# Non-efficiency in Automated Markets for the US and Mexico[1]

## *Ineficiencia en los mercados automatizados de EE.UU. y México*

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## Abstract

*This work analyzes the Efficient Markets Hypothesis (EMH) introduced by Fama (1970). The notion has been a cornerstone in theory and practice in financial markets, given its implications for predicting future prices. The efficiency of markets has been widely explored in the literature. Still, recent technological advances have made it possible to trade faster than ever. Hence, the question arises again to examine the efficiency of high-frequency markets, which has not yet been investigated in depth. The present work explores market efficiency at various frequencies, from 1 second to 10 days, in the United States (US) and Mexico's stock markets. The empirical distribution and correlation of the assets return series were modeled to try and gauge whether markets follow a random walk. Thus, one can conclude that information is instantly incorporated, and the market is efficient. Results show that the markets are not efficient for high frequencies, but above the 10-day threshold, these series follow a random walk with an asymptotically normal distribution. The conclusion is important for practitioners and academics since it suggests the possibility of forecasting prices in high frequencies using statistical tools.*

***Keywords:*** *Efficient market hypothesis, alpha-stable distributions, high-frequency trading, autocorrelation.*
***JEL Classification:*** *G12, C1, C88.*

## Resumen

*El presente trabajo muestra un análisis de la hipótesis de los mercados eficientes (EMH), introducida por Fama (1970), que ha sido piedra angular en la teoría y la práctica en los mercados financieros por sus implicaciones para la predicción de precios futuros. La eficiencia de los mercados ha sido ampliamente explorada en la literatura, pero los avances tecnológicos recientes han hecho posible comerciar más rápido que nunca, por lo que surge una vez más la cuestión de examinar la eficiencia de los mercados de alta frecuencia, que aún no ha sido investigada en profundidad. El trabajo explora la eficiencia del mercado en varias frecuencias, desde 1 segundo hasta 10 días, en los mercados bursátiles de Estados Unidos (EE.UU.) y México. Se modeló la distribución empírica y la correlación de las series de rendimiento de los activos para tratar de evaluar si los mercados siguen un paseo aleatorio y así se puede concluir que la información se incorpora instantáneamente y el mercado es eficiente. Los resultados muestran que los mercados no son eficientes para altas frecuencias, pero por encima del umbral de 10 días las series siguen un paseo aleatorio con una distribución asintóticamente normal. La conclusión es importante tanto para los profesionales como para los académicos, ya que sugiere la posibilidad de pronosticar precios con alta frecuencia mediante la utilización de instrumentos estadísticos.*

***Palabras clave:*** *hipótesis del mercado eficiente; distribuciones alfaestable; transacciones de alta frecuencia; autocorrelación.*
***Clasificación JEL:*** *G12, C1, C88.*

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# 1. Introduction

High-frequency trading entails computational processes and a communication infrastructure that allows information to arrive at time scales of the order of nanoseconds (Budish et al., 2015). Integrating information at high-frequency intervals brings us to the Efficient Markets Hypothesis (hereafter EMH), which suggests that new information (historical, public, and private) is reflected in prices immediately, making it impossible to outperform the market consistently.

Also, these algorithms often act as enhancers of the misbehavior of markets, and the volume of operation generated by the machines to date is significant, we ask ourselves: Is the market efficient for high frequencies?

This question is relevant not only from an academic point of view, but also from an industry perspective, given that the failure to comply with the EMH at a specific time scale would mean that it is possible to forecast prices on such a scale.

The literature on efficient markets is extensive. However, most studies use low-frequency data in one-day or larger intervals. Bessembinder and Chan (1998) and Fifield et al. (2005) conclude that developed markets exhibit some efficiency. For emerging markets, the evidence is mixed. Chen and Li (2006), Mobarek et al. (2008), Kristoufek and Vosvrda (2013), and Ratner and Leal (1999) show that emerging markets are not efficient. In contrast, Karemera et al. (1999) conclude that most emerging markets follow a random walk.

More recently, studies have explored market efficiency in high frequencies. Brogaard et al. (2014) open this line of research by examining the role of high-frequency traders in price discovery and price efficiency. Results are mixed as well. Heng et al. (2020) find that Australian futures markets are efficient. Danak and Patel (2020) study Indian markets and find that before 9 minutes, there is an arbitrage opportunity. Ftiti et al. (2020) show that oil markets exhibit long memory. Mensi et al. (2019) show that the Bitcoin and Ethereum markets are inefficient with intraday data. Mishra (2019) tests whether high-frequency prices of Indian futures of soy follow a martingale and finds that for intervals of 5 and 10 minutes, they do not. Leone and Kwabi (2019) explore if data from the FTSE100 follow a random walk to the millisecond using a variance ratio test. They find that there is no random walk. We aim to show that data does not follow a random walk. To do so, we rely on Gopikrishnan et al. (1999) and Plerou et al. (1999) to test for normality in high-frequency data. They focus on finding the parameters for an alpha-stable Levy distribution that suits the data.

The descriptive capabilities of this family of distributions allow us to know the parametric evolution when the time interval changes. Gnedenko and Kolmogorov (1968) show that the distribution is defined by the parameters $\alpha, \beta, \gamma, \delta$. For a stable random variable $t$ is stable, the characteristic function is

$$\varphi(t; \alpha, \beta, \gamma, \delta) = \exp\left(it\delta - |\gamma t|^{\alpha}(1 - i\beta\, sign(t)\ \Phi)\right)$$

$\alpha$, the stability exponent, describes the tails of the distribution. $0 < \alpha \leq 2$

- $\alpha = 2$, the distribution is normal.
- $1 < \alpha < 2$, the distribution has no finite variance.
- $\alpha = 1$, corresponds to the Cauchy distribution.
- $\alpha = 0.5$ y $\beta = 0$ corresponds to the Levy distribution.

When $\alpha$ is small, the asymmetry parameter $\beta$ is significant. As $\alpha$ increases, the significance of $\beta$ decreases. This parameter ranges from -1 to 1:

$\beta = 0$, the distribution is symmetric.

$\beta > 0$, the distribution is skewed to the right.

$\beta < 0$, the distribution is skewed to the left.

$\gamma$ and $\delta$ define, respectively, the scale or breadth and the location or central value of the distribution.

We first apply the test for normality as an exploratory analysis (Jarque & Bera, 1980). Then, we calculate the parameters of an alpha-stable distribution for each series of returns and its evolution over time intervals $\Delta_t$ from 1 second to 10 days. Finally, we test for autocorrelation of the returns using the Ljung and Box (1978) procedure.

To the best of our knowledge, no study has used this approach to test for market efficiency in high frequencies. Nor is there a study that contrasts the structure of a developed and emerging market for high frequencies.

# 2. Data and Results

## *2.1 Data*

There is no clear path to choose assets in the academic literature when discussing high-frequency trading. Thus, we turn to the industry. Picardo (2014) mentions that an asset is desirable for high-frequency algorithms if its volatility is low, its market capitalization is significant, and its price is not too high or inflated. He remarks that high-frequency traders lean towards blue chip stocks, companies that are stable income generators, have a high market capitalization, have a relatively high volume of market operations, and have reported positive profits for several years. These facts move us to choose the companies listed in Tables 1 and 2 and leave out popular companies such as Amazon and Alphabet due to their high volatility (see Table 1 and Table 2).

We use log returns for the selected stocks from March 7, 2018 to March 7, 2019.

The total record for both markets is 633,977,360 in one year. For the United States, the record is 539,834,024 for 24 stocks, and for Mexico, 78,863,574 for 35 stocks. This number would indicate that the volume of information generated by operations in the United States is approximately 6.9 times greater than that produced in Mexico.

Of the total records, 618,897,598, or 97.58%, occurred during open or trading hours to the public, and 2.4% of operations occurred once the market closed. For stocks in the US market, the percentage of operations after market hours is 2.65%. In Mexico, the percentage of operations that occur outside market hours is 0.72%.

The US stock with the most records is MSFT, with 50,946,661. It also has the highest number of records during market hours, with 49,517,823. FB has the highest number of records outside market hours, with 1,970,674, or 4.22% of its total operation.

The Mexican stock with the most records is WALMEX, with 5,648,948. It also has the highest number of records that occurred outside market hours, with 38,572, or 0.68% of its total operation. The stock that records the most operations outside of market hours in terms of its total operations is GCARSO, with 1.07% or 8126 operations.

The US stock with the highest number of trades per minute is FB, with 33,942 trades, and the corresponding Mexican stock is GENTERA, with 6521 operations.

The US stock that registered the highest number of trades in one second in the period is FB, with 4882 trades in the 39th second at 10:05 am, September 17, 2018. The Mexican ones were ALSEA and GENTERA, each with 243 records.

Nine of the 24 US stocks registered the highest number of trades per minute at the last minute of the trading day (14:59). For Mexico, only one share was identified, the maximum of which occurred at the last minute. However, out of the 35 shares, 23 registered their highest records in the last 20 minutes of the trading day. This period is used to calculate the weighted average price and closing price on the Mexican Stock Market.

**Table 1.** US List of Stocks

| | **Market Code** | **Name** |
|---|---|---|
| 1 | ABT | Abbott Laboratories |
| 2 | BAC | Bank of America Corporation |
| 3 | BMY | Bristol-Myers Squibb Company |
| 4 | C | Citigroup Inc. |
| 5 | CSCO | Cisco Systems, Inc. |
| 6 | F | Ford Motor Company |
| 7 | FB | Facebook, Inc. |
| 8 | FOXA | Twenty-First Century Fox, Inc. |
| 9 | GE | General Electric Company |
| 10 | GM | General Motors Company |
| 11 | HPQ | HP Inc. |
| 12 | INTC | Intel Corporation |
| 13 | KO | The Coca-Cola Company |
| 14 | MDLZ | Mondelez International, Inc. |
| 15 | MO | Altria Group, Inc. |
| 16 | MS | Morgan Stanley |
| 17 | MSFT | Microsoft Corporation |
| 18 | ORCL | Oracle Corporation |
| 19 | PFE | Pfizer Inc. |
| 20 | T | AT&T Inc. |

| | Market Code | Name |
|---|---|---|
| 21 | TWTR | Twitter, Inc. |
| 22 | USB | US Bancorp |
| 23 | VZ | Verizon Communications Inc. |
| 24 | WFC | Wells Fargo & Company |

Source: Prepared by the authors. Market Code, according to Bloomberg.

**Table 2.** Mexican Stock Market List of Stocks

| | Market Code | Name |
|---|---|---|
| 1 | AC | Arca Continental, S.A.B. de C.V. |
| 2 | ALFA | Alfa, S.A.B. de C.V. |
| 3 | ALPEK | Alpek, S.A.B. de C.V. |
| 4 | ALSEA | Alsea, S.A.B. de C.V. |
| 5 | AMX | América Móvil, S.A.B. de C.V. |
| 6 | ASUR | Grupo Aeroportuario del Sureste, S.A.B. de C.V. |
| 7 | BIMBO | Grupo Bimbo, S.A.B. de C.V. |
| 8 | BSMX | Grupo Financiero Santander, S.A. |
| 9 | CEMEX | Cemex, S.A.B. de C.V. |
| 10 | CUERVO | Becle, S.A.B. de C.V. |
| 11 | ELEKTRA | Grupo Elektra, S.A.B. de C.V. |
| 12 | FEMSA | Fomento Económico Mexicano, S.A.B. de C.V. |
| 13 | GAP | Grupo Aeroportuario del Pacífico, S.A.B. de C.V. |
| 14 | GCARSO | Grupo Carso, S.A.B. de C.V. |
| 15 | GENTERA | Gentera, S.A.B. de C.V. |
| 16 | GFINBUR | Grupo Financiero Inbursa, S.A.B. de C.V. |
| 17 | GFNORTE | Grupo Financiero Banorte, S.A.B. de C.V. |
| 18 | GMEXICO | Grupo México, S.A.B. de C.V. B |
| 19 | GRUMA | Gruma, S.A.B. de C.V. |

| | Market Code | Name |
|---|---|---|
| 20 | IENOVA | Infraestructura Energética Nova, S.A.B. de C.V. |
| 21 | KIMBER | Kimberly Clark de México, S.A.B. de C.V. A |
| 22 | KOF | Coca-Cola Femsa, S.A.B. de C.V. L |
| 23 | GMXT | GMéxico Transportes, S.A. de C.V. |
| 24 | LALA | Grupo Lala, S.A.B. de C.V. |
| 25 | LIVEPOL | El Puerto de Liverpool, S.A.B. de C.V. |
| 26 | MEGA | Megacable Holdings, S.A.B. de C.V. |
| 27 | MEXCHEM | Mexichem, S.A.B. de C.V. |
| 28 | NEMAK | Nemak, S.A.B. de C.V. |
| 29 | OMA | Grupo Aeroportuario del Centro Norte, S.A.B. de C.V. |
| 30 | PE&OLES | Industrias Peñoles, S.A.B. de C.V. |
| 31 | PINFRA | Promotora y Operadora de Infraestructura, S.A.B. de C.V. |
| 32 | RA | Regional, S.A.B. de C.V. |
| 33 | TLEVISA | Grupo Televisa S.A.B. |
| 34 | VOLAR | Controladora Vuela Compañía de Aviación, S.A.B. de C.V. |
| 35 | WALMEX | Walmart de México, S.A.B. de C.V. |

Source: Prepared by the authors. Market Code, according to Bloomberg.

## 2.2 Results

In Table 3 and Table 4, we present the preliminary analysis. These tables show the average values for mean, variance, skewness, kurtosis, and the logarithm of the Jarque-Bera statistic [2] for each stock in each market (see Table 3 and Table 4).

2. We do not present the value of the Jarque-Bera statistic because of its magnitude. Instead, we present the logarithm for comparison purposes. The p-value corresponds to the Jarque-Bera statistic, not the logarithm.

**Table 3.** Average Statistics for the US and Mexican Market Returns, for Time Intervals from 1 Second to 10 Days

| | Mean | | Standard Deviation | | Kurtosis | | Skewness | |
|---|---|---|---|---|---|---|---|---|
| **Dt** | **US** | **Mexico** | **US** | **Mexico** | **US** | **Mexico** | **US** | **Mexico** |
| 1 sec. | 0.0000% | 0.0000% | 0.0009 | 0.0009 | 72411.44 | 49692.17 | -1.0853 | -0.7602 |
| 5 secs. | 0.0000% | 0.0000% | 0.0009 | 0.0010 | 23942.08 | 16447.00 | -2.5049 | -1.7472 |
| 10 secs. | 0.0000% | 0.0000% | 0.0010 | 0.0011 | 18721.55 | 12862.73 | -3.0633 | -2.1302 |
| 15 secs. | 0.0000% | 0.0000% | 0.0011 | 0.0012 | 13359.87 | 9183.38 | -4.0396 | -2.8037 |
| 30 secs. | 0.0000% | 0.0000% | 0.0013 | 0.0013 | 9447.83 | 6495.41 | -4.1245 | -2.8457 |
| 1 min. | 0.0000% | -0.0001% | 0.0014 | 0.0016 | 5041.76 | 3471.45 | -3.0951 | -2.1590 |
| 5 mins. | -0.0002% | -0.0003% | 0.0023 | 0.0025 | 712.45 | 495.31 | -2.1110 | -1.4746 |
| 10 mins. | -0.0003% | -0.0005% | 0.0030 | 0.0033 | 299.28 | 210.45 | -1.4505 | -0.9967 |
| 15 mins. | -0.0006% | -0.0008% | 0.0038 | 0.0040 | 246.49 | 173.89 | -1.4315 | -1.0309 |
| 30 mins. | -0.0012% | -0.0017% | 0.0050 | 0.0054 | 107.49 | 77.91 | -1.0412 | -0.7996 |
| 1 hour | -0.0022% | -0.0031% | 0.0067 | 0.0072 | 53.41 | 39.80 | -0.8451 | -0.6469 |
| 2 hours | -0.0052% | -0.0068% | 0.0088 | 0.0092 | 27.72 | 21.94 | -0.7749 | -0.6642 |
| 4 hours | -0.0104% | -0.0139% | 0.0122 | 0.0128 | 16.16 | 13.64 | -0.6362 | -0.5588 |
| 1 day | -0.0240% | -0.0315% | 0.0172 | 0.0179 | 9.62 | 8.66 | -0.4854 | -0.4724 |
| 2 days | -0.0320% | -0.0477% | 0.0233 | 0.0248 | 6.98 | 7.14 | -0.6339 | -0.6457 |
| 3 days | -0.0555% | -0.0762% | 0.0295 | 0.0308 | 5.67 | 5.90 | -0.5660 | -0.6176 |
| 4 days | -0.0621% | -0.0898% | 0.0331 | 0.0344 | 5.42 | 5.37 | -0.6045 | -0.4806 |
| 5 days | -0.0811% | -0.1199% | 0.0380 | 0.0394 | 4.46 | 4.49 | -0.4544 | -0.4312 |
| 10 days | -0.1872% | -0.2570% | 0.0551 | 0.0563 | 3.42 | 3.43 | -0.2099 | -0.3105 |

Source: Prepared by the authors.

**Table 4.** Average Logarithm of the Jarque-Bera Statistic for the US and Mexican Market Returns for Time Intervals from 1 Second to 10 Days

| | Jarque-Bera log | P-value | Jarque-Bera log | P-value |
|---|---|---|---|---|
| **Dt** | **US** | **US** | **Mexico** | **Mexico** |
| 1 sec. | 35.92756 | 0.0010 | 35.55027 | 0.0010 |
| 5 secs. | 31.38863 | 0.0010 | 31.01134 | 0.0010 |
| 10 secs. | 30.54139 | 0.0010 | 30.16410 | 0.0010 |
| 15 secs. | 29.21663 | 0.0010 | 28.83934 | 0.0010 |
| 30 secs. | 28.16080 | 0.0010 | 27.78351 | 0.0010 |
| 1 min. | 26.34944 | 0.0010 | 25.97216 | 0.0010 |
| 5 mins. | 20.75078 | 0.0010 | 20.37363 | 0.0010 |
| 10 mins. | 18.08965 | 0.0010 | 17.71289 | 0.0010 |
| 15 mins. | 17.54719 | 0.0010 | 17.17054 | 0.0010 |
| 30 mins. | 14.90227 | 0.0010 | 14.52863 | 0.0010 |
| 1 hour | 12.92950 | 0.0010 | 12.55870 | 0.0010 |
| 2 hours | 10.92356 | 0.0010 | 10.57627 | 0.0010 |
| 4 hours | 9.14867 | 0.0010 | 8.81317 | 0.0010 |
| 1 day | 7.00473 | 0.0049 | 6.72252 | 0.0180 |
| 2 days | 5.33830 | 0.0281 | 5.52191 | 0.0267 |
| 3 days | 4.10258 | 0.0792* | 4.43838 | 0.0770* |
| 4 days | 3.89283 | 0.1156* | 3.90071 | 0.1193* |
| 5 days | 2.82891 | 0.1573* | 2.90360 | 0.1661* |
| 10 days | 1.23719 | 0.3487* | 1.42692 | 0.3183* |

Source: Prepared by the authors.

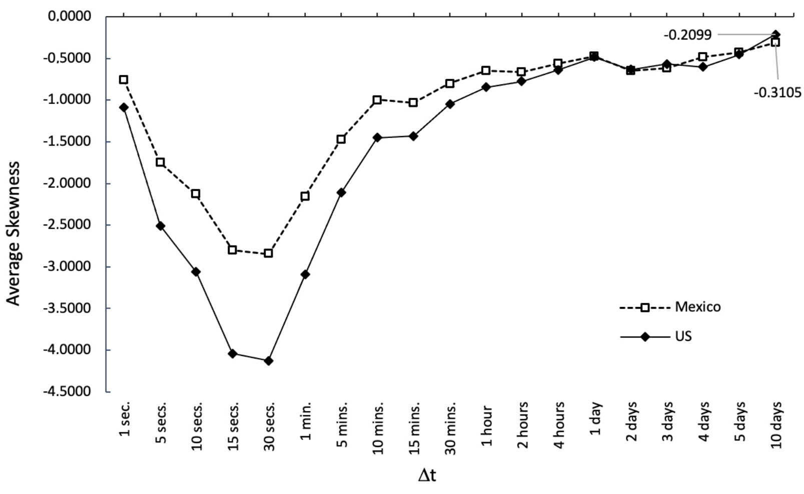
* Indicates the null hypothesis of normality is not rejected at the 95% confidence level.

The negative trend in the mean shows that, in the analysis period, stocks had generalized losses in both markets. We see a widely studied phenomenon regarding the standard deviation: the US and Mexican markets exhibit a linear co-movement

(Lahrech & Sylwester, 2011). For very small values of $\Delta_t$, the kurtosis is remarkably high. These values describe a clearly leptokurtic distribution.[3] Finding such high kurtosis values for small operating intervals tells us that the return values vary minutely. In percentage terms, the changes up or down are practically the same magnitude in absolute value.

Looking at skewness graphically (see Figure 1), we notice that the curve for both markets is similar, with the reservation that the US market has a more significant negative pronouncement. The skewness is less when $\Delta_t$ is between 10 seconds and 1 minute. This leads us to conclude two things: first, algorithms indeed change the structure of the market at high frequencies, and second, this happens regardless of the market's size and liquidity.

**Figure 1.** Skewness Average of Returns by Country for Each $\Delta_t$




Source: Prepared by the authors.

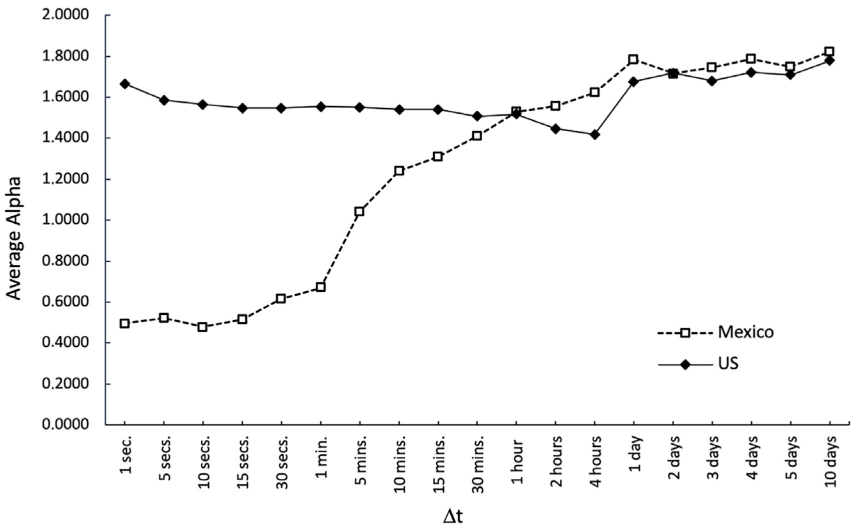
Then, we have the Jarque-Bera statistic. It is not until $\Delta_t$ is three days when, on average, the statistic is in the no-rejection zone at the 95% confidence level. Thus, we conclude that the distribution of returns is normal after this $\Delta_t$, but not before.

3. A leptokurtic distribution has fatter tails than a normal distribution, which means that extreme negative or positive values are more likely.

Next, we present the results for the $\alpha$-stable distribution analysis.[4] The parameters are estimated with the MATLAB stblfit function, which uses Koutrouvelis algorithm (Koutrouvelis, 1981). Figure 2 shows the average value of $\alpha$ for both markets (see Figure 2). For small values of $\Delta_t$, the value of $\alpha$ for Mexican stocks is 0.50, while it is 1.67 for American stocks. These results are far from each other, contrasting with the behavior observed in Table 3 (see Table 3). In this case, Mexican stocks in small intervals are far from being a stable distribution, and they stand out for having highly concentrated returns.

For both markets, as $\Delta_t$ increases, the value of $\alpha$ suggests an asymptotic approximation to the normal distribution.

**Figure 2.** $\alpha$ Average Values of Returns by Country for Each $\Delta_t$

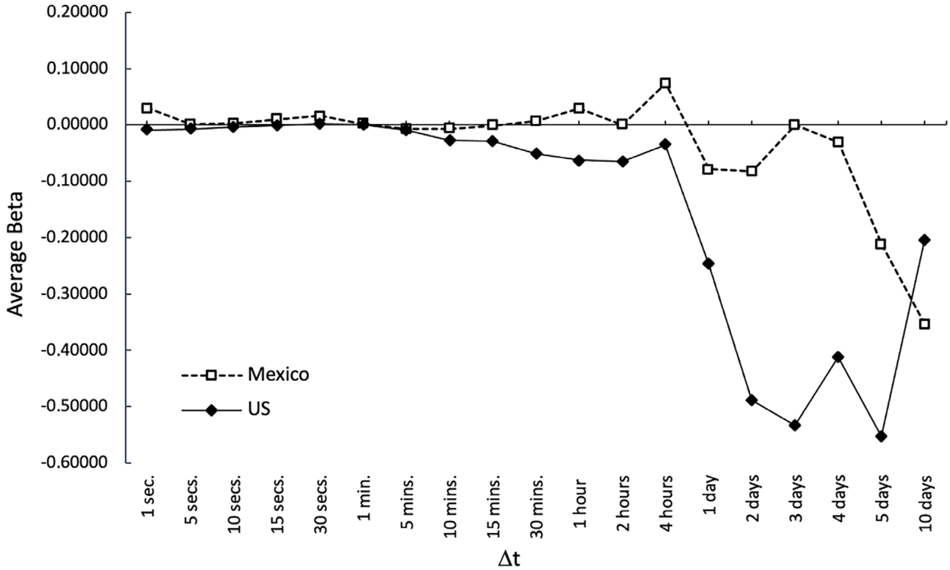



Source: Prepared by the authors.

4. According to Gnedenko and Kolmogorov (1968), a distribution is stable if any linear combination of two random variables that follow this distribution also follows this distribution (with different scale and location parameters). These distributions are defined by four parameters $\alpha$, $\beta$, $\gamma$, and $\delta$, out of which $\alpha$ is the most important, and it represents the stability of the distribution tails. An $\alpha$ equal to 2 corresponds to the normal distribution.

Figure 3 plots the averages of $\beta$ for both markets. For small values of $\Delta_t$, up to approximately 15 minutes, the factor $\beta$ is around zero. Above that interval, the distribution begins to show asymmetries with negative skewness (see Figure 3). But in conjunction with Figure 2, as $\alpha$ increases (from $\Delta_t$ = 1 hour), the value of $\beta$ loses significance (see Figure 2 and Figure 3).

**Figure 3.** $\beta$ Average Values of Returns by Country for Each $\Delta_t$




Source: Prepared by the authors.

We conclude that Mexican stocks follow the Levy distribution for intervals from 1 to 15 seconds. For higher $\Delta_t$, the distribution tends to be normal. The US stocks $\alpha$ values show that the distribution has no finite variance but approaches a normal distribution as $\Delta_t$ increases.

Finally, Table 5 shows the results of the autocorrelation test (see Table 5). We see the percentage of stocks in each market that exhibit autocorrelation in the returns for each $\Delta_t$. From 1 second to 1 minute, correlation is identified in 100% of the stock returns series. This proportion decreases to about 10% when $\Delta_t$ is 10 days. Table 4 also shows the average p-value for the Ljung-Box test, which reinforces the fact that autocorrelation exists in each $\Delta_t$ (see Table 4). The US market, however, shows a drop in the number of stocks that are autocorrelated faster than the stocks autocorrelated in the Mexican market. The existence of autocorrelation shows that the EHR—in its weak form, which states that prices follow a random walk—is not fulfilled.

**Table 5.** Results of the Ljung-Box Test: Percentage of Stocks that Exhibit Autocorrelation per Market and Average P-value of Test

| | **US** | | **Mexico** | |
|---|---|---|---|---|
| **Dt** | **% Stocks** | **Average p-value** | **% Stocks** | **Average p-value** |
| 1 sec. | 100.00 | 0.00000 | 100.00 | 0.00000 |
| 5 secs. | 100.00 | 0.00000 | 100.00 | 0.00000 |
| 10 secs. | 100.00 | 0.00000 | 100.00 | 0.00000 |
| 15 secs. | 100.00 | 0.00000 | 100.00 | 0.00000 |
| 30 secs. | 100.00 | 0.00000 | 100.00 | 0.00000 |
| 1 min. | 100.00 | 0.00000 | 100.00 | 0.00000 |
| 5 mins. | 95.83 | 0.00304 | 100.00 | 0.00002 |
| 10 mins. | 79.17 | 0.09620 | 97.1 | 0.00932 |
| 15 mins. | 62.50 | 0.15961 | 91.43 | 0.02359 |
| 30 mins. | 41.67 | 0.16960 | 77.14 | 0.06314 |
| 1 hour | 25.00 | 0.21256 | 77.14 | 0.08908 |
| 2 hours | 20.83 | 0.38655 | 62.86 | 0.11855 |
| 4 hours | 12.50 | 0.57136 | 37.14 | 0.21746 |
| 1 day | 20.83 | 0.47705 | 22.86 | 0.32931 |
| 2 days | 12.50 | 0.53658 | 17.14 | 0.36738 |
| 3 days | 12.50 | 0.43321 | 14.29 | 0.47851 |
| 4 days | 0.00 | 0.68369 | 8.57 | 0.46116 |
| 5 days | 8.33 | 0.61769 | 11.43 | 0.46870 |
| 10 days | 16.67 | 0.52391 | 11.43 | 0.46585 |

Source: Prepared by the authors.

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## 3. Discussion and Concluding Remarks

Although the information available is not decisive enough to dictate the presence of negotiation algorithms, the result is clear evidence that in certain time intervals, the skewness and kurtosis morphology denote highly concentrated and biased behavior, especially in very short time intervals, where human intervention is practically impossible. Notably, this phenomenon occurs in both markets analyzed, which is particularly interesting given the lower liquidity and smaller size of the Mexican market compared to the US market.

The Jarque-Bera tests confirm that, on average, the distributions of returns are not normal until $\Delta_t$ is 3 days. The values of $\alpha$ for the $\alpha$-stable distributions also confirm the non-normality before $\Delta_t = 10$. However, this analysis allows us to dig deeper into the evolution of the market structures as time passes. We can see that the US market is always closer to a normal distribution, while the Mexican market distribution varies greatly as $\Delta_t$ increases.

Autocorrelation tests show the existence of significant autocorrelation before $\Delta_t = 10$.

Overall, the results indicate that both markets do not follow a random walk and are thus inefficient in frequencies from 1 second to 10 days. This fact leads to the possibility of price predictability, which has significant implications for the financial industry and excellent opportunities for algorithms to profit from.

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