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ARTÍCULO

Do Fixed-Income ETFs Overreact? Evidence of Short-term Predictability following Extreme Price Shocks

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KEYWORDS:
Fixed-income exchange traded funds; Overreaction; Short-term return reversal; Price predictability

Abstract: This paper investigates the short-term price predictability of US fixed-income ETFs in reaction to one-day extreme returns. Based on an assessment of 582 extreme price movements of ETFs in the 2007-2014 period, we compare the normal hours returns ('open-to-close') and after-hours returns ('close-to-open') for a group of 87 ETFs. We find a stark contrast between what occurs in these two periods: on average only extreme returns that occur after-hours represent an overreaction, leading to a significant reversal in the following period. Our results suggest that markets during after-hours tend to be significantly more inefficient. These results carry important implications for both regulators and market practitioners.

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PALABRAS CLAVE:
Fondos cotizados en bolsa de renta fija; Reacción exagerada; Reversión del retorno a corto plazo; Previsibilidad de los precios

Resumen: Este artículo investiga la predictibilidad de los precios a corto plazo de los ETF de renta fija de EE. UU. en respuesta a choques extremos de precios. A través de una evaluación de 582 movimientos de precios extremos de los ETF en el período 2007-2014, comparamos los retornos durante el período normal (desde la apertura hasta el final de la sesión) y los retornos fuera de ese horario para un grupo de 87 ETFs. Encontramos un fuerte contraste entre lo que ocurre en estos dos períodos: en promedio, solo los retornos extremos que ocurren fuera del horario normal representan una reacción exagerada, lo que lleva a una reversión significativa en el siguiente período. Nuestros resultados sugieren que los mercados tienden a ser significativamente más ineficientes durante las horas extras. Estos resultados tienen implicaciones importantes tanto para los reguladores como para los profesionales del mercado.

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1. Introduction

The creation of Exchange Traded Funds (ETFs) is one of the most spectacular successes in financial innovation in the last decades. Today, the major ETFs are the most actively traded equity securities on the US stock exchanges. The US ETF market remains the largest in the world, accounting for more than 70 percent of ETF assets worldwide. Data from the Investment Company Institute show that by February 2017, 1,736 ETFs were listed in the US for assets worth $1.73 trillion, compared to $16.92 trillion in mutual funds. These numbers attest to the widespread demand for ETFs by market participants. For retail investors seeking to gain exposure to broad market indices, particular sectors or geographical regions, ETFs are a convenient, cost-effective tool. And institutional investors, including mutual funds and pension funds, use ETFs to invest in markets, to manage investor flows, or to hedge their exposures.

Fixed-income ETFs aim to track the performance of fixed-income securities and are nowadays one significant category of ETFs. In February 2007 they totaled $457.4 billion in assets. Fixed-income ETFs have exploded in terms of assets under management in recent years, far outpacing the equity ETF segment. From 2006 to 2016, total net asset in equity ETFs increased by a factor of 6, whereas the net assets in bond ETFs increased by a factor of 22 in the same period. Since fixed-income ETFs have become such an important investment vehicle in terms of both trading volume and dollar value outstanding, their performance and characteristics are of interest by themselves.

In this paper we investigate the response to the changes in the share price of fixed-income ETFs that occur within either normal trading hours and after-hours (more than 5% in either direction). Based on an assessment of 582 extreme price movements of US ETFs in the 2007-2014 period, we compare the normal hours returns (‘open-to-close’) and after-hours returns (‘close-to-open’) for a group of 87 fixed-income ETFs. We also segment the sample by ETF type and conduct a cross-sectional analysis to understand which factors may account for the existence of under/overreaction following extreme price movements.

Due to the relatively recent introduction of fixed-income ETFs, little research has been conducted analyzing their performance. In a recent paper, Amini *et al*. (2013) review the literature on the short term predictability of financial prices conditional on large prior price changes. They list papers that have focused on individual stocks, stock market indices, futures, Treasury bonds, equity ETFs, and closed-end funds. To the best of our knowledge, no study has addressed so far the short-term predictability of fixed-income ETFs following extreme one-day returns. Our paper aims to fill that gap.

We document a stark contrast between what occurs in normal hours and after-hours. On average only extreme returns that occur after-hours represent an overreaction, leading to a significant reversal in the following period. This result supports the proposition that normal and after-hours periods may be considered as two separate markets and suggests that markets during after-hours tend to be significantly more inefficient due to the influence of noise traders. Our findings suggest the existence of profitable market opportunities to contrarian investors. The implications of our results to regulators are also addressed in conclusions.

The remainder of the paper is structured as follows. We review the related literature in the second section. The third section describes the data and methods. The empirical results are presented and discussed in the fourth section. The final section provides a conclusion.

2. Literature Review

Given the lesser liquidity of the fixed-income market relative to the equity market, most of the literature on bond ETFs focuses on the difference between the market price and the net asset value (NAV) of the fund as well as on how quickly these discrepancies disappear. Evidence on this issue is rather mixed.

On one hand, several authors document the presence of significant deviations. For example, Rompotis (2010) shows that US fixed-income ETFs trade, on average, at a premium to their NAV and that premium is strongly persistent on a daily basis. Buetow and Henderson (2012) and Fulkerson *et al*. (2014) corroborate these findings. Buetow and Henderson (2012) report that tracking error tends to be larger for ETFs that invest in benchmark indices composed of less liquid assets, such as many sectors of the fixed-income market. Fulkerson *et al*. (2014) study 140 US fixed-income ETFs in the 2007-2011 period. The authors document substantial and persistent premiums to the NAV, which they attribute to lack of liquidity in the underlying bond portfolio. Some researchers focus on fixed-income ETFs from other countries and reach similar results. For example, Drenovak *et al*. (2012) examine the tracking performance of 31 eurozone sovereign debt ETFs in the 2007-2010 period. They conclude that funds underperform their respective benchmarks and that ETF’s tracking performance deteriorated significantly during the European sovereign debt crisis. Milonas and Rompotis (2015) study a sample of 38 German bond ETFs during the period from their inception to the end of 2010 and find a significant tracking error which is persistent on a quarterly basis.

On the other hand, some studies advocate that fixed-income ETFs exhibit a good tracking performance. For example, Rompotis (2011) shows that the tracking error of bond ETFs tends to be significantly lower that the tracking error of equity ETFs. Houweling (2012) analyses corporate (European and US) and sovereign (US) bond ETFs and finds that Treasury ETFs have, on average, been able to track their benchmarks. However, investment-grade corporate ETFs and, especially, high-yield corporate bond ETFs lag their benchmarks. The author argues that higher volatility of the corporate bonds increases the transaction costs resulting in higher underperformance. Tucker and Laipply (2013) conclude that not only does the ETF price move in line with the bond market, it appears to absorb price information more rapidly thus providing price discovery. Finally, Fulkerson *et al*. (2017) document the effects of arbitrage on the market of bond ETFs showing that ETFs trading at a premium (discount) to NAV tend to experience more creations (redemptions) than those trading in parity and that when these transactions occur, subsequent returns partially offset the premium or discount.

There is some evidence of price predictability on fixed-income ETFs. For example, Rompotis (2010) finds that the premium of ETFs to their NAV helps to predict future returns. More specifically, returns are found to be positively related to contemporaneous premium and to be negatively affected by the one lagged premium. Fulkerson *et al*. (2014) conclude that after-hours returns after a high premium (low discount) day are very large and negative (positive), while next-day returns are zero. Investors taking a long/short portfolio position based on observed premiums/discounts generate as alpha of almost 1% per month. Finally, Milonas and Rompotis (2015) show that German fixed-income ETFs exhibit a small size and momentum effect, which can be profitably exploited by investors.

More recently, authors such as Madhavan *et al*. (2016) and Golub *et al*. (2018) have presented proposals to increase transparency and further accelerate the ongoing evolution of fixed-income ETF markets.

Overall, the existing literature suggests that the fixed-income ETF market is not totally efficient and may offer investors opportunities to gain abnormal returns. Our paper provides new evidence on the pattern of overreaction and reversal by analysing price movements and counter-movements in reaction to one-day extreme returns.

3. Data and Methods

Our sample includes observations of daily opening and closing prices for all the NYSE-traded fixed-income ETFs between January 2007 and December 2014. Daily price data covering the 87 ETFs were obtained from the Bloomberg database.

Daytime returns are estimated as the log difference between the closing and opening prices on day t. Overnight returns are the log difference between the opening price on day t and the closing price on day $t-1$. Daytime period and overnight period together encompass a total of twenty-four hours.

The sample is further segmented by ETF type. ETFs can be classified as broad-based, or international, and allow investors to gain exposure to different segments of the market. Broad-based ETFs like the Barclays Global Investors or the iShares Lehman Aggregate Bond Fund allow the investor to cover US bonds with a single ETF. International funds like the SPDR Lehman International Treasury Bond ETF allow investment in the international bond markets. Our sample includes 70 broad-based ETF and 17 international ETF.

For a one-day horizon, the trigger to qualify for a sample in other studies for individual stocks is usually a daily absolute return of 10% or higher (e.g., Cox and Peterson, 1994; Choi and Jayaraman, 2009). Since it is plausible to assume that bonds are less volatile than stocks, we adopt a minimum trigger of 5%.

The number of extreme price increases (winners) and decreases (losers) across normal and after-hours periods by different types of ETFs are shown in panel A of Table 1. The entire sample consists of 582 extreme ETF price changes that satisfy the minimum 5% trigger level. A total of 359 (61.68%) observations qualify during normal hours versus 223 (38.31%) after-hours. As Panel B shows, of the entire sample, 327 (56.19%) are losers, and the remaining 255 (43.81%) are winners. In the two ETF types considered, the number of losers is higher than the number of winners. The majority of extreme price movements concentrate among the broad-based ETFs. Panel B of Table 1 shows that 72% of the 359 movements during normal hours and that 68% of the 223 movements during after-hours can be attributed to broad-based ETFs. In both ETF types, the number of normal hours observations is higher.

(See table 1)

Following Brown and Warner (1980), we apply a mean-adjusted returns model to identify the existence of overreaction following a large price movement. In accordance with the standard applications established in the litera-

Table 1: Distribution of fixed-income ETF sample that meets the 5% trigger

Panel A: Distribution of winners and losers across normal hours and after-hours								
	Winners (positive triggers)				**Losers (negative triggers)**			
	Normal hours		**After-hours**		**Normal hours**		**After-hours**	
International ETF	33	19%	48	28%	69	40%	24	14%
Broad-Based ETF	92	23%	82	20%	165	40%	69	17%
Entire Sample	125	21%	130	22%	234	40%	93	16%

Panel B: Distribution of subsamples across types of ETF								
	Total normal hours		**Total after-hours**		**Total winners**		**Total losers**	
International ETF	102	28%	72	32%	81	32%	93	28%
Broad-Based ETF	257	72%	151	68%	174	68%	234	72%
Entire Sample	359	100%	223	100%	255	100%	327	100%

ture, the expected returns are calculated using a 255-day estimation period ending fifteen days prior to the event.

We apply the testing framework of Madura and Richie (2004) to our dataset. Thus, the time horizon used to test for a correction is either the after-hours period following earlier extreme price movements during normal trading hours, or the normal hours following extreme price movements during the previous after-hours period.

We conduct a cross-sectional analysis to understand which factors may account for the existence of overreaction following extreme price movements. We considered the abnormal returns in reaction to extreme price movements to be conditional on the following characteristics: 1) the period assessed (normal hours versus after-hours), 2) the size of the extreme return (trigger) of the ETF, 3) the type of ETF, 4) the exposure of ETF to corporate bonds, 5) the volatility of the ETF, 6) the volume of the ETF, 7) the prevailing trend (bullish versus bearish) in the bond market, and 8) the existence of tax effects.

An extreme price movement is classified according to whether occurred in normal hours or after-hours with a dummy variable. One should expect a larger overreaction after-hours since the literature on equity ETFs suggest that prices on this period are less efficient (e.g., Barclay and Hendershot, 2003; Berkman *et al*., 2012). Moreover, according to Fulkerson *et al*. (2014), the predictability of fixed-income ETFs tends to be higher after-hours. The authors find that after-hour returns after a high premium (low discount) day are overwhelmingly large and negative (positive), while the next normal hours returns are essentially zero.

The trigger is measured as the return that allowed the ETF to qualify for the sample based on the +5% or -5% threshold level. We expect that a more extreme price movement may represent a greater degree of overreaction and lead to a larger reversal.

Each ETF is classified as broad-based or international. The two types are separately coded using a dummy variable representing international ETFs. It is plausible to admit that different ETF types may exhibit different sensitivities to pricing factors. For example, broad-based ETFs are expected to be subject to lower levels of overreaction because they represent a widely diversified holding of US bonds.

The exposure of ETFs to corporate bonds are also a factor that should be taken into account when one wants to understand the determinants of overreaction. Corporate bonds and treasury bonds represent different risk profiles and characteristics. Corporate bonds are in general the less transparent part of the bond market. The fixed-income market is generally an over-the counter market in which trades occur between private counterparts at negotiated prices. The same bond can be simultaneously traded in multiple locations at different prices, but participants are largely unable to observe these price discrepancies. In the case of corporate bonds, dealers may be reluctant to display in real time the actionable bid and offer prices. On the contrary, the market for US treasuries is relatively more transparent (Elton *et al*., 1999; Tucker and Laipply, 2013). An ETF is classified according to whether is exposed to corporate bonds with a dummy variable.

ETF volatility is measured as the abnormal standard deviation of returns over the past ninety days. The abnormal standard deviation of returns is computed as the difference between the standard deviation of returns observed over the past ninety days before the trigger day and the standard deviation of returns in the 255-day estimation period ending fifteen days prior to the event. The expected relationship between overreaction and volatility is not clear. In fact, while Brown *et al*. (1993) report a positive correlation between abnormal post extreme stock price movement returns and shifts in return volatility, it is also plausible to conjecture that the presence of noise traders in the market —proxied by a heightened volatility in prices— may drive informed investors off the market, thus mitigating the magnitude of short-term price reversals.

An ETF's liquidity is measured as the abnormal daily trading volume for the period in which the trigger occurred. The abnormal daily trading volume is defined as the difference between the trading volume observed in the trigger day and the average daily volume of trading in the 255-day estimation period ending fifteen days prior to the event. One expects that more liquid ETFs should be less susceptible to mispricing (and therefore to overreaction) because a sufficient number of informed investors is involved.

Fixed-income ETF strategies may vary for multiple interest rate scenarios, so it is important to consider the trend in the bond market (Gebler and Tucker, 2003). We applied the method proposed by Pagan and Sossounov (2003) to capture the prevailing trend (bullish versus bearish) in the US bond market, represented by the Bloomberg Barclays US Aggregate Bond Index. The method aims to identify the "peaks" and "troughs" during the sample period. A turning point "peak" ("trough") takes place when the logarithm of the Bloomberg Barclays US Aggregate Bond Index reaches the highest (lowest) value in a moving 8-month window.

The reaction to an extreme return may be partially explained by tax reasons. Thus, a dummy variable was used to classify extreme price movements according to whether they occurred in December or January. De Bondt and Thaler (1987) show that price reversals in the stock market have a very strong seasonal pattern - significant price reversals associated with loser stocks occur only in January. This suggests that tax loss selling may play a role especially on loser reversals.

Finally, year dummies were used to account for unobservable time-specific factors.

We apply the following multivariate model to all winners and losers to test for the significance of the trading period (normal versus after-hours):

$$\begin{aligned} AR_i = {} & \beta_0 + \beta_1\ AFTERHOURS_i + \beta_2\ TRIGGER_i \\ & + \beta_3\ INTLDUM_i + \beta_4\ CORPDUM_i + \beta_5\ ABN\_VOLATILITY_i \\ & + \beta_6\ ABN\_VOLUME_i + \beta_7\ BULLDUM_i + \beta_8\ TAXDUM_i \\ & + \beta_9\ Year08 + \beta_{10}\ Year09 + \beta_{11}\ Year10 + \beta_{12}\ Year11 \\ & + \beta_{13}\ Year12 + \beta_{14}\ Year13 + \beta_{15}\ Year14 + \varepsilon_i \end{aligned}$$

where:

AR = abnormal return during the period following the extreme return,

AFTERHOURS = the dummy variable, with a value of 1 if the return occurs after-hours and 0 otherwise,

TRIGGER = return of the ETF (must be >+5% or <-5%),

INTLDUM = the dummy variable, with a value of 1 if the ETF is an international fund and 0 otherwise,

CORPDUM = the dummy variable, with a value of 1 if the ETF exposed to the corporate bonds and 0 otherwise,

ABN_VOLATILITY = the abnormal standard deviation of returns observed over the past ninety days before the extreme return occurs,

ABN_VOLUME = abnormal volume of shares trading in the trigger day,

BULLDUM = the dummy variable, with a value of 1 if the bond market is in a bullish trend when the extreme price movement occurs and 0 otherwise,

TAXDUM = the dummy variable, with a value of 1 if the extreme return occurs during December or January and 0 otherwise, and

YEAR08, YEAR09, YEAR10, YEAR11, YEAR12, YEAR13 and YEAR14 = dummy variables, with a value of 1 if the extreme return occurs in the year 2008, 2009, 2010, 2011, 2012, 2013 or 2014, respectively, and 0 otherwise.

The model was tested for heteroscedasticity and corrected using White's test.

We also adapted the model to assess the cross-sectional variation in abnormal returns for the normal hours and after-hours in separate. In this case, the AFTERHOURS variable is excluded, being replaced by the dummy variable LOSDUM, to distinguish losers from winners. LOSDUM is assigned a value of 1 if the extreme return is negative and 0 otherwise.

Table 2: Full sample abnormal returns after after-hours triggers

	After-hours	**Normal hours**	**After-hours**	**24 hours**	**Continuation (+) or reversal (-) in the following period in proportion of the initial extreme return**	**Continuation (+) or reversal (-) in the following 24 hours in proportion of the initial extreme return**
	Period 0	**Period 1**	**Period 2**	**(Period 1-2)**		
Panel A. Winners (positive triggers)						
Trigger>=5%	7.34%	-2.44%	0.09%	-2.35%	-33.28%	-32.04%
(N = 130)	(11.81)***	(-6.11)***	(0.10)	(-4.49)***		
	100%:0%	*32%:68%*	*50%:50%*			
Trigger>=6%	8.32%	-3.05%	-0.08%	-3.12%	-36.63%	-37.57%
(N = 88)	(10.89)***	(-6.27)***	(-0.31)	(-4.88)***		
	100%:0%	*27%:73%*	*47%:53%*			
Trigger>=7%	9.26%	-3.57%	0.25%	-3.31%	-38.49%	-35.78%
(N = 59)	(9.84)***	(-6.01)***	(0.37)	(-4.23)***		
	100%:0%	*25%:75%*	*47%:53%*			
Panel B. Losers (negative triggers)						
Trigger<=-5%	-7.11%	1.35%	0.25%	1.60%	-19.00%	-22.47%
(N = 93)	(-7.68)***	(2.84)***	(0.45)	(2.41)**		
	0%:100%	*58%:42%*	*58%:42%*			
Trigger<=-6%	-8.50%	2.14%	0.11%	2.26%	-25.23%	-26.56%
(N = 50)	(-6.88)***	(3.31)***	(0.10)	(2.53)**		
	0%:100%	*64%:36%*	*54%:46%*			
Trigger<=-7%	-9.31%	2.14%	0.83%	2.97%	-23.00%	-31.90%
(N = 34)	(-6.28)***	(2.73)***	(1.12)	(2.77)***		
	0%:100%	*62%:38%*	*56%:44%*			

Note: Proportion of positive observations:proportion of negative observations shown in italics.
*Parentheses enclose t-statistics. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively using a 1-tailed test for significance.*

4. Results

4.1. Abnormal returns following the extreme price movements of ETFs

Table 2 shows the abnormal returns following after-hours triggers that occurred for the entire sample of winners and losers and the various subsamples. For the winners and losers, the results are shown for trigger levels of at least 5%, at least 6%, and at least 7%.

As shown in the table, the after-hours winners experience a significant negative return in normal hours, regardless of the trigger level. At least 68% experienced negative abnormal returns in normal hours. The reversal in normal hours suggests that the extreme returns that happened after-hours reflect an overreaction. It is noteworthy in the last two columns of table 2 that about one third of the mean extreme price movement of winners is reversed for the subsamples partitioned by different minimum trigger levels. Overall, a significant response follows an extreme price movement occurred after-hours. This suggests that some investors that trade in normal hours capitalize on the overreaction that occurred overnight.

The reversal is concentrated on the normal hours period following the after-hours period where the extreme return occurred. The size of the reversal in normal hours, during the following after-hours period, and over the combination of these two periods, is more pronounced when a larger trigger level is used. For example, the ETFs that qualify for a +5% trigger experience a mean abnormal return of -2.44% in normal hours, while the ETFs that qualify for a 7% trigger experience a mean abnormal return of -3.57%. Similar results hold for the twenty-four-hour period following the after-hours period when the extreme return occurred.

(See table 2)

Table 2 also shows that the after-hours losers experience a significant reversal in normal hours, regardless of the trigger level. While the proportion of positive and negative observations vary with the minimum trigger level used, at least 58% experienced positive abnormal returns in normal hours period. These findings confirm market overreaction

Table 3: Full sample abnormal returns after normal hours triggers

	Normal hours Period 0	After-hours Period 1	Normal hours Period 2	24 hours (Period 1-2)	Continuation (+) or reversal (-) in the following period in proportion of the initial extreme return	Continuation (+) or reversal (-) in the following 24 hours in proportion of the initial extreme return
Panel A. Winners (positive triggers)						
Trigger>=5%	7.65%	0.70%	-0.48%	0.23%	9.19%	2.96%
(N = 125)	(12.02)***	(1.70)*	(-1.48)	(0.30)		
	100%:0%	*51%:49%*	*48%:52%*			
Trigger>=6%	8.88%	0.92%	-0.68%	0.24%	10.31%	2.70%
(N = 78)	(10.88)***	(1.76)*	(-1.61)	(0.25)		
	100%:0%	*53%:47%*	*47%:53%*			
Trigger>=7%	9.85%	1.23%	-0.74%	0.49%	12.50%	4.94%
(N = 53)	(9.86)***	(1.95)*	(-1.45)	(0.50)		
	100%:0%	*60%:40%*	*45%:55%*			
Panel B. Losers (negative triggers)						
Trigger<=-5%	-7.40%	0.46%	0.25%	0.71%	-6.24%	-9.59%
(N = 234)	(-12.75)***	(1.52)	(0.73)	(1.61)		
	0%:100%	*59%:41%*	*53%:47%*			
Trigger<=-6%	-8.55%	0.49%	0.32%	0.82%	-5.78%	-9.55%
(N = 155)	(-12.19)***	(1.33)	(0.82)	(1.53)		
	0%:100%	*63%:37%*	*54%:46%*			
Trigger<=-7%	-9.68%	0.44%	0.63%	1.07%	-4.55%	-11.07%
(N = 104)	(-11.46)***	(0.97)	(1.46)	(1.68)*		
	0%:100%	*63%:37%*	*55%:45%*			

Note: *Proportion of positive observations:proportion of negative observations shown in italics.*

*Parentheses enclose t-statistics. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively using a 1-tailed test for significance.*

by the after-hours loser ETFs. The reversal of after-hours losers is heavily concentrated in the normal hours period.

As with winners, the size of the reversal for losers after-hours is more pronounced when the losers qualify for the higher trigger (larger loss) level. Moreover, the reversal tends to be more pronounced both in the following period and in a 24-hour period for after-hours winners than after-hours losers.

Table 3 shows the abnormal returns following extreme price changes of ETFs that occurred during normal hours for the overall sample of winners and losers and the various subsamples. The contrast with the results obtained previously is stark. Normal hours winners experience not a reversal but a continuation after-hours. In the case of normal hours losers, the reversal is not statistically significant, regardless of the trigger level.

Between 40% and 50% of extreme positive price fluctuations (winners) experience a negative return on the following after-hours period. It is meaningful that the abnormal returns become negative (although not statistically significant) in the following normal hours period (period 2). This suggests that the continuation which occurred after-hours was wrong and that the investors that operate in this period did not realize that the initial movement corresponded to an overreaction in prices. In spite of the correction observed in period 2, there is a continuation of prices that reaches between 2.70% and 4.94% of the initial extreme movement in the first 24 hours.

The size of the reversal in normal hours after the extreme return tends to be more pronounced for larger triggers.

(See table 3)

About 60% of negative extreme price variations (losers) experience positive abnormal returns on the following period. The size of the reversal in the first 24 hours is more pronounced when a larger trigger level is used and varies between 9.59% and 11.07% of the initial movement.

Overall, we observe significant differences on responses to extreme price movements between normal hours and after-hours periods. While normal hours extreme price movements do not experience, on average, any statistically significant reversion on the following period, after-hours extreme abnormal returns show, for the following period, a significant mean reversion of -2.44% for winners and 1.35% for losers, considering a trigger of 5%.

A comparison of the magnitude of reversal and continuation between the normal hours and after-hours periods is shown in table 4.

For normal hours winners qualifying for the 5% minimum trigger, the mean continuation after-hours is 0.70%, while for after-hours winners, there is a reversal in the following period of -2.44% on average. The mean difference between the two types of reactions is 3.14%, which is statistically different from zero. The results are similar for the 6% and 7% trigger levels.

Table 4: Test of difference in mean abnormal returns

Trigger	AR following Normal hours trigger	AR following After-hours trigger	Mean difference	t-stat.
5% winner	0.70%	-2.44%	3.14%	(6.22)***
6% winner	0.92%	-3.05%	3.96%	(5.61)***
7% winner	1.23%	-3.57%	4.80%	(5.13)***
5% loser	0.46%	1.35%	-0.89%	(1.88)*
6% loser	0.49%	2.14%	-1.65%	(1.57)
7% loser	0.44%	2.14%	-1.70%	(1.47)

Note: **, ** and *** represents significance at the 10%, 5% and 1% levels*

For normal hours losers that qualify for the 5% trigger, the reversal after-hours is of -0.46%; for after-hours losers, there is a reversal in the following period of 1.35% on average. The mean difference between the two types of reactions is -0.89%, which is statistically different from zero at a 10% significance level. The results for the 6% and 7% trigger levels were not statistically significant at conventional levels.

Thus, the returns observed suggest that there was a significant difference in the reaction in the two different periods, especially regarding extreme positive returns. In this sense, these findings suggest that normal and after-hours periods may be considered as two separate markets.

Since results may vary by ETF type, the analysis is repeated separately for each type in Table 5. The 5% trigger is used again here. Panel A shows the reaction of ETFs after an initial extreme return occurred during normal hours, while Panel B shows the results observed after an extreme return that took place after-hours.

(See table 5)

From Panel A it is possible to conclude that the after-hours returns represent a continuation of the extreme returns occurred during normal hours periods. This happens also in the 24-hour period following an extreme return during the normal hours period. The only statistically significant exception is the reversal of international ETF losers. These results are in general consistent with those found for the entire sample. Regarding the response in the 24-hour period following the extreme return, there is only reversal of normal hours losers.

Table 5 also highlights the stark contrast between the response to extreme returns observed in normal hours and after-hours. The mean reversal following after-hours winners and losers is statistically significant for both ETF types, although that reversal is more pronounced for winners than losers. These results are also consistent with those found for the entire sample. International ETFs experience the strongest reversal both in the following period and in the 24-hour period after the extreme return.

Differences of mean reversals after extreme price movements by types of ETF are summarized on Table 6. We compare the reversals by type within the separate subsamples of day winners, day losers, after-hours winners,

Table 5: Abnormal returns after an extreme price movement for ETF types

	Period 0	Period 1	Period 2	24 hours (Period 1-2)	Continuation (+) or reversal (-) in the following period in proportion of the initial extreme return	Continuation (+) or reversal (-) in the following 24 hours in proportion of the initial extreme return
Panel A - Normal Hours						
Winners (positive triggers)						
International ETF	8.27%	1.03%	-0.93%	0.10%	12.45%	1.15%
(N = 33)	(6.63)***	(1.29)	(-1.42)	(0.03)		
	100%:0%	*55%:45%*	*45%:55%*			
Broad Based ETF	7.42%	0.58%	-0.31%	0.27%	7.88%	3.68%
(N = 92)	(10.04)***	(1.21)	(-0.88)	(0.33)		
	100%:0%	*50%:50%*	*49%:51%*			
Losers (negative triggers)						
International ETF	-7.75%	0.85%	0.66%	1.51%	-10.96%	-19.52%
(N = 69)	(-7.30)***	(1.53)	(1.25)	(1.96)**		
	0%;100%	*64%:36%*	*61%:39%*			
Broad Based ETF	-7.25%	0.30%	0.07%	0.37%	-4.13%	-5.15%
(N = 165)	(-10.46)***	(0.82)	(0.05)	(0.65)		
	0%;100%	*58%:42%*	*50%:50%*			
Panel B - After Hours						
Winners (positive triggers)						
International ETF	7.96%	-3.45%	-0.15%	-3.60%	-43.30%	-45.23%
(N = 48)	(7.73)***	(-5.24)***	(-0.36)	(-4.14)***		
	100%:0%	*25%:75%*	*52%:48%*			
Broad Based ETF	6.97%	-1.85%	0.23%	-1.62%	-26.57%	-23.22%
(N = 82)	(8.96)***	(-3.69)***	(0.40)	(-2.48)**		
	100%:0%	*35%:65%*	*49%:51%*			
Losers (negative triggers)						
International ETF	-7.58%	1.84%	0.45%	2.29%	-24.30%	-30.19%
(N = 24)	(-4.20)***	(1.97)**	(0.47)	(1.78)*		
	0%;100%	*75%:25%*	*71%:29%*			
Broad Based ETF	-6.94%	1.18%	0.18%	1.36%	-16.99%	-19.53%
(N = 69)	(-6.44)***	(2.13)**	(0.25)	(1.75)*		
	0%;100%	*52%:48%*	*54%:46%*			

Note: *Proportion of positive observations:proportion of negative observations shown in italics.*

*Parentheses enclose t-statistics. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively using a 1-tailed test for significance.*

and after-hours losers. The 5% trigger level is used again to determine the ETFs that qualify for each sample.

(See table 6)

Panel A of Table 6 summarizes the continuation/reversals (as measured by abnormal returns), while Panel B shows comparisons. From Panel B it is possible to observe that the reversal of international ETFs is more pronounced than broad-based ETFs reversals in every circumstances. Also, Panel B shows that the greatest difference in their mean reversals is experienced following after-hours extreme positive returns, although that difference is not statistically significant at conventional levels. The difference in the mean reversals after extreme negative returns during normal hours periods is statistically significant at a 10% significance level.

Overall, our results show that international ETFs experience a greater degree of overreaction, which implies a more pronounced reversal in the following period.

Table 6: Comparison of abnormal returns by type of ETF

Panel A. Summary of abnormal return by type following a 5% trigger		
	International ETF	Broad-Based ETF
Normal hours winners	1.03%	0.58%
Normal hours losers	0.85%	0.30%
After-hours winners	-3.45%	-1.85%
After-hours losers	1.84%	1.18%
Panel B. Differences of abnormal return		
	AR intl - AR broad-based	
Normal hours winners	0.45%	
	(0.69)	
Normal hours losers	0.55%	
	(1.73)*	
After-hours winners	-1.60%	
	(-1.11)	
After-hours losers	0.66%	
	(0.74)	

Note: *Parentheses enclose t-statistics. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively using a 2-tailed test for significance.*

4.2. Multivariate analysis of ETF winners and losers

Results of the multivariate analyses of ETF winners and losers are shown in Tables 7 and 8. Table 7 shows results for the entire sample. For winner ETFs, the AFTERHOURS dummy variable is negative and significant, indicating that the reversal following an after-hours winner is more significant than the reversal following a normal hours winner. This result is consistent with the earlier finding that on average reversals among winners occur only following extreme gains observed during after-hours periods. In addition, the trigger variable is negative and significant. The coefficient of -0.356 indicates that the reversal (loss) is about 36% of the preceding extreme price movement on average, after controlling for other factors. The lack of significance of the INTLDUM variable corroborates the earlier comparisons of reversals between the two types of ETF under analysis. The CORPDUM variable is positive and significant at the 5% level, which indicates that the reversal is less pronounced when the ETF is exposed to the corporate bond market. The TAXDUM variable is negative and significant, which is consistent with the existence of relevant tax effects. The ABN_VOLATILITY variable is positive and significant, which indicates that the reversal following extreme winners tends to be less pronounced when ETF prices are more volatile. The year dummies show that there are significant negative unobservable time-specific effects in all the years except 2013, which suggest that there is a general trend towards more pronounced reversals following positive extreme returns.

A similar multivariate model was used to assess the entire sample of losers. The regression is not globally significant at conventional levels. The AFTERHOURS dummy variable is positive and significant at the 10% level, which suggests that the reversal following an after-hours loser is more pronounced than the reversal following a normal hours loser. This finding corroborates the earlier result that on average statistically significant reversals occur only following extreme losses observed during after-hours periods. The dummies referring to the years 2011 and 2013 show that there are significant negative unobservable time-specific effects in those periods.

Table 7: Cross-sectional regression of AR following extreme price returns for whole sample of ETFs

	Winners	**Losers**	**Normal hours**	**After-hours**
Intercept	0.076***	0.014	0.016	0.021
	(0.004)	(0.305)	(0.183)	(0.248)
AFTERHOURS	-0.030***	0.009*		
	(0.000)	(0.093)		
LOSDUM			0.009	-0.044
			(0.396)	(0.107)
TRIGGER	-0.356**	-0.047	0.082	-0.566***
	(0.039)	(0.507)	(0.258)	(0.003)
INTLDUM	-0.009	0.006	0.004	-0.008
	(0.300)	(0.220)	(0.485)	(0.314)
CORPDUM	0.020**	0.000	0.005	0.013
	(0.017)	(0.941)	(0.295)	(0.149)
BULLDUM	-0.014	0.000	-0.004	-0.015
	(0.215)	(0.985)	(0.552)	(0.149)
TAXDUM	-0.022***	-0.004	-0.007	-0.011
	(0.004)	(0.550)	(0.210)	(0.207)
ABN_VOLUME	-0.000	-0.000	-0.000*	-0.001**
	(0.399)	(0.114)	(0.089)	(0.045)
ABN_ VOLATILITY	1.079**	-0.245	0.117	0.850
	(0.031)	(0.443)	(0.686)	(0.112)
Year08	-0.043***	-0.009	-0.013	0.001
	(0.004)	(0.451)	(0.169)	(0.953)
Year09	-0.055***	-0.014	-0.017**	-0.011
	(0.000)	(0.169)	(0.042)	(0.433)
Year10	-0.068***	-0.011	-0.021**	-0.011
	(0.000)	(0.323)	(0.031)	(0.403)
Year11	-0.040***	-0.022**	-0.020**	0.000

	Winners	Losers	Normal hours	After-hours
	(0.006)	(0.042)	(0.040)	(0.982)
Year12	-0.030**	-0.010	-0.011	0.010
	(0.041)	(0.357)	(0.279)	(0.375)
Year13	-0.032	-0.023*	-0.018	
	(0.103)	(0.085)	(0.113)	
Year14	-0.038**	0.004	-0.021**	0.044*
	(0.019)	(0.802)	(0.030)	(0.056)
Observations	255	327	359	223
R-squared	0.232	0.046	0.039	0.270
F	22.13	1.123	1.369	6.549
Prob>F	0.00	0.33	0.16	0.00

Note: **, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.*

The dependent variable is the abnormal return (AR) following extreme price returns. AFTERHOURS is a dummy variable with a value of 1 if the extreme return occurs after-hours and 0 otherwise. LOSDUM is a dummy variable with a value of 1 if the extreme return is negative and 0 otherwise. TRIGGER is the extreme return of the ETF in the initial period. INTLDUM is a dummy variable with a value of 1 if the ETF is an international fund and 0 otherwise. CORPDUM is a dummy variable with a value of 1 if the ETF is exposed to corporate bonds and 0 otherwise. BULLDUM is a dummy variable with a value of 1 if the extreme return occurs during a bull market period and 0 otherwise. TAXDUM is a dummy variable with a value of 1 if the extreme return occurs during December or January and 0 otherwise. ABN_VOLUME is the abnormal volume traded in the day where the extreme return occurs. ABN_VOLATILITY is the abnormal standard deviation of returns observed over the past ninety days before the extreme return occurs. YEAR08, YEAR09, YEAR10, YEAR11, YEAR12, YEAR13 and YEAR14 are dummy variables with a value of 1 if the extreme return occurs in the year 2008, 2009, 2010, 2011, 2012, 2013 or 2014, respectively, and 0 otherwise. Robust p-value in parentheses.

Table 7 also shows the results from applying the multivariate model to all the observations where the extreme return happened during normal hours. The ABN_VOLUME variable is negative and significant at the 10% level, which indicates that larger reversals coincide with higher trading volume. The year dummies show that there are significant negative time-specific effects in the years 2009, 2010, 2011 and 2014.

The same model is estimated for all observations where the extreme price movement occurred after-hours. Not surprisingly, the degree of reversal is very strong. The TRIGGER coefficient is negative (-0.566) and highly significant indicating a reversal of more than half (57%) of the initial extreme return. Again, the ABN_VOLUME variable is negative and significant suggesting that larger reversals tend to occur in times of higher trading activity.

Table 8 displays the results of additional cross-sectional analysis that were conducted for each ETF type. Results suggest that the determinants of abnormal returns in normal hours and after-hours vary with ETF type. In fact, the reversal of extreme returns observed during normal hours is significantly influenced by the size of the trigger but only in the case of broad-based ETFs (Panel B).

Regarding the reaction to extreme returns occurred during after-hours periods, the reversal exists only for broad-based ETFs after controlling for other factors. Our multivariate analysis suggest that the more pronounced reversal that was previously observed for international ETFs (see Table 5) was due not to the type of the ETF in itself but to the circumstances in terms of trading volume and price volatility that surrounded the reversal. In percentage of the initial trigger, the reversal is 84% in the case of broad-based ETFs. In addition, the reversal of broad-based ETFs is less pronounced when the initial trigger is negative. For these ETFs the year dummies show that there are significant negative unobservable time-specific effects.

(See table 8)

For the sample of international ETF winners (Panel A), the AFTERHOURS dummy variable is negative and significant, which implies that the reversal (loss) is more pronounced for after-hours winners than normal hours winners. This is consistent with previous findings. The CORPDUM variable is positive and significant, which indicates that the reversal is less pronounced when the ETF is exposed to corporate bonds.

For the sample of international ETF, there are no statistically significant variables at conventional levels related to the circumstances surrounding the reaction to extreme negative price shocks.

For the sector broad-based winners (Panel B), the AFTERHOURS is negative and significant, which indicates that the reversal (loss) is more pronounced for after-hours winners than normal hours winners. The TAXDUM variable is also negative and significant which means that the reversal tends to be more pronounced in December and January. In addition, there are significant negative time-specific effects in all the years of the sample.

For the sample of broad-based ETF losers, ABN_VOLATILITY is negative and significant, suggesting that the reversal (gain) is more pronounced in times of lower volatility.

While the sensitivity of abnormal returns to cross-sectional characteristics varies by ETF type, it is possible to conclude the reversal is more pronounced in response to the extreme positive price movements that occur after-hours than those that occur during normal hours.

Table 8: Cross-sectional regressions of abnormal returns by ETF type after extreme price movements

	Panel A. International ETF				Panel B. Broad-Based ETF			
	Normal-hours	After-hours	Winners	Losers	Normal-hours	After-hours	Winners	Losers
Intercept	0.007	-0.047	-0.036	0.006	0.019	0.103***	0.086**	0.017
	(0.818)	(0.104)	(0.350)	(0.641)	(0.194)	(0.006)	(0.015)	(0.327)
AFTERHOURS			-0.040***	0.012			-0.023***	0.009
			(0.008)	(0.349)			(0.001)	(0.181)
LOSDUM	-0.003	0.010			0.015	-0.086**		
	(0.917)	(0.759)			(0.187)	(0.011)		
TRIGGER	-0.008	-0.228	-0.314	0.057	0.122*	-0.837***	-0.265	-0.087
	(0.967)	(0.291)	(0.154)	(0.696)	(0.097)	(0.001)	(0.275)	(0.298)
CORPDUM	0.004	0.028*	0.045***	-0.007	0.008	0.014	0.015	0.007
	(0.724)	(0.059)	(0.006)	(0.451)	(0.121)	(0.252)	(0.129)	(0.285)
BULLDUM	0.004	-0.008	-0.001	0.004	-0.008	-0.021*	-0.020	-0.002
	(0.780)	(0.675)	(0.956)	(0.729)	(0.253)	(0.093)	(0.133)	(0.747)
TAXDUM	-0.008	-0.012	-0.015	-0.011	-0.006	-0.013	-0.027***	0.001
	(0.323)	(0.350)	(0.152)	(0.306)	(0.414)	(0.304)	(0.005)	(0.906)
ABN_VOLUME	-0.000	-0.002***	-0.000	-0.001	-0.000	0.001	-0.000	-0.000
	(0.337)	(0.002)	(0.275)	(0.300)	(0.921)	(0.487)	(0.929)	(0.163)
ABN_ VOLATILITY	0.160	1.855**	1.276*	0.280	-0.080	-0.200	0.654	-0.954**
	(0.713)	(0.031)	(0.087)	(0.612)	(0.850)	(0.810)	(0.400)	(0.033)
Year08	0.004	0.007	0.044*	0.007	-0.020	-0.052*	-0.058***	-0.013
	(0.764)	(0.774)	(0.050)	(0.616)	(0.115)	(0.069)	(0.002)	(0.391)
Year09	-0.005	-0.009	0.010	0.007	-0.021*	-0.057**	-0.052***	-0.018
	(0.709)	(0.620)	(0.621)	(0.557)	(0.058)	(0.045)	(0.001)	(0.174)
Year10	-0.003			0.005	-0.026**	-0.069**	-0.082***	-0.019
	(0.779)			(0.561)	(0.036)	(0.012)	(0.000)	(0.193)
Year11	-0.023			0.006	-0.019	-0.045*	-0.045**	-0.022
	(0.169)			(0.644)	(0.120)	(0.084)	(0.017)	(0.138)
Year12	-0.004	0.036***	0.065***	0.002	-0.012	-0.055**	-0.046***	-0.016
	(0.701)	(0.009)	(0.005)	(0.828)	(0.389)	(0.042)	(0.009)	(0.308)
Year13	-0.013	0.039	0.083***	-0.038**	-0.023	-0.063**	-0.059**	-0.024
	(0.442)	(0.118)	(0.002)	(0.012)	(0.112)	(0.030)	(0.016)	(0.154)
Year14					-0.022*		-0.051***	0.003
					(0.084)		(0.004)	(0.889)
Observations	83	54	58	79	217	117	136	198
R-squared	0.028	0.413	0.340	0.055	0.060	0.255	0.206	0.072
F	6.42	8.324	4.426	84.29	1.397	3.258	16.4	1.241
Prob>F	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.25

Note: **, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.*

The dependent variable is the abnormal return (AR) following extreme price returns. AFTERHOURS is a dummy variable with a value of 1 if the extreme return occurs after-hours and 0 otherwise. LOSDUM is a dummy variable with a value of 1 if the extreme return is negative and 0 otherwise. TRIGGER is the extreme return of the ETF in the initial period. CORPDUM is a dummy variable with a value of 1 if the ETF is exposed to corporate bonds and 0 otherwise. BULLDUM is a dummy variable with a value of 1 if the extreme return occurs during a bull bond market period and 0 otherwise. TAXDUM is a dummy variable with a value of 1 if the extreme return occurs during December or January and 0 otherwise. ABN_VOLUME is the abnormal volume traded in the day where the extreme return occurs. ABN_VOLATILITY is the abnormal standard deviation of returns observed over the past ninety days before the extreme return occurs. YEAR08, YEAR09, YEAR10, YEAR11, YEAR12, YEAR13 and YEAR14 are dummy variables with a value of 1 if the extreme return occurs in the year 2008, 2009, 2010, 2011, 2012, 2013 or 2014, respectively, and 0 otherwise. Robust p-value in parentheses.

Conclusion

ETFs hold a fixed basket of securities, similar to a mutual fund, but they trade throughout the day at market-determined prices. They also differ from mutual funds in that they allow investors to sell securities short. The ease of trading of fixed-income ETFs allow uninformed investors to take positions in bond composites, which could allow for more volatile price movements.

Our paper examines the response to the changes in the share price of fixed-income ETFs that occur within either normal trading hours and after-hours (more than 5% in either direction). Based on an assessment of 582 extreme price movements of US ETFs in the 2007-2014 period, we document a stark contrast between what occurs in normal hours and after-hours. We show that there is a much more pronounced reversal of extreme price movements that occur after-hours. On average only extreme returns that occur after-hours represent an overreaction, leading to a significant reversal in the following period. On one hand, this result lends credit to the notion that normal and after-hours periods may be considered as two separate markets and corroborates the literature regarding equity ETFs suggesting that markets during after-hours tend to be more inefficient (e.g., Barclay and Hendershot, 2003; Berkman *et al*., 2012). On the other hand, our results contrast with those obtained by Madura and Richie (2004), who found a less pronounced reversal of extreme price movements of equity ETFs that occurred after-hours. These differing conclusions suggest that the market of fixed-income ETFs and the market for equity ETFs are inhabited by investors who follow dissimilar strategies.

The existence of a significant overreaction in ETF prices is somewhat surprising given that these instruments offer most advantages of a future contract such as liquidity and competitive pricing. They can be purchased on margin and sold short. Moreover, unlike most mutual funds, each ETF has a very specific investment objective, such as replicating a country bond index or a municipal bond index. Because ETFs have clearly defined objectives and are easy to trade, their prices should in theory closely follow fundamentals. Our results suggest that, in spite of these favorable characteristics, noise traders can significantly influence the short-term evolution of ETF prices. Other reasons such as changing risk premia or microstructure influences seem unlikely candidates to explain the reported patterns of short-term overreaction and reversal.

Our multivariate analyses show that the determinants of abnormal returns in normal hours and after-hours vary with ETF type, which suggests that international ETFs and broad-based ETFs are traded by different market participants. This finding is consistent with the result attained by authors such as Bailey *et al*. (2008) and Bekaert *et al*. (2017), according to which investors that are more prone to adopt international diversification strategies appear to have distinct socio-economic profiles (wealthier, more financial literate and more experienced, in the case).

Our findings have important implications for both regulator and market practitioners' purposes. First, as regards regulation, our results advise market regulators to concentrate their resources on overseeing the ETF pricing that occurs after-hours. The existence of overreaction in prices imply that some investors trade too much; and consequently they bear unnecessary trading costs. These excessive trading costs are found to be very significant economically: according to some estimates for the stock market, investors incur in losses that can reach between 0.7% and 2.2% of their respective GDP, *every year* (French, 2008; Barber *et al.*, 2008). Regulators should be concerned with the loss of wealth that seems to occur as well in fixed-income ETF markets. Second, for market practitioners, our findings suggest the existence of profitable market opportunities. During the sample period, for after-hours winners qualifying for the 5% minimum trigger, the mean reversal in the following period is -2.44%, while for after-hours losers, there is a reversal of 1.35% on average. Bid-ask spreads can be significant for ETFs that have low liquidity. However, considering the relatively low costs of investing in liquid ETFs and that the bid-ask spread on large capitalization US fixed-income ETFs lies typically between 1.3bp and 5.5bp (Golub *et al.*, 2013), our results suggest that there is room to profit from the pattern of overreaction and reversal at least in highly liquid ETFs.

We believe there is much more to investigate regarding the patterns of overreaction in the market of fixed-income ETFs. Further avenues of research may include repeating the tests for a larger sample; studying the impact of the global financial crisis on the overreaction phenomenon; implementing alternative estimation techniques, such as quantile regressions, that are less sensitive to the existence of outliers; and considering endogenous measures of overreaction, i.e., indicators that detect overreaction taking into account the statistical properties of the market at the time.

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