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Procyclical asset management and bond risk premia

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Abstract

We use unique institutional securities holdings data to examine the trading behaviour of delegated institutional capital and its impact on bond risk premia. We show that institutional fund managers trade strongly procyclically: they actively move into higher yielding, longer duration and lower rated securities as yields fall and spreads compress, and vice versa. Funds more exposed to negative yields increase their risk-taking more strongly, and this effect is particularly pronounced for those offering explicit minimum return guarantees. Institutional funds' investments have large and persistent price impact in both corporate and sovereign bond markets. We provide evidence that this procyclical behaviour is driven by career concerns among institutional fund managers.

Keywords: Institutional funds, institutional accounts, procyclical asset management, portfolio rebalancing, price impact, demand pressures, asset price volatility, career concerns

JEL Classification: G11, G23, E43

I. Introduction

Over the last few decades, there has been a growing interest in understanding the role of financial intermediaries for asset prices (Cuoco and Kaniel (2011), Basak and Pavlova (2013), Adrian et al. (2019), Koijen and Yogo (2019)). A little appreciated fact, however, is that many financial institutions do not manage their assets internally. Goyal and Wahal (2008) estimate that up to 82% of insurance companies, pension plans, endowments and foundations in the U.S. delegate at least part of their investments to third-party institutional asset managers. Typically, these managers allocate institutional money to loosely regulated financial vehicles called institutional accounts, or pool multiple accounts to create institutional funds.

In this paper, we examine the trading behaviour of institutional funds and its impact on bond risk premia. To this end, we employ a novel institutional securities holdings dataset from Germany, one of the largest asset management markets for financial intermediaries. In 2017, institutions delegated over €1.5 trillion to German institutional funds of which 77% were allocated to bonds.

We document that institutional funds have consistently increased the average duration and lowered the average rating on their bond portfolios between 2009 and 2017, a period characterized by broadly declining interest rates. The increase in risk-taking was considerably more pronounced than for banks, insurance companies, pension funds or the bond market as a whole. To control for passive changes in bonds yields, duration and ratings, we construct a buy-and-hold portfolio at the fund level (in the spirit of Barber and Odean (2000)) and focus on transactions that rebalance the portfolio away from this passive benchmark. We document that institutional funds invest strongly procyclically: they actively move into higher yielding, longer duration and lower rated securities as yields fall and spreads compress, and vice versa.

We then show that institutional funds' procyclical trading behaviour has significant price impact in bond markets. Using security-level variation in the demand of institutional funds, we find that bonds in greater demand from the institutional fund sector have significantly higher excess returns than bonds that experience less demand, controlling for differences in security characteristics as well as demand from all other institutional sectors and households.

Hence, institutional funds amplify bond price dynamics. Their price impact is highly persistent, but asymmetric: while buying pressures raise bond prices for more than a year, the price impact from selling pressures dissipates after about three months. The price impact is stronger when fund trades are correlated, and is particularly pronounced for those institutional funds that tilt their portfolios most aggressively away from their passive benchmarks.

While the price impact is larger for non-investment-grade bonds and increases with the residual maturity, we document a significant effect of institutional funds' demand on bond risk premia even in the highly liquid German sovereign bond market, ruling out illiquidity as an explanation. As a case in point, we examine the institutional trading patterns in the German government bond market during a major market sell-off – the Bund market tantrum of April-May 2015 (Figure 1). Institutional funds were aggressively selling long-term Bunds precisely at a time of tight liquidity conditions and sustained downward price pressure in these securities. Their trading behaviour contrasts starkly with institutional funds' own liability side, where redemption pressures were muted.

What incentivizes institutional fund managers to act procyclically? A large literature on delegated asset management links procyclical investment behaviour to balance sheet constraints. Retail mutual funds have been shown to invest procyclically in response to strong flow-return relationships (Chevalier and Ellison (1997), Sirri and Tufano (1998) and Goldstein et al. (2017)). Moreover, the pricing mechanism used by open-end mutual funds implies a first-mover advantage in the case of exit, which can lead to investor runs (Chen et al. (2010) Falato et al. (2020)) and potential fire sales (Coval and Stafford (2007)).

We show that such constraints are largely absent in institutional funds. As their retail counterparts, institutional funds rarely use leverage, securities lending or short-selling. But unlike retail funds, the institutional funds in our sample have concentrated ownership by law, mitigating investors' coordination problems, and face small and infrequent outflows. In fact, we find no relationship between past reach for yield and subsequent inflows to institutional funds. This is in sharp contrast to available evidence on retail funds (Choi and Kronlund (2017)) and suggests that institutional fund managers do not reach for yield to attract investor flows.

While funds' procyclical investment behaviour could also reflect constraints on the part of their investors, we show that their portfolio rebalancing is remarkably similar across types of institutional clients. This suggests an overarching incentive structure that is independent of the type of end investor. We provide evidence of both implicit and explicit incentives at the fund level in line with such a view. First, procyclicality is amplified when bond yields fall into negative territory. Funds shift their investments more strongly towards riskier securities the larger the share of bonds in their portfolio that trades at negative yields. This is in line with a broad-based incentive to deliver positive returns. The effect is even more pronounced for funds that offer their clients an explicit capital guarantee. Second, we document that the probability of a fund being terminated by the asset management company is significantly lower for funds that have invested more strongly in higher-yielding bonds in the previous six months. This suggests that managers reach for yield to prolong their mandates. However, the relationship between reach for yield and subsequent termination is non-linear. We find that past reach for yield predicts higher fund returns and lowers the probability of termination in normal times, but lowers returns and raises the probability of termination in times of market stress. We also document stronger reach for yield in the months before fund reviews. In sum, managerial career concerns appear to be at the core of why institutional funds rebalance their portfolios towards riskier securities in good times and safer securities in bad times.

Our findings fill an important gap in the literature on delegated institutional asset management. The bond trading behaviour of delegated institutional capital has to our knowledge not been studied, likely due to data limitations.[1] Data on debt holdings of U.S. institutional accounts is not publicly available. Instead, the literature has used confidential data from investment consultants, which is limited to voluntary reporting from a subset of the fund

[1]The existing literature on delegated institutional capital mainly deals with performance: while Gerakos et al. (2019) find that institutional funds outperform their self-reported benchmarks globally, Busse et al. (2010) show that performance is not persistent, and does not increase performance following investment consultant recommendations (Jenkinson et al. (2016)) or replacing existing managers (Goyal and Wahal (2008)). Lastly, Dyck and Pomorski (2011) find that delegating capital externally is considerably more expensive than in-house management. In this paper, we will refer to delegated institutional capital as institutional capital delegated to institutional asset managers. Institutions may also choose to delegate assets to institutional classes of retail mutual funds, which only differ from retail classes in terms of fees.

population. In contrast, our results are based on a full census due to mandatory reporting of all institutional funds in Germany. In addition to this unique granular dataset on fund holdings, we have access to the item-level securities holdings of all other institutional sectors in the German economy. When looking at the price impact of institutional funds, this allows us not only to control for other sectoral demands, but also to identify who is providing liquidity when institutional funds demand it. Moreover, we are able to compare the differential effect of institutional fund net purchases and sales on the prices of bonds that are issued in the same country by the same company, have the same seniority, issue-level rating and cashflow duration at any given time (Choi et al. (2020)).

Our paper contributes to the literature on career concerns in delegated asset management (Chevalier and Ellison (1999), Goyal and Wahal (2008), Berk et al. (2017)). Of the various managerial incentives discussed in the literature, having the fund terminated due to persistently poor performance can be a particularly severe career setback, resulting in large expected losses in compensation associated with a persistent drop in managers' reputation (Ellul et al. (2020)). We show that institutional fund managers buy (sell) risky assets in calm (stress) periods to reduce their probability of termination, as predicted theoretically by Guerrieri and Kondor (2012).

Our results are consistent with Rajan (2006)'s argument that investors reach for yield in the presence of lower interest rates. We add to a growing literature documenting procyclical investment behaviour in banks (Hanson and Stein (2015)), insurance companies (Becker and Ivashina (2015)), pension funds (Andonov et al. (2017)), US money market funds (Di Maggio and Kacperczyk (2017)), US corporate bond mutual funds (Choi and Kronlund (2017)) or even households (Lian et al. (2019)). Timmer (2018) also finds that German investment funds behaved procyclically between 2005-2014, and attributes this behavior to investor redemption risk. We point to the fact that over 75% of German investment funds are institutional funds, where redemption risk is muted, and propose career concerns as an equally powerful driver of procyclicality.

Our findings highlight that strongly procyclical investment behaviour can exist even in the absence of observable short-term funding squeezes, regulatory constraints, and leverage. Moreover, even in highly liquid markets, this procyclicality has a persistent price impact and contributes to asset price swings. Regulation addressing this procyclicality in institutional funds may have a stabilizing role on bond markets.

The remainder of this paper is organized as follows. In Section II we discuss our data and the institutional setting in which German institutional funds operate, and provide summary statistics. Section III introduces our measures of active portfolio rebalancing as well as fund-specific exposures to interest rate and credit risk used in the empirical analysis. Section IV provides empirical evidence that institutional funds rebalance their portfolios procyclically. Section V shows that this behaviour elicits a price impact, while Section VI discusses two sets of incentives that could potentially explain funds' procyclical investment behaviour. Additional tables showing a variety of robustness analyses are provided in a Supplementary Appendix.

II. Data and Institutional Setting

Institutional Setting

German institutional funds are regulated under the European Alternative Investment Fund Managers' Directive (AIFMD).[2] Institutional funds can only be marketed to qualified institutional investors. Semi-professional investors, such as high net-worth individuals, may become eligible conditional on investing at least € 10 million (mn), or at least € 0.2 mn plus a declaration of risk awareness and proof of expertise. Institutional asset management comes in the form of individual institutional accounts that are managed separately, or as institutional funds which pool several institutional accounts. However, ownership remains concentrated: by law, an institutional fund can have a maximum of ten institutional investors.

To set up an institutional fund, institutional clients must sign a contractual agreement with an authorized German asset management company.[3] The contract sets out the fund

[2]Institutional funds are different from institutional share classes of retail mutual funds, which are regulated under the more restrictive UCITS (Undertakings for Collective Investment in Transferable Securities) Directive.

[3]All German asset management companies are authorized and regulated by the German Federal Financial

rules, the investment restrictions and the term of the mandate (fixed term or indefinite). The asset management company appoints a manager, sometimes at the recommendation of the client, and is responsible for its monitoring.

Institutional accounts are open-ended, and virtually all funds allow redemption at a daily frequency. However, in practice, investor flows are rare. Anecdotal evidence suggests that client outflows are generally announced or even negotiated with the fund manager in advance. Although leverage, derivatives and short-selling are permitted, they are not commonly used.[4] Fund rules do not require authorization from BaFin; a notification is sufficient. This means that changes in the fund's investment strategy, eligible assets and leverage limits can be implemented in days rather than months. Also, institutional funds do not need to publish a prospectus.

Besides offering greater investment flexibility, institutional funds may provide additional advantages to their clients compared to an institutional class of a mutual fund. Fund managers may time their trading to smooth clients' earnings and optimize tax returns. Most European life insurance companies sell participating policies that force them to distribute recognized profits to policyholders. Funds may defer the recognition of profits and therefore smooth distributions. Clients also enjoy more transparency (full holdings and the trading history can be requested on demand) and control: the client, the asset management company and the depositary are all represented in an advisory investment committee. While the client cannot dictate individual investment decisions, it can influence the fund management by exercising its voting rights.

While our data only cover the German market, German institutional funds are in many respects representative of the broader European market. All European institutional funds are regulated under the AIFMD. While national authorities can in principle depart from this directive and impose stricter rules, this is not done in practice. Recent data from the

Supervisory Authority (BaFin) in accordance with the German Investment Code (*Kapitalanlagegesetzbuch* - KAGB).

[4]In practice, the asset management company must set appropriate leverage limits in coordination with the client, taking into account the funds' asset quality as well as regulatory constraints (currently a 30% leverage limit applies to German securities-based institutional funds), and include them in the fund rules. These leverage limits are then monitored and enforced by the German financial regulator (BaFin)

European Securities Markets Authority (ESMA (2019)) suggest that many characteristics of the German fund market (discussed in greater detail below) extend to the European level: insurance companies and pension funds are the largest institutional clients; the bulk of European institutional funds are securities-based funds following fixed income strategies; fund ownership is highly concentrated; and the use of leverage is limited.

Data Collection

We collect data on German institutional accounts from three sources. Information on funds and asset management companies comes from the Deutsche Bundesbank's Investment Funds Statistics. The data are collected at the level of institutional funds, which may incorporate one or several (up to 10) individual client accounts. Bond prices and characteristics come from the European System of Central Banks' (ESCB) Centralised Securities Database (CSDB). Lastly, we obtain data on the securities holdings of all German institutional sectors from the German Securities Holdings Statistics.

The Deutsche Bundesbank's Investment Funds Statistics collects information on all authorized German open-ended investment funds on a monthly basis. At issuance, funds must report their name, sponsor, ISIN, type (retail or specialized), investment focus, as well as various investment clauses, including the utilization of earnings (distributive or accumulative fund), the length of the investment mandate (fixed-term or unlimited), the capital-protection and indexing status. Funds must notify the Bundesbank immediately of any changes in these features, as well as whether they are being liquidated, merged, have suspended redemptions or are having their securities transferred to another fund. Each month, funds must report the composition of their assets and liabilities, their security-level holdings, NAV, fund units, gross inflows and outflows. The reporting date is the end of the month, and data must be submitted within five business days. Our sample is a full census. All reportings are mandatory and without any reporting threshold which provides us with a survivorship bias-free database of all institutional funds in Germany.

Each month BaFin informs new investment funds about their reporting obligation to the

Bundesbank. In addition, the Bundesbank regularly checks the list of new investment funds as published by BaFin and requires identified non-filers to submit the data.

The CSDB records prices and characteristics for all securities issued by euro area entities or held by euro area institutional investors. It includes the issuance and maturity dates, ESA 95 instrument type, nominal amounts outstanding, price, currency, the coupon type, rate, date and frequency, the yield to maturity, the interest accrued since last coupon, information on the name, sector and domicile of the issuer as well as asset and issuer ratings from DBRS, Fitch, Moody's and S&P. In line with the Eurosystem collateral framework, we consider the best asset rating assigned by the four rating agencies.

We merge the security holdings data from the Investment Fund Statistics with the pricing data from CSDB at the security-month level. The period of analysis is September 2009 to June 2017. The frequency is monthly.

Summary Statistics

As of June 2017, the German open-ended investment fund sector accounted for some € 2 trillion (tn) in assets under management (AUM) across 6,343 investment funds. While funds were offered by 106 asset management companies, the industry is relatively concentrated, with the largest five investment companies overseeing 49.9% of the overall assets. Institutional funds accounted for 76% of the sector-wide assets (€ 1.51 tn), the remainder being attributed to retail funds. 84.4% of institutional funds' assets (€ 1.27 tn) was concentrated in securities-based funds, whose main focus is investment in bonds and equities. Real estate funds and funds of funds accounted for 3.4% and 6.5% of the sector assets, respectively, while hedge funds and money market funds remained relatively small, with less than 1% of the overall AUM. Within securities-based institutional funds, mixed funds accounted for 63.8% of the assets, followed by bond funds (27.2%) and equity funds (9%). Most funds are actively managed, with less than 2% reported as index funds.

We restrict the sample to actively-managed institutional funds by removing funds which either self-report as indexed, or have variations of the term "index" in their name. Concerning the fund type, we concentrate on bond as well as mixed funds with bond investments. We demonstrate robustness to this sample choice in the results section. We remove funds with predefined termination dates, as the limited investment horizon might justify a different investment behavior. We also remove funds which are currently being liquidated, report suspended redemptions, are being merged, acquired or are acquiring some other fund (unless termination is the main focus of the analysis (as is the case in Section VI). Finally, to ensure some commonality in investment focus, we drop funds which, over their sample lifetime, had never held euro area bonds. At the security level, we remove entries with missing issuer information, missing price and yield information, or where the price reported in CSDB diverges by more than 10% from the price implied by the ratio of market to nominal values reported in the Securities Holdings Statistics. We finally remove the handful of cases where funds report short positions. After conducting all quality checks, we get a sample of 4,407 institutional funds across 57 fund families. As of June 2017, our sample of funds accounted for € 1.03 tn in assets under management, and 23.6 million individual (fund-month-ISIN) holdings over 56,986 fixed income securities, with a cumulative market value of € 655 bn.

Table I reports the main fund characteristics and their portfolio allocation over the entire sample period. The average fund is about ten years old, has €300 million in AUM, a cash buffer of 5% of AUM and no leverage. It invests nearly 80% of its securities in bonds and allocates roughly 10% each to equities and fund shares. The financial sector is the most important sector in asset allocation (on average 46.4%), followed by sovereigns (39.1%) and non-financial corporations (14.5%). The average fund's bond portfolio consists of 96 different bonds with a duration of 5.3 years. Most of the bond portfolios are located between the prime grade and upper medium grade on the $S\&P$ rating scale, with an average portfolio rating of $AA-$ and ranging from $BBB+$ and AAA at the 5th and 95th percentile.

Institutional funds rarely exhibit inflows or outflows. On a monthly basis, 95% of all funds do not record any outflows and less than 3% record inflows. Moreover, aggregate outflows appear to be uncorrelated with either mutual fund outflows or measures of aggregate financial conditions like the Composite indicator of systemic stress (CISS) of Holló et al. (2012). The near absence of flows suggests that investments in institutional funds are primarily made when the funds are set up and withdrawn when the funds are terminated. On the other hand, fund terminations are not uncommon. Over the span of our sample, no less than 1392 institutional funds have been terminated (an average of 20 funds per month). Typically, terminations are negotiated among investors and communicated to the manager in advance.

Table II presents the breakdown of fund unit holdings by institutional sector as of May 2017. Out of the € 1032.9 bn in institutional funds assets, 96.5% is held domestically. The largest institutional clients are insurance companies, with € 385.4 bn (37.3%) of the assets, followed by pension funds (€ 167.4 bn), local and regional banking entities (€ 112.4 bn) and non-financial corporations (€ 88.5 bn, mostly in corporate pension plans). Other sectors (churches, foundations and endowments collectively defined as non-profits) take up another € 30.3 bn in delegated assets.

To motivate the analysis in the next section, Figure 2 displays the evolution of bond portfolio duration and credit rating for the median as well as the 25th and 75th percentile of the German institutional fund distribution since 2009. The chart shows that institutional funds have strongly and persistently rebalanced their portfolios towards more interest and credit risk over the last decade. However, the credit quality of debt issuance is known to deteriorate during prolonged periods of low interest rates (Greenwood and Hanson (2013)). Could institutional funds' portfolio rebalancing simply reflect the increased supply of riskier bonds? Figure 3 shows that this is not the case. The institutional fund sector's shift towards higher credit and interest rate risk has been considerably more pronounced than for retail funds, banks, and insurance companies. Moreover, using the universe of all sovereign and corporate bonds issued or held by European Economic Area investors to proxy for the aggregate bond supply, we show that institutional funds' shift towards higher credit and interest rate risk is considerably stronger than what can be accounted for by increased supply. Institutional funds are not merely taking up riskier bond issues, but (consistent with our price impact results) appear to be displacing other investors in risky assets in the secondary markets.

III. Measurement

The documented shift in the riskiness of institutional funds' bond holdings can result from both passive changes in the riskiness of bonds ouststanding and active choices made by institutional fund managers. In this section, we define a set of measures that track how institutional funds actively rebalance their fixed income portfolios. As they operate with a small number of institutional clients, German institutional fund managers are not required to publicly disclose their benchmarks. As a result, we propose a measure of active portfolio rebalancing that does not rely on external benchmarking. Specifically, we define an institutional fund manager's internal benchmark as her previous period portfolio carried forward to current-period prices, and compute active rebalancing as the change in portfolio composition originating from any transactions that move the portfolio away from that benchmark.[5] We examine portfolio rebalancing along three dimensions: yield to maturity, duration and credit rating. We consider overall net transactions, as well as gross purchases and gross sales separately. As we are interested in how institutional funds' investment behavior responds to changes in the term structure of interest rates, we propose and motivate a novel way to identify fund-specific exposures to interest rate and credit risk. The section concludes with a summary of these measures.

I. Active Portfolio Rebalancing

Between any two dates $t-1$ and t, the composition of a fixed income portfolio valued at market prices can change for two main reasons: the manager carries out transactions in the underlying securities (active rebalancing) or there are changes in the market prices of the underlying securities which change their portfolio weights (passive rebalancing). To identify active rebalancing, we use the following strategy: Let $u_{f,i,t}$ and $u_{f,i,t-1}$ denote the nominal holdings (i.e holdings at par) of fund f in security i at time t and $t-1$, respectively, and $p_{i,t}$

[5] Similar holdings-based internal benchmarks have been used by Barber and Odean (2000) in the context of the stock holdings of individual investors, Grinblatt and Titman (1993) for the stock holdings of mutual funds and Lakonishok et al. (1992b) for the stock holdings of pension funds. Barber and Odean (2000) refers to this benchmark as the "own-benchmark". We implement this measure for bond holdings.

denote the market price of security i at time t, expressed as percentage of par. The current portfolio of fund f at time t can be expressed as a vector of market value portfolio shares:

$$\omega_{\mathbf{f},\mathbf{t}}{}' = \left[\frac{u_{f,i,t}p_{1,t}}{\mathbf{u_{f,t}}'\mathbf{p_t}} \dots \frac{u_{f,n,t}p_{n,t}}{\mathbf{u_{f,t}}'\mathbf{p_t}}\right]$$

where the boldfaced variables denote vectors. We then define a fund-internal benchmark portfolio, which is the hypothetical portfolio that would have resulted from a manager receiving last month's portfolio and executing a pure buy-and-hold strategy. The internal benchmark portfolio can similarly be expressed as a vector of market value portfolio shares:

$$\omega_{\mathbf{f},\mathbf{t}}^{\mathbf{b}}{}' = \left[\frac{u_{f,i,t-1}p_{1,t}}{\mathbf{u_{f,t-1}}'\mathbf{p_t}} \dots \frac{u_{f,n,t-1}p_{n,t}}{\mathbf{u_{f,t-1}}'\mathbf{p_t}}\right]$$

We define the active change in portfolio yield to maturity from transactions as the difference between the weighted average yield to maturity on the actual fund portfolio and its internal benchmark portfolio:

$$\Delta Ytm_{f,t} = \omega_{\mathbf{f},\mathbf{t}}{}'\mathbf{Ytm_t} - \omega_{\mathbf{f},\mathbf{t}}^{\mathbf{b}}{}'\mathbf{Ytm_t}$$

Note that our measure is not contaminated by revaluation adjustments (passive rebalancing), as both portfolios are evaluated at time t prices. We can compute similar measures for portfolio average duration and ratings, respectively:

$$\Delta Dur_{f,t} = \omega_{\mathbf{f},\mathbf{t}}{}'\mathbf{Dur_t} - \omega_{\mathbf{f},\mathbf{t}}^{\mathbf{b}}{}'\mathbf{Dur_t}$$

$$\Delta Rat_{f,t} = \omega_{\mathbf{f},\mathbf{t}}{}'\mathbf{Rat_t} - \omega_{\mathbf{f},\mathbf{t}}^{\mathbf{b}}{}'\mathbf{Rat_t}$$

Throughout the paper, we refer to these three indicators as measures of funds' reaching for yield, duration, and rating, respectively. As an extension, we also look at the contribution of gross purchases and sales, separately, in driving the computed portfolio rebalancing. We denote $\Delta Ytm(P)$, $\Delta Dur(P)$, $\Delta Rat(P)$ as the changes to portfolio yield to maturity, duration, and credit rating arising from purchases, and $\Delta Ytm(S)$, $\Delta Dur(S)$, $\Delta Rat(S)$, from sales.

Figure 4 plots the time series and cross-sectional distribution of monthly changes in average portfolio yield to maturity, ΔYtm (upper chart), Macaulay duration ΔDur (middle chart), and rating ΔRat (lower chart) arising from transactions for our sample of actively-managed, German bond and mixed institutional funds from November 2009 through June 2017. The charts show that a large fraction of funds have actively increased their portfolio yield to maturity, have increased the duration, and have lowered the average credit rating of their portfolios from one month to the next. This tendency was particularly pronounced from around mid-2012 through 2015, and abated somewhat since.

II. Measuring Funds' Exposure to Interest Rate and Credit Risk

We seek to analyze how institutional funds' portfolio rebalancing responds to changes in the term structure of interest rates. Following Gilchrist and Zakrajsek (2012), we employ securities-level data to derive a fund-specific measure of interest rate and credit risk. Specifically, for each bond, we construct a synthetic risk-free security having exactly the same cashflows as the original security, each discounted at the corresponding maturity zero-coupon Bund rate. This returns a price and a yield for the synthetic risk-free bond. We then define a security-specific credit spread as the difference between the yield on the original risky bond and its synthetic risk-free counterpart. Next, for each synthetic risk-free security, we subtract the 3m Bund rate to obtain a security-specific term spread. We weight each security-specific term and credit spreads by their respective market value portfolio weights to obtain a fund-specific term and credit spread. We will refer to our fund-specific term and credit spreads as $Fslope$ and $Fspread$, respectively. $Fspread$ and $Fslope$ measure how much of the yield compensation earned by a fund is due to exposures to interest rate versus credit risk.

The top panel of Figure 5 provides a stylized representation of our yield decomposition for two funds whose portfolio yield is assumed to be identical, but whose exposure to interest rate and credit risk is different. As the term structure of interest rates varies, the $Fspread$ and $Fslope$ shed light on how these changes map into the actual compensation that different funds extract from their portfolio-level risk exposures. The bottom panel of Figure 5 plots the time series and cross-sectional dynamics for $Fslope$ and $Fspread$. The risk-free curve underlying this decomposition is the German Nelson-Siegel-Svensson zero-coupon Bund curve. The short rate is defined as the 3m Bund rate. The fund-specific slope ($Fslope$) moves closely with the 5Y Bund slope (top chart, correlation coefficient = 0.97). The median $Fslope$ slightly exceeds the Bund towards the end of the sample, indicating a gradual but sustained increase in funds' portfolio durations. Our $Fspread$ also correlates closely with commonly-used measures of corporate credit risk (bottom chart, here the Bank of America Merrill Lynch Euro-Area AA Corporate Bonds option-adjusted yield spread to the Government), while at the same time illustrating the large heterogeneity in institutional funds' exposures to credit risk.

IV. Evidence on Portfolio Rebalancing

In this section, we empirically study whether institutional funds actively rebalance their fixed income portfolios in response to changes in the yield curve. To answer this question, we run a fixed effects panel regression:

$$\Delta YTM_{f,t} = \alpha_f + \alpha_t + \beta_1 Fslope_{f,t-1} + \beta_2 Fspread_{f,t-1} + \gamma fund\ controls_{f,t-1} + \epsilon_{f,t} \qquad (1)$$

where α_f and α_t are fund and time fixed effects, $\Delta YTM_{f,t}$ is our measure of active yield change from transactions, and $Fslope_{f,t-1}$ and $Fspread_{f,t-1}$ proxy the fund's lagged exposure to interest rate and credit risk, respectively. We control for lagged fund-specific characteristics such as the fund's age, assets under management, portfolio shares of cash, equities and derivatives, current and past net flows, as well as the fund's gross return, excess return with respect to the fund category average (bond vs. mixed funds) and excess return with respect to the fund family average over the previous 6 months.

If institutional funds invest procyclically, we would expect a fall in the funds' compensation for interest rate and credit risk to be associated with a reallocation of their portfolios towards higher-yielding securities. Specifically, we would expect the coefficients $\beta 1$ and β_2 in the above regression to be statistically significantly lower than zero. The first column of Table III shows that this is indeed the case. Quantitatively, a one percentage point lower

$Fslope$ ($Fspread$) prompts managers to actively increase the average yield on their fixed income portfolio at an average rate of 4.8 (4.0) bps per month, respectively. Looking at the alternative specifications in columns II and III (which replace ΔYTM with $\Delta YTM(P)$ and $\Delta YTM(S)$), we find that funds rebalance their portfolios by simultaneously selling lower-yielding securities and purchasing higher-yielding ones. That said, most of the contribution to funds' active portfolio yield changes originates from purchases of higher-yielding assets.

We also computed the weighted average yield to maturity on all newly purchased securities, and compared it with the weighted average yield to maturity on all previously existing securities for the same fund in the same month. We found that a one percent lower $Fslope$ ($Fspread$) increases the gap between the average yield on newly purchased vs. existing securities by a sizeable 42 (16) bps.[6]

Next, we test whether the observed increase in portfolio yields arises from taking more interest rate or credit risk, or both. Columns IV-IX of Table III replicate the above specification using as dependent variables the active change in portfolio rating ($\Delta Rat_{f,t}$) and portfolio duration ($\Delta Dur_{f,t}$), respectively. Interestingly, funds significantly increase their portfolios' average credit risk (i.e. lower their credit rating) in response to declining credit spreads (by 0.03 notches [7] for every 1% lower credit spread), but not term spreads. Similarly, funds significantly adjust their portfolio duration in response to declining term spreads (by 0.33 years for every 1% lower term spread), but not credit spreads. One interpretation might be that funds tailor their portfolio response depending on the underlying risk shock. As with the changes in portfolio yield to maturity, the rebalancing in both portfolio duration and

[6]As we include funds' cash, equity, and derivatives holdings as controls, we rule out the possibility that funds replace higher risk-taking in their fixed income portfolio with higher cash balances or lower exposures to potentially riskier asset classes such as equities or derivatives. In column V of Table A2 in the Supplementary Appendix, we also show that portfolio rebalancing is equally strong for funds which do not hold equities at all. Furthermore, funds do not seem to alter their cash positions in response to higher risk-taking in their bond portfolios.

[7]The magnitude of portfolio rebalancing increases with the horizon. In Table A3 in the Supplementary Appendix, we compute the cumulative active change in portfolio ratings $\Delta Rat_{f,t,t+h}$ over horizons ranging from $h = 1$ to $h = 12$ months ahead, and regress it on previous-period term and credit spreads, controlling for fund and time fixed effects and further lags of term and credit spreads. We find that a 1 percentage point lower $Fspread$ is associated with a 0.18 notches lower average fund portfolio rating after 12 months. (We also computed longer-horizon yield and duration rebalancing. However, both measures mechanically increase with the horizon as the underlying buy and hold portfolio gradually matures. As we are unable to isolate this effect, we have chosen not to report the results.)

portfolio ratings is achieved primarily through purchases of higher-duration or lower-rated securities rather than sales of lower-duration or higher-rated securities.

We then explore how reach for yield differs between institutional and retail funds. As institutional funds face little if any redemption risk, the results are indicative of how different liability structures affect risk-taking behavior on the assets side. Therefore, we replicate the regression specification in Equation (1) for a sample covering both institutional and retail funds. To capture the differential response of retail mutual funds, we interact $Fslope_{f,t-1}$ and $Fspread_{f,t-1}$ with a dummy variable taking a value of 1 if the fund is reported as retail. If funding (outflow) constraints matter, we would expect the coefficient on the interaction to be significantly lower than zero. Table IV reports the results for the three measures, $\Delta YTM_{f,t}$ (columns I-III), $\Delta Rat_{f,t}$ (IV-VI) and $\Delta Dur_{f,t}$ (VII-IX). Overall, the results confirm that procyclical risk taking behavior exists in both retail and institutional funds, with retail funds being slightly more responsive to changes in interest rates. A one percentage point lower $Fslope$ is associated with a 7.4 bps per month average yield increase in retail mutual funds, compared to 5.3 bps per month for institutional funds. However, despite their considerably more stable funding structure, institutional funds invest almost as procyclically as retail funds.

Finally, we investigate how reach for yield varies across types of institutional clients. Different institutions likely face different investment constraints, and might choose investment mandates whose strategies are best aligned with these constraints. To assess if there is heterogeneity in risk-taking across institutional clients, we rerun Equation (1) separately for funds which are held entirely by one of the five largest institutional sectors: banks, insurance companies, pension funds, non-financial corporations and non-profits. Table A1 shows that funds' portfolio rebalancing is similar across sectors, with little variation of the relevant coefficients across the five types of institutions. In unreported results, we also find no meaningful variation in average reach for yield across these sectors, controlling for time and asset management company fixed effects. While there might be important within-sector heterogeneity that we do not observe, our results indicate that the documented reach for yield behaviour is pervasive across sectors of ultimate fund owners. This suggests that incentives which are independent of the institutional frictions of the end investor are most likely to explain the procyclical investment behavior. We discuss several such incentives in Section VI.

Our portfolio rebalancing results are robust (and actually quantitatively larger) over different sample periods: see Table A2 columns I-III. Winsorizing the portfolio rebalancing at the 5 and 95 percentile of the cross-sectional distribution to remove outliers or value-weighting observations by funds' assets under management does not change our results (columns IV-V). Moreover, it does not matter whether the fund-specific risk-free slope is defined in terms of German yields or euro area OIS swap rates. Lastly, results are robust to adding a short rate as an additional regressor. While a drop in the three-month risk-free short rate is associated with a statistically significant increase in funds' portfolio rebalancing, we chose not to include the short rate as it features little variation over most of our sample due to the "zero lower bound".

To address the potential endogeneity of $Fslope$ and $Fspread$, we have lagged all regressors by one month. If one is still concerned about reverse causality, we have also performed the following two stage least squares instrumental variable strategy. We proxy the average fund exposure to the slope of the term structure of interest rates by the difference between the 5Y Bund and 3m Bund yields (the term spread). We then instrument changes in the term spread by high-frequency identified ECB monetary policy communication shocks from Leombroni et al. (2018) to identify a plausibly exogenous component in month-to-month term spread changes.[8] In the second stage, we regress $\Delta YTM_{f,t}$ on the predicted term spread in first differences, controlling for fund fixed effects and time-varying fund characteristics. The results, reported in Table A4, show that a 100 bps contractionary shock to the term spread results in a 11-13 bps contemporaneous increase in funds' reach for yield.

[8] The monetary policy shocks are computed as the common component of changes in a sample of overnight index swap rates with maturities between 1m and 12m and swap rates with maturities between 2Y and 5Y in a 60 minute window around the ECB press conference. The sample ends in December 2015 when the ECB communication procedure changed and no longer allowed to separately identify communication from policy rate shocks.

V. Price Impact

Thus far, we have provided evidence that institutional funds actively rebalance their portfolios in response to changes in the underlying interest rate environment. This portfolio rebalancing is strongly procyclical: funds turn to increasingly higher-yielding, longer-duration and lower-rated assets as yields fall and spreads compress (and vice versa). Given the overall size of the institutional fund sector, it seems plausible that this behavior may affect asset markets, by driving prices away from their fundamentals, or creating excess volatility (Cuoco and Kaniel (2011), Guerrieri and Kondor (2012), Basak and Pavlova (2013)). However, the link between institutional funds' trading behavior and asset prices has not been documented empirically. In this section, we provide direct evidence for this relation using proprietary security-by-security holdings data for all German institutional funds and other institutional sectors.

I. Contemporaneous Price Impact

In our analysis, we focus on euro area, euro-denominated sovereign and corporate bonds held by our sample of German institutional funds. This limits the cross-sectional heterogeneity in asset characteristics and ensures that German institutional fund holdings represent a non-negligible share of the total issuance. Applying this filter yields a sample of 16,624 fixed income securities, with a total amount outstanding of € 25.76 tn. For each security, we compute the one-month realized excess return ($rx_{i,t}$) as the difference between the bond's realized one-month holding period return and the realized one-month German Bund rate. [9] We specify, for each security, two proxies for institutional fund-sector excess demand, which are scaled to ensure comparability across securities. The first defines an excess demand of the fund sector in security i at time t as the net change in fund sector holdings over the total

[9] We define the holding period return as the total return earned by holding the bond over the period, including any coupons and changes in accrued interest. Specifically, the 1-month holding period return for security i and time t is:

$$hpr^1_{i,t} = \frac{p_{it} + cpn_{i,t} + ai_{i,t}}{p_{i,t-1} + ai_{i,t-1}} - 1$$

where $p_{i,t}$ denote the end-of month clean price, $cpn_{i,t}$ is the coupon payment and $ai_{i,t}$ the accrued interest. We have also replicated the analysis using differences in log clean prices (as in Timmer (2018)) and all results were essentially unchanged.

amount outstanding for that security:

$$ExDem_{i,t} = \frac{Buy_{i,t} - Sell_{i,t}}{Amount\ Outstanding_{i,t}} \times 100 \tag{2}$$

Exdem is a continuous variable on $[-100, 100]$, where $100(-100)$ means the fund sector has acquired (sold) the entire amount outstanding in a given security. Note that *ExDem* can be zero in cases where transactions occur only within the fund sector, or when transactions with other sectors entirely cancel each other out. The second measure, inspired by Lakonishok et al. (1992a), defines excess fund sector demand as the net change in total fund sector holdings over the gross change in fund sector holdings for security i at time t:

$$ExLSV92_{i,t} = \frac{Buy_{i,t} - Sell_{i,t}}{Buy_{i,t} + Sell_{i,t}} \tag{3}$$

$ExLSV92$ is a continuous variable on $[-1, 1]$, where -1 refers to unanimous selling pressure, 1 stands for unanimous buying pressure, and 0 stands for cases where within-sector buy and sell demands completely cancel out. While both measures' numerator captures net buying, differences in the denominator lead to different interpretations of the two measures. $ExDem_{i,t}$ places more weight on transactions that are large with respect to the total outstanding stock of a fixed income security. By contrast, $ExLSV92$ puts more emphasis on how asymmetric the buying pressures are within the fund sector (strong demand pressures vs. strong supply pressures), regardless of how this pressure compares in magnitude to the overall stock outstanding.

One potential concern could be that fund-specific demand shocks may be correlated with other sectors' demands. To address this issue, we merge data on securities holdings from all institutional sectors from the German Securities Holdings Statistics. Since January 2013, around 2,000 financial institutions domiciled in Germany have been reporting, on a monthly basis, all securities held in their own accounts, as well as in the custody accounts of resident and non-resident customers. These customers are further broken down by institutional sector. In practice, the German SHS contains all securities held by German counterparties, as well as holdings of virtually all German-issued securities held by foreigners. The sectoral breakdown follows the 2010 European System of Accounts (ESA) guidelines. Specifically, we identify 10 institutional sectors: Central Banks (CB), Centralized Securities Depositories (CSD), Central, Regional and Local Government and Government Agencies (GOV), Households (HH), Insurance Companies (IC), Monetary Financial Institutions (MFI), Money Market Funds (MMF), Non-Financial Corporations (NFC), Other Financial Intermediaries (OFI) and Pension Funds (PF). We further add all holdings of Retail Mutual Funds (RF) from the German Investment Fund Statistics. For each sector s, we compute the excess demand $ExDem_{s,i,t}$ as the net change in the sector holdings over the total value outstanding of that security. To further control for changes in the supply outstanding [10], we remove all observations where there are changes in units outstanding due to either tap issuance or bond buybacks.

To get an estimate of institutional funds' price impact, we regress the one-month realized excess bond return on institutional fund excess demand, controlling for other sectors' demands, lagged sector demands and lagged securities returns (collected in the vector $\mathbf{z_{i,t-1}}$):

$$rx_{it} = \alpha_i + \alpha_t + \beta_f ExDem_{i,t} + \sum_s \beta_s ExDem_{s,i,t} + \gamma' \mathbf{z_{i,t-1}} + \epsilon_{i,t} \tag{4}$$

The regression includes security fixed effects to account for differences in time-invariant security characteristics, time fixed effects to account for any common factors driving the cross-section of excess returns and past three months excess returns to account for potential momentum trading (as documented by Timmer (2018)). Results are reported in Table V. Column I shows results for the full sample. Columns II and III present results for securities for which we record institutional fund sector transaction activity in the current month. The effect of institutional funds' excess demand on excess bond returns is economically large for both measures. The estimated coefficient for $ExDem$ in column II implies that a 1% increase in fund sector holdings (as a percentage of market value outstanding) in security i is

[10] As an extension, to isolate the effect of primary market trading, we have replicated the results excluding all bonds with less than 90 days since issuance. The results are essentially identical, suggesting that our price impact findings are entirely reflective of secondary market trading.

associated, on average, with a 6 bps higher realized return contemporaneously. The results using the $LSV1992$ measure, shown in column III, suggest that for any given security, a shift from "balanced demand" (buys and sells are equal and cancel each other out) to unanimous buying pressure in the institutional fund sector is associated, on average, with 49.4 bps higher realized excess returns.

Taken jointly, our results indicate that institutional funds' trading has price impact: institutional fund sector demand tends to be associated with higher excess returns and is stronger when buying or selling pressures are correlated across funds.

II. A Panel Difference-in-Differences Design

To further control for differences in time-varying security characteristics, we turn to a panel difference-in-differences design and look within groups of bonds with comparable characteristics (see Choi et al. (2020)). Specifically, we identify bonds issued in the same country by the same company and having the same issue-level rating and duration at some given time t. The issue rating proxies for issue-specific characteristics like secured/unsecured status.[11] To discretize duration, we rank securities, at every time t, based on their Macaulay duration and assign them into 20 duration quantiles (discretizing duration in annual buckets returned similar results). We assign such securities into groups, narrowing our attention to those groups with non-zero variation in institutional fund sector excess demand. Our filtered sample comprises 5,202 bonds from 290 different issuers. On average, there are 2.59 bonds in a group. The average bond has an amount outstanding of about € 1 bn. Within groups, our control group is the subset of securities which do not receive fund demand shocks (or receive relatively smaller shocks, if all group securities are demanded). The "treatment" is the fund sector demand shock. To exploit this within variation, we regress bond excess returns on fund sector demands, controlling for contemporaneous and lagged sectoral demands, lagged

[11] Typically, for a given issuer in our sample, secured bonds (Pfandbriefe), preferred senior unsecured bonds, non-preferred senior unsecured (also known as senior junior) bonds and subordinated bonds each have different issue ratings.

returns and group × time FE ($\alpha_{g,t}$)):

$$rx_{i,t} = \alpha_{g,t} + \beta ExDem_{i,t} + \sum_s \beta_s ExDem_{s,i,t} + \gamma' \mathbf{z_{i,t-1}} + \epsilon_{i,t} \tag{5}$$

Results are reported in column I of Table VI and suggest that a 1% increase in fund sector holdings (as a percentage of market value outstanding) for a security i is associated, on average, with a 4.5 bps higher contemporaneous realized excess return. Looking at the remaining sectoral demands, we find that retail mutual funds and money market funds are momentum investors ($\hat{\beta}_s > 0$), whereas insurance companies and to a lesser extent pension funds are contrarians ($\hat{\beta}_s < 0$, see Timmer (2018)). That is, insurance companies and pension funds provide the liquidity demanded by institutional investment funds.

As institutional funds shifted their portfolios towards bonds with lower ratings and longer durations (Figure 3), we analyze how the price impact of institutional funds varies in the cross section of bonds. First, columns IV-V of Table VI replicate the difference-in-differences analysis separately for pairs of bonds in different maturity buckets. For every bond in our paired sample, we compute the weighted average residual maturity of its cashflows. We split the paired sample into bonds with weighted average residual maturity smaller or greater than 10 years. We find that the price impact is essentially zero for cashflows with residual maturities of less than 10 years. The price impact rises to 21 bps for bonds whose cashflows have, on average, more than 10 years to mature. Next, we partition the bond universe into pairs of bonds rated above BBB versus BBB and below, and replicate the analysis on each sample separately. The results are reported in columns VI-VII of Table VI. Here, a 1% increase in fund sector holdings for a given security i (as a percentage of market value outstanding) is associated with a 5 bps higher contemporaneous realized excess return, on average, if the pair is rated above BBB. By contrast, the price impact is up to 9 times higher (42.6 bps) for bonds rated BBB and below. As before, the result controls for past and contemporaneous demand of other sectors and past realized returns.

Finally, one might be concerned that our results simply reflect market microstructure issues related to illiquidity.[12] To alleviate this concern, columns VIII-X report results for corporates, sovereign and German sovereign bonds separately. We find that institutional funds' trading is associated with strong contemporaneous price effects even in sovereign bond markets. Specifically, within groups of essentially identical securities, a 1% increase in institutional fund sector holdings for a given security i (as a percentage of market value outstanding) is associated with a 5.6 bps higher contemporaneous realized excess return in sovereign bonds, and a 6.8 bps higher contemporaneous realized excess return in German sovereigns. This compares to a 5.4 bps average price effect for non-sovereign bonds and rules out the possibility that our findings are driven solely by relatively more illiquid corporate bonds.

In conclusion, we find considerable heterogeneity in the effect of institutional funds' demand pressures on bond prices. The largest contemporaneous price impacts are documented for long-term and non-investment-grade bonds.

III. Price Impact and Reach for Yield

We now examine the extent to which the documented price impact is related to institutional funds' reach for yield (RFY) behavior. Our strategy goes as follows: each month, funds are ranked based on their contemporaneous RFY activity. Funds are then assigned into 5 quintiles. For each quintile, the excess demand measure is computed as net purchases from quintile q in security i at time t, divided by the security's nominal amount outstanding.[13] Price impact regressions are run separately for each RFY quintile, controlling for other sector demands, lagged quintile demands, lagged other-sector demands and lagged returns, time and

[12] Our bond pricing data are based on the last closing price in the month. This provides two challenges. First, we do not know when the closing price was last updated. It could be that, for different securities in the pair, the last prices were posted at different times of the month. This raises the possibility that the information might differ. Second, we do not know whether the closing price was a bid or an ask. This means that the price impact could reflect bid-ask spreads in fundamentally identical securities, rather than movements in the equilibrium (mid-price) away from the fundamental. These problems are alleviated in liquid bond markets (such as the German Bund market) as the distance between trades diminishes and the bid-ask spread narrows.

[13] There are cases where transactions between different quintiles cancel each other out in full, such that the overall transactions into and out of the fund sector come to zero. We eliminate these transactions as most of these cases occur among members of the same asset management company.

security fixed effects.

$$rx_{i,t} = \alpha_i + \alpha_t + \beta_q ExDem_{q,i,t} + \sum_s \beta_s ExDem_{s,i,t} + \gamma' \mathbf{z_{i,t-1}} + \epsilon_{i,t} \qquad \forall \quad q = 1..5 \tag{6}$$

Figure 6 plots mean coefficients and 95% confidence bands on the price impact of the different RFY quintiles. The top panel of Table VII shows the associated regressions. The relationship between reach for yield and price impact follows a clear V-shaped pattern. Demands originating in funds at either the top or the bottom of the RFY distribution have a statistically significant price impact. The coefficient is positive, implying that a 1% stronger net demand pressure is associated with around 30 bps higher realized bond excess returns. This is not the case for funds ranked in the middle of the distribution. These funds have no price impact. This indicates that funds that are reaching for yield (playing it safe) are willing to internalize higher price impacts in order to tilt their portfolios towards riskier (safer) bonds.

To get a better sense of the effect of buy and sell pressures on excess bond returns, we split *ExDem* into two series: a buying (selling) variable which equals the excess demand series when positive (negative), and zero otherwise. Looking at the differential importance of purchases and sales, we see that demand from the top of the RFY distribution reflects mostly buying pressures, while demand originating at the bottom of the RFY distribution reflects mostly selling pressures. To formalize this point, we modify regression (6) by breaking down the fund sector excess demand into net buying and net selling:

$$rx_{i,t} = \alpha_i + \alpha_t + \beta_q^1 buy_{q,i,t} + \beta_q^2 sell_{q,i,t} \sum_s \beta_s ExDem_{s,i,t} + \gamma' \mathbf{z_{i,t-1}} + \epsilon_{i,t} \quad \forall \quad q = 1..5 \tag{7}$$

The results are provided in the lower panel of Table VII. The coefficient on buying pressures is significant for top RFY quintile funds, while the coefficient on selling pressures is not. The opposite is true for bottom RFY quintile funds: the coefficient is positive and significant only for selling pressures. The magnitude of the coefficients is economically meaningful: buying pressures originating in top RFY funds are associated with 45.6 bps higher contemporaneous realized excess returns. Conversely, selling pressures originating in bottom RFY funds are associated with 40.9 bps lower contemporaneous realized excess returns. Collectively, these results suggest that funds' impact on bond prices is inherently linked to their tendencies to reach for yield, or conversely, fly to safety.

In what follows, we examine the persistency of price impacts stemming from funds in the top and bottom RFY quintile by repeating the previous analysis for longer bond holding period returns. Specifically, for each security at time t, we compute cumulative returns by compounding the 1 month holding period returns over the next $h = [0, 23]$ periods. The cumulative returns are then annualized by multiplying by 12 and dividing by the holding period. We then compute cumulative excess returns by subtracting, for each annualized cumulative return computed over time $t \rightarrow t + h$, the annualized zero-coupon Bund rate of maturity h at time t.[14] Price impact regressions are run separately for each RFY quintile, at each horizon, using a local projections method (Jordà (2005)). As before, we control for other sector demands, lagged fund quintile demands, lagged other-sector demands and lagged returns, time and security fixed effects. We interpret the coefficient of funds' excess demand on cumulative excess returns as a measure of long term price impact:

$$rx_{i,t\rightarrow t+h} = \alpha_i + \alpha_t + \beta_q ExDem_{q,i,t} + \sum_s \beta_s ExDem_{s,i,t} + \gamma' \mathbf{z_{i,t-1}} + \epsilon_{i,t+h} \quad \forall \quad q = 1..5 \quad (8)$$

Figure 7 plots the regression coefficients and 95% confidence bands from the long-term local projections of future cumulative realized excess returns on fund demand, for top and bottom RFY quintiles. Table VIII provides the results for a selected set of horizons. The price impact stemming from institutional funds' buying and selling pressures is highly persistent. The effects on cumulative excess returns last up to 12 months. However, the price response is asymmetric. For top RFY funds, where buying pressures dominate, the price impact exhibits an initial hump shape and slow reversal. On the other hand, for bottom RFY funds, where selling pressures dominate, price pressures dissipate over 3-4 months. Table A5 in the

[14]For instance, take a 24-month holding period starting at time t. The cumulative excess return for security i is then obtained by borrowing at the $2Y$ Bund rate at time t, buying security i at time t, holding it for 24 months and selling it at the end of $t + 23$.

Supplementary Appendix shows that the eventual price reversal is partially explained by the unwinding of the inventories of institutional funds' liquidity providers. We have not found notable differences in the identity of liquidity providers trading with top versus bottom RFY funds. Instead, the asymmetric response in cumulative returns suggests that upward price pressures are in general more difficult to correct and is broadly consistent with the existence of short-selling constraints for a variety of institutional investors.

VI. Incentives

Our previous results show that institutional funds invest strongly procyclically. This behavior is pervasive across time and across types of institutional clients, and generates persistent price impact in bond markets. We now turn to the potential driving forces behind this behavior by looking at some of the incentives that might determine institutional fund managers to invest procyclically. We examine explicit incentives - rebalancing driven by clauses or restrictions explicitly stated in the investment mandates, and implicit incentives: rebalancing in response to the probable actions of investors (institutional clients) or employers (asset management companies).

I. Explicit Incentives

Fund managers might face explicit incentives to invest in a procyclical fashion if they have issued minimum return guarantees to their investors. We exploit a particular contractual design present in a subset of institutional funds in our sample to explore if this is the case. Capital-protected funds feature, as part of their investment mandate, a capital guarantee clause. According to this clause, the asset management company sponsoring the fund commits to return the initial invested amount in full at the end of a pre-specified term. The guaranteed period may change on a rolling basis (i.e. an investment today is guaranteed for the next five years) or may be fixed (investment guaranteed until January 1, 2020). In essence, capital-protected funds issue zero-return guarantees.

A total of 136 actively-managed capital-protected institutional funds exist in our sample. As of June 2017, there were 72 capital-guaranteed funds still active, cumulating some € 13.2 bn in assets under management, representing roughly 1% of the overall German institutional funds market. On average, capital-protected funds earn lower yields, take less credit risk (average $Fspread$ is 99 bps vs. 124 bps) and invest in bonds with shorter maturities (5.1 years vs. 6.3 years) than conventional funds. Based on these portfolio characteristics, capital-guaranteed funds appear to be relatively safer. However, the presence of zero-return guarantees could induce risk-shifting in the presence of negative yields.

To identify the effect of zero-return guarantees in the context of negative yields, we devise the following empirical strategy: We restrict the analysis to the period post-July 2012, as this is the first month in our sample when securities start trading at negative yields (the first to do so were Danish short-term government bonds). To identify fund-specific exposures to negative yields, we compute, for each fund f at time t, the market value share of assets in their benchmark portfolio currently trading at negative yields (denoted $Share_{f,t}$ and expressed as a continuous variable on $[0, 1]$). Our implicit assumption is that a fund holding portfolio is indicative of its desired, or "benchmark" portfolio allocation (see Section III). When assets in the benchmark portfolio start trading at negative yields, a strategy that purchases according to the benchmark allocation and holds the assets to maturity results in losses on those assets acquired at negative yields. The managers may buy such securities and speculate that with some probability, they could sell them in the future at even lower yields, or avoid such securities altogether. In either case, $Share_{f,t}$ provides an estimate of how tightly the negative yields constraint is binding. To analyze whether funds more exposed to negative yields reach for yield more, we run the following fund and time fixed effects regression:

$$\Delta Ytm_{f,t} = \alpha_f + \alpha_t + \beta_1 Fslope_{f,t-1} + \beta_2 Fspread_{f,t-1} + \delta Share_{f,t-1} + \gamma' \mathbf{z_{f,t-1}} + \epsilon_{f,t} \quad (9)$$

where the vector $\mathbf{z_{f,t-1}}$ refers to a set of fund-specific controls defined in Table IX. The fixed effects capture differences in reach for yield levels across funds and time. The coefficients on $Fslope$ and $Fspread$ account for the fact that funds differ in their exposures to credit and interest rate risk, but also that reach for yield already intensifies with lower interest rates, as documented in the previous section. δ is our coefficient of interest. It measures the additional impact of negative yields on funds' reach for yield. The LHS column in Table IX reports the results, and shows that δ is positive and statistically significant. All else equal, funds that are fully exposed to negative yields ($Share$=1) enter transactions which, on average, increase their portfolio yield by 7 bps more than funds not exposed to negative yields at all ($Share$=0). The results suggest that, cross-sectionally, the presence of negative yields creates additional incentives to rebalance portfolios for all funds. To assess the differential effect of minimum return guarantees in capital-protected funds, we run the following specification:

$$\begin{aligned}\Delta Ytm_{f,t} =& \alpha_f + \alpha_t + \beta_1 Fslope_{f,t-1} + \beta_2 Fspread_{f,t-1} + \delta_1 Share^b_{f,t-1} + \delta_2 Share^b_{f,t-1}\#CP+ \\ &+ \gamma_1' \mathbf{z_{f,t-1}} + \gamma_2' Inter_{f,t-1} + \epsilon_{f,t}\end{aligned} \tag{10}$$

CP is a binary variable indicating whether the fund is capital-protected. The first three constant terms capture differences in levels across funds and time. Specifically, the fund fixed effect captures any differences in fund-level observed and unobserved time-invariant characteristics. The next three coefficients capture sensitivities from changes in slope, credit spreads and negative yields, which are common to all funds. The vector of interaction terms accounts for the fact that conventional and capital-guaranteed funds have different portfolio characteristics and may therefore respond differently to changes in market yields. The coefficient δ_2 is our coefficient of interest. It measures the additional effect that the presence of negative yields exerts on capital-protected funds, compared to regular funds. The right column of Table IX reports the results. δ_2 is positive and significant. Holding the exposure to negative yields constant, the presence of zero-return guarantees increases the intensity of reach for yield by an average of 4.9 bps per month. In fact, capital-protected funds appear to be roughly twice as responsive to negative yields compared to conventional funds (11.6 bps vs. 6.7 bps), after controlling for observed differences in fund characteristics.

We have thus provided one example of an explicit incentive which intensifies procyclical portfolio rebalancing towards higher yields in funds which are otherwise deemed the safest and least prone to such type of investment behavior. But while minimum return guarantees in institutional funds (or their institutional clients) can help account for their risk-shifting behavior in a low-yield environment, they cannot rationalize, in isolation, institutional funds' tendencies to participate in bond market sell-offs, such as the 2015 Bund market tantrum discussed in the Introduction. Absent short-term funding shocks from either clients (there is very limited outflow risk) or creditors (there is little if any leverage) and with zero-return guarantees only binding at some later maturity date, institutional funds have the option to wait for the best timing to rebalance their portfolio back to a more conservative portfolio allocation. We now turn to one example of an implicit incentive that could rationalize our findings.

II. Implicit Incentives

A large body of prior literature focuses on two sources of implicit incentives. The first relates to incentives arising from the agency relationship between fund companies and investors, specifically focusing on how investors' decisions to invest or withdraw from a fund affect the fund manager's investment behavior. A key empirical result is that flows chase past performance (Berk and Green (2004), Chevalier and Ellison (1997) and Sirri and Tufano (1998), Chen et al. (2010), Sialm et al. (2015) and Goldstein et al. (2017)). The argument goes that managers with compensation tied to assets under management have an incentive to artificially increase performance by taking risk, provided investors cannot properly adjust for risk. A second source of implicit incentives stems from agency frictions within asset management companies - between the fund manager and the fund sponsor. Career concerns - the prospect of promotion, demotion or termination - may affect fund managers' investment behavior (Chevalier and Ellison (1999), Goyal and Wahal (2008)).

II.A Flows

We begin by showing that the flows channel is largely absent in institutional funds. Specifically, we define the fund percentage net flows as:

$$Flow_{f,t} = \frac{u_{f,t} - u_{f,t-1}}{u_{f,t-1}} \times 100 \tag{11}$$

where $u_{f,t}$ is the number of investment fund units for fund f at time t, and regress fund flows on the fund average reach for yield rank over the previous six months, controlling for past returns, fund fixed effects and fund time-varying characteristics:

$$Flow_{f,t} = \alpha_f + \beta Rank\Delta Ytm_{f,t-6,t-1} + \gamma' \mathbf{z_{f,t-1}} + \epsilon_{f,t} \tag{12}$$

Table X shows the results for retail funds, institutional funds and the joint retail and institutional sample, for the full sample or broken-down into calm vs. stress periods.[15] In line with the existing literature (Choi and Kronlund (2017)), we find that retail investors are sensitive to funds' past reach for yield. Retail funds consistently ranking high in the RFY tournament experience about 0.2% higher monthly inflows in calm periods, with the effect dampening by 0.08% for every one standard deviation increase in market stress (columns I and II). In contrast, institutional investors are insensitive to past reach for yield (columns III and IV). This is in line with our earlier observation that institutional funds rarely experience flows, and suggests that the implicit incentives at play for retail funds are likely not present for institutional funds. Instead, we build on the career concerns literature and ask whether the prospect of a mandate termination can partly explain institutional fund managers' procyclical investment behavior.

[15]We illustrate the differential response of investors flows to past reach for yield in calm vs. stress periods by interacting the reach for yield rank with a proxy for bond market stress - the Euro-Area Composite Indicator of Systemic Stress (CISS) bond subindex of Holló et al. (2012), expressed in historical standard deviations. The results are robust to various other measures of stress (e.g. BBB-AAA spread, 30 days implied bond volatilities).

II.B. Mandate Termination

Asset management companies must immediately notify BaFin of their decision to terminate a fund. These funds have all been initially reported as indefinite-term mandates (i.e. mandates which are in principle renewable, without a preset termination date). Over the span of our sample, 1,392 institutional fund mandates were terminated.[16] While we do not observe managerial outcomes directly, we assume that terminating a fund mandate coincides with a negative outcome for the fund manager: the manager will either be fired or will have to wait until a new mandate becomes available.

Figure 8 shows the relationship between reach for yield and the subsequent probability of termination. The x-axis plots a measure of longer-horizon reach for yield. Specifically, each month, we rank funds based on their contemporaneous reach for yield performance. The most aggressive fund gets 1, the least aggressive 0. We then average the ranks over a period of 6 months and allocate funds into 5 groups: top (most aggressive) with average ranks above 0.8 through bottom (least aggressive) with average ranks below 0.2.[17] The y-axis plots the subsequent probability of termination. There is a monotonic relationship between past reach for yield and subsequent termination. On average, funds persistently reaching for yield have statistically and economically significantly lower probabilities of termination than funds persistently playing it safe. The probability of termination for funds in the top RFY group is 0.27% per month, compared to 0.87% in the bottom RFY group. To account for additional confounding variables, we repeat the analysis using a random effects probit model:

$$P(term)_{f,t} = \beta Rank\Delta Ytm_{f,t-6,t-1} + \gamma' \mathbf{z_{f,t-1}} + \epsilon_{f,t} \tag{13}$$

where the dependent variable $P(term)_{f,t}$ is a $(0,1)$ dummy which takes a value of 1 if fund f is terminated at time t. $Rank\Delta Ytm_{f,t-6,t-1}$ measures the fund's past average reach for

[16]By mandate termination we mean termination of the fund as a whole. Where the fund has multiple institutional investors, it means that all investors simultaneously terminate their mandates. Mandate termination by only a subset of the investors would be recorded as an outflow.

[17]We chose 6 months to account for the fact that re-auctioning an investment mandate is costly and time consuming, so clients may look at longer periods of persistent behavior before taking a termination decision. The results are robust to different horizons.

yield ranking from $t-6$ through $t-1$. Fund controls $\mathbf{z_{f,t-1}}$ include past excess returns and squared excess returns to control for the (potentially non-linear) termination-performance relationship, as well as asset management company total AUM, to account for the fact that a large fund sponsor may have more alternatives (such as hiring multiple managers) before terminating a mandate, as well as the mandate anniversaries, as mandate reviews tend to happen mechanically at fixed frequencies.[18] The left column of Table XI reports the coefficients as average marginal effects. Reaching for yield more than other funds (and doing so persistently) lowers the probability of termination. Specifically, a fund which consistently ranks highest in the reach for yield distribution reduces its monthly termination probability by 0.52% on average. By comparison, the unconditional average monthly probability of termination in our sample is 0.49%. The results are robust to the ranking horizon.

To test whether periods of market stress are associated with greater sensitivity to managers' investment behavior, we interact $Rank\Delta Ytm_{f,t-6,t-1}$ with our measure of financial stress.

$$\begin{aligned} P(term)_{f,t} =& \beta Rank\Delta Ytm_{f,t-6,t-1} + \delta Rank\Delta Ytm_{f,t-6,t-1}\#Stress_t + \gamma_1' \mathbf{z_{f,t-1}} + \\ &+ \gamma_2 Stress_t + \epsilon_{f,t} \end{aligned} \tag{14}$$

The second column of Table XI reports the results. The effect of reaching for yield is strongest when market volatility is lowest (topping the reach for yield distribution over the previous 6 months lowers the subsequent monthly probability of termination by 1%) and declines by approximately 0.27% for every one standard deviation increase in market stress. For levels of market stress more than two standard deviations above the average, past reaching for yield increases the probability of termination. We find somewhat similar dynamics when interacting with measures of term and credit spreads. In other words, the effect is non-linear: reaching for yield lowers a fund's probability of termination in normal times, but increases it in stress times.

[18]Results indeed suggest that being in the month prior to the mandate anniversary increases the monthly probability of termination by 0.15%, By comparison, the month immediately after the mandate anniversary decreases the probability of termination.

Why would asset management companies or their clients condition termination on past RFY? One hypothesis is that reaching for yield predicts future fund returns. To test this hypothesis, we regress the six month average future fund returns on previous six month average fund reach for yield, controlling for past returns, fund age, fund size and fund fixed effects. We consider raw fund returns, returns in excess of fund category average and returns in excess of fund family average. To account for time-series variation in returns unrelated to investment behavior, we rank returns each month and run the regression in ranks. Table XII shows that funds persistently reaching for yield over the previous six months rank $6-8\%$ higher in the subsequent return distribution, but fall $1-2\%$ in the ranking for every one standard deviation increase in bond market stress. This suggests that unconditionally, managers seem to reach for yield to outperform their peers, but rebalance to avoid underperforming their peers in stress periods.

II.C. Mandate Reviews

In the previous subsection, we have argued that managers may reach for yield to pass mandate reviews and avoid termination. Anectodal evidence, also supported by our data on terminations, suggests that mandate reviews tend to occur at fixed intervals, and most often, at mandate anniversary dates. We exploit this institutional feature to formulate another test for career concerns: if managers reach for yield to pass mandate reviews, we would expect managerial reach for yield to be higher before, but not after, a mandate anniversary date. We test this hypothesis by running the following fixed effects regression:

$$\Delta Ytm_{f,t} = \alpha_t + \alpha_f + \sum_{k=-6}^{5} \beta_k \mathbb{1}_{t,k} + \epsilon_{f,t} \tag{15}$$

where the first two coefficients are time and fund fixed effects, and $\mathbb{1}_{t,k}$ is a dummy variable set to 1 whenever the fund is k months away from its mandate anniversary at time t. Month 0 is the omitted category, so that all β_k coefficients are normalized by the reach for yield at mandate anniversary. We test whether RFY in the months before $(k = -3, -2, -1)$ or after the anniversary $(k = 1, 2, 3)$ is different from zero. Figure 9 plots the β_k coefficients with

95% confidence intervals around the anniversary date. These coefficients show that reach for yield is indeed more pronounced in the months leading up to mandate anniversaries. A joint coefficient test confirms that $\Delta Ytm_{f,t}$ is larger in the three months before the mandate anniversary (F-statistic: 12.7, p-value: 0.0004) but not afterwards (F-statistic: 2.18, p-value: 0.1398).

II.D. Robustness

As highlighted by Goyal and Wahal (2008)), mandates are often terminated for reasons unrelated to the performance or the reach for yield ability of the manager. Fund investment strategies might fall out of fashion, asset management companies might be acquired or go out of business, or sponsors might shift their asset allocations. By omitting such factors, we might incorrectly attribute some of the terminations to managerial reach for yield. First, older funds are more likely to be terminated, but may also have a reduced ability or incentives to reach for yield if they follow outdated investment strategies or if the managers themselves are older and approaching retirement (Chevalier and Ellison (1999)). This might lead to a mechanical negative relationship between past reach for yield and future probability of termination in older funds. Second, termination decisions might be known by managers in advance, reducing their incentives to reach for yield. Finally, asset management companies may prematurely exit our sample due to mergers, acquisitions or closure. We address these issues and provide the results in the Supplementary Appendix. Table A6 replicates the reach for yield termination relationship for different fund age groups and shows that the relationship is pervasive across age groups. Table A7 replicates the reach for yield termination relationship allowing only for information available up to six months prior to the termination decision being communicated to BaFin. In Table A8 we rerun the reach for yield termination relationship removing all fund terminations occurring in a six months window (three months before and three months after) surrounding the date at which the parent asset management company exits the sample.[19] All our results are unchanged.

[19]A total of 16 asset management companies (Kapitalanlagegesellschaften - KAGs) exit our sample prematurely, and we observe the date at which this sample exit happens.

In sum, the results in this section confirm that fund managers act on implicit and explicit incentives to engage in pro-cyclical investment behavior.

VII. Conclusion

In this paper, we exploited a unique granular dataset to study the investment behavior of institutional funds, financial intermediaries which manage institutional investors' money. We documented that these institutional funds rebalance their portfolios in a strongly procyclical fashion: they increase their portfolio shares of higher-yielding, longer-duration, and lower-rated assets in response to lower interest rate spreads. We also showed that this investment behavior elicits price impact: controlling for other sectors' demand, the net bond purchases of institutional funds significantly raise bond prices for more than a year. The price impact of net sales is also significant but shorter-lived.

While we have provided some empirical support for explicit and implicit incentives for fund managers to engage in procyclical asset management, our results raise a number of issues for future research. First, we find that the investment behavior of institutional funds substantially differs from that in other sectors. Specifically, the liquidity that institutional funds demand in the process of purchasing higher-yielding securities is provided by the same sectors that also represent the main owners of institutional fund shares. The rationale behind the investment strategy at the level of ultimate ownership needs to be better understood.

Second, we documented that institutional funds increase the riskiness of their bond portfolios in response to lower interest rate spreads, and that bond purchases in turn drive up bond prices. This raises the potential for destabilizing feedback loops in which bond risk premia are driven to unsustainably low levels that can ultimately lead to sudden snap backs in interest rates (Morris and Shin (2016)). To what extent the documented institutional fund behavior contributes to such patterns and what this implies for financial stability and monetary policy transmission remain open questions.

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Figure 1: **Institutional Trading Patterns During the Bund Tantrum**

This chart plots the institutional trading pattern in German Bunds with residual maturities under 10Y, broken down by maturity, during the Bund market tantrum of April-June 2015. The institutional sectors considered are institutional funds, retail mutual funds, banks and insurance companies. Trades are defined as changes in the holdings of Bunds of each respective maturity, aggregated at the sectoral level, between the April 2015 and May 2015 reportings. The dynamics of the Bund zero-coupon Nelson Siegel Svensson smoothed yield curve, at two reference dates around the holdings reporting dates (April 21st marking Bill Gross' "short of a lifetime" tweet), are provided for reference. Aggregate outflows defined as fund units redeemed as a percentage of previous-period fund units outstanding. Holdings data from the German Securities Holdings Statistics. Outflow data from the German Investment Fund Statistics.

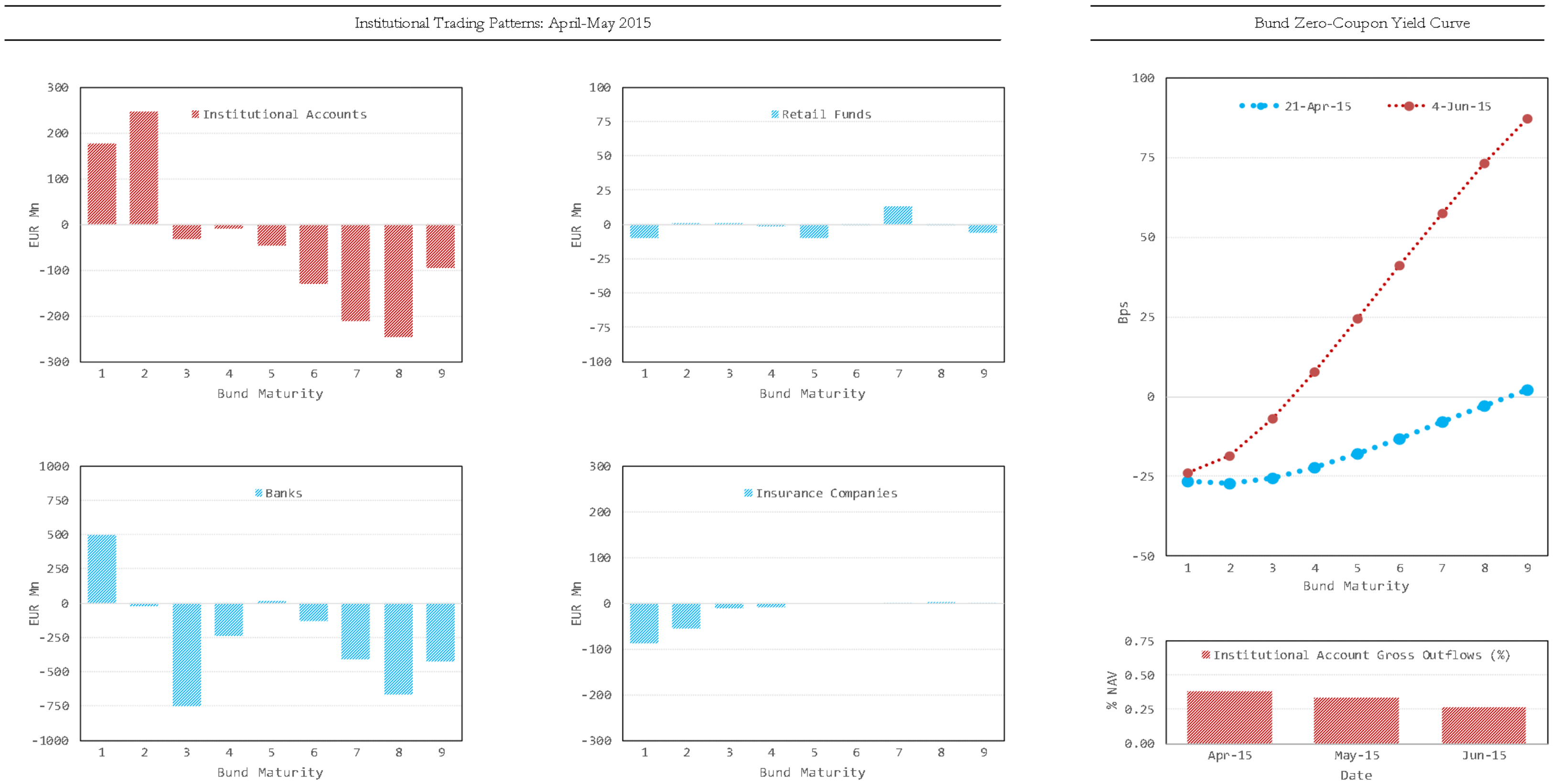
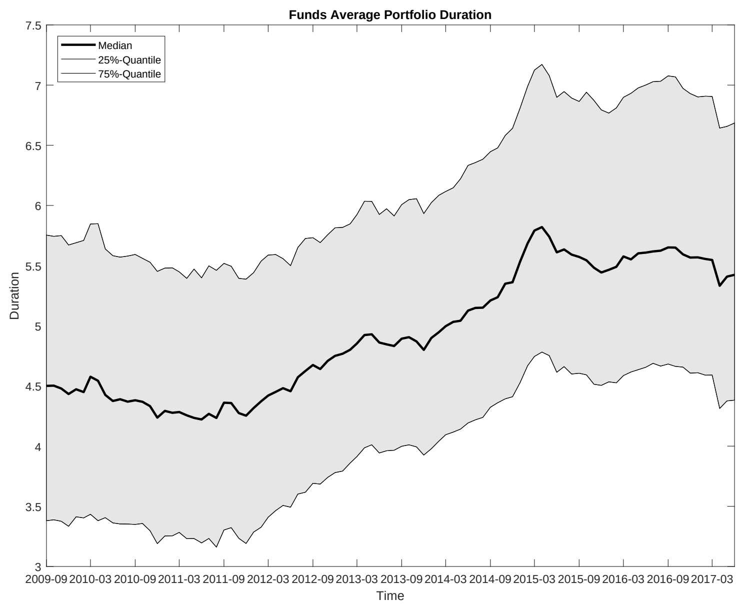


Figure 2: **Institutional Funds' Bond Portfolio Characteristics**

This figure illustrates the time series and cross-sectional distribution of institutional funds' portfolio average duration and ratings. For each fund, we define the portfolio average Macaulay duration as a weighted average of individual securities duration, weighted by their market value share in overall portfolio holdings. Similarly, we define the portfolio average rating as the weighted average of individual securities ratings, weighted by their market value share in overall portfolio holdings. At the security level, the asset rating refers to the best asset rating of four credit rating agencies (DBRS, Fitch, Moody's and S&P). Individual ratings are converted on a numerical scale from 1 to 24, where 24 is highest (AAA), following the Eurosystem Eligible Assets Database guidelines. Once aggregated, portfolio ratings are reconverted to an alphanumerical scale, using the S&P rating scale, for illustration. The black line plots the median fund. The shaded gray area plots the interquartile range of the fund distribution. Data at fund × month level. Data on securities holdings from the German Securities Holdings Statistics. Data on securities characteristics from CSDB.



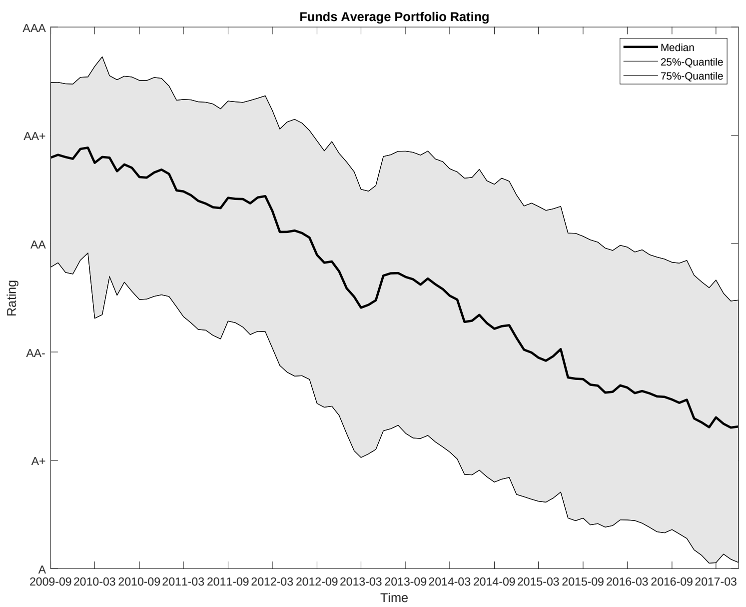


Figure 3: **Portfolio Rebalancing across Institutional Sectors**

This figure plots the distribution of fixed income holdings by Macaulay duration (upper panel) and credit rating (lower panel) for 4 different German institutional sectors and the market at two different points in time: December 2009 (sample start) and June 2017 (sample end). Each panel considers, in clockwise direction, the set of all corporate and sovereign bonds held by actively managed institutional funds, actively-managed retail funds, banks and insurance companies, respectively. The bottom-left chart plots the evolution of the bond market portfolio, defined as all corporate and sovereign bonds issued or held by European counterparties from CSDB. The bottom-right chart plots the distribution of fixed income holdings for institutional funds as deviations from the market portfolio. The rating refers the best asset rating of four credit rating agencies (DBRS, Fitch, Moody's and S&P), converted to the S&P rating scale. Data on securities holdings at institutional sector level from the German Securities Holdings Statistics. Data on securities characteristics from CSDB. Data on retail and institutional funds' characteristics from the German Investment Fund Statistics.

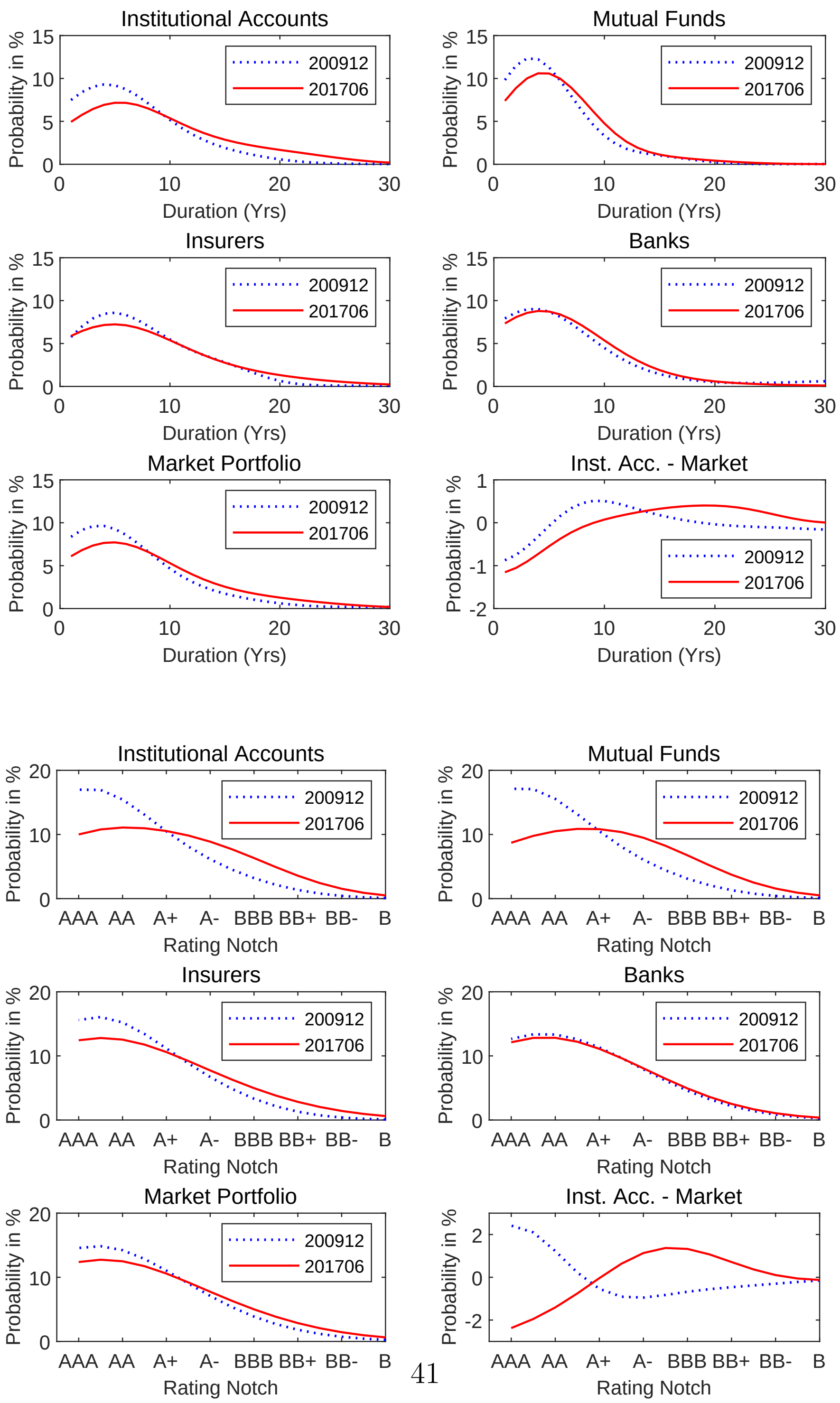
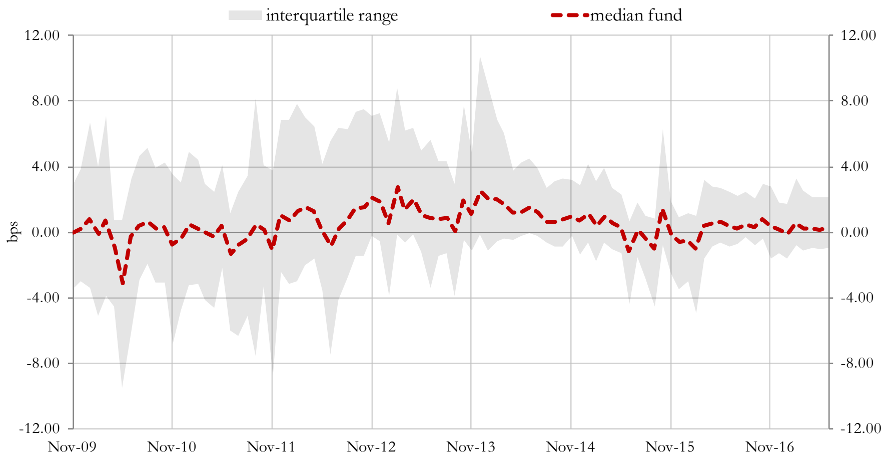
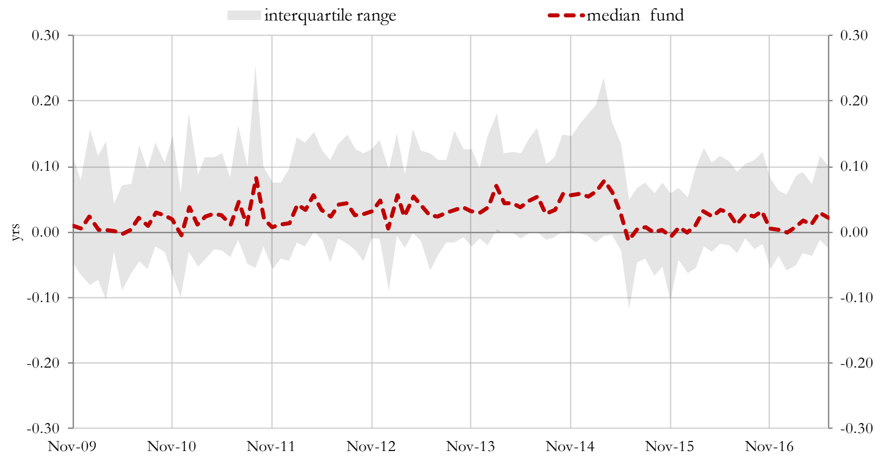


Figure 4: **Changes in Bond Portfolio Characteristics from Transactions**

This figure plots the time series and cross-sectional distribution of monthly changes in average portfolio yield to maturity (upper chart), Macaulay duration (middle chart) and rating (lower chart) arising from transactions. The sample refers to actively-managed, institutional German bond and mixed funds. Every period, we winsorize the distribution at 5% and 95% to control for outliers. The dotted lines follow the median fund. The shaded regions track the interquartile range. Data for the period Nov. 2009 - Jun. 2017.





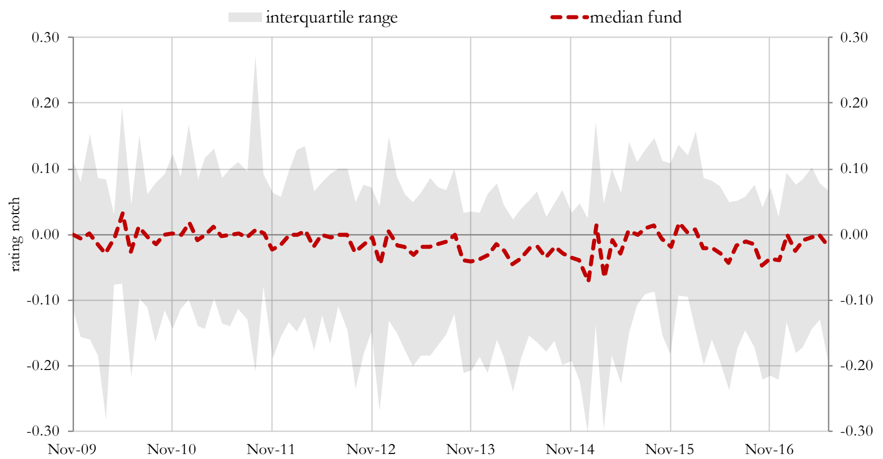
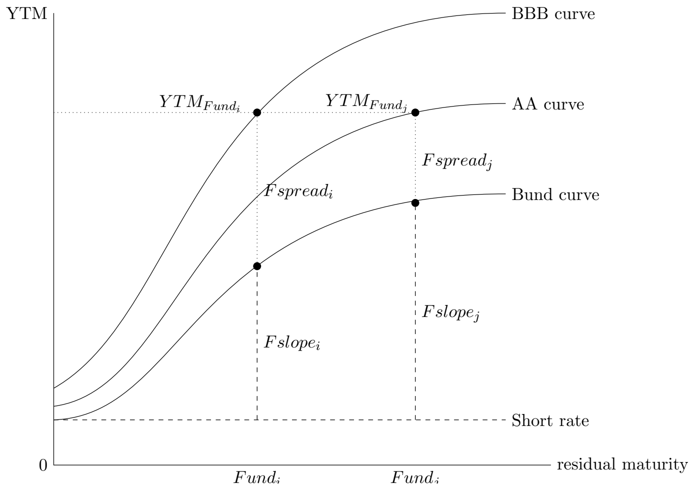


Figure 5: **Decomposing Funds' Portfolio Yield**

(A) This figure provides a stylized representation of our decomposition of a fund portfolio yield to maturity into three components: a short-term interest rate, a fund-specific interest rate spread ($Fslope$) and a fund specific credit spread ($Fspread$), for two hypothetical funds with an identical yield to maturity but different exposures to interest rate and credit risk. $Fspread$ is defined as the difference between a fund's portfolio yield to maturity and the yield to maturity on a portfolio of zero-coupon Bunds replicating the fund cashflows. The Fslope is the difference between the yield to maturity on the Bund replicating portfolio and the short rate.



(B) This figure plots the time series and cross-sectional distribution of our fund-specific measure of interest rate risk ($Fslope$) and credit risk ($Fspread$) against some commonly-used market benchmarks over the period November 2009-June 2017. The bottom panel plots funds' $Fspread$, defined as the difference between a fund's portfolio yield to maturity and the yield to maturity on a portfolio of zero-coupon Bunds replicating the fund cashflows, against the Euro-Area AA Corporate Bond option-adjusted yield spread to the Government from Bank of America Merrill Lynch. The top panel plots funds' $Fslope$, defined as the difference between the yield to maturity on the fund-specific Bund replicating portfolio and the 3m Bund rate, against the 5Y Bund slope, computed as the difference between the smoothed zero-coupon 5Y and 3m Bund rates. The dotted lines follow the median fund. The shaded regions depict the interquartile range. Figures are based on our sample of actively-managed institutional German bond and mixed funds. The frequency is monthly.

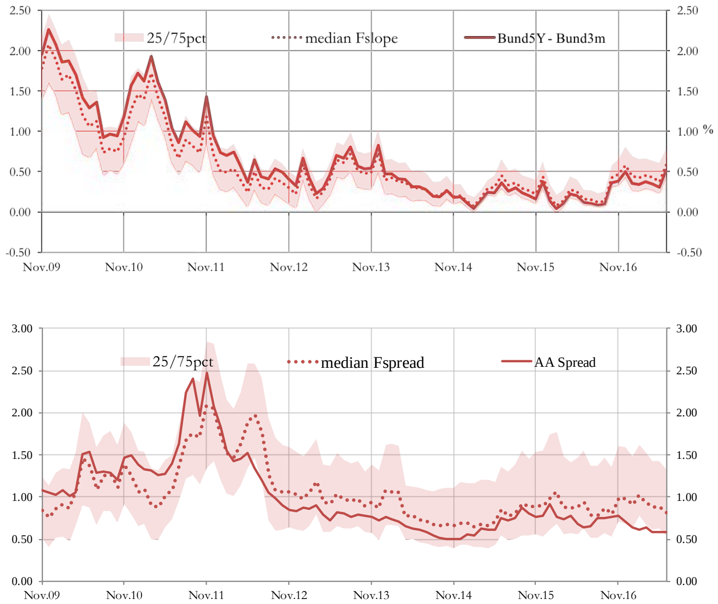


Table I: **Institutional Funds' Summary Statistics**

This table reports summary statistics for our sample of institutional funds. Outflows are defined as fund units redeemed as a percentage of previous-period fund units outstanding. Net flows are defined as the difference between fund units issued and redeemed, as a percentage of previous period fund units outstanding. Debt is defined as the difference between the fund's total assets and net asset value, where the net asset value is computed as the number of fund units outstanding × repurchase price per unit. The portfolio-averaged yield to maturity, duration and ratings are obtained, for each fund × month, by value weighting the individual bonds in the portfolio. The asset rating represents the best asset rating of 4 credit rating agencies (DBRS, Fitch, Moody's and S&P), converted to the S&P rating scale. Duration refers to the Macaulay duration. The number of bonds refers to those bonds for which accurate price and yield information exists. The sectoral breakdown (sovereign, financials and non-financial corporations) follows the European System of Accounts (ESA) 1995 for reportings prior to January 2015, and ESA 2010 thereafter. The data comes from the German Investment Fund Statistics.

Variable	N	P5	P50	P95	Mean	SD
Age (Yrs)	245230	0.75	8.76	21.10	9.68	6.56
Size (€mn)	245230	16.19	78.87	1068.50	294.35	1330.77
Netflows (%)	243949	0.00	0.00	2.68	0.72	11.33
Outflows (%)	243920	0.00	0.00	0.00	0.36	3.71
Debt/Assets (%)	245230	-0.01	0.00	0.00	0.00	0.52
Cash (%AUM)	245230	0.25	2.76	18.33	5.30	8.01
Derivatives(%AUM)	245230	0.00	0.00	1.41	0.40	2.39
Securities (%AUM)	245230	79.72	96.08	99.04	94.53	8.62
of which:						
Equities		0.00	0.00	39.60	9.79	15.09
Fund Shares		0.00	0.00	52.77	11.16	18.34
Bonds		34.08	83.94	100.00	78.99	22.46

Bond Portfolio Summaries

Variable	N	P5	P50	P95	Mean	SD
Sovereigns (% Total)	245230	0.00	35.20	100.00	39.06	31.56
Financials (% Total)	245230	0.00	45.46	94.82	46.42	26.18
Corporates (% Total)	245230	0.00	6.53	57.50	14.50	18.82
Ytm (% p.a.)	245230	0.13	1.75	4.25	1.93	1.46
Time-to-Maturity (Yrs)	245230	2.51	5.40	12.24	6.28	3.87
Duration (Yrs)	245230	2.43	4.92	8.98	5.31	2.62
Rating notches	242308	$BBB+$	$AA-$	AAA	$AA-$	1.88
No. bonds	245230	6	39	367	96.40	189.88

Table II: **Institutional Funds' Ownership Statistics**

This table reports the ownership structure of the German institutional fund sector. The ownership information comes from the German Securities Holdings Statistics. Single Sector Owned refers to funds 100% owned by a single domestic institutional sector, as defined in the German SHS. The difference between Total and Single Sector Owned refers to funds whose ownership is shared by two or more domestic or foreign institutional sectors. All of these funds are at least partially-owned domestically. Within the 710 fully-owned bank funds, one fund is jointly owned by two different bank types. This appears in Other Banks. Foreign Owned refers to funds 100% owned by a single foreign institutional sector. The sample is all active, open-ended bond and mixed German institutional funds. Data as of May 2017.

Sector	No. Funds	NAV (Euro Bn)
Total	2535	1032.9
Single Sector Owned	2223	899.8
Banks	710	112.4
Savings Banks	399	58.1
Cooperative Banks	225	35.1
Mortgage Banks	50	10.4
Other Banks	36	8.8
Pension Funds	334	167.4
Insurance Companies	320	385.4
Non-Financial Corp.	306	88.5
Non-profits	230	28.5
Investment Funds	170	87.3
Others	153	30.3
Foreign Owned	61	36.1

Table III: **Institutional Funds' Portfolio Rebalancing and the Yield Curve**

This table illustrates institutional funds' portfolio rebalancing in response to changes in the yield curve. ΔYtm is the portfolio-averaged yield change from current-period securities transactions. ΔYtm(P) is the component arising from purchases. ΔYtm(S) is the component arising from sales. ΔRat is the change in the portfolio-averaged credit rating from current-period transactions. ΔRat(P) is the component arising from purchases. ΔRat(S) is the component arising from sales. ΔDuration represents the change in a fund's average bond portfolio Macaulay duration due to current-period transactions. ΔDur(P) and ΔDur(S) are the components arising from purchases and sales, respectively. *Fspread* is a fund-specific risk spread computed as the difference between the average yield on a fund's bond portfolio and the equivalent-duration Nelson-Siegel Svensson zero-coupon Bund rate. *Fslope* is a fund-specific risk-free slope computed as the difference between the Nelson-Siegel Svensson zero-coupon Bund rate having the same duration as the fund's bond portfolio and the 3m zero-coupon Bund rate. The fund controls are log(fund age) log(fund size), log(fund family size), lagged cash share, lagged equities share, lagged derivatives share, lagged 1m and 6m average returns and 6m excess fund returns with respect to their fund family and fund class. We control for previous-period net flows. The sample is all active, open-ended, bond and mixed German institutional funds. All series are monthly and reported in percentage points. Standard errors are two-way clustered at fund and time levels. *t*-stats in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	ΔYtm	ΔYtm(P)	ΔYtm(S)	ΔRat	ΔRat(P)	ΔRat(S)	ΔDur	ΔDur(P)	ΔDur(S)
L.Fslope	-0.048***	-0.038***	-0.013***	-0.006	-0.010	0.008	-0.329***	-0.247***	-0.113***
	(-4.89)	(-3.36)	(-4.04)	(-0.88)	(-1.46)	(1.47)	(-11.52)	(-9.90)	(-4.65)
L.Fspread	-0.040***	-0.037**	-0.012***	0.030***	0.024***	0.014***	-0.012	-0.002	-0.007**
	(-3.00)	(-2.27)	(-8.22)	(7.45)	(6.95)	(5.24)	(-1.26)	(-0.19)	(-2.02)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.057	0.067	0.073	0.039	0.071	0.071	0.072	0.086	0.071
N	191120	179627	143695	183756	167443	131681	191120	179176	142954

Table IV: **Funds' Portfolio Rebalancing and the Yield Curve: Institutional vs. Retail Funds**

This table illustrates funds' portfolio rebalancing in response to changes in the yield curve. ΔYtm is the portfolio-averaged yield change from current-period securities transactions. ΔYtm(P) is the component arising from purchases. ΔYtm(S) is the component arising from sales. ΔRat is the change in the portfolio-averaged credit rating from current-period transactions. ΔRat(P) is the component arising from purchases. ΔRat(S) is the component arising from sales. ΔDur represents the change in a fund's average bond portfolio Macaulay duration due to current-period transactions. ΔDur(P) and ΔDur(S) are the components arising from purchases and sales, respectively. $Fspread$ is a fund-specific risk spread computed as the difference between the average yield on a fund's bond portfolio and the equivalent-duration Nelson-Siegel Svensson zero-coupon Bund rate. $Fslope$ is a fund-specific risk-free slope computed as the difference between the Nelson-Siegel Svensson zero-coupon Bund rate having the same duration as the fund's bond portfolio and the 3m zero-coupon Bund rate. RF is a dummy set to 1 whenever the fund is reported as retail. The fund controls are log(fund age) log(fund size), log(fund family size), lagged cash share, lagged equities share, lagged derivatives share, lagged 1m and 6m average returns and 6m excess fund returns with respect to their fund family and fund class. We control for previous-period net flows. The sample is all active, open-ended, bond and mixed German retail and institutional funds. All series are monthly and reported in percentage points. Standard errors are two-way clustered at fund and time levels. t-stats in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	ΔYtm	ΔYtm(P)	ΔYtm(S)	ΔRat	ΔRat(P)	ΔRat(S)	ΔDur	ΔDur(P)	ΔDur(S)
L.Fslope	-0.053***	-0.044***	-0.014***	-0.004	-0.006	0.009*	-0.342***	-0.270***	-0.109***
	(-5.58)	(-4.06)	(-3.99)	(-0.58)	(-0.94)	(1.72)	(-12.38)	(-11.09)	(-5.19)
L.Fspread	-0.042***	-0.039**	-0.012***	0.030***	0.025***	0.014***	-0.012	-0.003	-0.007**
	(-3.27)	(-2.51)	(-6.95)	(7.82)	(7.26)	(5.56)	(-1.35)	(-0.28)	(-2.07)
L.Fslope # RF	-0.021**	-0.020*	-0.004	-0.000	0.006	-0.005	-0.034**	-0.048***	0.003
	(-2.34)	(-1.94)	(-1.07)	(-0.03)	(1.17)	(-1.25)	(-2.58)	(-3.33)	(0.031)
L.Fspread # RF	-0.015	-0.022	0.006	0.003	0.001	0.003	0.000	-0.001	-0.004
	(-0.87)	(-1.05)	(1.04)	(0.51)	(0.11)	(0.57)	(0.04)	(-0.10)	(-0.74)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.067	0.079	0.086	0.041	0.071	0.076	0.069	0.083	0.072
N	228374	213313	171786	217813	197116	156010	228374	212816	171008

Table V: **Price Impact: Demand Pressures and Excess Bond Returns**

This table shows results from a security-level fixed-effects panel regression on the institutional fund-sector excess demand as a potential determinant for bond excess returns. The dependent variable is the 1m bond excess return, computed as the difference between the 1m bond holding period return and the 1m Bund rate. ExDem is a measure of institutional fund sector excess demand defined, for a given security, as the difference between gross fund sector purchases and gross fund sector sales, divided by the security's market value outstanding. LSV1992 is inspired by Lakonishok et al. (1992a) and defines excess demand, for a given security, as the ratio of total fund sector net monthly transactions to total fund sector gross monthly transactions. We control for the previous 3m bond excess returns, contemporaneous and lagged sectoral demands. Sector definitions are provided in the text. All series are monthly and reported in percentage points. We apply Huber-White standard errors. *t*-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

	Full sample	No zeroes	No zeroes
Variable	1m Excess Return	1m Excess Return	1m Excess Return
ExDem	0.041***	0.060***	
	(3.82)	(3.78)	
LSV1992			0.494***
			(12.60)
Exdem RF	0.069	0.151	0.236*
	(1.45)	(1.12)	(1.68)
Exdem CB	0.144***	0.152***	0.151***
	(6.58)	(6.02)	(6.01)
Exdem IC	-0.022	-0.009	0.000
	(-1.37)	(-0.48)	(0.01)
Exdem MFI	-0.001	-0.004	-0.003
	(-0.49)	(-0.75)	(–0.65)
Exdem MMF	0.079**	0.256***	0.148
	(2.47)	(4.73)	(1.32)
Exdem NFC	0.015	0.067	0.099
	(0.33)	(0.70)	(1.02)
Exdem PF	-0.090	-0.293	-0.422
	(-0.76)	(-0.74)	(-1.01)
Security FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Past demands	Yes	Yes	Yes
Past returns	Yes	Yes	Yes
R2	0.256	0.368	0.372
N	197714	105807	104693

Table VI: **Price Impact: A Panel Difference-in-Differences Analysis**

This table provides additional evidence on the contemporaneous price impact of fund-sector excess demand. We identify bonds issued in the same country by the same company, having the same issue-level rating and duration (in integer years) at some given time t. We assign such securities into groups, restricting attention to those groups with non-zero variation in fund excess demand. We then regress bond excess returns on fund sector demands, controlling for contemporaneous and lagged sector demands, lagged returns and group $\times$ time FE. The dependent variable is the 1m bond excess return, computed as the difference between the 1m bond holding period return and the 1m Bund rate. ExDem is a measure of fund-sector excess demand defined, for a given security, as the difference between gross fund-sector purchases and gross fund-sector sales, divided by the security's market value outstanding. Sector definitions are provided in the text. All series are monthly and reported in percentage points. We use Huber-White standard errors. t-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

	Full sample	Full sample	Full sample	$< 10Y$	$> 10Y$	Above BBB	BBB and under	Corporate	Sovereign	German sovereign
Variable	1m Excess Return	1m Excess Return	1m Excess Return	1m Excess Return	1m Excess Return	1m Excess Return	1m Excess Return	1m Excess Return	1m Excess Return	1m Excess Return
ExDem	0.045***	0.041***	0.056***	0.012	0.213***	0.046***	0.426***	0.054**	0.056**	0.068**
	(2.71)	(2.41)	(3.00)	(1.08)	(3.78)	(2.69)	(2.64)	(2.45)	(2.14)	(2.34)
ExDem RF	0.220*	0.162	0.219*	0.225*	0.024	0.246**	-1.028	0.195	0.447	0.483*
	(1.78)	(1.61)	(1.85)	(1.72)	(0.08)	(2.07)	(-1.22)	(1.50)	(1.81)	(1.87)
ExDem CB	0.245**	0.088**	0.100**	0.054	0.602*	0.100**	12.223	0.304*	0.063	0.064*
	(2.27)	(2.47)	(2.41)	(1.56)	(1.93)	(2.42)	(0.84)	(1.89)	(1.62)	(1.78)
ExDem IC	-0.079**	-0.096**	-0.098**	-0.062	-0.112**	-0.095**	-0.276	-0.109**	-0.025	-0.010
	(-2.29)	(-2.23)	(-2.39)	(-1.33)	(-2.02)	(-2.28)	(-0.96)	(-2.37)	(-0.43)	(-0.19)
ExDem MFI	0.006	0.007	0.006	0.000	-0.006	0.005	0.150	0.007	0.009	0.010
	(1.10)	(1.16)	(1.06)	(0.06)	(1.38)	(0.86)	(1.23)	(0.99)	(0.70)	(0.79)
ExDem MMF	0.057*	0.058*	0.099***	0.057**	-22.021	0.092***	0.122	0.052**	0.009	0.010
	(1.80)	(1.80)	(3.23)	(2.10)	(-0.46)	(2.97)	(1.48)	(2.40)	(0.70)	(0.79)
ExDem NFC	0.148	0.145	0.182	0.125	1.564	0.185	0.866	0.028	0.493*	0488*
	(1.50)	(1.36)	(1.45)	(1.03)	(1.43)	(1.45)	(1.25)	(0.20)	(1.91)	(1.84)
ExDem PF	0.187	0.061	0.158	0.506**	0.070	0.130	1.879*	0.176	0.022	0.230
	(1.54)	(0.45)	(1.09)	(2.45)	(0.14)	(0.92)	(1.82)	(1.04)	(0.07)	(0.66)
Group × Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past demands	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past returns	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.002	0.002	0.017	0.015	0.033	0.018	0.046	0.017	0.019	0.031
N	67217	61706	57604	50537	7067	53962	3642	38424	19183	10239

Table VII: **Price Impact Breakdown by Reach for Yield Quintile**

This table shows results from a fixed effects panel regression of bond excess returns on fund-level excess demand, broken down by RFY quintile. Each month, funds are ranked based on their contemporaneous RFY performance. Funds are then assigned into 5 quintiles. In the top panel, for each quintile, the excess demand measure is computed as net purchases from quintile i in security j at time t, divided by the security's nominal amount outstanding. In the bottom panel, the excess demand variable is further decomposed into buying and selling pressure, respectively. The buying variable equals the excess demand series when positive, and zero otherwise. The selling variable equals the excess demand series when negative, and zero otherwise. Price impact regressions are run separately for each RFY quintile, controlling for other sector demands, lagged quintile demands, lagged other-sector demands and lagged returns, time and security fixed effects. We use Huber-White standard errors. t-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively. For the top panel, the coefficients and associated confidence bands can be found in Figure 6

RFY quintile	Top	2	3	4	Bottom
ExDem	0.301**	0.182**	-0.008	0.200**	0.302**
	(2.33)	(2.28)	(-0.06)	(2.15)	(2.66)
Time FE	Yes	Yes	Yes	Yes	Yes
Security FE	Yes	Yes	Yes	Yes	Yes
Past demands	Yes	Yes	Yes	Yes	Yes
Past returns	Yes	Yes	Yes	Yes	Yes
R2	0.385	0.400	0.420	0.412	0.371
N	73281	65255	42635	45157	70296

RFY quintile	Top	2	3	4	Bottom
Buying	0.456**	0.327*	-0.074	0.238	0.198
	(2.24)	(1.76)	(-0.30)	(1.62)	(1.42)
Selling	0.112	0.166*	0.051	0.167	0.409**
	(0.87)	(1.83)	(0.28)	(1.24)	(2.16)
Time FE	Yes	Yes	Yes	Yes	Yes
Security FE	Yes	Yes	Yes	Yes	Yes
Past demands	Yes	Yes	Yes	Yes	Yes
Past returns	Yes	Yes	Yes	Yes	Yes
R2	0.385	0.400	0.420	0.412	0.371
N	73281	65255	42635	45157	70296

Table VIII: **Long-Term Price Impact: Top vs. Bottom RFY Quintile**

This table shows results from a set of local projections of future cumulative bond excess returns on current excess fund demand. For each security at time t, cumulative returns are computed by cumulating the 1m holding period returns over the next $h = [0, 23]$ periods. The cumulative returns are then annualized by multiplying by 12 and dividing by the holding period. We then compute cumulative excess returns by subtracting for each annualized cumulative return computed over time $t - t + s$ the annualized Bund zero-coupon rate of maturity s at time t. Each month, funds are ranked based on their contemporaneous RFY performance. Funds are then assigned into 5 quintiles. For each quintile, excess demand is computed as net purchases from quintile i in security j at time t, divided by the security's nominal amount outstanding. Price impact regressions are run separately for the top and bottom RFY quintile, at ever more distant horizons, controlling for other sector demands, lagged quintile demands, lagged other-sector demands and lagged returns, time and security fixed effects. We apply Huber-White standard errors. t-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Top Quintile	rx_t	$rx_{t,t+1}$	$rx_{t,t+2}$	$rx_{t,t+3}$	$rx_{t,t+6}$	$rx_{t,t+12}$	$rx_{t,t+23}$
ExDem_t	0.301**	0.387***	0.384***	0.350***	0.217***	0.100***	0.035
	(2.33)	(5.45)	(6.73)	(6.36)	(5.04)	(3.84)	(1.52)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Security FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past demands	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past returns	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.385	0.410	0.424	0.431	0.468	0.572	0.668
N	73281	69675	66292	63214	57203	39999	20441

Bottom Quintile	rx_t	$rx_{t,t+1}$	$rx_{t,t+2}$	$rx_{t,t+3}$	$rx_{t,t+6}$	$rx_{t,t+12}$	$rx_{t,t+23}$
ExDem	0.302**	0.152**	0.159**	0.113**	0.082*	0.029	0.008
	(2.64)	(2.17)	(2.44)	(2.01)	(1.95)	(0.80)	(0.30)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Security FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past demands	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Past returns	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.371	0.399	0.415	0.429	0.468	0.568	0.685
N	70296	66678	63227	60077	54087	37556	18634

Figure 6: **Price Impact Breakdown by RFY Quintile**

This figure plots mean coefficients and 95% confidence bands on the price impact of different RFY quintiles. Each month, funds are ranked based on their contemporaneous RFY performance. Funds are then assigned into 5 quintiles. For each quintile, the excess demand measure is computed as net purchases from quintile i in security j at time t, divided by the security's nominal amount outstanding. Price impact regressions are run separately for each RFY quintile, controlling for other sector demands, lagged quintile demands, lagged other-sector demands and lagged returns, time and security fixed effects. Confidence bands are constructed from Huber-White standard errors.

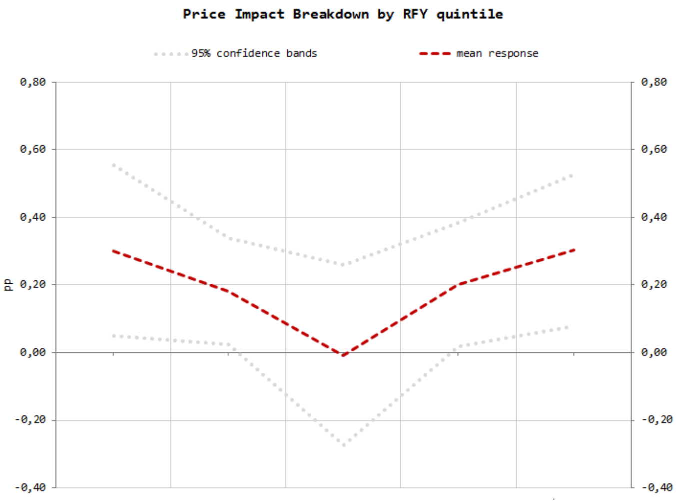


Figure 7: **Long-Term Price Impact: Top vs. Bottom RFY Quintile**

This figure plots mean coefficients and 95% confidence bands on a set of local projections of funds excess demand on cumulative bond excess returns. For each security at time t, we compute cumulative returns by cumulating the 1 month holding period returns over the next $h = [0, 23]$ periods. The cumulative returns are then annualized by multiplying by 12 and dividing by the holding period. We then compute cumulative excess returns by subtracting for each annualized cumulative return computed over time $t - t + s$ the annualized Bund zero-coupon rate of maturity s at time t. The regression controls for 1-period lagged demands, lagged excess returns, other sectors' demands, time and security fixed effects. Confidence bands are constructed from Huber-White standard errors.

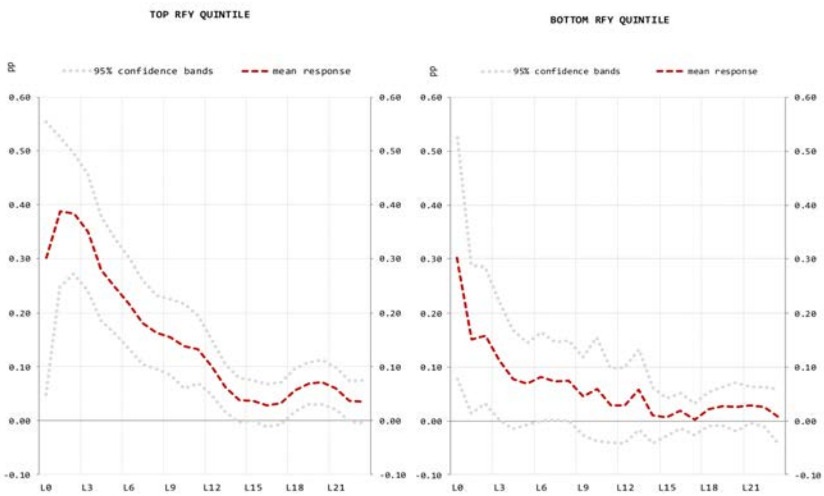


Table IX: **Explicit Incentives: Reach for Yield and Capital Guarantees**

This table reports results from a fixed effects panel regression on the relationship between institutional funds' reach for yield and zero-return guarantees in the context of negative yields. The dependent variable ΔYTM measures the fund portfolio yield change from current-period transactions. Share is the market value share of a fund's holding portfolio currently trading at negative yields. CP is a dummy variable taking the value 1 if a fund is capital-protected. The Fspread is the difference between a fund's portfolio yield to maturity and the yield to maturity on a portfolio of zero-coupon Bunds replicating the fund cashflows. *Fslope* is the difference between the yield to maturity on the Bund replicating portfolio and the 3m Bund rate. Duration refers to the fund portfolio average Macaulay duration, defined as a weighted average of individual securities duration, weighted by their market value share in overall fund portfolio holdings. Fund controls are lagged log(age) log(AUM), 6m lagged average returns and 6m excess fund returns with respect to their fund family and fund class. In all cases involving interaction terms, we control for the main effects in the regression. The sample period is 07/2012-06/2017. All series are monthly and reported in percentage points. T-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	ΔYTM	ΔYTM
L.Share	0.070***	0.067***
	(4.73)	(4.37)
L.Share # CP		0.049***
		(2.66)
L.Fslope	-0.213***	-0.213***
	(-8.76)	(-8.75)
L.Fspread	-0.081***	-0.081***
	(-3.59)	(-3.51)
L.Fslope # CP		-0.017
		(-0.78)
L.Fspread # CP		-0.004
		(-0.18)
L.Duration # CP		-0.000
		(-0.57)
Fund FE	Yes	Yes
Time FE	Yes	Yes
Fund controls	Yes	Yes
R2	0.036	0.036
N	124123	124123

Table X: **Implicit Incentives: Reach for Yield and Fund Flows**

This table shows results from a fixed effects panel regression on the relationship between past Reach for Yield and subsequent fund flows for three different samples: retail funds, institutional funds, and the joint sample. The dependent variable represents a fund net flow (inflows-outflows) as a percentage of last period net asset value. RankRFY is a continuous variable on [0,1], where the fund ranking highest in hypothetical Reach for Yield tournament ranks 1. Reach for Yield is defined as the change in portfolio yields from transactions. Stress is the Bond Market Composite Index of Systemic Stress (CISS), expressed in terms of historical standard deviations. Fund controls are lagged log(age) log(AUM), 6m lagged average returns and 6m excess fund returns with respect to their fund family and fund class. T-stats are reported in parantheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

	Retail		Institutional		Joint	
Variable	Flow	Flow	Flow	Flow	Flow	Flow
Rank RFY$_{t-6,t-1}$	0.041	0.185**	0.003	0.011	0.002	0.024**
	(1.22)	(2.47)	(0.90)	(1.28)	(0.39)	(2.33)
Rank # Stress$_t$		-0.079**		-0.005		-0.012***
		(-2.12)		(-1.20)		(-2.58)
Stress$_t$ (Bond CISS)		-0.214**		0.033***		0.022*
		(-2.20)		(4.25)		(1.85)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.051	0.051	0.102	0.102	0.056	0.056
N	37829	37829	198777	198777	233155	233155

Figure 8: **Reach for Yield and Mandate Termination: Supportive Evidence**

This figure maps the monthly probability of termination to the tendencies to reach for yield over the 6 months prior to termination in institutional funds. Each month, institutional funds are ranked based on their RFY performance. The most aggressive fund gets 1, the least aggressive 0. The monthly rank is then averaged across the 6 months prior to a fund termination. Funds are then split into 5 categories: top: funds with an average rank above 0.8, 2: average rank between 0.6 and 0.8, 3: average rank between 0.4 and 0.6, 4: average rank between 0.2 and 0.4 and 5: average rank below 0.2. The red triangles plot the observed average monthly probability of termination within each of the 5 average RFY categories. The shaded bars plot 95% confidence intervals, defined as +/- 1.96 the standard error of each category respective mean. Results based on 1,392 terminations from 212,225 fund × month observations.

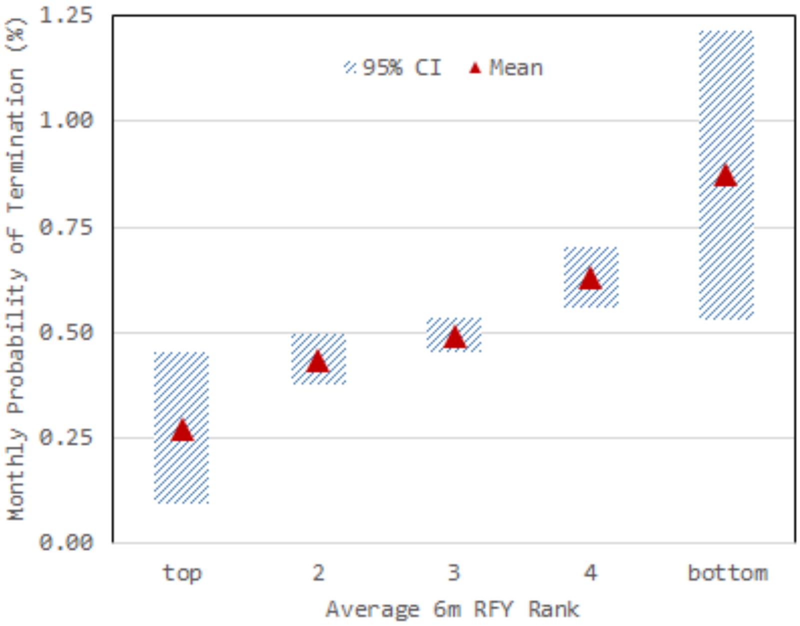


Table XI: **Funds' Reach for Yield and Mandate Termination**

This table reports results from a random effects panel probit model on the relationship between reach for yield and the probability of mandate termination for the sample of actively-managed, bond and mixed institutional funds. The dependent variable is a (0,1) dummy taking the value 1 if the fund will be terminated in the next period and zero otherwise. Rank RFY is the fund average RFY rank over the previous 6m. Rank Return is the fund lagged cumulative 6m gross return ranking. Rank RetFam is the ranking of the fund lagged cumulative 6m gross return in excess of the family average. All ranks are normalized [0,1], with 1 designating the best performing fund. Stress is the Bond Market Composite Index of Systemic Stress (CISS), expressed in terms of historical standard deviations. Reported figures are average marginal effects. Pseudo-R^2 is computed as the increase in the log-likelihood of the full model compared to the constant only model, divided by the log-likelihood of the constant only model. T-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	P(termination)	P(termination)
Rank RFY$_{t-6,t-1}$	-0.0052***	-0.0100***
	(-4.65)	(-3.94)
Rank # Stress		0.0027**
		(2.13)
Rank Return$_{t-7,t-1}$	-0.0024***	-0.0023***
	(-2.94)	(-2.87)
Rank RetFam$_{t-7,t-1}$	-0.0002	-0.0002
	(-0.27)	(-0.28)
Age	0.0000	0.0000
	(0.81)	(0.87)
ln(Fund Size)	-0.0013***	-0.0013***
	(-9.17)	(-9.14)
ln(Family Size)	-0.0008***	-0.0008***
	(-6.53)	(-6.50)
Mandate Anniversary	0.0015***	0.0015***
	(3.15)	(3.15)
Stress		-0.0013*
(Bond CISS)		(-2.04)
Pseudo R2	0.0172	0.0176
N	212225	212225

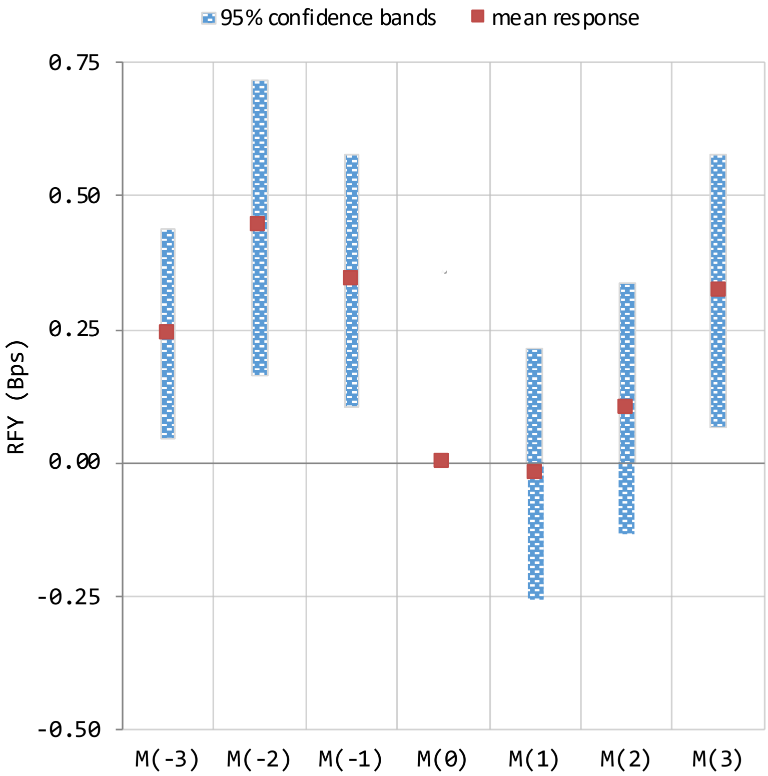
Table XII: **Reach for Yield and Future Returns**

This table reports results from a fund-level predictive regression of past reach for yield on future returns. The dependent variable are the fund 6m average return, 6m average return in excess of the family average, and 6m average return in excess of the category average, respectively. All returns are ranked within their respective categories (all funds if no category specified). Stress is the Bond Market Composite Index of Systemic Stress (CISS), expressed in historical standard deviations. Standard errors are clustered at the fund level. t-stats in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	Rank $Rt_{t+1,t+6}$	Rank $RtFam_{t+1,t+6}$	Rank $RtCat_{t+1,t+6}$	Rank $Rt_{t+1,t+6}$	Rank $RtFam_{t+1,t+6}$	Rank $RtCat_{t+1,t+6}$
Rank $RFY_{t-6,t-1}$	0.0792***	0.0637***	0.0693***	0.1108***	0.0867***	0.0844***
	(16.15)	(12.92)	(13.98)	(10.47)	(6.45)	(7.89)
Rank # $Stress_t$				-0.0181***	-0.0028	-0.0086
				(-3.35)	(-0.51)	(-1.57)
Rank $Rt_{t-6,t-1}$	-0.2012***	-0.0810***	-0.0308***	-0.2016***	-0.0811***	-0.0311***
	(-37.84)	(-15.15)	(-5.74)	(-37.91)	(-15.16)	(-5.78)
Rank $RtFam_{t-6,t-1}$	0.0119***	-0.0920***	0.0038	0.0121***	-0.0919***	0.0038
	(3.16)	(-24.20)	(0.98)	(3.20)	(-24.19)	(1.00)
Rank $RtCat_{t-6,t-1}$	0.1486***	-0.1189***	-0.0358***	0.1485***	0.1188***	-0.0359***
	(31.65)	(25.18)	(-7.55)	(31.63)	(25.17)	(-7.57)
$Stress_t$				0.0112***	0.0025	0.0070**
				(4.01)	(0.89)	(2.47)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.0107	0.0090	0.0046	0.0108	0.0091	0.0047
N	188667	188667	188667	188667	188667	188667

Figure 9: **Reach for Yield around Mandate Anniversaries**

This figure plots institutional funds reach for yield around mandate anniversary dates. The red squares plot the average month to month reach for yield, controlling for time and fund fixed effects, for funds × month observations in the 3 months before and after a mandate anniversary date (the β_k coefficients in equation 15). The blue bars plot 95% confidence intervals. The anniversary month is the omitted category (so the coefficient associated with month 0, β_0, is normalized to zero.)



Supplementary Appendix

Table A1: **Funds' Portfolio Rebalancing by Ownership**

This table replicates the results in Table III Column I separately for the 5 largest classes of institutional clients: banks, insurance companies, pension funds, non-financial corporations and non-profits. The regression specification (variable definitions, choice of controls and FE, standard error clustering options) follow exactly from column I of Table III. Standard errors are two-way clustered at fund and time levels. *t*-stats in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

	Banks	Insurance Companies	Pension Funds	Non-Fin. Corp.	Non-Profits
Variable	ΔYtm	ΔYtm	ΔYtm	ΔYtm	ΔYtm
L.Fslope	-0.050***	-0.025***	-0.046***	-0.046***	-0.035***
	(-6.82)	(-2.96)	(-4.26)	(-6.97)	(-5.15)
L.Fspread	-0.030***	-0.006	-0.043	-0.042***	-0.039***
	(-3.03)	(-0.31)	(-1.05)	(-3.15)	(-4.56)
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes
R2	0.009	0.006	0.009	0.012	0.013
N	58216	30706	27437	27493	20240

Table A2: **Funds' Portfolio Rebalancing and the Yield Curve: Robustness**

This table replicates the results in Table III Column I over several subsamples. Columns I-III split the overall sample (92 months) into three equal-sized subperiods (31/32 months each) and rerun the regression on each subsample at a time. Column IV shows the coefficients after removing outliers in the dependent variable (change in fund portfolio average yield from transactions - ΔYtm). Outliers are defined as ΔYtm observations lying below the 5th and above the 95th percentile of each month's ΔYtm cross-sectional distribution. Column V shows results for a subset of funds which have no exposure to equities. Finally, column VI reports coefficients from a specification with each fund × month observation weighted by the fund's net asset value. The regression specification (variable definitions, choice of controls and FE, standard error clustering options) follow exactly from column I of Table III. Standard errors are two-way clustered at fund and time levels. *t*-stats in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

	Nov.2009 - May.2012	Jun.2012 - Dec.2014	Jan.2015- Jun.2017	5-95% Winsorisa-tion	Equity-Free Funds	Value Weighted
Variable	ΔYtm	ΔYtm	ΔYtm	ΔYtm	ΔYtm	ΔYtm
L.Fslope	-0.094***	-0.158***	-0.116***	-0.017***	-0.049***	-0.038**
	(-7.02)	(-3.97)	(-11.04)	(-9.78)	(-3.25)	(-2.10)
L.Fspread	-0.091***	-0.084**	-0.108***	-0.010***	-0.033*	-0.020**
	(-13.72)	(-2.21)	(-12.85)	(-8.81)	(-1.76)	(-2.16)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
R2	0.119	0.131	0.102	0.126	0.057	0.058
N	62624	63904	64483	173014	104885	191120

Table A3: **Longer-Horizon Portfolio Rebalancing**

This table shows results from a set of local projections of funds' cumulative change in portfolio ratings on past changes in the term structure. $\Delta \text{Rat}_{t,t+h}$ is the fund h-period cumulative change in rating defined as the difference between the average rating on a portfolio formed at $t+h$ and evaluated at $t+h$ and the average rating on a portfolio formed at t and evaluated at $t+h$. The rating stands for the best asset rating of 4 credit rating agencies (DBRS, Fitch, Moody's and S&P), converted to the S&P rating scale (1 unit = 1 rating notch). Fspread is a fund-specific risk spread computed as the difference between the average yield on a fund's bond portfolio and the equivalent-duration zero-coupon Bund rate. Fslope is a fund-specific risk-free slope computed as the difference between the zero-coupon Bund rate of the same duration as the fund's portfolio duration and the 3m zero-coupon Bund rate. Further, two lags of Fslope and Fspread are included. All series are monthly and reported in percentage points. Standard errors are two-way clustered at fund and time levels. t-stats in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	$\Delta \text{Rat}_{t,t+1}$	$\Delta \text{Rat}_{t,t+3}$	$\Delta \text{Rat}_{t,t+6}$	$\Delta \text{Rat}_{t,t+9}$	$\Delta \text{Rat}_{t,t+12}$
L.Fslope	-0.012	-0.090*	-0.104	-0.061	-0.002
	(-1.34)	(-1.95)	(-1.66)	(-0.80)	(-0.03)
L.Fspread	0.004	0.058***	0.121***	0.149***	0.179***
	(1.37)	(5.37)	(6.63)	(7.28)	(7.63)
Fund FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
R2	0.045	0.071	0.117	0.156	0.196
N	175122	195494	193083	184554	174647

Table A4: **Funds' Portfolio Rebalancing Robustness: IV**

This table looks at the response of institutional funds portfolio rebalancing to plausibly exogenous changes in the term structure of interest rates via two-stage least squares. The procedure is as follows: In the first stage, we regress monthly changes in bund term spread (defined as the difference between the 5Y bund and the 3m Bund) on high-frequency identified ECB monetary policy communication shocks from Leombroni et al. (2018) and obtain predicted changes in the bund term spread. In the second stage, we regress (contemporaneously) changes in funds' RFY ($d\Delta YTM$) on the predicted changes in bund term spread. ΔYtm is the portfolio-averaged yield change from current-period securities transactions and d denotes first differences. The fund controls are log(fund age) log(fund size), log(fund family size), lagged cash share, lagged equities share, lagged derivatives share, lagged 1m and 6m average returns and 6m excess fund returns with respect to their fund family and fund class. T-stats are reported in parantheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	dΔYTM	dΔYTM
Δ Term Spread	-0.129***	-0.111***
	(-3.02)	(-2.85)
Fund FE	Yes	Yes
Controls	No	Yes
N	112112	104880

Table A5: **Reversal in Liquidity Providers' Inventories**

For every security i for which the institutional fund sector has been the only sector taking one side of the trade at a given time t, we identify all sectors taking the other side of the trade. We call these sectors liquidity providers, and we denote the total amount of liquidity provided $ExSup_{i,t}$. We then track, for each trade, the cumulative inventory changes of liquidity providers up to horizon h, denoted $ExSup_{t,t+h}$. This table shows results from a set of local projections of future cumulative inventory changes on current excess fund demand. Inventory regressions are run separately at ever more distant horizons, controlling for lagged other-sector demands, time and security fixed effects. We apply Huber-White standard errors. t-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

	$ExSup_{t,t+1}$	$ExSup_{t,t+2}$	$ExSup_{t,t+3}$	$ExSup_{t,t+6}$	$ExSup_{t,t+12}$
ExDem_t	-0.439***	-0.242	-0.006	-0.061	-0.093
	(3.40)	(1.41)	(0.05)	(0.54)	(0.92)
Time FE	Yes	Yes	Yes	Yes	Yes
Security FE	Yes	Yes	Yes	Yes	Yes
Past demands	Yes	Yes	Yes	Yes	Yes
R2	0.084	0.020	0.007	0.006	0.005
N	26446	25016	24220	21123	15745

Table A6: **Reach for Yield and Mandate Termination by Fund Age**

This table replicates the random effects panel probit model on the relationship between reach for yield and the probability of mandate termination (from Table X) separately over 4 fund age buckets: relatively young funds ($< 5Y$), young-mature funds ($5 - 10Y$), mature-old funds ($10 - 15Y$) and old funds ($> 15Y$). The dependent variable is a (0,1) dummy taking the value 1 if the fund will be terminated in the next period and zero otherwise. Rank RFY is the fund average RFY rank over the previous 6m. Rank Return is the fund lagged cumulative 6m gross return ranking. Rank RetFam is the ranking of the fund lagged cumulative 6m gross return in excess of the family average. All ranks are normalized [0,1], with 1 designating the best performing fund. Reported figures are average marginal effects. Pseudo-R^2 is computed as the increase in the log-likelihood of the full model compared to the constant only model, divided by the log-likelihood of the constant only model. T-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Fund Age	$< 5Y$	$5 - 10Y$	$10 - 15Y$	$> 15Y$
Variable	P(termination)	P(termination)	P(termination)	P(termination)
Rank RFY$_{t-7,t-1}$	-0.0021	-0.0062**	-0.0045*	-0.0087***
	(-1.01)	(-2.53)	(-1.74)	(-3.73)
Rank Return$_{t-7,t-1}$	0.0004	-0.0010	-0.0044**	-0.0048***
	(0.24)	(-0.57)	(-2.27)	(-3.05)
Rank RetFam$_{t-7,t-1}$	-0.0018	-0.0032*	0.0022	0.0012
	(-1.13)	(-1.82)	(1.30)	(0.80)
ln(Fund Size)	-0.0012***	-0.0018***	-0.0010***	-0.0012***
	(-4.63)	(-6.15)	(-3.38)	(-4.43)
ln(Family Size)	-0.0003	-0.0007***	-0.0008***	-0.0014***
	(-1.40)	(-2.95)	(-2.91)	(-5.33)
Mandate Anniversary	-0.0007	-0.0024*	-0.0016	-0.0025**
	(-0.64)	(-1.81)	(-1.27)	(-2.09)
Pseudo R2	0.0094	0.0098	0.0262	0.0267
N	59048	51575	44013	57587

Table A7: **Reach for Yield and Mandates Robustness: Anticipated Termination**

This table replicates the random effects panel probit model on the relationship between reach for yield and the probability of mandate termination (from Table XI) allowing only for information available up to 6 months prior to the termination decision being communicated to BaFin to explain the termination decision. Variable definitions follow from Table X. Reported figures are average marginal effects. Pseudo-R^2 is computed as the increase in the log-likelihood of the full model compared to the constant only model, divided by the log-likelihood of the constant only model. T-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	P(termination)
Rank $\text{RFY}_{t-12,t-7}$	-0.0034***
	(-2.98)
Rank $\text{Return}_{t-12,t-7}$	-0.0030***
	(-3.57)
Rank $\text{RetFam}_{t-12,t-7}$	-0.0001
	(-0.15)
Age_{t-6}	0.0000
	(0.95)
ln(Fund Size_{t-6})	-0.0010***
	(-6.74)
ln(Family Size_{t-6})	-0.0009***
	(-6.79)
Mandate Anniversary_{t-6}	0.0000***
	(0.02)
Pseudo R2	0.0137
N	192674

Table A8: **Reach for Yield and Mandates Robustness: Premature KAG Exit**

Asset management companies may prematurely exit our specialized fund sample due to mergers, acquisitions or closure. We identify 16 asset management companies (KAGs) which exit the sample prematurely and the date at which this sample exit happens, and then rerun the RFY termination relationship (from Table XI) removing fund terminations occuring in a 6 months window (3m before 3m after) around the date at which the parent asset management company exits the sample. Variable definitions follow from Table X. Reported figures are average marginal effects. Pseudo-R^2 is computed as the increase in the log-likelihood of the full model compared to the constant only model, divided by the log-likelihood of the constant only model. T-stats are reported in parentheses. ***,**, and * indicate statistical significance at the 1%, 5% and, 10% level, respectively.

Variable	P(termination)	P(termination)
Rank RFY$_{t-7,t-1}$	-0.0050***	-0.0099***
	(-4.54)	(-3.93)
Rank # Stress		0.0027**
		(2.16)
Rank Return$_{t-7,t-1}$	-0.0023***	-0.0023***
	(-2.92)	(-2.89)
Rank RetFam$_{t-7,t-1}$	-0.0003	-0.0003
	(-0.37)	(-0.39)
Age	0.0000	0.0000
	(0.53)	(0.50)
ln(Fund Size)	-0.0012***	-0.0012***
	(-9.09)	(-9.05)
ln(Family Size)	-0.0005***	-0.0005***
	(-4.10)	(-4.06)
Mandate Anniversary	0.0015***	0.0015***
	(2.60)	(2.59)
Stress		-0.0011*
(Bond CISS)		(-1.83)
Pseudo R2	0.0150	0.0155
N	211388	211388

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