Does US Interest Rate Sentiment Impact Latin American ETFs?

¿Impacta el sentimiento estadounidense de las tasas de interés en los fondos latinoamericanos negociados en bolsa (ETF)?

Humberto Valencia Herrera

EGADE Business School, Tecnológico de Monterrey, Mexico

Received: February 27, 2024.
Approved: May 13, 2024.

Abstract

This article examines the dependence of Exchange Traded Fund (ETF) returns in six Latin American countries on interest rate and the Federal Reserve (FED) sentiment in the United States (US) news, during the period 2022 to 2023. For each country, robust regressions with zero to two lags for positive and negative sentiments, and previous returns were used. It was found that sentiment is statistically significant for some lags of ETF returns in Brazil, Chile, and Peru, in both, local currency and US dollar. The Latin American 40 ETF also depends on sentiment in US currency. Furthermore, a moment effect on returns in US currency and a mean reverting effect in local currency was identified. A panel data model for the considered countries' ETFs with random effects and zero to two lags in the change of sentiment shows that all considered changes in sentiment are statistically significant for returns, except for the change in positive sentiment without lags.

Keywords: *sentiment, ETF, returns, interest rate, Latin America.*
JEL Classification: *G11, G15.*

Resumen

En este artículo se analizó la dependencia de los rendimientos de fondos cotizados en bolsa (ETF) de seis países latinoamericanos respecto al sentimiento en relación con las tasas de interés y la reserva federal (FED) en las noticias de Estados Unidos (EE.UU.) durante el período de 2022 a 2023. Para cada uno de los fondos se usaron regresiones robustas con cero a dos rezagos para sentimientos positivos y negativos, y las rentabilidades previas. Se encontró que el sentimiento es estadísticamente significativo para algunos rezagos en los retornos de los ETF de Brasil, Chile y Perú, tanto en la moneda local como en el dólar estadounidense. El ETF Latin American 40 depende asimismo del sentimiento respecto a la moneda estadounidense. También hay un efecto de momento sobre los rendimientos en moneda estadounidense y un efecto de reversión media en moneda local para todos los ETF considerados. El modelo de datos de panel para los ETF de los países considerados con efectos aleatorios y dos rezagos muestra que todos los cambios en el sentimiento considerados son estadísticamente significativos para los rendimientos, excepto el cambio en el sentimiento positivo sin rezagos.

Palabras clave: *sentimiento, fondos negociados en bolsa, retornos, tasa de interés, Latinoamérica.*
Clasificación JEL: *G11, G15.*

1. Introduction

The use of sentiment information in financial markets is an expanding field that has captured the attention of both practitioners and academics. In this article, we delve into a novel area of research, exploring how shifts in US interest rate sentiment, as reflected in US news, can impact Latin American stocks ETF returns on a daily basis. This investigation into the relationship between changes in sentiment from news and social media and future asset returns is a recent development. We are not aware of any existing studies that have examined how changes in sentiment in US news about the US Fed policy can influence the asset prices of other countries on a daily basis. This paper aims to fill this gap by examining these dynamics for Latin American stock ETFs.

The dynamic may be understood as follows: Changes in economic expectations modify the information available in the markets. Changes in US inflation expectations and economic activity determine the actions of the FED. Analysts and financial commentators consider this information, and this changes the tone of published news. News sentiment and other information influence decision-makers in financial markets and result in changes in asset prices. Although many economic and financial articles consider that changes in monetary policy directly affect treasuries and bond prices, these also influence stock prices. In the case of foreign shares, this effect has two facets: directly on companies and indirectly through the exchange rate. The direct effect is due to changes in the economic potential of companies, which translates into changes in their share price. An interest rate increase in the United States will increase the financing cost of companies that fund themselves there, including foreign companies. As a result, their share prices will fall. Countries that have governments financed in US currency will have higher financial costs. Their taxpayers, both companies and consumers, will have to pay for the increased interest rate. The indirect effect through the exchange rate is mixed. Because most Latin American countries produce raw materials and other goods, an increase in interest rates in the United States will result in a fall in their international economic activity and the depreciation of the local currency. Such a situation is evident in countries with high export activity, such as Chile, Brazil, and Peru. In addition, if the monetary policy of the country in question consists of offering high interest rates in local currency to attract capital, as could be the case of Mexico, an increase in the US funding rate may signal that the local funding rate will remain high. As a result, the local currency will appreciate against the US dollar. The local interest rate policy can counteract the restrictive effect of a policy of increasing rates by the FED. Other factors may also be at play. For example, in the event of a policy to increase investments and favor export activity, as in the case of Mexico, changes in economic activity resulting from increased interest rates in the United States will not necessarily result in the depreciation of the local currency. As a result, there can be differences in the impact of sentiment news and other information on returns in US and local currencies.

The rest of the paper is organized as follows: the next section describes the theoretical framework, followed by a discussion of the employed methodology. The third section includes the main results, and the last section contains the conclusions and recommendations.

2. Theoretical Framework

The literature that uses data mining to extract sentiment information from news and social media is relatively recent. Investors' sentiment, captured by social media in communications related to companies, is relevant to investment returns. However, most of the research has been done for the US market. In this respect, Wu and Gu (2023) propose a simplified mechanism for capturing market sentiment using tweets from Twitter (now X) for stocks in the US market. Mendoza-Urdiales et al. (2022) show that Twitter sentiment is important for explaining changes in returns concerning a moving average for some stocks in the US market, while Cristescu et al. (2023) show a lagged relationship between news and some US stocks.

While many studies address the importance of news for US stock markets, few papers consider news sentiment and its impact on stocks in developing countries. For example, Wu et al. (2022) found that mixing information with sentiment derived from news and stock market reactions offers predictive power for stocks in Vietnam. Chari et al. (2023) propose an aggregate indicator of market sentiment based on the news in India and analyze its relationship with the aggregate Indian stock market on a daily basis.

Ample related economic literature measures market sentiment using proxy variables. Many of these studies have centered on US market sentiment and its relevance for the US market using variables that attempt to mimic market sentiment. For example, Kabiri et al. (2023) document its importance in explaining phenomena during the Great Depression of 1920 to 1934. Han et al. (2022) found that market sentiment impacts US stock returns. Nakhli et al. (2022) observed a bidirectional relationship between market sentiment and stock market performance in the US. However, Ur et al. (2023), who used the Baker and Wurgler (2006) sentiment index to predict US stock behavior, found that the index has weak predictive power. Nevertheless, when combined with other indicators, the overall predictive power of the model improves. Dumiter et al. (2023) use the daily sentiment index downloaded from the Federal Reserve Bank of San Francisco and show that it related strongly to the US stock market from 2004 to 2022. Using another economy, Chen et al. (2022) found an asymmetric effect of investor sentiment on stock excess returns using the Shanghai Stock Exchange 50 Index Stocks. Lv et al. (2022) analyze the impact of investor sentiment on stock returns for more than 35 years and found that the relationship has changed over time. While it used to be trending, more recently, it has become mean reverting.

Some papers have used sentiment analysis based on communications to consider aspects of monetary policy. For example, Tadle (2022) analyzes the Federal Open Market Committee (FONC) communications using sentiment analysis, showing that these have an impact on the future rates of Fed funds. The minutes were also shown to have an impact on the US dollar exchange markets, with the tone of the FONC minutes modifying financial market expectations.

The economic relationship between monetary policy and asset markets has been well addressed for closed economies using data in relatively long intervals of one month or more. Many papers consider treasuries and bonds as well as stocks for a national economy. The FED target rate affects short- and long-term interest rates because it modifies expectations on interest rate markets (Ehrmann & Fratzscher, 2007). As a result, prices for bonds and treasuries change. However, they also affect stocks. For example, Bernanke and Kuttner (2005) show that the unexpected component of the target rate influences equity prices in the US. They extend Kuttner's seminal work using Fed funds futures and evaluate the impact of the unexpected component of the target rate changes on equity prices. Labadie and Giovannini (1991) show an inverse contemporary relationship between nominal stock returns and nominal interest rates, although this is not statistically significant in the US. For Brazilian stocks, De Pontes and Rêgo (2022) show that domestic interest rates have less influence on stock returns than Gross Domestic Product, Risk Brazil, and Ibovespa points. For ASEAN-5 countries, Juhro et al. (2021) find a negative relationship between interest rate movements in a contractionary monetary policy shock and real stock prices, although the movement lags for two months.

Other papers have analyzed how changes in the US FED monetary policy affect prices and returns of foreign bonds, treasuries, and stocks over time. There is ample economic literature that documents its effect in the long run for many countries using monthly, quarterly, or yearly data. For example, for Asian markets, Yang and Hamori (2014) analyze the economic effect of the US monetary policy on the Singaporean, Thai, and Indonesian stock markets, using monthly returns and US Treasury bill rates from 1990 to 2012. They found that during the boom period, there was an inverse relationship, which disappeared during the recession period. Hindrayani et al. (2019) found that the US monetary policy had a negative effect on ten ASEAN stock markets during economic expansion periods, using yearly data for the period 2008-2016. Using monthly returns, Zubair Muntaz and Smith (2019) analyze the economic relationship between US interest rates and European stock markets. They found a positive relationship for many of the analyzed European stock markets, except for the Finnish, Swedish, UK, Slovenian, and Ukrainian markets. The relationship is more robust in developed markets than in developing ones, and changed during the crisis period. Lakdawala et al. (2021) analyze how surprises in the change of the Fed policy rate affect international bond yields. They found that for advanced economics, the transmission is through the term premium in yields. For emerging markets, the expected component of yields reacts to uncertainty. For Latin American stocks, Cabezón (2012) used quarterly data to show that changes in the US interest rate affect Chilean stocks.

3. Methodology

In this section we discuss the data and estimated variables, together with the models and equations employed throughout the paper.

We used ETFs denominated in US dollars from six Latin American countries: iShares MSCI Brazil ETF (EWZ), iShares MSCI Mexico ETF (EWW), iShares MSCI Chile ETF (ECH), Global X MSCI Argentina ETF (ARGT), iShares MSCI Peru and Global Exposure ETF (EPU), and Global X MSCI Colombia ETF (GXG). We also considered the iShares Latin America 40 ETF (ILF). Table 1 shows the considered ETFs, the total asset value, and the average volume as of December 20, 2023 (see Table 1).

Table 1. Latin America ETFs, General Information

Symbol	ETF Name	Country	Assets ($MM)	Average Volume
EWZ	iShares MSCI Brazil ETF	Brazil	$5,933	23,871,064
EWW	iShares MSCI Mexico ETF	Mexico	$1,995	2,460,109
ECH	iShares MSCI Chile ETF	Chile	$612	498,994
ARGT	Global X MSCI Argentina ETF	Argentina	$116	60,338
EPU	iShares MSCI Peru and Global Exposure ETF	Peru	$97	16,537
GXG	Global X MSCI Colombia ETF	Colombia	$37	19,811
ILF	iShares Latin America 40 ETF	Broad Latin America	$1799	1,208,117

* Assets and average volume reported on December 20, 2023.

Source: VettaFi, https://etfdb.com/

Using ETF prices, we calculated the return and other statistics for the period 2022 to 2023, as shown in Table 2. Argentina ETF (ARGT) has the highest standard deviation (7.23) of all the considered ETFs in the period of analysis. All ETF funds are skewed to the right, except Peru ETF (EPU), which is skewed to the left, and Chile ETF (ECH), which has almost no skew (0.02). Furthermore, all ETF funds show positive kurtosis. The most platykurtic fund is Mexico ETF (EWW), with kurtosis of 1.77, as shown in Table 2 (see Table 2).

Table 2. Summary Statistics for Prices and Sentiment Indicators, 2022-2023

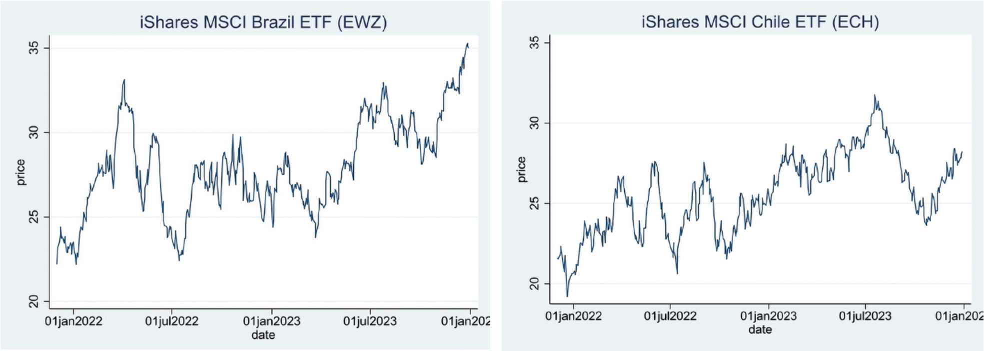
	Closing Price					
Stock Names	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
Latin America ETF(ILF)	23.31	2.25	0.26	2.55	18.54	29.33
Brazil ETF (EWZ)	27.92	2.76	0.20	2.53	22.23	35.27
Mexico ETF (EWW)	52.63	6.90	0.25	1.77	41.98	68.46

	Closing Price					
Stock Names	**Mean**	**Std. Dev.**	**Skewness**	**Kurtosis**	**Minimum**	**Maximum**
Chile ETF (ECH)	25.52	2.45	0.02	2.44	19.20	31.77
Argentina ETF (ARGT)	35.43	7.23	0.42	2.13	22.84	52.25
Peru ETF (EPU)	28.51	2.86	-0.17	2.40	22.04	34.60
Colombia ETF (GXG)	21.22	3.39	0.88	2.65	16.52	29.44
Sentiment Indicator						
Positive Sentiment	0.24	0.04	-1.72	13.00	0.00	0.36
Negative Sentiment	0.08	0.05	1.52	8.13	0.00	0.39

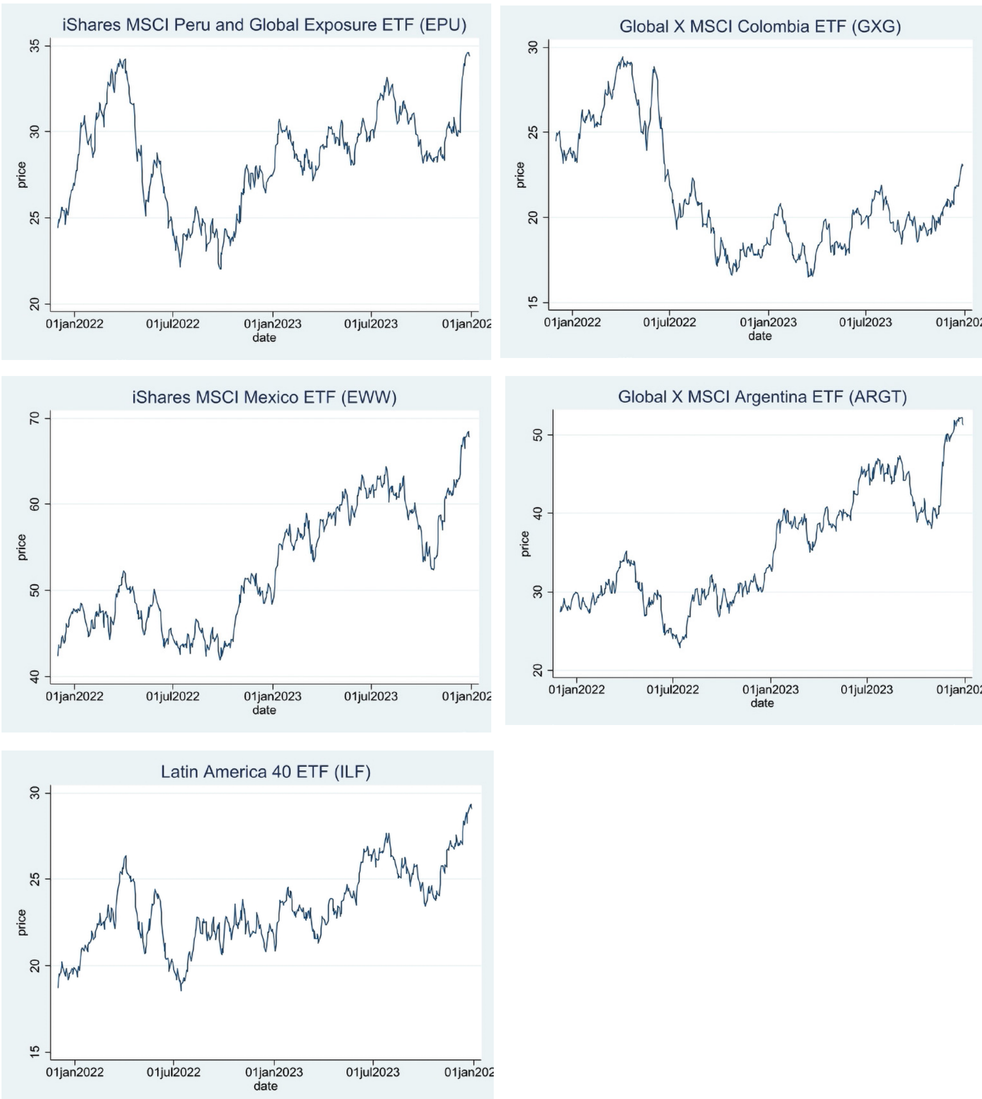
Source: Prepared by the author.

Except for Chile, ETF prices in these countries demonstrated a peak during the first semester of 2022. All countries, except Columbia, exhibit prices that increased during the second semester of 2022 and the first semester of 2023. The same increasing tendency can be observed at the end of 2023, as shown in Figure 1 (see Figure 1).

Figure 1. Prices of Latin America ETFs



https://doi.org/10.36105/theanahuacjour.2024v24n1.04



Source: Prepared by the author.

For sentiment analysis, we used news from Google News as an RSS feed, and searched for news using the terms: interest rate, FED, or Federal Reserve in the

United States. We downloaded the available news, up to one hundred articles, for each calendar day during 2022 and 2023.

We used the VADER (Valence Aware Dictionary for Sentiment Reasoning) algorithm (Hutto & Gilbert, 2014) to estimate a positive and a negative sentiment indicator from the first line of each news item. VADER uses a given lexicon of words, labeled according to their semantic meaning as positive or negative. Using a sample of microblog-like texts (tweets), the lexicon was curated and validated. Lexicon tokens were classified and assigned a sentiment intensity score from -4 to 4, from very negative to very positive. These lexical features were then combined with five rules that considered syntactical and grammatical conventions that emphasize sentiment intensity: the use of an exclamation point (!) increases the intensity of the sentiment; while a word in all caps, among non-caps words, emphasizes the sentiment implied by the word. The use of degree modifiers also modifies the intensity of a word, for example, “the market is extremely optimistic”. Based on the tri-gram preceding a sentiment-laden lexicon expression, we were able to capture 90% of events that involved a negation flipping the meaning of a text. Based on the algorithm, a text received a positive, negative, and neutral lexicon rating, on a scale of zero to one. We named the VADER positive (negative) lexicon, rating the news positive (negative) sentiment indicator. In addition, before submitting the text to the VADER algorithm, we filtered the text for the stop words suggested in the VADER corpus. Stop words refer to words that are so common that they have very little meaning, such as “the”, “a”, or “is”. For these purposes, we used the VADER open source code available at nltk (nltk/nltk/sentiment/vader.py in github.com), version 3.3.2.

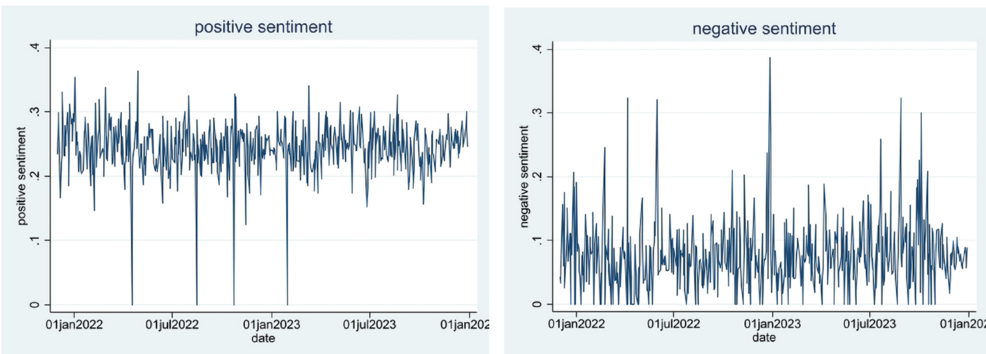
For each business date, we calculated a positive daily sentiment indicator and a negative daily sentiment indicator. The daily polarity indicators refer to these daily indicators.

The positive (negative) daily sentiment indicator on business day t is an average of the positive (negative) news sentiment in the news on that day, only considering the news with positive (negative) indicators greater than 0.1 if the following day is a business day. In the case that one or more non-business days follow day t, we calculated the daily positive or negative sentiment indicator of business day t as an average of the positive or negative sentiment in the news on that day and all the following non-business days before a business day, excluding news with polarity indicators less than or equal to 0.1.

The mechanics of calculating the positive and negative daily sentiment indicators consider that at closing time on day t, an investor can take a position on the ETFs based on the news sentiment of that day and the previous day. When there is a holiday or a weekend on the previous day, information from the news during the holiday or the weekend can be used, in addition to the news of the day.

Regarding interest rate sentiment, a positive sentiment indicator of two or three is most frequent, with few periods at the zero level. However, a negative sentiment is less pronounced, normally falling between zero and two during the period of analysis, with some peaks above two, as shown in Figure 2 (see Figure 2).

Figure 2. Positive and Negative US Interest Sentiment Indicators



Source: Prepared by the author.

For each ETF *i*, we also calculated the forward returns for one business day using the equation:

$$f_{i,t,T} = ln(P_{i,t+1}) - ln(P_{i,t}), \quad (1)$$

where $P_{i,t}$ is the closing price of fund i in business day t.

Our research employed robust regressions for each ETF, considering its returns as the dependent variable, with the independent variables comprising changes in the daily positive and negative polarity indicators, Δp_t, $= p_t - p_{t-1}$ and Δn_t, $= n_t - n_{t-1}$ for the day under consideration, the day before, and the day before that, that is m =2. Therefore, we captured the changes on the polarity indicators for the day, as well as for the one and two previous days. To consider the momentum or the mean reverting effects in returns, we considered the previous day's return, $r_{i,t-1}$ in the equation for each asset *i*.

$$r_{i,t} = a_i + b_{i,1} * r_{i,t-1} + \sum_{T=0}^{m} b_{i,2,T} * \Delta p_{t-T} + \sum_{T=0}^{m} b_{i,3,T} * \Delta n_{t-T} + \varepsilon_{i,t} \tag{2}$$

We repeated this exercise, considering the returns in local currency, using the exchange rate provided by yahoo.com for each date.

Following this, we conducted panel data regressions for both fixed and random effects. We then employed the Hausman (1978) test to determine the validity of these models. A panel model allows for an explanation of variations in the returns of the considered assets through time as a group, as well as for the combination of temporal and cross-sectional information in the same model: variations through time and between the different assets. In this case, changes in sentiment regarding the different assets and within each asset over time explain the returns.

A panel model also allows for the simultaneous modeling of the effect of changes in the independent factors for all assets while allowing for different constants for each asset. A different constant for each asset allows for a constant difference in returns among different assets. That is, it allows for constant factors that explain these differences, as shown in equation (3),

$$r_{i,t} = a_i + b_1 * r_{i,t-1} + \sum_{T=0}^{m} b_{2,T} * \Delta p_{t-T} + \sum_{T=0}^{m} b_{3,T} * \Delta n_{t-T} + \varepsilon_{i,t} \tag{3}$$

Sometimes, an equation that models the constant as drawn randomly for the sample of assets explains these differences. In this case, a random panel model can be used. The advantage of a random panel is that the model results are more generalizable than a fixed panel. If the above is not the case, the difference in magnitude of the returns of the assets is specific to each asset, and we must independently estimate the constant for each asset. That is, we must prefer a fixed panel model.

We used the Hausman (1978) test to examine whether the constant factor explaining differential returns of assets can be a random draw from a distribution. In this case, the test recommends a random panel model.

4. Analysis of Results

We begin by discussing the results of each individual regression considering the ETF returns in USD dollars, followed by the results of each individual ETF with returns in local currency. We then discuss the observed results using a panel model with random effects, given that the Hausman (1978) test showed this to be better than a fixed effects model.

The returns in US dollars of all considered ETFs, except EWW from Mexico, show a positive effect from changes in the negative sentiment in US interest rates and a negative effect from changes in the positive sentiment. However, the effects are only statistically significant in the following cases: EWZ, the ETF from Brazil, shows a statistically significant effect from changes in the negative sentiment with no and one lag, and coefficients of 0.0379 and 0.0189, respectively. The ETFs from Chile and Peru, ECH, and EPU, respectively, show statistically significant negative effects from changes in the positive sentiment with one lag, and regression coefficients of -0.0616 and -0.0347, respectively. In the case of the ETF ILF, its regression also has a statistically significant positive coefficient for changes in the negative sentiment with no lags (0.0318). It is worth noting that all regressions show a moment effect on returns from the previous day, although this was only statistically significant for EPU, GSG, and ILF ETFs, with coefficients of 0.1141, 0.1300, and 0.0943, respectively, as can be observed in Table 3 (see Table 3).

When considering ETF returns in local currency, the pattern of a positive effect on returns from a change in negative sentiment and a negative effect on returns from a change in positive sentiment is maintained for the ETFs of the considered countries, except in the cases of Mexico and Peru. In the latter exceptions, the coefficient does not differ from zero, with a confidence level of 95%. For EWZ Brazil, the coefficients for the change in negative sentiment without lags and with one lag are positive and statistically significant, at 0.0380, and 0.0442, respectively. For ECH Chile, coefficients for the change in positive sentiment without lags and with one lag are negative and statistically significant, at -0.0482 and 0.0821, respectively. For EPU Peru, coefficients for a change in positive sentiment with one lag and with two lags are negative and statistically significant, that is, -0.0614 and -0.0388, respectively, as can be appreciated in Table 4 (see Table 4).

Contrary to the results using US dollars, in local currency, the ETFs of all countries show mean reversion. The coefficients with respect to the previous return are negative, more than minus one, and statistically significant. That is, -0.2939, -02464, -02798, -0.0127, -0.1643, and -0.1359, for the EWZ, EWW, ECH, ARGT, EPU, and GXG ETFs, respectively.

Table 3. Latin America ETF Returns in USD as a Function of US Interest Rate Sentiment and Previous Returns

Country		**Brazil**	**Mexico**	**Chile**	**Argentina**	**Peru**	**Colombia**	**LatinAmerica40**
ETF		EWZ	EWW	ECH	ARGT	EPU	GXG	ILF
Return	L1	0.0612	0.0491	0.0002	0.0643	0.1141 *	0.1300 *	0.0943 *
		1.42	1.09	0	1.53	2.73	3.14	2.15
Δ positive	.	-0.0178	-0.0175	-0.0297	-0.0270	-0.0060	-0.0056	-0.0255
		-0.98	-1.32	-1.63	-1.46	-0.44	-0.38	-1.66
	L1	-0.0322	-0.0158	-0.0616 *	-0.0349	-0.0347 *	-0.0230	-0.0345
		-1.52	-1.01	-2.89	-1.61	-2.19	-1.33	-1.93
	L2	-0.0280	0.0069	-0.0286	-0.0135	-0.0201	-0.0080	-0.0246
		-1.56	0.52	-1.57	-0.73	-1.49	-0.54	-1.61
Δ negative	.	0.0365 *	0.0064	0.0108	0.0256	0.0081	0.0199	0.0318 *
		2.63	0.63	0.77	1.8	0.78	1.74	2.71
	L1	0.0379 *	-0.0155	0.0072	0.0209	0.0058	0.0206	0.0233
		2.31	-1.28	0.43	1.24	0.47	1.52	1.67
	L2	0.0189	-0.0088	0.0178	0.0034	0.0106	0.0072	0.0121
		1.36	-0.86	1.26	0.24	1.01	0.63	1.03
constant		0.0012	0.0010	0.0006	0.0018 *	0.0005	0.0001	0.0011
		1.51	1.57	0.67	2.09	0.83	0.06	1.42

* Ninety-five percent confidence level. For each independent variable, the first row is the coefficient; the second row is the t value.
Source: Prepared by the author.

Table 4. Latin America ETFs Returns in Local Currency as a Function of US Interest Rate Sentiment and Previous Returns

		Brazil	**Mexico**	**Chile**	**Argentina**	**Peru**	**Colombia**
		EWZ	EWW	ECH	ARGT	EPU	GXG
return	L1	-0.2939 *	-0.2464 *	-0.2798 *	-0.0127	-0.1643 *	-0.1359 *
		-7.07	-5.67	-6.88	-0.59	-3.66	-3.24
Δ positive	.	-0.0169	-0.0174	-0.0482 *	-0.0297	-0.0255	-0.0139
		-0.89	-1.22	-2.29	-1.56	-1.36	-0.80
	L1	-0.0257	-0.0237	-0.0821 *	-0.0361	-0.0614 *	-0.0356
		-1.15	-1.42	-3.32	-1.62	-2.81	-1.75
	L2	-0.0222	0.0018	-0.0296	-0.0109	-0.0388 *	-0.0140
		-1.17	0.12	-1.4	-0.57	-2.08	-0.81
Δ negative	.	0.0380 *	0.0169	0.0084	0.0258	0.0053	0.0254
		2.59	1.54	0.52	1.76	0.37	1.89
	L1	0.0442 *	-0.0093	0.0128	0.0172	-0.0015	0.0157
		2.55	-0.71	0.67	0.99	-0.09	0.99
	L2	0.0274	-0.0103	0.0244	0.0042	0.0151	0.0210
		1.87	-0.93	1.5	0.29	1.05	1.56
constant		0.0011	0.0005	0.0008	0.0040 **	0.0004	-0.0001
		1.25	0.73	0.81	4.58	0.46	-0.1

* Ninety-five percent confidence level. For each independent variable, the first row is the coefficient, the second row is the t value.

Source: Prepared by the author.

The Hausman (1978) test suggests the use of a random effects model. The test cannot reject the hypothesis that the results from the fixed effects model are equal to those of the random effects model with a 95% confidence level. The p value is 99.9%. Therefore, we consider the results from the random effects model reported in Table 5 (see Table 5).

The panel data results of the random effects model suggest that, on aggregate, there is dependence of returns in Latin America on changes in interest rate sentiment in the US, and the effect is persistent over various days. The coefficients from a positive change with zero, one, and two lags are all negative, -0.0133, -0.0362, and -0.0153, respectively. They are statistically significant with one and two lags. The coefficients from a positive change with zero, one, and two lags are all negative, -0.0133, -0.0362, and -0.0153, respectively. They are statistically significant with one and two lags. The coefficients from a negative change are all positive from none to two lags, 0.0198, 0.0155, and 0.0150, respectively, and statistically significant. It is also worth noting that the effect of the changes has the opposite sign: ETF returns are lower with a positive change in interest rate sentiment in the US, while if a change in negative sentiment occurs, the ETF returns are higher. In addition, there is a persistent moment effect from the previous day in the returns. The coefficient is 0.0599 and statistically significant (see Table 5).

Table 5. ETF Returns in USD in Latin America as a Function of US Interest Rate Sentiment, Panel Data Results

		Latin America Countries ETFs			
		RE		FE	
Return	L1	0.0599	*	0.0594	*
		3.35		3.32	
Δ positive	.	-0.0133		-0.0132	
		-1.93		-1.93	
	L1	-0.0362	*	-0.0362	*
		-4.51		-4.51	
	L2	-0.0153	*	-0.0153	*
		-2.23		-2.23	

		Latin America Countries ETFs			
		RE		FE	
Δ negative	.	0.0198	*	0.0198	*
		3.74		3.74	
	L1	0.0155	*	0.0155	*
		2.48		2.48	
	L2	0.0150	*	0.0150	*
		2.83		2.83	
Constant		0.0006		0.0006	
		1.86		1.86	

RE: random effects, FE, fixed effects, * 95% confidence.

ETFs from Brazil, Mexico, Chile, Argentina, Peru, and Colombia.

Source: Prepared by the author.

5. Conclusions and Recommendations

In the case of the ETFs from Brazil, Chile, and Peru, EWZ, ECH, and EPU, there is dependence on interest rate sentiment from US news both in local currency and in US dollars. The dependence is also observed for ITF, the Latin American 40 ETF. The effect is more clearly observed using a panel data model with random effects, where all coefficients for changes in sentiment are statistically significant, except for the change in positive sentiment without lags.

This dependency is likely related to the importance of exports and dependence on US funding of the companies in the considered ETF. This is an area for further research.

The dependency on previous ETF returns depends on the considered currency. In the US currency, we observed a moment effect. In local currency, we observed a mean reverting effect. We recommend further analysis with emphasis on the changes in exchange rates.

For Mexico, neither positive nor negative sentiment indicators helped predict ETF returns. This is probably due to the high integration of the Mexican market with the US market, which makes the news available promptly to all investors on an intraday basis. This finding supports the efficient market hypothesis.

For further areas of research, an extension of the analysis to other markets and instruments is recommended, as well as the consideration of news related to other economic and financial policies, such as those of the European Central Bank. Another promising area of research is the impact of sentiment news on asset prices on an intraday basis and the sentiment captured in social media communications.

References

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, 61, 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market's reaction to federal reserve policy? *The Journal of Finance*, 60(3), 1221–1257. https://doi.org/10.1111/j.1540-6261.2005.00760.x

Cabezón, F. (2012). Assessing the effects of foreign financial shocks in the Chilean economy. *Revista de Análisis Económico*, 27(2), 121–143. http://dx.doi.org/10.4067/S0718-88702012000200004

Chari, S., Desai, P. H., Borde, N., & George, B. (2023). Aggregate News Sentiment and Stock Market Returns in India. *Journal of Risk & Financial Management*, 16(8), 376. https://doi.org/10.3390/jrfm16080376

Chen, M., Guo, Z., Abbass, K., & Huang, W. (2022). Analysis of the impact of investor sentiment on stock price using the latent Dirichlet allocation topic model. *Frontiers of Environmental Science*, 10, article 1068398. https://doi.org/10.3389/fenvs.2022.1068398

Cristescu, M. P., Mara, D. A., Nerișanu, R. A., Culda, L. C., & Maniu, I. (2023). Analyzing the Impact of Financial News Sentiments on Stock Prices—A Wavelet Correlation. *Mathematics*, 11 (23), article 4830. https://doi.org/10.3390/math11234830

De Pontes, L. S. & Rêgo, L. C. (2022). Impact of macroeconomic variables on the topological structure of the Brazilian stock market: A complex network approach. *Physica A: Statistical Mechanics and Its Applications*, 604, article 127660. https://doi.org/10.1016/j.physa.2022.127660

Dumiter, F. C., Turcaș, F., Nicoară, Ștefania A., Bențe, C., & Boiță, M. (2023). The Impact of Sentiment Indices on the Stock Exchange—The Connections between Quantitative Sentiment Indicators, Technical Analysis, and Stock Market. *Mathematics* (2227-7390), 11(14), article 3128. https://doi.org/10.3390/math11143128

Ehrmann, M., & Fratzscher, M. (2007). Communication by Central Bank Committee Members: Different Strategies, Same Effectiveness? *Journal of Money, Credit and Banking*, 39(2–3), 509–541. https://doi.org/10.1111/j.0022-2879.2007.00034.x

Han, Z., Sakkas, N., Danbolt, J., & Eshraghi, A. (2022). Persistence of investor sentiment and market mispricing. *Financial Review*, 57, 617–640. https://doi.org/10.1111/fire.12301

Hausman, J. A. (1978). Specification test in econometrics. *Econometrica* 46 (6), 1251–1271. https://doi.org/10.2307/1913827

Hindrayani, A., Putri, F. K. & Puspitasari, I. F. (2019). Spillover effect of US monetary policy to ASEAN stock market. *Journal Economia. Review of Business and Economic Studies*, 15(2) 213–242. https://doi.org/10.21831/economia.v15i2.26314

Hutto, C. J., & Gilbert, E. E. (2014). VADER: A Parsimonious rule-based model for sentiment analysis of social media text. Eighth International Conference on Weblogs and Social Media (ICWSM-14). Ann Arbor. https://doi.org/10.1609/icwsm.v8i1.14550

Juhro, S. M., Iyke, B. N., & Narayan, P. K. (2021). Interdependence between monetary policy and asset prices in ASEAN-5 countries. *Journal of International Financial Markets, Institutions and Money*, 75, article 101448. https://doi.org/10.1016/j.intfin.2021.101448

Kabiri, A., James, H., Landon-Lane, J., Tuckett, S., & Nyman, R. (2023). The role of sentiment in the US economy: 1920 to 1934. *Economic History Review*, 76, 3–30. https://doi.org/10.1111/ehr.13160

Labadie, A. G. P. & Giovannini, P. (1991). Asset prices and interest rates in cash-in-advance models. *Journal of Political Economy*, 99(6), 1215–1251. https://doi.org/10.1086/261798

Lakdawala, A., Moreland, T., & Schaffer, M. (2021). The international spillover effects of US monetary policy uncertainty. *Journal of International Economics*, 133, article 103525. https://doi.org/10.1016/j.jinteco.2021.103525

Lv, Y., Piao, J., Li, B., & Yang, M. (2022). Does online investor sentiment impact stock returns? Evidence from the Chinese stock market. *Applied Economics Letters*, 29(15), 1434–1438. https://doi.org/10.1080/13504851.2021.1937490

Mendoza-Urdiales, R. A., Núñez-Mora, J. A., Santillán-Salgado, R. J., & Valencia-Herrera, H. (2022). Twitter Sentiment Analysis and Influence on Stock Performance Using Transfer Entropy and EGARCH Methods. *Entropy*; 24(7), 874. https://doi.org/10.3390/e24070874

Nakhli, M. S., Dhaoui, A., & Chevallier, J. (2022). Bootstrap rolling-window Granger causality dynamics between momentum and sentiment: Implications for investors. *Annals of Finance*, 18, 267–283. https://doi.org/10.1007/s10436-021-00399-z

Tadle, R. C. (2022). FOMC minutes sentiments and their Impact on financial markets. *Journal of Economics and Business*, 118, article 106021.https://doi.org/10.1016/j.jeconbus.2021.106021

Ur Rehman, M., Raheem, I. D., Al Rababa'a, A. R., Ahmad, N., & Vo, X. V. (2023). Reassessing the predictability of the investor sentiments on US stocks: The role of uncertainty and risks. *Journal of Behavioral Finance*, *24* (4), 450–465. https://doi.org/10.1080/15427560.2022.2037598

Wu, S. & Gu, F. (2023). Lightweight scheme to capture stock market sentiment on social media using sparse attention mechanism: a case study on Twitter. *Journal of Risk and Financial Management*,16 (10), 440. https://doi.org/10.3390/jrfm16100440

Wu, S., Liu, Y., Zou, Z., & Weng, T. H. (2022). S_I_LSTM: Stock price prediction based on multiple data sources and sentiment analysis. *Connection Science*, 34, 44–62. https://doi.org/10.1080/09540091.2021.1940101

Yang, L. & Hamori, S. (2014). Spillover effect of US monetary policy to ASEAN stock markets: Evidence from Indonesia, Singapore1 and Thailand. *Pacific-Basic Finance Journal*, 26, 145-155. https://doi.org/10.1016/j.pacfin.2013.12.003

Zubair Mumtaz, M. & Smith, Z. A. (2019). Examining spillover effect of US monetary policy to European stock markets: A Markov-Switching approach. *Estudios de Economia*, 46(1), 89-124. http://dx.doi.org/10.4067/S0718-52862019000100089

About the author

Dr. Humberto Valencia Herrera has an extensive career as a researcher, teacher, and professional in finance, economics, and management. He holds a PhD and a Master's Degree in Economics and Decision Sciences from the Engineering Economic Systems Department, now part of the Management Science and Engineering Department at Stanford University, United States. He has been a finance, economics, management, and industrial engineering professor and researcher, and has collaborated with educational institutions in Mexico and the United States, such as the Tecnológico de Monterrey, the Universidad Iberoamericana, and Stanford University. He has numerous publications in international and national academic journals. He is currently researching the use of artificial intelligence for investment decision-making, financial economics, energy economics, and technological development economics. He believes in the efficient and responsible management of businesses and economies, balancing environmental and social considerations with human needs.

humberto.valencia@tec.mx
https://orcid.org/0000-0002-4843-5965