
Non-efficiency in Automated Markets for the US and Mexico¹

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

**Montserrat
Reyna**

*Universidad Anáhuac
México, Mexico*

**Armando
Tapia**

*Tecnológico de
Monterrey, Mexico*

**Ricardo
Mansilla**

*Centro de Investigaciones
Interdisciplinarias en
Ciencias y Humanidades,
UNAM, Mexico*

**Ninfa Rodríguez
Chávez**

*Université Paris 1
Panthéon Sorbonne,
France*

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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.

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 α , β , γ , δ . For a stable random variable t is stable, the characteristic function is

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

α , 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 α is small, the asymmetry parameter β is significant. As α increases, the significance of β 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.

γ and δ 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 Δ_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	BMJ	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 statistic² 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

Dt	Mean		Standard Deviation		Kurtosis		Skewness	
	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.

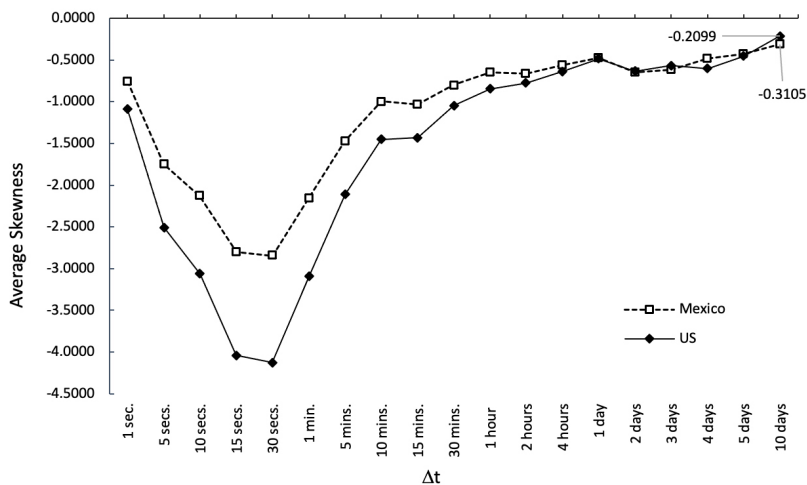
* Indicates the null hypothesis of normality is not rejected at the 95% confidence level.

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 Δ_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 Δ_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 Δ_t



Source: Prepared by the authors.

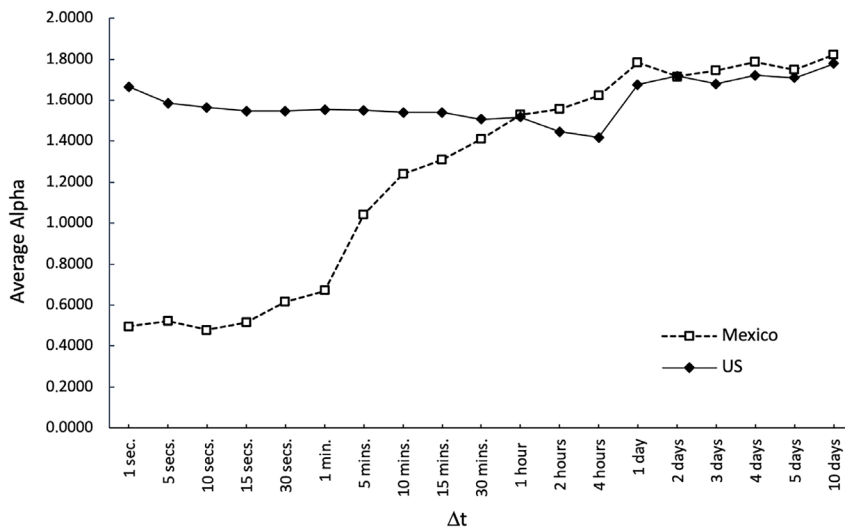
Then, we have the Jarque-Bera statistic. It is not until Δ_t is three days when, on average, the statistic is in the no-rejection zone at the 95% confidence level. Thus, we conclude that the distribution of returns is normal after this Δ_t , but not before.

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 α -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 α for both markets (see Figure 2). For small values of Δ_t , the value of α 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 Δ_t increases, the value of α suggests an asymptotic approximation to the normal distribution.

Figure 2. α Average Values of Returns by Country for Each Δ_t

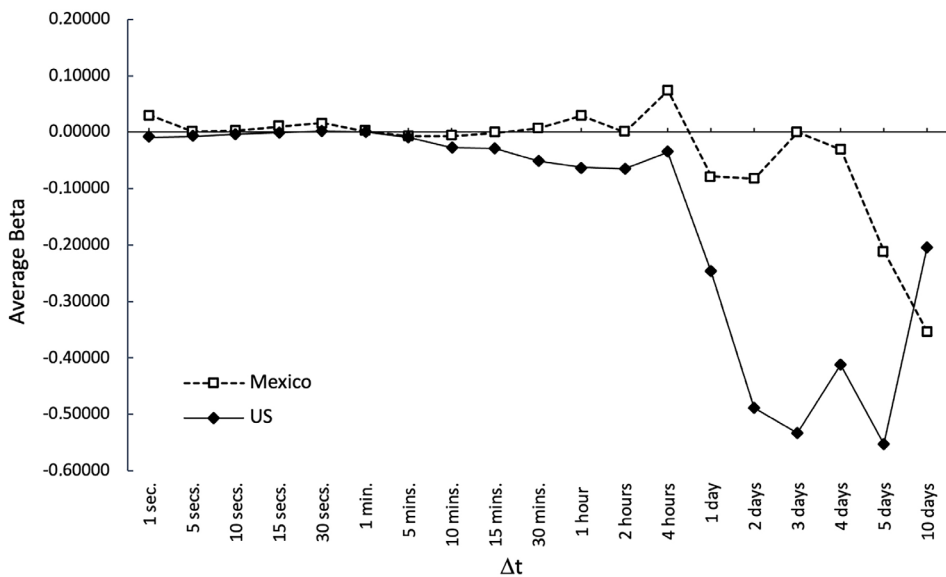


Source: Prepared by the authors.

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 α , β , γ , and δ , out of which α is the most important, and it represents the stability of the distribution tails. An α equal to 2 corresponds to the normal distribution.

Figure 3 plots the averages of β for both markets. For small values of Δ_t , up to approximately 15 minutes, the factor β 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 α increases (from $\Delta_t = 1$ hour), the value of β loses significance (see Figure 2 and Figure 3).

Figure 3. β Average Values of Returns by Country for Each Δ_t



Source: Prepared by the authors.

We conclude that Mexican stocks follow the Levy distribution for intervals from 1 to 15 seconds. For higher Δ_t , the distribution tends to be normal. The US stocks α values show that the distribution has no finite variance but approaches a normal distribution as Δ_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 Δ_t . From 1 second to 1 minute, correlation is identified in 100% of the stock returns series. This proportion decreases to about 10% when Δ_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 Δ_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.

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 Δ_t is 3 days. The values of α for the α -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 Δ_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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References

- Bessembinder, H., & K. Chan. (1998). Market Efficiency and the Returns to Technical Analysis. *Financial Management*, 27(2): 5-17. <https://www.jstor.org/stable/3666289>
- Budish, E., Cramton, P., & Sim, J. (2015). The High-Frequency Trading Arms Race: Frequent Batch Auctions as a Market Design Response. *The Quarterly Journal of Economics*, 130(4), 1547-1621. <https://doi.org/10.1093/qje/qjv027>
- Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-Frequency Trading and Price Discovery. *The Review of Financial Studies*, 27(8), 2267-2306. <https://doi.org/10.1093/rfs/hhu032>
- Chen, K., & Li, X. (2006). Is Technical Analysis Useful for Stock Traders in China? Evidence from the SZSE Component A-Share Index. *Pacific Economic Review*, 11(4): 477-488. <https://doi.org/10.1111/j.1468-0106.2006.00329.x>
- Danak, D., & Patel, N. (2020). A Study of Efficiency of Index Futures, Lead-Lag Relationship, and Speed of Adjustments in India Using High-Frequency Data. *Indian Journal of Finance*, 14(4), 7-23. <https://doi.org/10.17010/ijf/2020/v14i4/151705>
- Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383-417. <http://dx.doi.org/10.2307/2325486>
- Fifield, S., D. Power, & D. Sinclair. (2005). An Analysis of Trading Strategies in Eleven European Stock Markets. *European Journal of Finance*, 11(6): 531-548. <https://doi.org/10.1080/1351847042000304099>
- Ftiti, Z., Jawadi, F., Louhichi, W., & Madani, M. E. A. (2020). Are Oil and Gas Futures Markets Efficient? A Multifractal Analysis. *Applied Economics*, 53(2), 164-184. <https://doi.org/10.1080/00036846.2020.1801984>
- Gnedenko, B. V., & Kolmogorov, A. N. (1968). *Limit Distributions for Sums of Independent Random Variables*. Addison-Wesley.
- Gopikrishnan, P., Plerou, V., Nunes Amaral, L. A., Meyer, M., & Stanley, H. E. (1999). Scaling of the Distribution of Fluctuations of Financial Market Indices. *Physical Review E* 60(5), 5305-5316. <https://doi.org/10.1103/PhysRevE.60.5305>
- Heng, P., Niblock, S. J., Harrison, J. L., & Hu, H. (2020). The Impact of High-Frequency Trading on Australian Futures Market Liquidity and Efficiency. *Journal of Derivatives*, 27(4), 51-76. <https://doi.org/10.3905/jod.2020.1.097>
- Jarque, C. M., & Bera, A. K. (1980). Efficient Tests for Normality, Homoscedasticity and Serial Independence of Regression Residuals. *Economics Letters*, 6(3), 255-259. [https://doi.org/10.1016/0165-1765\(80\)90024-5](https://doi.org/10.1016/0165-1765(80)90024-5)
- Karemera, D., K. Ojah & J.A. Cole. (1999). Random Walks and Market Efficiency Tests: Evidence from Emerging Equity Markets. *Review of Quantitative Finance and Accounting*, 13(2), 171-188. <https://doi.org/10.1023/A:1008399910942>

- Koutrouvelis, I. A. (1981). An Iterative Procedure for the Estimation of the Parameters of Stable Laws. *Communications in Statistics—Simulation and Computation*, 10(1), 17–28. <https://doi.org/10.1080/03610918108812189>
- Kristoufek, L., & M. Vosvrda. (2013). Measuring Capital Market Efficiency: Global and Local Correlations Structure. *Physica A: Statistical Mechanics and Its Applications*, 392(1): 184–193. <https://doi.org/10.1016/j.physa.2012.08.003>
- Lahrech, A., & Sylwester, K. (2011). US and Latin American Stock Market Linkages. *Journal of International Money and Finance*, 30(7), 1341–1357. <https://doi.org/10.1016/j.jimonfin.2011.07.004>
- Leone, V., & F. Kwabi. (2019). High Frequency Trading, Price Discovery and Market Efficiency in the FTSE100, *Economics Letters*, 181, 174–177. <https://doi.org/10.1016/j.econlet.2019.05.022>
- Ljung, G. M., & Box, G. E. (1978). On a Measure of Lack of Fit in Time Series Models. *Biometrika*, 65(2), 297–303. <https://doi.org/10.1093/biomet/65.2.297>
- Mensi, W., Lee, Y., Al-Yahyaee, K. H., Sensoy, A., & Yoon, S. (2019). Intraday Downward/Upward Multifractality and Long Memory in Bitcoin and Ethereum Markets: An Asymmetric Multifractal Detrended Fluctuation Analysis. *Finance Research Letters*, 31, 19–25. <https://doi.org/10.1016/j.frl.2019.03.029>
- Mishra, S. (2019). Testing Martingale Hypothesis Using Variance Ratio Tests: Evidence from High-Frequency Data of NCDEX Soya Bean Futures. *Global Business Review*, 20(6), 1407–1422. <https://doi.org/10.1177/0972150919848937>
- Mobarek, A., A. Sabur, & R. Bhuyan. (2008). Market Efficiency in Emerging Stock Market: Evidence from Bangladesh. *Journal of Emerging Market Finance*, 7(1): 17–41. <https://doi.org/10.1177/097265270700700102>
- Picardo, E. (2014, June 2). Top Stocks High-Frequency Traders (HFTs) Pick (BAC,F,CSCO,INTC). HedgeChatter. Retrieved on October 26, 2020 from: <https://www.hedgechatter.com/top-stocks-high-frequency-traders-hfts-pick-bacfcscointc/>
- Plerou, V., Gopikrishnan, P., Nunes Amaral, L. A., Meyer, M., & Stanley, H. E. (1999). Scaling of the Distribution of Price Fluctuations of Individual Companies. *Physical Review E*, 60(6), 6519–6529. <https://doi.org/10.1103/PhysRevE.60.6519>
- Ratner, M., & Leal, R. P.C. (1999). Tests of Technical Trading Strategies in the Emerging Equity Markets of Latin America and Asia. *Journal of Banking and Finance*, 23(12): 1887–1905. [https://doi.org/10.1016/S0378-4266\(99\)00042-4](https://doi.org/10.1016/S0378-4266(99)00042-4)

■ About the authors

Montserrat Reyna is a research professor at the School of Economics and Business at Universidad Anáhuac México. She holds a PhD in Financial Sciences from EGADE Business School, an undergraduate degree in Mathematics from Universidad Nacional Autónoma de México (UNAM), and is a CFA Charterholder. Her research interests focus on investment theory and risk management of investment portfolios. She has several articles published in peer-reviewed journals of recognized quality and book chapters. She has been a speaker at several international conferences. She carries out consulting projects in data science applied to finance.

montserrat.reyna@anahuac.mx (Corresponding author)

<http://orcid.org/0000-0002-2793-6365>

Armando Tapia has a Ph.D. in Financial Sciences from the EGADE Business School and an MBA in Finance from the Instituto Tecnológico Autónomo de México (ITAM). His research interests focus on investment theory, investment portfolio management, and data science applied to stock market finance. He has professional experience in the financial industry in the field of pension fund investments and investment strategies for hedge fund portfolios. He has been a speaker at several international conferences. Tapia's teaching experience is in the field of programming for finance and economics.

armando.tapia@tec.mx

<https://orcid.org/0000-0002-9003-8015>

Ricardo Mansilla holds a PhD in Mathematics from the University of Havana and a master's degree in Economics from Carleton University. His extensive teaching experience includes teaching mathematics, statistics, and economics courses at various levels and universities in Mexico and abroad. He has participated as a speaker at various international conferences. He has extensive scientific production in applied statistics, including applications to medicine, economics, demography, and finance, in authorship and coordination of books, book chapters, and more than 70 articles.

mansy@unam.mx

<https://orcid.org/0000-0002-1248-0959>

Ninfa Rodríguez Chávez graduated from the Université Paris 1 Panthéon Sorbonne with a master's degree in Management, specializing in Finance and Social Responsibility, and holds a bachelor's degree in Accounting from the Universidad Nacional Autónoma de México (UNAM). Her research is focused on financial markets and the financial inclusion of vulnerable groups. She has participated as a speaker at international conferences. Her professional experience is centered on corporate finance in different industries and countries.

ninfa.rodriguezchavez@gmail.com

