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Investor behaviour and reaching for yield: evidence from the sterling corporate bond market

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Abstract

We provide evidence on how corporate bond investors react to a change in yields, and how this behaviour differs in times of market-wide stress. We also investigate 'reaching for yield' across investor types, as well as providing insights into the structure of the corporate bond market. Using proprietary sterling corporate bond transaction data, we show that insurance companies, hedge funds and asset managers are typically net buyers when corporate bond yields rise. Dealer banks clear the market by being net sellers. However, we find evidence for this behaviour reversing in times of stress for some investors. During the 2013 'taper tantrum', asset managers were net sellers of corporate bonds in response to a sharp rise in yields, potentially amplifying price changes. At the same time, dealer banks were net buyers. Finally, we provide evidence that insurers, hedge funds and asset managers tilt their portfolios towards higher risk bonds, consistent with 'reaching for yield' behaviour.

Key words: Corporate bonds, trading volume, investment decisions, banks, insurer, non-bank financial institutions, cyclicality, financial stability.

JEL classification: G11, G12, G15, G21, G22, G23.

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1 Introduction

The market for corporate debt plays a crucial role in the global financial system by providing funding to the real economy. However, little is known about investment behaviour in the secondary corporate bond market. Who buys corporate bonds when yields are rising and who is on the other side of the trade? And how do different investor types react in times of market-wide stress? For example, if large investors were to behave in a 'procyclical' manner - i.e. selling bonds as prices fall and buying as prices rise - they might amplify yield moves, potentially causing markets to overshoot. Sharp and sustained falls in corporate bond prices may reduce the ability of some companies to raise finance, which could affect their investment decisions and potentially threaten their solvency. Understanding the behaviour of end investors has become even more pressing since the financial crisis. Dealer banks have decreased their inventories of corporate debt by at least 50% (Dick-Nielsen and Rossi, 2016), leading to an increased cost of immediacy and heightened potential for the investment decisions of large investors to move market prices.

A growing theoretical literature analyses the trading behaviour of financial institutions in fixed-income assets. Rajan (2005) finds that investment managers have strong incentives to take risk due to their compensation structure. He also shows that the underlying incentives to 'reach for yield' are even stronger in a low interest rate environment. Feroli et al. (2014) suggest that this return chasing can reverse sharply during market 'tantrums' (such as the 'taper tantrum' in 2013), resulting in a bond sell-off by delegated investors. By contrast, banks become 'illiquidity seekers' in stress periods, as proposed by Diamond and Rajan (2011). Hanson et al. (2015) show that banks have a comparative advantage at holding illiquid fixed-income assets with substantial price volatility. 'Sticky deposits', protected by deposit insurance, serve as a relatively stable source of funding compared to shadow banks.

We provide novel empirical evidence for these theoretical predictions. Thus far empirical research has been constrained by a lack of comprehensive trade data in many markets. We are able to fill this gap in the literature with proprietary transaction-level data from the Financial Conduct Authority's Zen database. The unique feature of the dataset is that it includes the identity of both counterparties, allowing us to analyse differences in trading behaviour across institutions. The data cover all sterling corporate bond trades for firms regulated in the UK, or branches of UK firms regulated in the EEA. We combine the transaction data with a hand-collected classification of firms into broad investor types. Finally, we match our data to publicly-available information on the corresponding bonds such as issue data and maturity.

Our main contribution to the literature is to analyse the heterogeneity in relatively high frequency investment behaviour across different investor types: dealer banks, non-dealer banks, insurance companies, hedge funds and asset managers. We examine investor behaviour in the sterling corporate bond market by regressing the lagged change in bond yields on the logarithm of buy and sell volume, controlling for a range of factors. Over the period 2011-2016, we find that insurance companies, hedge funds and asset managers, on average, significantly increase purchases and reduce sales of sterling corporate bonds following an increase in corporate bond yields. Dealer banks clear the market by reducing purchases and increasing sales. This result is robust across various regression specifications, including changing the dependent variable to number of trades, and using the change in corporate bond spreads rather than the change in yields.

However, we find that the average behaviour reverses in times of stress. For example, during the 2013 'taper tantrum', asset managers sold more and bought less in response to a rise in yields, potentially amplifying yield changes. Asset managers may face incentives to behave procyclically in stress periods given their exposure to short-term benchmarks and redemption risk (e.g. Buffa et al. (2014), Feroli et al. (2014) or Goldstein et al. (2016)). At the same time, dealer banks were net buyers, thereby clearing the market. These findings are consistent with the theoretical predictions of Diamond and Rajan (2011) and Hanson et al. (2015) that banks behave countercyclically during stress periods in fixed-income markets. More generally, we find that when the VIX is high (in the top decile), asset managers respond much less to an increase in yields, only slightly increasing their purchases.

We also perform a cross-sectional analysis of the relationship between bond characteristics and investor behaviour. For dealer banks, insurers and asset managers, the coefficients on the change in yields increase with the bond residual maturity. With regard to credit quality, we find the largest magnitudes for high yield bonds, followed by investment grade and unrated bonds.

What drives the heterogeneous behaviour across different investor types? In the US corporate bond market, 'reaching for yield' has been cited as a key driver of investor behaviour (e.g. Becker and Ivashina (2015), Choi and Kronlund (2016) or Kacperczyk and Schnabl (2013)). Therefore we explore the heterogeneity in the 'reaching for yield' behaviour across investor types in the sterling corporate bond market. We construct three 'reaching for yield' factors to capture buying or selling of i) higher yielding lower rated bonds, ii) higher yielding longer maturity bonds, or iii) higher yielding bonds within the same credit-quality and maturity bucket (Choi and Kronlund, 2016). We regress these factors on the logarithm of buy and sell volume and find statistically significant coefficients on all three factors for hedge funds and asset managers. Therefore both investor types tilt their portfolios to higher yielding bonds, either within a given credit risk and maturity bucket, or by pushing further along the credit and duration risk spectra. Consistent with Becker and Ivashina (2015), we find that insurance companies primarily 'reach for yield' by favouring higher yielding bonds within the same credit quality and maturity bucket, and to a lesser extent through longer maturity bonds.

Our results have important financial stability implications. First, the procyclical behaviour of asset managers in times of stress could amplify asset price moves and increase volatility. Such disruption to the corporate bond market could have an adverse impact on real economic activity given the critical function this market performs in directly providing lending to the real economy. Second, 'reaching for yield' behaviour could reflect responses to regulatory factors and may also provide evidence of an excessive compression in risk premia, possibly creating vulnerability to a correction.

2 Related literature

There is a growing theoretical literature about the trading behaviour of financial institutions in fixed-income markets. A significant part of this literature focuses on banks (e.g. Diamond and Rajan (2011), Greenwood et al. (2015) or Shleifer and Vishny (2010)). Hanson et al. (2015) show that traditional banks hold illiquid bonds during stress periods because of their relatively stable source of funding when compared to shadow banks. Diamond and Rajan (2011) confirm that banks load up on liquidity risk in order to profit from high returns when the depressed value of illiquid assets recovers. For delegated portfolio management, Guerrieri and Kondor (2012) find that fund managers underestimate tail events and shift to riskier assets. However, as investors adjust their risk assessment, they engage in a flight-to-safety and markets become increasingly fragile (Gennaioli et al., 2012). In their model of the corporate bond market, Baranova et al. (2017) show that redemptions from open-ended investment funds and the resulting sales of corporate bonds can materially increase spreads.

On the empirical front, our approach is closely related to two papers that provide insights about the investment behaviour of different investor types in debt securities for the German market (Abassi et al. (2016), Timmer (2016)). Using quarterly holdings data of financial institutions in Germany, Timmer (2016) shows that banks and investment funds exhibit procyclical investment behaviour, i.e. buy securities when prices rise. On the contrary, insurance companies and pension funds act as a stabilising force and buy when prices fall. Using a similar dataset, Abassi et al. (2016) find that - during the crisis - German banks with higher trading expertise invested in securities that had a larger price drop; with the strongest effects for low-rated and long-term securities. Our proprietary transaction dataset allows us to provide novel evidence on investment behaviour at a higher frequency, focusing solely on the corporate bond market. This higher-frequency data also allows us to analyse disruptive events such as the 'taper tantrum' period in 2013.

Finally, our paper also contributes to the literature that provides empirical evidence for 'reaching for yield'. Di Maggio and Kacperczyk (2017) and Kacperczyk and Schnabl (2013) show that U.S. money funds reach for yield and shift to riskier asset classes, particularly in response to policies that maintain low interest rates. Becker and Ivashina (2015) provide similar evidence for the US insurance sector: companies reach for yield within regulatory risk categories. The authors also find that the effect is procyclical, i.e. 'reaching for yield' is less attractive in economic downturns. Choi and Kronlund (2016) show that mutual funds have an incentive to reach for yield in order to attract inflows from investors, in particular during low interest rate periods. Our paper confirms the results of these studies and provides novel evidence for different magnitudes in the degree of 'reaching for yield' across investor types.

3 Data and measurement

3.1 Data

We collect data from several sources. First, we employ the proprietary Zen database maintained by the Financial Conduct Authority (FCA).[1] The database contains transaction-level information on trading in sterling corporate and government bonds for all firms regulated in the UK, or branches

[1]The database has previously been used in Aquilina and Suntheim (2016) and Benos and Zikes (2016).

of UK firms regulated in the EEA. We focus exclusively on corporate bonds in our analysis. Our dataset includes the identity of both counterparties, allowing us to analyse cross-sectional differences in trading behaviour. Each transaction report also includes the date, time, quantity, price, International Securities Identification Number (ISIN), a buyer/seller flag and trading capacity information. Second, using an unique hand-collected dataset, we can attribute an investor type to each firm identity.[2] Thus we know which counterparty of the trade is an asset manager, insurance company, hedge fund, dealer or non-dealer bank.[3] Third, we also match the transaction data to publicly-available information on the corresponding bonds from Bloomberg: specifically issuance date, maturity date, amount issued, coupons, ratings and issuer industry. Finally, we obtain VIX market volatility data from the Chicago Board Options Exchange, yield curve data from the Bank of England and bond index returns from Markit. Our dataset covers the period between 1 September 2011 and 31 December 2016. Prices and quantities are winsorised at the 1% level to reduce the impact of outliers.[4] After filtering out all duplicates, erroneous entries, firm-internal trades and primary market trading,[5] we are left with 3,304,930 observations.

The comprehensive transaction data allow us to analyse investment behaviour across different investor types and institutions. Thus far, the empirical literature in this field has been limited to the use of quarterly market prices and holdings data for the German market (Abassi et al. (2016), Timmer (2016)). Therefore our primary contribution to the literature is a higher-frequency analysis of investor behaviour across different industries using actual transaction prices. However, the main drawback to using our dataset is that we can capture who executes the trade, but not necessarily who the beneficial owner is. For example, an asset manager might execute a trade on behalf of a pension fund. In our dataset, we would not be able to distinguish this from an asset manager trade originating from, for instance, an open-ended investment fund.

[2]The counterparty identity is at firm level, so unfortunately we cannot categorise at a finer level, e.g. splitting out open-ended funds within the asset manager class. The investor type allocation is imperfect since some investors could be allocated to different types (e.g. insurance companies with asset manager arms). However, our results are robust to moderate changes in the investor type allocation.

[3]Our non-dealer bank category also includes securities firms.

[4]The robustness of the results is not affected by the winsorisation.

[5]We exclude primary market trading by removing any trades that take place on the day of issuance, for newly issued bonds. However, our results are robust to the inclusion of primary market trading.

3.2 Defining volume and trade-weighted yield measures

In the spirit of Abassi et al. (2016), our main measure for bond trading activity is the natural logarithm of the buy or sell volume, $ln(Volume^{Buy/Sell})$, where $Volume^{Buy/Sell}$ refers to the amount bought ($Buy\ Volume$) or sold ($Sell\ Volume$) of bond i in week t. Thus the measure separately examines buying and selling behaviour across bonds. For each bond, we calculate the measure by aggregating the individual transaction volumes in one week:

$$Buy\ Volume = max(Net\ Volume, 0)$$
$$Sell\ Volume = max(-Net\ Volume, 0)$$

In the first part of the paper, we measure $Net\ Volume$ on the investor type level to find out, in absolute terms, which sectors are net buyers or net sellers of a bond with respect to yield changes. For example, the dependent variable $Sell\ Volume$ takes a positive value (equal to $-Net\ Volume$) if an investor type has been a net seller of bond i in week t. For this particular type-bond-week combination, the dependent variable $Buy\ Volume$ equals zero. By construction, we only include non-zero type-bond-week combinations in our sample. Note that we choose the weekly frequency in order to have a balance between a sufficiently high frequency but also capturing slower moving investors. Later we also measure $Net\ Volume$ at the individual institution level in order to analyse differences in the magnitude of the reaction to yield changes across investor types. $Buy\ Volume$ and $Sell\ Volume$ then refer to the weekly amount bought or sold of bond i by institution z.

For robustness, we also use $\#Buy\ Trades$ or $\#Sell\ Trades$ to measure bond trading activity. As the name suggests, the measure refers to the net number of trades per investor type, bond and week. Again, we separately examine buying and selling behaviour by constructing the buy/sell variables in the same way as shown for transaction volumes.

Since bond trades of different sizes occur at very different yields, we use trade-weighted yields in the spirit of Bessembinder et al. (2009). We calculate the weighted average weekly yield across all transactions in week t for each bond i, with the weights being the ratio of the individual transaction volume to the total trading volume for bond i in week t. Because yields are highly serially correlated in our sample, we use the weekly first difference $\Delta yield$ in our regressions. Weekly first differences in yields have an effective mean of zero (around -0.006%), a standard deviation of 0.29%, and negligible serial correlation. In our robustness tests we also employ trade-weighted spreads instead of yields, with similar results in both statistical and economic terms.

4 The sterling corporate bond market

Corporate bond markets perform a critical function in the financial system, providing funding to the real economy. Sterling corporate bonds are issued by both UK and non-UK domiciled firms (Elliott and Middeldorp, 2016). And bond financing has become increasingly important for companies since the financial crisis. As noted in Bank of England (2016): "on a cumulative basis, virtually all net financing raised by private non-financial business since the crisis has been in the form of bond rather than bank finance".

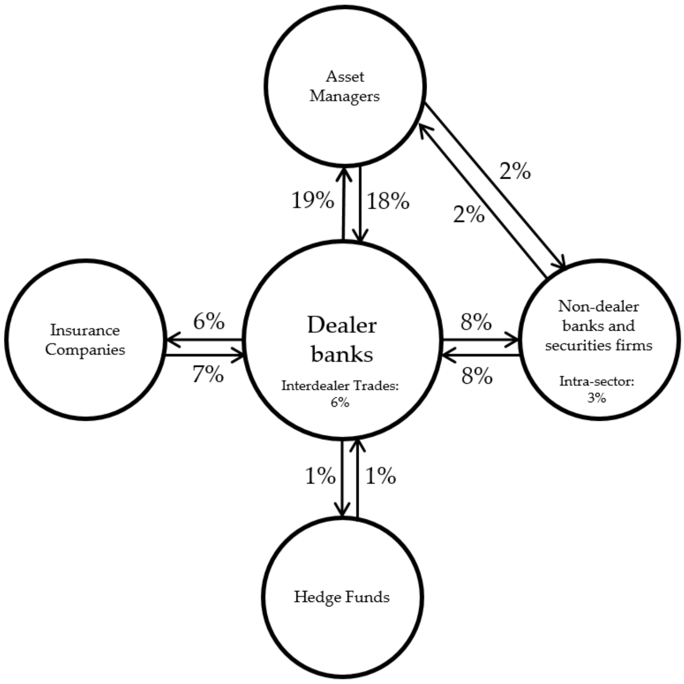

Figure 1: *Trading volume between different investor types*[6]

The sterling corporate bond market is an over-the-counter market, with almost all trading intermediated by dealer banks. Figure 1 shows the transaction network in the sterling corporate

[6] As a percentage of total trading volume. Arrows point from seller to buyer. We do not report the transaction market shares where the flows are less than 1% of total trading volume (which, on aggregate, account for 7% of the total trading volume). We also do not report the market share of transactions in which the second counterparty is missing (11%). Note that the transaction market shares do not add up to 100% due to rounding.

bond market. Trades between dealer banks and asset managers account for more than one third of the trading volume in our sample, followed by transactions between dealers and insurance companies, which account for around 13% of trading volume. The volume of transactions between most non-dealer investors (e.g. asset manager to insurance company) is very small and not reported in Figure 1. Overall, the data show that dealer banks are the counterparty for around 84% of all transactions in the sterling corporate bond market.

Table 1: *Trade characteristics*

This table reports the summary statistics of variables that characterise the secondary market for sterling corporate bonds. Our dataset covers the period from September 2011 to December 2016. 'Market Volume' refers to the average gross trading volume in the sterling corporate bond market per day in £ bn. '# trades' measures the average number of trades in the market per day. '# unique bonds', '# unique issuers' and '# unique counterparties' measure the number of distinctive bonds, issuers and counterparties in the sample. 'Trade size' measures the size of an average trade in the market. 'Yield' and 'Spread' refer to the average yield-to-maturity and spread over UK government bonds in percentage points; measured separately for the three credit quality categories. 'Investment grade' refers to bonds with a credit rating of BBB- or higher. 'High yield' refers to bonds with a credit rating of BB+ or lower. 'Unrated' refers to bonds that do not have a rating. The first six columns refer to individual quarters (only the first column) or years, and the last column shows the figures for the entire sample.

	2011:Q4	**2012**	**2013**	**2014**	**2015**	**2016**	**Full Sample**
Market volume (per day in £bn)	0.97	1.28	1.48	1.50	1.45	1.43	1.41
# trades (per day)	2,046	2,629	2,799	2,586	2,529	2,485	2,582
# unique bonds	2,281	3,340	3,451	3,568	3,779	3,580	7,067
# unique issuers	538	595	622	641	672	665	836
# unique counterparties	1,373	1,905	1,903	1,844	1,826	1,708	2,773
Trade size (in 1000)	472.7	493.8	531.2	578.6	572.1	581.6	546.8
Yield (in ppts)							
Investment grade	5.0	4.4	3.5	3.3	2.8	2.5	3.4
High yield	9.0	7.4	5.9	5.9	6.1	6.3	6.4
Unrated	3.7	3.2	3.0	3.1	3.0	3.2	3.1
Spread (in ppts)							
Investment grade	2.7	2.5	1.4	1.1	1.3	1.5	1.6
High yield	6.9	5.9	4.2	3.7	4.6	5.3	4.8
Unrated	2.6	2.4	1.7	1.5	1.7	2.5	2.0

Table 1 provides trade statistics for our sample. Our dataset covers 7,067 unique bonds, 836 unique issuers and 2,773 unique counterparties. An average trade has a size of around £550,000. We observe an average daily trading volume of £1.4bn. This compares with an average daily trading volume of $25bn in the US corporate bond market over the same period (as documented by the TRACE transaction database). The yields of investment grade bonds have generally been falling since 2011. In contrast to this, the yields of high yield bonds and unrated bonds slightly increased between 2014 and 2016, having also declined in the earlier part of the sample. Spreads over UK government bonds decreased from 2011 to 2014, but gradually increased thereafter for all three credit quality categories.

Table 2: *Bond characteristics*

This table provides descriptive statistics for the bonds in our sample. All figures in the table are trade-weighted percentages. Our dataset covers the period from September 2011 to December 2016. 'Investment grade' refers to bonds with a credit rating of BBB- or higher. 'High yield' refers to bonds with a credit rating of BB+ or lower. 'Unrated' refers to bonds that do not have a rating. 'Issue size' measures the amount issued of a bond in £m. 'Age' refers to the time in years since issuance. 'Time to maturity' measures the time in years until a bond reaches its maturity date. 'Industry' refers to a broad industrial classification of the issuing firm. Note that the percentages do not always add up to 100% due to rounding.

Credit quality	
Investment grade	67.5%
High yield	15.4%
Unrated	17.2%
Issue size	
Small (<£100m)	1.4%
Medium (£100m - £500m)	54.6%
Large (>£500m)	44.0%
Age	
<1 year	17.8%
1 - 3 years	25.0%
3 - 5 years	19.4%
5 - 10 years	24.0%
>10 years	13.8%
Time-to-maturity	
<1 year	7.1%
1 - 3 years	14.8%
3 - 5 years	15.4%
5 - 10 years	27.2%
>10 years	35.6%
Industry	
Finance	46.9%
Industrial	15.8%
Utilities	6.9%
Other	30.4%

Table 2 shows the bond characteristics. An average bond is five years old and has a residual maturity of around nine years. More than two thirds of the bonds in our sample have an investment grade rating, 15% are high yield bonds and 17% of the bonds are unrated. The fraction of unrated bonds may be surprisingly high. However, the number reflects the trend that many large multinationals merely rely on the reputation of the firm and issue bonds without rating in order to reduce expenses for fees. This notion is supported by the yield data in Table 1, in which we show that the average yield of unrated bonds is similar to the average yield of investment grade bonds. Finally, almost half of the bonds in our sample are issued by financial companies, 16% by industrial firms, and 7% by companies from the utilities sector.

5 Results

5.1 Main Results

We first examine the general impact of a change in yield on the buying and selling behaviour of different investor types. Hanson and Stein (2015) study the demand effects of 'yield-oriented' investors and document a shift to higher-yielding, longer-term bonds in order to improve short-term measures of reported performance. We want to know more about the relationship between trading activity and yields across different investor types. We estimate the following regression model at the weekly level for each investor type j separately:

$$ln(Volume^{Buy/Sell})^{j}_{i,t} = \sum_{k=1}^{4} a^{j}_{k} \Delta yield_{i,t-k} + \alpha^{j}_{i,m} + b^{j} \Delta Controls_{t-1} + \xi^{j}_{i,t} \qquad (1)$$

where $Volume^{Buy/Sell}$ refers to the amount bought ($Buy\ Volume$) or sold ($Sell\ Volume$) of bond i by investor type j at week t. Using aggregated volume measures allows us to analyse whether an entire sector is a net buyer or a net seller of a bond following a change in yields. We use lagged values of weekly trade-weighted yields (with $k = \{1, 2, 3, 4\}$) in order to ensure that the investor has the information about the bond's yield at the time of the trade. Given that large trading volumes can significantly affect the price of a bond, the lags also mitigate endogeneity issues. We cluster standard errors at the bond level and include bond*time fixed effects ($\alpha_{i,m}$) at the year-month level to control for all time-varying, unobserved characteristics of individual bonds. By eliminating all unobserved bond heterogeneity, the fixed effects allow us to isolate the effect of changes in yields on trading volume. We also control for general market movements and market stress by including weekly first differences of the iBoxx Sterling Corporate Bond index, the UK government bond term spread (spread between a 10-year and a 1-year UK government bond) and the VIX index.

The results (Table 3) are statistically and economically significant. We find that when corporate bond yields rise (i.e. prices fall) in a given week, then the following week - at a sector level - insurance companies, hedge funds and asset managers increase purchases and reduce sales, and dealers reduce purchases and increase sales. The size of the impact is largest for insurance companies, followed by dealer banks, hedge funds and asset managers. A 10bp increase in corporate bond yields leads corporate bond purchases the following week to increase by 18% for insurance companies, 11% for hedge funds, 10% for asset managers and to decrease by 11% for dealer banks.[7]

There is also a highly statistically significant effect from changes in yields at longer lags (up to three weeks for insurance companies, and up to four weeks for dealers, hedge funds and asset managers). Furthermore, the magnitude of the coefficients is broadly similar (but with opposite signs) for $Buy\ Volume$ and $Sell\ Volume$ within each investor type. These results are robust across different specifications of the dependent variable (number of trades instead of volume) and using corporate bond spreads rather than yields. See Section 6 for a range of robustness checks.

Our overall results show that dealer banks on average sell when yields rise (i.e. prices fall), primarily facilitating trades for other investor types. Consistent with Timmer (2016), we find that insurance companies are generally countercyclical, i.e. when yields rise (so prices fall), they buy. In contrast to Timmer (2016), we find that asset managers on average behave countercyclically. Besides different sample periods and country coverage, one explanation is that we use weekly corporate bond transaction data whereas Timmer (2016) uses quarterly holdings data for a broader range of fixed income securities. Asset managers behave differently at these different frequencies: when we aggregate our variables on a quarterly basis, we also find that asset managers behave procyclically on average (though the result is not statistically significant).[8] Therefore we provide novel evidence for a higher frequency, countercyclical investment behaviour of asset managers, which is consistent with the theoretical predictions of Guerrieri and Kondor (2012) and Rajan (2005). However, the different results could also reflect compositional effects. As noted above, we cannot distinguish between activity from different types of funds within the broad asset manager sector, and different types of funds might behave differently. In the spirit of Goldstein et al. (2016) and Jiang et al. (2016), we might expect to see some procyclical behaviour from open-ended investment funds as they sell bonds to meet redemptions in the face of a sharp rise in yields. On the other hand, a significant proportion of asset manager trades are likely to be on behalf of institutional investors such as pension funds, which may be less reactive to market moves.[9]

The countercyclical behaviour, on average, of asset managers and insurance companies could

[7] As the dependent variable is the natural logarithm of buy or sell volume, the percentage change in buy or sell volume coming from a change in yields Δx is $100(e^{\beta \Delta x} - 1)$, where β is the estimated coefficient, e.g. as shown in Table 3.

[8] The coefficients on the first lag of the change in quarterly yields are positive (but statistically insignificant) and thus indicate procyclical behaviour of asset managers at this frequency. These results are available upon request.

[9] Only 0.46% of trades in our sample directly involve a pension fund counterparty. However, UK pension funds held over £70bn of sterling corporate bonds at the end of 2015 (over 15% of the market).

Table 3: *Trading behaviour across financial institutions*

The dependent variable in Panel A is the logarithm of the amount bought for each bond i during week t in the period from September 2011 to December 2016; separately measured for each investor type. In Panel B, the dependent variable is the logarithm of the amount sold for each bond i during week t; also separately measured for each investor type. '$\Delta yield_{i,t-k}$' is the first difference of the trade-weighted yield of bond i during week t-k, with up to four lags k. '$\Delta TermSpread_{t-1}$' is the lagged first difference of the spread between a 10-year and a 1-year UK government bond. '$\Delta iBoxx_{t-1}$' and 'ΔVIX_{t-1}' are the lagged first differences of iShares' iBoxx Sterling Corporate Bond index and CBOE's VIX index, respectively. All regressions are at the weekly level and estimated using ordinary least squares. We include bond*time fixed effects at the monthly level. Robust standard errors clustered at bond level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Panel A

	Dependent variable: Buys				
	Dealer banks	Non-dealers	Insurers	Hedge funds	Asset managers
	(1)	(2)	(3)	(4)	(5)
$\Delta yield_{i,t-1}$	-1.214***	0.046	1.625***	1.035***	0.988***
	(0.122)	(0.089)	(0.310)	(0.234)	(0.106)
$\Delta yield_{i,t-2}$	-1.273***	0.054	1.225***	1.125***	1.140***
	(0.130)	(0.099)	(0.289)	(0.272)	(0.116)
$\Delta yield_{i,t-3}$	-1.025***	-0.048	0.594**	0.764***	0.877***
	(0.113)	(0.093)	(0.270)	(0.274)	(0.101)
$\Delta yield_{i,t-4}$	-0.510***	-0.028	-0.150	0.456*	0.531***
	(0.094)	(0.086)	(0.275)	(0.245)	(0.091)
$\Delta TermSpread_{t-1}$	1.935***	-0.633	0.970	0.495	-1.037**
	(0.456)	(0.466)	(0.951)	(1.678)	(0.452)
$\Delta iBoxx_{t-1}$	0.126**	-0.031	0.088	0.119	-0.040
	(0.056)	(0.055)	(0.110)	(0.202)	(0.057)
ΔVIX_{t-1}	0.051***	0.001	0.022	-0.027	-0.033***
	(0.009)	(0.009)	(0.019)	(0.034)	(0.009)
Bond* time fixed effects	Y	Y	Y	Y	Y
Observations	162,189	114,348	43,278	11,206	146,800
R-squared	0.285	0.360	0.464	0.530	0.342

Panel B

	Dependent variable: Sells				
	Dealer banks	Non-dealers	Insurers	Hedge funds	Asset managers
	(1)	(2)	(3)	(4)	(5)
$\Delta yield_{i,t-1}$	1.255***	-0.023	-1.662***	-0.927***	-0.983***
	(0.122)	(0.083)	(0.308)	(0.238)	(0.104)
$\Delta yield_{i,t-2}$	1.307***	0.014	-1.140***	-1.059***	-1.121***
	(0.130)	(0.097)	(0.295)	(0.258)	(0.114)
$\Delta yield_{i,t-3}$	1.082***	0.113	-0.531*	-0.669**	-0.862***
	(0.112)	(0.091)	(0.278)	(0.265)	(0.101)
$\Delta yield_{i,t-4}$	0.540***	0.012	0.226	-0.419*	-0.508***
	(0.095)	(0.084)	(0.277)	(0.243)	(0.094)
$\Delta TermSpread_{t-1}$	-1.747***	0.353	-1.493	-0.643	1.075**
	(0.458)	(0.449)	(0.976)	(1.618)	(0.446)
$\Delta iBoxx_{t-1}$	-0.099*	0.023	-0.170	-0.128	0.050
	(0.056)	(0.054)	(0.114)	(0.194)	(0.056)
ΔVIX_{t-1}	-0.053***	-0.005	-0.040**	0.021	0.029***
	(0.009)	(0.009)	(0.019)	(0.033)	(0.009)
Bond* time fixed effects	Y	Y	Y	Y	Y
Observations	162,189	114,348	43,278	11,206	146,800
R-squared	0.292	0.351	0.464	0.512	0.334

also reflect a simple portfolio rebalancing story: when yields rise, the value of bonds in investors' portfolios falls, so investors buy more bonds to rebalance their portfolio back to the desired weight. Furthermore, the countercyclicality of insurance companies could also be driven by their duration mismatch: when yields rise, the duration of both assets and liabilities decreases. Due to the longer maturity profile of the insurers' liabilities, the negative duration gap becomes smaller after an increase in yields (Domanski et al., 2017). Therefore insurers have less incentive to 'hunt for duration' and more freedom to behave in a countercyclical fashion. Alternatively, an increase in yields could make bonds look more attractive to investors, so they increase purchases. Such behaviour could be related to 'reaching for yield', which we discuss further below. The apparent procyclical behaviour of dealer banks can be attributed to their market-making activities, i.e. being on the other side of the trade when yield-chasing investors want to buy or sell. Moreover, as we discuss below, the average behaviour described above is very different to how asset managers respond in stressed market conditions.

5.2 Differences in magnitude across investor types

We now want to compare the magnitudes of the effect of yield changes on trading volume across investor types. To this end, we create indicator variables for each investor type and interact these with the first lag of yield changes. We specify the following regression model at the weekly level:

$$ln(Volume^{Buy/Sell})_{i,z,t} = \sum_{j=1}^{5} a_j \Delta yield_{i,t-1} * Type\ Indicator_z^j + \alpha_{i,j,m} + b\Delta Controls_{t-1} + \xi_{i,z,t} \quad (2)$$

where $Volume^{Buy/Sell}$ now refers to the amount bought ($Buy\ Volume$) or sold ($Sell\ Volume$) of bond i by institution z at week t. $Type\ Indicator_z^j$ are indicator variables that equal one if firm z belongs to investor type j. Therefore we now use our entire sample for the regressions instead of using subsamples of each investor type. For instance, this regression model allows us to analyse whether the reaction to yield changes is stronger for insurance companies vis-à-vis asset managers. Thus it reflects the effect for an average institution belonging to investor type j instead of analysing whether the entire sector is a net buyer or a net seller as in Equation (1). We use bond*investor-type*time ($\alpha_{i,j,m}$) fixed effects at the year-month level in order to account for any unobserved, time-varying heterogeneity, such as changing preferences of an investor type for certain bond characteristics. We also report results for a specification with separate bond*time and investor-type*time fixed effects. Standard errors are clustered at the bond and individual investor level.

Table 4: *Differences in magnitudes across financial institutions*

The dependent variable in columns (1) and (2) is the logarithm of the amount bought for each bond i during week t in the period September 2011 to December 2016; separately measured for each institution z. In columns (3) and (4), the dependent variable is the logarithm of the amount sold for each bond i during week t; also separately measured for each institution z. '$\Delta yield_{i,t-1} * InvestorType_z^j$' is the first difference of the trade-weighted yield of bond i during week *t-1* multiplied with an indicator variable that equals one if firm z belongs to investor type j. We use '$\Delta TermSpread_{t-1}$', '$\Delta iBoxx_{t-1}$' and 'ΔVIX_{t-1}' as controls in our regressions. All regressions are at the weekly level and estimated using ordinary least squares. We include bond*time, investor-type*time and bond*investor-type*time fixed effects at the monthly level. Robust standard errors clustered at bond and individual investor level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

	Dependent variable:			
	Buys		Sells	
	(1)	(2)	(3)	(4)
$\Delta yield_{i,t-1} * Dealer_z$	-0.223***	-0.379***	0.243***	0.395***
	(0.061)	(0.058)	(0.060)	(0.058)
$\Delta yield_{i,t-1} * NonDealer_z$	0.083	0.048	-0.106*	-0.072
	(0.059)	(0.059)	(0.059)	(0.060)
$\Delta yield_{i,t-1} * Insurer_z$	0.452***	0.973***	-0.443**	-1.082***
	(0.149)	(0.214)	(0.178)	(0.228)
$\Delta yield_{i,t-1} * HedgeFund_z$	0.464***	0.412***	-0.456***	-0.325**
	(0.135)	(0.155)	(0.143)	(0.145)
$\Delta yield_{i,t-1} * AssetManager_z$	0.113***	0.232***	-0.101**	-0.222***
	(0.044)	(0.041)	(0.043)	(0.039)
Controls	Y	Y	Y	Y
Investor-type*time fixed effects	Y	N	Y	N
Bond*time fixed effects	Y	N	Y	N
Bond*investor-type*time fixed effects	N	Y	N	Y
Observations	1,769,497	1,697,761	1,769,497	1,697,761
R-squared	0.040	0.173	0.036	0.169

The results (Table 4) have the same sign and are similarly strong statistically as the aggregate investor type regressions. But the magnitudes of the coefficients are smaller. This reflects composition effects as the dependent variable is $Buy\ Volume$ or $Sell\ Volume$ at a firm level, rather than aggregated to a sector level (which nets out offsetting individual buys and sells within each sector).

Columns (2) and (4) of Table 4 show the results for the specification with bond*investor-type*time fixed effects. A 10bp increase in corporate bond yields leads individual insurance companies to increase their corporate bond purchases the following week by 10% on average. The analogous figures for individual hedge funds is 4% and asset managers 2%. Dealer banks reduce their purchases by 4%. As in the investor type regressions, the magnitude of the coefficients are broadly similar (but with opposite signs) for $Buy\,Volume$ and $Sell\,Volume$.

5.3 State contingency

Although we want to know how investors react to a change in yield in 'normal' times, their reaction in times of stress is particularly important from a financial stability perspective. Whilst our sample period does not include the financial crisis, we do have some episodes of stress which we can use to examine the state contingency of our results. We find that the behaviour of some investors changes during stressed conditions, with asset managers becoming less countercyclical and, in the case of the 'taper tantrum', becoming procyclical.

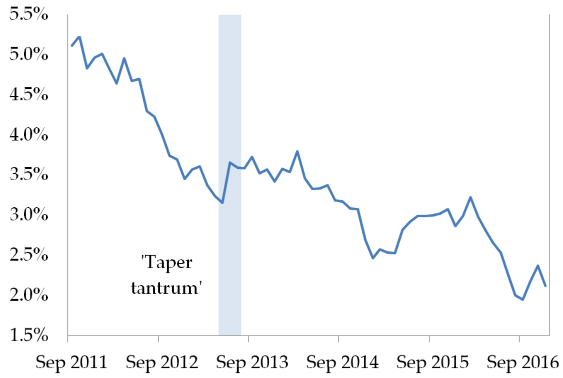

Figure 2: *Yield on investment grade bonds*

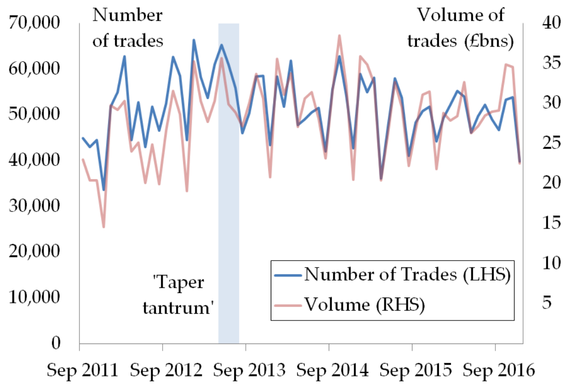

Figure 3: *Number and volume of trades per month*

One exogenous key stress event in our sample period is the so-called 'taper tantrum' of 2013, when financial markets reacted strongly to Federal Reserve Chairman Bernanke's comments that the pace of asset purchases would be moderated later that year (Neely et al., 2014). There was a large rise in yields and increased volatility in government and corporate bond markets, not just in the US but also in other advanced and emerging markets (e.g. Bank of England (2013), Fischer (2015) or Sahay et al. (2014)). Of particular relevance for our study, there were spillovers from the 'taper tantrum' to the sterling corporate bond market: yields increased sharply (Figure 2) and there was a modest fall in trading volume (Figure 3). Between the beginning of May and end of July 2013, sterling investment grade yields rose by 51bps, compared to 68bps for US dollar investment grade yields over the same period.

To test whether investor behaviour was different at this time, we construct an indicator variable equal to one for the 'taper tantrum' period (i.e. May - July 2013), and zero otherwise. We then interact the indicator variable with the lagged change in yields. We return to our baseline Equation (1) and run the regression separately for each investor type (as in Table 3).

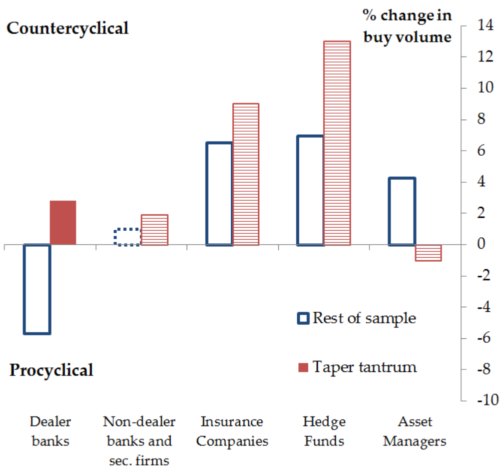

Figure 4: *Impact of a 10bp increase in yields on buy volume*[10]

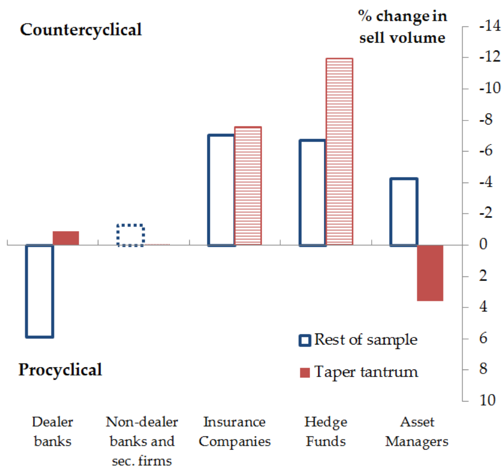

Figure 5: *Impact of a 10bp increase in yields on sell volume*[10]

As shown in Panel A of Table 5 and Figures 4 & 5, investor behaviour during the 'taper tantrum' was opposite to our headline results. Asset managers switched from being countercyclical to being procyclical. This reversal of their yield-chasing behaviour is consistent with the model of Feroli et al. (2014). Moreover, the magnitude of the 'taper tantrum' interaction coefficients is larger for $Sell\ Volume$ than for $Buy\ Volume$. This was accommodated by dealer banks switching to being countercyclical. These findings are consistent with the theoretical predictions of Hanson et al. (2015) and Diamond and Rajan (2011): in stress periods, banks stabilise the market because they have an comparative advantage in holding fixed income assets due to their relatively stable source of funding compared to shadow banks. For non-dealer banks, insurance companies and hedge funds, there was no statistically significant difference in how these investor types responded to a change in yields during this period.

Procyclical behaviour in times of stress could further increase volatility and amplify the drop in bond prices, thereby potentially destabilising the market. Such disruption to the secondary

[10] Hashed/dashed bars indicate no statistically significant coefficient.

Table 5: *State contingency of investment behaviour*

The dependent variable in columns (1) - (5) is the logarithm of the amount bought for each bond i during week t in the period September 2011 to December 2016; separately measured for each investor type. In columns (6)-(10), the dependent variable is the logarithm of the amount sold for each bond i during week t; also separately measured for each investor type. In Panel A we report the results for the 'taper tantrum' period. '$\Delta yield_{i,t-k}$' is the first difference of the trade-weighted yield of bond i during week *t-k*, with up to four lags k. For clarity, we only report the first lag in the table. '$\Delta yield_{i,t-1} * TT_t$' is the first difference of the trade-weighted yield of bond i during week *t-1* multiplied with an indicator variable that equals one for all weeks in the 'taper tantrum' period (May-August 2013), and zero otherwise. In Panel B we report the results for high-VIX periods. 'VIX_t^{high}' is an indicator variable that equals one for all weeks in which the average VIX was in the top decile of its in-sample distribution. For clarity, we do not report the individual coefficients for the 'TT_t' and 'VIX_t^{high}' indicator variables. We use '$\Delta TermSpread_{t-1}$', '$\Delta iBoxx_{t-1}$' and 'ΔVIX_{t-1}' as controls in our regressions. All regressions are at the weekly level and estimated using ordinary least squares. We include bond*time fixed effects at the yearly level for Panel A, and at the monthly level for Panel B. Robust standard errors clustered at bond level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Panel A: 'Taper Tantrum'

	Dependent variable: Buys					*Dependent variable: Sells*				
	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta yield_{i,t-1} * TT_t$	0.864***	0.090	0.234	0.550	-0.518	-0.662**	0.126	-0.054	-0.574	0.784**
	(0.313)	(0.292)	(0.513)	(0.812)	(0.318)	(0.309)	(0.297)	(0.536)	(0.832)	(0.308)
$\Delta yield_{i,t-1}$	-0.586***	0.098	0.631***	0.672***	0.416***	0.572***	-0.128*	-0.731***	-0.697***	-0.433***
	(0.083)	(0.079)	(0.168)	(0.172)	(0.073)	(0.082)	(0.075)	(0.171)	(0.175)	(0.072)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bond*time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	167,132	122,474	56,228	16,468	152,481	167,132	122,474	56,228	16,468	152,481
R-squared	0.062	0.107	0.143	0.254	0.097	0.071	0.096	0.145	0.228	0.086

Panel B: VIX

	Dependent variable: Buys					*Dependent variable: Sells*				
	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta yield_{i,t-1} * VIX_t^{high}$	0.732***	-0.116	-0.115	-0.282	-0.482***	-0.761***	0.155	0.427	0.462	0.468***
	(0.206)	(0.191)	(0.604)	(0.477)	(0.181)	(0.206)	(0.176)	(0.599)	(0.502)	(0.180)
$\Delta yield_{i,t-1}$	-1.357***	0.071	1.651***	1.056***	1.075***	1.403***	-0.056	-1.745***	-0.976***	-1.068***
	(0.133)	(0.094)	(0.340)	(0.257)	(0.118)	(0.134)	(0.089)	(0.345)	(0.260)	(0.116)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bond*time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	162,189	114,348	43,278	11,206	146,800	162,189	114,348	43,278	11,206	146,800
R-squared	0.285	0.360	0.464	0.530	0.342	0.292	0.351	0.464	0.512	0.334

market could affect primary market activity, with an adverse impact on real economic activity given the critical function this market performs in providing lending to the real economy. For asset managers, particularly in the case of open-ended investment funds, the procyclical behaviour during the 'taper tantrum' could have reflected a need to sell assets to meet redemptions (in the spirit of Goldstein et al. (2016) and Jiang et al. (2016)).

To explore what happens more broadly in times of stress, we use the VIX index of US equity implied volatility as a measure of market-wide volatility.[11] We create a variable to indicate when the VIX is in the top decile of its in-sample distribution (above 22.5 ppts for our sample) and then interact the indicator variable with the first lag in yield changes to see the impact of a change in yields on trading activity in more volatile markets (Panel B of Table 5).

For asset managers, a high level of the VIX reduces the magnitude of the coefficient on the change in yields. When the VIX is low, a 10bp increase in yields increases asset manager purchases by 11%. When the VIX is high, a 10bp increase in yields only increases asset manager purchases by 6%. Overall, asset managers still behave countercyclically when the VIX is high. But the reduced magnitude of countercyclicality could reflect increased procylicality during times of stress amongst some asset managers (e.g. open-ended funds), partly offsetting the 'reaching for yield' from other asset managers. The increased procyclicality could be due to binding risk constraints: portfolio managers would like to buy bonds because yields have just risen (as they would do normally), but can't because it would make their portfolio too risky, e.g. breach Value-at-Risk constraints. For the other investor types, the coefficients on the change in yields remain significant for low VIX, but there is no additional or offsetting effect for high VIX.

Overall, we find heterogeneous responses to different levels of stress across investor types. First, we find no evidence for hedge funds altering their average behaviour in times of stress. Asset managers, however, were net sellers of corporate bonds during the 'taper tantrum'. Furthermore, they also buy significantly less when the VIX is in its top decile. The lower stress capacity of asset managers can be attributed to their relatively fragile funding when compared to insurance companies or banks (Feroli et al. (2014), Goldstein et al. (2016)).

[11] Note that we already included the VIX as a control variable in our regression set-up.

5.4 Different bond characteristics

The fixed effects in our regression model control for the impact of bond characteristics such as credit quality, maturity, and the industry of the issuer. However, we want to know more about differences in the effect of yield changes on trading volume based on these characteristics.

In our dataset bonds are categorised as either investment grade, high yield or unrated. To examine the different impact for different credit qualities, we interact indicator variables for investment grade and high yield bonds with the change in yield (Panel A of Table 6). The coefficient on the change in yield gives the impact for unrated bonds. The coefficients on the interaction terms give the additional effect for investment grade and high yield bonds, respectively. Overall, there is a bigger impact for investment grade and high yield bonds than for unrated bonds. There is also genereally a bigger impact for high yield than for investment grade bonds.

For example, for dealers a 10bp increase in yields leads to a 7% fall in purchases for unrated bonds, a 14% fall for investment grade bonds, and a 20% fall for high yield bonds. For insurance companies, a 10bp increase in yields leads to an 10% increase in purchases for unrated bonds, 20% for investment grade bonds and 23% for high yield (though coefficient on additional impact for investment grade bonds is statistically insignificant). For asset managers, a 10bp increase in yields leads to a 8% increase in purchases for unrated bonds, a 13% increase for investment grade bonds, and a 17% increase for high yield bonds.[12]

To test the impact of the time-to-maturity of a bond, we create an interaction term for the change in yields and the residual maturity of the bonds (Panel B of Table 6). Mechanically, a given yield change has a bigger price impact for longer maturity bonds. Therefore we expect a positive coefficient on the interaction term for insurers, asset managers and hedge funds, and a negative coefficient on the interaction term for dealer banks. Whilst the average maturity in our sample is nine years, some bonds have much longer maturities (around 4% of the bonds in our sample have maturity greater than 30 years). We might therefore also expect a non-linear relationship between maturity and impact of a change in yields on trading activity. To test this, we also interact the change in yields with the square of the maturity. Overall, our results are consistent with Hanson and Stein (2015): for dealer banks, insurers and asset managers we find that the impact of a

[12]For hedge funds, a 10bp increase in yields leads to a 7% increase in purchases for unrated bonds. There is no statistically significant difference for investment grade bonds and high yield bonds.

Table 6: *The impact of different bond characteristics*

The dependent variable in columns (1) - (5) is the logarithm of the amount bought for each bond i during week t in the period September 2011 to December 2016; separately measured for each investor type. In columns (6)-(10), the dependent variable is the logarithm of the amount sold for each bond i during week t; also separately measured for each investor type. '$\Delta yield_{i,t-k}$' is the first difference of the trade-weighted yield of bond i during week *t-k*, with up to four lags k. For clarity, we only report the first lag in the table. In Panel A, '$\Delta yield_{i,t-1} * IG_{i,t}$' is the first difference of the trade-weighted yield of bond i during week *t-1* multiplied with an indicator variable that equals one for all investment grade bonds, and zero otherwise. '$HY_{i,t}$' is an indicator variable that equals one for all high yield bonds, and zero otherwise. In Panel B, '$Maturityi_t$' is the time-to-maturity of bond i. '$Maturity^2_{i,t}$' is the squared time-to-maturity of bond i. For clarity, we do not report the individual coefficients for the '$IG_{i,t}$', '$HY_{i,t}$' and '$Maturityi_t$' variables. We use '$\Delta TermSpread_{t-1}$', '$\Delta iBoxx_{t-1}$' and 'ΔVIX_{t-1}' as controls. All regressions are at the weekly level and estimated using ordinary least squares. We include bond*time fixed effects at the monthly level. Robust standard errors clustered at bond level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

	Dependent variable: Buys					*Dependent variable: Sells*				
	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs
Panel A: Ratings	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta yield_{i,t-1} * IG_{i,t}$	-0.753***	0.120	0.868	0.419	0.426**	0.694***	-0.128	-1.167**	-0.358	-0.490***
	(0.200)	(0.171)	(0.561)	(0.478)	(0.175)	(0.200)	(0.161)	(0.549)	(0.538)	(0.175)
$\Delta yield_{i,t-1} * HY_{i,t}$	-1.461***	0.381	1.090*	0.836	0.842***	1.364***	-0.241	-1.019	-0.826	-0.893***
	(0.315)	(0.260)	(0.659)	(0.526)	(0.293)	(0.314)	(0.243)	(0.669)	(0.540)	(0.296)
$\Delta yield_{i,t-1}$	-0.749***	-0.030	0.943**	0.705**	0.757***	0.824***	0.041	-0.795**	-0.609**	-0.724***
	(0.128)	(0.107)	(0.389)	(0.284)	(0.111)	(0.125)	(0.102)	(0.379)	(0.287)	(0.106)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bond*time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	162,189	114,348	43,278	11,206	146,800	162,189	114,348	43,278	11,206	146,800
R-squared	0.285	0.360	0.464	0.530	0.342	0.292	0.351	0.465	0.512	0.334
Panel B: Maturities										
$\Delta yield_{i,t-1} * Maturity_{i,t}$	-0.067**	-0.037	0.157**	-0.068	0.097***	0.056*	0.043	-0.174**	0.081	-0.103***
	(0.033)	(0.032)	(0.076)	(0.121)	(0.034)	(0.033)	(0.031)	(0.075)	(0.121)	(0.034)
$\Delta yield_{i,t-1} * Maturity^2_{i,t}$	-0.002	0.002	0.000	0.004	-0.001	0.002	-0.002*	0.000	-0.006	0.001
	(0.001)	(0.001)	(0.002)	(0.006)	(0.001)	(0.001)	(0.001)	(0.002)	(0.006)	(0.001)
$\Delta yield_{i,t-1}$	-0.909***	0.124	0.691*	1.238***	0.657***	0.984***	-0.116	-0.637	-1.120***	-0.628***
	(0.148)	(0.130)	(0.382)	(0.396)	(0.134)	(0.149)	(0.121)	(0.391)	(0.403)	(0.129)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bond*time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	162,189	114,348	43,278	11,206	146,800	162,189	114,348	43,278	11,206	146,800
R-squared	0.285	0.360	0.464	0.530	0.342	0.292	0.351	0.465	0.512	0.334

change in yields on trading activity is significantly larger for longer maturity bonds.[13] The more pronounced effect for high yield and longer maturity bonds could be related to 'reaching for yield', which we discuss further below.

5.5 Reaching for yield

'Reaching for yield' has been cited as a key driver of investor behaviour in the US corporate bond market. For example, Becker and Ivashina (2015) show that, conditional on credit ratings, insurance companies are systematically biased towards higher-yield, higher CDS-premium bonds. Choi and Kronlund (2016) analyse US bond funds' 'reaching for yield' behaviour, which they define as funds taking more risk by tilting their portfolios towards bonds with higher yields than their benchmarks. They find that funds generate higher returns and attract more inflows from investors when they 'reach for yield', especially during periods of low interest rates.

We perform a cross-sectional analysis to test whether investors tilt their portfolios towards bonds with higher yields relative to other bonds in the same rating and/or maturity categories. As in Choi and Kronlund (2016), we construct three 'reaching for yield' factors:

1. *'Reaching for rating' (RFR):*

$$RFR_{i,t} = yield_{i,t}^{Rating} - yield_t^{avg}$$

   where $yield_{i,t}^{Rating}$ is the trade-weighted average weekly yield of all bonds with the same rating as bond i and $yield_t^{avg}$ is the trade-weighted average weekly yield of the entire sample as the benchmark to compare to (since we do not have information on the benchmarks used (if any) by each investor). The measure captures the higher yield that can be attributed to holding lower rated bonds.

[13] In this context, we also used the first difference in prices instead of yields as the main independent variable. There were no statistically significant coefficients for the interaction terms of the first difference in prices and maturity / squared maturity.

2. *'Reaching for maturity' (RFM):*

$$RFM_{i,t} = yield_{i,t}^{RM} - yield_{i,t}^{Rating}$$

where $yield_{i,t}^{RM}$ is the trade-weighted average weekly yield of all bonds in the same rating and maturity bucket as bond i. The measure captures the higher yield that can be attributed to holding longer maturity bonds while keeping the rating class constant.

3. *'Reaching for yield within a rating and maturity category' (RFRM):*

$$RFRM_{i,t} = yield_{i,t} - yield_{i,t}^{RM}$$

where $yield_{i,t}$ is the trade-weighted average weekly yield of bond i. The measure helps us to identify when sectors invest in bonds with relatively higher yields within a given rating and maturity category. This component is particularly relevant for firms that have mandates restricting the credit quality and/or the maturity of bonds they can invest in.

We return to $Volume^{Buy/Sell}$ on the investor type level to find out how different sectors reach for yield with respect to the three categories. We estimate the following regression model at the weekly level for each investor type j separately:

$$ln(Volume^{Buy/Sell})_{i,t}^{j} = a^j RFR_{i,t-1} + b^j RFM_{i,t-1} + c^j RFRM_{i,t-1} + \alpha_{i,m}^{j} + d^j Controls_{t-1} + \xi_{i,t}^{j} \quad (3)$$

We find statistically significant coefficients on all three 'reaching for yield' factors for dealer banks, hedge funds and asset managers (Table 7). The coefficients on all three components are negative for dealers, suggesting that they facilitate the 'reaching for yield' behaviour of the other investor types (at least in the short run). For asset managers, the coefficients are similar for each component: asset managers buy more and sell less of above-average yielding bonds. This holds between ratings, maturities and within a rating and maturity category. Our finding underlines the intrinsic incentives to 'reach for yield' in the asset management industry: being compensated based on both assets under management and relative investment performance, portfolio managers

Table 7: *Reaching for yield*

The dependent variable in Panel A is the logarithm of the amount bought for each bond i during week t in the period September 2011 to December 2016; separately measured for each investor type. In Panel B, the dependent variable is the logarithm of the amount sold for each bond i during week t; also separately measured for each investor type. As in Choi and Kronlund (2016), '$RFR_{i,t-1}$' is a lagged 'reaching for rating' measure and captures the higher yield that can be attributed to holding lower rated bonds. '$RFM_{i,t-1}$' is a lagged 'reaching for maturity' measure and captures the higher yield that can be attributed to holding longer maturity bonds while keeping the rating class constant. '$RFRM_{i,t-1}$' is a lagged 'reaching for yield within a rating and maturity category' measure and captures the higher yield of bonds within the same rating and maturity class. We use '$\Delta TermSpread_{t-1}$', '$\Delta iBoxx_{t-1}$' and 'ΔVIX_{t-1}' as controls in our regressions. All regressions are estimated using ordinary least squares. We include bond*time fixed effects at the monthly level. Robust standard errors clustered at bond level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Panel A

	Dependent variable: Buys				
	Dealer banks	Non-dealers	Insurers	Hedge funds	Asset managers
	(1)	(2)	(3)	(4)	(5)
$RFR_{i,t-1}$	-1.027***	0.111	0.324	1.104***	1.018***
	(0.090)	(0.091)	(0.208)	(0.270)	(0.089)
$RFM_{i,t-1}$	-1.050***	0.149**	0.506***	0.852***	0.996***
	(0.080)	(0.076)	(0.183)	(0.219)	(0.076)
$RFRM_{i,t-1}$	-1.098***	0.100	0.828***	0.997***	1.000***
	(0.075)	(0.068)	(0.177)	(0.192)	(0.069)
Controls	Y	Y	Y	Y	Y
Bond*time fixed effects	Y	Y	Y	Y	Y
Observations	203,913	132,454	51,896	12,960	179,273
R-squared	0.301	0.372	0.469	0.534	0.361

Panel B

	Dependent variable: Sells				
	Dealer banks	Non-dealers	Insurers	Hedge funds	Asset managers
	(1)	(2)	(3)	(4)	(5)
$RFR_{i,t-1}$	0.962***	-0.191**	-0.306	-1.042***	-1.020***
	(0.090)	(0.088)	(0.214)	(0.264)	(0.089)
$RFM_{i,t-1}$	0.999***	-0.208***	-0.459**	-0.837***	-1.019***
	(0.080)	(0.074)	(0.193)	(0.220)	(0.074)
$RFRM_{i,t-1}$	1.056***	-0.117*	-0.775***	-0.909***	-1.025***
	(0.075)	(0.065)	(0.187)	(0.197)	(0.068)
Controls	Y	Y	Y	Y	Y
Bond*time fixed effects	Y	Y	Y	Y	Y
Observations	203,913	132,454	51,896	12,960	179,273
R-squared	0.311	0.363	0.472	0.519	0.349

can generate additional inflows and beat their benchmark by moving into higher-yielding bonds (Choi and Kronlund, 2016).

For insurance companies, the coefficient on 'reaching for yield within a rating and maturity category' is almost twice the size of the coefficient on 'reaching for maturity'. The coefficient on 'reaching for rating' is statistically insignificant. This is consistent with insurers' 'reaching for yield' within regulatory risk categories, as described in Becker and Ivashina (2015). In particular, insurance companies often have strict rating and maturity constraints, limiting their ability to move into higher-yielding, riskier bonds. At the same time, many life insurance products include covenants that guarantee minimum returns regardless of market conditions, thereby creating strong incentives to 'reach for yield' within the regulatory boundaries (Haltom, 2013).

The coefficients on 'reaching for rating' and 'reaching for yield within a rating and maturity category' are broadly similar on each component for hedge funds, with the coefficient on 'reaching for maturity' a little smaller but still economically and statistically significant. This finding is consistent with Rajan (2005): in a low interest rate environment, hedge fund managers can increase their compensation by adding risk in order to achieve nominal returns that exceed a minimum threshold.

6 Robustness

Our results suggest that changes in yields have a significant impact on the trading volume of corporate bonds across different investor types. In order to ensure that our results are not driven by our measure of trading activity, we also conduct our regression analysis with the natural logarithm of a bond's total of trades over one week as the dependent variable (see Yamani and Rakowski (2016)). The results are shown in Panel A of Table 8. The effect of yield changes on the number of trades is statistically and economically still highly significant. An increase in yields has a positive impact on the buying activity of non-dealer banks, insurance companies, hedge funds and asset managers, and a negative impact on the number of buy-trades for dealer banks. Analogous to our headline results in Table 3, we find the largest magnitudes for insurers and dealer banks.

Secondly, we also alter the main independent variable in our model. Many market participants use spreads above risk-free rates as a pricing mechanism and to compare the relative performance between bonds. Given the practical importance of this measure, we want to find out whether our

Table 8: *Robustness*

In Panel A, the dependent variable in columns (1) - (5) is the logarithm of the number of trades for each bond i during week t in the period September 2011 to December 2016; separately measured for each investor type. In columns (6)-(10), the dependent variable is the logarithm of the number of trades for each bond i during week t; also separately measured for each investor type. '$\Delta yield_{i,t-k}$' is the first difference of the trade-weighted yield of bond i during week t-k, with up to four lags k. For clarity, we only report the first lag in the table. In Panel B, the dependent variable in columns (1) - (5) is the logarithm of the amount bought for each bond i during week t in the period September 2011 to December 2016; separately measured for each investor type. In columns (6)-(10), the dependent variable is the logarithm of the nominal amount sold for each bond i during week t; also separately measured for each investor type. '$\Delta spread_{i,t-k}$' is the first difference of the trade-weighted spread of bond i over UK government bonds during week t-k, with up to four lags k. For clarity, we only report the first lag in the table. We use '$\Delta TermSpread_{t-1}$', '$\Delta iBoxx_{t-1}$' and 'ΔVIX_{t-1}' as controls in our regressions. All regressions are at the weekly level and estimated using ordinary least squares. We include bond*time fixed effects at the monthly level. Robust standard errors clustered at bond level are reported in parentheses. ***: Significant at 1% level; **: significant at 5% level; *: significant at 10% level.

Panel A: Number of trades as dependent variable

	Dependent variable: Buys					*Dependent variable: Sells*				
	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta yield_{i,t-1}$	-0.104***	0.025**	0.139***	0.091***	0.092***	0.114***	-0.010	-0.103***	-0.041*	-0.072***
	(0.012)	(0.011)	(0.027)	(0.028)	(0.010)	(0.011)	(0.011)	(0.027)	(0.024)	(0.012)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bond*time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	139,935	89,502	37,816	10,013	127,757	139,935	89,502	37,816	10,013	127,757
R-squared	0.439	0.518	0.475	0.543	0.499	0.446	0.521	0.491	0.507	0.479

Panel B: Spreads as independent variable

	Dependent variable: Buys					*Dependent variable: Sells*				
	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs	Dealers	Non-dealers	Insurers	Hedge funds	Asset mgrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta spread_{i,t-1}$	-1.193***	0.087	1.603***	0.956***	0.927***	1.248***	-0.023	-1.595***	-0.876***	-0.909***
	(0.121)	(0.093)	(0.299)	(0.226)	(0.101)	(0.121)	(0.089)	(0.297)	(0.230)	(0.097)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bond*time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	159,413	112,076	42,969	11,081	144,308	159,413	112,076	42,969	11,081	144,308
R-squared	0.286	0.361	0.463	0.527	0.343	0.293	0.352	0.464	0.509	0.335

results remain significant when we use spreads instead of yields as our main independent variable. For each bond, we calculate the nominal yield spread to a UK government bond that matches its maturity. As before, we use trade-weighted weekly spreads in order to account for the fact that trades of different volumes occur at significantly different spreads. The results are presented in Panel B of Table 8. The coefficients on the lagged spread are highly significant for all investor types (except for non-dealer banks). We also find that the magnitudes of the coefficients are very similar to our headline results in Table 3. Again, we find the largest magnitudes for insurers and dealer banks.

7 Concluding Remarks

We contribute to the literature on investor behaviour in corporate bond markets, providing evidence on how investors react to a change in yields, and how this behaviour differs in times of market-wide stress. We also find different magnitudes of 'reaching for yield' behaviour across investor types. The proprietary transaction-level data for the sterling corporate bond market allows us to gain important insights into this fairly opaque over-the-counter market and to provide robust evidence on relatively high frequency behaviour at individual institution and investor type level.

We show that insurance companies, hedge funds and asset managers are net buyers after corporate bond yields rise. This pattern reverses in times of stress for some investors. During the 2013 'taper tantrum', asset managers were net sellers in response to a sharp rise in yields, potentially amplifying price changes. Finally, we provide evidence that insurers, hedge funds and asset managers tilt their portfolios to higher yielding and potentially riskier bonds, consistent with 'reaching for yield' behaviour.

Our results have important financial stability implications. Our findings underline the importance of banks as liquidity providers in stress periods (in the spirit of Diamond and Rajan (2011) and Hanson et al. (2015)). We also highlight the procyclical behaviour of asset managers during times of stress. This may reflect individually rational re-assessments of the risk-return trade-off following an increase in yields. But such behaviour could amplify a bond sell-off and increase volatility. Finally, we find pronounced 'reaching for yield' behaviour across a range of investor types. Again, such behaviour may be individually rational. But collectively it could lead to an excessive compression of risk premia, potentially leaving asset prices vulnerable to a correction.

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