from the IPSA (Chiles principal stock index) for the aforementioned dates; see Table 1 for expected returns. The values obtained were retrieved from the Santiago Stock Exchange (Bolsa de Comercio de Santiago). The data points used were once daily closing values for the event date as well as five market open days after and 2 days before as well as an additional 60 market open days before. This allows for 60 values for the calculation of $E[R]$ (expected return) as well as an 8-day event window. In the event of the market being closed on the day of the event, the next market open day was taken as the event day. A total of 1768 data points were used, although some were repeat values as there was some overlap in event windows. Over the entire data set, the highest daily increase was 6.9%, the lowest daily drop was -5.86% and the average daily return was -0.01%.

2.2. Methodology

The Mean Adjusted Model Method for event studies was used to calculate $E[R]$, essentially a 60-day pre-event average. This decision was made as a result of other methods

Table 1. Expected returns for selected events. Source: Santiago Stock Exchange, Authors' Calculations.

Number	Event date	$E[R]$
1	28/6/2016	0.02%
2	31/3/2017	0.27%
3	6/4/2017	0.23%
4	19/7/2017	0.07%
5	14/8/2017	0.08%
6	22/1/2018	0.09%
7	8/3/2018	0.22%
8	2/4/2018	−0.04%
9	3/4/2018	−0.04%
10	4/4/2018	−0.03%
11	15/6/2018	−0.01%
12	10/7/2018	−0.10%
13	1/8/2018	−0.10%
14	7/8/2018	−0.08%
15	24/9/2018	−0.02%
16	1/12/2018	−0.06%
17	1/5/2019	−0.08%
18	3/5/2019	−0.09%
19	5/5/2019	−0.09%
20	16/5/2019	−0.14%
21	18/6/2019	−0.07%
22	29/6/2019	−0.05%
23	1/8/2019	−0.04%
24	5/8/2019	−0.03%
25	13/8/2019	−0.03%
26	23/8/2019	−0.02%

relying on regression and the calculation of slope, intercept, α, and β, and this is inappropriate when working with a stock index as opposed to a specific stock. $E[R]$ was calculated separately for each event resulting in 26 distinct values. Having compiled the necessary data and calculated expected returns for the period in question this study proceeded to perform statistical analysis. A variant of a methodology commonly used in event studies such as [18–21] was used. This methodology was selected because it is very common in literature for event studies. This methodology determines abnormal returns, cumulative abnormal returns, and average cumulative abnormal returns in order to conclude the magnitude and nature of the effect of an event on market values (negative or positive). This analysis determined the average cumulative abnormal return for each event using the following methodology:

$$\mathrm{AR}_{it} = R_{it} - E[R_{it}],$$

where AR_{it} = abnormal return i on day t of the event window;

$$\mathrm{CAR}_t = \sum_{i=1}^{n} \mathrm{AR}_{it},$$

where CAR_t = cumulative abnormal return for the event;

$$\mathrm{CAAR}_t = \frac{\sum_{i=1}^{n} \mathrm{AR}_{it}}{n},$$

where CAAR_t = cumulative average abnormal return for the event.

CAR values below zero indicate that an event has caused a negative impact, whereas a value over zero would indicate a positive impact. The larger this value, the more significant the impact of the event. Values closer to zero indicate that independent of any daily volatility in AR, over the course of the event the impact was neutral.

Additionally, an estimation of monetary variation was made by assessing the impact of CAR for each event on the overall market capitalization of the IPSA at that time. As no historic information of market capitalization was available, but IPSA values were readily available an effort was made to discern the exact relationship between IPSA values and the overall market capitalization of the index. Both IPSA and market capitalization values were registered for several days and linear regression was used to determine the relationship between the two. As the two had a strong correlation ($R^2 = 0.9244$) these values were then used to determine an estimated value for each event ($Y = 27465X - 764032$ with Y being estimated market cap and X being the current IPSA value) which could then be employed in conjuncture with each event CAR value to determine the overall market capital gain or loss as a result.

For the purposes of this study, a comparison of CAAR before and after the event window was used to determine the market reaction. A paired t-test of two samples for means was conducted to test whether there were statistically significant differences in CAR before and after trade war events, and if so what type of reaction had been elicited (positive or negative). t-tests are generally used to determine that the chance data are behaving randomly within normal behavior or if a specific event has altered its behavior. Generally, a P value below 0.05 signifies a statistically significant event. The t-test considered an α of 0.05.

The analysis considered a period of 2 market open days before and 5 market open days after each event in addition to the event day itself, as evidence exists that considering longer periods of time tends to create bias in results as shown in [24]. We calculated the cumulative average abnormal return for a statistically representative population of events within the overall framework of the trade war, and outlined some macro impact of the trade war on Chilean equity markets.

3. Results and analysis

From this point forward each event will be referred to as a number between 1 and 26 according to their date of occurrence with the most recent events having the highest values. For a full table description of events selected see annexed documents. The expected returns for each of the events being studied were calculated and the results were as follows:

Having calculated $E[R]$, AR and CAR were now calculated. A sample of 3 events was graphed in order to illustrate the effect of the event on CAR over the course of the time frame studied.

In the case of event 1 CAR drops strongly in the days before the event, and then makes a strong comeback before finishing the period with a slightly positive CAR at 0.44%. This would indicate that event 1 of the trade war provoked a slightly positive reaction from the IPSA index.

In the case of event 12, the event begins with a strongly positive reaction in CAR, which dips in the days directly after the announcement but then returns in the last few

Table 2. Final CAR values for each event period. Source: Santiago Stock Exchange, Authors' calculations.

Event	CAR at event window end
1	0.44%
2	−1.71%
3	−0.49%
4	0.28%
5	−0.08%
6	0.89%
7	−0.87%
8	3.09%
9	2.89%
10	1.50%
11	−2.97%
12	2.92%
13	−0.16%
14	−1.51%
15	−0.88%
16	−1.09%
17	−2.19%
18	−1.57%
19	−3.56%
20	−0.67%
21	1.12%
22	0.12%
23	−1.43%
24	−2.61%
25	−2.34%
26	0.82%

days, finishing with a CAR of 2.92%. This would indicate that event 1 of the trade war provoked a strongly positive reaction from the IPSA index.

In the case of event 19, the period began with a strong downturn which intensified over the course of the timeframe culminating in a CAR value of −3.56%. This would indicate that event 19 of the trade war provoked a strongly negative reaction from the IPSA index. CAR values for individual periods are given in Table 2.

A simple analysis of CAR value results for the last day of each event without considering statistical significance or pre-event tendency reveals 16 negative market reactions as well as 10 positive reactions. This would indicate that although some events were processed positively by the market, but the overall reaction was negative, with an aggregate value of -10.04%.

Applying the percentual variation in CAR for each event to the total market capitalization at that time permitted the estimation of total IPSA market capitalization loss or gain as a result of the trade war. Variations in market Capitalization are presented in Table 3. Event impacts on CAAR pre- and post-event are in Table 4.

The Cumulative effect on market capitalization was determined to be a net negative equivalent to a loss of approximately 13 billion USD in market valuation.

Having calculated both AR and CAR for each of the events, a paired t-test of two samples for means was conducted in order to determine the impact of the event (negative or positive) as well as whether the event provoked a statistically significant response in markets.

Upon examination of the two-tail paired t-test of two samples for means and the difference in CAAR values pre and during the events it was concluded that 18 of 26 events

Table 3. Variation in market capitalization. Source: Santiago Stock Exchange, Authors' Calculations.

Event	IPSA	Market Cap. thousands USD	Event CAR	Variation thousands USD
1	3936	$107.339.032	0.4%	$474.624
2	4783	$130.612.598	−1.7%	($2.231.554)
3	4898	$133.749.651	−0.5%	($652.007)
4	5037	$137.585.962	0.3%	$388.299
5	5064	$138.311.312	−0.1%	($110.806)
6	5828	$159.299.516	0.9%	$1.418.488
7	5576	$152.390.970	−0.9%	($1.330.471)
8	5503	$150.364.877	3.1%	$4.642.805
9	5534	$151.238.264	2.9%	$4.368.971
10	5543	$151.468.695	1.5%	$2.279.372
11	5470	$149.478.307	−3.0%	($4.440.479)
12	5323	$145.440.128	2.9%	$4.245.695
13	5398	$147.502.200	−0.2%	($231.364)
14	5328	$145.579.375	−1.5%	($2.192.000)
15	5386	$147.152.845	−0.9%	($1.295.837)
16	5152	$140.726.585	−1.1%	($1.534.877)
17	5142	$140.449.463	−2.2%	($3.079.299)
18	5132	$140.195.137	−1.6%	($2.194.649)
19	5124	$139.972.396	−3.6%	($4.976.034)
20	4978	$135.949.872	−0.7%	($915.888)
21	5041	$137.675.223	1.1%	$1.540.743
22	5063	$138.288.517	0.1%	$160.430
23	4941	$134.935.315	−1.4%	($1.923.420)
24	4780	$130.529.379	−2.6%	($3.412.119)
25	4846	$132.320.372	−2.3%	($3.091.626)
26	4649	$126.910.316	0.8%	$1.046.308

Table 4. Event impact on CAAR pre- and post-event. Source: Santiago Stock Exchange, Authors' calculations.

Event identifier	CAAR PRE	CAAR EVENT	DIFF.	Reaction
1	0.22%	−0.01%	−0.24%	Negative
2	1.11%	−0.01%	−1.12%	Negative
3	−0.04%	−0.14%	−0.10%	Negative
4	1.19%	0.35%	−0.84%	Negative
5	0.04%	−0.31%	−0.35%	Negative
6	1.12%	0.41%	−0.71%	Negative
7	−2.44%	0.12%	2.56%	Positive
8	−0.97%	1.48%	2.45%	Positive
9	−1.42%	2.06%	3.48%	Positive
10	−1.22%	0.76%	1.98%	Positive
11	1.14%	−1.67%	−2.81%	Negative
12	−1.44%	1.45%	2.89%	Positive
13	1.59%	0.59%	−1.00%	Negative
14	0.50%	−1.06%	−1.56%	Negative
15	1.37%	0.23%	−1.13%	Negative
16	−0.95%	0.38%	1.33%	Positive
17	0.26%	−1.07%	−1.33%	Negative
18	−0.45%	−0.88%	−0.44%	Negative
19	−0.96%	−1.78%	−0.82%	Negative
20	−1.55%	0.07%	1.62%	Positive
21	0.24%	0.07%	−0.17%	Negative
22	0.30%	−0.24%	−0.54%	Negative
23	−0.80%	−2.15%	−1.35%	Negative
24	−1.02%	−2.19%	−1.17%	Negative
25	−2.20%	−1.83%	0.37%	Positive
26	0.53%	−1.77%	−2.30%	Negative

Table 5. *t*-test for determination of significance. Source: Santiago Stock Exchange, Authors' Calculations.

Event identifier	*t*-stat	$P(T \leq t)$ two-tail	*t*-Critical two-tail	Event type
1	0.90	0.399	2.36	Non-sig.
2	3.50	0.010	2.36	Significant
3	0.24	0.818	2.36	Non-sig.
4	1.71	0.130	2.36	Non-sig.
5	1.76	0.122	2.36	Non-sig.
6	4.26	0.004	2.36	Significant
7	−3.52	0.010	2.36	Significant
8	−3.85	0.006	2.36	Significant
9	−6.60	0.000	2.36	Significant
10	−4.25	0.004	2.36	Significant
11	6.02	0.001	2.36	Significant
12	−9.56	0.000	2.36	Significant
13	2.76	0.028	2.36	Significant
14	5.09	0.001	2.36	Significant
15	1.19	0.272	2.36	Non-Sig.
16	−5.43	0.001	2.36	Significant
17	9.52	0.000	2.36	Significant
18	3.31	0.013	2.36	Significant
19	2.98	0.021	2.36	Significant
20	−10.39	0.000	2.36	Significant
21	0.61	0.564	2.36	Non-Sig.
22	2.18	0.065	2.36	Non-Sig.
23	3.19	0.015	2.36	Significant
24	3.20	0.015	2.36	Significant
25	−0.84	0.431	2.36	Non-Sig.
26	3.84	0.006	2.36	Significant

studied provoked statistically significant reactions from the IPSA index, see Table 5. Among those results ($n = 18$) considered to be significant 11 provoked a negative change in CAAR when compared with pre-event CAAR, 7 pushed the market into a positive reaction. Considering the results of CAR, CAAR and the *t*-test it can be concluded that on aggregate the U.S.-China Trade War had a strongly negative effect on the IPSA when compared with periods of normal market performance.

3.1. Robust testing for normality

Distributions of stock market returns are often presented as bell-shaped curves. This representation implies that stock returns are normally distributed, which can depend on the period analyzed and the frequency of sampling prices to calculate returns. For e.g. a return distribution that contains returns realized during the financial crisis will be very different than one covering a different period. However, expected returns in our case are far from the normal distribution, mainly due to the presence of outliers – see the first boxplot and histogram in Figure 3.

For the purpose of testing for normality of the above-presented data sets, we use selected classical tests for normality as well as selected robust normality test (see [25]). So, in total, we used four classical tests for normality – Anderson-Darling (AD) test, Jarque-Bera (JB) test, Lilliefors (LT) test, and Shapiro–Wilk (SW) test. For the purpose of comparison, we also used four robust tests for normality – robust Jarque-Bera (RJB) test, medcouple (MCLR) test, and two variants of the RT class tests introduced by [25].

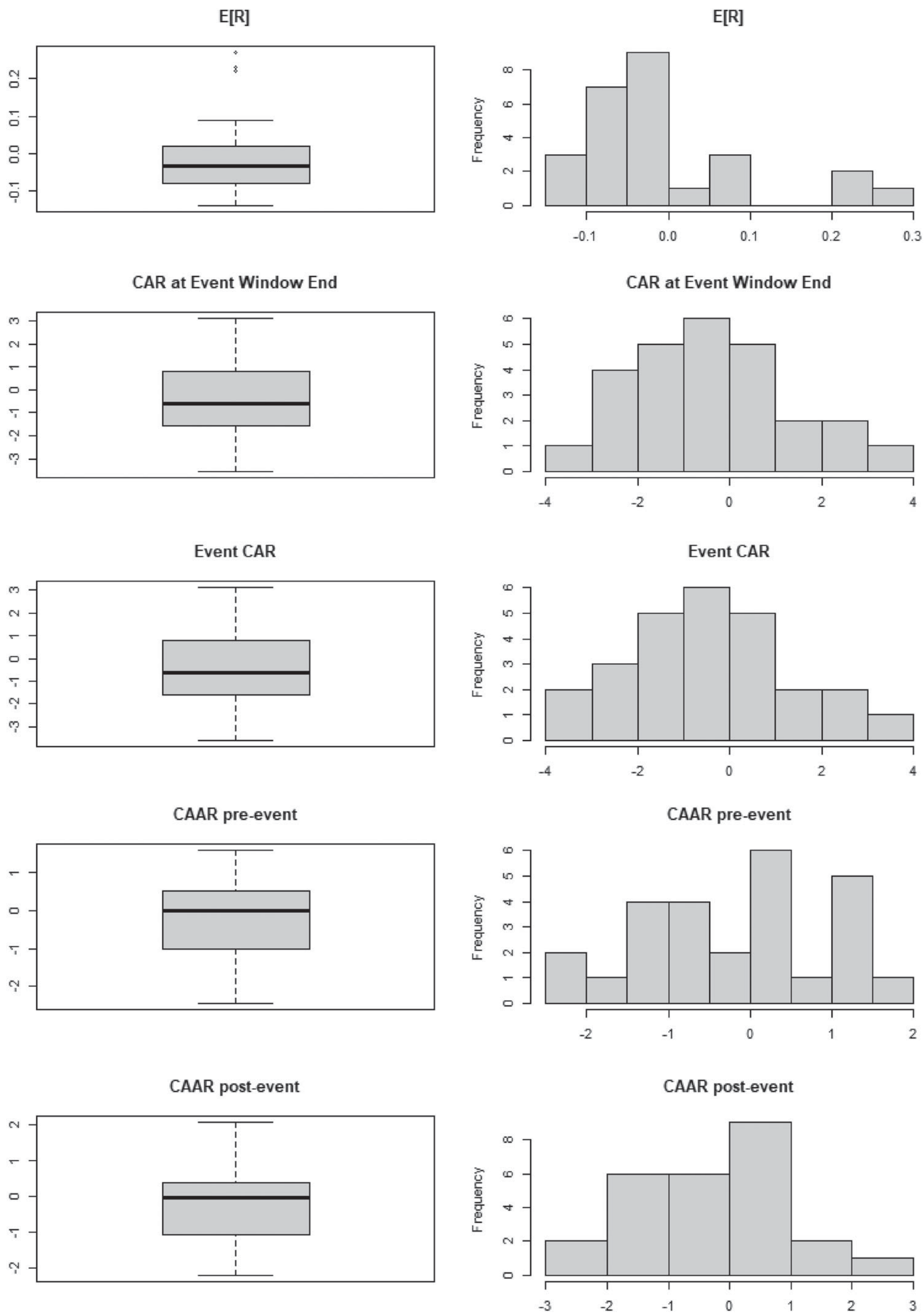


Figure 3. Boxplot and Histograms for the analyzed data sets.

The descriptive statistics are presented in Table 6 and boxplots and histograms are in Figure 3. Only the first dataset, expected return E[R] is characterized by significant asymmetry, above-normal kurtosis, and the presence of outliers. Therefore, all tests reject the null hypothesis of normality of distribution, at a 5% significance level – see

Table 6. Descriptive statistics for the analyzed data sets.

	Min	Median	Mean	Max	SD	Skewness	Kurtosis
E[R]	−0.14	−0.04	−0.01	0.27	0.11	1.38	4.03
CAR at event window end	−3.56	−0.58	−0.39	3.09	1.78	0.34	2.50
Event CAR	−3.60	−0.60	−0.40	3.10	1.78	0.35	2.52
CAAR pre-event	−2.44	0.00	−0.23	1.59	1.14	−0.16	1.99
CAAR post-event	−2.19	−0.01	−0.27	2.06	1.15	−0.05	2.30

Table 7. Results of testing for normality for the analyzed data sets, 1 = CAR at Ev. Wdw. End, 2 = Ev. CAR, 3 = CAAR pre-event, 4 = CAAR post-event.

test	E[R]		1		2		3		4	
	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value	statistic	p-value
AD	1.768	0.000	0.223	0.814	0.226	0.804	0.429	0.293	0.539	0.154
JB	9.430	0.013	0.783	0.572	0.770	0.579	1.207	0.363	0.539	0.711
LT	0.248	0.000	0.082	0.922	0.083	0.916	0.122	0.395	0.142	0.191
RJB	32.977	0.005	0.632	0.618	0.629	0.620	1.030	0.399	0.139	0.923
SW	0.825	0.000	0.970	0.618	0.970	0.627	0.955	0.311	0.951	0.247
MCLR	6.801	0.047	0.492	0.910	0.484	0.912	3.674	0.234	3.995	0.200
MMRT1	8.524	0.011	0.931	0.517	0.952	0.508	1.955	0.218	1.378	0.352
MMRT2	6.055	0.015	0.977	0.507	0.998	0.498	2.216	0.180	1.665	0.283

Table 7 for p-values of tests for normality for the analyzed datasets. However, at the 1% significance level, some tests do not reject the null hypothesis – specifically the Jarque–Bera test, the medcouple test, MMR1, and MMRT2 tests that are more robust than other tests.

4. Modeling of changes in trade volumes

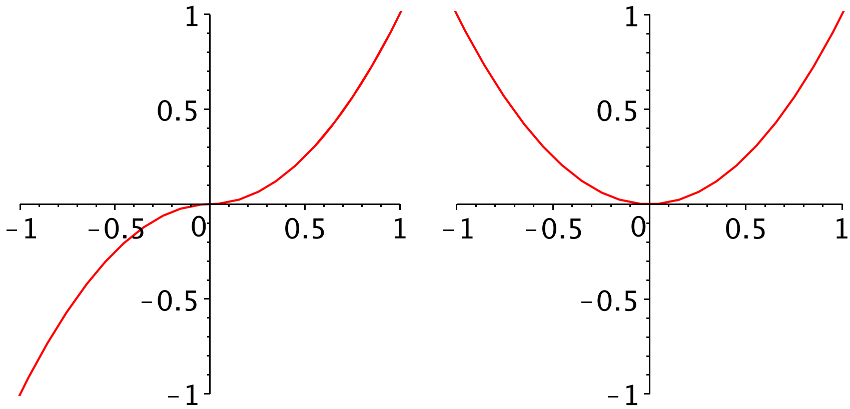
In this section, using the delta method constructed confidence interval, we will show significant statistical differences between trading volumes measured by IPSA before and after the change point. Consider a probability space $(\Omega, \mathcal{F}, P)$ and a measurable space (S, Σ), on which a stochastic process lives, i.e. a collection of S-valued random variables, which can be written as $\{r(t, \omega) : t \in T\}$ (to reflect that it is actually a function of two variables). We usually use shorten notation r_t.

Assume that IPSA r_t evolves as a real-valued stochastic process. Note that at each point in time, the expectation $m(t) := E[r_t]$ of the random variable is the mean (we assume here only L^2 processes). Thus, the mean and also variance $w(t) = E[r_t^2] - E[r_t]^2$, in general, is a function of time.

We now define a new statistical quantity, aggregated IPSA for $u, v \in T, u < v$

$$RC(u, v) := \int_u^v m(t)\ \mathrm{d}t \tag{1}$$

In addition to classical power function $x^k, x \in \mathbb{R}, k \in \mathbb{N}$, we use the notation $x^{k^*} := |x|^k \mathrm{sgn}(x), x \in \mathbb{R}$ is a signed power function which guarantees that power $k \geq 0$ might be real for any real values of x. Clearly, functions x^m and x^{m^*} are different for negative values, since x^{m^*} is odd, see e.g. case $m = 2$ in Figure 4. Suppose that $r_0 = A, r_0' = B \in \mathbb{R}$ and σ is nonnegative. For intern local dynamics (of IPSA), as will be clear later, we use Chan–Karolyi–Longstaff–Sanders model (1992) with a fixed parameter k



(a) $x^{2^*} = |x|x$ (b) x^2

Figure 4. Graphs of power functions on $[-1, 1]$. (a) $x^{2^*} = |x|x$ and (b) x^2.

$$dp_t = (\theta - \beta p_t)\ dt + p_t^k\ \sigma\ dW_t \tag{2}$$

For convergence of interest rate models of this type see [26].

Note that (2) involves several known processes. The Cox–Ingersoll–Ross model supposes $k = 1/2$, the Geometric Brownian motion model supposes $k = 1$ and $k = 0$ implies the famous Ornstein–Uhlenbeck model or the Vasicek model. We focus later here on the last case.

Note that the stock market index, is an index that measures a stock market, or a subset of the stock market, that helps investors compare current stock price levels with past prices to calculate market performance. Typically stock market dynamics are modeled by a Stochastic Differential Equation. Here we consider that the IPSA is driven by the following two-dimensional IVP (two-factor model), where (2) is explicitly included for $a = -\beta$ and $b = \theta$. For a better understanding and its good properties see [27] or [28].

$$\begin{aligned} dr_t &= \left[f\ r_t + c\ p_t^{m^*} + e\right] dt, \\ dp_t &= [a\ p_t + b] dt + \sigma\ p_t^k\ dW_t, \\ r_{t_0} &= A,\ \ r'_{t_0} = B. \end{aligned} \tag{3}$$

This model is unique in the way of raising power by p_t. For classical power p_t^m and more general settings see e.g. [27] or [28]. Note that by changing the assumption of raising power three situations could arise. The solution (with common values of all parameters) could coincide, could coincide only for a specific interval, or could be different on the whole interval of existence, see [27]. Note that the value of m is in the role of stabilization of the process's speed and may influence the value of σ, which is a very interesting fact.

Now, for simplicity, we suppose that $k = 0$, and we are also forced to consider that $c \neq 0$. We obtain specific time-integral of signed powered Ornstein–Uhlenbeck process. The system (3) reduces to the nonlinear model, in which r_t can be found explicitly, see [27] or [28], e.g. for $t_0 = 0$ we have $r_t = e^{ft} \int_0^t e^{-fs}((\sigma \int_0^s e^{-av}\ dW_v + \frac{b(1-e^{-as})}{a} + \beta_m)^{m^*} e^{mas}\ c + e)\ ds + Ae^{ft}$, where $\beta_m = \left(\frac{B}{c}\right)^{\frac{1}{m}^*}$.

We also assume that $f=0$ and $m=1$ are in order to obtain estimable parameters problems. Note also that the proper estimation of m is quite a difficult open problem. In addition, in the case when $m=1$, the model (3) reduces to the following system

$$\begin{aligned} \mathrm{d}r_t &= [c\ p_t + e]\mathrm{d}t, \\ \mathrm{d}p_t &= [a\ p_t + b]\mathrm{d}t + \sigma\ \mathrm{d}W_t, \\ r_{t_0} &= A,\ \ r'_{t_0} = B. \end{aligned} \tag{4}$$

It is a special case of the linear stochastic equation (for more details see [29]):

$$\begin{aligned} d\mathbf{X}_t &= (\mathbf{A}(t)\ \mathbf{X}_t + \mathbf{a}(t))\ dt + \boldsymbol{\sigma}(t)\ \mathrm{d}\boldsymbol{W}_t, \quad t_0 \le t < \infty, \\ \mathbf{X}_{t_0} &= \xi, \end{aligned} \tag{5}$$

where $d \times d, d \times 1$ and $d \times r$ matrices (in our case $d=2$ and $r=2$) $\mathbf{A}(t), \mathbf{a}(t)$ and $\boldsymbol{\sigma}(t)$ are nonrandom, measurable, and locally bounded, whereas one can obtain an explicit solution in the form

$$\mathbf{X}_t = \boldsymbol{\Phi}(t)\left[\boldsymbol{\Phi}(t_0)^{-1}\xi + \int_{t_0}^{t} \boldsymbol{\Phi}(s)^{-1}\ \mathbf{a}(s)\ \mathrm{d}s + \int_{t_0}^{t} \boldsymbol{\Phi}(s)^{-1}\ \boldsymbol{\sigma}(s)\ \mathrm{d}\mathbf{W}_s\right], \tag{6}$$

where $\boldsymbol{\Phi}$ is a fundamental matrix, i.e. the matrix solution of the problem $\boldsymbol{\Phi}(t)' = \mathbf{A}(t)\boldsymbol{\Phi}(t)$. Clearly

$$\mathbf{m}(t) := E[\mathbf{X}_t] = \boldsymbol{\Phi}(t)\left[\boldsymbol{\Phi}(t_0)^{-1}\xi + \int_{t_0}^{t} \boldsymbol{\Phi}(s)^{-1}\ \mathbf{a}(s)\ \mathrm{d}s\right] \tag{7}$$

4.1. Fitting the model

Here, we focus on parameters of the model (4). Since it is a special case of (5) we have $\xi = (A,B), \boldsymbol{a}(t) = (e,b), \boldsymbol{\sigma}(t) = (0,\sigma)$ and $\boldsymbol{\Phi}(t) = \begin{pmatrix} 1 & \frac{c}{a}\mathrm{e}^{at} \\ 0 & \mathrm{e}^{at} \end{pmatrix}$, and from (6) and the first line in (7) we have

$$r_t = m(t) + \frac{c\sigma}{a}\int_{t_0}^{t} (\mathrm{e}^{a(t-s)} - 1)\ \mathrm{d}W_s$$

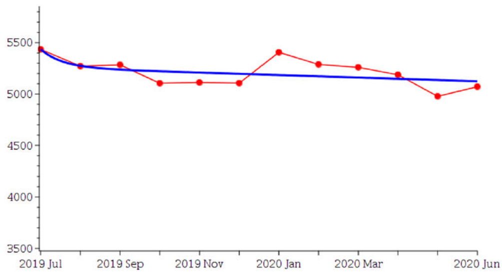
and

$$m(t) = \frac{c(Ba+b)\mathrm{e}^{a(t-t_0)} + (e(t-t_0)+A)a^2 - ((t-t_0)b+B)ca - bc}{a^2} \tag{8}$$

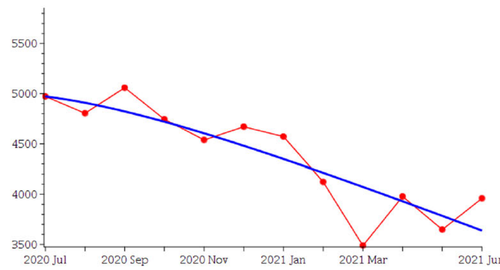
Note that for $a \to 0$ we have from (8) that $m(t) \to (Bc+e)(t-t_0) + A + \frac{bct^2}{2} - t_0bct + \frac{bct_0}{2^2}$ and for $c \to 0$ that $m(t) \to e(t-t_0) + A$. Variance can be easily computed by using Ito isometry on $E[r_t^2]$ yielding

$$w(t) = \frac{c^2\sigma^2}{a^2}\int_{t_0}^{t} (\mathrm{e}^{a(t-s)} - 1)^2\ \mathrm{d}s = \frac{c^2\left(\mathrm{e}^{2a(t-t_0)}/2 - 2\ \mathrm{e}^{a(t-t_0)} + 3/2 + a(t-t_0)\right)\sigma^2}{a^3} \tag{9}$$

with $w(t) \to c^2\sigma^2(1/3\ t^3 - t^2t_0 + t\ {t_0}^2 - 1/3\ {t_0}^3)$, if $a \to 0$ and $w(t) \to 0$, if $c \to 0$.



(a) Before



(b) After

Figure 5. Fitting of $m(t)$ on two real data periods. (a) Before and (b) after.

We have fixed the time-change point as 42 due to a 6-month delay due to the COVID period, thus we have two problems with different estimated parameters (we have used (8) and for given experimental data procedure `NonlinearFit()` from package `Statistics` in software `Maple 2019`):

(i) $t_0 = 31, A = r_{31} = 5434.44, B = r_{32} - r_{31} = -164.00 \Rightarrow \hat{a} = -1.800, \hat{b} = -14.858, \hat{c} = 2.052, \hat{e} = 4.847$

(ii) $t_0 = 43, A = r_{43} = 4972.36, B = r_{44} - r_{43} = -167.99 \Rightarrow \hat{a} = -0.296, \hat{b} = -124.795, \hat{c} = 0.399, \hat{e} = 17.216$

In Figure 5 one can see the situation before and after the threshold time-point with values from i) and ii) respectively.

Now, based on the data-driven confidence intervals approach for diffusion processes [30] and nonparametric delta method [31], we consider $100(1-\alpha)\%$ asymptotic normal confidence interval of the form

$$\left(RC(u,v) - z_{1-\alpha/2}\sqrt{V(u,v)},\ \ RC(u,v) + z_{1-\alpha/2}\sqrt{V(u,v)}\right), \tag{10}$$

where $V(u,v) = \int_u^v w(t)\ dt$ is the aggregated variance. We also assume that σ is for both periods in i) and ii) equal to 1. See also Figure 6 where variances given by (9) with estimated parameters from i) and ii) are plotted. Note also that in the definition of RC and V can time averaging be used by dividing it by the interval width. In our setup and for $\alpha = 0.05$, we receive two non-overlapping confidence intervals, for choice $z_{1-\alpha/2} = 1.96$. Namely, these intervals are $(57176.91, 57209.10)$ before, and $(48184.98, 48210.48)$ after the change-point time.

Note that estimation of parameters a, b and thus also of σ can be obtained from data $p_{t_i} = \frac{r_{t_{i+1}} - r_{t_i}}{\delta}$ (in the sense of discretization with suitable positive δ) by MLE or OLS for OU process, see e.g. [32].

5. Discussion and conclusions

As resumed in Subsection 1.1, economic theory lets little doubt that protectionism and trade barriers can negatively affect *allocative efficiency* and hence provoke overall welfare losses. This article contributes to the discussion in economic theory giving evidence that welfare

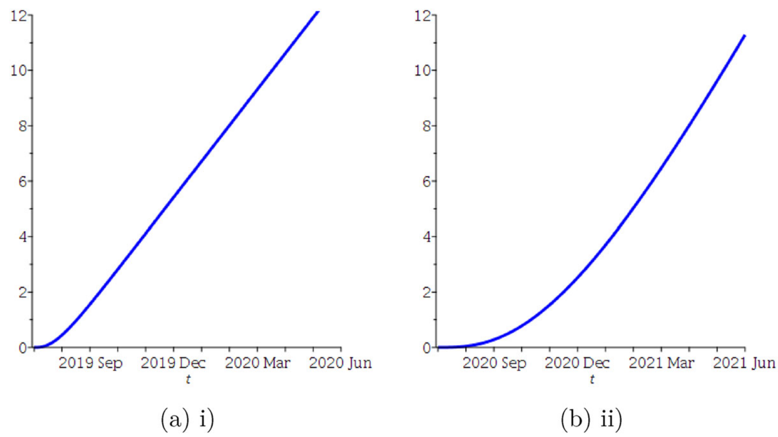


Figure 6. Graphs of $w(t)$ for two different periods. (a) (i) and (b) (ii).

losses do not only occur in the economies that are the targets of the protectionist measure but even in third economies, which are not directly part of the 'trade war', here Chile.

However, the impact of the US-Chinese trade war on the stock markets in Chile (and probably elsewhere) is not necessarily at all times the same. The world financial system sliders into crisis at regular intervals. Evidence exists that the long economic waves, the so-called Kondratieff waves, are, in fact, cycles of the financial system [33,34]. Symptoms that indicate that we are close to the next mega-crisis, comparable to the Great Depression, are money supply and debt having reached unprecedented levels in all industrialized economies and, associated herewith, the increasing number of credit defaults and speculative bubbles on stock and real estate markets (as well as other perceived 'save havens' such as gold or cryptocurrencies).

The reason why the financial system falls into deep crisis at regular intervals is unfortunately not well understood in economics. A cause could be the unnatural design of our money, see [35] and [13]. The closer we get to the inevitable collapse [36] and the bigger the price bubbles on stocks and other investment markets already are, the higher the probability that markets can be impacted by negative trade signals such as trade wars. Hence, it is not necessarily protectionism that causes the statistically significant market reactions, but these could be merely triggered by such events. On the other hand, the closer the world financial system gets to collapse, the more nervous become politicians and it is more likely that protectionist measures will be applied. This could explain the positive correlation between protectionism and the Great Depression authors [6] and [11] mentioned. It would be interesting to conduct the same study after the next crisis and the reset of the financial system, i.e., when money supply is still low, and we will consequently see less volatility and only little speculative bubbles on investment markets. Likely, a trade war would then have less impact on the expected returns of stock markets.

This study attempts to determine the impact of policy announcements in the U.S. Sino trade war between 2016 and 2019 on Chilean equity markets. The mean adjusted model method for event studies was used to determine expected returns and a CAR and CAAR based methodology comparing values within and outside of event windows was used to determine market reactions. This analysis showed a strong negative reaction to the trade war in overall terms. A two-tail paired t-test of two samples for means was employed to discern if the market reaction was statistically significant, and in most cases, it was (18 of 26 events). The majority of those events considered significant (11 of 18 significant events) produced negative reactions on the IPSA. The difference between periods is also confirmed by introduced cumulated measures of trade volumes.

We found that the Chilean stock exchange market reacts to the economic war between the US and China. We can of course suggest that this influence on expected returns is because of the trade ties; however, this does not necessarily need to be the case. It could be that investors at the stock exchange are nervous and so any event in the trade war provokes investors to sell stocks in Chile (and elsewhere). The influence on the Chilean market is not necessarily causal to the trade ties. The market, as measured by the IPSA, has been efficient in processing new information in a timely manner. As such local capital markets performed well pricing in the expectations of new volatility in world trade and adjusting equity valuations accordingly.

One of the limitations of this study methodology is that it gauges market valuations based on expectations of economic results, but not the economic results in and of themselves. A possible opportunity to follow up on this study would be employing a CGE or other economic assessment model to measure GDP or other variations. Additionally, studies could be performed to assess variations in firm earnings in relation with the trade war, and additionally compare market reaction with real world earnings.

Here, we used 7 days window, which allows us mainly to concentrate on the immediate reaction of the stock market to the announcement of some information. We do not study possible overreactions of the market and delays. We address partially capital issues, and the relationship between the current and capital account of the balance of payments is not addressed. Instead of this, we show that domestic (Chilean) capital markets were influenced in a certain direction.

Acknowledgement

We acknowledge the support of the Editors and the informative and insightful suggestions of Referees.

Funding

Jozef Kiselák was supported by the Slovak Research and Development Agency under Contract no. APVV-21-0369 and by the grant VEGA MŠ SR 1/0526/20. Milan Stehlík acknowledges ANID Chile COVBIO0003.

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