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Are there "day-of-the-week" and "holiday" anomalies in the mexican stock market?

¿Hay anomalías "día de la semana" y "día festivo" en el mercado accionario mexicano?

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Abstract

This research examines the presence of the Day-of-the-Week (DOW) and Holiday Effect (HE) anomalies on the Mexican Stock Exchange's (MSE) Índice de Precios y Cotizaciones -Price and Quotation Index- (IPC), as well as on the Large, Medium and Small Capitalization subindices of the same market. The empirical estimation was performed with GARCH family models. We found that the DOW effect was consistently present in both the returns and volatility of the IPC and the three subindices. The Holiday Effect was also present in the volatility of the four series; however, this effect was only detected for the Medium Capitalization subindex's returns series.

JEL Code: C58, G11, G14
Keywords: day-of-the-week effect; holiday effect; calendar anomalies; market efficiency; GARCH model

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Resumen

Esta investigación examina la presencia de las anomalías Día de la Semana (DOW) y Efecto Día Festivo (HE) en el Índice de Precios y Cotizaciones (IPC) de la Bolsa Mexicana de Valores, así como en los subíndices de Capitalización Grande, Mediana y Pequeña del mismo mercado. La estimación empírica fue realizada con modelos de la familia GARCH. Encontramos que el efecto DOW estuvo presente consistentemente en los rendimientos y la volatilidad del IPC y en los tres subíndices. El Efecto Día Festivo también estuvo presente en la volatilidad de las cuatro series; sin embargo, este efecto fue detectado solamente en la serie de rendimientos del subíndice de Mediana Capitalización.

Código JEL: C58, G11, G14.
Palabras clave: efecto día de la semana; efecto día festivo; anomalías de calendario; eficiencia del mercado; modelo GARCH

Introduction

The Efficient Markets Hypothesis (EMH) postulates that securities' prices in financial markets are highly sensitive to the arrival of new information which is rapidly reflected in prices through many buy and sell decisions. The speed and volume of the transactions triggered by new information arrival eliminate any distortions in prices, and prevents investors earn extraordinary returns (Fama, 1970). Thus, the EMH implies that the information contained in historical asset prices is not useful to predict future returns since such prices are independent of each other, and follow unpredictable paths, known as random walks.

However, there is increasing evidence of the existence of market anomalies (Gayaker, Yalcin, & Berument, 2020; Plastun, Sibande, Gupta, & Wohar, 2020; Rossi, 2015). Among these anomalies are the so-called calendar (or seasonal[1]) effects such as the Day-of-the-Week (DOW) Effect (Anwar, Okot, & Suhendra, 2021; Santillán Salgado, Fonseca Ramírez, & Nelson Romero, 2019; Tadepalli & Jain, 2018; Vogelaar, Pimenta, Lima, & Gaio, 2014; Yardımcı & Erdem, 2020; Zhang, Lai, & Lin, 2017) and the Holiday Effect (HE) (Caporale & Plastun, 2017; Dumitriu & Stefanescu, 2020; Eidinejad & Dahlem, 2021; Marques, 2014; Mazviona, Mah, & Choga, 2021). The DOW and HE anomalies studied in the context of the MSE are the subject of interest in this paper. As in the case of other reported market anomalies (Bohl, Ehrmann, & Wellenreuther, 2020; Niroomand, Metghalchi, & Hajilee, 2020), these seasonal effects are at odds with the EMH and require a careful documentation and analysis.

The DOW and the HE anomalies for the Mexican market have been the subject of several studies, but their findings are frequently contradictory (e.g., Duarte, Sierra, & Garcés, 2013; Rojas & Kristjanpoller, 2014; Winkelried & Iberico, 2018). The present research contributes to the literature on

[1] Among the seasonal anomalies that have been reported in the literature are the January effect (Rozeff & Kinney, 1976), the turn-of-the-month effect (Ariel, 1987)), and the Halloween indicator (Bouman & Jacobsen, 2002), among several others.

calendar anomalies of the Mexican Stock Exchange (MSE) by examining that market's capitalization subindices besides the aggregate stock market index, the Índice de Precios y Cotizaciones (IPC), to contrast both seasonal effects in different subsamples. Another innovation consists on the estimation of GARCH-family models with dummy variables for the analysis.

The main findings were that the DOW Effect was consistently present in both the returns and the volatility of the MSE index and different subindices. Similarly, the Holiday Effect was present in the volatility of the four series examined. However, it was absent from the return's series, except in the case of the Medium Capitalization subindex.

The second part of this paper briefly reviews the literature on stock market anomalies and highlights the contributions of DOW and HE studies that have focused on the Mexican market. The third part describes the estimation methodology; the fourth part reports some relevant descriptive statistics of the data, and the estimation results; the fifth part presents the main conclusions.

Brief literature review

The day-of-the-week effect

Starting with the studies carried out by French (1980) and Gibbons & Hess (1981), many papers have reported the Weekend Effect with positive Friday average returns and negative Monday average returns. The literature has also documented statistically different average stock returns throughout the different days of the week.

Some of the more recent studies that discuss the Day of the Week (DOW) effect include, Zhang et al. (2017) who applied a GARCH model along with a rolling-window sampling strategy to study the DOW effect in the stock indices in 28 stock markets from 25 developed and emerging countries. The study concluded that the anomaly was present in all markets examined. Tadepalli & Jain (2018) employed ARIMAX modeling to examine the presence of the DOW effect in several indices of the Indian equity market and found a widespread existence of the DOW anomaly. Bahcivan & Karahan (2022) used a recently developed statistical method called Generalized Autoregressive Score (GAS) in combination with State-Space Modeling to overcome the intraday correlation dynamics due to non-synchronous trading and market noise to estimate intraday correlations in the Turkish equity market. The study found an upward trend at the closing of Monday's trading session, possibly associated with the opening of the US markets. A high correlation was reported across different market conditions and days of the week during periods of high volatility, including a "distinguishable path for the beginning of the week". Gkillas, Vortelinos,

Babalos, & Wohar (2021) studied the DOW effect with an international dataset, focusing on the bid-ask spread determinants, and find evidence of an international DOW impact of prices, volatility, and volume on bid-ask spreads.

The DOW effect has also been examined to some extent in the Mexican stock market. The study performed by Cabello & Ortiz (2003) in the MSE between 1986 and 2001 showed that average returns on Mondays were statistically the lowest of the week, while average returns on Thursdays were the highest. Winkelried & Iberico (2018) concluded that the MSE presented significantly negative Monday returns between 1995 and 2014. They also concluded that the positive Friday effect was not present in Mexico's stock market during that period. Zhang et al. (2017) applied GARCH (1, 1) specifications and found a significantly positive Wednesday effect in the returns of the MSE between 1994 and 2016. By applying the stochastic dominance approach, Kristjanpoller & Muñoz (2012) identified Monday and Friday anomalies in the Mexican equity market. Seif, Docherty, & Shamsuddin (2017) concluded that the IPC's average returns on Friday were significantly the highest of the week.

Conversely, Rojas & Kristjanpoller (2014) did not find any DOW anomaly in the IPC between 1997 and 2008 by applying Bonferroni's test. The results of the GARCH in mean (GARCH-M) model used by Torres & Alonso (2010) also rejected the presence of the DOW effect in the Mexican market between 2001 and 2009. The GARCH specifications used by Kristjanpoller (2012a) found no evidence of the DOW effect in the returns of the MSE from 1993 to 2007, even though that study identified a significantly negative Friday effect in volatility in the IPC. Evidence on the presence of the DOW effect for the Mexican market seems inconclusive, and this topic remains a fertile field for exploration.

The holiday effect

Numerous studies have found that stock returns are higher on the day before a stock market holiday. This anomaly, known today as the pre-holiday effect, was initially reported by Fields (1934). Five decades later, Lakonishok & Smidt (1988) found a related post-holiday stock market anomaly.

Dumitriu & Stefanescu (2020) looked for the presence of the holiday effect in four important stock indices of the U.S. market between January 1990 and April 2020. Their results using GARCH models denoted the existence of what they called the "Extended Holiday Effect". In an analysis of the HE anomaly in the Thai stock market, the GARCH and EGARCH models used by Chancharat, Maporn, Phuensane, & Chancharat (2018) identified significantly positive pre- and post-holiday effects from 1992 to 2016. Similarly, the OLS specifications used by Gama & Vieira (2013) found significant evidence of the holiday effect in the Portuguese equity market between 2003 and 2012.

The OLS regressions used by Marques (2014) on the MSE and five other Latin American stock markets[2] showed that the HE was not significant between 2007 and 2012. Similarly, Seif et al. (2017) and Winkelried & Iberico (2018) did not find evidence of the holiday effect in the IPC. Duarte, Sierra, & Garcés (2013) found no evidence of the post-holiday effect on the Mexican equity market between 2002 and 2013. By contrast, (Kristjanpoller, 2012b) concluded a significant presence of the post-holiday anomaly in the MSE, although the pre-holiday effect was not significant.

In brief, the literature has reported conflicting results on the presence of the DOW and HE in the stock market in different periods and for different geographies. Thus, the objective of this research is to determine the existence of these calendar anomalies in the Mexican Stock Exchange. The work hypothesis of this paper is that the DOW and HE effects exist on the returns and volatility of the four indices of the MSE, but that they have recently vanished. The confirmation of our hypothesis would mean that MSE market efficiency has increased.

Methodological aspects

This work studies the presence of the DOW and the HE on the MSE's IPC (S&P/BMV IPC), as well as on the large-capitalization (S&P/BMV IPC LargeCap), medium-capitalization (S&P/BMV IPC MidCap) and small-capitalization (S&P/BMV IPC SmallCap) stock indices. The modeling approach is based on an Autoregressive Moving Average with GARCH effects (ARMA-GARCH) model with dummy variables, represented as equation (1), below:

$$r_t = \alpha_0 + \alpha_1 D_{1,t} + \alpha_2 D_{2,t} + \alpha_3 D_{3,t} + \alpha_4 D_{4,t} + \sum_{j=1}^{p} \eta_j r_{t-j} + \varepsilon_t \tag{1}$$

where r_t corresponds to the daily return of the IPC (or one of the subindices) on period t, α_0 is the intercept that captures the average Monday return, that is, the reference date (c') for this model is Monday. Coefficients α_1, α_2, α_3, and α_4 are the differences between the average return on Monday and the average returns on Tuesday, Wednesday, Thursday, and Friday, respectively, $D_{i,t}$ is the dummy variable corresponding to the i-th day of the week from Tuesday (i = 1) to Friday (i = 4), and ε_t is the random disturbance.

[2] Argentina, Brazil, Chile, Colombia, and Peru.

Two additional dummy variables were added to equation (1) to examine the pre-holiday and post-holiday effects in the Mexican stock market, as in equation (2), below:

$$r_t = \alpha_0 + \alpha_1 D_{1,t} + \alpha_2 D_{2,t} + \alpha_3 D_{3,t} + \alpha_4 D_{4,t} + \alpha_5 D_{PRH,t} + \alpha_6 D_{POH,t} + \sum_{j=1}^{p} \eta_j r_{t-j} + \varepsilon_t \tag{2}$$

$D_{PRH,t}$ is equal to one for the days before a holiday (i.e., pre-holidays) and zero otherwise, while $D_{POH,t}$ is equal to one for the days after a holiday (i.e., post-holiday) and zero otherwise.

Considering the multiple market turbulence episodes that occurred during the sample period, an ARMA-GARCH model, capable to estimate the parameters of changing volatility, was selected. Anytime ARCH-LM tests did not reject the null hypothesis of constant variance of ε_t, OLS regression models were used to estimate equations (1) and (2). On the other hand, when the ARCH–LM test rejected the constant variance null, GARCH (1, 1) models were used to determine the conditional variance of the error term (Caporale & Zakirova, 2017; Seif et al., 2017). Furthermore, Engle (2001) argues that this specification is the simplest and most robust of all volatility models and that it can be adapted and broadened in numerous ways.

Following Caporale & Zakirova (2017), Kristjanpoller & Arenas (2015), and Kristjanpoller (2012a), an ARMA-GARCH (i.e., AR(m)-GARCH (p, q)) specification was used:

$$r_t = \psi_0 + \sum_{i=1}^{m} \phi_i r_{t-i} \tag{3}$$

$$r_t = \gamma_0 + \sum_{i \neq c,}^{n} \zeta_i D_{i,t} + \sum_{j=1}^{p} \eta_j r_{t-j} + \varepsilon_t \tag{4}$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \sum_{i \neq c,}^{n} \delta_i D_{i,t} \tag{5}$$

In expression (4), which represents the mean equation of the GARCH (1, 1) model, r_{t-j} denotes the jth lag of the returns. The number of lags to be used was determined based on the results of the AR(p)

model described by equation (3), and only those lags that turned out to be significant and contributed to minimizing the Akaike information criterion (AIC) were included in the final version of the model.

In equation (5) α_1 and β_1 represent the variance equation's coefficients for the lags of the error term and the variance, respectively. Connolly (1989) asserts that it is feasible to expand the GARCH model to include other effects in the conditional variance. Hence, the δ_i, the dummy variable coefficients, capture the average impact of the i-th calendar effect on volatility, both on direction and size, relative to a certain calendar reference date (c') to circumvent the dummy variable trap.

Besides using the conventional GARCH (1,1) model with dummy variables, this research also estimated the Exponential GARCH (EGARCH) model proposed by Nelson, (1991) and the Threshold GARCH (TGARCH) specification developed independently by Glosten, Jagannathan, & Runkle (1993) and Zakoïan (1994), revised to include exogenous variables (dummy variables in this case), following an approach similar to the procedure described for GARCH parameterizations (Begiazi & Asteriou, 2015). Equations (6) and (7) represent the TGARCH (1, 1) and EGARCH (1, 1) models used to examine asymmetrically clustered volatility, respectively[3]:

$$\sigma^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 \bar{I}_{t-1} + \beta_1 \sigma_{t-1}^2 + \sum_{i \neq c'}^{n} \delta_i D_{i,t} \tag{6}$$

$$\log(\sigma_t^2) = \omega + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-i}} \right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 log(\sigma_{t-1}^2) + \sum_{i \neq c'}^{n} \delta_i D_{i,t} \tag{7}$$

Coefficient $\bar{I}_{t-1}$ in equation (6) is an indicator variable that takes the value of 1 when $\varepsilon_{t-1} < 0$ and zero otherwise, so that bad news have an impact of $\alpha_1 + \gamma_1$ and good news have an impact of α_1 only. If γ_1 is statistically different from zero, the data have a threshold effect; and when $\gamma_1 > 0$ negative shocks will have larger effects on volatility than positive shocks. Equation (6) is subject to the following restrictions: $\omega \geq 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \gamma_1 \geq 0$.

The γ_1 coefficient in equation (7) is related to asymmetry since such a leverage coefficient should be significantly negative[4] if there is greater volatility after negative shocks. Thus, the existence of

[3] The mean equations for the TGARCH and EGARCH models are determined in a similar way than the GARCH model mean equation.

[4] Asymmetry was originally associated with financial leverage, so this was called leverage effect, although today there is a consensus that these variables are unrelated (Kang, 2011). In this context, leverage has also been defined as the tendency of volatility to increase when returns decrease and to decrease when returns increase (Enders, 2015).

leverage effects is tested by the hypothesis that $\gamma_1 < 0$. Also, there is an asymmetric impact whenever γ_1 is statistically different from zero. Moreover, given that the logarithm of the conditional variance, rather than the conditional variance itself, is parameterized, the implied value of σ_t^2 cannot be negative, which prevents the need to include artificial nonnegativity constraints on the model parameters.

GARCH family models fail to capture the non-normality of the data, so we use a non-parametric Kruskal-Wallis (K-W) test to examine the differences between the returns on a specific day of the week and other days. Equation (8) represents the K-W model:

$$H = \left(\frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j} \right) - 3(N+1) \tag{8}$$

where N is the total number of observations, R_j^2 is the average rank of observations in the j-th group, k is the number of groups, and n_j is the total number of observations in the j-th group.

Data and results

Daily observations on the closing level of the IPC and the three subindices were retrieved from Economática. The complete sample period for the IPC comprised from January 3, 2000 to September 28, 2018. However, due to data availability limitations the series for the LargeCap, MidCap, and SmallCap indices only include observations from October 26, 2006, to September 28, 2018[5].

Ortiz Bolaños, Hernández Henao, & Quintanilla Dieck (2015), Russo & Katzel (2012), and Santillán-Salgado (2015), among others, have stressed the extensive influence of the Subprime Mortgages Crisis and its consequence, the Great Recession (2007-2009), on the social, economic, and financial arenas around the globe. The European Sovereign Debt Crisis started during the autumn of 2009 also had important economic and financial consequences, in several regions of the world (Cabello, Moncarz, & Ortiz, 2015). Given the extraordinary nature of the period, we considered it appropriate to determine the performance of the calendar anomalies in the MSE before, during, and after the two financial crises episodes, an issue rarely examined in the literature.

[5] The publication of the three capitalization subindices started on October 16, 2006.

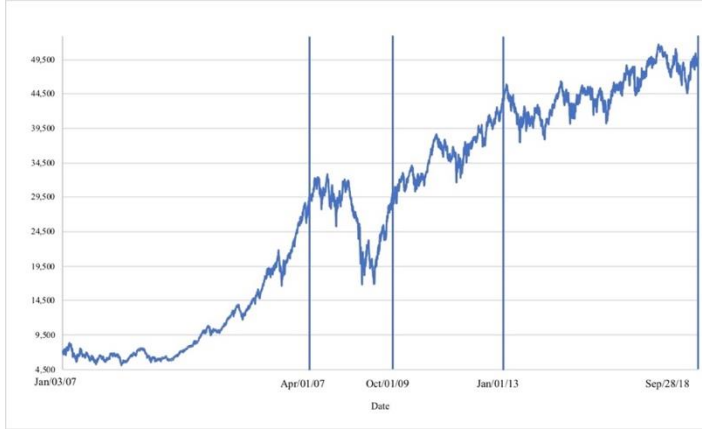

Figure 1. Evolution of the IPC 2007-2018.
Source: Authors' own elaboration with data retrieved from Economática.

The complete period was divided in four subperiods: a) before the Great Recession, from January 2000 to March 2007; b) during the Great Recession, from April 2007 to September 2009; c) during the Eurozone Sovereign Debt Crisis, from October 2009 to December 2012; and, d) after the Eurozone crisis, from January 2013 to September 2018 (see Figure 1).

The subperiods for the IPC were determined based on previous studies (Cabello et al., 2015; Do, Powell, Singh, & Yong, 2018; Russo & Katzel, 2012; Santillán-Salgado, 2015). In the case of the subindices, the full period was divided into two subperiods: a) from October 2006 to September 2009 and b) from October 2009 to September 2018, due to data availability limitations (see Figure 2).

To analyze the returns of the Mexican stock market indices, daily data were used to compute the logarithmic returns of the four indices in the sample:

$$r_t = ln(P_t) - ln(P_{t-1}) \tag{9}$$

In equation (9) r_t is the close-to-close continuous return corresponding to day t, P_t is the index adjusted closing price on day t, P_{t-1} is the index adjusted closing price on the previous day, t – 1.

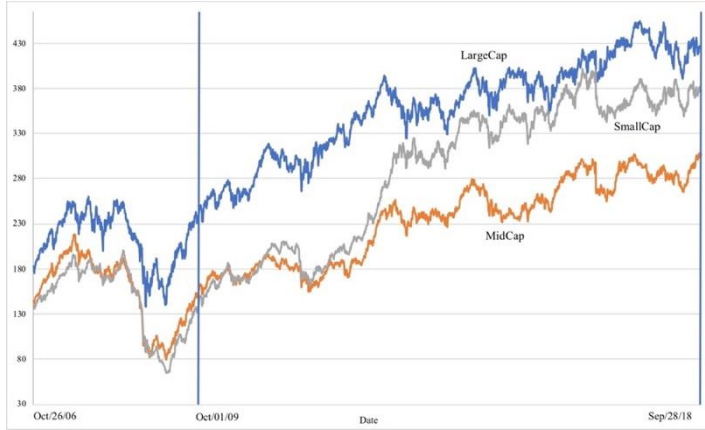

Figure 2. Evolution of the Capitalization Size Subindices 2006-2018.
Source: Authors' own elaboration with data retrieved from Economática.

Table 1 displays descriptive statistics for the returns of the IPC, along with the results of the Augmented Dickey-Fuller (ADF) and KPSS unit root tests for the whole period, as well as the four subperiods of interest. Table 2 shows the same information for the IPC LargeCap, the IPC MidCap, and the IPC SmallCap indices.

According to the Jarque-Bera test[6] in Table 1 and Table 2, the indices' returns did not follow a normal probability distribution. Regarding the subindices, the returns of the IPC SmallCap exhibited the highest daily mean and median, as well as the lowest standard deviation. The LargeCap index presented the highest standard deviation.

[6] Additional Jarque-Bera test results not shown here to save space, indicate that monthly returns of all four series were normally distributed during the October 2009 - September 2018 subperiod. This was also the case for the IPC LargeCap and the IPC SmallCap monthly returns during the October 2006 – September 2009 subperiod.

Table 1
IPC's Returns Descriptive Statistics: Daily Data

	Full Period	Pre-crises	Great Recession	European Crisis	Post-crises
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Mar/31/2007	Apr/01/2007 - Sep/30/2009	Oct/01/2009 - Dec/31/2012	Jan/01/2013 - Sep/28/2018
Descriptive Statistics:					
Mean	0.0396%	0.0738%	0.0026%	0.0474%	0.0083%
Median	0.0308%	0.0778%	0.0354%	0.0397%	0.0000%
Maximum	10.4407%	7.0199%	10.4407%	4.1672%	3.5251%
Minimum	-8.2673%	-8.2673%	-7.2661%	-6.0620%	-4.6789%
Standard deviation	1.2546%	1.3764%	1.8832%	0.9778%	0.8130%
Skewness	0.02839	-0.10756	0.31270	-0.55201	-0.19315
Kurtosis	8.81	6.21	6.88	6.70	5.02
Jarque-Bera	6882.78	816.93	421.13	526.07	264.26
ρ-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Observations	4890	1890	653	848	1499
Unit Root/Stationarity Tests:					
ADF					
t statistic	-31.081	-30.989	-23.470	-18.279	-19.032
ρ-value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
KPSS					
t statistic	0.160	0.022	0.178	0.044	0.046
ρ-value	> 0.10	> 0.10	> 0.10	> 0.10	> 0.10

Source: Authors' own elaboration with data retrieved from Economática.

Table 2
Size Indices Descriptive Statistics: Daily Data

	IPC LargeCap	IPC MidCap	IPC SmallCap
	Oct/26/2006 – Sep/28/2018		
Descriptive Statistics:			
Mean	0.0270%	0.0242%	0.0321%
Median	0.0206%	0.0368%	0.0478%
Maximum	10.2629%	9.3894%	6.8350%
Minimum	-7.1685%	-8.6734%	-6.8070%
Standard deviation	1.1835%	1.0389%	0-9644%
Skewness	0.14122	-0.73202	-0.76078
Kurtosis	11.01	11.87	9.81
Jarque-Bera	8321.10	10475.63	6309.82
ρ-value	< 0.01	< 0.01	< 0.01
Observations	3112	3112	3112
Unit Root/Stationarity Tests:			
ADF			
t statistic	-25.234	-11.325	-14.017
ρ-value	< 0.01	< 0.01	< 0.01
KPSS			
t statistic	0.074	0.070	0.089
ρ-value	> 0.10	> 0.10	> 0.10

Source: Authors' own elaboration with data retrieved from Economática.

Day-of-the-week effect results

The IPC and size indices DOW effect's ordinary least squares regressions for the full period and the subperiods exhibited ARCH effects, except for the IPC model estimated for the European Sovereign Debt Crisis subperiod. According to Akaike's Information Criterion (AIC), the EGARCH (1, 1) model was the most appropriate parameterization in all cases where GARCH-family models were applicable, as described earlier[7]. We used a quasi-maximum likelihood (QML) estimation since none of the EGARCH models' residuals followed a normal probability distribution (Bollerslev & Wooldridge, 1992).

Table 3
Day-of-the-Week: IPC

	Full Period	Pre-crises	Great Recession	European Crisis	Post-crises
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Mar/31/2007	Apr/01/2007 - Sep/30/2009	Oct/01/2009 - Dec/31/2012	Jan/01/2013 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
Mean Equation					
Monday (Constant)	0.00062 **	0.00061	0.00010	0.00138 ***	0.00032
Tuesday (D_1)	-0.00046	0.00029	-0.00086	-0.00138	-0.00019
Wednesday (D_2)	-0.00041	0.00055	-0.00066	-0.00023	-0.00056
Thursday (D_3)	-0.00050	0.00061	0.00059	-0.00157	-0.00098 ***
Frday (D_4)	-0.00048	-0.00030	0.00036	-0.00134	-0.00029
Variance Equation					
Monday (Constant)	-0.03385	-0.20210	0.26922	----	-0.16896
Tuesday (D_1)	-0.06618	-0.03109	-0.73815 **	----	0.06134
Wednesday (D_2)	-0.28219 **	-0.15355	-0.43786 *	----	-0.11495
Thursday (D_3)	-0.20536 *	-0.16385	-0.69780 ***	----	0.02398
Frday (D_4)	-0.36264 ***	-0.47659 **	-0.44262	----	-0.12709
ε^2_{t-1}	--	--	--	----	--
σ^2_{t-1}	--	--	--	----	--
ε^2_{t-1} ($\varepsilon^2_{t-1} < 0$)	--	--	--	----	--
$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	0.12654 ***	0.11371 ***	0.10458 ***	----	0.03731 *
$\varepsilon_{t-1}/\sigma_{t-1}$	-0.08157 ***	-0.11858 ***	-0.09995 ***	----	-0.10184 ***
log (σ^2_{t-1})	0.98668 ***	0.96842 ***	0.98620 ***	----	0.98226 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' own elaboration with data retrieved from Economática.

[7] Tables comparing the OLS, EGARCH, GARCH, and T-GARCH statistics are not included here due to space limitations but are available upon request.

Table 3 reports the output for the EGARCH model corresponding to the IPC, for the full period and the four subperiods. Monday's average returns were significantly positive during the full period and the European Crisis subperiod, which conflicts with the results regarding the presence of the Monday effect in the MSE reported by Cabello & Ortiz (2003) and Winkelried & Iberico (2018). The Kruskal-Wallis tie-adjusted test failed to reject the null hypothesis of equal returns on different days of the week[8]. All days of the week exhibited significantly lower volatility relative to Mondays during the full period or the subperiods. Fridays had the lowest volatility, a result that agrees with Kristjanpoller (2012a). However, the DOW effect in volatility disappeared during the last two subperiods.

The results presented in Table 4 show evidence of the DOW effect in the large-capitalization index, since Thursday average returns were statistically lower than Monday average returns throughout the full period and the last subperiod. The returns of the IPC SmallCap index displayed a significant positive Friday effect in the complete period and the last subperiod. Also, the Kruskal-Wallis test rejected the hypothesis of equal returns on all days of the week during the full period. Thus, the presence of the Friday effect found by the EGARCH specification in the IPC SmallCap between 2006 and 2018 seems robust, a result that agrees with those reported in the literature for the MSE (Kristjanpoller & Muñoz, 2012; Seif et al., 2017; Winkelried & Iberico, 2018), even though not specifically for the small-capitalization index. Interestingly, during the subperiod 2006-2009, which roughly corresponds to the Great Recession, none of the size indices exhibited a significant presence of the DOW anomaly. Moreover, this calendar effect was consistently absent in the returns of the IPC MidCap throughout all time intervals.

Regarding the outcomes of the DOW analysis in the variance equations, all size indices exhibited significantly reduced volatility on at least one day of the week during the full period and at least one of the subperiods. Noticeably, Wednesdays displayed the largest number of statistically lower volatility coefficients.

In brief, the IPC mean returns presented evidence of the presence of the DOW effects, since Monday and Thursday returns were statistically different from those on other days of the week. Such an effect appeared in the two last subperiods examined, a result that opposes the notion of an increase in the MSE efficiency. The DOW effect was also detected in the volatility of the IPC, but it has recently disappeared.

[8] The Kruskal-Wallis tests were performed for all periods and subperiods of the IPC and the IPC size-related indices. These results are not reported for the sake of brevity but are also available upon request.

Table 4
Day-of-the-Week: IPC Size Indices

	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
Mean Equation									
Monday (Constant)	0.00070 **	0.00042	0.00017	-0.00026	0.00017	0.00028	0.00074 **	0.00040	0.00008
Tuesday (D_1)	-0.00084 *	-0.00050	-0.00026	-0.00009	-0.00008	-0.00086	-0.00089 *	-0.00043	-0.00007
Wednesday (D_2)	-0.00077	0.00021	0.00044	0.00075	0.00111	0.00078	-0.00077	0.00009	0.00054
Thursday (D_3)	-0.00095 **	-0.00022	0.00029	0.00131	0.00124	0.00071	-0.00119 **	-0.00043	0.00027
Frday (D_4)	-0.00071	-0.00029	0.00124 ***	0.00018	0.00139	0.00095	-0.00061	-0.00062	0.00120 **
Variance Equation									
Monday (Constant)	-0.03903	-0.16733	-0.00145	0.21026	0.12121	0.15090	-0.27844 **	-0.81756 ***	-0.29558
Tuesday (D_1)	0.01200	-0.01181	-0.39271	-0.40861	-0.52748	-0.56579	0.15135	0.19869	-0.29508
Wednesday (D_2)	-0.30711 **	-0.39214 **	-0.28591	-0.64292 **	-0.45997	-0.25024	-0.16983	-0.37897 **	-0.31704
Thursday (D_3)	-0.25187 *	-0.09789	-0.18433	-0.78070 ***	-0.56254 **	-0.55551 *	-0.04559	0.11096	-0.02538
Frday (D_4)	-0.21770	-0.19491	-0.45520 **	-0.44629	-0.57316 *	-0.70677 **	-0.12789	-0.03334	-0.36968
ε^2_{t-1}	--	--	--	--	--	--	--	--	--
σ^2_{t-1}	--	--	--	--	--	--	--	--	--
ε^2_{t-1} ($\varepsilon^2_{t-1} < 0$)	--	--	--	--	--	--	--	--	--
$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	0.10893 ***	0.16505 ***	0.137523 ***	0.11281 ***	0.17156 ***	0.15438 ***	0.08925 ***	0.16648 ***	0.11039 ***
$\varepsilon_{t-1}/\sigma_{t-1}$	-0.09183 ***	-0.06150 ***	-0.037743 **	-0.11760 ***	-0.06838 **	-0.04778	-0.09983 ***	-0.11017 ***	-0.05782 ***
log (σ^2_{t-1})	0.98811 ***	0.98068 ***	0.982972 ***	0.98087 ***	0.98322 ***	0.98322 ***	0.97394 ***	0.92659 ***	0.95777 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' own elaboration with data retrieved from Economática

The returns of the size-related indices also displayed evidence of the DOW effect, mainly in the IPC LargeCap index. However, that anomaly was not found in the returns of the IPC or the size indices in the subperiod corresponding to the Great Recession. The financial turmoil during that severe crisis episode increased the standard deviation of daily returns[9], which, in turn, might have caused the lack of statistical significance of the DOW coefficients.

Holiday effect results

Except for the model used for the Eurozone Crisis subperiod, the residuals of all OLS regressions for the IPC showed heteroskedasticity, a finding that coincides with the results of the DOW examination for the same interval. As in the case of the DOW effect analysis, the EGARCH specifications were the best fit. Again, the residuals did not follow a normal distribution, so we applied QML estimation. The results of the EGARCH models for the IPC and the size indices are presented in Table 5 and Table 6, respectively.

[9] As can be observed in Table 1, the IPC daily standard deviation was almost 0.83 percentage points higher during the 2007 – 2009 subperiod than the average of the other three subperiods.

Table 5
Holiday Effect: IPC

	Full Period	Pre-crises	Great Recession	European Crisis	Post-crises
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Mar/31/2007	Apr/01/2007 - Sep/30/2009	Oct/01/2009 - Dec/31/2012	Jan/01/2013 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
Mean Equation					
No post-holiday Monday (Constant)	0.00053 **	0.00059	-0.00018	0.00128 *	0.00033
Tuesday (D_1)	-0.00044	0.00022	-0.00037	-0.00147	-0.00023
Wednesday (D_2)	-0.00039	0.00033	0.00008	-0.00017	-0.00055
Thursday (D_3)	-0.00040	0.00062	0.00032	-0.00149	-0.00091
Frday (D_4)	-0.00034	-0.00013	0.00068	-0.00122	-0.00023
Pre-holiday (D_{PRH})	-0.00090	-0.00120	-0.00520	-0.00066	-0.00058
Post-holiday (D_{POH})	0.00089	0.00197	0.00542	0.00274	-0.00048
Variance Equation					
No post-holiday Monday (Constant)	-0.11771	-0.17150	0.14930	----	-0.25676
Tuesday (D_1)	-0.00162	-0.03408	-059150 **	----	0.11209
Wednesday (D_2)	-0.20674 *	-0.12944	-0.40356	----	-0.07197
Thursday (D_3)	-0.15420	-0.15899	-0.63645 **	----	0.07837
Frday (D_4)	-0.22301 *	-0.43211 **	-0.27425	----	-0.03391
Pre-holiday (D_{PRH})	-0.61945 ***	-0.70218 ***	-0.85285 **	----	-0.35240 *
Post-holiday (D_{POH})	0.77557 ***	0.78186 ***	0.98297 ***	----	0.45299 **
ε^2_{t-1}	----	----	----	----	----
σ^2_{t-1}	----	----	----	----	----
ε^2_{t-1} ($\varepsilon^2_{t-1} < 0$)	----	----	----	----	----
$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	0.13333 ***	0.11036 ***	0.11681 ***	----	0.05444 **
$\varepsilon_{t-1}/\sigma_{t-1}$	-0.08611 ***	-0.11120 ***	-0.10270 ***	----	-0.10119 ***
log (σ^2_{t-1})	0.98585 ***	0.97351 ***	0.98326 ***	----	0.97990 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' own.

The results in Table 5 suggest that IPC did not display significant abnormal returns before or after the holidays in any of the intervals examined. Also, the corresponding Kruskal-Wallis tests for all time intervals failed to reject the null hypothesis that the returns on holidays and non-holidays were the same. Therefore, the absence of the HE in the returns of the IPC seems robust. This result agrees with the findings recently reported in the literature (Seif et al., 2017; Winkelried & Iberico, 2018) but opposes the conclusions reached by Kristjanpoller (2012b) regarding the post-holiday effect on the MSE.

The results of the variance equations denote that there was significantly lower pre-holiday volatility in the complete sample period and the pre-crises and Great Recession subperiods. Moreover, post-holiday volatility was statistically higher throughout each of the time intervals considered, except for the European Crisis subperiod[10].

[10] Although not discussed here for the sake of brevity, several findings regarding the presence of the DOW effect in the IPC and the size-related indices can be confirmed from the results presented in

According to the results displayed in Table 6, there were significantly higher than average post-holiday returns and statistically higher post-holiday volatility in the IPC MidCap in 2006-2018. The IPC LargeCap showed a comparable pattern in the first subperiod. So, in both instances, higher post-holiday returns might be related to higher volatility. On the other hand, the Kruskal-Wallis tests discovered no indication of the HE in the size indices. As in the case of the IPC, lower pre-holiday volatility was followed by higher post-holiday variance in the size indices. So, there is a tendency for post-holidays to exhibit higher returns and higher volatility, while pre-holidays present lower returns and lower volatility in the four indices.

Table 6
Holiday Effect: IPC Size Indices

	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
Mean Equation									
No post-holiday Monday (Constant)	0.00063 *	0.00021	0.00025	-0.00063	-0.00068	0.00040	0.00071 **	0.00030	0.00018
Tuesday (D_1)	-0.00086 *	-0.00051	-0.00027	-0.00015	-0.00034	-0.00119	-0.00090 *	-0.00050	-0.00015
Wednesday (D_2)	-0.00076	0.00025	0.00039	0.00103	0.00120	0.00089	-0.00080	0.00013	0.00044
Thursday (D_3)	-0.00084 **	-0.00003	0.00013	0.00130	0.00162	0.00031	-0.00108 **	-0.00032	0.00012
Frday (D_4)	-0.00055	-0.00006	0.00101 **	0.00091	0.00183 *	0.00029	-0.00054	-0.00026	0.00198 *
Pre-holiday (D_{PRH})	-0.00098	-0.00004	-0.00045	-0.00234	-0.00059	-0.00115	-0.00061	0.00011	-0.00026
Post-holiday (D_{POH})	0.00079	0.00277 **	-0.00080	0.00617 **	0.00348	-0.00114	0.00009	0.00222 *	-0.00027
Variance Equation									
No post-holiday Monday (Constant)	-0.15709	-0.33999 **	-0.08612	0.13417	0.09264	0.06238	-0.40231 **	-1.08476 ***	-0.33605 *
Tuesday (D_1)	0.11098	-0.07818	-0.32410	-0.30888	-0.49617	-0.68668 *	0.25698	0.311049	-0.19816
Wednesday (D_2)	-0.20252	-0.33539 **	-0.23187	-0.56606 **	-0.46941	-0.39520	-0.06628	-0.289248	-0.21805
Thursday (D_3)	-0.17287	-0.00075	-0.12739	-0.70391***	-0.53160 **	-0.45898 *	0.02587	0.207132	0.01082
Frday (D_4)	-0.02897	-0.02191	-0.32494 *	-0.31725	-0.54378	-0.74515 **	0.05388	0.153934	-0.21720
Pre-holiday (D_{PRH})	-0.61224***	-0.71981 ***	-1.05028 ***	-1.01605 ***	-0.98411 ***	-1.43130 ***	-0.47674 **	-0.590328 ***	-0.88869 ***
Post-holiday (D_{POH})	0.73907 ***	0.96209 ***	1.09206 ***	1.00807 ***	1.01547 ***	1.61033 ***	0.62674 ***	0.983767 ***	0.88415 ***
ε^2_{t-1}	--	--	--	--	--	--	--	--	--
σ^2_{t-1}	--	--	--	--	--	--	--	--	--
ε^2_{t-1} ($\varepsilon^2_{t-1} < 0$)	--	--	--	--	--	--	--	--	--
$\lvert\varepsilon_{t-1}/\sigma_{t-1}\rvert$	0.11446 ***	0.16505 ***	0.14311 ***	0.11124 ***	0.17679 ***	0.21063 ***	0.09976 ***	0.20354 ***	0.10737 ***
$\varepsilon_{t-1}/\sigma_{t-1}$	-0.09790 ***	-0.06150 ***	-0.04275 **	-0.11927 ***	-0.07960 **	-0.06924	-0.10255 ***	-0.11317 ***	-0.06196 ***
log (σ^2_{t-1})	0.98643 ***	0.98068 ***	0.98127***	0.98079 ***	0.97944 ***	0.97462 ***	0.97198 ***	0.91364 ***	0.96133 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Source: Authors' own.

In summary, our results show that the greatest number of DOW and HE anomalies on volatility occurred during the Great Recession in the four indices. Nevertheless, the DOW effect on returns appeared in the last two subperiods, that is, during the European Debt Crisis and post-crises subperiods.

The results also reveal that, overall, the IPC and the size indices' returns were subject to significant shocks to the conditional variance and volatility clustering, a condition that rejects the EMH (Kumar & Dhankar, 2009). The large size of the latter term suggests that variance was persistent and changed only slowly through time. Also, the significantly negative coefficient values of the $\varepsilon_{t-1}/\sigma_{t-1}$ terms of the EGARCH models' variance equations imply that the impact of bad news was larger to that of good news on the performance of the indices' volatility. There were, however, some exceptions to this pattern, most noticeably the cases of the IPC during the European Debt Crisis (Table 3 and Table 5), and the IPC SmallCap between 2006 and 2009 (Table 4 and Table 6).

The key findings of this research are reported in Table 7. The results of the regression models fail to reject the presence of the DOW effect in the returns of the IPC, the IPC LargeCap, and the IPC SmallCap in the full sample period. This conclusion agrees with the results reported by Kristjanpoller & Muñoz (2012), Seif et al. (2017), and Winkelried & Iberico (2018).

Table 7
Findings Overview

	IPC				IPC LargeCap			
	Returns		Volatility		Returns		Volatility	
Anomaly	The anomaly exists (H_A)	The anomaly disappeared (H_B)	The anomaly exists (H_C)	The anomaly disappeared (H_D)	The anomaly exists (H_A)	The anomaly disappeared (H_B)	The anomaly exists (H_C)	The anomaly disappeared (H_D)
Day-of-the-Week-Effect	Failed to reject	Rejected	Failed to reject	Failed to reject	Failed to reject	Rejected	Failed to reject	Rejected
Holiday Effect	Rejected*	---	Failed to reject	Rejected	Rejected*	---	Failed to reject	Rejected

	IPC MidCap				IPC SmallCap			
	Returns		Volatility		Returns		Volatility	
Anomaly	The anomaly exists (H_A)	The anomaly disappeared (H_B)	The anomaly exists (H_C)	The anomaly disappeared (H_D)	The anomaly exists (H_A)	The anomaly disappeared (H_B)	The anomaly exists (H_C)	The anomaly disappeared (H_D)
Day-of-the-Week-Effect	Rejected*	---	Failed to reject	Rejected	Failed to reject*	Rejected	Failed to reject	Failed to reject
Holiday Effect	Failed to reject	Failed to reject	Failed to reject	Rejected	Rejected	---	Failed to reject	Rejected

* Robust according to ANOVA and/or Kruskal-Wallis tests

Source: Authors' own.

The hypothesis that the DOW anomaly has recently vanished was rejected for these three indices. Such findings diverge from some reports in the literature regarding the disappearance of this calendar effect from the stock markets in other equity markets (Tadepalli & Jain, 2018; Zhang et al., 2017), and the DOW effect seems to be persistent in Mexico's Stock Exchange. In contrast, the hypothesis about the existence of the DOW effect in the returns of the IPC MidCap was consistently rejected, since

the regression analyses did not find any evidence of its presence. Moreover, this finding is robust, according to the Kruskal-Wallis test.

The regression models consistently failed to reject the hypothesis that there is a DOW effect in the volatility of the four indices examined, and also failed to reject the hypothesis that this anomaly has disappeared from the volatility of the IPC and the small-capitalization index.

Conclusions

Market efficiency is a subject of great interest for policymakers and investors in charge of designing investment strategies. According to the EMH, investors cannot systematically beat the market through the inherent information of asset prices. However, the reported existence of market regularities, such as the Day-of-the-Week (DOW) and the Holiday Effect (HE), questions the absolute validity of this notion.

Although our results reveal that the DOW effect did not exist on the IPC MidCap, we find supporting evidence for the presence of the DOW effect on the returns of the IPC, large- and small-capitalization indices, and on the four indices' volatility. Specifically, the results show evidence of Monday and Thursday effects in the returns of the IPC LargeCap, as well as a Friday anomaly in the IPC SmallCap. Furthermore, such effects have not disappeared from the size-related indices' returns. The time- and size-related disaggregation of the series we performed allowed the identification of a recent significantly negative Thursday effect in the returns of the IPC and IPC LargeCap. This outcome contrasts with the findings reported in the literature regarding the vanishing of the DOW effect (Alt, Fortin, & Weinberger, 2011; Plastun, Sibande, Gupta, & Wohar, 2019) and questions the increase of efficiency in the MSE.

The results obtained for the DOW IPC's volatility agree with those reported by Kristjanpoller (2012a), since the analysis found reduced volatility on Fridays; the small-capitalization index also showed that effect. Thus, the notion that Fridays are 'good' days for liquidity traders (Kiymaz & Berument, 2003) was confirmed for the IPC and SmallCap indices. Also, the analyses indicate that the IPC had significantly lower volatility on Wednesdays. The same anomaly was also present in the large- and medium-capitalization indices throughout the examined subperiods.

The regression model tests rejected the hypothesis that the HE was present in the returns of the IPC, the IPC LargeCap, and the IPC SmallCap, a conclusion that was further supported by the Kruskal-Wallis test results. This result agrees with the findings of other studies that report the absence of the holiday effect in the MSE (Duarte et al., 2013; Winkelried & Iberico, 2018). In contrast with the conclusion of nonexistence of the DOW effect in the IPC MidCap, the results denote a significant presence

of the HE in the returns of that index from 2006 to 2018. This coincides with the conclusions reported in the literature about the existence of such an anomaly in the MSE (Duarte et al., 2013; Kristjanpoller, 2012b; Seif et al., 2017).

A pattern of low pre-holiday volatility and high post-holiday volatility in the four indices was significant and consistent across all time intervals considered. Our results indicate no evidence that this phenomenon disappeared from the size-related indices, which also challenges the notion of an increase in the MSE efficiency. A plausible explanation for the DOW effect is that volatility is higher on Friday and lower on Monday, and so are the corresponding average returns for those days (Campbell & Hentschel, 1992). However, that explanation does not hold in the case of the MSE's indices. In any case, for example, significantly higher Monday average returns were generally accompanied by lower, although not significant, volatility.

On the other hand, the explanation proposed by Campbell & Hentschel (1992) for the Weekend Effect seems reasonable for the pre-holiday and post-holiday volatility and returns relationship found in this research. It has also been suggested that the HE may be explained by behavioral factors such as the change in the mood of investors before and after holidays (Dumitriu & Stefanescu, 2020; Gama & Vieira, 2013). In the case of the MSE, the significantly lower pre-holiday and higher post-holiday volatility patterns may, respectively, may relate to higher and lower trading volumes since such variables do not always move in tandem (Bollerslev, Li, & Xue, 2018). Moreover, liquidity traders are reluctant to trade in periods where the prices are more volatile (Foster & Viswanathan, 1990; Kiymaz & Berument, 2003). However, the pre-holiday and post-holiday pattern in the MSE leaves the door open for further research.

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