The Impact of Innovation: Evidence from Corporate Bond ETFs

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Abstract

Using distinct features of corporate bond ETFs, financial innovation is found to have a significant and long-term positive valuation impact on the systemically important underlying. A one standard deviation increase in ETF ownership reduces high yield and investment grade bond spreads by 20.3 and 9.2 basis points, respectively, implying an average monthly price increase of 1.03% and 0.75%. Two novel quasi-natural experiments exploit exogenous changes in ETF eligibility to confirm the effect. Examining theoretical explanations for the effect, ETFs are found to decrease liquidity trader participation, increase institutional ownership, and insignificantly or negatively impact the liquidity of individual bonds.

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1. Introduction

As traditional financial markets evolve and innovations emerge, the impact of new investment vehicles on the underlying securities remains a central question for policy makers, researchers, and practitioners. To date, attempts to answer this question have produced conflicting theoretical predictions and empirical evidence. For instance, Conrad (1989), Detemple and Jorion (1990), and Jordan and Kuipers (1997) find a positive price impact from options and Treasury bond futures supporting the theories of Detemple and Selden (1991) and Ross (1976) that innovation improves trading opportunities. In contrast, Danielsen and Sorescu (2001) and Sorescu (2000) attribute a negative valuation effect from option introductions following 1980 to lower short sale constraints as predicted by Miller (1977). This paper contributes to the literature by examining the impact of an increasingly important investment alternative, the Exchange Traded Fund (ETF), and by using a novel identification strategy to overcome endogeniety issues common in financial innovation research.

In complete and frictionless markets, basket securities like ETFs are redundant assets that have no impact on the prices of the underlying. However, in certain circumstances Banerjee and Graveline (2013), Gorton and Pennacchi (1993), and Grossman (1988) argue that composite securities may alter the investment universe leading to a valuation effect. Additional theories of a positive valuation effect suggest that innovation changes the composition of traders in the underlying through either a migration of liquidity traders to the lower transaction and adverse selection costs of the basket (Gorton and Pennacchi, 1993) or an increase in informed investors due to improved trading opportunities, greater hedging alternatives, and increased information (Cao, 1999; Massa, 2002). Further, since the majority of ETFs are index-based, Basak and Pavlova (2013) predict that institutions may tilt their portfolios towards constituents, leaving non-index securities unaffected. The theorized changes result in a higher proportion of informed investors, which all else equal, leads to a positive valuation effect from decreased investment risk and more revealing trades (Easley and O'Hara, 2004). Conversely, Banerjee and Graveline (2013) and Danielsen and Sorescu (2001) claim that reduced scarcity and short sale constraints lead to a negative price effect from innovation.[1] Theories also suggest liquidity may decrease due to higher adverse selection risk from a liquidity trader exodus (Dow, 1998; Gammill and Perold, 1989; Gorton and Pennacchi, 1993; Subrahmanyam, 1991) or increase due to index arbitrage (Fremault, 1991; Kumar and Seppi, 1994). Given these conflicting views, ETF constituency provides a formidable laboratory to study the impact of innovation on the underlying securities. This paper finds that ETFs have a long-term positive valuation effect on constituents due to reduced liquidity trader participation and greater informed investor ownership, while liquidity is insignificantly or negatively impacted supporting the predictions of Gorton and Pennacchi (1993), amongst others.

Two recent salient market developments are the prodigious growth of the systemically important corporate bond market and the emergence of ETFs. Between 2000 and 2014, corporate debt outstanding increased over 130% to $7.8 trillion according to SIFMA, while ETF assets grew from $65.6 billion in equity-based products to approximately $2 trillion with offerings spanning nearly every investment class. At the intersection of these developments lie corporate bond ETFs. Although smaller than equity based ETFs, this study focuses on corporate bond ETFs for four key reasons. First, distinct institutional features provide a clean identification strategy to obtain plausibly exogenous variation in ETF eligibility. Second, ETFs distinctively alter the corporate bond investment universe by providing intraday pricing previously unavailable from major bonds indices and enhancing the set of investable index offerings. Specifically, to date there are no high yield specific index mutual funds and

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[1] The direction of price effect in Banerjee and Graveline (2013) is dependent on the relative dominance of the substitution effect and the wealth effect. However, the authors claim that the most natural relationship would be a negative price effect.

94% of investment grade index funds have large Treasury bond holdings.[2] Third, corporate bond ETFs have been flagged by regulators and practitioners as a potential systemic threat due to the sharp contrast between the liquid and transparent ETF market and illiquid Over the Counter (OTC) bond market.[3] Finally, given the importance of ETFs as an investment vehicle and debt financing to corporations, this study has implications for both asset pricing and corporate finance.

To examine the impact of innovation on the underlying bonds, a sample of monthly bond observations from January 2009 to November 2013 is used. For the valuation effect, I estimate a fixed effects model and two quasi-natural experiments to address concerns that the introduction of and inclusion in new financial vehicles are not random events (Mayhew and Mihov, 2004). In the fixed effects model, monthly observations of volume-weighted yields over the maturity-matched swap rate are regressed on ETF ownership, credit risk measures, lagged liquidity proxies, and both bond and time fixed effects. Relying on within bond variation, I find that a one standard deviation increase in ETF ownership decreases yield spreads by 20.3 basis points for high yield bonds and 9.2 basis points for investment grade bonds. Economically, for the median (mean) high yield and investment grade constituent these reductions imply a monthly yield spread decrease of 4.6% (3.7%) and 6.8% (5.6%) and correspond to a monthly price increase of 0.97% (1.03%) and 0.53% (0.75%).

Two quasi-natural experiments exploit the rules-based nature of the indices followed by corporate bond ETFs to provide further evidence of the valuation effect from ETF constituency. The experiments rely on the rules governing the Markit benchmarks followed by two important ETFs: the iShares iBoxx

[2] Of the 75 distinct investment grade bond index funds identified by Morningstar 22 are benchmarked to either international markets, government securities, or mortgage backed securities. Of the remaining 53 funds, 45 follow the Barclays US Aggregate or Barclays US Government/Credit indices and 5 the BlackRock CoRI indices. The remaining 3 funds that follow corporate bond dedicated indices are offered by Vanguard and have an ETF specific share class.

[3] The Financial Stability Oversight Committee lists the growth of corporate bond ETFs as an emerging systemic threat. While, Goldman Sachs' credit team has examined claims of an "ETF Bid" in corporate bond yields and Carl Ichan blamed BlackRock ETFs for the "liquidity crisis" in corporate bonds.

$ High Yield Corporate Bond ETF (HYG) and the iShares iBoxx $ Investment Grade ETF (LQD). The first experiment studies the impact of a rule change that removed a cap on the number of HYG constituents on bonds purchased immediately following the event, with the original ETF bonds whose weightings decreased serving as the control group. In this context, the key identifying assumption is that the cap was the only impediment to the prior inclusion of the treatment bonds. Using a difference-in-difference framework, I find that the yields of the treatment bonds are 138 basis points lower than the control group over the six-month transition period. For the median (mean) bond in the experiment this equates to an additional 21.3% (13.1%) reduction yield spread and a 6.69% (6.84%) price increase. The second experiment exploits the strict three-year minimum time to maturity threshold followed by LQD. Bonds sold due to the rule have 4.5 basis points higher yield spreads following their exit from the ETF relative to maturity matched non-LQD investment grade bonds. The results imply a 5.7% (4.4%) spread increase and a 1.0% (0.92%) price decrease for the median (mean) bond in the sample.

The paper continues by examining if the nature of the valuation effect is temporary due to demand pressure or permanent due to broader market developments. To do so, for each of the six months following ETF inclusion cross-sectional regressions of the change in spread relative to the base spread from the month prior to constituency on an ETF dummy, the base spread, and time fixed effects are conducted. Using bonds from the same issuer and the five nearest neighbors from propensity score matching as two control groups the positive valuation effect is shown to be long-term, with point estimates increasing over time and remaining significant six months after the initial inclusion event.[4]

[4] I also considered studying the exit effect, but found an insufficient number of bonds that were sold without an associated ratings change and then remained outside of the ETF universe for six months. Given the significant growth in assets over the time of this study, this should not be too surprising.

Next, two potential explanations for the valuation effect are examined: changes in the composition of traders and improved liquidity. For each bond-month the percentage of total volume attributed to different trade types is computed. Since transaction costs in the corporate bond market are inversely related to size (Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007), retail-sized trades, defined as those less than $100,000 (Goldstein, Hotchkiss, and Sirri, 2007), are posited to be used by uninformed investors or institutional traders with capital needs. Four ETF activity proxies are constructed to account for different qualities of ETF trading: ETF ownership, creation and redemption intensity (Da and Shive, 2013), ETF turnover, and ETF short interest. Summary statistics support the theoretical predications of an increase in the proportion of informed traders for high yield and investment grade ETF bonds as the of volume attributed to liquidity traders is 35.6% and 37.3% lower, the average mutual fund ownership is 29.7% and 58.7% greater, and the number of mutual fund holders nearly doubles in constituency months. Fixed effects regressions empirically confirm these results. Lagged ETF activity is found to have a significant negative impact on the proportion of retail trading in the underlying markets. While contemporaneous ETF activity significantly increases both the level of mutual fund ownership and the number of mutual fund investors.

I conclude by investigating if increased liquidity in the underlying bonds is responsible for the valuation effect. Fixed effects regressions of several liquidity proxies on lagged measures of ETF activity and other controls show an insignificant liquidity impact for high yield constituents. In the investment grade market liquidity, as measured by the transaction costs proxies, is significantly negatively related to ETF ownership, turnover, and short interest. The contrast in results is surprising given the increased risk associated with high yield bonds. However, the majority of trades in the high yield market are in excess of $1 million, while in investment grade markets liquidity traders represent the majority likely making the change in trader composition more impactful. While individual bond liquidity is not responsible for lower yields; it remains possible that the ability to manage corporate bond exposure through ETFs positively impacts complete market liquidity.

The astounding asset growth and exceptional liquidity of ETFs has attracted the attention of academics, with most studies focusing on equity-backed products. To date, empirical evidence has found an uncertain impact on liquidity. Hegde and McDermott (2004) find decreased transaction costs for Dow Jones 30 stocks following the Diamond ETF introduction. In broader samples, Hamm (2014) and Israeli, Lee, and Sridharan (2016) find a negative relationship between ETF holdings and the liquidity of underlying stocks, corroborating the results of this paper. Additional research finds that ETF ownership of stocks increases volatility (Ben-David, Franzoni, and Moussawi, 2014) and co-movement (Da and Shive, 2013). This paper contributes by examining the valuation impact using an original identification strategy and by extending the focus to corporate bond offerings.

Finally, this paper adds to the literature on the structure of the bond market. Using the 2002 introduction of trade level reporting, Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2007) and Goldstein, Hotchkiss, and Sirri (2007) document a negative relationship between transparency and transaction costs. Primarily motivated by the financial crisis, Bao, Pan, and Wang (2011), Chen, Lesmond, and Wei (2007), Dick-Nielsen, Feldhütter, and Lando (2012) and Friewald, Jankowitsch, and Subrahmanyam (2012) demonstrate the importance of liquidity as a determinant of yield spreads. Following these transformative events, the market is in the midst of another change as traditional market makers reduce inventories, making ETFs important participants about which little is known. This paper helps to understand some of the effects related to the emergence of this innovation in the traditional market.

2. Background

Fixed income ETFs were introduced to the US market in July 2002 by iShares from Barclays Global Investors, now owned by BlackRock. Fig. 1 documents the rapid growth in assets under management for three ETF types. The first is all fixed income ETFs, such as government, municipal, and money market funds. The second includes all ETFs that hold corporate bonds, specifically pure corporate bond ETFs and total bond market ETFs. The third is pure corporate bond ETFs. Also plotted is the growth in ETF monthly volume over total TRACE volume in ETF bonds over the period, which documents the growing popularity of ETFs as a fixed income investment alternative, with $2 of ETFs traded for every $5 of the underlying at its peak level.

[Insert Fig. 1]

2.1. ETF structure

Since this paper attempts to discern the impact of ETFs on the traditional market, it is important to understand the mechanisms that link the instrument to the underlying. Simply put, ETFs are basket securities traded on an exchange as a single stock. The hybrid structure of ETFs combines the advantages of traditional mutual funds and Closed-End Funds (CEFs), with lower management fees, greater transparency, and tax efficiencies to attract investors (Poterba and Shoven, 2002). Although registered under the Securities and Exchange Commission (SEC) Act of 1934 and the Investment Company Act of 1940 (ICA), the in-kind creation and redemption feature that distinguishes ETFs requires relief from certain governance provisions. Key exemptions are related to sections of the ICA that require redeemable individual securities, continuous offerings, and trading only at the Net Asset Value (NAV), while prohibiting transactions with affiliated persons.

2.1.1. ETF origination

An ETF is created by a sponsor who specifies the investment objective, index, and tracking methodology of the fund. Fixed income benchmarks are very large, with eligibility based on strict size, maturity, and ratings thresholds making inclusion and exclusion information-free events, unlike most equity index changes (Dick-Nielsen, 2013). Due to the size of the benchmarks, fixed income ETFs generally employ a representative sampling strategy, rather than the strict indexing strategy utilized by the majority of equity offerings. The duties of the sponsor include daily publishing and management of portfolio holdings. Generally, ETF management is much simpler than mutual fund management because most transactions occur between investors on the exchange without sponsor involvement. Instead, Authorized Participants (APs) – market makers, specialists, and institutional investors – handle transactions in the underlying associated with sizeable creation and redemption demand. Since managers do not trade in the underlying to meet investor orders commissions, expenses, and capital gains are suppressed.

One of my identification strategies relies heavily on an important sponsor, iShares. Not only was iShares the first to introduce fixed income ETFs, but it also continues to represent approximately 50% of the market. In particular, I focus on two of their funds, HYG and LQD. These ETFs were the first and remain the largest offerings in their respective investment class. Of particular importance, is that the indices used by HYG and LQD are administered by Markit rather than Barclays. Using ETFs that follow Markit indices allows me to disentangle an ETF specific effect.

2.1.2. ETF trading

ETF trading occurs in two venues, the primary and secondary markets. The primary market is used by ETFs to handle liquidity shocks in the secondary market, to ensure that orders are filled, and to arbitrage excessive price deviations from NAV. This market is the direct channel linking ETFs to the underlying. It involves large transactions between APs and the sponsor in the in-kind creation and redemption process. An AP creates ETF shares by depositing the specified basket – a portfolio of securities and any cash component – with the fund sponsor in exchange for a creation unit (typically 50,000 ETF shares).[5] Upon receipt of the creation unit, the AP can sell the ETF shares in the secondary market. Redemption reverses the process with the AP collecting ETF shares and exchanging the redemption unit for a basket of underlying. Due to this process, the number of shares outstanding of ETFs may fluctuate daily allowing for de minimis deviations from NAV. The secondary ETF market represents the supply and demand features that characterize common stocks, where buyers and sellers of the ETF transact directly on the exchange.

3. Data description

This section details the comprehensive monthly dataset constructed from the period January 2009 to November 2013. First, corporate bond transaction data is sourced from TRACE. Initially introduced on July 1, 2002, the TRACE database now contains data for 99% of the transactions in the corporate bond market. Reflecting the drive for improved transparency, the original corporate bond ETF was introduced on July 22, 2002 concurrent with the first stage of TRACE. To avoid the confounding effects of the TRACE introduction and to study a period when the assets held by ETFs are no longer

[5] The cash component accounts for creation fees (ranging from $250 to $1,500 per unit), accrued coupon payments, interest on coupon payment, any capital gains less losses that have not been reinvested since the last distribution, and small amounts to cover rounding in the number of shares delivered

negligible, the data begins in 2009. For all transactions with an observable CUSIP in the TRACE historical database, I match bond level characteristics from Bloomberg on eight-digit CUSIP. Using these descriptive characteristics, I exclude all variable rate, sinking fund, perpetual, convertible, preferred, asset-backed, and Rule 144A securities. The final dataset includes only fixed rate bullet, callable, and putable bonds. In addition, for each bond I create an average rating using numerical conversions of S&P, Moody's, and Fitch ratings. Finally, I filter out possibly erroneous trades using the method of Dick-Nielsen (2009). The yield spread of a bond is calculated as the monthly volume-weighted yield over the maturity matched risk-free proxy. Following, Blanco, Brennan, and Marsh (2005), Collin-Dufresne and Solnik (2001), Feldhütter and Lando (2008), Grinblatt (2001), Hull, Predescu, and White (2005) and Longstaff (2004) the swap rate is used as the risk-free proxy. Using the TRACE database, I also compute monthly liquidity statistics for each bond.

Next, I identify and classify ETFs using the CRSP Survivor-Bias-Free U.S. Mutual Fund database and hand collected data from fund fact sheets and prospectuses. Corporate bond ETFs are identified using the *et_flag* and *crsp_obj_cd* fields of the CRSP Mutual Fund Summary dataset and the ETF database website.[6] I then use prospectuses to catalog the ETFs into one of twelve broad classifications and six subclasses.[7] Finally, for each ETF identified as having maturity based eligibility, I find the maximum and minimum time to maturity thresholds. Since this paper studies the corporate bond market, I focus on those ETFs that hold corporate bonds: broad-based and pure corporate. In total, I identify 97 ETFs that have some portion of their holdings in corporate bonds. Of this total, 73 are pure corporate ETFs and 24 are broad-based fixed income ETFs.

[6] http://etfdb.com/type/bond/all/

[7] Broad Classifications: (1) Government, (2) Money Market, (3)Municipals, (4) Mortgage Backed Securities, (5) Inflation-Protected, (6) Emerging Markets, (7) Preferred, (8) International Government, (9) Closed-End Funds, (10) Loans, (11) Broad-Based, and (12) Pure Corporate. Subclasses: (a) Inverse, (b) Leverage, (c) High Yield, (d) Investment Grade, (e) Maturity Based, (f) Bullet

Holdings data for TRACE bonds is primarily sourced from the CRSP Mutual Fund Quarterly Database, but with three critical modifications. First, the information for ETFs not affiliated with a mutual fund begins with regularity only in 2010. The missing data is particularly problematic because iShares represented 100% of corporate credit ETFs until 2007 and approximately 50% of the segment's assets as of the end of the sample. I address this issue by replacing the iShares data from the CRSP holdings database with the complete time series of month end holdings from the company's website. To ensure the accuracy of the correction, I compare the months for which I have overlapping data and find that over 99% of the holdings match. Historical monthly holdings for non-iShares providers, such as SPDRs, Powershares, and ProShares, are unavailable leading to a potential underestimation of ETF holdings prior to 2010. Second, I account for portfolios that report holdings for all funds under one portfolio number. For instance, Vanguard considers ETFs as a separate share class of their mutual funds. To identify the portion of a portfolio's holdings attributable to the ETF, I find the weight of the ETF's total net assets relative to the total net assets of all associated funds. I then multiply this weight by the portfolio's holdings of each bond to obtain the ETF specific holdings. Third, I account for differences in monthly reporting by ETFs and quarterly reporting by mutual funds. To compute monthly estimates from quarterly reports I apply the reported end of quarter holdings to all months of the quarter. I then multiply the holding by the percentage change in fund assets between the reporting date and the observation month.

Next, I obtain the daily price, volume, and returns of the ETFs from the CRSP US Daily Stock Database. In addition, I get daily shares outstanding and short interest data from Compustat. The daily shares from Compustat are updated with greater frequency than those from CRSP and thus give a more accurate view of the creation and redemption activities of the ETFs. Finally, I collect issuer-level credit risk controls from the Compustat Quarterly Fundamental File and compute equity volatility from the CRSP Daily Stock Database. The Compustat data is merged with the TRACE dataset on a six-digit CUSIP and the CRSP data is merged using the stock CUSIP from Compustat. In total I compile 496,840 bond-month observations on 20,311 individual bonds from 2,945 issuers.

Throughout the study I consider the implications of ETFs on the high yield and investment grade bonds separately to account for differences in the two subclasses. Further, all variables are winsorized at the 1% and 99% levels by investment grade status to mitigate the influence of outliers. Table 1 presents summary statistics of the observable characteristics of bonds held by ETFs for at least one month of the sample relative to non-ETF bonds.

[Insert Table 1]

Panel A documents the summary statistics for the 110,263 bond-month observations in the high yield market, representing 5,927 bonds from 1,496 issuers. In this market 26.7% of bond-months, 23.6% of individual bonds, and 46.6% of issuers have positive ETF ownership. Panel B reports the summary statistics for the 386,577 bond-month observations for 15,231 individual bonds from 1,754 issuers in the investment grade market. In this market, 39.2% of bond-months, 32.1% of individual bonds, and 65.6% of issuers are associated with ETF holdings. Comparing the summary statistics in both panels it appears that ETFs generally hold bonds with lower yields, but more institutional ownership and significantly greater issuance size. In the investment grade market, ETF bonds have a lower average yield spread despite a higher average rating of A- relative to non-ETF bonds average rating of A. The discrepancy can be attributed to the prevalence of financial sector bonds in the non-ETF sample. Despite constituting 41% of the total investment grade market, only 15.2% of bonds from financial institutions are classified as ETF bonds. This underrepresentation is the result of financial institutions having more bonds per issuer, but lower average issuance size. Specifically, the mean amount outstanding for a bond in this sector is $172 million making the average financial bond ineligible for inclusion in many ETFs which have issuance size thresholds of $250 million to $750 million. These summary statistics demonstrate the importance of controlling for bond specific characteristics to avoid the endogeneity concerns discussed in the next section.

Table 1 also provides insight into the nature of index funds in the corporate bond market. Since index funds are considered the closest competitors, many have questioned if ETFs are replacing them (Agapova, 2011; Guedj and Huang, 2010). In equity markets the proliferation of index funds and ETFs following the same benchmark may be perplexing; however, the corporate bond index fund market is not as well developed. According to Morningstar there are zero high yield bond index funds, supporting the near zero average ownership levels found in Panel A. In investment grade markets, 50 of the 53 index funds in Morningstar follow indices such as the Barclays Aggregate that have a sizeable allocation in government bonds, while the remaining three corporate bond specific funds are Vanguard offerings with an ETF share class. In my sample, 73 ETFs are corporate bond specific, suggesting that this new product expands the investment opportunities of investors rather than attempting to replace the existing index fund.

4. Empirical methodology and results

This section details the empirical methodology and results. However, I first detail the endogeneity concerns common to studies of financial innovation. As described in Mayhew and Mihov (2004), studies of financial innovation, particularly those that look at the introductory event, are associated with the potential for both cross-sectional and time-series endogeneity.

4.1. Endogeneity concerns

Cross-sectional endogeneity arises if the bonds selected for inclusion in an ETF differ from those not selected on some observable or unobservable dimensions. Unlike equity ETFs, the size of bond indices and the characteristics of the corporate bond market make full replication impractical, if not impossible. In their attempts to replicate the cash flow, duration, industry, and rating characteristics of the benchmark it is possible that managers could hold bonds that are likely to outperform or the most liquid index bonds. While the liquidity story is highly plausible, concerns of managers picking bonds likely to outperform are less plausible because ETFs focus on tracking error and replication rather than absolute performance.

Time-series endogeneity occurs because ETF introductions are the result of decisions made by sponsors. Since sponsors are often associated with traditional money managers, it is likely that product introductions are made in anticipation of themes advantageous to the investment universe covered by the ETF. If it is true that sponsors create instruments in expectation of changing demand, time-series endogeneity may cause a spurious relationship between ETFs and the outcome variable of interest. Next, I develop a fixed effects model and two quasi-natural experiments to address these endogeneity concerns in the study of ETFs impact on yield spreads.

4.2. The valuation effect: Fixed effects panel regressions

My attempts to identify a causal relationship from the ETF market to the valuation of the underlying, as measured by corporate bond spreads, begin with a fixed effects panel regression. To address correlations between bonds from the same firm and between all bonds in the same month, standard errors are clustered at both the issuer and month levels. In particular I run the specification,

$$Spread_{i,t} = \alpha_i + \lambda_t + \gamma\%ETF_{i,t} + \beta_1 X_{i,t} + \beta_2 Liquidity_{i,t-1} + \varepsilon_{i,t}. \quad (1)$$

where $Spread_{i,t}$ is the volume-weighted average of the yield spread of bond i to the linearly interpolated maturity matched swap rate in month t. I incorporate bond level fixed effects, α_i, to account for time invariant bond heterogeneity. These fixed effects are critical to the inclusion of bonds with option features, which constitute a large portion of my sample, as well as, the use of bonds from different sectors. Date fixed effects, λ_t, control for common shocks and trends, which are particularly important in light of increasing ETF assets and declining spreads found over the sample period. $\%ETF_{i,t}$ is the percentage of total ETF ownership of bond $i's$ amount outstanding. The coefficient of interest is γ, with a negative value interpreted as a positive valuation effect due to the inverse relationship between yields and prices.

Since two way fixed effects are used, the only necessary covariates, $X_{i,t}$, are those that vary at the bond and date level. The controls include $Rating_{i,t}$, the numerical average of the S&P, Moody's, and Fitch ratings, to account for the impact of ratings changes.[8] I follow Blume, Lim, and Mackinlay (1998) by controlling for credit risk with $Leverage_{i,t}$, the market value of leverage; $Operating_{i,t}$, the ratio of operating income to sales; $LT\ Debt_{i,t}$, the ratio of long-term debt to assets; and four pretax interest coverage dummies, $Pretax\ Dummies_{i,t}$; as well as, $Equity\ Vol_{i,t}$, equity volatility from Campbell and Taksler (2003).[9] In some specifications, mutual fund ownership, $\%MF_{i,t}$, and index fund ownership, $\%Index_{i,t}$, are included to ensure the results are robust to controlling for other institutional investors.

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[8] Results are robust to the use of S&P ratings dummies.

[9] The pretax dummies are defined using pretax interest coverage ratio (PIRC) equal to EBIT over interest expense. Since the distribution is known to be highly skewed dummies are created to allow for a non-linear relationship. The first dummy equals the PIRC if it is less than 5 and 5 otherwise. The second dummy equals zero if PIRC is below 5, 10 if PIRC is above 10, and PIRC minus 5 for values between. The third dummy equals zero if the PIRC ratio is below 10, PIRC minus 10 if it is between 10 and 20, and 10 if above. The fourth dummy equals zero if PIRC is below 10, IRC minus 20 if IRC is between 20 and 100, and 80 if IRC is above 100.

4.2.1. Liquidity measures

Finally, I control for lagged liquidity, $Liquidity_{i,t-1}$, using measures from the corporate bond literature and a common liquidity factor found from Principal Component Analysis (PCA). The first measure is the Imputed Roundtrip Cost (IRC) from Feldhütter (2012), which is a proxy for the percentage effective spread. IRC focuses on two or three trades of the same size happening on the same day, an Imputed Roundtrip Trade (IRT). The measure is computed as the difference between the highest and lowest price in an IRT over the highest price. Next, $Bid\ Ask$ is the bid-ask spread of Hong and Warga (2000) and Chakravarty and Sarkar (2003). Using trading side indicators, the measure is calculated as the difference in the dollar weighted average price of trades transacted on the ask side minus the dollar weighted average price of trade transacted on the bid side. $Amihud$ is a measure of the price impact of trade developed by Amihud (2002) and in this study measures the basis point price impact of a $1 million trade. $Zeros$ is calculated as the sum of zero trade days and zero return days over total trading days in a month. Finally, $Turnover$ is used.

Since there is no consensus in the literature on the appropriate measure of liquidity, I conduct a PCA to see which measures capture the information most relevant to liquidity in order to construct a factor that maximizes the explanatory power. Following Korajczyk and Sadka (2008), I standardize all measures so that they represent liquidity, rather than illiquidity.[10] The measures are normalized to account for magnitude discrepancies, which can lead to overweighting. Defining $L_{i,t}^{j*}$, for bond i in month t for the j liquidity measure (j=1,2,…,5), the normalized measure is $L_{i,t}^{j} = (L_{i,t}^{j*} - \mu^{j})/\sigma^{j}$, where

[10] Since higher measures of IRC, $Bid\ Ask$, $Amihud$ and $Zeros$ are indicative of higher transaction costs, price impact, and infrequent trading these proxies are multiplied by -1.

μ^j and σ^j are the mean and standard deviation of liquidity measure j. Panel A of Table 2 presents the principal component loadings on each of the five liquidity measures.

[Insert Table 2]

The first component explains 43.48% of the variation in the liquidity variables and is a transaction cost proxy. The second component explains 22.11% of the variation and is a trading activity measure with the highest loadings on $Turnover$ and $Zeros$. The remaining principal components explain 34.41% of the total variation and do not have clear interpretations. Going forward, the first principal component, $PC1$, will be used as an additional measure of liquidity. Summary statistics for the proxies are also presented in Table 2. Panel B documents the distributions of each variable in their original form and Panel C the correlations after being converted to measures of liquidity. Appendix A provides further computational details.

4.2.2. Results

Panel A of Table 3 presents the results of the fixed effects panel regression in the high yield market, while Panel B is for the investment grade market. The first column of each panel runs the test with only the credit risk controls, while column two includes $PC1_{t-1}$ as the liquidity proxy, and column three controls for both mutual fund and index fund ownership. Although bond level fixed effects encompass industry effects, I follow Graham, Leary, and Roberts (2015) and Rajan and Zingales (1995) by running the regressions on the sample of non-financial sector bonds in columns 4 and 5. Since the yields of bonds with options reflect premiums and discounts relative to bonds without, their spreads may behave differently. To ensure that the inclusion of bonds with option features is not contaminating my findings, bond level fixed effects are included in all regressions and columns six and seven repeat the analysis on fixed rate bullet bonds only.

[Insert Table 3]

Regardless of the specification the coefficient on $\%ETF$ is negative and significant, indicating a positive valuation impact. The average of the coefficients from the first three columns indicate that a one standard deviation increase in the portion of a bond held by the ETF leads to a 20.3 basis points lower yield spread for the high yield market and a 9.2 basis points lower yield spread for the investment grade market. Economically, for the median (mean) high yield and investment grade constituent these reductions imply a monthly yield spread decrease of 4.6% (3.7%) and 6.8% (5.6%) and correspond to a monthly price increase of 0.97% (1.03%) and 0.53% (0.75%). The coefficient on mutual fund ownership is negative and significant, but is more than three times smaller than that on ETF ownership. Despite similar investment objectives, the coefficient on index ownership is insignificant in both specifications. The absence of significance can be attributed to the lack of index fund ownership in high yield bonds and minimal within bond variation in investment grade index ownership. For investment grade bonds, the median (mean) monthly change in index ownership is 0.0% (-0.09%) reflecting the buy-and-hold strategy common to index funds (Beneish and Whaley, 1996; Chen, Noronha, and Singal, 2004) and the reliance on a high cash buffer by bond mutual funds (Choi and Shin, 2015; Hoseinzade, 2015).

While the panel setting achieves the objective of addressing endogeneity associated with ETF selection of bonds and time trend, it relies strictly on within bond variation for identification of a causal relationship. To further examine the relationship between ETFs and corporate bond yields, I execute two quasi-natural experiments.

4.3. The valuation effect: Quasi-natural experiments

In this section, I detail the two quasi-natural experiments used to obtain exogenous variation in ETF status. The corporate bond index market provides a clean setting to study inclusion and exclusion events given that eligibility is dictated by strict rules. Typically these rules are based on publicly available bond characteristics, such as amount outstanding, total issuer amount outstanding, rating, age, and time to maturity. In this study, the experiments focus on the largest high yield and investment grade ETFs: HYG and LQD. As the original and largest offerings in their investment classes they provide a fair representation of the impact of corporate bond ETF market as a whole. Moreover, these ETFs are the only index products explicitly benchmarked to Markit indices, allowing for the ETF effect to be disentangled from a broader index fund effect.

The particular experiments that I focus on involve both an inclusion and an exclusion event. The inclusion experiment utilizes a rule change that expanded the universe of eligible bonds by removing a cap on the number of index constituents. The exclusion experiment involves a three-year minimum time to maturity threshold. In both settings, I run the difference-in-difference specification

$$Spread_{i,t} = \alpha_i + \lambda_t + \delta(Treatment_i * Post_t) + \beta_1 X_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where $Treatment_i$ is equal to one for bonds whose eligibility status is changed by the rule and zero for the control group. $Post_t$ is equal to one for the months following the event. The covariates, $X_{i,t}$, include average rating, leverage, operating, long-term debt, and equity volatility. I do not include the pretax dummies of the panel regression because they do not vary sufficiently over the small windows studied. Again, in some tests I control for mutual fund and index fund ownership. The coefficient of interest in both studies is δ, which identifies the differential effect of the event on the treatment group relative to the control group in the months following the eligibility change.

4.3.1. Quasi-natural experiment #1: The expansion of the index universe

In this quasi-natural experiment, I focus on a rule change to the index followed by HYG to obtain a clean setting to test the casual relationship between ETFs and the underlying bond spreads. Specifically, on June 22, 2009 the Markit Group issued a press release modifying the eligibility guidelines for the iBoxx High Yield Liquid Index followed by HYG effective immediately upon rebalancing on June 30th. The new rule transitioned the existing index from an equal-weighted 50 bond index to a three-percent-capped value-weighted index including all bonds meeting the eligibility requirements outlined in Appendix B. At the time of transition nearly 300 bonds met the new standards, a number that grew significantly during record years of high yield bond issuance. The stated rationale was that the high yield market had doubled in size since the inception of the index making the limited number of constituents "less representative of the entire liquid high yield market."[11] The transition from the original index of 50 bonds held on month end May 2009 to the expanded index occurred over a six month period to allow a "gradual and orderly shift." The ideal setting would be a completely unexpected rule change, but it is likely that bond market participants anticipated this redefinition since market makers and bankers sit on the Technical Committee charged with identifying constituents and recommending rule changes and consultants, regulators, and investors make up the Oversight Committee responsible for reviewing recommendations. However, given the difficulty of accessing the high yield market it is unlikely that front running was a significant factor in the six trading days between the announcement of the rule change and the implementation. Also, anticipation would bias against significant results.[12]

[11] http://www.markit.com/assets/en/docs/products/indices/news/2009/06/Markit_iBoxx_USD_LQ_HY_Rule_changes_20090622.pdf

[12] LQD also had its 100 member constituent cap removed. However, the change was highly anticipated since it was announced three months after the HYG rule change. Therefore, the HYG change is more of an exogenous shock and is the only one considered.

To validate this event as a credible identification method, I first ensure that the ETF follows the index rules and then I identify treatment and control groups. Fig. 2 plots the number of holdings by the ETF. This figure illustrates that the ETF closely adheres to the holdings restriction prior to the announcement and quickly adjusts its holdings to reflect the removal of the constituent caps. Panel B of Fig. 2 shows detailed holding numbers in the months around the rule change. In the months immediately preceding the rule change, the ETF held slightly more than the 50 index constituents. This deviation from the index is due to the inclusion of a money market fund in the holdings count and remnant positions. For instance, in January 2009 there are fifty-six total holdings including one money market fund and five positions whose weightings decreased over 50% from December and were eliminated from the portfolio in the following months.

[Insert Fig. 2]

Panel B also shows that HYG gradually bought the bonds of the expanded index, most likely reflecting the pro-rata adjustment during the transition period. HYG made the largest purchase of expansion bonds in July, the month immediately following the announcement, so I consider all bonds acquired in this period as the treatment group. I use the original index constituents, which see their average weighting fall from 1.97% in May to 0.84% in December, as the control group. Using the original bonds mitigates concerns of selection bias discussed in Section 4.1, since both groups are composed of bonds in the ETF universe. The key identifying assumption of this experiment is that the only thing preventing the treatment group from prior constituency in HYG was the cap. In the difference-in-difference specification of equation (2), $Treatment_i$ is equal to one for expansion bonds and zero for the original bonds.

Since the rule change was implemented gradually, I consider a six-month window around the event. Thus, $Post_t$ equals zero from January to June and equals one from July to December. I limit the number of periods to the number of transition months to reduce potential serial correlation issues detailed by Bertrand, Duflo, and Mullainathan (2004). Using multiple pre- and post-periods is only valid if the common trend assumption underlying the difference-in-difference specification is satisfied. To provide evidence that this assumption is met, I plot the time series of average spreads for the two groups in Fig. 3. I also plot the average yields of bonds on the eligible list provided by Markit upon announcement of the amendment that are not purchased by the ETF in the six-month transition period. The spreads of these bonds do not experience a similar movement lower indicating the ETF effect dominates the index effect. The figure ends in December 2011 when the weightings of control bonds stabilize at lower levels. The divergence of the yields of treatment and control bonds begins immediately upon the inclusion of the treatment bonds with the effect continuing to accumulate overtime. The gradual nature of the effect can be attributed to the measured implementation of the rule change and the ongoing reduction of weightings in the original bonds. In particular, there is a significant divergence of the treatment and control group between April and May 2010 which can be attributed to a sizeable redemption event that the sponsor used to reduce its holdings of the original bonds, while keeping the weighting of the treatment bonds unchanged. Finally, the difference between the falsification and the other groups accelerates following May 2010, reflecting a period of immense growth for HYG, when the number of shares outstanding increased from 58.6 million to 98.4 million between May 2010 and May 2011.

[Insert Fig. 3]

Table 4 presents the results for the econometric tests of the high yield rule change. To ensure that the same bonds are included in the pre and post sample, I require that each bond have non-missing observations for all variables in each month of the study. Column one does not include the covariates to allow for a larger sample size.

[Insert Table 4]

The sign on the covariate of interest in this quasi-natural experiment, ($Treatment_i * Post_t$), is negative and significant in all models, supporting the findings of the fixed effects panel that ETF inclusion is associated with lower yields and thus higher valuations. In particular, bonds purchased by the ETF due to the expansion of the eligible universe have yield spreads 138 basis points lower than the original constituents following the rule change. Economically, this change equates to an additional 21.3% (13.1%) reduction yield spread and a 6.69% (6.84%) price increase for the median (mean) bond in the experiment. The contrasting large and significantly positive sign on the index variable can be attributed to a lack of power due to only twelve observations with non-zero index ownership.

4.3.2. Quasi-natural experiment #2: Maturity-based exclusion

ETFs with rules-based eligibility provide the setting for my next quasi-natural experiment. I focus specifically on funds with an inclusion or exclusion maturity threshold because eligibility is less likely to be associated with credit risk or a credit event. These ETFs, typically called long-term, intermediate-term, and short-term, stipulate in their prospectuses the maximum and minimum remaining maturity necessary for eligibility along with any other qualifiers. However, the majority of the 27 funds initially designated as maturity-based follow Barclays indices, which are also the most common benchmarks for index funds. Therefore, I again consider the iShares ETFs. Plotting the time to maturity remaining the last time a bond is held by the ETF relative to the cutoff, I find that LQD follows the rule as documented by the sharp jump in the number of sales around the 36 months to maturity threshold in Fig. 4.[13]

[Insert Fig. 4]

For identification, I establish the treatment group as bonds sold by LQD for maturity reasons. From Fig. 4, it appears that the majority of sales occur in a one-month window around the threshold, and thus I deem any bond sold within this region as a treatment group bond. A control group is needed to allow for the possibility that there is something distinctive impacting bonds upon crossing the cutoff. I use all investment grade bonds with non-zero mutual fund ownership that have three years to maturity on the date of a LQD maturity-based sale as the control group. Any bond that with a broad ratings change, for instance from A to AA, in the period considered is eliminated from the sample to mitigate the impact of external events.[14]

[Insert Fig. 5]

Fig. 5 plots the average yield spread for the treatment and control groups used in my difference-in-difference specification relative to LQD's sale. The spreads of both groups are on the natural downward trajectory into maturity, supporting the assumption of common trend. Furthermore, it appears that the natural downward trend pauses only for treatment bonds in the month immediately following LQD's sale (month zero) and that the average spread of treatment bonds moves higher than that of the control group in subsequent months. This result suggests that the positive valuation impact

[13] HYG sales do not exhibit the same threshold behavior.

[14] Results are robust to the exclusion of bonds with any ratings change (i.e. A to A-), a ratings change only in the pre period, or a ratings change in the month of treatment.

of constituency in this important ETF is removed from the bonds. Interestingly, even during the months immediately before the cutoff when the ETF is selling the bond putting upward pressure on yields, the spreads still continues to move lower. It is not until LQD is no longer involved in the bond that the yields of the two groups diverge.

To test the statistical significance of the results presented in Fig. 5, I again use the difference-in-difference regression of equation (2). In this setting $Treatment_i$ is set to one for those bonds sold by LQD due to maturity and zero for non-LQD bonds with three-year time to maturity. $Post_t$ is one for the months after an ETF completely exits a bond. For instance, if a bond last appears in the holdings report on January 2011 with three years to maturity, I assume that it is sold in February due to the eligibility rule. The post period begins in March 2011. To account for this shift, the cutoff for control bonds is the month following the three-year threshold. A three-month window around the event is considered.

Table 5 reports the results of the maturity-based quasi-natural experiment regression. Since the event being studied is an exclusion, the interpretation of the coefficient is the opposite of the first experiment. The results are also supportive of ETFs causing lower yields for member bonds. More specifically, the bonds sold by LQD for maturity reasons have 4.5 basis points higher relative yield spreads in the three months following the sale than do other investment grade bonds held by mutual funds that cross the three-year time to maturity threshold on the same date. The results implies a 5.7% (4.4%) spread increase and a 1.0% (0.92%) price decrease for the median (mean) bond. The columns of Table 4 account for the ETF's activity in the treatment bonds in the month of the last reported holding. Columns 3 and 4 eliminate bonds whose weight decreased more than 50% in the prior month, indicating that a remnant position is reported in the final month, and columns 5 and 6 use a 10% cutoff.

[Insert Table 5]

4.4. A temporary or permanent valuation effect?

The results above document a significantly positive valuation effect in a broad panel and two quasi-natural experiments. In this section, I conduct cross-sectional regressions to address the temporary or permanent nature of the valuation effect. A temporary effect, in which the bond's spread falls and immediately reverts, would be expected if buying by ETFs creates an order imbalance that exerts price pressure on the bonds which quickly dissipates. A permanent effect, which is not fully reversed within a few months, is suggestive of a broader change in the underlying.

To formally test the nature of this effect, I identify the first month of ETF constituency for each bond, $m = 1$. I then use Propensity Score Matching (PSM) to identify two control groups. First, for all bonds without a broad ratings change on the date of an inclusion event, the following logit is conducted using bond characteristics in the month prior to the event, $m = 0$:

$$ETF_{i.1} = a + \beta_1 Spread_{i,0} + \beta_2 Rating_{i,0} + \beta_2 T2M_{i,0} + \beta_3 Age_{i,0} + \beta_4 Size_{i,0} + \beta_5 Coupon_{i,0} \qquad (3)$$

ETF_i is a dummy set to one for bonds included in an ETF and zero otherwise. This methodology controls for the bond characteristics visible to the ETF sponsor when selecting a constituent. Treatment bonds are then matched with their five nearest neighbors based on p-scores computed in the event month. In this setting, a control bond is eliminated from the sample if it experiences a broad-based ratings change, it is added to an ETF, or its treatment match is no longer in the sample.

Second, to control for issuer-specific factors I match bonds purchased by the ETF with bonds from the same issuer. For most bonds, particularly in the high yield market, there is at most one other non-ETF bond from the same issuer. When there are multiple potential controls, I match each treatment bond to its one closest issuer peer based on the above PSM, excluding rating. To maintain larger sample sizes, I rematch each month, $m = 1,2, \ldots ,6$, based on the characteristics observable in the month prior to the inclusion event, $m = 0$. While this sample ideally controls for issuer-specific effects, a significant number of treatment bonds were eliminated due to the absence of an issuer match in the inclusion month.

In both settings, I conduct the following cross-sectional regressions for each month, $m = 1,2, \ldots ,6$:

$$\Delta Spread_{i,m-0} = a + \lambda_t + \beta_1 ETF_i + \beta_2 Spread_{i,0} + \varepsilon_\mathrm{i} \tag{4}$$

To ease in the interpretation of the coefficient the dependent variable is $\Delta Spread_{i,m-0}$, the change in spread for bond i, between month m ($m = 1,2, \ldots ,6$) and the month prior to the ETF purchase ($m = 0$). ETF_i is a dummy set to one for bonds included in an ETF and zero for control bonds and λ_t is a time fixed effect.

Table 6 reports the results in Panel A for high yield and in Panel B for investment grade.

[Insert Table 6]

The first column reports the results of the regression in the month prior to the inclusion of the treatment bonds, with the base spread equal to that from month, $m = -1$. If the design is valid there should be no noticeable yield effect in the month prior to inclusion. In each setting, the coefficient on the ETF dummy is statistically insignificant confirming the validity of the design. However, in the high yield issuer matched sample the coefficient on the ETF dummy in the month prior to treatment is negative and large, although not statistically significant, reflecting the difficulty of finding appropriate within issuer matches in this market.

If the effect was temporary, the coefficient on ETF would be significantly negative in the first month and either insignificant or positive in the following months. In contrast, the coefficients on ETF are negative in month 1 with the point estimates increasing overtime supporting the notion of a long-term effect. For investment grade bonds, whose average weighting in month one is 0.26% which doubles by month three, the effect in the issuer matched sample the coefficient is significantly negative for month one, but only negative and insignificant in the PSM sample. Nevertheless, in both samples the point estimates grow overtime and are negative and statistically significant up to six months after the inclusion event. For high yield bonds whose average weighting in month one is 0.42%, the coefficient in the first month is significantly negative in both samples, with the effect remaining large and significant six months beyond inclusion in the PSM sample. In the issuer matched sample where the coefficient in the first column was sizably negative, the coefficients beyond month three are insignificant despite remaining largely negative reflecting the limited sample size of treatment bonds with at least one bond from the same issuer. Regardless of the setting, the evidence points to a long-term positive valuation effect with point estimates of the effect increasing with longer time intervals and remaining significant for both markets up to 6 months from inclusion. This finding is inconsistent with the price reaction upon introduction being temporary, but instead supports the notion that ETFs have a long-term impact due to broader changes in the underlying. Having established a permanent positive valuation effect the paper proceeds to test theoretical explanations for this finding.

4.5. ETFs impact on the composition of traders and liquidity

Under the assumption that ETF bonds differ from the control bonds only because of inclusion in the new investment product, the literature suggests two potential reasons for the documented long-term increased valuation. First, ETFs change the composition of traders in the underlying. Gorton and

Pennacchi (1993) predict that new basket securities induce a migration of liquidity traders from the underlying to the new investment. Following the migration, informed investors have less camouflage with which to disguise their trades, making prices more responsive to their trades, and thus lowering returns. Rather than a migration, Cao (1999) and Massa (2002) theorize that innovation results in greater participation from institutional investors. Cao (1999) theorizes that new assets may facilitate informed investors' participation in the underlying market by increasing their ability to hedge and speculate due to lower costs of executing the ETF trade than the series of trades necessary to replicate the basket and reduced short sales restrictions. Massa (2002) suggests innovation provides a hedge against additional risk of greater ownership and an additional signal resulting in increased risk sharing as suggested by Sharpe (1991). Further, since the majority of ETFs are index-based Basak and Pavlova (2013) predict that institutions may tilt their portfolios towards constituents, leaving non-ETF bonds unaffected. The predictions of these papers support the rational expectations equilibrium model of Easley and O'Hara (2004), who find that ceteris paribus, a higher fraction of informed investors increases prices by decreasing the risk for informed traders and by making their trades more revealing. Second, Fremault (1991) and Kumar and Seppi (1994) suggest that basket securities improve the liquidity of the underlying, which may decrease the illiquidity premium documented in the literature.

To investigate the impact of the new investment vehicles on these characteristics of the market, I construct four different proxies of ETF activity, which are discussed in greater detail in Appendix C. The first is the percentage of the bond held by all ETFs, $\%ETF$. Second, I use a measure of the intensity of creation and redemption activity of an ETF developed by Da and Shive (2013). $C/R\ Intensity$ is the weighted average of the standard deviation of the number of ETF shares outstanding divided by the mean shares outstanding during a month of all ETFs holding a bond. The activity associated with C/R

Intensity reflects the direct involvement of the affiliates of the ETF in a bond. Third, I use a weighted average monthly turnover of all ETFs holding the bond, $ETF\ Turnover$. While ETF turnover itself should not lead directly to activity in the underlying, it does reflect greater investor demand for exposure to the underlying and ease of executing hedging, arbitrage, and liquidity motivated strategies. Finally, I use $Short$ as the weighted average of short interest in the ETFs holding a specific bond. While shorting firm-specific risk is possible in the individual lending markets, executing a large basket of short positions would entail a significant search cost or a fixed period contract. Therefore, ETFs may be a convenient instrument for investors to initiate short positions in the corporate bond market to take a directional view or to hedge existing positions. Furthermore, the ability to short is another critical distinction of ETFs from other index products. Table 7 presents the distributions and correlations of these proxies for ETF activity. Interestingly, at all levels of the distribution the activity proxies are greater for high yield bonds, which is likely reflective of the reach for yield that occurred during the sample period.

[Insert Table 7]

I begin by considering theoretical predications that basket securities change the composition of traders in the underlying. To do so, I first examine the impact of ETFs on the proportion of total bond, i, volume in month, t, attributed to trades of different size bins, b, $\%Volume\ by\ Type_{i,b,t}$. Following Goldstein, Hotchkiss, and Sirri (2007), I denote all trades less than $100,000 as retail. In the corporate bond market, transaction costs are decreasing in trade size reflecting the power of institutional traders (Edwards, Harris, and Piwowar, 2007; Goldstein, Hotchkiss, and Sirri, 2007). Since an institutional trader would have lower transaction costs by trading in larger sizes, it is likely that the retail bin reflects the activity of uninformed retail traders and institutional investors with capital needs.

Therefore, I use this bin as a proxy for the activity of liquidity traders in the underlying bonds. I develop further trade bins using the levels of truncation in TRACE. For high yield bonds, Bin 2 is composed of trades between $100,000 and $1 million. Bin 3 includes trades greater than $1 million. For investment grade bonds, Bin 2 is the same as for high yield bonds. Bin 3 includes trades between $1 million and $5 million. Finally, trades greater than $5 million constitute Bin 4. I also consider the impact of ETF activity on mutual fund ownership, either the percentage of a bond outstanding held by active mutual funds or the number of mutual fund holders. Table 8 provides summary statistics on the mean and median percentage of volume attributable to each bin, as well as, mutual fund ownership. Panel A presents the results for bonds never held by an ETF relative to those held for at least one month by an ETF. Bonds held by ETFs generally trade in larger transaction sizes and have larger mutual fund ownership, while retail trading is far more prominent in the investment grade market. Panel B breaks down the summary statistics for bonds held by ETFs into the months of constituency and non-constituency. For high yield and investment grade ETF bonds the portion of volume attributed to liquidity traders is 35.6% and 37.3% lower, the average mutual fund ownership is 29.7% and 58.7% greater, and the number of mutual fund holders nearly doubles when the bond is held by the ETF.

[Insert Table 8]

To test the significance of these statistics, I run the following regression

$$\%Volume\ by\ Type_{i,b,t} = \alpha_i + \lambda_t + \rho ETF\ Activity\ _{i,t-1} + \beta_1 X + \varepsilon_{i,t}. \tag{5}$$

where bond level fixed effects, α_i, and time fixed effects, λ_t, are included. $ETF\ Activity_{i,t-1}$ is the lagged value of one of the four activity proxies. I also control for lagged mutual fund ownership using $\%MF_{i,t-1}$ and $\%Index_{i,t-1}$, while $Rating_{i,t}$ is included to account for events related to ratings changes.

Lagged independent variables are used to address concerns of simultaneity; for instance, a higher proportion of institutional trades driving ownership.

To examine if ETF activity increases institutional ownership I run the following regression:

$$MF\ Ownership_{i,t} = \alpha_i + \lambda_t + \rho ETF\ Activity_{\ i,t} + \beta_1 MF\ Ownership_{i,t-1} + \beta_2 Rating_{it} + \varepsilon_{i,t}, \qquad (6)$$

where $MF\ Ownership$ is either the portion of a bond's amount outstanding held by mutual funds, $\%MF$, or the number of mutual fund holders, $\#\ MF$. In this regression, contemporaneous ETF activity is used to identify conditions in the ETF market that encourage simultaneous investment in the individual bonds by active mutual funds, whose investment process should be distinct from ETF market dynamics and index rules. The standard errors are clustered at the issuer and bond level. Table 9 reports the results.

[Insert Table 9]

Table 9 documents that for nearly every measure of $ETF\ Activity$ in both the high yield and investment grade markets the proportion of retail trades decreases and mutual fund investment increases. The decrease in monthly volume attributed to retail traders is between 7.9 to 63.5 basis points for high yield bonds and 11.8 to 58.7 basis points for investment grade bonds. The coefficients on mutual fund ownership are mostly positive providing some evidence that both the level of investment and number of investors increase when a bond is held by more active ETFs. In particular, the coefficients on ETF Turnover suggest that managers invest in bonds held by ETFs with active secondary markets, where hedging, speculating, and arbitrage strategies are easier to implement.

Since liquidity has been shown to be an important determinant of yield spreads, I conclude my analysis by examining the impact of ETF activity on the liquidity of the underlying bonds. ETFs could increase the liquidity of the underlying through their direct participation or as theories predict by reducing limits to arbitrage (Fremault, 1991; Kumar and Seppi, 1994). Conversely, if ETFs offer a low transaction and adverse selection cost alternative, liquidity traders may exit the market leaving a higher proportion of informed investors in the underlying market reducing liquidity as predicted by Dow (1998), Gammill and Perold (1989), Gorton and Pennacchi (1993), and Subrahmanyam (1991). Using the proxies discussed above, I test the impact of ETF activity on the liquidity of constituent bonds using the two-way fixed effects regression,

$$Liquidity_{i,t} = \alpha_i + \lambda_t + \rho ETF\ Activity_{\ i,t-1} + \beta_1 X + \varepsilon_{i,t}. \tag{7}$$

where $Liquidity_{i,t}$ is one of the six liquidity proxies, α_i is the bond level fixed effect and λ_t the time fixed effect. $ETF\ Activity_{i,t-1}$ is the lagged value of one of the four activity proxies. I also control for $\%MF_{i,t-1}$ and $\%Index_{i,t-1}$. These three controls are lagged to account for reverse causality, the most liquid bonds attracting institutional ownership. $Rating_{i,t}$ is included to account for potential liquidity spikes related to ratings changes. The standard errors are again clustered at the issuer and month level. The variables have been standardized to indicate liquidity, so that a positive ρ indicates higher liquidity and a negative coefficient lower liquidity

Table 10 presents the results for the various ETF activity proxies for the high yield market in Panel A and investment grade market in Panel B. For high yield bonds all measures, including the principal component, are suggestive of an insignificant relationship between the ETF and the liquidity of the underlying high yield bond. In the investment grade market, trading activity proxies, turnover and zeros are inconclusive. However, the coefficients on $PC1$ and most transaction cost proxies are strongly indiciatve of ETFs having a deleterious impact on liquidity. On average a 1% increase in the lagged ETF ownership of bond leads to a 4.2 basis point increase in the IRC, a $0.05 increase in the bid-ask spread, and 3.9 basis point increase in the price impact of a $1 million trade. The coefficients on the creation and redemption measure are negative, but insignificant suggesting that the direct activity of parties affiliated with the ETF itself have not affected the liquidity of the underlying. The coefficients on index ownership are also negative in the investment grade market implying that the buy and hold strategy and large cash buffers may negatively impact liquidity by reducing the supply of bonds available for trade. The contrast in results between the two markets is surprising given the increased risk associated with high yield bonds. However, as show in Table 8 the majority of trades in the high yield market are in excess of $1 million with the distribution spread more evenly across all trade bins, while liquidity traders represent the majority of transactions in the investment grade market. Therefore, the change in the composition of traders exhibited above is more likely to impact the investment grade market.

[Insert Table 10]

While the liquidity of the underlying bonds is insignificantly or negatively impacted, overall bond market liquidity may actually improve as ETFs provide a low bid-ask spread and high volume alternative to gain and maintain exposure to corporate bond markets. Therefore, it remains possible that the ability to trade in ETFs has actually decreased the sensitivity of yield spreads to liquidity as suggested by (Ben-Rephael, Kadan, and Wohl, 2015).

5. Conclusion

As financial markets evolve, regulators, practitioners, and academics are left to question the role of emerging innovations in traditional markets. Recently, the historically opaque and illiquid corporate bond market has undergone a radical transformation. Despite significant growth in the amount of assets outstanding, traditional market makers are retreating due to higher regulatory costs. Financial innovation, particularly ETFs, are playing an increasingly vital role in this systemically important market. The emergence of liquid and transparent ETFs linked to the illiquid and opaque underlying market has raised concerns of regulators who have highlighted corporate bond ETFs as potential systemic threats.

Distinct features of corporate bond ETFs allow for this paper to obtain clean identification strategies to provide evidence of the impact of innovation on the underlying. Using fixed effects models and two quasi-natural experiments that obtain exogenous variation in ETF eligibility, I provide new evidence that innovation has a positive valuation effect on the underlying. Cross-sectional regressions for each of the six months following an inclusion event document a long-term effect, suggestive of an underlying market change rather than a temporary demand shock. I also find that ETF activity is inversely related the proportion of volume attributable to liquidity traders and positively related to the level of investment by and number of mutual fund holders. Finally, I rule out improved liquidity as a potential explanation for the lower yield effect as the impact of ETF activity is insignificant for high yield bonds and even negative for investment grade bonds. Nevertheless, it remains possible that overall liquidity is improved as investors can now transact in the highly liquid ETFs. Taken together, the results of this paper support theories that claim innovation can alter the dynamics of the underlying market.

A1: Liquidity proxies

Variable	Description
PC1	Following Korajczyk and Sadka (2008) and Dick-Nielsen, Feldhütter, and Lando (2012), I compose a liquidity proxy, PC1, as the first principal component. PCA utilizes all the information from the various measures to compute a proxy that maximizes the explanatory power. To execute the PCA, I follow Korajczyk and Sadka (2008), by standardizing all measures to represent liquidity, rather than illiquidity. I also account for magnitude discrepancies, by normalizing the liquidity measures. I do so by defining $L_{i,t}^{j*}$, for bond i in month t for the j liquidity measure (*j*=1,2,…,5). The standardized measure is $L_{i,t}^{j} = (L_{i,t}^{j*} - \mu^{j})/\sigma^{j}$, where μ^{j} and σ^{j} are the mean and standard deviation of liquidity measure j. Monthly PC1 is generated using the loadings produced from this analysis.
IRC	(Feldhütter, 2012) develops a method to identify associated trades and then compute a measure of transaction costs without relying on side identifiers. The method exploits a common occurrence in the corporate bond market where a bond will trade two to three times in a very short window on the same day with the same volume, an IRT, following a period of inactivity. Since corporate bonds trade on an OTC, he claims these groups of trades likely occur when a dealer is finally able to match a buyer and seller, collecting the bid-ask spread. For each IRT, the IRC is computed as $$IRC = \frac{P_{max} - P_{min}}{P_{min}} * 100,$$ where P_{max} is the highest price and P_{min} is the lowest price within an IRT. The daily estimate of the roundtrip cost is the average IRC for all IRTs in a day and the monthly IRC is the median daily observation.
Bid Ask	TRACE provides an indicator of B (S) when a dealer buys from (sells to) a customer, indicating a transaction occurring at the bid (ask) price. Following, (Chakravarty and Sarkar, 2003; Hong and Warga, 2000) these indicators are used to compute a measure of the bid-ask spread as, $$Bid\ Ask_{i,t} = \sum_{n=1}^{N} P_n^A w_n^A - \sum_{m=1}^{M} P_m^B w_m^B.$$ Formally, this measure is the dollar-weighted average price of the N trades transacted at the ask side minus the dollar weighted average price of the M trades transacted on the bid side. The measure requires at least one buy and one sell transaction each day. To eliminate any crossed quote measures, I set any negative observations to zero to maintain the intuition of the measure as a transaction cost. The monthly bid-ask measure is the median daily measure.

Amihud Developed in the style of Kyle's (1985) lambda measure, Amihud's measure is a low-frequency proxy for the price impact of a trade. Computed as

$$Amihud_{i,t} = \frac{1}{N_t}\sum_{j=1}^{N_t}\frac{|r_j|}{v_j} * 10^6$$

where N_t is the number of returns on day t, r_j is the return of consecutive transactions, and v_j is the dollar volume of a trade. This measure can be interpreted as the basis points price movement per one million dollars of traded volume. The monthly Amihud measure is the median daily measure.

Turnover Computed as

$$Turnover_{i,t} = \frac{Volume_{i,t}}{Amount\ Outstanding_{i,t}} * 100$$

Turnover represents the portion of a bond's total issuance that trades monthly.

Zeros (Lesmond, Ogden, and Trzcinka, 1999) (LOT) suggest bonds whose prices stay stagnant over long periods or bonds that do not trade for long periods are likely to be less liquid. The zeros measure is computed as the total days in which a bond does not trade or has zero return over the total trading days in the month,

$$Zeros_{i,t} = \frac{(Zero\ Return\ Days + Zero\ Trade\ Days)_{i,t}}{Trading\ Days_t} * 100$$

Implicitly this proxy measures if the benefits of trade exceed the transaction costs, which include spread, commission costs, expected price impact costs, and possible opportunity cost of informed trade.

A2: Details of changes in eligibility requirement for the Markit High Yield Index

The following table documents the eligibility requirements of the Markit iBoxx USD Liquid before and after the rule change. High Yield Index followed by the iShare high yield ETF, ticker HYG. On June 22nd, 2009, Markit announced new eligibility requirements for its index to be effective on June 30th.

	High Yield (HYG)	
	Before 6/2009	**After 6/2009**
Issue Amount Outstanding	\$200 mln	\$400 mln
Issuer Amount Outstanding	-	\$1 bln
Weighting Method	Equal	Market Value
Weighting Cap	-	3%
Ratings	Highest	Average
Time to Maturity	15≤T2M≤3	15≤T2M≤3*
*Changed to 15≤T2M≤1 on 4/30/12		

A3: ETF activity proxies

Variable **Description**

%ETF A basic measure of ETF ownership in a bond computed as:

$$\%ETF_{i,t} = \frac{\sum_{k=1}^{K} Par\ Value\ Held_{i,k,t}}{Amount\ Outstanding_{i,t}} * 100,$$

which is the sum of the par value held by the set of K ETFs holding bond i in month t as a fraction of bond $i's$ amount outstanding.

C/R Intensity Da and Shive (2014) develop a measure of the intensity of creation and redemption activity of an ETF. The measure is calculated as

$$C/R\ Intensity_{i,t} = \frac{\sum_{k=1}^{K}\left(w_{i,k,t} *\ SD\ Shares_{k,t}\right)}{\sum_{k=1}^{K} w_{i,k,t}} * 100,$$

where,

$$SD\ Shares_{k,t} = \frac{\sigma(shrout)_{k,t}}{\mu(shrout)_{k,t}}$$

Creation and redemption could drive underlying liquidity since APs need to compile or sell baskets of the underlying security to maintain the ETF.

ETF Turnover The ability to quickly trade a basket of bonds is fundamental to the appeal of fixed income ETFs. The turnover of associated ETFs is computed as

$$ETF\ Turnover_{i,t} = \frac{\sum_{k=1}^{K}\left(w_{i,k,t} *\ Turnover_{k,t}\right)}{\sum_{k=1}^{K} w_{i,k,t}} * 100,$$

which is the weighted average monthly turnover of the set of K ETFs that hold bond i during month t. $Turnover_{k,t}$ is total monthly share volume over the average ETF shares outstanding in the month.

Short ETFs are a convenient instrument for investors to initiate short positions for a directional view or to hedge existing positions. The proxy is computed as

$$Short_{i,t} = \frac{\sum_{k=1}^{K}\left(w_{i,k,t} *\ SI_{k,t}\right)}{\sum_{k=1}^{K} w_{i,k,t}} * 100,$$

where

$$SI_{k,t} = \frac{\mu(short)_{k,t}}{\mu(shrout)_{k,t}},$$

The measure is the monthly weighted average of the short interest ratio of the set of K ETFs that hold bond i in month t. The short interest ratio is the average number of shares of the ETF held short over the average number of ETF shares outstanding.

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Fig. 1: The Growth of the Fixed Income ETF Market

This figure presents the growth in assets under management of the three categories of fixed income ETFs since the inception of the market in June 2002: all fixed income ETFs, only ETFs that hold corporate bonds (Corporate & Total Bond ETFs), and finally strict corporate bond ETFs. In addition, the proportion of corporate bond ETF dollar volume over TRACE dollar volume in bonds held by ETFs is reported using the right vertical axis.

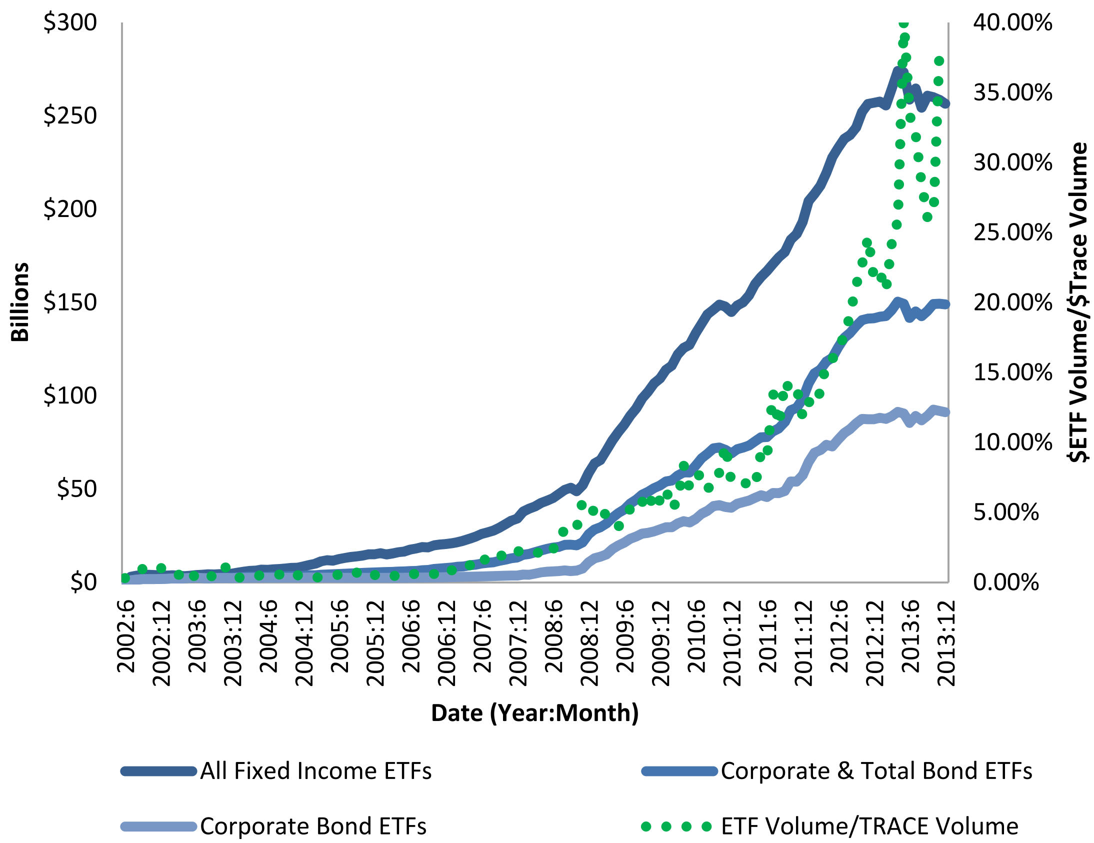
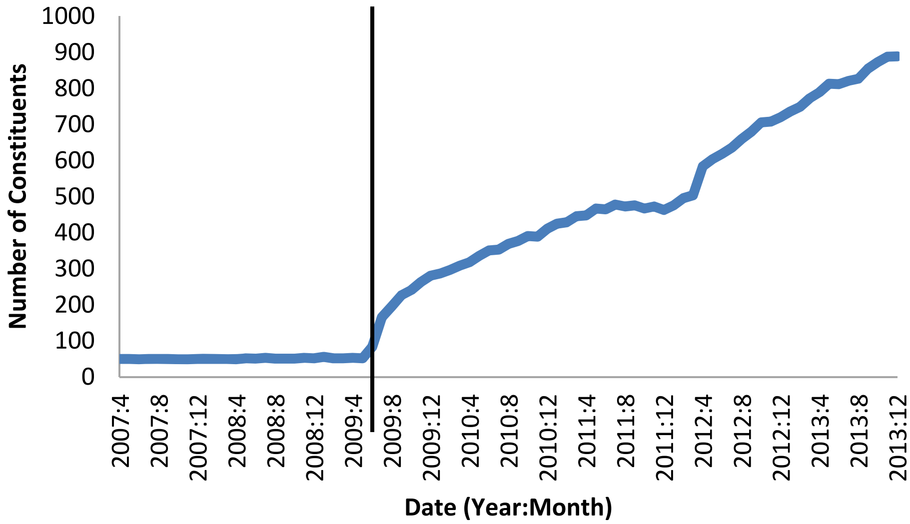


Fig. 2: HYG Rule Change

Panel A: The Growth in Holdings of HYG

The figure plots the number of holdings by the iShares High Yield Liquid ETF, HYG. The vertical line shows the date that the index administrator, Markit, removed the cap on the number of constituents for the index followed by this ETF.



Panel B: The Number of Holdings of HYG around the Rule Change

The number of holdings by HYG is presented in a table to identify the treatment and control groups for the quasi-natural experiment. Those bonds held by the ETF prior to the rule change are used as the control and labeled original below. Bonds included in the phase of the greatest increase in holdings are the treatment and labeled expansion below.

Date	# Holdings	Group
Jan 2009	56	
Feb 2009	52	
Mar 2009	52	
Apr 2009	53	
May 2009	52	Original – Control
Jun 2009	84	
Jul 2009	166	Expansion – Treatment
Aug 2009	196	
Sep 2009	227	
Oct 2009	241	
Nov 2009	263	
Dec 2009	281	

Fig. 3: High Yield Rule Change

The average of monthly volume-weighted yield spreads over the swap rate for the bonds impacted by the June 2009 rule change are plotted below. The HYG Original bonds are those that were held by the ETF in the month before the 50 bond constituent cap was removed. The HYG Expansion bonds are those purchased by the ETF in July 2009. Also included in the figure are the bonds that were on the index list upon the rule change announcement, but were not purchased by the ETF.

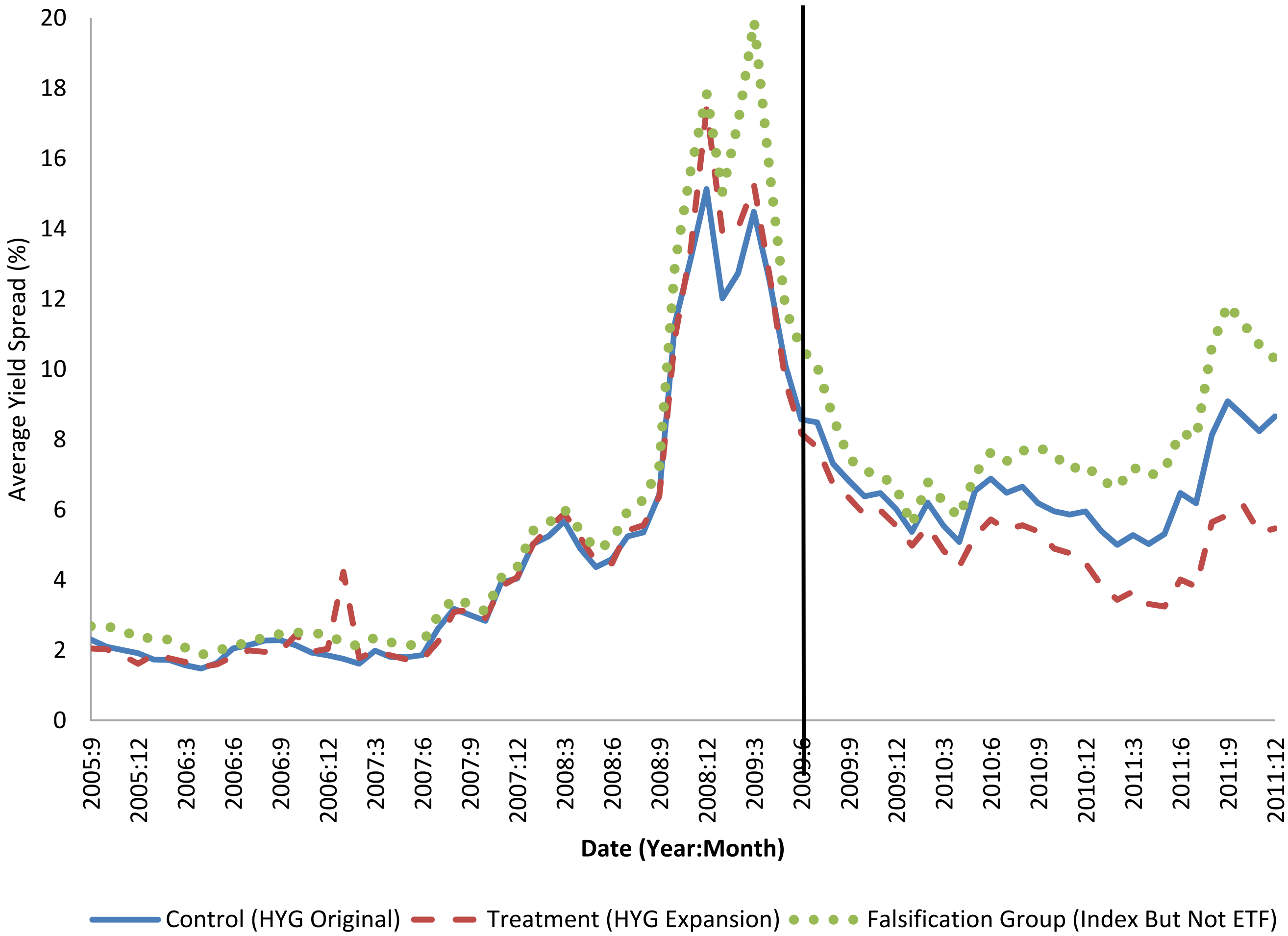


Fig. 4: LQD Sales Relative to Three Year Time to Maturity Threshold

This figure shows the propensity of LQD to follow the three year minimum time to maturity rule established by the index. Specifically, the figure reports the time to maturity of a bond at the last month it is reported as a holding by LQD relative to the threshold. The treatment group is identified in the highlighted areas as "forced" maturity based sales.

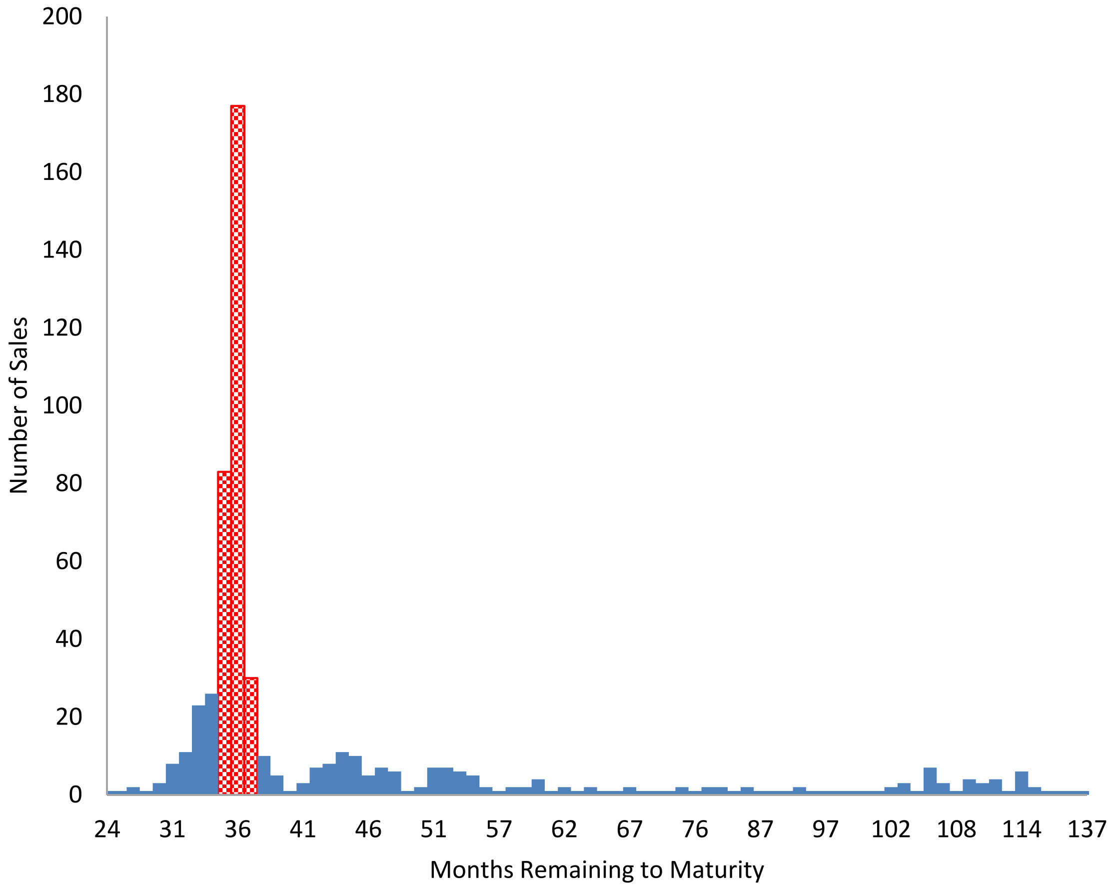


Fig. 5: Yield Spreads Before and After Three Year Time to Maturity Threshold

This figure documents the average monthly volume-weighted yield spread of the treatment and control groups in the maturity based experiment. The plot includes all bonds used in difference-in-difference specification. The treatment group is composed of bonds sold between one month prior to and two months after crossing the three year threshold for which there are observable credit controls and spread observations in the three months before and after the maturity based sale. The control group includes matched investment grade bonds held by mutual funds with three years remaining to maturity on the date of a maturity based sale by LQD. For the treatment group time zero is the month after the sale by LQD. For instance if a bond last appeared in LQD's holdings on January 2009 (month t = -2), sale is assumed to occur in February 2009 (month t = -2), and month t = 0 is March 2009. For control bonds time zero is the month following the crossing the three year cutoff.

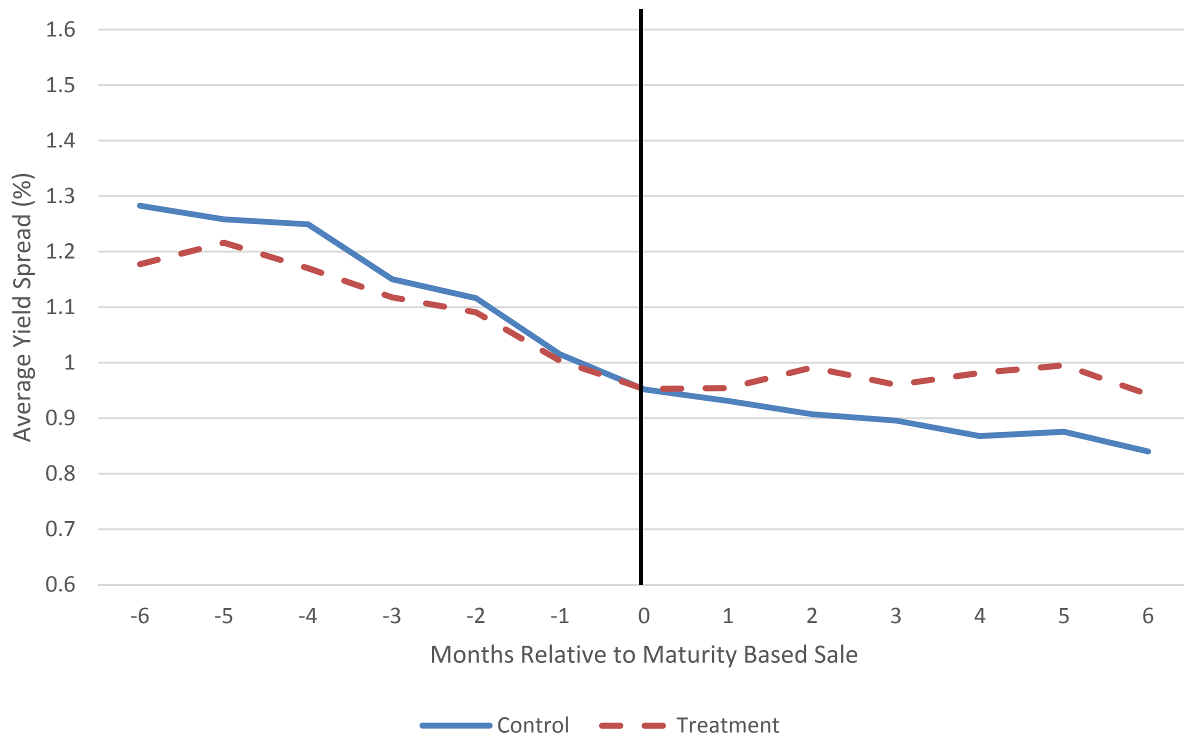


Table 1: Corporate Bond Summary Statistics

Summary statistics of observable characteristics of bonds held by ETFs for at least one month relative to those not held by ETFs. The data is composed of 496,840 bond-month observations for the sample period January 2009 to November 2013. ETF bonds are those held by a corporate bond ETF for at least one month. Panel A presents the high yield market statistics for 110,263 observations. 29,403 observations on 1,401 individual bonds from 697 issuers with some ETF ownership, while 4,526 bonds from 799 issuers are non-ETF bonds. Panel B documents the characteristics of the 386,577 bond-month investment grade observations of which 151,617 observations are associated with ETFs. There are 4,886 individual ETF bonds from 1,151 issuers and 10,345 non-ETF bonds from 603 issuers.

		Panel A: High Yield Bonds			**Panel B: Investment Grade**		
		Mean	**Median**	**Stdev**	**Mean**	**Median**	**Stdev**
Non-ETF Bonds	Yield Spread	8.99	5.71	10.37	2.74	2.14	2.25
	Mutual Fund Ownership	6.61	0.41	11.14	0.79	0.00	3.37
	Index Fund Ownership	0.00	0.00	0.07	0.01	0.00	0.12
	Coupon	6.70	6.85	2.39	5.50	5.50	1.36
	Amount Outstanding (mlns)	157.2	100.0	282.6	55.2	10.7	128.4
	Rating	14.40	14.00	2.71	5.88	6.00	2.19
	Time to Maturity	6.53	4.76	5.49	10.32	8.61	7.37
	Age	6.17	5.48	5.15	5.73	4.93	4.64
	Leverage	56.54	60.39	31.25	62.94	65.37	37.33
	Operating	18.96	13.31	18.95	24.53	25.52	16.81
	Long-Term Debt	34.01	32.77	23.93	23.84	19.84	16.97
	Volatility	1.06	0.71	1.06	1.25	0.81	1.16
ETF Bonds	Yield Spread	5.56	4.37	5.33	1.64	1.36	1.39
	ETF Ownership	1.38	0.30	1.99	0.82	0.38	1.03
	Mutual Fund Ownership	20.89	19.61	14.18	6.47	4.15	7.03
	Index Fund Ownership	0.11	0.00	0.41	1.23	0.89	1.25
	Coupon	7.88	7.75	1.74	5.58	5.70	1.51
	Amount Outstanding (mlns)	607.8	475.0	528.1	732.9	500.0	630.4
	Rating	13.73	13.50	2.39	7.09	7.33	1.99
	Time to Maturity	6.39	5.76	4.03	10.14	6.73	8.89
	Age	3.28	2.36	3.06	4.30	3.29	3.65
	Leverage	55.23	53.12	28.31	48.74	35.04	46.87
	Operating	24.84	18.65	22.04	25.19	25.04	16.24
	Long-Term Debt	43.95	41.08	21.95	24.78	22.97	13.37
	Volatility	0.96	0.69	0.94	1.23	0.93	1.02
Total	Yield Spread	7.56	5.10	8.80	2.20	1.76	1.96
	ETF Ownership	0.57	0.00	1.45	0.40	0.00	0.83
	Mutual Fund Ownership	12.56	7.22	14.34	3.58	0.30	6.17
	Index Fund Ownership	0.05	0.00	0.27	0.61	0.00	1.07
	Coupon	7.19	7.13	2.22	5.54	5.60	1.43
	Amount Outstanding (mlns)	345.1	250.0	460.6	388.3	250.0	564.4
	Rating	14.10	13.67	2.59	6.47	6.50	2.18
	Time to Maturity	6.47	5.30	4.93	10.23	7.48	8.15
	Age	4.97	4.01	4.63	5.02	4.02	4.25
	Leverage	55.96	57.14	29.99	55.98	50.13	42.87
	Operating	21.66	15.70	20.63	24.86	25.37	16.53
	Long-Term Debt	38.44	37.51	23.59	24.30	21.62	15.31
	Volatility	1.02	0.70	1.01	1.24	0.88	1.09

Table 2: Liquidity Principal Components Analysis and Liquidity Summary Statistics

This table shows the summary statistics of the monthly liquidity proxies: (1) the median Imputed Roundtrip Cost (IRC), (2) the median dollar weighted bid-ask spread (Bid Ask), (3) the median Amihud measure of the price impact of a trade, (4) total monthly Turnover, and (5) the percentage of total monthly trading days in which a bond has zero returns or zero trading (Zeros). Panel A presents the loadings on each of the five liquidity variables and the cumulative explanatory power of each component from a Principal Components Analysis. IRC, Bid Ask, Amihud, and Zeros are standardized to represent liquidity and all proxies are normalized to account for differences in magnitudes. Panel B shows the distribution of the liquidity proxies prior to liquidity standardization, while Panel C documents the correlations of the proxies in their liquidity standardized form. All proxies are winsorized at the 1% and 99% level by investment grade status

Panel A: Principal Component Loadings

	PC1	PC2	PC3	PC4	PC5
IRC	0.5791	-0.2175	-0.0318	-0.2386	0.7479
Bid Ask	0.4806	-0.1694	0.3026	0.7901	-0.1564
Amihud	0.5611	-0.1370	0.0368	-0.5107	-0.6358
Turnover	0.1474	0.7814	0.5849	-0.1269	0.0975
Zeros	0.3115	0.5428	-0.7510	0.2047	-0.0500
Cum. % Explained	43.48%	65.59%	81.07%	93.48%	100.00%

Panel B: Distribution of Liquidity Proxies

	PC1	IRC	Bid Ask	Amihud	Turnover	Zeros
1%	-5.474	0.000	0.000	0.000	0.015	0.000
5%	-2.983	0.000	0.088	0.092	0.097	4.545
10%	-1.948	0.032	0.174	0.400	0.254	13.636
25%	-0.559	0.101	0.369	3.749	0.905	33.333
50%	0.457	0.292	0.991	19.593	2.365	65.517
75%	0.994	0.709	2.069	54.387	4.973	86.364
90%	1.322	1.311	3.125	124.745	9.481	94.737
95%	1.476	1.829	3.905	205.592	14.607	95.455
99%	1.753	2.857	6.194	552.876	40.564	96.296

Panel C: Correlation of Liquidity Proxies

	PC1	IRC	Bid Ask	Amihud	Turnover	Zeros
PC1	1.000					
IRC	0.854	1.000				
Bid Ask	0.709	0.483	1.000			
Amihud	0.827	0.659	0.403	1.000		
Turnover	0.217	0.026	0.078	0.098	1.000	
Zeros	0.459	0.238	0.151	0.222	0.211	1.000

Table 3: Valuation Effect Fixed Effects Panel Regression

Panel A reports for high yield and Panel B for investment grade the results of the two way fixed effects regression

$$Spread_{i,t} = \alpha_i + \lambda_t + \gamma\%ETF_{i,t} + \beta_1 X_{i,t} + \beta_2 Liquidity_{i,t-1} + \varepsilon_{i,t}$$

$Spread_{i,t}$ is the spread of the volume-weighted monthly yield of bond i over the maturity-matched swap rate in month t. α_i is the bond fixed effect and $\lambda_t$is the time fixed effect. $\%ETF_{i,t}$ is the percentage of a bond's amount outstanding held by ETFs. A negative γ, indicates a positive valuation effect due to the inverse relationship between yields and prices. Covariates, $X_{i,t}$, that vary at the bond-month level are used. $Rating_{i,t}$ is the average of numerical conversion of S&P, Moody's, and Fitch ratings, $Leverage_{i,t}$ is the market-value of firm leverage, $Operating_{i,t}$ is operating income to sales, $LT\ Debt_{i,t}$ is the ratio of long-term debt to assets, and $Eq.Vol_{i,t}$ is the volatility of the firm's equity. Unreported $Pretax\ Dummies$ are also included. Columns 1-3 of each panel report results for the full sample with column 2 controlling for the first principal component as the lagged liquidity proxy, $Liquidity_{i,t-1}$. Column 3 controls for mutual fund ownership, $\%MF_{i,t}$, and index fund ownership, $\%Index_{i,t}$. Columns 4 and 5 exclude financials and columns 6 and 7 exclude bonds with call or put features. All proxies are winsorized at the 1% and 99% level by investment grade status. t-statistics with standard errors clustered by issuer and month are reported below the coefficients. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent Variable: Maturity-Matched Yield Spread to Swap Rate														
	Panel A: High Yield Bonds							**Panel B: Investment Grade Bonds**						
	Full Sample			**Ex-Financials**		**Ex-Bonds w/ Options**		**Full Sample**			**Ex-Financials**		**Ex-Bonds w/ Options**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
%ETF	-0.105**	-0.103***	-0.097**	-0.108***	-0.098***	-0.251**	-0.234**	-0.088***	-0.086***	-0.092***	-0.063***	-0.056***	-0.059***	-0.065***
	-2.45	-2.99	-2.18	-2.81	-2.96	-2.37	-2.35	-4.03	-4.92	-4.67	-5.93	-5.76	-3.53	-4.20
Rating	0.568	0.399*	0.565	0.734***	0.794***	0.032	0.134	0.169***	0.179***	0.171***	0.144***	0.172***	0.139**	0.207***
	1.36	1.77	1.36	3.11	3.20	0.12	0.68	3.10	3.00	3.20	3.80	4.12	2.30	3.04
Leverage	0.119***	0.110***	0.119***	0.108***	0.103***	0.160***	0.139***	0.040***	0.039***	0.039***	0.033***	0.032***	0.043***	0.044***
	6.49	7.12	6.48	6.56	6.04	4.86	5.24	6.62	7.44	6.61	6.14	5.42	5.36	4.86
Operating	-0.031**	-0.018***	-0.032**	-0.013**	-0.010*	-0.034**	-0.018	-0.004	-0.003	-0.003	-0.007***	-0.005***	-0.011***	-0.008*
	-2.47	-3.06	-2.49	-2.06	-1.80	-2.08	-1.66	-0.92	-0.82	-0.87	-3.16	-3.08	-2.68	-1.96
LT Debt	-0.044**	-0.046**	-0.043**	-0.053**	-0.053**	-0.031	-0.060	-0.009	-0.010*	-0.009	-0.005	-0.007*	-0.004	-0.002
	-2.13	-2.26	-2.13	-2.29	-2.39	-0.61	-1.21	-1.47	-1.94	-1.40	-1.58	-1.84	-0.45	-0.23
Eq. Vol	-0.244*	-0.223*	-0.243*	-0.247**	-0.245**	-0.059	0.010	0.005	0.006	0.004	0.009	0.006	0.018	-0.004
	-1.75	-2.00	-1.75	-2.58	-2.48	-0.33	0.07	0.16	0.32	0.14	0.54	0.48	0.51	-0.15
PC (Lag)		-0.800***			-0.732***		-0.438***		-0.025			-0.066***		-0.097***
		-4.62			-3.99		-3.60		-1.22			-7.46		-4.11
%MF			-0.029*							-0.019***				
			-1.89							-4.33				
%Index			0.058							0.025				
			0.46							1.53				
Bond FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sqr	0.725	0.722	0.726	0.717	0.710	0.775	0.752	0.784	0.776	0.785	0.865	0.862	0.859	0.851
Obs.	58,935	47,017	58,935	46,826	39,485	10,237	6,601	315,261	209,487	315,261	134,815	100,060	98,904	60,585

Table 4: The Valuation Effect of Index Expansion on High Yield Bonds

This table reports the results of difference-in-difference regressions to estimate the effect of ETF inclusion on bonds added due to a rule change that expanded the universe of eligible bonds using:

$$Spread_{i,t} = \alpha_i + \lambda_t + \delta(Treatment_i * Post_t) + \beta_1 X_{i,t} + \varepsilon_{i,t}.$$

$Spread_{i,t}$ is the spread of the monthly volume-weighted yield of a bond i over the maturity matched swap rate in month t. α_i is a bond fixed effect and λ_t is a time fixed effect. $X_{i,t}$ are covariates that vary at the bond-month level. The controls include $Rating_{i,t}$ the average of numerical version of S&P, Moody's, and Fitch ratings, $Leverage_{i,t}$ the market-value of firm leverage; $Operating_{i,t}$, operating income to sales; $LT\ Debt_{i,t}$ the ratio of long-term debt to assets; and $Eq.Vol_{i,t}$ the volatility of the firm's equity. In the final column, mutual fund ownership, $\%MF_{i,t}$, and index fund ownership, $\%Index_{i,t}$, are also controlled for. $Treatment_i$ is equal to one for bonds added to the ETF in the month following the rule change, July 2009. The control group is composed of bonds originally held by the index whose weighting decreased due to the rule change. $Post_t$ equals one from July to December to account for the six-month transition from the original index to the expansion index and equals zero from January to June. $Treatment_i * Post_t$ is equal to one for treatment bonds following their inclusion in the ETF. A negative δ indicates a positive valuation effect because of the inverse relationship between yields and prices. t-statistics based on robust standard errors are reported below the coefficients. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent Variable: Yield Spread to Maturity-Matched Swaps Rate			
	(1)	(2)	(3)
Treatment * Post	-1.313**	-1.467**	-1.347**
	-2.42	-2.43	-2.28
Rating		-0.923**	-0.910**
		-2.39	-2.40
Leverage		0.131***	0.154***
		4.37	4.81
Operating		0.015	0.009
		1.43	0.84
LT Debt		-0.158	-0.191*
		-1.60	-1.83
Eq. Vol		-0.687***	-0.737***
		-2.92	-3.20
% MF			-0.113***
			-2.81
% Index			0.921**
			2.04
Bond FE	Y	Y	Y
Time FE	Y	Y	Y
R-sqr	0.748	0.766	0.773
Obs.	936	576	576

Table 5: The Valuation Effect of Maturity-Based Sales on Investment Grade ETF Holdings

This table reports the results of the difference-in-difference regressions used to estimate the effect of ETF exclusion on bonds sold due to a minimum time to maturity threshold using the specification

$$Spread_{i,t} = \alpha_i + \lambda_t + \delta(Treatment_i * Post_t) + \beta_1 X_{i,t} + \varepsilon_{i,t}$$

where $Spread_{i,t}$ is the spread of the volume-weighted yield of bond i over the maturity-matched swap rate in month t. α_i is the bond fixed effect and λ_t is the time fixed effect. $X_{i,t}$ are covariates that vary at the bond-month level. The controls include $Rating_{i,t}$ the average of numerical version of S&P, Moody's, and Fitch ratings, $Leverage_{i,t}$ the market-value of firm leverage, $Operating_{i,t}$ operating income to sales, $LT\ Debt_{i,t}$ the ratio of long-term debt to assets, and $Eq.Vol_{i,t}$ the volatility of the firm's equity. In some specifications mutual fund ownership, $\%MF_{i,t}$ and index fund ownership, $\%Index_{i,t}$ are also controlled for. $Treatment_i$ is equal to one for bonds sold by LQD between in a one-month window around the three-year time to maturity threshold. The control group is composed of investment grade bonds with three years to maturity and non-zero mutual fund holdings on the date of a maturity based sale. $Post_t$ equals one the month after the bond is sold by the ETF. To account for this shift $Post_t$ is equal to one for control bonds one month after the threshold is crossed. $Treatment_i * Post_t$ is equal to one for treatment bonds following their sale. Any bond with a broad rating change during the sample period are excluded from the sample. The different columns account for various weighting changes (Δw) in the month prior to sale. t-statistics with robust standard errors are reported below the coefficients. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Dependent Variable: Yield Spread to Maturity-Matched Swaps Rate						
	All		$\Delta w < 50\%$		$\Delta w < 10\%$	
	(1)	(2)	(3)	(4)	(7)	(8)
Treatment * Post	0.045**	0.044**	0.056***	0.056***	0.041*	0.040*
	2.35	2.30	2.66	2.64	1.83	1.81
Rating	0.232**	0.234**	0.195	0.194	0.213	0.211
	1.98	2.00	1.55	1.54	1.40	1.40
Leverage	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	3.12	3.16	3.14	3.17	3.00	3.02
Operating	0.004**	0.004**	0.004**	0.004**	0.003**	0.004**
	2.49	2.53	2.52	2.55	2.02	2.06
LT Debt	0.009***	0.009***	0.009***	0.009***	0.007**	0.007**
	2.83	2.85	2.85	2.86	2.13	2.13
Eq. Vol	0.009	0.009	0.010	0.010	0.007	0.006
	0.93	0.87	1.00	0.94	0.66	0.60
%MF		0.002		0.002		0.000
		0.67		0.73		0.07
%Index		0.021***		0.019**		0.021***
		2.92		2.54		2.62
Bond FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
R-sqr	0.96	0.96	0.96	0.96	0.96	0.96
Obs.	3,102	3,102	2,958	2,958	2,628	2,628

Table 6: The Permanence of the Valuation Effect using Propensity-Score and Issuer-Matched Controls

This table reports the results of cross-sectional regressions to estimate the valuation impact of a bond's initial inclusion in an ETF using

$$\Delta Spread_{i,m-0} = a + \lambda_t + \beta_1 ETF_i + \beta_2 Spread_{i,0} + \varepsilon_i$$

Where $\Delta Spread_{i,m-0}$ is the change in spread for bond i, between month m ($m = 1, \ldots, 6$) and the month prior to the ETF purchase ($m = 0$). $m = 1$ represents the first time the bond appears in ETF holdings. ETF_i is a dummy set to one for bonds included in an ETF and zero for control bonds. Controls are determined using propensity scores estimated using a the following logit of the ETF dummy on bond characteristics observable in the month prior to an inclusion event:

$$ETF_{i,1} = a + \beta_1 Spread_{i,0} + \beta_2 Rating_{i,0} + \beta_2 T2M_{i,0} + \beta_3 Age_{i,0} + \beta_4 Size_{i,0} + \beta_5 Coupon_{i,0}$$

Two samples are then used. The first matches each treatment bond with its five nearest neighbors identified in the month of inclusion. Control bonds are removed from the sample in later months if they are subsequently included in an ETF, have a broad ratings change (AA to A), or their treatment match exits the sample. The second sample conducts the logit each of the m months after inclusion using bond characteristics from month $m = 0$. Each treatment bond is matched to its nearest neighbor from the same issuer, without replacement. t-statistics with standard errors clustered by issuer and month are reported below the coefficients. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

		Panel A: High Yield							Panel B: Investment Grade						
Controls		[-1,0]	[0,1]	[0,2]	[0,3]	[0,4]	[0,5]	[0,6]	[-1,0]	[0,1]	[0,2]	[0,3]	[0,4]	[0,5]	[0,6]
5 Nearest Neighbors	ETF	-0.005	-0.120***	-0.163***	-0.257***	-0.194**	-0.293*	-0.383**	0.029	-0.015	-0.043*	-0.085***	-0.119***	-0.123***	-0.130***
		-0.09	-2.90	-3.38	-3.37	-2.05	-1.98	-2.64	1.18	-0.69	-1.74	-3.65	-4.92	-4.21	-3.35
	Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	R-sqr	0.41	0.30	0.40	0.48	0.50	0.47	0.46	0.32	0.26	0.43	0.56	0.69	0.77	0.78
	N	3,581	3,766	3,516	3,340	3,103	2,886	2,733	7,830	8,616	7,812	7,499	7,137	6,812	6,430
Issuer Matched	ETF	-0.163	-0.107*	-0.181**	-0.191**	-0.128	-0.166	-0.141	-0.010	-0.055**	-0.079***	-0.087***	-0.122***	-0.121***	-0.124***
		-1.19	-1.95	-2.49	-2.09	-1.53	-1.53	-1.09	-0.54	-2.66	-4.70	-3.64	-5.58	-5.68	-4.32
	Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	R-sqr	0.78	0.77	0.85	0.85	0.91	0.95	0.95	0.60	0.50	0.68	0.83	0.87	0.91	0.92
	N	646	715	673	632	584	550	499	2,406	2,814	2,693	2,668	2,561	2,512	2,423

Table 7: ETF Activity Summary Statistics

This table shows the statistics for ETF activity in corporate bonds. %ETF is the percentage ownership of a bond by all ETFs. C/R Intensity is the measure of the standard deviation of ETF shares outstanding over the mean number of shares. ETF turnover the monthly share volume over the average ETF shares outstanding. Short is the short interest of the ETF. The last three proxies are computed as the weighted average of the variable for all ETFs holding the bond. Panel A shows the distribution of the proxies. Panel B documents the correlation among the different measures. All proxies are winsorized at the 1% and 99% level by investment grade status.

Panel A: Distribution of ETF Activity Proxies

	High Yield				**Investment Grade**			
	%ETF	C/R Intensity	ETF Turnover	Short	%ETF	C/R Intensity	ETF Turnover	Short
1%	0.002	0.000	0.303	0.079	0.007	0.000	0.304	0.075
5%	0.038	0.082	0.488	0.173	0.040	0.079	0.478	0.163
10%	0.078	0.252	0.574	0.245	0.080	0.233	0.559	0.229
25%	0.232	0.672	0.717	0.400	0.220	0.642	0.693	0.373
50%	0.678	1.440	0.930	0.688	0.613	1.349	0.882	0.611
75%	1.783	2.780	1.356	1.177	1.526	2.640	1.208	0.966
90%	3.117	5.130	1.919	2.315	2.653	4.810	1.709	1.497
95%	4.085	7.167	2.427	2.467	3.372	6.589	2.169	2.143
99%	6.540	14.690	4.920	6.949	4.151	12.965	4.058	4.960

Panel B: Correlation of ETF Activity Proxies

	%ETF	C/R Intensity	ETF Turnover	Short
%ETF	1.000			
C/R Intensity	-0.022	1.000		
ETF Turnover	0.044	0.528	1.000	
Short	0.197	0.315	0.406	1.000

Table 8: Percentage of Volume by Trade Size

This table presents summary statistics on the percentage of total monthly volume attributed to trades in each size bin. Retail represents the dollar volume from trades of less than or equal to $100,000. Bin 2 represents the total volume from trades greater than $100,000 and less than $1M. For high yield bonds, Bin 3 is the total dollar volume from all trades greater than or equal to $1M. For investment grade bonds, Bin 3 is the volume of trades between $1M and $5M and Bin 4 is total volume of trades greater than or equal to $5M. Panel A presents the statistics for all bonds categorized by if a bond if held for at least one month by an ETF. Panel B documents the figures for ETF bonds only in the months they are an ETF constituent relative to months they are not.

Panel A: Non-ETF Bonds and ETF Bonds					
		High Yield		**Investment Grade**	
		Mean	**Median**	**Mean**	**Median**
Non-ETF Bonds	Retail	55.00	58.67	87.15	100.00
	Bin 2	19.37	3.01	7.04	0.00
	Bin 3	25.63	0.00	4.11	0.00
	Bin 4	-	-	1.72	0.00
	%MF	6.61	0.41	0.79	0.00
	# MF	6.59	1.00	0.74	0.00
ETF Bonds	Retail	11.05	4.61	15.98	6.30
	Bin 2	26.23	22.65	24.84	17.40
	Bin 3	62.73	69.44	37.39	37.62
	Bin 4	-	-	21.89	0.00
	%MF	20.89	19.61	6.47	4.15
	# MF	42.15	35.00	18.70	11.00
Total	Retail	36.66	12.41	52.17	41.71
	Bin 2	22.23	16.47	15.79	4.47
	Bin 3	41.11	47.09	20.47	0.00
	Bin 4	-	-	11.63	0.00
	%MF	12.56	7.22	3.58	0.30
	# MF	21.41	9.00	9.57	2.00
Panel B: ETF Bonds Only					
Non- ETF Months	Retail	14.31	5.12	22.75	8.81
	Bin 2	25.54	20.74	23.88	14.58
	Bin 3	60.15	68.81	33.63	30.32
	Bin 4	-	-	20.00	0.00
	%MF	17.55	15.54	4.41	2.05
	# MF	26.35	22.00	8.41	5.00
ETF Months	Retail	9.21	4.38	14.26	5.91
	Bin 2	26.61	23.42	25.09	17.95
	Bin 3	64.18	69.69	28.23	38.80
	Bin 4	-	-	22.37	12.99
	%MF	22.77	21.69	7.00	4.76
	# MF	51.05	44.00	21.31	14.00

Table 9: ETF Activity and the Composition of Traders

This table reports the results of regressions of proxies for the composition of traders on four ETF activity proxies, $ETF\ Activity_{i,t}$, for bond i in month t. The first three columns of Panel A for high yield bonds and first four columns of Panel B for investment grade bonds report the results of the regression

$$\%Type\ Volume_{i,t} = \alpha_i + \lambda_t + \rho ETF\ Activity\ _{i,t-1} + \beta_1 Rating_{i,t} + \beta_2 \%Ownership_{i,t-1} + \varepsilon_{i,t}.$$

$\%Type\ Volume_{i,b,t}$is the percentage of total monthly volume attributed to trades of different size bins, b, for bond i in month t. α_i is the bond fixed effect and λ_t is the time fixed effect. $Rating_{i,t}$ is the numerical average rating from S&P, Moody's and Fitch and is not reported. Lagged mutual fund ownership $\%MF_{i,t-1}$, and index fund ownership, $\%Index_{i,t-1}$ are controlled for. The ETF activity proxies are lagged ETF ownership, $\%ETF_{i,t-1}$, creation and redemption intensity, $C/R\ Intensity_{i,t-1}$, $ETF\ Turnover_{i,t-1}$, and a measure of the short interest in an ETF, $Short_{i,t-1}$. The last three proxies are computed as the weighted average of the variable for all ETFs holding the bond. *Retail* is all trades less than $100,000. Bin 2 is trades between $100,000 and $1 million. For the high yield market Bin 3 has all trades in excess of $1million. For the investment grade market Bin 3 includes all trades between $1 million and $5 million and Bin 4 has trades greater than $5 million.

The last two columns regress measures of mutual fund ownership, $\%MF_{i,t}$ and $\#MF_{i,t}$ the number of mutual funds holding the bond on the proxies for ETF activity using

$$MF_{i,t} = \alpha_i + \lambda_t + \rho ETF\ Activity_{i,t} + \beta_1 Rating_{i,t} + \beta_2 MF_{i,t-1} + \varepsilon_{i,t}$$

t-statistics with standard errors clustered at the issuer and month levels are reported below the coefficients. * indicates significance at 10%, ** at 5%, and *** at 1%.

	Panel A: High Yield					Panel B: Investment Grade					
	Retail	**Bin 2**	**Bin 3**	**%MF**	**# MF**	**Retail**	**Bin 2**	**Bin 3**	**Bin 4**	**%MF**	**# MF**
%ETF	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(6)
%ETF				0.14*	0.283**					0.27	-0.001
				1.73	2.54					0.62	-0.01
%ETF (Lag)	-0.635***	0.678***	-0.044			-0.587***	1.305***	0.662***	-1.396***		
	-5.11	5.47	-0.27			-3.15	6.88	3.94	-5.99		
%MF (Lag)	-0.111***	0.033	0.078***	0.762***		-0.085***	-0.079***	0.022	0.138***	0.784***	
	-4.37	1.37	3.12	17.53		-3.62	-3.94	1.06	4.94	17.19	
%Index (Lag)	-2.656***	-1.574*	4.230***			0.099	0.896***	0.019	-1.046***		
	-4.96	-1.74	3.34			0.83	4.45	0.15	-4.78		
# MF (Lag)					0.937***						0.922***
					24.18						27.39
C/R Intensity	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(6)
C/R Intensity				0.025*	0.001					0.024***	0.057**
				1.88	0.05					2.79	2.40
C/R Intensity (Lag)	-0.079**	0.187***	-0.108***			-0.118***	0.023	0.104***	-0.012		
	-2.29	3.94	-2.78			-4.35	0.56	3.17	-0.28		
ETF Turnover	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(6)
ETF Turnover				0.160*	0.247*					0.139**	0.295**
				1.96	1.74					2.65	2.66
ETF Turnover (Lag)	-0.389***	0.564***	-0.175			-0.272***	0.262	0.102	-0.097		
	-3.76	3.57	-1.11			-3.21	1.51	1.20	-0.90		
Short Interest	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(6)
Short Interest				0.028	0.027					0.062**	0.129
				0.70	0.37					2.36	1.24
Short Interest (Lag)	-0.114	0.212***	-0.098			-0.189**	0.329***	0.099	-0.246*		
	-1.66	2.77	-1.03			-2.62	2.85	1.15	-2.00		
Bond FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	93,345	93,345	93,345	93,345	93,345	336,102	336,102	336,102	336,102	336,102	336,102

Table 10: Liquidity Fixed Effects Panel Regression

This table reports the results of regressions of the six liquidity proxies, $Liquidity_{i,t}$ for bond i in month t on four lagged ETF activity proxies, $ETF\ Activity_{i,t-1}$ for the high yield market in Panel A and the investment grade market in Panel B from

$$Liquidity_{i,t} = \alpha_i + \lambda_t + \rho ETF\ Activity\ _{i,t-1} + \beta_1 X + \varepsilon_{i,t}.$$

The dependent variables are standardize to represent liquidity, rather than illiquidity. α_i is the bond fixed effect and λ_t is the time fixed effect. $\%MF_{i,t-1}$ and $\%Index_{i,t-1}$ are the previous month's active and index fund ownership, respectively, and $Rating_{i,t}$ is the numerical average rating from S&P, Moody's and Fitch. The dependent variables used are lagged ETF ownership, $\%ETF_{i,t-1}$, a measure of creation and redemption intensity, $C/R\ Intensity_{i,t-1}$, $ETF\ Turnover_{i,t-1}$, and a measure of the short interest in an ETF, $Short_{i,t-1}$. The last three ETF activity proxies are computed as the weighted average of the variable for all ETFs holding the bond. The lagged ownership of mutual funds and index funds is controlled for in all regressions, with their coefficient reported once. The coefficients on rating are unreported. t-statistics with standard errors clustered at the issuer and month levels are reported below the coefficients. * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

	Panel A: High Yield Bonds						Panel B: Investment Grade Bonds					
Dependent Variable:	**PC1**	**IRC**	**Bid Ask**	**Amihud**	**Turnover**	**Zeros**	**PC1**	**IRC**	**Bid Ask**	**Amihud**	**Turnover**	**Zeros**
%ETF	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
%ETF (Lag)	-0.005	-0.004*	-0.010	-0.096	0.046	0.170	-0.118***	-0.042***	-0.045**	-3.899***	-0.625***	-2.272***
	-0.78	-1.78	-1.19	-0.34	0.90	0.91	-4.54	-4.72	-2.21	-3.71	-8.00	-8.26
%MF (Lag)	0.005***	0.001**	0.003**	0.210***	0.019**	0.181***	0.006***	0.000	0.007***	0.089	0.069***	0.083***
	4.14	2.37	2.31	3.67	2.65	6.94	3.63	0.02	4.80	1.19	5.26	2.73
%Index (Lag)	-0.011	0.002	-0.019	0.434	0.492	-1.331**	-0.089***	-0.024***	-0.065***	-2.917***	-0.460***	-0.834***
	-0.46	0.22	-0.60	0.32	1.12	-2.51	-4.75	-3.52	-4.15	-4.22	-6.34	-4.77
C/R Intensity	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
C/R Intensity (Lag)	-0.001	-0.000	-0.001	-0.126*	0.005	0.047	-0.002	-0.002	-0.003	-0.106	0.040***	0.057
	-0.56	-1.07	-0.97	-1.75	0.45	1.26	-0.96	-1.64	-0.98	-0.95	3.64	1.35
ETF Turnover	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
ETF Turnover (Lag)	0.000	-0.002	0.000	-0.468	0.015	0.400**	-0.017*	-0.007**	-0.016**	-0.897*	0.082**	0.038
	0.00	-1.17	0.01	-1.39	0.41	2.32	-1.96	-2.10	-2.00	-1.87	2.48	0.33
ETF Short Interest	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Short Interest (Lag)	-0.005	-0.003**	-0.008	-0.535*	0.008	0.393***	-0.023**	-0.007**	-0.020**	-0.778**	-0.025	-0.110
	-1.05	-2.10	-1.63	-1.96	0.22	3.16	-2.64	-2.34	-2.56	-2.36	-0.86	-1.08
Bond FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	78,819	90,041	79,646	91,431	93,432	93,432	246,667	317,261	251,972	325,621	336,478	336,478