Are there pricing spillovers within ETFs? Evidence from Emerging Market Corporate Bonds

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Are there pricing spillovers within ETFs? Evidence from Emerging Market Corporate Bonds [*]

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Abstract

Financial theories implicitly predict that the entry of a new security into an exchange-traded fund (ETF) could impact the price of the other constituents of that ETF. We test these theories using data from Emerging Market corporate bonds between 2012 and 2017. We find that the inclusion of a new bond into the ETF lowers the relative price of constituent bonds that were ex-ante similar to the entrant. Additionally, we find that part of this effect tends to be transitory. These facts also hold with most alternative measures of bond similarity and proxies for returns. Additionally, the effect is stronger for less liquid bonds and when the short-run ability to absorb this entry shock is more limited. In sum, part of the fall in prices might be consistent with price-pressure models (e.g. Duffie, 2010)

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Key Words: Exchange-Traded Funds (ETFs), Segmented markets, liquidity, corporate debt, Emerging Markets, i-Shares

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1. Introduction

Recently, Financial Economics has explored the evolution of assets within Exchange-Traded Funds (ETFs), for example in terms of pricing, risk, liquidity, portfolio allocation, and issuance (see Ben-David et al, 2018; Bhattacharya and O'Hara, 2017; Agapova et al, 2018). In this debate, however, the literature has been silent about spillovers from one asset to another within each ETF. Specifically, on how the entry of a new asset impacts the prices of other assets in the fund. This gap is important because it could speak to potential avenues of contagion within EFTs (see Pagano et al, 2019). Our paper measures this cross-asset effect, using the context of Emerging Market Corporate bonds.

In theory, including an asset into an ETF could impact not only its own-price but also the prices of other similar assets in the bundle. The theoretical predictions are nonetheless ambiguous. The effects may be permanent, as predicted by models of equilibrium repricing, downward-sloping demand curves (e.g. Barberis and Shleifer, 2003), or informativeness (Ben-David et al, 2018). Alternatively, the effects could be transitory, as argued by liquidity-based models of price pressure (e.g. Duffie, 2010) and inventory risk (Friewald and Nagler, 2018).

To explore these issues, we conduct a joint event study on the inclusion of 177 bonds into the i-Shares Emerging Market Corporate Bonds ETF between its inception in 2012, and until 2017. We look at the differential impact of the additions on the bonds that were already in the fund, depending on their similarity to the entrant. We find that there is an economically and statistically significant impact. In the month of the inclusion, the price of bonds with high covariance with the entrant security falls by around 95 basis points relative to the ones with low covariance; where highly similar bonds have covariance above one standard deviation from the mean, while low similarity corresponds to one standard deviation below the mean. We find that part of this cross-security effect is transitory. Moreover, the impact is stronger for less liquid bonds and when there is little short-run ability to absorb this entry shock. At least some of the observed effect is coherent with models of price-pressure due to binding short-run liquidity, including models remarking the inventory risk of financial intermediaries.

The main result is robust to using other similarity measures instead of the covariance of past returns, like the correlation and the bi-variate elasticity of returns between bonds. Some results were qualitatively consistent when, instead of covariances, we used common bond characteristics. For instance, when a pair of bonds came from the same country and industry.

Emerging Market´s corporate bonds are a relevant sub-asset class that has expanded at an enormous pace, with total issuance being now as large as the high-yield bond market in the U.S. or the Emerging Market sovereign bond market (see ISOCO, 2019). Besides this increasing relevance, there are also a few methodological advantages of the specific ETF we use. First is that within this single ETF we can have different countries with heterogeneous characteristics, enabling the use of the above-mentioned measures of similarity (e.g. common country). Bonds have advantages over stocks, as well. For fundamental reasons, fixed income securities tend to be less volatile. This makes it easier to detect non-fundamental pricing effects (e.g. due to price pressure), if there are any. Also, looking at cross effects in bonds extends what the literature learned about these cross effects in stocks. The niche of Emerging Market corporate debt has another crucial advantage when considered as a partially segmented market. Namely that these bonds are fewer, meaning that each new addition is large *vis-á-vis* the market of reference. Indeed, as a fraction of the entire Emerging corporate debt market, the typical bond being added in our data is about 25 times larger than Apple´s 2019 $7 billion issuance. This large relative size would make it easier to detect a potential effect. Finally, despite being widely traded, when looking at monthly frequency these corporate bonds also display heterogeneous levels of liquidity. This variation allows for additional tests across assets, helping to dig deeper into the channels mediating cross-asset effects.

Various papers show that becoming part of an index is not innocuous for a security (Shleifer; 1986; Barberis et. al, 2005; Greenwood, 2008; Wurgler, 2011). A usual argument is that many funds follow indices and, therefore, the demand for a security increases when it is added to such indicators. If for some reason demand is not perfectly elastic, then this index-inclusion may influence pricing. Because of their increasing size and the fact that most of them track indices, ETFs are a natural new setting to explore these issues.

Research on ETFs started with equity, exploring pricing (see, Hedge and McDermott, 2004; Hamm, 2014; Israeli et.al, 2019), volatility (Ben-David et.al, 2018), and co-movement (Da and Shive, 2018). A more recent strand of the literature has moved into bonds. Within the bond-ETF literature, there are at least two views regarding pricing and liquidity. In theory, ETFs have the advantage of providing liquidity, which can lead to greater price discovery (as in Grossman, 1989). On the other hand, the same ability to trade the funds at high frequency could depress the liquidity of the underlying assets, increase their volatility, and potentially generate contagion (Pagano et al, 2019). There is evidence on both the bright and the dark side. Danhauser (2017) shows that bonds with more ETF ownership tend to have lower spreads and that this is partly due to higher liquidity in both high-yield and investment-grade bonds. But noise trading in the ETF can introduce non-fundamental increases in the volatility of underlying stocks (Ben-David et al, 2018; Chinco and Fos, 2019), perhaps especially when the underlying assets are hard to trade (Krause et al, 2013; Bhattacharya and O'Hara, 2017). They can also increase price fragility due to information linkages (Bhattacharya and O'Hara, 2017; Agapova et al, 2018). As mentioned before, this literature focuses on whether being part of the ETF influences the newly included security.[1]

Our contribution is to document cross-asset effects within ETFs. The small existing literature on these cross-security effects focused mostly on stocks and stock indices, instead of corporate bonds or ETFs (Braun and Larrain, 2009; Chan et al, 2012; Shi et al, 2018). The paper closest to our work is Newman

[1] Also, some papers look at how the inception of the ETF impacts the underlying markets, as in commodities or real estate investment trusts (e.g. Beckmann et al, 2020).

and Rierson (2003) in the sub-niche of fixed income for European Telecoms. Our contribution is to bring some of these insights into the context of ETFs and to Emerging Markets. [2] Moreover, our multi-region and multi-sector approach is more general than the previously mentioned paper.

The rest of the paper is structured as follows. Section 2 discusses various theoretical predictions. Section 3 presents the data and methodology. In section 4 we estimate the cross-bond effects after a new constituent enters the ETF. Section 5 explores the heterogeneity of the response, while section 6 concludes with a few remarks.

2. What do existing theories predict?

Here we discuss the various theoretical frameworks behind cross-bond effects after a new bond enters the reference market. These explanations do not need to be mutually exclusive in their mechanisms, but they are a useful guide to organize our subsequent empirical analysis.

A common prediction across the various models, summarized in Table 1, is that the price of assets that are like the new entrant will be depressed after the entry event. However, the various models do have other differential predictions.

[2] There are also anecdotes of cross-price effects. For example, when a new bond from the same issuer comes to the market, like in April 2019, when Saudi Aramco launched its first corporate bond. Subsequently, the "sovereign Saudi dollar bonds had their biggest daily decline since early March of that year" (Thomson Reuters; Barbuscia 2019).

Table 1. Summary of the families of theoretical models and their predictions after the entry of a new asset to the relevant market.

Family of Models	**Prediction for entry**
Flat bond demand curve that shifts (e.g. CAPM). **General equilibrium**	*Permanent* negative impact of entry on the prices of similar bonds.
Downward sloping demand stemming from limits to arbitrage (and partial equilibrium). (e.g. Shleifer, 1986; Kaul, Mehrotra, and Morck, 2003)	*Permanent* negative impact of entry on the prices of similar bonds.
Price Pressure due to liquidity (e.g. Duffie, 2010).	*Transitory* negative impact of entry on the prices of similar bonds. Effect is stronger when liquidity is more constrained.
Information from securities outside the index, which is lost when they join the index. (Durnev et al, 2003; implicitly suggested in Bhattacharya and O'Hara, 2017; Ben-David et al , 2018; Agapova et al, 2018)	*Permanent* negative effect on similar incumbent securities. Effect might be stronger the more informative the entrant bond.

The first family of models follows a general equilibrium argument in a world without market frictions *a la* CAPM. Under standard assumptions (see Merton, 1980; Braun and Larraín 2009), the price of the assets that constitute a market is given by the covariance between them. The higher the covariance with the average asset – i.e. the market portfolio-, the higher the risk premium, and the lower the price. The entry of a new asset redefines the portfolio of reference. The change in the price of an asset already in the portfolio depends on the sign of the covariance with the entrant. If the covariance is positive, the asset becomes more correlated with the market, and therefore commands a higher premium. On the contrary, if the covariance is negative, the asset becomes a better hedge to the market portfolio, and its price increases[3].

A second possibility is simply that demand curves for each asset are not flat, but instead downward sloping (e.g. Shleifer, 1986). This may happen because of the existence of frictions that restrict arbitrage, meaning that market participants have a limited capacity to bear. The price of an asset in this context is given by the supply of the asset; if supply increases, then the quantity demanded increases and the price falls. This fall in price, in turn, reduces the demand for other substitute assets, and therefore the price of these also falls. The higher the degree of substitutability, the larger the impact. We focus on the covariance, but the slope of the demand may also respond to other characteristics of the asset. For instance, the behavioral literature (e.g. Barberis and Shleifer, 2003) argue that investors tend to allocate their wealth using "investment styles", which may be belonging to the S&P 500 Index, being a growth or value asset, or being part of the same industry or country. Assets of a similar "style" would be the ones that are hit the most by the entry of a new asset. Of course, this mechanism needs arbitrage to be limited somehow. If the probability of inclusion of a bond is uncertain to arbitrageurs, because the actual composition is private information, then the strategy of going short on assets with high covariance with the entrant and long in assets with low covariance would be risky.

Price spillovers can also originate from informational limitations. As ETFs grow, assets are increasingly traded in packages. Some fear that this may lower the quality of the prices of assets inside the fund (Bhattacharya and O'Hara, 2017; Ben-David et al, 2018; Agapova et al, 2018). In the limit, if no trading occurs outside the fund, relative prices among constituents will be undetermined. In that context, and if some arbitrage is possible, then assets outside the fund may serve as anchors to the price of those securities inside. The more similar the asset, the higher the informational advantage of having it traded

[3] There is a second round of effects since the as the price of incumbent assets changes, the market is redefined. Unless the entrant asset is extremely large, this effect is of second order.

outside the fund. When an asset becomes part of the fund, the pricing of similar assets becomes more difficult. This may be considered a risk and induce a higher premium, and consequently a lower price. The implication is, again, that assets like the entrant would fall in price relative to those not so alike. Furthermore, the effect should be larger the more informative the asset entering the fund was when trading outside.

The fourth channel is liquidity, generating a so-called "price pressure" as in Duffie's (2010) Presidential Address (see also, Chacko et al, 2016, Chiu et al, 2012; and Hurlin et al, 2019). When buyers incorporate a new security to their portfolio, they may need to disproportionally sell or buy other preexisting securities at the same time. The degree of the discount may be correlated with the IPO covariance if investors sell similar stocks to finance the acquisition of the new asset. As investors build up liquidity again, then prices of these similar bonds may rebound. Liquidity in the bond market is even more important because these are traded over the counter. Market makers need to hold inventory because search and bargaining are not automatic; this creates inventory risk (Fiewald and Naggle, 2017; Goldstein and Hotchkiss, 2017). If these intermediaries are liquidity constrained, they will have limited risk-bearing capacity and, therefore, care about the characteristics of their portfolio. Note that this trading does not need to be taking place for those that trade the ETF itself, but it might well be made by those traders of individual Emerging Market bonds. Also, anecdotal evidence from practitioners suggests that liquidity relates to the dynamics of inventory and pricing within bond ETFs.[4] Importantly, the crucial difference between this last channel and all the previously discussed ones is that liquidity predicts a *transitory* price movement instead of a permanent one (e.g. Harris and Gurel, 1986; Duffie's,

[4] For example, Bank of America (2019) performed the following experiment: "Instead of exchanging [a basket of] bonds with the ETF, we kept it for customers who might interested in buying the individual bonds at a price. We could have given the bonds to the ETF, but we didn't. After the trade that we didn't do, we tracked the progress of these bonds for two weeks; only 60% had sold. It took a month to sell all the bonds. It takes a long time to liquidate a portfolio of bonds. An ETF trade can do the same thing in an hour, but at a cost." (Bank of America, 2019).

2010; Dick-Nielsen, J. and Rossi, M., 2018; Cespa and Foucault, 2014; Malamud, 2015). This will be important in our testing of sections 4 and 5.

There are other theoretical alternatives. For example, one family of explanations has to do with the industrial organization in the input market or the product market. Obtaining financing via an issuance can improve the competitive position of the issuer *vis-à-vis* its competition, plausibly generating a reduction in the value of the securities that this competitor had issued (e.g Hsu et al, 2010; Hong et al, 2008). But this effect seems less likely to show up in our context for at least three reasons. First is because bonds only reveal company profitability when firms are expected to be under serious financial stress, unlike stocks. And the typical bond in this ETF is not under that much stress. Second, the entry into the ETF is not, by itself, an issuance. In contrast, a portion of this event is anticipated. Third is that here we are dealing with many bonds that come from different emerging markets, so firms tend to compete much less with each other in the product or input market.

We are not claiming the above theories are the only ones that matter for cross-effects of an ETF inclusion. For instance, if the index is value-weighted by the amount outstanding, like most corporate bond ETFs, then the effects of entry might be dependent on weighting. But in our analysis, we control for fixed bonds characteristics and control for the amount outstanding, so we can focus on the above theories, related to similarity with the entrant.

Equipped with the conceptual framework above, we can now move to empirics.

3. Data and Similarity measures

3.1. Sources

Our list of bonds comes from the securities that belong to the ISHARES ™ J.P. Morgan Emerging Market Corporate Bond ETF (CEMB). This ETF started on April 17, 2012 (inception), trading in the secondary market two days later, on April 19. The ETF follows an index that "*includes the most liquid corporate bonds issued in US Dollars (USD) by corporations domiciled in the most prominent emerging markets*."

Additionally, we obtained information on each bond issuance from Bloomberg and Thomson. The sample period goes from June 2012 to June 2017. We get bond prices and yields for the same last day of the month in which EFT portfolios are recorded on the i-Shares website. Our main dependent variable consists of returns calculated from the yield to maturity and the duration at the end of the month.[5] Bid-ask spreads come from Bloomberg.

3.2. Sample Construction and Entry events

We restrict our sample to fixed coupon bonds. This leaves us with 16,866 bond-month observations and 441 unique bonds. Based on that, we built all the possibilities between pairs of bonds. Our estimation sample is then a combination of the triplet defined by {bond i, bond j and monthly time}. Of course, only a fraction of all the theoretical pairs of bonds $\{i, j\}$ had meaningful overlapping in their timespans. For our preferred sample the number of unique bonds in the index grew from 78 to 305. Overall, we measure 177 events of entry of a bond j; with an average of approximately 39 incumbents in each event. The country, industry, and timing of the events are detailed in Table A1 in the Appendix.

3.3. Measures of Bivariate Similarity Across Bonds

[5] In the case of callable bonds, we use the yield to worst (YTW). In the text we will use YTM or YTW interchangeably.

Our empirical exercise requires having a measure of similarity across bonds (a.k.a connectedness; Andrada-Félix et al, 2018). For that purpose, we compute the covariance $\sigma_{i,j}$ between all pairs of overlapping bonds i and j during a timeframe before each bond enters the ETF. We also consider the bivariate elasticity of returns (a.k.a. beta coefficient), and the bivariate correlation coefficient of the previous regression, all using data before the entry of a bond to the ETF and excluding a window of 3 months before the entry event.[6] Importantly, if we were working with issuances instead of inclusions in the ETF then we would not have any data points to estimate these pre-entry covariances.[7]

Using the post-entry covariance would have been problematic since these covariances are jointly determined with the prices of bonds. Indeed, the changes in the composition of the portfolio that lead to changes in these covariances are at the heart of some of the mechanisms we explore. Still, to get a sense of the stability of the similarity coefficients, it is worth looking at the difference between pre-sample and post-sample measures. Figure B1 in the Appendix plots a non-parametric regression of the beta coefficients before and after the sample. As can be seen, the average beta post sample is significantly correlated with the pre-sample one (p-value <0.01). Of course, the correlation is not perfect. Interestingly, the higher bivariate elasticities within each bond-pairs tend to increase after the bond enters the ETF, although on average the before and after correlations remain similar (see Appendix B). It is worth noting that using pre-sample estimated similarities as regressors introduces measurement error. This may dilute our coefficients of interest in section 4, working against finding significant differences.

[6] As measure of similarity we used the bivariate distribution of the changes in YTM or in bond prices, instead of using returns. This was a way to avoid the nuisances of calculating maturities and convexities before bonds joined the ETF. The measures of similarity calculated using the pre-sample changes in YTM or those calculated using the changes in (log) prices have a relevant correlation. For our main exercise we use those based on monthly changes in YTM.

[7] Moreover, we restrict the calculation to time series that have at least 8 datapoints. We acknowledge this is not a large time series, but if any, the errors in the measurement of covariances would push our results against finding significant results.

Another sanity check for our bivariate measures of bond similarity is how they correlate with obvious priors of return co-movement. One would expect that pairs of bonds that come from the same country tend to co-move together. In Table B1 we test this by regressing the cross-bond similarities against a "Same country" indicator, which takes the value one if the two bonds belong to the same country and zero otherwise. The results show that firms of the same country tend to have stronger similarities. For example, they have a beta that is on average 0.15 higher, a correlation coefficient that is 0.2 units larger, and a covariance that is 0.17 units larger than when bonds come from different countries.

For the pre-sample similarities we start after August 2009, to avert the declining phase of the Global Financial Crisis. The pre-sample window ends in $t-5$ months to avoid overlapping with our event window. Subsequently, we estimate the effects strictly after the inception of the ETF (April 2012). This leaves out the mechanical entrance of the "pioneer" bonds that started the ETF. We restrict the estimation to pairs of bonds for which we had at least T=10 observations pre-sample as to compute the covariances σ_{ij}, elasticities ϵ_{ij} and correlation ρ_{ij}.

3.4. Descriptive Statistics of the Sample

Table 2 presents the descriptive statistics of our main estimation sample. The YTM of bonds is 4.4% p. a.; while the average monthly return is minus 0.8%. The amount outstanding is on average \$ 0.9 billion, in a range from 0.2 to 3 billion. The average bond has a duration of 8 years. Importantly, the average covariance with the entrant bond is 0.24, with the standard deviation being a bit more than twice the mean. The average correlation between bonds is close to 0.5 and the average bivariate elasticity is around 0.8. For ease of interpretation, some of our results will be scaled by the standard deviations of σ , ϵ and ρ.

Table 2. Summary statistics

Descriptive statistics of our main estimation sample of incumbent bonds i, including some pairwise similarity measures. For detailed definitions see section 3. YTM is yield to maturity of the bond. Return corresponds to the monthly return. Amount Oust is the amount outstanding in USD, using scientific notation for the order of magnitude. Duration corresponds to the duration in years. Calculation of bivariate similarity measures is on section 3.3. Pairwise similarities are all computed before the event window. They include covariance, correlation and slope or elasticity between bonds.

	Obs	Mean	Std. Dev.	Min	Max
YTM i	6,745	4.4	2.9	-2.3	57.4
Return i	6,745	-0.008	0.047	-0.175	0.193
Amount Oust i	6,745	9.3E+08	4.6E+08	2.3E+08	3.0E+09
Duration i	6,745	8.1	3.4	0.0	12.1
Bivariate similarity measures					
Covariance: i,j	6,745	0.24	0.54	-0.14	4.04
Correlation: ρ i,j	6,745	0.52	0.25	-0.61	0.99
Elasticity: beta i,j	6,745	0.83	1.20	-1.95	8.60

Table D1 in the Appendix performs and analysis of variance of the returns. Bond fixed effects of column (1) explain less than 2% of the variance of returns. Time effects explain around 20% of the variance, as displayed in the R2 of Column (2). Adding the interaction of country-time or rating-time explain around half of the total variance (In columns (3) and (4)), although there might be little variation within each group, in some cases. Simultaneously adding both interactions picks 71% of the variation.

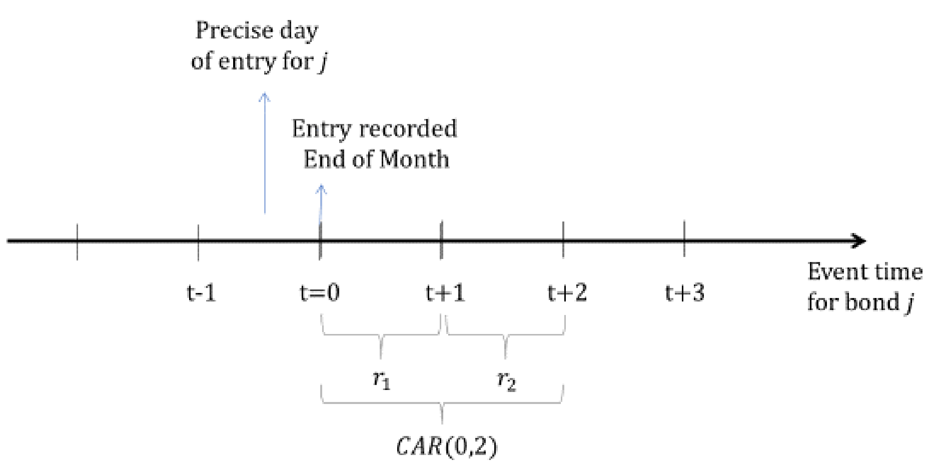
4. Main estimation of cross-bond effects when a security joins the ETF

4.1. Identification and Estimation Method for Cross-Security Effects

Figure 1 offers a timeline of the entry of a bond into an ETF. This helps to explain our identification strategy. In our estimation, instant t=0 corresponds to the end of the month in which the new portfolio of the ETF is publicly disclosed on the website. As a matter of subscripts, events are defined around the entry of the "joining" bond j; but the bonds we use for the regression are the $i$ncumbent bonds i. As a benchmark, if all the effect were immediately after the posting of the new portfolio, then bond returns would jump at r_1. In practice, we compute cumulative abnormal returns for various months.

Figure 1. Timing of measurement around the entry of a new bond ***j*** to the ETF

A diagram displaying the timing of the entry of a new bond into the ETF and the subsequent measure of returns and cumulative returns.



Importantly, our effects of interest are not the returns or CARs themselves, but how these returns change depending on whether the incumbent bonds are similar or different from the joining one. Our estimating equation explains incumbent bond returns r_{it} based on the interaction of similarity and event-times. Thus, we look at the dynamics of the cross-sectional differences of incumbent bonds. In particular, the baseline equation is

$$r_{it} = \sum_{\tau=-5}^{5} \theta_\tau \left[Similarity_{ij} \times Event_{jt}\right] + \gamma X_{it} + \lambda_{jt} + \mu_{ij} + \epsilon_{ijt} \qquad \text{[Eq. 1]}$$

; where the coefficients of interest are the θ_τ ; which describe the differential returns between similar and dissimilar bonds during the event window. As usual, a cumulative return would come from aggregating these θ_τ appropriately as $\text{CAR}(\tau_{initial}, \tau_{final}) \equiv \sum_{\tau_{initial}}^{\tau_{final}} \theta_\tau$.

The basic $Similarity_{ij}$ is the pre-window covariance in returns between incumbent and joining bond. In robustness tests, we would also use other definitions of bond similarity. $Event_{jt}$ is an appropriate set of dummy variables of each event time month jt. Note that the interaction $Similarity_{ij} \times Event_{jt}$ is a continuous variable that varies by the triplet bond i – bond j - time t, but that takes a value of zero when each $Event_{jt}$ dummy is turned off.

The estimating equation also has a bond-pair fixed effect, μ_{ij}, which absorbs any time-invariant relation between the incumbent and entrant bond. Similarly, it has an interacted time fixed effect λ_{jt} that is potentially different per each entry event jt. In practical terms, this latter demeaning also partials out the macroeconomic variation or the issuer time-varying characteristics of the entrant bond. Importantly, previous studies that look at the effect of entry on the entrant (i.e. own effect) cannot have this fixed effect. These fixed effects mean that we can control for any effect of market timing in the inclusion of ETFs that impacts all incumbent bonds simultaneously. To complement the above structure of fixed effects, we also add a vector of time-varying controls of the incumbent bond, X_{it}. This vector includes the natural log of Amount Outstanding and Duration.

The Context for Testing

Before jumping into the results, it is worth explaining a few advantages and limitations of our specific setting for identification and statistical detection of an effect. Let's start by remarking that there is a plausible case for a shock to a segmented market. Using an ETF of Emerging Markets corporate bonds allows for relatively large shocks *vis-à-vis* this submarket of interest market (see Braun and Larrain, 2009). In fact, a single security in the overall global market might be too tiny to detect any effects. Furthermore, our setting has the additional advantage of having periods of contractions and expansions of the ETF, as we will exploit in Section 5.

At the same time, our setting also helps in the quest for a liquidity effect. First, in comparison to studying the issuance of a new bond, an ETF inclusion event does not imply an additional net supply of the security. This may reduce the likelihood of explanations of Section 2 that rely on the additional quantity supplied. [8] Moreover, the inclusion of a bond in the ETF is not something that should take investors as a surprise, because it is preceded by its issuance and by the inclusion into the benchmark index (e.g. CEMBI). The latter follows a formula, so market participants are likely to anticipate at least a portion of it. [9], leaving more room for liquidity-based explanations.

To clarify, we are not claiming that our findings are relevant for all ETFs at all times. Our estimates should be understood as a local effect (LATE, as in Imbens and Angrist, 1994). We further acknowledge this is a single ETF and it may not be representative of other traded funds. But it is still a useful laboratory for our purposes.

[8] The fact that we are not looking at issuance but to inclusion in the ETF helps mitigating various standard confounders in the literature of cross-price effects (e.g. Braun y Larrain, 2009). For example, if the firm joining the market gets more funding, then it may steal market share from competitors, and therefore competitors' securities may fall simply because of competition in the product market and not because of the theories remarked in Table 1.

[9] The only uncertainty about the inclusion is for bonds in which the ETF provider (i.e. Blackrock's I-shares) decides to sample instead of mechanically include all index constituents. ETF issuers do not have a contractual mandate to exactly follow the index, but they still want to follow it.

4.2. Baseline Results

Table 3 displays our baseline results, showing both CAR and abnormal returns around the entry of a new bond. As a similarity measure, the various specifications use the pairwise covariance σ_{ij} , which the regression interacts with each dummy of event time. The table displays the returns and the corresponding CARs, going from event time $t = 0$ to $t = +4$. Al specifications include bond-pair fixed effects and entrant bond interacted with time fixed effect. This latter effect controls for any aggregate macro trend in the global bond market.

Table 3. Returns and CARs (bps) on similar incumbent bonds i around entry of bond j

This Table displays abnormal returns and cumulative abnormal returns in basis points estimated from Equation (1) using various measures of similarity. The theoretical investment strategy corresponds to long bonds of high similarity with respect to entrant (1 SD), while shorting bonds of low similarity (minus 1 SD vis-à-vis the entrant). Rows indicate the event-time window, while columns express dsiplay the $Similarity_{ij}$ used. CARs start a time t=0. Columns (1) and (2) use the covariance; columns (3) and (4) use the correlation coefficient and Column (5) and (6) use the bivariate elasticity. The St Dev of covariance, correlation and elasticity is on Table 2. For timing see Figure 1. All estimations contain fixed effects as in the baseline regression. Underlying standard errors are clustered by the interaction of bond i's ISIN and monthly time. Symbols *, **, *** mean significance at 10%, 5% and 1% respectively.

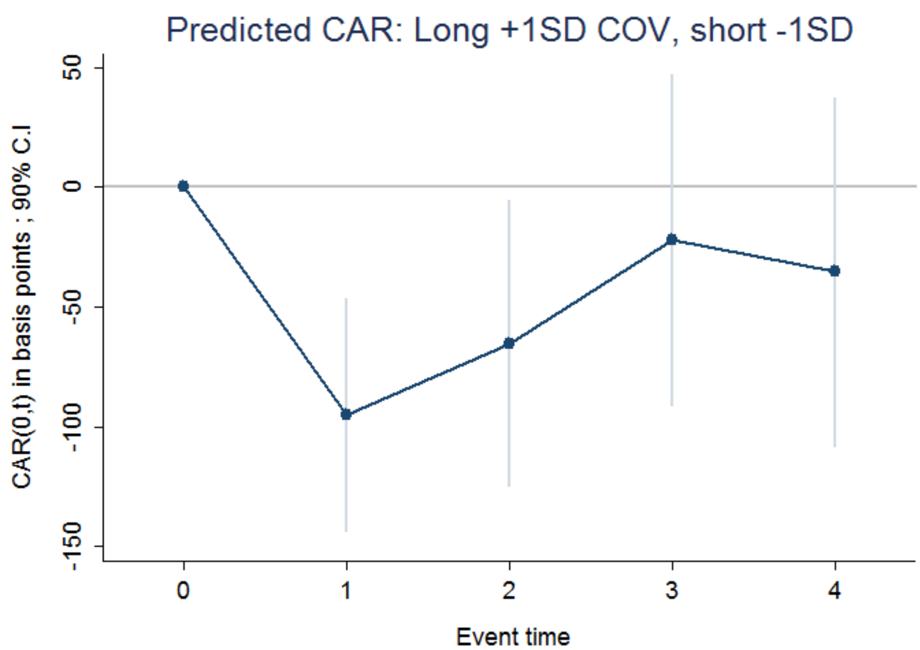
Similarity:	Covariance		Correlation		Elasticity (beta coef)	
Estimate:	return	CAR(0,t)	return	CAR(0,t)	return	CAR(0,t)
	basis points of strategy long similar bonds					
Time period	(1)	(2)	(3)	(4)	(5)	(6)
t = 0		0		0		0
t+1	-95**	-95**	-33**	-33**	-23**	-23**
	(29)	*(29)*	*(12)*	*(12)*	*(7)*	*(7)*
t+2	30	-65	-9	-41**	12*	-10
	(25)	*(36)*	*(11)*	*(14)*	*(6)*	*(9)*
t+3	43	-22	27*	-14	8	-3
	(30)	*(42)*	*(12)*	*(18)*	*(7)*	*(10)*
t+4	-13	-35	-4	-19	-3	-5
	(23)	*(44)*	*(11)*	*(20)*	*(5)*	*(10)*
N	192464	192464	192464	192464	192464	192464

Column (1) shows that at month $t+1$ there is a negative and statistically significant return of -95 bps between incumbent bonds 1 standard deviation above the mean covariance $\sigma_{i,entrant}$ and the bonds 1 standard deviation below the average covariance. Column (2) follows the CAR for the sequence of returns. It displays a CAR that is significant for t+1 and borderline insignificant for the subsequent periods, with negative point estimates. Columns (3) to (6) perform an equivalent exercise using alternative measures of proximity, namely the pairwise correlation and the pairwise elasticity, finding similar results, although some significant CARs lasting one or two months. Summing up, Table 3 finds there is an economically and statistically significant drop in prices of bonds similar to the entrant, in comparison to less-related bonds in the same ETF.

These results imply that, in theory, one could arbitrage going long on bonds of high covariance to the entrant. Figure 2 displays the CAR of that strategy, coherent with Column (2) of Table 3.

Figure 2. CAR of a strategy shorting incumbent bonds low σ_{ij} with respect to the entrant, and long in bonds with high σ_{ij}

This figure shows the dynamics of cumulative abnormal returns CAR(0,t) coming from our baseline specification in Table 3. The implicit trading strategy corresponds to long bond with 1 st dev above average in covariance with the entrant, while shorting bonds 1 st dev below the mean in covariance with the entrant . Numerically, the value of CAR at t=1, CAR(0,1) is 95 bps. Standard errors are clustered by the interaction of bond i's ISIN and time. Plotted 90% confidence intervals. Event time is in months.



Importantly, it shows the negative effect is partially reversed in the following months because the effect goes from -95bps to 34 bps in the "long run" of period $t+4$. The long-run CAR is within the confidence interval of a zero, meaning that one cannot reject that the effect disappears completely in the following months. Looking through the lens of the models discussed in Section 2, this fading out of the effect is *not* consistent with models of equilibrium repricing, downward-slopping demand curves, or information, because they all predict a permanent effect. In contrast, this transitory effect on CARs, even if it were partial, is a footprint supporting liquidity-based explanation, along the lines of Duffie's (2010). Section 5 runs additional tests along these lines.[10]

Before moving forward, it is worth benchmarking our magnitudes above with the literature on cross-securities effects. Overall, the effect here is in the same order of magnitude than others in the literature. First, using the basic formula of models of equilibrium repricing[11], considering the average weight of the bonds in the ETF and assuming a risk aversion of $\gamma = 2.9$, the long-run price impact should be approximately 11bps. Second, in the case of Newman & Rierson (2003), the Deutsche Telekom bond represented 15.5% of the value of European telecom bond market and it reduced the price of other telecom bonds by 23bps. Overall, our magnitudes would have been three times the size in the long run, but we cannot reject that they were the same. Finally, we compare our results with Braun and Larrain (2009)'s IPOs representing 0.25% of a market. In that paper, the prices of similar securities decreased by 80bps on impact. Considering the longer duration, we are getting about the same magnitude as them.

4.3. Robustness

In this section, we perform a variety of tests that show the baseline results are robust to changes in the measurement of various LHS and RHS variables, as well on the specification.

First, we tried alternative LHS measures that may less theoretical meaning as bond returns, but that are easier to compute. Namely, the $\Delta \log Price$ and the ΔYTM of the bonds. The latter measure, of course, should be interpreted in the opposite sense since yields and prices move in the opposite

[10] As clarification, it is important to note that finding an increase similar bonds is *not* a mechanical effect stemming just from the covariance between securities. First, if it were mechanical, it may well be constant rather than exactly around the dates of entry into the ETF. Specially under the null that ETF inclusion should not impact prices. Second, our specification is about the interaction of the entry event times the covariance (see section 4.1), not just the covariance. While not explicitly included in the regression, the standalone covariance term is wiped out due to the fixed effects by bond pair $\{i, j\}$. Therefore, our estimation is about something different that happens after entry.

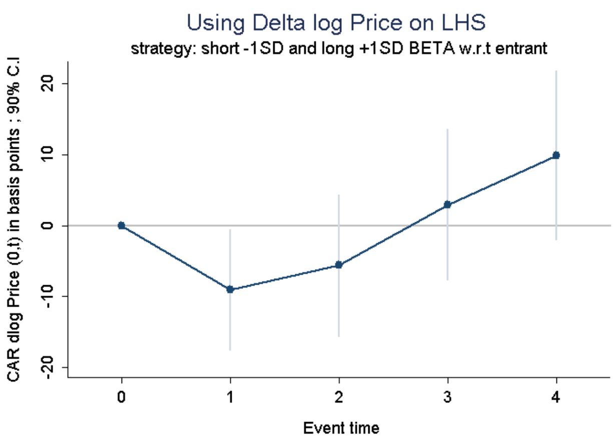
[11] From Braun and Larrain (2009) we have a formula of repricing after an increase in supply given by $\Delta E[r_i] = \gamma\ \omega_j\ \sigma_{i,j}$, with γ the risk aversion coefficient and ω_j the weight of the bond on the ETF. The left-hand side is the change in expected return and the last term on the right is the covariance with the entrant security j

direction. Results are shown in Figure 3, which follows the same methodology as Figure 2, except for this change in the LHS. Overall, the qualitative picture of lower cumulative returns remains robust to these alternative LHS variables. The significant effects are also transitory, coherent with liquidity-based explanations.

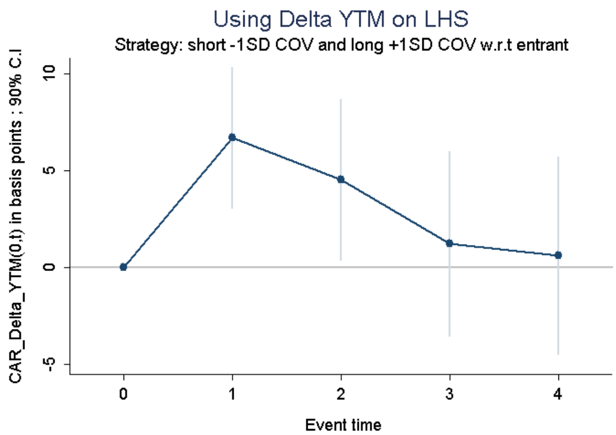
Figure 3. CAR using alternative left-hand-side measures related to returns

Figure shows estimated CARs starting from t=0 as in Figure 2, but estimated using two alternative proxies for returns on the LHS of the regression. Panel (a) uses month-to-month change in prices, while panel (b) use month-to-month changes in yield to maturity. Given that returns and ΔYTM move in opposite directions, the transitory increase in panel (b) is coherent with the previously mentioned transitory drop in returns and changes in log prices. As before, the implicit trading strategy corresponds to long bonds high covariance with the entrant, while shorting bonds with low covariance. Standard errors clustered by the interaction of bond i's ISIN and monthly time. Plot has 90% confidence intervals.

Panel (a) Bond price increase (LHS is $\Delta \ln Price$)



Panel (b) Change in Yield to Maturity



Second, we also test alternative models of asset pricing that correct for different factors. Table 4 shows that the drop of returns at $t = 1$ is robust to using excess returns *vis-à-vis* one market factor, namely the CEMBI index in Column (1), as well as a more complex 5-factor model in column (2). Importantly, the subsequent CARs show that there is no significant effect after t=+2. Again, the action is around the entry of a similar bond and tends to be transitory. An additional method of event-by-event estimation also points to a drop in returns. [12]

[12] To further check the robustness of the results to methodological modifications we separately estimated each of the 177 entry events and look at the effect on incumbent bonds. That is, we estimate 177 regressions, each one of them looking at the cross-sectional difference among incumbents of high and low covariance with the entrant bond. This used the equation $r_{i,t=1} = \alpha_j + \theta_j\, COV_{ij} + \epsilon_i$. The mean and median estimated θ_j was fact negative and statistically significant, coherent with our previous exercises. Table not shown.

Table 4. Estimations with alternative models of excess returns: Market and Five Factors

This Table shows the estimated returns from period zero to one (r_1) and two alternative measures of Cumulative Abnormal Returns, calculated using the coefficients and interpretations as in the baseline, using cross-bond covariance. Column (1) uses a single factor to get returns, the return of CEMBI. Column (2) uses five factors: CEMBI, SMB, HML, momentum factor, and global liquidity. Beyond the returns, the first measure of CAR goes from month zero to two, CAR(0,2), and the other for the subsequent two months CAR(2,4). Since this table mixes both returns and cumulative returns for different periods, instead of standard errors the table reports in t-statistics in brackets. Underlying standard errors are clustered as in the baseline. *, **, and *** represent significance at 10%, 5% and 1%.

	(1) One Factor	(2) Five factors
Return r_1 (bps)	-66*	-68*
	[-2.39]	*[-2.53]*
CAR(0,2) (bps)	-28	-29
	[-0.83]	*[-0.88]*
CAR(2,4) (bps)	-1	-3
	[-0.04]	*[-0.10]*
N	90358	81209

As mentioned, the specific $Similarity_{ij}$ variable in our specifications is not essential for our main finding. In fact, when in Table 3 we changed the covariance for other related measures, most of the results remain qualitatively robust, showing a *transitory* negative return.

So far, we have used similarity measures based on the relation between the prices of the different bonds. This is reasonable if one has in mind the traditional mean-variance asset pricing model. However, the argument extends more generally to characteristics that investors deem important for the submarket. In what follows, we explore whether incumbent bonds that share one relevant characteristic with the entrant are more negatively affected than bonds that do not. The similarity measure, for instance, will take the value one if both bonds in the pair are issued by firms from the same country, the same industry, or other combination; being zero otherwise. Table 5 displays the Cumulative Abnormal Returns using these different measures of similarity. Since these are dummy variables, the coefficients should be interpreted directly as the additional return when a bond shares the same characteristic with the entrant. In Column (2), incumbent bonds that share the industrial sector of the entrant display a CAR of -35bps that is significant for one time period and then becomes insignificant but still negative. This is qualitatively similar to our baseline, in the sense of a negative and transitory effect on the value of similar bonds, although slightly delayed. Instead of just the industry, column (4) uses the same sector-region combination (e.g. Energy in Latin America) as a measure of similarity. It also finds a negative effect (CAR of -60bps), but here one cannot rule out the effect is more long-lasting. [13]

[13] Interestingly, the combination of similarity that delivered the largest CAR was the interaction of industrial sector and world region. Anecdotally, this coincides with the combination of characteristics (e.g. European Telecoms) emphasized by Newman and Rierson (2004) and cited in Duffie (2010).

Summing up, even these discrete measures of bond similarity support the baseline finding of similar returns dropping after entry of a new bond. While these characteristics matter, in the rest of the paper we stick to use the covariance as our baseline, since the σ_{ij} are theoretically more grounded.[14]

Table 5. Cumulative returns using common characteristics as a measure of similarity.

Table displays the evolution of CARs starting in t-1 and until the time labeled in each column. Unlike other tables, the theoretical investment strategy corresponds to long bonds with a dummy of 1 for similarity and shorting bonds with dummy 0 similarity. The definition of similarity of bonds would be different in each column. For all columns the dummy is made based on the condition that relates bonds i and j. Column (1) uses a dummy for belonging to the same country. Column (2) does it when both bonds belong to companies of the same industrial sector. Column (3) is when the companies belong to the same world region using the World bank definition (e.g. Latin America). The measure of similarity of Column (4) is one if the bond is issued by a company of the same sector and world region of the entrant bond. Column (5) uses a dummy equal to one if both bonds are investment grade or neither of them is investment grade. Standard errors follow the baseline in Table 3. Symbols *, ** and *** represent significance at 10%, 5% and 1% respectively.

	CAR(-1, t) of investment strategy long similar / short not similar				
Similarity dummy:	Same Country	Same Sector	Same Region	Same Sector & Region	Same Investment Grade
Event time	(1)	(2)	(3)	(4)	(5)
t=0	-1	-6	-1	4	-4
	(1)	*(5)*	*(1)*	*(6)*	*(5)*
t+1	-1	-8	-0	-17	2
	(2)	*(12)*	*(2)*	*(17)*	*(9)*
t+2	1	-35**	2	-55**	12
	(3)	*(16)*	*(2)*	*(24)*	*(11)*
t+3	1	-28	2	-60**	16
	(3)	*(19)*	*(3)*	*(27)*	*(14)*
N	991827	991827	989157	989157	883364

[14] The main difference between this use of characteristics and the measures based on covariance is that the former tends to jump one period later.

5. Heterogeneity and Channels

As mentioned, the transitory effect on CARs found in our baseline estimations is a first footprint suggesting that price-pressure models of liquidity may explain some of the results. To dig deeper into the channels that might be mediating this cross-price effect, in this section we explore heterogeneity of our main effect, taking advantage of both time series and cross-sectional differences. The results support the view that some of the effect might be due to liquidity.

5.1. Liquidity

If liquidity is a major determinant of the cross-price effects, then we would observe that the effect should be larger for less liquid bonds.[15] This is indeed the case, as documented in Table 6. Even though the bonds in our sample are among the most liquid emerging market corporate bonds, there is variation in their liquidity. Here we display the results of our baseline estimations, splitting the sample between the top and bottom 20% of incumbent bonds, sorted by bid-ask spread. While the samples are of course smaller, the effect for the low liquidity sample is negative and significant; while in the high liquidity sample, we do not observe such behavior, with a statistically insignificant point estimate.

Using an ETF offers a unique laboratory to explore additional features of our pricing effect. Namely, since ETFs shares outstanding can permanently expand or contract, one can look at whether the effect fades out when ETF constituents face a stronger demand. As a brief primer, ETF shares could be endogenously "produced" by traders that sell to the issuer the ETF components, in exact proportions. This mechanism helps to keep the ETF's price close to its NAV. New shares are created when there is additional demand or when arbitrageurs try to profit from turning packages of individual bonds into

[15] March-Dallas, et al (2018) explore the characteristics of leveraged ETFs and their liquidity. In contrast, here we think about individual bonds.

the ETFs. Importantly, the above dynamics for shares creation and destruction has implications for our story of traders selling similar bonds when a new bond enters the ETF.

Table 6: Heterogeneity of CAR (bps), for high and low liquidity of incumbent bonds.

Estimated CARs between t=0 and t=2, from a theoretical strategy, that invests in incumbent bonds that have one unit of higher covariance with the entrant bond while shorting those with lower covariance. The estimating equation follows our baseline. The difference is that the sample is split according to quintiles of the bid-ask spread measured before the estimation window. Column (1) shows the estimates for quintile 1, which is the most liquid, while column (2) shows the effect for the 5th quintile, being the most illiquid. Standard errors in parenthesis, clustered as in the baseline. Significance on column (1) is just above 10% (p-value 0.0106), but with the opposite sign than in the baseline of Column (2). Symbols *, **, *** are significance at 10%, 5% and 1% level.

	(1) Top quintile of liquidity, bond i	(2) Bottom quintile of liquidity, bond i
CAR (0,2) in basis points	6.81*	-50.0**
Standard error of CAR above	(4.18)	(22.1)
FE Country × $Time$ ($monthly$)	YES	YES
FE Rating	YES	YES
FE Bond j ISIN × $Time$ ($monthly$)	YES	YES
FE Bond j ISIN × Bond i ISIN	YES	YES

On the one hand, when the ETF is expanding, there is no need to sell similar bonds when a new bond joins the ETF. This is because the expansion of the ETF generates additional demand for all the constituents of the fund. In some way, it's like a high tide that lifts all boats. On the other hand, when the shares outstanding of the ETF are stagnant or dropping, then our mechanism should be more important because there is less demand for these constituent bonds.

Table 7 shows results that are consistent with the liquidity channel. Our finding of a penalty for similar bonds disappears for periods of ETF expansion (see Column 1). In contrast, when the ETF is not expanding there is a statistically significant CAR of minus 86 bps (Column 2). Thus, the effect we have been studying is mitigated when the ETF expands.

Table 7. CAR(0,2) splitting sample by expansions of the ETF's shares outstanding

CAR(0,2) equivalent to our baseline, but splitting sample between periods of expansions (Col 1) vs non-expansions of the ETF (Col 2). Estimating equation and theoretical trading strategies implicit are the same as in the baseline. Fixed effects are described in the last rows of each column. Standard errors in parenthesis, clustered by the interaction of bond i's ISIN and monthly time. Symbols *, ** mean 10 and 5% significance.

	(1) Periods of Net Creation of ETF shares	(2) Other periods
CAR (0,2) in basis points	27.4	-86.0**
Standard error of CAR above	(44.3)	(42.5)
FE Country × $Time$ $(monthly)$	YES	YES
FE Rating	YES	YES
FE Bond j ISIN × $Time$ $(monthly)$	YES	YES
FE Bond j ISIN × Bond i ISIN	YES	YES

5.2. FURTHER TESTS

So far, the finding of a transitory and negative cross-bond effect seems more coherent with liquidity-based explanations than with fundamental supply or demand explanations, although no explanation can be completely discarded. Section 2 also points out that the price drop for bonds that are similar to the entrant could be caused by low quality of pricing, since ETF constituents may have lost their "similar benchmark". According to this theory, this benchmark might have worked while being outside the ETF, but not after joining it. Two pieces of evidence suggest that this explanation is less likely, although we cannot rule our informativeness is not playing a role. On the one hand, we tend to find a transitory effect instead of the permanent effect suggested in Table 1 for this theory. On the other hand, the ETF is not a majoritarian portion of the Emerging Markets corporate bond market and we did not find significant differences in individual bond return correlations with the ETF before and after entry. As an additional test, we follow Duvnek (2003) and define the informativeness of a bond as $(1 - R^2)$; in a regression between bond returns and market returns, the latter proxied by CEMBI. These informativeness measures are computed with data before entry into the ETF. They aim to measure how much the pricing of a bond depends on bond specifics instead of simply following the index. Using this measure, we follow the same procedure as in our baseline specification but now splitting the sample by the above-mentioned informativeness of the entrant bond. Results in Appendix C, however, do not find any significant effect of these tests.

6. Concluding remarks

Using data from widely traded Emerging Market corporate bonds between 2012 and 2017, we document evidence of negative pricing spillovers after a bond enters an ETF. In particular, the ETF constituent bonds that were *ex-ante* more similar to the new entrant tended to lose value, *vis-à-vis* constituents that were dissimilar to the entrant. In most specifications this negative effect is transitory. Furthermore, additional analysis shows that this negative spillover is stronger for illiquid incumbent bonds, while the effect disappears in moments when ETF constituent bonds face stronger demand. Our findings are consistent with various theories of asset pricing (Section 2) but suggest that part of the effect may come from liquidity models of price-pressure, along the lines of Duffie (2010).

Our work was the first systematic analysis of how constituents of a fixed income ETF may have pricing spillovers after the entry of a new constituent. Subsequent research may want to look at other ETFs, broader types of spillovers, and the evolution of inventories. It may also explore econometric instruments for the decision behind ETF inclusions.

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APPENDIX

APPENDIX A: SAMPLE

Table A1. Country and Industry composition of entrant bonds

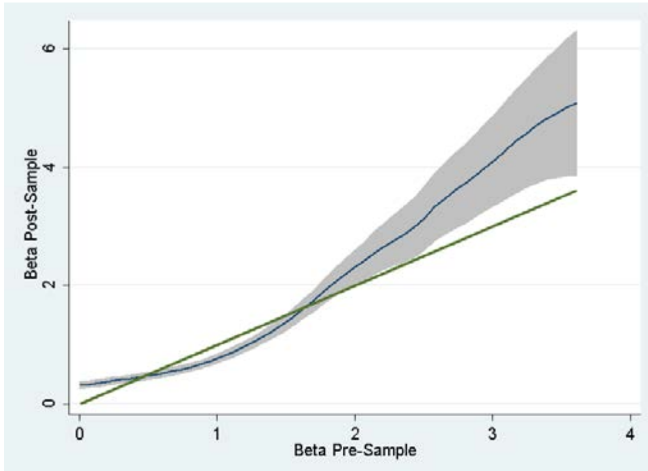
	Obs
Azerbaijan	1
Brazil	19
Chile	6
China	15
Colombia	2
Hong Kong	7
India	9
Indonesia	2
Israel	2
Jamaica	2
Kazakhstan	3
Korea (South)	29
Malaysia	1
Mexico	20
Peru	1
Philippines	2
Qatar	7
Russian Federation	20
Singapore	3
South Africa	2
Thailand	2
Turkey	2
Ukraine	1
United Arab Emirates	13
United Kingdom	1
Venezuela	5

	Obs
Basic Materials	16
Communications	10
Consumer, Cyclical	1
Consumer, Non-cyclical	3
Diversified	4
Energy	37
Financial	64
Government	12
Industrial	13
Utilities	17

	Obs
2012m5	34
2012m6	4
2012m9	1
2012m10	18
2012m11	6
2013m1	19
2013m3	16
2013m5	15
2013m6	7
2013m10	3
2013m11	1
2013m12	9
2014m1	2
2014m5	7
2014m6	1
2014m7	2
2014m9	4
2014m11	2
2014m12	1
2015m3	6
2015m4	4
2015m6	3
2015m7	2
2015m9	2
2015m10	1
2016m5	3
2016m6	1
2016m9	2
2016m10	1

APPENDIX B: BIVARIATE MEASURES OF BOND SIMILARITY

Figure B1. Cross-bond return elasticities estimated before and after own entry into ETF



Beta pre and post sample cutting 5% of extreme values on each side

The graph displays the non-parametric regression mean between the bivariate elasticity of returns (beta) pre- sample and the same beta post- sample for each bond pair. Beta es the coefficient obtained from the bivariate regression between change yield to maturity of bond *i* and change yield to maturity of bond j. It drops the top and bottom 10% of betas pre-sample. The gray area represents the non-parametric confidence interval at 95%. The straight line is a 45-degree line for equality between pre-and post-beta coefficients. The overall distribution of the beta coefficients has the following descriptive statistics: the mean is 0.924, the percentile 5% is 0.0074, the percentile 95% is 3.6097, Std. Dev is 1.451 and N is 14,837 observations. Using a parametric linear regression instead of a 45 degrees line of slope 1, yields a slope of 1.42 Samples are restricted to coefficients estimated with at least 10 observations.

Table B1. Regressing bivariate measures of similarity against dummy "*Same-country*".

PANEL A (5% winsorized)	(1) Bivariate Elasticity	(2) Bivariate Correlation	(3) Bivariate Covariance
1 [Same country]	0.150***	0.213***	0.178***
	(0.0266)	(0.0219)	(0.0327)
Observations	13,358	13,358	13,358
R-squared	0.348	0.221	0.212
Country of bond i	YES	YES	YES
Country of bond j	YES	YES	YES

The panel regression displays the relation between different measures of similarities and same country, clustering by country pair. Where same country is a dummy that is 1 if there the country of bond i is the same as the country of bond j; and zero otherwise. In the regression the beta pre-sample dropped the top 5% (value 3.61) and the bottom 5% (value 0.0074).

APPENDIX C: INFORMATIVENESS RESULTS.

Table C1. Cumulative abnormal returns, CAR(0,2), splitting sample by informativeness of the entrant bond

Regression similar to baseline but splitting sample according to bond informativeness. It retains the same interpretation of an implicit trading strategy as in the baseline. Informativeness $(1 - R^2)$ of a regression explaining bond j returns on CEMBI index (see Durnev et al, 2003). Informativeness is estimated before the entry window. Column (1) runs the baseline regression for the top quintile of informativeness. Column (2) does the same thing but for the bottom quintile if informativeness. For the regression, the structure of fixed effects used in the estimation is available in the last four rows. The standard errors in the regression are clustered by the interaction of incumbent bond and (monthly) time. CARs were computed adding up coefficients and using the Delta Method. CAR standard errors in parenthesis. Symbols *, ** and *** means significance at 10%, 5% and 1% respectively.

	(1) Top quintile informativeness of entrant bond j	(2) Bottom quintile of informativeness of entrant bond j
CAR (0,2)	140	-74
Standard error of CAR above	(234)	(72.9)
FE Country $\times$ $Time$ $(monthly)$	YES	YES
FE Rating	YES	YES
FE Bond j ISIN $\times$ $Time$ $(monthly)$	YES	YES
FE Bond j ISIN $\times$ Bond i ISIN	YES	YES

APPENDIX D: ANALYSIS OF VARIANCE.

Table D1. Analysis of Variance with R2 of return regressions with various Fixed Effects

	LHS: Returns of bonds (monthly)				
	(1)	(2)	(3)	(4)	(5)
R-squared	0.02	0.20	0.54	0.58	0.71
<u>Fixed effect</u>					
Bond	YES	NO	YES	YES	YES
Time	NO	YES	YES	YES	YES
Country-Time	NO	NO	YES	NO	YES
Rating-Time	NO	NO	NO	YES	YES
Observations	7,257	7,260	7,023	6,808	6,520

This table shows regressions of monthly bond returns using different sets of fixed effects and no other covariate. The goal is to measure the fraction of overall variance explained by each set of fixed effects, as the R2. Specification (1) uses only bond fixed effect. Specification (2) uses only time fixed effect. Specification (3) controls for bond characteristics and the interaction country-time, which includes any macroeconomic price or quantity. Specification (4) uses also the interaction of rating and time, for events impacting all bonds of a given classification. Finally, specification (5) includes all fixed effects by country-time and credit rating-time.