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A Test of the Market Efficiency of the Integrated Latin American Market (MILA) Index in Relation to Changes in the Price of Oil

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ABSTRACT

The purpose of this paper is to study if there is a Granger causality relationship between the price of oil and the prices of the stocks that compose the Integrated Latin American Market (MILA) index. Our analysis found that from the perspective of the efficient market hypothesis, there is no empirical evidence that there is a Granger causality relationship between the price of oil and other commodities and the stocks that compose the MILA index. Therefore, it is possible to conclude that based on the evidence, it is not possible to create an arbitrage strategy based on the price of oil and copper to achieve abnormal returns in the MILA stock market. In order to test for the Granger causality between the underlying variables, we used a leveraged bootstrap test developed by Hatemi (2012).

Keywords: Market Efficiency, Asymmetric Granger Causality, Asset-pricing Models, MILA Index, Oil Prices
JEL Classifications: G14, G15

1. INTRODUCTION

The purpose of this paper is to test the efficient market hypothesis (EMH) in relation to the stocks that compose the Integrated Latin American Market (MILA) Index and their relationship to the price of oil. This contribution is relevant in the context of the member countries of the MILA (Colombia, Chile, and Peru), whose economies, as is the case is most emerging markets, are believed to be driven by the price of commodities.

The paper is structured as follows: in Section 2, we describe the origin of the MILA, in Section 3, we explore the EMH under the context of asymmetric volatility and oil prices, in Section 4, we explain why the leveraged bootstrap test developed by Hatemi (2012) is adequate for testing asymmetric data, in Section 5, we present our results, and finally, in Section 6, we conclude.

2. THE INTEGRATED LATIN AMERICAN MARKET (MILA)

The stock markets that are part of MILA[1] play a fundamental role in creating economic synergy among its members. Since its inception in 2009, the member organizations have gone through extensive efforts to promote MILA as the premier choice for access to three of the more stable capital markets in Latin America. These three markets are quite homogenous, not only from the point of view of their geographic location, common language, and culture, but because the largest capitalization companies that are listed in those markets are from the commodities sector.

For the purpose of clarity, we will give a brief description of some of the companies that compose the MILA and their close relationship to the commodities sector. After the agreement was signed by the member organizations in 2009, the common market finally became operational on May 30, 2011. From that date onwards, any investors in those three countries could access the other markets using their local currency and do this through their local brokerage firms. One particular aspect of this integration

1 MILA: The Integrated Latin American Market is the result of the cooperation agreement signed in 2009 between the Santiago Stock Exchange, the Colombian Stock Exchange, and the Lima Stock Exchange. Other members to the agreement are the clearance and settlement institutions of the three countries: Deceval (Colombia), Cavali (Peru), and DCV (Chile) http://www.mercadomila.com/QuienesSomos

process is that it was possible to achieve integration without the need for mergers and acquisitions among the members. The MILA integration was possible through the harmonization of the technological platforms and of the regulatory frameworks of the clearing and settlement organizations in each country. On the legal front, one of the major advances was to recognize listed stocks from member countries through the free trade of listed stocks in the harmonized electronic routing system.

The companies that are listed in the MILA index have an interesting capitalization value by international standards. In order to track the listed companies, S&P Dow Jones developed a tracking index called the S&P MILA 40, which has an average capitalization of 8, 643 billion dollars.[2] The participation in this index by country of origin of the listed companies is as follows: 49.7% Chile, 39.1% Colombia, and 11.2% Peru. The index is composed of 40 companies in the three countries and is rebalanced 2 times per year (once in March and again in September) using a floating capitalization criteria. Recently, the fund manager, Horizon, incorporated a new exchange-traded fund called the “Horizon S&P MILA 40” that can be negotiated either in dollars or in local currency, in the case of investors from MILA member countries.

The relationship between the listed MILA companies and the price of commodities is quite clear when we explore the economic activity of the largest companies in the index and their relative market capitalization participation as a percentage of the total market capitalization of the local stock market indices. For example, in the Colombian case, the stocks with the largest capitalization are Ecopetrol and Pacific Rubiales, with their principal economic activity being oil exploration and production. Each company has a market capitalization of USD 71, 256, 303, 042 and USD 4, 470, 611, 496, respectively. This represents 22.94% of the COLCAP, which is the index that tracks the companies listed in the Colombian Stock Exchange. As expected, their average daily trading volume is USD 15, 522, 845 and USD 9, 484, 247, which is high by emerging market standards.[3]

In the case of the Chilean Stock Exchange, commodities-related companies represent 23%[4] of the total market capitalization of their principal index (IPSA[5]). The commodities-related companies are COPEC (a Chilean oil company) with 9.79% of relative market capitalization to total market capitalization, SQM (a Chilean Chemical and Mining Society) with 3.29%, which is a mining company dedicated to the exploration, processing, and commercialization of sodium nitrate, and CAP (a Pacific steel company) with 2.27%, which is a steel producer. Their respective market capitalizations are USD 17, 168, 094, 218, USD 8, 096, 002, 855, and USD 2, 269, 807, 281.[6]

Finally, the Peruvian Stock Exchange shows the highest participation of commodities-related companies relative to its market capitalization. In the case of the Peruvian Stock Exchange, companies in the mining sector are responsible for 52.21%[7] of the capitalization of the Peruvian stock index (IGBVL). The most representative companies are Southern Copper, the Cerro Verde Mining Society, and the Buenaventura mining company. Southern Copper is ranked as one of the biggest copper companies in the world, and its total market capitalization amounts to 25, 787 billion dollars and 24.7% relative market capitalization to total market capitalization of the Peruvian Stock Index. The Cerro Verde Mining Society also mines for copper and other related metals, with a market capitalization of 8156 billion dollars and a market capitalization participation of 6.54%. Finally, the Buenaventura mining company mines silver, gold, and other precious metals, with a market capitalization of 3528 billion dollars and 5.25% market capitalization.

Even though the importance of commodities-related companies in the MILA is evident, there are only a few studies that have explored the effect of the fluctuation of international oil prices on the general level of stock prices in these countries. Therefore, the main objective of this paper is to explore the relationship between the fluctuation of the price of oil and the general level of stock prices in these countries. In order to explore this effect, we use the semi-strong form of the EMH in which the assumption is that all available information, with the exception of insider trading, is incorporated in the price. Therefore, if the market is efficient in this sense, there should not be any evidence of causality between the price of oil and the general level of daily stock prices in the MILA Index. Intuitively, we can hypothesize that given the high concentration of commodities companies in the MILA, stock prices should react to negative shocks in the prices of commodities. However, it is important to find empirical evidence to corroborate if this relationship is indeed true. In order to empirically test this relationship, we used a non-parametric asymmetric Granger causality test, as developed by Hatemi. In the next sections, we argue as to why the proposed model is adequate for testing the semi-strong form of the EMH using our underlying data.

3. THE EMH IN THE CONTEXT OF ASYMMETRIC VOLATILITY AND OIL PRICES

The EMH postulates that in an efficient market, stock prices reflect all available public information (Fama, 1970). In this paper, we are interested in testing the semi-strong form of the EMH where today’s prices adjust immediately to all available public information. The traditional methodology for testing the EMH under the semi-strong form is usually based on event studies. The most common variations of event studies in the EMH semi-strong context are the contagion effect, dividend announcements, and any other kind of economic announcements in which we can categorize the level of “surprise” relative to a market consensus in order to measure the impact of the “surprise” on stock prices.

2 http://us.spindices.com/indices/equity/sp-mila-40-index

3 As of February 28, 2014. Source: Bloomberg.

4 http://www.bolsadesantiago.com/Composicion%20de%20Indices%20Bursatiles/01.Ficha%20T%C3%A9cnica%20%C3%8Dndice%20IPSA.pdf

5 IPSA (the Selective Stock Price Index) is the most important index in the Santiago Stock Exchange and comprises the largest 40 capitalization stocks in the country and their member weightings (inclusions/exclusions) are rebalanced once a year.

6 As of February 28, 2014. Source: Bloomberg.

7 As of February 20, 2014. Source: Bloomberg.

One thing that we can find in common in these studies is that price movements associated with negative news or negative surprises have a higher impact on stock prices than positive ones do. In the case of the dividend effect or drift, there is evidence that omissions (not paying or reducing the amount of an expected dividend payment) have on average a negative impact on stock prices (a drop of around 7%), which is larger than the positive impact (an increase of 3%) of initiations which occur when the amount of dividend paid to investors exceeds previous expectations (Healy and Palepu, 1988; Michaely et al., 1995). Another example regarding the impact of negative news on stock prices is the denominated contagion effect, which holds that in times of economic crisis, the interdependencies and correlations among international markets are statistically and significantly higher than those observed during tranquil (non-crisis) periods (Bekaert et al., 2005). From the theoretical point of view, this anomaly is known as the leverage or asymmetric volatility effect, and can be partially explained by the premises of capital structure theory, as postulated by (Modigliani and Miller, 1958). The basic idea is that when stock prices fall, the market value of the firm drops, and this causes the debt-to-equity ratio (leverage) of the firm to increase, which in turn increases the risk premium demanded by investors. Therefore, the rate of return demanded by the investor increases and this causes the stock price to drop (Black, 1976; Hamada, 1972). However, there is also the competing view that volatility feedback is a more coherent explanation of what causes negative shocks to have a higher impact on stock prices than positive shocks do. The reasoning behind volatility feedback is that returns are not correlated to volatility, but instead are conditional on volatility changes. In other words, if we believe that returns are explained by an asset-pricing model such as the capital asset-pricing model, then the expected return is only conditional on the covariance risk (beta) of the stock relative to the market portfolio. If this belief holds, then the risk premium is time-varying, and as bad news (good news) causes volatility increases (dampening), this leads to higher (lower) rates of return and lower (higher) stock prices due to the increase (decrease) in the beta coefficients between the market and the stock (Bekaert and Wu, 2000; Campbell and Hentschel, 1992). Even though there is evidence of a correlation between conditional volatility and returns, the observed patterns are often unpredictable, too small, and transaction costs too high in order to implement an effective arbitrage strategy that effectively rejects the EMH in its semi-strong form. One of the most difficult aspects of testing market efficiency is the "joint-hypothesis" problem; this means that in order to test efficiency, one should rely on an asset-pricing model that correctly reflects the information contained in the prices. Therefore, the "joint-hypothesis" problem is that when we find anomalies (inefficiency) in the behavior of returns, it is hard to determine if these anomalies are either attributable to problems in the asset-pricing model of choice or to the market being inefficient (Fama, 1970; 1991). Therefore, since asymmetry in financial series is persistent, it is important that the underlying model incorporates asymmetry or leverage in order to avoid possible bias due to model misspecification and the "joint-hypothesis" problem. Sadorsky (1999) also observed an asymmetric reaction in the prices of stocks to news originating from the oil market, but in this case, positive shocks have a greater effect on stock prices than negative shocks do.

There is an extensive amount of research about the relationship between stock markets and oil prices. Usually the statistical methods employed to test the relationship between oil prices and stock markets range from a simple ordinary least squares regression, multi-factor, vector autoregressive model (VAR) to co-integration, to many others. For example, using a multi-factor model, Chen et al. (1986) found that the impact of oil prices relative to other macroeconomic factors on the prices of stocks was negligible. However, a recent study by Basher et al. (2012) found evidence that changes in the price of oil had a significant impact in the case of prices of stocks in emerging markets, but that this relationship can be inconclusive, depending on the multi-factor model applied to the data. In the case of multivariate autoregressive models, Papapetrou (2001) not only studied the effects of oil prices on stock prices, but also on other macroeconomic variables, and found that oil prices had a significant effect on employment and economic growth in the case of Greece. However, it is important to mention that most of the literature on the subject has been focused on developed rather than on emerging markets.

In the context of the EMH and oil prices, co-integration is the preferred method for testing market efficiency due to the non-stationary nature of the data-generating process of commodities time series that tend to be closely related to macroeconomic variables (Crowder and Hamed, 1993). For this paper, we analyze the semi-strong informational efficiency of the MILA market to changes in the prices of oil and copper. We assume that spot commodity prices (especially oil) are informationally efficient in the semi-strong sense, since commodities markets are homogenous and driven mainly by changes in macroeconomic fundamentals that affect supply and demand. Therefore, we hypothesize that if the MILA market is efficient, changes in the prices of oil should be instantaneously reflected in the stock prices of the companies that compose the index, and that there should be no causality between the variables. For additional robustness, we also include the price of copper in the analysis, given that there are companies in the MILA that are active players in this commodity sector. In the next section, we will describe our variables of interest and explain why the asymmetric causality model developed by Hatemi is adequate for these kinds of data.

4. DATA AND THE MODEL

The data contain daily price information from March 2011 to February 2014 for the MILA, the spot price of oil (CL1), and copper (HGA) (Figure 1). In Figures 2 and 3, we can observe the cumulative positive and negative returns for each of the series in our dataset. We use daily data in order to observe how the MILA incorporates negative and positive information from shocks originating from the price of oil and copper.

For this paper, we use the method developed by Hatemi (2003; 2012) that incorporates bootstrap and optimal lag-selection techniques for determining Granger (1969) causality between the variables. In this case, we are trying to determine the causality between the MILA Stock Market Index and the price of oil and copper. Granger mathematically defines instant causality as

Figure 1: Historical price series for MILA (SPMILA), oil spot (CL1), and copper (HGA)

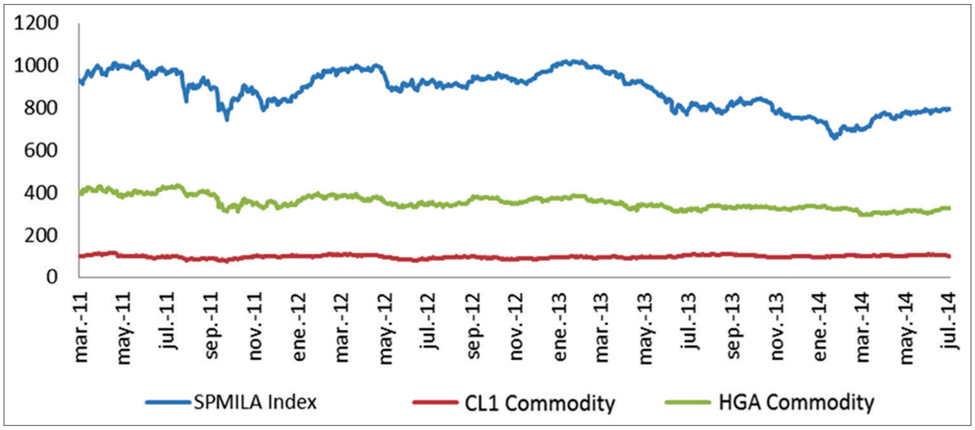


Figure 2: Cumulative positive returns for MILA (SPMILA), oil spot (CL1), and copper (HGA)

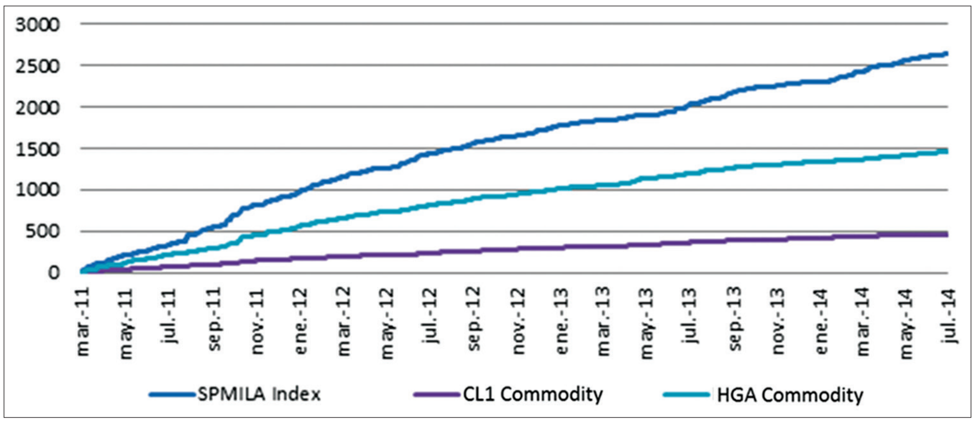
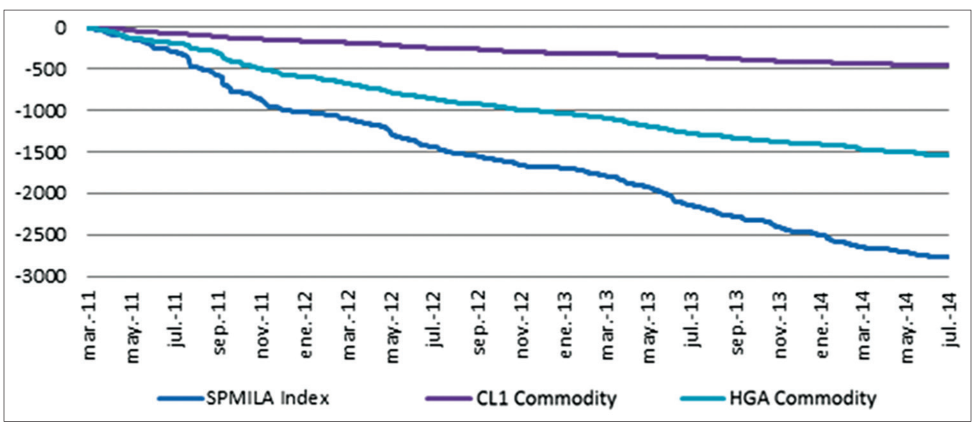


Figure 3: Cumulative negative returns for MILA (SPMILA), oil spot (CL1), and copper (HGA)



"feedback" between stationary variables. Since Granger, there has been an increasing amount of literature about modifications to the original test that can incorporate other innovations such as asymmetric data. One of the most interesting modifications is the one suggested by Hatemi (2012), where the author proves that by using bootstrapping, one can address the biases that arise from conditional autoregressive heteroscedasticity. Hatemi (2012) argues that traditional causality studies assume that the impact of positive shocks is the same as the impacts of negative shocks in absolute terms, which, in the case of a financial series, become a highly restrictive assumption due to the asymmetric nature of the underlying data.

Hatemi (2012) argues that by using bootstrapping along with asymmetric Granger causality, you can address many of the issues that arise from testing the EMH with the traditional Granger causality framework. As an example, Hatemi (2012) uses this method to measure the causality of oil shocks relative to the stock market index of the United Arab Emirates under an EMH framework.

Additionally, other authors have used the Hatemi (2012) method to demonstrate causality in other economic setups. Tugcu et al. (2012) used the method to demonstrate causality between no renewable energy and economic growth in G7 countries. The results show strong causality between no renewable energy and economic growth in Canada, France, the United States, England, and Japan. Tiwari et al. (2013) use the model to demonstrate causality between the price of oil and the real interest rate in Romania. The results show evidence of strong causality between the price of oil and the real interest rate in the short and long term in Romania. Using a similar setup to the previous studies, we will use the model of asymmetric causality, as proposed by Hatemi (2012), to measure the informational efficiency of the MILA Stock Market in relation to positive and negative shocks in the price of oil. We will also analyze the same relationship for the price of copper for robustness purposes.

As argued by Hacker and Hatemi (2006), the Granger causality test and its modifications have been extensively used in almost all fields of economic research. In addition, there have been important modifications to the original test. Of special interest is the modified Wald test (MWALD), as developed by Toda and Yamamoto (1995). These authors demonstrated that a Wald test based on bootstrap sampling has smaller error margins than when based on asymptotic distributions.

In the Hatemi (2012) setup, we begin with a VAR model of order p, VAR(p):

$$X_t = \upsilon + A_1 X_{t-1} + \ldots + A_p X_{t-p} + e_t, \quad (1)$$

Where X is the vector of dependent variables and p is the optimal lag determined by using the criteria suggested by Hatemi (2003):

$$HJC = \ln\left(\det \hat{\Omega}_j\right) + j\left(\frac{n^2 \ln T + 2n^2 \ln(\ln T)}{2T}\right),\ j = 0, \cdots, p. \quad (2)$$

Where $\hat{\Omega}_j$ is the variance-covariance matrix of the residuals of the VAR model without optimization, VAR (j), n is the number of variables, and T is the sample size. The null hypothesis of no causality is:

H_0: the row m, column k element in Ar equals zero for $r = 1,\ldots, p$. (3)

By utilizing some additional mathematical denotations, it is possible to redefine the VAR model as:

$$Y = DZ + \varepsilon \quad (4)$$

Where D is the estimator matrix, Z the regressor matrix, and ε is the error matrix. The null hypothesis of non-Granger causality is then presented as:

$$H_0: C\beta = 0 \quad (5)$$

Which can be tested via the following modified Wald statistic (Toda and Yamamoto, 1995):

$$\text{Wald} = (C\beta)' \left[C\left((Z'Z)^{-1} \otimes S_U\right)C'\right]^{-1} (C\beta) \sim \chi^2_p, \quad (6)$$

Here β = $vec(D)$, where vec is the column-stacking operator; Ä is the Kronecker product, and C is a (pxn)(1+pxn) indicator matrix that has elements of ones and zeros. The variance-covariance matrix from the VAR model that is restricted is defined as $S_U = (\text{å}_U{}'\text{å}_U)/(T-b)$. Note that b represents the number of estimated parameters in the model. Assuming normal distribution, the Wald statistic of equation (6) is distributed as χ^2 asymptotically with degrees of freedom equal to the lag order p. However, if the normal assumption is not fulfilled and the volatility is time-varying, then the asymptotic critical values based on the χ^2 distribution are not accurate. It is at this point that we use the "leverage bootstrapping," as suggested by Hatemi (2012), and we correct for the asymmetry that is common in financial series in order to relax the normality assumption. The basic idea is that in each bootstrap, we recalculate the MWALD statistic from equation (6) at least 10,000 times in order to obtain the empirical distribution. After obtaining these 10,000 replications, we find the (α) th upper quantile of the distribution of the bootstrapped Wald test. This quantile provides the (α)-level of significance "bootstrap critical value" (c^*_α). Finally, we compare the estimated Wald statistic based on the original one simulated with the bootstrap critical value. Therefore, if the estimated Wald statistic is higher than the bootstrap critical value (c^*_α), it means that the null hypothesis of non-causality can be rejected at the α level of significance.

5. RESULTS

Initially, we test for stationarity in the series using the augmented Dickey and Fuller (1979) unit root test. As expected, all the series show evidence of unit roots. Additionally, we test the series for normality using Doornik and Hansen (2008), and for ARCH effects, we use Hacker and Hatemi (2005). In all cases, we reject the hypothesis of normality in the series and there is evidence of autoregressive conditional heteroscedasticity in four of the six Granger causality tests. These results are presented in Table 1.

The optimal lags are calculated with Hatemi (2003) optimal selection criteria or the HJC criterion form equation (2). When we applied the leveraged bootstrap methodology to the MWALD statistic, we obtained the results shown in Table 2.

From the results obtained in Table 2, we fail to reject the null hypothesis that neither positive nor negative shocks in the price of oil and copper Granger causes price changes in the MILA Stock Index. This evidence supports the hypothesis that the MILA Stock

Table 1: Granger causality results and *P* values for rejecting the null of multivariate normality and ARCH effects

Direction of causality	Normality	ARCH effects	Optimal lag
CL1+≠MILA+	0.000	0.076	2
HGA+≠MILA+	0.000	0.198	2
CL1−≠MILA−	0.000	0.286	3
HGA−≠MILA−	0.000	0.012	3
CL1≠MILA	0.000	0.000	3
HGA≠MILA	0.000	0.000	3

Oil (CL1), Copper (HGA). The symbol A≠B means that variable A does not cause B. For example, CL1+≠MILA+ means that a positive shock in oil does not cause positive shocks in the MILA Index. A+and 1+are positive shocks. A− and 1− are negative shocks

Table 2: Test value statistic for the Granger causality test and critical test values for the leveraged bootstrap procedures for negative and positive shocks

Direction of causality	Test value	Critical bootstrap value 1%	Critical bootstrap value 5%	Critical bootstrap value 10%
CL1+≠MILA+	1.302	6.578	3.835	2.68
HGA+≠MILA+	3.054	9.378	6.107	4.621
CL1−≠MILA−	3.778	10.047	6.129	4.614
HGA−≠MILA−	1.661	9.727	6.174	4.647
CL1≠MILA	1.046	9.433	6.136	4.708
HGA≠MILA	1.93	9.762	6.254	4.749

The symbol A≠B means that variable A does not cause B. For example, CL1+≠MILA+ means that a positive shock in oil does not cause positive shocks in the MILA Index, A+ and 1+ are positive shocks. A− and 1− are negative shocks. The critical bootstrap value is presented for the 1%, 5%, and 10% significance level

Market in informationally efficient in the semi-strong sense and that all available public information is incorporated in the stock prices with respect to shocks in the price of oil and copper.

6. CONCLUSIONS

In conclusion, after testing the EMH in the semi-strong form using the Granger causality framework suggested by Hatemi (2012), we can conclude that there is no empirical evidence that can lead us to reject the null hypothesis of non-causality at any conventional level of significance. Therefore, it is possible to conclude that based on the evidence, it is not possible to create an arbitrage strategy based on the price of oil and copper to achieve abnormal returns in the MILA Stock Market.

Therefore, we can argue that at least under a Granger causality framework, the MILA Stock Market in informationally efficient in the semi-strong sense to shocks originating from changes in the price of oil and copper. Additionally, we can argue that the stocks that compose the MILA instantaneously reflect the information that originates form positive and negative shocks in the prices of these commodities. Finally, since we failed to reject the null hypothesis of efficiency, it is not possible to generate abnormal returns in the MILA Stock Market based on public information derived from shocks in the price of oil and copper.

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