The Dealer Warehouse – Corporate bond ETFs

Caitlin D. Dannhauser
Villanova University

Egle Karmaziene
Vrije Universiteit
Swedish House of Finance
Tinbergen Institute

ABSTRACT

ETFs add a new layer of market-making to the corporate bond market that improves the market quality of the underlying bonds. Dealers use the flexibility of the primary corporate bond ETF market as a warehouse to manage inventory. The face value of ETF holdings in investment grade (high yield) bonds is 9.1% (25.9%) greater on the downgrade date than thirty days prior. Bonds eligible for inclusion in ETFs with the most active primary markets overreact less than other downgraded bonds from the same issuer. This new layer of market-making leads to a negative relation between ETF ownership and idiosyncratic volatility.

1. Introduction

Corporate bond markets have transformed over the past two decades. Dealers have retreated from the over-the-counter (OTC) market following heighted regulatory constraints (Bao et al., 2018; Bessembinder et al., 2018). Concurrently, the share of corporate bonds held by investors offering a liquidity transformation has grown from 7.2 percent in the first quarter of 2002 to 23.0 percent in the first quarter of 2021.[1] Among these emerging investors, the extent of the liquidity transformation is heightened by the distinctive features of exchange-traded funds (ETFs).

Two features distinguish ETFs from open-end mutual funds. First, the secondary exchange trading of ETFs provides a liquid alternative to the illiquid underlying market. This feature has been utilized by retail investors to access the market, institutional investors to alter exposures, and regulators to stabilize the broader market during COVID-19. Second, the primary ETF market involves the in-kind exchange of a basket of the underlying for ETF shares. The exchange occurs between the ETF and authorized participants (APs), who are often dealers. Rather than exactly replicating the index, corporate bond ETFs use representative sampling. This standard allows funds to hold a subset of the index bonds as constituents and to use smaller, negotiated baskets in the in-kind exchange with APs. In this paper, we study if the primary ETF market is used by dealers to mitigate inventory constraints during periods of idiosyncratic shocks.

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[1] The statistics were computed using data from the Financial Accounts Z.1 files from the Board of Governors of the Federal Reserve. A graph of the figures can be found here: https://fred.stlouisfed.org/graph/?g=Wt5M

We focus on downgrades to identify periods where corporate bond dealer inventory costs are heightened (Dick-Nielsen and Rossi, 2019). We study downgrades from any of the three main rating agencies that do cross the investment grade threshold. Doing so ensures the bonds remain on average eligible for the same subset of ETFs. Using daily ETF holdings data, we find that the face value of ETF holdings begins to increase thirty trading days before the downgrade event, consistent with the market anticipating these events (Figure 1).[2] Relative to thirty days before the event the face value of ETF holdings is 9.1% and 25.9% greater for investment grade and high yield bonds, respectively, on the downgrade date. ETF holdings begin to revert five days after the event but remain approximately 4% higher than the base levels up to thirty days after.

In a logistic regression that controls for bond and trading day fixed effects and other observables associated with ETF inclusion, the amount of a bond in the primary market baskets increases 19.03% on the downgrade date. The results suggest that dealers absorb underlying market selling pressure from downgrades and then use the ETF primary market to deliver the bonds via in-kind creation. Thus, the dealer can provide liquidity in response to the idiosyncratic event without bearing subsequent inventory risk.

[2] Anecdotally, a bond that is downgraded but remains eligible for inclusion in the largest investment grade ETF, iShares iBoxx investment grade ETF (ticker LQD), experiences a 7.8% increase in LQD ownership in the five days after the downgrade event.

By providing a warehouse for dealers to offset inventory risk in response to shocks, ETFs may impact the price response to these events and the bond's volatility. To investigate the impact of ETFs on the underlying corporate bonds we exploit market details to address common endogeneity concerns. In bond markets benchmark inclusion is dictated by bond and issuer level characteristics that are determined at issuance.[3] By comparing two bonds from the same issuer (Choi et al., 2020), we control for changes in fundamental risk and information environments. We further restrict the sample to bonds with non-zero ETF ownership to address the endogenous decision by sponsors to include a bond in the ETF universe.

To assess the impact of ETFs on the underlying bonds we consider a bond's returns around a downgrade. Our empirical strategy utilizes the rules-based nature of corporate bond benchmarks to investigate bonds from issuers with at least two issuances maturity experiencing a broad ratings downgrade (e.g., AA to A) in the same week. We use an issue amount outstanding threshold differential to identify bonds eligible for inclusion in the original investment grade ETF, ticker LQD, which has an active primary market. LQD requires that a bond have an average numerical conversion of rating of 10.5, a minimum time to maturity of three years, a minimum issue amount outstanding of $750 million, and at least $2 trillion in issuer amount outstanding. Treatment bonds have amount

[3] Changes in investment grade status are an exception to this statement. In our study we focus on changes within investment grade status rather than across.

outstanding of $750 million and thus are eligible for LQD inclusion. Control bonds meet all LQD inclusion thresholds, except the amount outstanding. Thus, potential exposure to ETF primary markets is determined at the bond's issuance. Comparing the weekly excess returns of downgraded bonds from the same issuer in the twelve-week window around a downgrade, we find that bonds with greater exposure to ETFs overreact less to the downgrade. Treatment and control bonds exhibit parallel trends in weekly abnormal returns up to a month before the downgrade. However, treatment bonds have a smaller cumulative reaction to the downgrade than control bonds. In the weeks following the downgrade, the returns of the two groups converge. The pattern of more negative returns followed by a greater rebound by control bonds suggests an overreaction by bonds ineligible for LQD inclusion. Since the pattern may reflect the illiquidity of the underlying, we run regressions controlling for liquidity and other known determinants of the liquidity of bond, including size, age, and time to maturity. The regressions support the preliminary patterns.

The use of the primary market by market makers to address idiosyncratic bond events suggests that in corporate bond markets ETFs may buffer the illiquid underlying. As described in the alternative hypothesis by Ben-David et al. (2018), ETFs may provide a new layer of market-making power, which dampens liquidity shocks to the underlying. Following this rational, we conjecture whether ETF ownership decreases the volatility of the underlying corporate bonds. As in Cao et al. (2021) and Chung et al. (2019), we compute corporate bond idiosyncratic risk as the variance of the error terms from factor model regressions of daily excess bond returns. We find a negative and statistically significant relationship between ETF ownership and idiosyncratic volatility. The results are robust to issuer-by-date-by-seniority fixed effects and other controls. A one percentage point increase in ETF ownership, which is driven by changes in the primary market, is associated with a 6% decrease in liquidity.

This paper contributes to an emerging literature that highlights the results of the flexibility of representative sampling for sponsors, underlying liquidity, arbitrage, and ETF investors. To-date representative sampling is found to allow sponsors to actively manage their baskets to enhance the liquidity transformation (Shim and Todorov, 2021; Koont et al., 2022) but generates a hidden cost for ETF investors due asymmetric information (Reilly, 2022). Further, Pan and Zeng (2019) highlight how balancing inventory constraints impedes ETF arbitrage.

The paper also contributes to the broader research on the impact of ETF ownership on underlying constituents. In equity markets where the underlying are traded on similar exchanges, ETF ownership has been found to increase non-fundamental volatility (Ben-David et al., 2018), comovement (Da and Shive, 2018), stock information efficiency (Glosten et al., 2021) and liquidity comovement (Agarwal et al., 2018). Short selling capabilities of ETFs improves liquidity (Karmaziene and Sokolovski, 2021) and decreases post earnings announcement drift (Huang et al., 2021). Brogaard et al. (2021) and Box et al. (2021) caution that the findings of the equity literature may not be broadly applicable. In corporate bond markets, the impact of ETFs may be distinguished by the extent of the liquidity transformation, the impediments to non-AP arbitrage, and the standard of representative sampling. The literature on corporate bonds has investigated the impact on underlying valuation (Dannhauser, 2017), transmission of fundamental systemic shocks (Dannhauser and Hoseinzade, 2021), liquidity (Holden and Nam, 2019), and commonality in liquidity (Çötelioglu, 2019).

We also contribute to the growing literature on corporate bond market. Recent research examines the contribution of idiosyncratic and systematic risk to returns (Chung et al., 2019; Bai et al., 2021). Overall, the findings of this study have implications for both corporate finance as debt is the largest source of financing for corporations and for asset pricing given the success of ETFs in illiquid markets.

2. Data

In this section we detail the data used in our study. Section 2.1 discusses the various sources and the construction of our key variables. Summary statistics are discussed in section 2.2.

2.1. Data sources and measures

Fund level data including assets under management, returns, fees, objective codes, fund name, and expense ratio comes from the Center for Research in Security Prices (CRSP) Mutual Fund Database. We restrict our sample to corporate bond funds using

CRSP and Lipper Objective Codes.[4] ETFs are identified using the CRSP indicator flag. Index funds are identified using fund name from CRSP following Appel et al. (2016), Busse and Tong (2012) and Iliev and Lowry (2014) and the CRSP database index fund flag equal to D or B.[5] A fund is identified as an index mutual fund if at any point in fund history it is flagged by the name search or a CRSP identifier and is not flagged as an ETF. We eliminate leveraged or inverse funds.[6] We account for the Vanguard structure by determining the weight of total fund assets managed by the ETF.

Daily ETF holdings data is obtained from Morningstar Direct. We have the full sample of corporate bond ETFs that report daily holdings from April 2017 to October 2022. In addition, we have the holdings of the twenty largest corporate bond ETFs back to January 2015. The twenty ETFs account for 92 percent of December 2020 assets of daily reporting ETFs and 61 percent of total corporate bond ETF assets.[7] We eliminate any holdings reported on full corporate bond market holidays using the SIFMA calendar and any holdings reported on weekends. For bond i from issuer j we compute the total number of holdings by all ETFs, K, on day, t, as:

$$ETF\ Holdings_{i,j,t} = \sum_{k=1}^{K} Notional\ Value_{i,j,k,t}. \tag{1}$$

[4]We restrict the sample to funds with CRSP objective codes beginning with IC or Lipper Objective Codes equal to A, BBB, SII, SID, IID, or HY.

[5] Index funds are flagged if the CRSP fund name contains the following strings: *SP, DOW, Dow, DJ* or if the lowercase version of the CRSP fund name contains: *index, idx, indx, ind_* (_indicates space), *aggregate, composite, russell, s&p, s and p, s & p, msci, Bloomberg, kbw, nasdaq, nyse, stoxx, ftse, wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, or 5000.*

[6] Inverse and leveraged funds are identified if the lowercase version of their name contains the following strings: *plus, enhanced, inverse, 2x, 3x, ultra, 1.5x, 2.5x.*

[7] Vanguard funds report holdings monthly.

Primary market activity is imputed as the sum of the change in the reported notional holding of each ETF that reports bond i as a holding on trading day t:

$$Primary\ ETF_{i,j,t} = \sum_{k=1}^{K} (ETF\ Holdings_{i,j,k,t} - ETF\ Holdings_{i,j,k,t-1})\,. \qquad (2)$$

The construction of this variable follows Shim and Todorov (2021) and Koont et al. (2022) in assuming that the average net basket for an ETF is representative of all creation and redemption baskets in a day. Positive values of the variable imply that the bond was included in the negotiated creation baskets of ETFs and negative values imply redemption basket inclusion.

Monthly holdings are obtained from CRSP. To account for missing observations, we impute monthly holdings as the most recent reported holdings adjusted by the fund's flow. To account for representative sampling, if there is no change in holdings between two CRSP report dates, we use the lagged holdings rather than the imputed value. We impute the bonds held by the ETF share class of Vanguard by taking the percentage of assets in the ETF times the bonds held by the portfolio. To account for missing observations, we impute monthly holdings as the most recent reported holdings adjusted by the fund's flow. To account for representative sampling, if there is no change in holdings between two CRSP report dates, we use the lagged holdings rather than the imputed value. We impute the bonds held by the ETF share class of Vanguard by taking the percentage of assets in the ETF times the bonds held by the portfolio. Following the literature, we compute $ETF\ Ownership$, the total number of shares held by all ETFs, K, over the bond's amount outstanding as shown in the equation below,

$$ETF\ ownership_{i,j,t} = \frac{\sum_{k=1}^{K} Bonds\ held_{i,j,k,t}}{Amount\ outstanding_{i,j,t}}. \tag{3}$$

Active mutual fund ownership, $AMF\ ownership$, and index mutual fund ownership, $IMF\ ownership$ are constructed following equation (3). We adjust ETF and index fund ownership for the Vanguard structure. Table 1 presents summary statistics of the funds in our sample.

[Insert Table 1]

Bond trading data comes from the Enhanced Trade Reporting and Compliance Engine (TRACE) filtered for possibly erroneous trades using the methodology of Dick-Nielsen (2009). Following Bao et al. (2018) and Bessembinder et al. (2008), we remove trades of less than \$100,000 in par value. We eliminate transactions with prices under \$5 following Bali et al. (2021). The return of bond i from issuer j on day t is computed as

$$R_{i,j,t} = \frac{P_{i,j,t} + C_{i,j,t} + AI_{i,j,t}}{P_{i,j,t-1} + AI_{i,j,t-1}} - 1. \tag{4}$$

$P_{i,j,t}$ is the value-weighted transaction price of bond i on day t. $C_{i,j,t}$ is the coupon payment, if any, and $AI_{i,j,t}$ is accrued interest. In our study of bond downgrades, we rely on weekly returns, $R_{i,j,w}$ computed in a similar manner.

To estimate idiosyncratic risk, conduct rolling regressions of daily excess returns on a three-factor bond model following Cao et al. (2021) and Chung et al. (2019). The three-factor bond model of Bessembinder et al. (2008) and Fama and French (1993) uses returns to the Bloomberg Barclays aggregate index from Bloomberg plus factors for the unexpected changes in interest rates, $TERM_t$, and default, DEF_t, computed with data from the Federal Reserve Economic Database.[8] For the corporate bond specific pricing model, we regress the of excess return of bond i from issuer j on trading day t in month m on the returns of factors, f, as follows

$$R_{i,j,t,m} - r_{f,t,m} = \alpha + \beta_1 \left(R_{AGG,t,m} - r_{f,t,m} \right) + \beta_2 TERM_{t,m} + \beta_3 DEF_{t,m} + \epsilon_{i,j,t,m}. \tag{5}$$

Error terms from the equation (5) regressions are used to compute the monthly measure of idiosyncratic risk as:

$$IR_{i,j,m} = var\left(\epsilon^F_{i,j,t,m} \right). \tag{6}$$

Table 2 presents summary statistics for the bond level characteristics in our sample.

[Insert Table 2]

3. Results

This section details the results of our empirical study. Section 3.1 begins with a study of ETF primary market activity around downgrades. Section 3.2 considers the impact of ETFs on abnormal bond returns around downgrades and on broad idiosyncratic risk.

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[8] Following Fama and French (1993), we define the default factor as the difference in returns between a market portfolio of long-term corporate bonds and long-term government bonds.

3.1. ETF Primary Market Activity & Idiosyncratic Bond Shocks

To begin we investigate the pattern of primary market activity around downgrade events. A downgrade event occurs if the rating from S&P, Moodys, or Fitch decreases on a given day. To address downgrades clustering in time we consider only events where there is no other rating change in the previous sixty days. We also restrict the sample to downgrades that are not associated with crossing the investment grade threshold by any of the three agencies. Doing so ensures that the potential asset base of ETFs that the bonds are eligible for remains constant and that selling pressure by restricted investors such as insurance companies does not drive the results. In Figure 1 we plot the total number of bonds held by all ETFs on the trading days relative to the date of downgrade $t = 0$. Panel A presents the results for investment grade bonds and Panel B for high yield bonds As shown the total number of bonds held by ETFs increases in the month prior to the downgrade event for both investment grade and high yield bonds. This result is consistent with informed traders anticipating ratings events. At the peak ETF holdings of investment grade bonds are 9.6% and high yield bonds are 26.9% higher relative to thirty trading days before the downgrade. Thirty days after the event, the holdings of investment grade bonds by ETFs remain elevated at 5% of the level thirty days before the downgrade. For high yield bonds, there is a sharper reversion, but ETF holdings remain 4% higher than the level thirty days before the downgrade. In aggregate close to $1 billion notional value of bonds are included in creation baskets on the event date. Prior to the event creations are heightened suggestive of the asymmetric information advantage of APs studied by Reilly (2022). The days following the event downgraded bonds slowly exit the ETFs via redemptions supporting the findings of Koont et al. (2022).

To test the statistical significance of the effect we use the full panel of daily holdings and run the following regression:

$$\log\left(Primary\ ETF_{i,j,t}\right) = \alpha_i + \lambda_t + \beta_1 Downgrade_{i,j,t} + \beta_2 X_{i,j,t} + \epsilon_{i,j,t.} \quad (7)$$

The dependent variable is the log of one plus the total primary bond market activity by all ETFs in bond i from issuer j on trading date t. Bond fixed effects, α_i, control for time-invariant characteristics of the bond. λ_t are trading date fixed effects to control for market level events. The key covariate of interest β_1 reflects the effect of a downgrade event on primary market activity. A positive value suggests the bonds are delivered to the ETFs by APs from the ETFs as part of a creation basket. The vector of time-varying bond-level controls include the log of amount outstanding, the average rating, the log of age, and the log of time to maturity. Standard errors are clustered at the bond and trade date levels. The results of the specification are shown in Table 3.

[Insert Table 3]

Column 1 presents the results for the full sample of investment grade bonds. Column 2 includes only observations from bonds that experience a downgrade at one point in the sample. Column 3 restricts the sample to a one-month window around the event. In each sample, the coefficient of interest is positive and significant in each column. Focusing on the one-month window sample, on a downgrade day the amount of primary market activity in a bond increases 19.03%.[9] Overall, the results of this section suggest that the flexibility of corporate bond ETF primary markets is used to offset inventory accumulation during idiosyncratic shocks.

3.2. ETFs and Abnormal Bond Returns Around Downgrades

The results of the primary activity around the downgrades suggest that ETFs may be used as a warehouse by dealers. Thus, the dealers can provide liquidity to underlying market sellers without bearing the inventory risk. To examine the effect of ETFs in periods of idiosyncratic firm-specific shock, we look at downgrades of corporate bonds. As before, we focus on downgrades within the investment grade category. Therefore, we do not consider bonds that cross the investment grade status. Doing so ensures that bonds remain eligible for inclusion in the same ETFs and that we do not conflate the effect with endogenous liquidity demands associated with changes in investment grade status.

Our empirical strategy utilizes the rules-based nature of corporate bond benchmarks and the concentration of primary market activity for investment grade ETFs in LQD. LQD requires that a bond have an average numerical conversion of rating of 10.5, a minimum time to maturity of three years, a minimum issue amount outstanding of $750

[9] The economic magnitude is computed as $e^{0.1742426}$-1.

million, and at least $2 trillion in issuer amount outstanding. The sample consists of bonds from issuers with at least two issuances with at least three years to maturity experiencing a broad ratings downgrade (e.g., AA to A) in the same week. We use the issue amount outstanding threshold differential to identify bonds eligible for inclusion in the more liquid, LQD. Treatment bonds have amount outstanding of $750 million and thus are eligible for LQD inclusion. Control bonds are ineligible because their amount outstanding is less than $750 million. To circumvent liquidity issues, we keep bonds that trade each week during the twelve-week period surrounding the downgrade event. To avoid blending the effects of several downgrades of the same issuers' bonds, we keep only downgrades at least 25 weeks apart.

In Figure 2 we plot abnormal returns to bonds in the treatment and control groups around the downgrade event in week 0. Abnormal returns are computed as the weekly return of a bond over a portfolio of maturity and rating matched bonds following Bessembinder et al. (2008). Panel A presents weekly abnormal returns. Panel B plots cumulative abnormal returns. Visually, the two types of bonds exhibit parallel trends in weekly returns up to a month before the downgrade. However, treatment bonds have a smaller cumulative reaction to the downgrade than control bonds. In the weeks after the downgrade, the returns of the two groups tend to converge. The pattern of more negative returns followed by a greater rebound by control eligible bonds suggests an overreaction by bonds ineligible for LQD inclusion. The basic pattern rules out the negative effect from ETF inclusion but does not distinguish between a positive and null effect.

[Insert Figure 2]

To empirically test the effect, we run the following weekly issuer-by-date, $\gamma_{j,w}$, fixed effects regressions,

$$exret_{i,j,w} = \gamma_{j,w} + \sum_{w=-4}^{4} \beta_{\mathrm{i,w}}(d_w * ETF_{ij,t-1}) + \beta_2 ETF_{i,j,t-1} + \beta_3 X_{i,j,t-1} + \epsilon_{i,j,w}. \quad (8)$$

The dependent variable, $exret_{i,j,w}$, is the excess weekly return of bond i from issuer j in week w in excess of the return on matched rating-maturity bin. d_w is an event-period dummy relative to the downgrade week, $w = 0$. ETF is one of two proxies — $ETF\ ownership$ or an indicator for LQD eligibility. We control for observable bond characteristics $X_{i,j,t-1}$. Table 4 reports the results of the regressions. Column (1) uses ETF ownership and column (2) the LQD dummy variable.

[Insert Table 4]

In the weeks surrounding the downgrade, bonds with higher ETF ownership and meeting the LQD standard experience significantly higher returns. Even controlling for a number of bond characteristics, a bond with additional percentage point of ETF ownership has 0.155 percentage point higher returns on the downgrade week. The downgrade week variable of LQD is insignificant, but bonds eligible for LQD have 0.54 percentage point higher returns the week after the downgrade. Cumulative excess returns of bonds with greater ETF ownership is 0.272 percentage points than a bond from the same issuer. Bond's meeting LQD's eligibility standard have 0.596 percentage points greater returns. Overall, the results of this section suggest that bonds with greater exposure to ETFs overreact less to the idiosyncratic shock.

3.3. ETFs and Idiosyncratic Risk

In equities, ETF ownership is associated with higher volatility driven by AP and non-AP arbitrage conducting secondary ETF market shocks to the underlying. These results suggest that the liquidity buffer alternative hypothesis of Ben-David et al. (2018) may apply to corporate bond ETFs. Rather than the framing of traders with liquidity needs migrating to the basket security, our results are suggestive of the additional layer of market-making. That is the ETFs buffer the underlying from either the forced selling of the market maker to avoid inventory risk or from large pricing swings associated with inventory risk. This hypothesis is in line with Bessembinder et al. (2018) conjecture that the bank-affiliated dealers are increasingly less likely to commit their capital to provide liquidity.

To empirically test the effect, using a sample of matched bonds, we run the following monthly regression:

$$IR_{i,j,m} = \gamma_{j,m} + +\beta_1 ETF\ ownership_{i,j,m-1} + \beta_3 X_{i,j,m-1} + \epsilon_{i,j,m} \tag{9}$$

The dependent variable, $IR_{i,j,m}$ is idiosyncratic return volatility of bond i from issuer j in month m. $ETF\ ownership_{i,j,m-1}$ refers to the lagged fraction of bond amount outstanding held by ETFs. The vector X of time-varying bond-level characteristics includes controls for ETF primary market activity, ownership by index mutual funds and active mutual funds, the age, the average rating, illiquidity, time to maturity, the amount outstanding, coupon payments and indicators for existence of various covenants.

In Table 5 we report the results of regressions from equation (9) using $IR_{i,j,m,t}$ as the dependent variable. The results show that ETF ownership is negatively related to idiosyncratic risk, opposing the findings in equity ETFs. In the simplest regression model, a one percentage point increase in ETF ownership leads to a 0.771 decrease in idiosyncratic risk (Table 5, Column 1). Controlling for a number of bond characteristics and augmenting the regression with bond type or bond type-month fixed effects decreases the coefficient, but preserves its sign and statistical significance. In the most robust regression specification, we show that a percentage point increase in ETF ownership leads to a 0.186 decrease in idiosyncratic risk (Table 5, Column 4). This decrease corresponds to an 6% decline for the median bond in our sample.

In column (5) we remove observations in the top 5% of *IR* and *ETFOwnership* variables. The results are robust to the exclusion of outliers. Finally, we investigate whether the ETF ownership–risk relationship rises only from the illiquid bonds. ETF membership may affect the liquidity only of such bonds. However, the empirical evidence suggests that it is not the case. The ETF ownership – risk relationship is negative and significant in the subsamples of more and less liquid bonds (Column 6 and 7).

[Insert Table 5]

4. Conclusion

In this paper we document that the flexibility of ETF in-kind creation and redemption adds a new layer of market-making to the underlying corporate bond market. During periods of idiosyncratic shocks – notably downgrades – dealers deliver downgraded bonds to the ETF in creation baskets. Doing so reduces the inventory risk associated with market making in these bonds. We find that downgraded bonds with greater ETF ownership reach their fundamental price faster than other downgraded bonds from the same issuer. Specifically, the bond returns in the week of the downgrade are less negative and experience less of a reversal. Thus, corporate bond ETFs have become a warehouse for dealers to address idiosyncratic shocks.

The above results suggest that in corporate bonds the flexibility of the in-kind creation and redemption baskets provides a liquidity buffer for market makers. Supporting this conjecture, we find that greater corporate bond ETF ownership lowers the idiosyncratic volatility of bonds. Unique to the corporate bond market, we are able to control for fundamental risk and news by comparing two bonds from the same issuer and same seniority on the same date.

Overall, the results of this paper suggest that the findings of the equity ETF literature may not be applicable to situations where exact replication and instantaneous non-AP arbitrage are impeded by the liquidity mismatch between the ETF and the underlying. Further, the findings of this paper suggest that ETFs in-kind creation and redemption may have altered the microstructure of the underlying OTC market.

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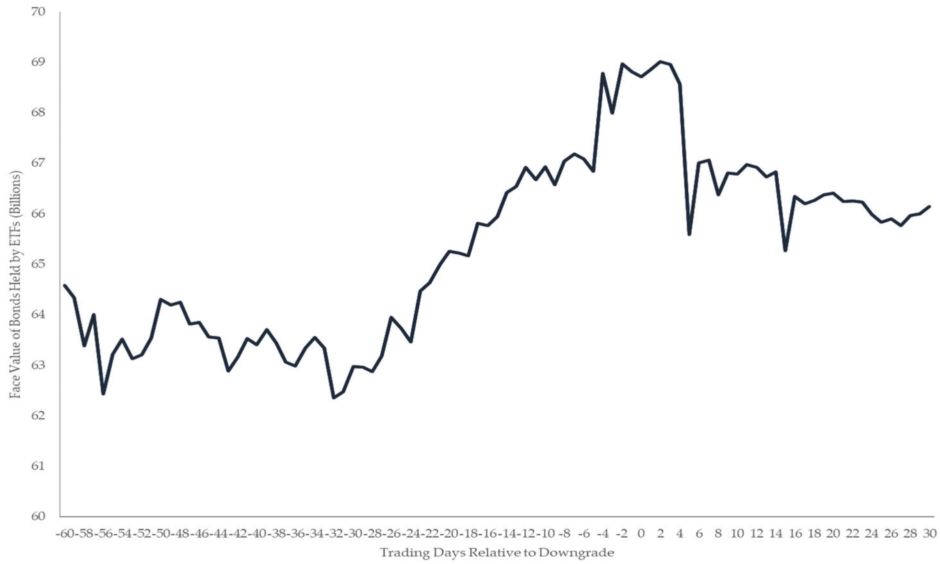
Figure 1
ETF Holdings Around Bond Downgrades

This figure plots the total number of bonds held by ETFs around a downgrade by one of the three main rating agencies on date 0. Panel A presents results for investment grade bonds and Panel B for high yield bonds. We require no other downgrades to occur in the previous sixty trading days and the bond to maintain its investment grade status.

Panel A: Investment Grade Bonds



Panel B: High Yield Bonds

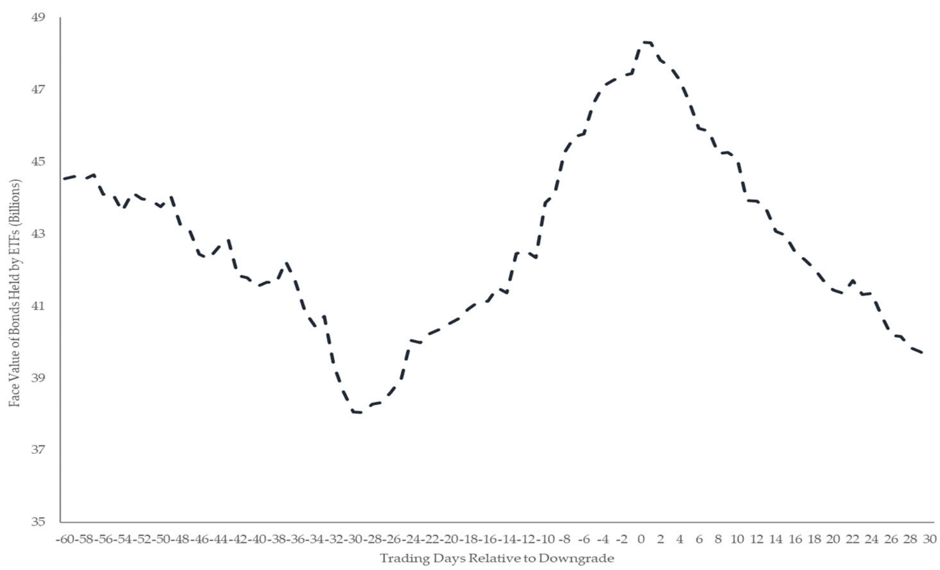


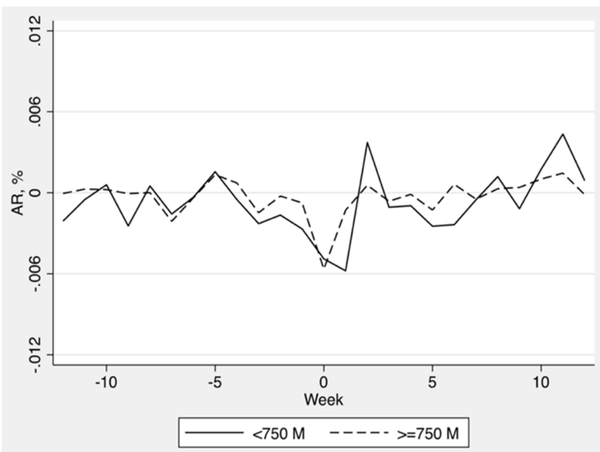
Figure 2

Abnormal returns around bond downgrade events

These figures display weekly returns of bonds from the same issuer around a broad downgrade (ex. AA to A) that remains above the investment grade threshold in week 0. Panel A plots the average weekly returns in excess of a portfolio of maturity and ratings matched bonds. Panel B plots the average cumulative abnormal returns. Treatment bonds are eligible for inclusion in the iBoxx $ USD investment grade ETF, ticker LQD ETF eligible. These bonds have at least $750 million in amount outstanding and three years time to maturity. Control bonds from the same bond experience a downgrade and have at least three-years-time to maturity, but have less than $750 million in amount outstanding. We require the bonds to have returns for each week around the event.

Panel A

Abnormal returns



Panel B

Cumulative abnormal returns

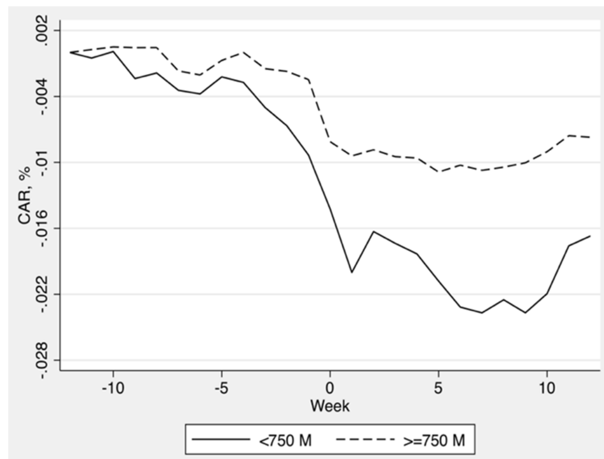


Table 1

Summary statistics

This table presents summary statistics for the variables used in the sample over the period from 2015 to 2021. *ETF Ownership*, $IMF\ Ownership$ and $AMF\ Ownership$ represent the fraction of bond's amount outstanding owner by ETFs, index mutual funds and active mutual funds, in %. *ETF Primary* and *Turnover OTC* are the ratios of bond dollar-amount used in creating ETFs and traded on an exchange to amount outstanding, in %.

	count	mean	sd	min	median	max
ETFOwnership	113,440	3.74	1.73	0.02	3.63	11.31
ETFPrimary	113,440	0.27	0.45	0.00	0.09	3.78
IMFOwnership	113,440	2.39	1.63	0.00	2.41	7.96
AMFOwnership	113,440	7.85	7.18	0.00	5.66	45.05
TurnoverOTC	113,440	0.08	0.08	0.00	0.05	0.66

Table 2
Summary statistics

This table presents summary statistics for the variables used in the sample over the period from 2015 to 2021. IR is a measure of bond's idiosyncratic risk. The remaining variables represent bond's issuance level characteristics. AOm is the bond's amount outstanding in millions, $T2M$ and Age are bond's time to maturity and age in years. *Rating* is the numeric conversion of the letter rating (AAA = 1, AA+ = 2, AA = 3, AA- = 4, and so forth). $Amihud$ is Amihud (2002) illiquidity measure. *Coupon* is a bond's coupon rate in %. The following variables count the number of restrictions on dividend payout (*Div_covenant*), events (*Event_covenant*), financial (*Financial_covenants*), investments (*Investment_covenants*).

	count	mean	sd	min	median	max
IR	113,440	4.49	5.01	0.46	3.06	65.77
Age	113,440	3.59	2.70	0.07	3.07	19.28
AOm	113,440	1,081.95	691.17	205.96	984.11	4,317.48
T2M	113,440	7.63	7.35	1.04	5.04	29.67
Rating	113,440	8.16	3.09	1.00	8.00	20.00
Amihud	113,440	0.04	0.05	0.00	0.02	0.35
Coupon	113,440	3.97	1.47	1.05	3.75	11.00
Dividend_cov	113,440	0.18	0.68	0.00	0.00	3.00
Event_cov	113,440	1.48	0.87	0.00	2.00	3.00
Financial_cov	113,440	2.61	1.83	0.00	3.00	9.00
Investment_cov	113,440	1.56	1.33	0.00	1.00	6.00

Table 3

Creation Activity around downgrades

The table reports the results of the following regression: $\log(ETF\ Primary_{i,j,t}) = \alpha_i + \lambda_t + \beta_1 Downgrade_{i,j,t} + \beta_2 X_{i,j,t} + \epsilon_{i,j,t.}$ The dependent variable is the log of one plus the total primary bond market activity by all ETFs in bond i from issuer j on trading date t.. *Downgrade* is a dummy variable taking a value of one on the date of a downgrade. The vector X of time-varying bond-level controls includes the log of amount outstanding (*log_AO*), the average rating (*Rating*), the log of age (*log_Age*), and the log of time to maturity (*log_T2M*). All regressions include issue and day fixed effects. The regressions use the entire sample observations of investment grade bonds (Column 1), downgraded bonds only (Column 2) and the observations falling within a 30-day window only (Column 3). Standard errors are clustered at the bond and trade date levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	ETFPrimary	ETFPrimary	ETFPrimary
Downgrade	0.134**	0.128**	0.142***
	(0.053)	(0.053)	(0.050)
log_AO	1.258***	1.353***	0.528***
	(0.057)	(0.090)	(0.120)
log_Age	-0.007	0.010	0.044
	(0.012)	(0.017)	(0.064)
log_T2M	0.554***	0.534***	0.592***
	(0.023)	(0.028)	(0.081)
Rating	0.028*	0.024	0.065**
	(0.017)	(0.021)	(0.031)
Observations	11,137,647	4,816,458	409,524
R-squared	0.259	0.244	0.302

Table 4

Excess returns around downgrades

The table reports the results of the following regression: $exret_{i,j,w} = \gamma_{j,w} + \sum_{w=-4}^{4} \beta_{i,w}(d_w * ETF_{ij,t-1}) + \beta_2 ETF_{i,j,t-1} + \beta_3 X_{i,j,t-1} + \epsilon_{i,j,w}$. The dependent variable is the return of bond in excess of the average return of a portfolio of bonds with similar ratings and maturities. d_w is a dummy variable taking a value of one w weeks after the issuer's broad downgrade event (e.g. AA to A, etc.). ETF represents one of two proxies for a bond's exposure to ETFs. Column (1) uses ETF ownership and column (2) is a dummy equal to one if a bond qualifies for membership in LQD with amount outstanding greater than $750 million. Regressions include the lagged of the following control variables Turnover OTC, IMF ownership, AMF ownership, log of Age, Rating, Amihud, T2M, and the log of amount outstanding. All regressions include issuer-week fixed effects, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	ETF ownership	LQD
	(1)	(2)
d_{-4} x ETF	0.023	-0.008
	(0.047)	(0.172)
d_{-3} x ETF	0.134***	0.091
	(0.047)	(0.150)
d_{-2} x ETF	0.052	0.276*
	(0.052)	(0.157)
d_{-1} x ETF	-0.032	-0.147
	(0.052)	(0.294)
d_0 x ETF	0.155**	0.005
	(0.066)	(0.186)
d_1 x ETF	-0.025	0.540**
	(0.078)	(0.249)
d_2 x ETF	0.025	-0.041
	(0.068)	(0.221)
d_3 x ETF	-0.060	-0.120
	(0.074)	(0.272)
d_4 x ETF	0.077	-0.050
	(0.071)	(0.202)
ETFOwnership(t-1)	-0.005	0.010
	(0.017)	(0.015)
LQD		-0.098**
		(0.043)
Observations	5,258	5,258
R-squared	0.556	0.556

Table 5

Idiosyncratic return volatility

This table reports the results of regressions from the following panel regression: $IR_{i,j,m} = \gamma_{j,m} + +\beta_1 ETF\ ownership_{i,j,m-1} + \beta_3 X_{i,j,m-1} + \epsilon_{i,j,m}$. The dependent variable is idiosyncratic return volatility of bond I from issuer j in month m. ETFOwnership refers to the fraction of bond amount outstanding held by ETFs. The vector X of time-varying bond-level controls includes the fraction of bond amount outstanding used in the ETF primary market (*ETFPrimary*), owned by index mutual funds (*IMFOwnership*) and active mutual funds (*AMFOwnership*), the log of age (*log_Age*), the average rating (*Rating*), Amihud (2002) illiquidity measure (*Amihud*), the log of time to maturity (*log_T2M*), log of amount outstanding (*log_AO*), *Coupon.* The regression also controls for the number of restrictions the bond has on dividend payout (*Div_covenant*), events (*Event_covenant*), financial (*Financial_covenants*), investments (*Investment_covenants*). The regressions include issuer-month fixed effects (Columns 1-3), bond type fixed effects (Column 3) and bond type-month fixed effects (Columns 4-7). Standard errors clustered at the issue and month level are presented in parenthesis below the coefficient. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	IR	IR	IR	IR	IR	IR	IR
ETFOwnership	-0.771***	-0.185***	-0.185***	-0.186***	-0.192***	-0.155***	-0.197***
	(0.034)	(0.013)	(0.013)	(0.013)	(0.015)	(0.016)	(0.019)
ETFPrimary		-0.111***	-0.114***	-0.117***	-0.082***	-0.076	-0.125*
		(0.039)	(0.039)	(0.039)	(0.028)	(0.057)	(0.063)
IMFOwnership		0.016	0.016	0.017	0.025***	0.015	0.029*
		(0.011)	(0.011)	(0.011)	(0.009)	(0.012)	(0.016)
AMFOwnership		-0.004	-0.004	-0.004	-0.003	-0.012***	0.003
		(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)
TurnoverOTC		-1.776***	-1.801***	-1.795***	-1.384***	-0.833**	-2.857***
		(0.257)	(0.256)	(0.259)	(0.141)	(0.335)	(0.380)
log_Age		0.220***	0.222***	0.225***	0.184***	0.271***	0.213***
		(0.025)	(0.024)	(0.025)	(0.015)	(0.024)	(0.037)
Rating		0.130*	0.679	0.262	-0.030	0.508	1.011
		(0.074)	(0.556)	(0.681)	(0.475)	(0.899)	(0.632)
Amihud		2.000***	2.115***	2.079***	1.404***	-6.570*	2.086***
		(0.676)	(0.667)	(0.657)	(0.351)	(3.768)	(0.660)
log_T2M		2.436***	2.437***	2.441***	2.114***	2.336***	2.603***
		(0.115)	(0.114)	(0.114)	(0.046)	(0.124)	(0.127)
log_AO		-1.007***	-1.011***	-1.006***	-0.796***	-0.594***	-1.249***
		(0.047)	(0.048)	(0.047)	(0.036)	(0.042)	(0.059)
Coupon		-0.015	-0.013	-0.015	-0.019	-0.063***	0.041*
		(0.015)	(0.015)	(0.015)	(0.012)	(0.019)	(0.022)
Dividend_cov		-0.058	-0.052	-0.056	-0.009	0.046	-0.046
		(0.054)	(0.054)	(0.053)	(0.043)	(0.056)	(0.085)
Event_cov		-0.038*	-0.036*	-0.041*	-0.024	-0.022	-0.050
		(0.021)	(0.020)	(0.021)	(0.017)	(0.022)	(0.030)
Financial_cov		-0.008	-0.011	-0.012	-0.005	-0.022	-0.012
		(0.014)	(0.014)	(0.014)	(0.011)	(0.015)	(0.022)
Investment_cov		-0.003	-0.000	0.001	-0.017	0.000	0.010
		(0.019)	(0.020)	(0.020)	(0.015)	(0.021)	(0.028)
Observations	112,777	112,777	112,774	112,499	100,384	49,179	55,501
R-squared	0.782	0.865	0.866	0.866	0.791	0.863	0.884