The Tracking Efficiency of Bond ETFs

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ABSTRACT

This paper examines the existence and determinants of tracking errors for 2 bond exchange traded funds (ETFs) and 2 mutual funds that track the same indices in the US and the emerging markets (EM) in 2013-2018. Results show that all funds underperform their indices. However, ETF net asset value (NAV) produces the smallest tracking error when compared to the mutual fund NAV and the ETF price. In addition, the tracking errors for the EM funds are significantly greater than those of their US counterparts. The results also demonstrate that NAV and price are cointegrated for both bond ETFs, which is logical and reassuring for investors. The results likewise suggest that for both bond ETFs, when there is a price to NAV discrepancy today, it is in part (~2/3) corrected in the change in price tomorrow. Similarly, price to NAV error today makes up only a part of the price to NAV error tomorrow for both ETFs, a larger portion for the EM bond ETF vs. the US bond ETF. However, given that only a fraction of the mispricing is corrected, this suggests that price today may be forward-looking. Furthermore, the findings in this paper confirm that fluctuations in the stock market and changes in interest rates affect the price changes for both bond ETFs. The volatility in the underlying index only has an effect on the daily price to NAV mispricing of the EM bond ETF. Finally, FX fluctuations indirectly affect price changes in the EM bond ETF, even though it is comprised of foreign dollar-denominated bonds.

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I. INTRODUCTION

An increasing number of economists have turned their attention to exchange-traded funds (ETFs) because they are one of the most important financial innovations in decades (Lettau and Madhavan 2018). According to EY, "global ETF assets, which totaled just $417b in 2005, had reached $4.4t by the end of September 2017 — a cumulative average growth rate (CAGR) of around 21%...and ETF assets have the potential to hit $7.6t (by 2020)" (Kealy, et al. 2017, 4). This idea is reinforced by BlackRock, the largest provider of ETFs, who sees ETF assets reaching above $12t by 2023 (Small, et al. 2018). Bond ETFs still make up a small share of the total ETFs globally. Nevertheless, as Blackrock's Fixed Income Product Strategist explains, "Fifteen years ago, there were only a handful of bond ETFs. Today, there are more than 1,200 of them, trading in a market worth $840 billion globally (source: BlackRock, as of 8/31/2018)" (Schenone, 2018). Moreover, in a recent note, the CFRA Research Director of ETF and Mutual Fund Research, Todd Rosenbluth wrote, "Though fixed income offerings represent 17 percent of the exchange traded product market, the category's $63 billion of net inflows year-to-date [2018] through Sept. 7th were a 36-percent share." (ETF Professor, 2018). Thus, though there have been many who have spoken against bond ETFs, their popularity is unmistakably on the increase.

So, what is a bond ETF? A bond ETF is a basket of fixed income securities that trade on equity exchanges as a single stock. From the very beginning, the combination of the very liquid ETFs and the increasingly less-liquid bonds (especially corporate bonds) was both extremely questionable and improbable. Numerous individuals mistrusted their viability and attractiveness. Nonetheless, the bond market continued to expand over the past decade and ETFs gained momentum with institutional and retail investors. These developments left bond ETFs in a sweet spot as an increasingly appealing investment instrument.

Bond ETFs do not replicate the indices they track but instead sample them (Vanguard (2009); Schwab (2009)). This reduces transaction costs because the bond market is large and oftentimes there can be problems with liquidity (Bao, Pan, and Wang (2011); Dick-Nielsen, Feldhutter and Lando (2012)). Consequently, in order to drive costs down, bond ETFs maintain a portfolio designed to mimic cash flows, duration, quality and callability of the indices they track.

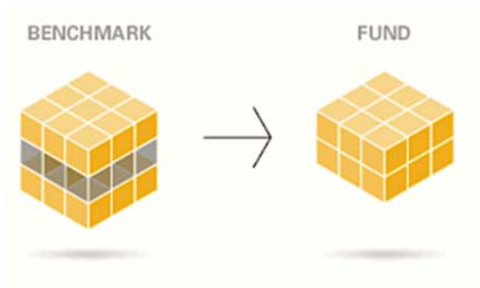

Image source: https://advisors.vanguard.com/VGApp/iip/site/advisor/etfcenter/article/ETF_HowETFIndexed

On average, ETFs commit to investing about 80% of their funds mimicking the index bonds. The commitment of the iShares Core U.S. Aggregate Bond ETF (AGG) and that of the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB) stand at 90% (both ETFs are considered in this paper). However, the latter is able to reduce commitment to only 80% when necessary. Normally, the bond ETFs rebalance their portfolios close to the index revision dates in order to decrease tracking error.

There are several major reasons why this analysis is useful. First, my results aim to narrow the gap in research about bond ETFs, which as described above, are becoming all the more relevant and abundant. This paper not only looks at ETFs but also compares their tracking abilities to the those of mutual funds (that track the same indices), which have been around for a much longer period of time. Second, from the point of view of investors the analysis of bond ETF tracking errors remains widely misunderstood and requires clarification. Some individuals attribute all tracking errors to fund management and trading fees, and therefore claim that investors are best off purchasing shares of ETFs that have the lowest management fees. However, this strategy may not be optimal because some ETFs may not in fact track their indices accurately. Thus, this paper will look at both the ability of an ETF net asset value (NAV) to track its index and the price fluctuations around the NAV itself that are likely to reflect the demand for the fund also. Even though tracking errors can be small, they can still negatively affect returns. Third, to the best of my knowledge, there has been limited research on the tracking abilities of bond ETFs that try to replicate the returns of emerging markets indices. Most of the literature is focused on the ETFs of the United States (and less so, of Europe). However, countries such as China, India, Brazil, South Africa, Russia and other developing nations have become increasingly important to investors due to their fast-growing economies and prospects of higher returns. Unsurprisingly, the iShares J.P. Morgan USD Emerging Markets Bond ETF (studied in this paper) alone has ~$17.5Bn worth of assets. An analysis of the tracking abilities of an emerging markets (EM) bond ETF is important because it is not obvious if results found in the academic literature for U.S. (and European) equity and bond ETFs translate directly to EM bond ETFs.

The results of my paper provide information regarding the existence and determinants of tracking errors. I find that both ETFs and mutual funds underperform their indices, which is consistent with previous literature. However, my analysis suggests that ETF NAV produces the smallest tracking error, the mutual fund NAV is second best, and the ETF price has the largest tracking error of the index. I also find that tracking errors for the EM funds are much greater than those of their US counterparts. The results in this paper also show that for both bond ETFs NAV and price are cointegrated and their difference is a stationary process. The results likewise indicate that for both bond ETFs, when there is a price to NAV difference today, it is adjusted to a certain degree (~2/3) in the change in the price tomorrow. In a similar manner, I observe that price to NAV error today makes up only a part of the price to NAV error tomorrow for both ETFs, a larger portion in the EM bond ETF vs. the US bond ETF. However, given that only a fraction of the price to NAV error is corrected tomorrow, this suggests that price today may be forward-looking. Furthermore, the findings in this paper confirm that fluctuations in the stock market and changes in interest rates affect the price changes for both bond ETFs. The volatility in the underlying index only has an effect on the daily price to NAV mispricing of the EM bond ETF and it is likely that this can be attributed in part to higher transaction costs in the EM. Finally, FX fluctuations indirectly affect price changes in the EM bond ETF, even though it tracks an index that only incorporates foreign dollar-denominated bonds and no bonds denominated in local currencies.

The remainder of the paper is structured as follows: Section 2 provides the relationship of my analysis to other empirical papers on bond ETFs. Section 3 defines variables and presents the data sets. Section 4 outlines the methodology and shows the results. Section 5 concludes.

II. PREVIOUS WORK

Though the number of studies has been growing, the current existing literature on equity ETFs is still relatively limited. Papers available regarding bond ETFs are even more sparse. However, below I present some of the key findings related to the analysis in this paper.

ETFs have similarities with closed-end mutual funds, but they also possess very unique characteristics. Thus, ETFs trade continuously during the day on exchanges as stocks do. Therefore, unlike mutual funds, the prices of ETFs are determined by supply and demand and not by the NAV calculated at the end of the day. This feature suggests that ETF prices may as a result be susceptible to stock market fluctuations and this paper investigates the matter further.

Moreover, as described by Charupat and Miu (2013), ETFs uniquely use the creation/redemption process, whereby preselected traders can buy (sell) creation units (large blocks of shares) of an ETF directly from (to) the fund issuer at the NAV. Thus, as described in the respective prospectuses, the iShares Core U.S. Aggregate Bond ETF (AGG) and the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB) (both analyzed later on in this paper) issue/redeem shares to pre-approved market participants in blocks of 100,000 shares or multiples thereof (creation units). Creation units can be issued or redeemed in exchange for a daily-specified portfolio of designated securities (and an amount of cash). Therefore, the creation/redemption process should in principle ensure that the market price of a fund stays close to its NAV, potentially influencing the tracking abilities of ETFs vs. mutual funds. Aber, et al. (2012) previously compared 4 ETFs to their mutual fund counterparts and found that both fund types have approximately the same degree of co-movement with their benchmarks but differ slightly in their tracking ability.

So, what are the causes of tracking error in ETFs? Buetow and Henderson (2012) discuss two sides to the tracking errors of ETFs. First, tracking errors appear when the NAV of the fund does a poor job of tracking the index itself. Second, price fluctuations around the NAV can also produce tracking errors. The price of the ETF may not only be a direct representation of the NAV, but it can also incorporate the demand for the fund itself. Consequently, it is possible that ETFs can generate returns that will be different from those of their respective underlying indices. Nevertheless, if price and NAV are cointegrated then long-run returns must be close to equal. These ideas will be investigated in this paper. In fact, a comprehensive analysis will look into the determinants of price to NAV discrepancies, daily price changes and daily NAV changes.

Charupat and Miu (2013) outline four factors that affect tracking errors (excluding leveraged or inverse ETFs):

1) Management fees

2) Transaction costs

3) Indirect replication/sampling

4) Dividends

Management fees are part of the expense ratio (% of assets deducted annually for fund expenses) and are normally lower for ETFs vs. mutual funds. This is supported by Table 1 in this paper. In addition, Milonas and Rompotis (2006) previously found that tracking errors are positively related to the management fees in Swiss ETFs. Charupat and Miu (2013) claim that transaction costs tend to be higher when the underlying indexes are more volatile, translating to higher tracking errors. An analysis of the effects of volatility of the underlying index on price to NAV mispricing will be conducted in this paper to explore the issue further. Moreover, Charupat and Miu (2013) also state that indirect replication/sampling of the index can result in lower transaction costs but increase the overall tracking errors. When an ETF uses direct replication, the securities in the ETF are the same as those in the index and the returns should be similar but transaction costs will be higher. Thus, it appears that the main task of the manager of the fund is to find the optimal balance between the degree of index replication and the cost of the replication.

This paper looks at not only US bond funds but also EM bond funds. Blitz and Huij (2012) previously found that the tracking errors of global emerging markets ETFs are substantially higher than those for developed markets ETFs. What's more, their findings showed that ETFs that use statistical index replication techniques are especially likely to have high tracking errors. These ideas can be supported by Domowitz, Glen and Madhavan (2001) who deduced that transaction costs for stocks in emerging markets are twice as high as transaction costs for U.S. stocks. Bekaert, Harvey and Lumsdaine (2002) and Chiyachantana, Jain, Jiang and

Wood (2004) also observed price pressure effects in the EM space. This also suggests that the aforementioned creation/redemption process may be more challenging to achieve in emerging markets (especially with the less liquid fixed income instruments), leading to higher price to NAV discrepancies and consequently, higher tracking errors of EM bond ETFs. Finally, previous studies have shown that foreign fixed-income dollar-denominated securities can indirectly be impacted by fluctuations in the currency exchange rates e.g., increased likelihood of financial distress due to debt dollarization (Delikouras, et al. 2015). Thus, if changes in currency exchange rates affect bonds, and consequently the NAV of ETFs, they may have an additional impact on the price of ETFs. More research will be conducted on the topic in this paper to see if there is further evidence to support this claim.

III. DATA SELECTION

As alluded to before, ETFs and mutual funds are both instruments which bundle securities to offer easily accessible diversified solutions to investors. However, ETFs trade continuously throughout the day and utilize a creation/redemption process for their shares, which may impact the tracking abilities of these funds. To shed more light on this issue, this paper compares 2 bond ETFs vs. 2 bond mutual funds that track the same indices respectively.

For the analysis, two actively traded ETFs have been selected, the iShares Core U.S. Aggregate Bond ETF (AGG) and the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB). The iShares Core U.S. Aggregate Bond ETF seeks to track the investment results of the Bloomberg Barclays US Aggregate Bond Index, which “is a broad-based flagship benchmark that measures the investment grade, US dollar-denominated, fixed-rate taxable bond market. The index includes Treasuries, government-related and corporate securities, MBS (agency fixed-rate and hybrid ARM pass-throughs), ABS and CMBS (agency and non-agency)"[1] (Bloomberg: LEGATRUU:IND). The iShares J.P. Morgan USD Emerging Markets Bond ETF seeks to track the investment results that correspond to the price and yield of the J.P. Morgan Emerging Markets Bond Index. The J.P. Morgan Emerging Market Bond Index (EMBI) "was formed in the early 1990s after the issuance of the first Brady bond and has become the most widely published and referenced index of its kind" (J.P. Morgan: Index Suite). The J.P. Morgan Emerging Market Bond Index (EMBI) is composed of only U.S. dollar-denominated, emerging market bonds. Consequently, the iShares J.P. Morgan USD Emerging Markets Bond ETF provides access to the sovereign debt of 30+ emerging market countries in a single fund.

Two conventional open-end mutual funds which track the two aforementioned indices have also been chosen for comparative purposes, iShares U.S. Aggregate Bond Index Fund (previously the BlackRock U.S. Total Bond Index Fund; BMOIX) and T. Rowe Price Emerging Markets Bond Fund (PREMX). The ability of each ETF in efficiently tracking the investment returns of its respective index in comparison to the corresponding mutual will be examined. Moreover, it is important to highlight that these ETFs and mutual funds were chosen specifically not only because they track the same indices but also to determine whether there are differences in tracking an index comprised of US bonds and one made up of Emerging Markets bonds. Thus, for example, the iShares J.P. Morgan USD Emerging Markets Bond ETF does not necessarily trade concurrently with its constituents (i.e. the Emerging Markets bonds). Some of the ETF's holdings may be traded on exchanges in other time zones, which may have a direct impact on tracking efficiency. The ETFs and mutual funds chosen for this research are summarized in Table 1.

[1] MBS are Mortgage Back Securities, ARM is adjustable rate mortgages, ABS are asset backed securities, and CMBS are commercial mortgage backed securities.

TABLE 1: Summary of ETFs and Mutual Funds Examined in This Study

Type	*Ticker*	*Provider*	*Inception Date*	*Index*	*Net expense ratio*	*Net Assets (as of 03/26/2019)*
ETF	AGG	iShares	09/22/2003	Bloomberg Barclays US Aggregate Bond	0.05%	$57.85Bn
Mutual Fund	BMOIX	iShares	04/28/1993	Bloomberg Barclays US Aggregate Bond	0.10%	$1.39Bn
ETF	EMB	iShares	12/17/2007	J.P. Morgan Emerging Markets Bond (EMBI)	0.40%	$17.41Bn
Mutual Fund	PREMX	T. Rowe Price	12/30/1994	J.P. Morgan Emerging Markets Bond (EMBI)	0.92%	$5.94Bn

The principal source of the data is Bloomberg and the official websites of ETFs, mutual funds and index providers. The NAVs and dividend distributions for the iShares ETFs and mutual fund were obtained from the iShares website (www.ishares.com). The NAVs and dividend distributions for the T. Rowe Price Emerging Markets Bond Fund were acquired from the T. Rowe website (www3.troweprice.com). All dividends were added back to NAV on the days distributed and incorporated as part of the return calculations for each fund. ETF prices were taken from Yahoo! Finance (https://finance.yahoo.com). As demonstrated in Table 1, the ETFs and the mutual funds in this research have traded in excess of 5 years providing adequate data for analysis. The data regarding the daily levels of the indices (LEGATRUU:IND, EMBI:IND, SPX:IND) was obtained from Bloomberg. I used the 10-YR Treasury Rate as a proxy to see the effects of interest rate changes on the tracking efficiency of ETFs because the weighted average maturity for iShares Core U.S. Aggregate Bond ETF (AGG) is 7.88 years and that for iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB) is 12.03 years. Data on the 10-YR Treasury Rate was obtained from Yahoo! Finance. Finally, I used the Trade Weighted U.S. Dollar Index (Emerging Markets Economies, Goods and Services) as a proxy for the fluctuating exchange rates in the emerging markets. I obtained data on this index from the Economic

Research website at the Federal Reserve Bank of St. Louis (https://research.stlouisfed.org/about.html). The Trade Weighted U.S. Dollar Index (Emerging Markets Economies, Goods and Services) is a measure of the USD relative to EM currencies. A positive increase in the Trade Weighted U.S. Dollar Index (Emerging Markets Economies, Goods and Services) corresponds to a stronger dollar and vice versa.

IV. METHODOLOGY AND RESULTS

DAILY RETURN ERRORS AND TRACKING ERRORS

I began the performance analysis of ETFs by juxtaposing them to their respective mutual funds that target the same benchmark indices. I calculated the daily returns for each ETF using both the end-of-day NAV and the daily adjusted closing price (equations (1) and (2)). For the mutual funds, I used equation (1) to calculate the daily returns because the price is determined by the NAV at closing. NAVs are normally determined for most funds at 4:00pm ET. The index returns were calculated using equation (3).

(1) $$r_{NAV,t} = \ln(\frac{NAV_t}{NAV_{t-1}})$$

(2) $$r_{Price,t} = \ln(\frac{Price_t}{Price_{t-1}})$$

(3) $$r_{Index,t} = \ln(\frac{Index_t}{Index_{t-1}})$$

Using these returns, I calculated the cumulative daily return, *R*, using equation (4) for the 5-year timeframe for each bond ETF, mutual fund and bond index. The cumulative daily return is a typical ETF industry practice to demonstrate index-tracking ability e.g., accessible on the iShares website (Aber, et al. 2009).

(4) $$R = \sum_{t=1}^{T} r_t$$

where
$r_t - r_{NAV,t}$ / $r_{Price,t}$ / $r_{Index,t}$

Findings

Graph 1 illustrates the cumulative daily returns for the iShares Core U.S. Aggregate Bond ETF (AGG) using its NAV and price, for the iShares U.S. Aggregate Bond Index Fund (BMOIX) and for the Bloomberg Barclays US Aggregate Bond index itself. Graph 2 depicts the cumulative daily returns for the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB) using its NAV and price, for the T. Rowe Price Emerging Markets Bond Fund (PREMX) and the J.P. Morgan Emerging Market Bond index. Graph 1 demonstrates that both the AGG ETF (using NAV and price) and the BMOIX mutual fund underperform the Bloomberg Barclays US Aggregate Bond index, which is consistent with conclusions drawn from similar studies involving equity ETFs. The AGG NAV tracks the Bloomberg Barclays US Aggregate Bond index most closely, the AGG price is second best and the BMOIX NAV has the largest difference in daily cumulative return from that of the index in the 5-year timeframe investigated in this paper. Graph 2 presents similar findings in that the EMB ETF (using NAV and price) and the PREMX mutual fund underperform the J.P. Morgan Emerging Market Bond index. With regards to tracking abilities, the situation is not as apparent as in Graph 1. At certain times, the daily cumulative return of the EMB NAV is closest to that of the J.P. Morgan Emerging Market Bond index. At other times, however, the PREMX NAV daily cumulative return mimics that of its index more precisely. When comparing Graph 1 and Graph 2, it is evident that the tracking abilities of the US ETF and mutual fund are superior to their EM ETF and mutual fund counterparts. This discrepancy in tracking can be attributed to higher transaction costs in the emerging markets and geographical time-zone differences between the funds and the underlying securities.

Thereafter, I evaluated the daily return errors for all the funds by determining the difference between the daily NAV and index returns. For the ETFs, I also calculated the daily return errors by subtracting the daily index returns from the price returns. I put together the descriptive statistics for the daily tracking errors to gain a better understanding of the index-tracking abilities of the ETFs in comparison to their mutual fund counterparts. I tested the daily return errors for serial correlations. Moreover, I assessed the root mean square error (RMSE), which in turn is also known as the tracking error (TE), for each fund. Thus, a mean-variance analysis was applied to measure each bond ETF return's deviation from its respective index return. I used equations (5) and (6) to quantify the tracking errors, which stem from a generally-applied definition in academic literature (e.g., Markowitz (1987); Roll (1992)) that tracking error is the standard deviation between the fund's returns ($r_{NAV,t}$ or $r_{Price,t}$) and that of the benchmark index returns ($r_{Index,t}$) over time.

(5) $$TE = \sqrt{\sum_{t=1}^{N}(r_{NAV,t} - r_{Index,t})^2/N}$$

(6) $$TE = \sqrt{\sum_{t=1}^{N}(r_{Price,t} - r_{Index,t})^2/N}$$

Findings

The results of the above-mentioned analysis are displayed in Table 2. It is apparent that the iShares Core U.S. Aggregate Bond ETF using its NAV and price (columns 1 and 2, respectively) and the iShares U.S. Aggregate Bond Index Fund (column 3) have lower tracking errors (RMSE) than the iShares J.P. Morgan USD Emerging Markets Bond ETF using its NAV and price (columns 4 and 5, respectively) and the T. Rowe Price Emerging Markets Bond Fund (column 6). This is in line with our observations above. For both the US and the EM, the ETF NAV has the smallest tracking error, the ETF price has the largest tracking error and the mutual fund NAV is in the middle of the two.

COINTEGRATION TESTS

Next, I checked whether the price and NAV of the ETFs in this study are cointegrated. Given that the prices and NAVs are the values of the same assets in a given ETF, it would be logical to assume that they are cointegrated processes. If arbitrage exists to correct any deviations of the price from the NAV, this difference is a stationary process. Thus, the system of prices, NAVs and differences between the two is expected to be a cointegrated system and the Price – NAV difference characterizes the error correction term.

A two-step approach to testing for cointegration between price and NAV was followed. First, the augmented Dickey-Fuller (ADF) test was performed to determine the time series properties of each variable based on unit root tests. The ADF test is based on regression specification (7) with the inclusion of a constant and a trend.

$$\Delta Y_t = \alpha_0 + \lambda t + \tau Y_{t-1} + \sum_{j=1}^{m} \alpha_j \Delta Y_{t-j} + \varepsilon_t \quad (7)$$

where

$\Delta Y_t = Y_t - Y_{t-1}$ and Y_t – the variable under consideration (i.e. $Price_t$ or NAV_t)

t – linear time trend

m – the number of lags in the dependent variable that generates a white noise error term to account for higher-order serial correlation, achieved by minimizing Akaike's Information Criterion (AIC)

ε_t – the stochastic error term.

The stationarity of the variable is tested using H_0: $|\tau| = 1$ and H_1: $|\tau| < 1$. The critical values of the ADF statistic as described in MacKinnon (2010) were used to test this hypothesis. H_0 was not rejected if a time series was non-stationary i.e. taking first or higher order differencing of Y_t was necessary to achieve stationarity.

Next, having tested the stationarity of each time series, I looked for cointegration between the price and NAV of each ETF using the Engle-Granger two-stage procedure. Initially, I tested both variables for unit roots and estimated two cointegration regressions between price and NAV using OLS. Then, I tested the stationarity of the error processes of the two cointegration regressions generated in the first step. According to Engle and Granger (1987), there must be an error-correction model representation present where the errors are corrected as the system moves toward the long-run equilibrium if $Price_t$ and NAV_t are cointegrated. This is represented by regression specifications (8) and (9).

(8) $\Delta NAV_t = \theta_0 + \sum_{j=1}^{m} \theta_{1j} \Delta\, Price_{t-j} + \sum_{j=1}^{m} \theta_{2j} \Delta NAV_{t-j} + \delta F_{t-1} + \varepsilon_{1t}$

(9) $\Delta Price_t = \varphi_0 + \sum_{j=1}^{m} \varphi_{1j} \Delta\, NAV_{t-j} + \sum_{j=1}^{m} \varphi_{2j} \Delta Price_{t-j} + \omega G_{t-1} + \varepsilon_{2t}$

where

F_{t-1} and G_{t-1} – the error-correction terms

ε_{1t} and ε_{2t} – the stochastic error terms

If the error-correction models given in equations (8) and (9) are sound, the coefficients δ and ω capture the adjustments of ΔNAV_t and $\Delta Price_t$ towards long run equilibrium, NAV_{t-j} and $\Delta Price_{t-j}$ describe the short run dynamics and the $Price_t$ and NAV_t series are cointegrated.

Findings

Tables 3 and 4 present the results of unit root tests obtained using the augmented Dickey-Fuller test and the Engle-Granger two-step cointegration procedure to determine whether the NAV and price are cointegrated for both ETFs. The evidence in Table 3 confirms the presence of unit roots in all the series. For both ETFs, the two series are I(1) given that the null hypothesis of a unit root in the first difference is rejected in favor of the alternative hypothesis that the series, in first difference, are stationary. In the Engle-Granger two-step cointegration procedure, the results of the ADF test applied to the residuals of the cointegration equations suggest evidence of cointegration between NAV and price in both the US and EM bond ETFs. Thus, these results show that NAV and price for both ETFs will follow the same path in the long-run, which confirms my initial idea that long-run returns must be close to equal.

TIME SERIES REGRESSION ANALYSIS

Next, I ran a number of time series regressions to delve deeper into the tracking abilities of ETFs and discover what influences the daily price changes and price to NAV mispricing of the US and EM ETFs in this paper.

N.B. I was concerned about the autocorrelation in the residuals of my regression analysis because I wanted to make sure my coefficients were significant, and the standard error was not underestimated. Consequently, I conducted the Durbin-Watson test. The Durbin-Watson statistics for all my regressions were close to 2 (value of 2 implies no autocorrelation) and therefore no adjustments were made to the data to correct for serial correlation of the residuals.

(i) Initially, I explored whether the change in NAV of an ETF tomorrow is impacted not only by the change in the level of the respective index but also by the price

error relative to NAV today. To see whether there is information priced in today that may tell us about the change in NAV tomorrow, I used regression specification (10) to test this idea on both ETFs. I assumed that in the case that the β coefficient in the regression specification is positive, this would suggest that the price is forward-looking and predictive of the NAV tomorrow.

(10) $$\Delta NAV_{t+1} = \alpha \Delta INDEX_{t+1} + \beta(P_t - NAV_t) + \gamma$$

Findings

Column 1 in Table 5 suggests that the price today is not foretelling of the NAV change tomorrow for the iShares Core U.S. Aggregate Bond ETF (AGG) because the β coefficient is not statistically significant. Nevertheless, for the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB) the hypothesis is confirmed. The β coefficient for the $(P_t - NAV_t)$ variable in column 2 of Table 5 is positive and significant at the 1% significance level. As mentioned above, this implies that the change in NAV tomorrow is not only the change in the Index tomorrow but also in part the price difference relative to NAV today. In other words, the price today is predictive of the NAV change tomorrow for the EM ETF. It is likely that this can partially be explained by the fact the underlying markets are geographically located in time zones which are different from the ones in which the ETFs trade. Thus, for example, today's prices in the US for instruments comprised of foreign securities reflect the effects of events in the world today that may take place after the foreign markets have already closed.

(ii) I also investigated whether the price change tomorrow is predicted not only by the change in NAV tomorrow but also by the price error to NAV today. I used regression specification (11) to study this point with respect to both ETFs. I was

keen to see if price of an ETF tomorrow adjusts as a result of its price error today. A negative α coefficient between 0 and -1 would suggest that a positive price to NAV difference today would be corrected in the price change tomorrow i.e. the pricing error would be going away.

(11) $$\Delta P_{t+1} = \alpha(P_t - NAV_t) + \beta \Delta NAV_{t+1} + \gamma$$

Findings

Table 6 implies that there is indeed a relationship between the price to NAV difference today and the change in price tomorrow. The α coefficients are negative, less than zero, greater than -1, and significant at the 1% significance level for both the iShares Core U.S. Aggregate Bond ETF (Column 1) and the iShares J.P. Morgan USD Emerging Markets Bond ETF (Column 2). When there is a price to NAV discrepancy today, it is in part (~2/3) corrected in the change in price tomorrow, which bodes well for the tracking ability of both ETFs.

(iii) In a similar manner, I wanted to investigate the relationship between the price error relative to NAV tomorrow and that of today. I used regression specification (12) to achieve this goal. A positive α coefficient less than 1 would suggest that today's pricing error is declining tomorrow. The coefficient value would represent what fraction of the price to NAV discrepancy today goes away tomorrow.

(12) $$(P_{t+1} - NAV_{t+1}) = \alpha(P_t - NAV_t) + \gamma$$

Findings

Table 7 has the results for the regression specification (12). Both the α coefficients for the iShares Core U.S. Aggregate Bond ETF (Column 1) and the iShares J.P. Morgan USD Emerging Markets Bond ETF (Column 2) are positive and below 1. These indicate that pricing error today does partially go away tomorrow for both ETFs. However, given that only a fraction of the mispricing today is corrected tomorrow, this suggests that not all of the price to NAV difference is noise and price may tell us something about the future (this is reconfirmed in the previous two regressions). Moreover, the α coefficient for the EM ETF is greater than that for the US ETF and this alludes to the fact that a larger fraction of the mispricing error today is corrected tomorrow in the former. This phenomenon makes sense given that foreign bonds trade outside the United States creating informational lags that can generate larger price to NAV errors that are addressed the following trading day.

(iv) One of the advantages of bond ETFs is that they trade in a similar manner to stocks on exchanges. As a result, I decided to analyze using regression specification (13) whether stock market fluctuations affect the change in price of the ETFs given the equity-like properties of the latter. As noted earlier, I used the daily changes in the S&P 500 index as a proxy for the day-to-day variations in the stock market. A positive δ below 1 would demonstrate that a change in price of an ETF tomorrow is not only affected by the change in NAV tomorrow and the price to NAV mispricing today, but also by the stock market fluctuations tomorrow.

(13) $$\Delta P_{t+1} = \alpha(P_t - NAV_t) + \beta \Delta NAV_{t+1} + \delta \Delta SP_{t+1} + \gamma$$

Findings

The results in Table 8 confirm the existence of a relationship between fluctuations in the stock market and ensuing changes in the prices of bond ETFs in this paper. The δ coefficients for both the iShares Core U.S. Aggregate Bond ETF (Column 1) and the iShares J.P. Morgan USD Emerging Markets Bond ETF (Column 2) are positive.[2] Both δ coefficients are statistically significant at the 1% significance level, which suggests that the finding is robust and that stock market fluctuations do in fact have a weighty effect on bond ETFs.

(v) It is well known that bond prices and interest rates have an inverse relationship. Therefore, if interest rates have an effect on the NAV of ETFs, they may have an additional effect on the price of the ETFs also. Using regression specification (14), I studied whether a change in price of an ETF tomorrow is not only affected by the change in NAV tomorrow and the price to NAV mispricing today, but also by the change in interest rates tomorrow. I used the daily fluctuations in the 10-YR Treasury Rate as a proxy for the daily interest rate changes given the weighted average maturity of the two ETFs, as described in the DATA section of this paper.

$$\Delta P_{t+1} = \alpha(P_t - NAV_t) + \beta\Delta NAV_{t+1} + \delta\Delta IR + \gamma \quad (14)$$

Findings

Table 9 reveals interesting findings with regards to the effect of interest rates on the prices of ETFs. Counterintuitively, the δ coefficient in column 1 suggests that when interest rates rise, there are significant (at 1% level), positive effects on the price changes of the iShares Core U.S.

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[2] AGG: $\sigma_{\Delta S\&P}$ ~18, $\sigma_{\Delta P}$ ~ 0.22; EMB: $\sigma_{\Delta S\&P}$ ~18, $\sigma_{\Delta P}$ ~0.44

Aggregate Bond ETF (AGG). On the other hand, the δ coefficient in column 2 is negative and posits that a positive interest rate change will have an additional negative effect on the change in price of the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB). Further research is necessary to understand fully how interest rates influence the prices of bond ETFs.

(vi) Subsequently, I looked at the effect of the volatility of the underlying benchmark index on the price to NAV mispricing using regression specification (16) for each ETF. My hypothesis was that the price to NAV mispricing may be greater when the index itself is more volatile because it may be more challenging to track it. I expected the α coefficient to be positive in this scenario. The volatility of the index for each day was calculated using the information for the previous 20 trading days of the index using equation (15).

(15)
$$\sigma_{I,t} = \sqrt{\sum_{t-19}^{t} r_{Price,t}^{2} / N} \times \sqrt{\#\ of\ observations\ in\ a\ year}$$

(16)
$$|P_t - NAV_t| = \alpha \sigma_{I,t} + \gamma$$

Findings

The α coefficient on $\sigma_{I,t}$ in Column 1 of Table 10 is not statistically significant and therefore does not support the idea that volatility in the Bloomberg Barclays US Aggregate Bond index leads to greater price to NAV mispricing for the iShares Core U.S. Aggregate Bond ETF (AGG). Nevertheless, the α coefficient on $\sigma_{I,t}$ in Column 2 of Table 10 is positive and significant at the 1% significance level. This backs the idea that volatility in the J.P. Morgan Emerging Markets

Bond index has an effect on the daily price to NAV mispricing of the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB). This effect can be attributed to the fact that trading costs can be higher in the EM and consequently higher volatility in the underlying index results in greater tracking errors.

(vii) The iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB) tracks the J.P. Morgan Emerging Markets Bond index which only incorporates dollar-denominated bonds. However, as mentioned earlier, previous studies have shown that foreign fixed-income dollar-denominated securities can indirectly be affected by changes in the currency exchange rates e.g., increased likelihood of financial distress due to debt dollarization (Delikouras, et al. 2015). Thus, if changes in currency exchange rates affect bonds, and consequently the NAV of ETFs, they may have an additional impact on the price of ETFs. Consequently, for the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB), I looked into whether the price change tomorrow is affected by the fluctuations in foreign currency exchange rates using regression specification (19). As previously mentioned, I used the Trade Weighted U.S. Dollar Index (Emerging Markets Economies, Goods and Services) as a proxy for the fluctuating exchange rates in the emerging markets.

(17) $$\Delta P_{t+1} = \alpha(P_t - NAV_t) + \beta\Delta NAV_{t+1} + \delta\Delta FX_{t+1} + \gamma$$

<u>*Findings*</u>

The δ coefficient on ΔFX_{t+1} in table 11 is negative and statistically significant at the 1% significance level. This implies that a positive increase in the Trade Weighted U.S. Dollar Index (Emerging Markets Economies, Goods and Services) i.e. a stronger dollar tomorrow has a negative effect on the change in price of the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB) tomorrow. This reinforces the idea discussed above that currency exchange rate fluctuations affect foreign dollar-denominated bonds and the price of ETFs that include such financial instruments.

V. CONCLUSION

In this paper, I examine the existence and determinants of tracking errors for bond ETFs, specifically the iShares Core U.S. Aggregate Bond ETF (AGG) and the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB). For comparative purposes, I initially juxtapose them with their respective closed-end mutual funds, the iShares U.S. Aggregate Bond Index Fund and the T. Rowe Price Emerging Markets Bond Fund (PREMX), which track the same indices respectively. I find that all funds underperform their indices, which is consistent with previous literature. However, my analysis suggests that ETF NAV produces the smallest tracking error, the mutual fund NAV is second best, and the ETF price has the largest tracking error of the index. I also find that tracking errors for the EM funds are significantly greater than those of their US counterparts.

Next, I find that the NAV and price are cointegrated for both ETFs. The results suggest that the long-run returns for both must be close to equal. Thereafter, I run a number of time series regressions to delve deeper into the tracking abilities of ETFs and determine what influences the daily price changes and price to NAV mispricing of the US and EM bond ETFs. I conclude that for the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB), the price today is predictive of the NAV change tomorrow but this is not the case for the iShares U.S. Aggregate Bond Index Fund (AGG). I discover for both ETFs that when there is a price to NAV discrepancy today, it is in part (~2/3) corrected in the change in price tomorrow, which bodes well for the tracking ability of both ETFs. In a similar manner, I observe that price to NAV error today makes up only a part of the price to NAV error tomorrow for both ETFs. However, given that only a fraction of the mispricing today is corrected tomorrow, this again suggests that not all of the price to NAV difference is noise and price may tell us something about the future. Moreover, a larger fraction of the mispricing error today is corrected tomorrow in the EM ETF vs. the US ETF. This phenomenon makes sense given that foreign bonds which make up the EM ETF trade outside the United States creating informational lags that can generate larger price to NAV errors that are addressed the following trading day.

My findings likewise confirm the existence of a relationship between fluctuations in the stock market and the subsequent changes in the prices of bond ETFs. This is understandable given the equity-like properties of the bond ETFs. Afterwards, I find that when interest rates increase, there are significant, positive effects on the price changes of the iShares Core U.S. Aggregate Bond ETF (AGG) but negative effects on the price changes of the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB).

Furthermore, I establish that volatility in the J.P. Morgan Emerging Markets Bond index has an effect on the daily price to NAV mispricing of the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB). There is no evidence to support that this relationship exists between the Bloomberg Barclays US Aggregate Bond Index and the iShares U.S. Aggregate Bond Index Fund (AGG).

Finally, a positive change in the FX of foreign currencies i.e. a stronger dollar tomorrow has a negative effect on the change in price of the iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB) tomorrow. Though, the J.P. Morgan Emerging Markets Bond index only incorporates dollar-denominated bonds, previous studies have shown that foreign fixed-income dollar-denominated securities can indirectly be affected by changes in the currency exchange rates. Thus, my analysis confirms that changes in currency exchange rates affecting bonds, and consequently the NAV, have an additional impact on the price of the EM ETF in this study.

Going forward, it makes sense to conduct an extended analysis including a larger sample of bond ETFs, both in the developed and developing countries, to underpin the findings generated in this study.

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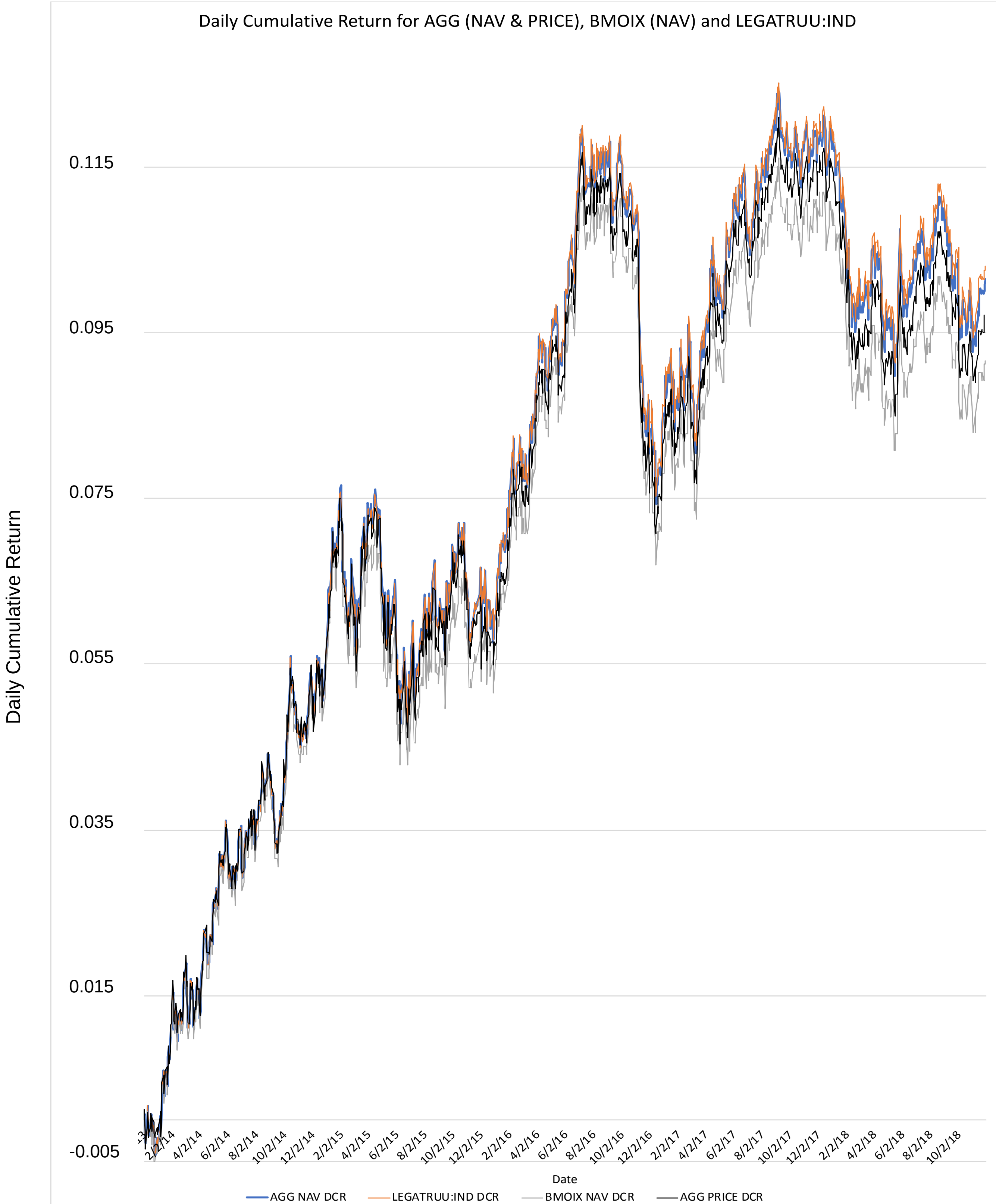
Graph 1: Daily Cumulative Return for AGG (NAV & PRICE), BMOIX (NAV) and LEGATRUU:IND



Graph 2: Daily Cumulative Return for EMB (NAV & PRICE), PREMX (NAV) and EMBI:IND

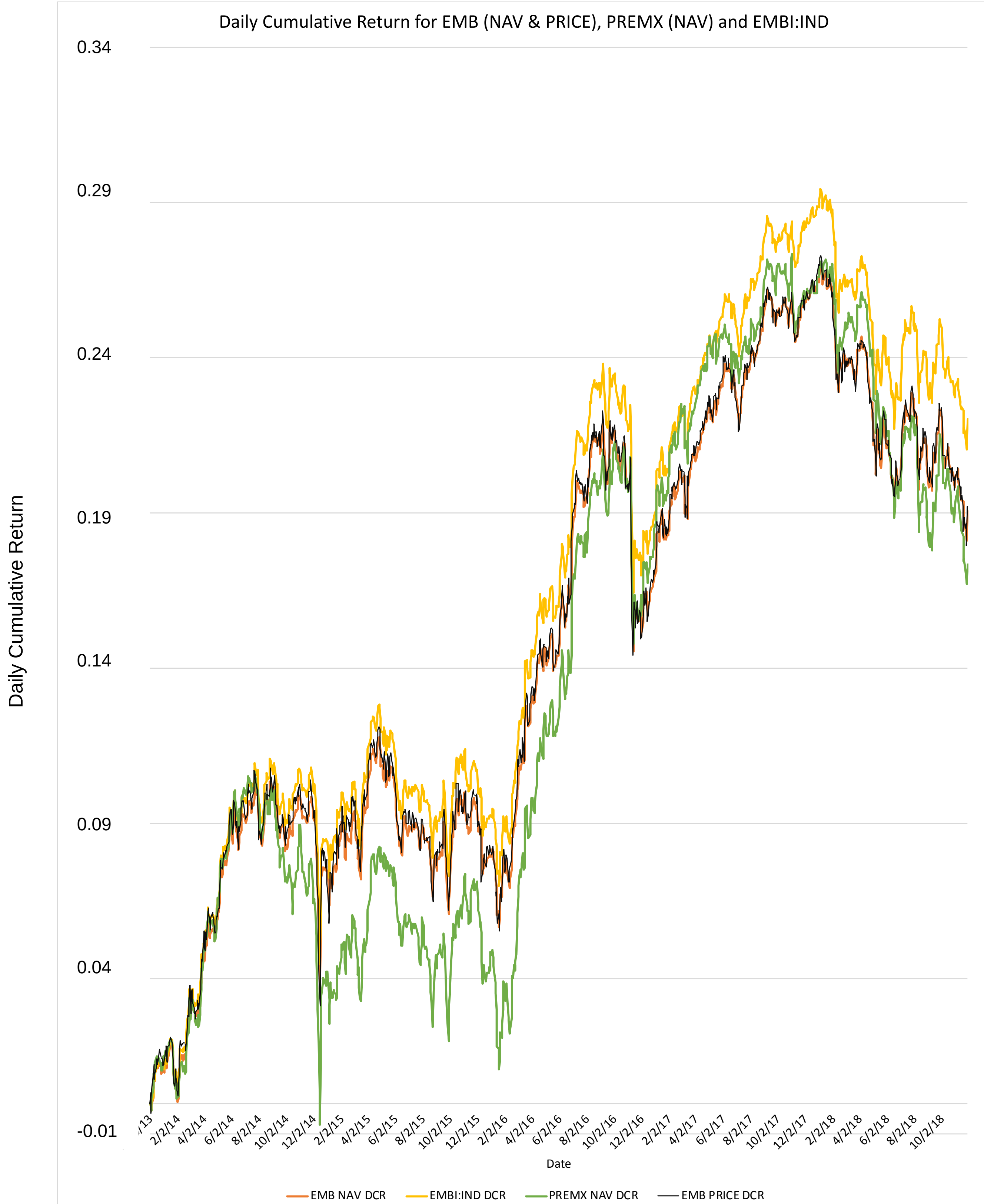


Table 2: Summary Statistics – Return and Tracking Errors

	AGG		BMOIX	EMB		PREMX
	e(I - NAV)	e(I - P)	e(I-NAV)	e(I - NAV)	e(I - P)	e(I-NAV)
Mean	1.319E-06	4.602E-06	9.241E-06	2.411E-05	2.376E-05	3.444E-05
Median	2.144E-06	1.948E-05	6.563E-06	3.282E-05	5.537E-06	1.866E-04
Standard Deviation	5.981E-05	7.882E-04	4.185E-04	2.465E-04	2.315E-03	1.630E-03
Kurtosis	4.028E+01	1.336E+00	-2.854E-01	1.824E+00	9.911E+00	3.929E+00
Skewness	-1.556E-01	4.939E-02	8.615E-03	-3.260E-01	5.913E-02	-9.349E-01
Minimum	-6.113E-04	-3.727E-03	-1.178E-03	-1.421E-03	-1.907E-02	-8.278E-03
Maximum	7.353E-04	3.440E-03	1.492E-03	1.015E-03	1.995E-02	7.758E-03
Count	1250	1250	1248	1234	1234	1235
Corr(Et, Et-1)	-4.335E-01	-4.754E-01	-4.615E-01	-9.130E-02	-3.875E-01	6.750E-03
RMSE	5.980E-05	7.879E-04	4.184E-04	2.476E-04	2.314E-03	1.629E-03

NOTES to TABLE 2:
AGG – iShares Core U.S. Aggregate Bond ETF
BMOIX – iShares U.S. Aggregate Bond Index Fund
EMB – iShares J.P. Morgan USD Emerging Markets Bond ETF
PREMX - T. Rowe Price Emerging Markets Bond Fund
e(I – NAV) – the daily error term calculated as the difference between level of Index and fund NAV
e(I – P) – the daily error term calculated as the difference between level of Index and fund price
Time Period: 12/02/2013 – 11/30/2018
Kurtosis reported is not excess kurtosis

Table 3: Augmented Dickey-Fuller Tests and Engle-Granger Two-Step Procedure for Cointegration – iShares Core U.S. Aggregate Bond ETF (AGG)

ADF Tests

	X var	Y var	X diff	Y diff
tau-stat	-2.0011411	-2.0919177	-26.763571	-14.500565
tau-crit	-3.4137244	-3.4137244	-3.413727	-3.413727
stationary	no	no	yes	yes
aic	-0.2105469	-0.2230012	-0.2089329	-0.216535
bic	-0.1899968	-0.210687	-0.1924929	-0.1794252
lags	2	0	1	6
coeff	-0.007216	-0.0073922	-1.0966803	-1.1650231
p-value	> .1	> .1	< .01	< .01

Engle-Granger Test

alpha	0.05
type	2
max lags	11
criteria	aic

tau-stat	-8.8667698
tau-crit	-3.7881801
cointegrated	yes
lags	11
p-value	< .01

Table 4: Augmented Dickey-Fuller Tests and Engle-Granger Two-Step Procedure for Cointegration – iShares J.P. Morgan USD Emerging Markets Bond ETF (EMB)

ADF Tests

	X var	Y var	X diff	Y diff
tau-stat	-2.7778578	-2.7959252	-19.861097	-15.37246
tau-crit	-3.4137664	-3.4137664	-3.4137691	-3.4137691
stationary	no	no	yes	yes
aic	0.59281532	1.17400855	0.59805037	1.17737727
bic	0.61357991	1.19894234	0.61882853	1.21068764
lags	2	3	2	5
coeff	-0.007445	-0.0100038	-0.7963381	-1.0404073
p-value	> .1	> .1	< .01	< .01

Engle-Granger Test

alpha	0.05
type	2
max lags	11
criteria	aic

tau-stat	-11.387424
tau-crit	-3.7882788
cointegrated	yes
lags	4
p-value	< .01

Table 5: Regression-Based Tests – Specification (10)

	AGG: (ΔNAV_{t+1})	$EMB(\Delta NAV_{t+1})$
$(\Delta INDEX_{t+1})$	0.055*** (740.848)	0.223*** (305.345)
$(P_t - NAV_t)$	0.001 (0.205)	0.012*** (2.798)
Intercept	0.000	-0.005
R^2	0.997	0.989
# of Observations	1250	1234
Durbin-Watson Statistic	2.454	1.853

***, ** and * denote significance at the 1%, 5% and 10% level respectively. t-statistics are shown in parentheses. P-values and t-statistics are based on heteroskedasticity- and autocorrelation-robust standard errors following Arellano (1987).

Table 6: Regression-Based Tests – Specification (11)

	AGG: (ΔP_{t+1})	EMB: (ΔP_{t+1})
$(P_t - NAV_t)$	-0.653*** (-20.864)	-0.688*** (-24.158)
(ΔNAV_{t+1})	0.954*** (85.630)	1.246*** (58.757)
Intercept	0.037	0.199
R^2	0.856	0.737
# of Observations	1250	1234
Durbin-Watson Statistic	2.142	2.142

***, ** and * denote significance at the 1%, 5% and 10% level respectively. t-statistics are shown in parentheses. P-values and t-statistics are based on heteroskedasticity- and autocorrelation-robust standard errors following Arellano (1987).

Table 7: Regression-Based Tests – Specification (12)

	AGG: $(P_{t+1} - NAV_{t+1})$	EMB: $(P_{t+1} - NAV_{t+1})$
$(P_t - NAV_t)$	0.329*** (10.556)	0.446*** (16.257)
Intercept	0.038	0.160
R^2	0.082	0.177
# of Observations	1250	1234
Durbin-Watson Statistic	2.150	2.131

***, ** and * denote significance at the 1%, 5% and 10% level respectively. t-statistics are shown in parentheses. P-values and t-statistics are based on heteroskedasticity- and autocorrelation-robust standard errors following Arellano (1987).

Table 8: Regression-Based Tests – Specification (13)

	AGG: (ΔP_{t+1})	EMB: (ΔP_{t+1})
$(P_t - NAV_t)$	-0.662*** (-21.390)	-0.659*** (-23.641)
(ΔNAV_{t+1})	0.972*** (85.030)	1.186*** (54.321)
(ΔSP)	0.001*** (5.825)	0.003*** (8.464)
Intercept	0.037	0.188
R^2	0.860	0.752
# of Observations	1249	1233
Durbin-Watson Statistic	2.149	2.139

***, ** and * denote significance at the 1%, 5% and 10% level respectively. t-statistics are shown in parentheses. P-values and t-statistics are based on heteroskedasticity- and autocorrelation-robust standard errors following Arellano (1987).

Table 9: Regression-Based Tests – Specification (14)

	AGG: (ΔP_{t+1})	EMB: (ΔP_{t+1})
$(P_t - NAV_t)$	-0.686*** (-21.387)	-0.683*** (-23.975)
(ΔNAV_{t+1})	1.211*** (19.614)	1.237*** (57.528)
(ΔIR)	1.322*** (4.230)	-0.377*** (-2.384)
Intercept	0.037	0.197
R^2	0.858	0.738
# of Observations	1249	1233
Durbin-Watson Statistic	2.120	2.145

***, ** and * denote significance at the 1%, 5% and 10% level respectively. t-statistics are shown in parentheses. P-values and t-statistics are based on heteroskedasticity- and autocorrelation-robust standard errors following Arellano (1987).

Table 10: Regression-Based Tests – Specification (16)

	AGG: ($\lvert P_t - NAV_t \rvert$)	EMB: ($\lvert P_t - NAV_t \rvert$)
$\sigma_{I,t}$	-0.028	0.809*** (2.695)
Intercept	0.087	0.309
R^2	0.000	0.006
# of Observations	1231	1215
Durbin-Watson Statistic	1.594	1.358

***, ** and * denote significance at the 1%, 5% and 10% level respectively. t-statistics are shown in parentheses. P-values and t-statistics are based on heteroskedasticity- and autocorrelation-robust standard errors following Arellano (1987).

Table 11: Regression-Based Tests – Specification (17)

	EMB: (ΔP_{t+1})
($P_t - NAV_t$)	-0.679*** (-23.687)
(ΔNAV_{t+1})	1.193*** (48.710)
(ΔFX_{t+1})	-0.088*** (-4.270)
Intercept	0.198
R^2	0.741
# of Observations	1221
Durbin-Watson Statistic	2.147

***, ** and * denote significance at the 1%, 5% and 10% level respectively. t-statistics are shown in parentheses. P-values and t-statistics are based on heteroskedasticity- and autocorrelation-robust standard errors following Arellano (1987).