Cyclical Investment Behavior across Financial Institutions *

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Abstract

This paper contrasts the investment behavior of different financial institutions in debt securities as a response to price changes. For identification, I use unique security-level data from the German Microdatabase Securities Holdings Statistics. Banks and investment funds respond in a pro-cyclical manner to price changes. In contrast, insurance companies and pension funds act counter-cyclically; they buy after price declines and sell after price increases. The heterogeneous responses can be explained by differences in their balance sheet structure. I exploit within-sector variation in the financial constraint to show that tighter constraints are associated with relatively more pro-cyclical investment behavior.

Keywords: Portfolio Allocation, Investment Behavior, Financial Markets, Debt Securities, Balance Sheet Constraints

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

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1 Introduction

Do all institutional investors exhibit similar investment behavior? Which institutions act as stabilizers and which act as amplifiers of shocks? What drives differences in behavior across financial institutions? To answer these questions, I explore a unique security-by-security holdings dataset provided by the Deutsche Bundesbank.

I present evidence that banks and investment funds respond pro-cyclically to price changes, i.e. they buy securities whose prices are rising and sell them when prices are falling. In contrast, insurance companies and pension funds are counter-cyclical investors, i.e. they buy when prices are falling and sell when prices are rising. In the baseline specification, I regress the percentage change in nominal holdings of the debt security of each sector on the lagged percentage price change of these securities, controlling for observed and unobserved time-invariant security characteristics as well as unobserved and observed time-specific factors. I find that a 10 percent price decrease in the last quarter is associated with a 1.4 percent and 3.6 percent reduction in the nominal amount held by investment funds and banks, respectively. In contrast, insurance companies and pension funds increase their nominal amount held by 4.3 percent when the price of a security dropped by 10 percent in the previous quarter.

This behavior may be attributed to differences in the fragility of the balance sheet structure of these sectors. This can be confirmed by exploiting within-sector variation in the balance sheet constraints. First, the pro-cyclical investment behavior is stronger for banks that are relatively less capitalized. Second, investment funds that face more outflows act more pro-cyclically relative to other investment funds. Third, the counter-cyclical investment behavior of insurance companies and pension funds is weaker when their negative duration gap rises.

I also present evidence that banks' and investment funds' balance sheet constraints tighten when they suffer losses on their security holdings. While losses on the security holdings of investment funds lead to outflows, banks' capital constraints tighten when they suffer losses on their security holdings. Since banks and investment funds are averse to tightening constraints and price changes exhibit a short-term momentum factor, pro-cyclical investment behavior can be rational. In contrast, the liability side of insurance companies and pension funds is relatively more stable and movements in their balance sheets are relatively orthogonal to economic and financial conditions. This makes insurance companies and pension funds more capable of absorbing losses on a short-term horizon and enables them to act in a counter-cyclical fashion.

The pro-cyclical investment behavior of investment funds and banks resulted in relatively mild losses on their security holdings during the European sovereign debt crisis. Although insurance companies and pension funds suffered severe losses on their security holdings during the sovereign debt crisis, they outperformed banks and investment funds in the medium term. More generally, while bond prices fall at short horizons after insurance companies and pension funds have bought them, they revert after several quarters, leading to larger capital gains in the medium run. In contrast, bond prices rise at short horizons after banks and investment funds have acquired them but fall in the medium run.

In order to shed light on these questions, security-level data is indispensable. In this paper I use unique, confidential security-by-security holdings data provided by the Deutsche

Bundesbank (the German central bank) covering the period from 2005 Q4 through 2014 Q4. This study is the first that uses security-level data of the German Microdatabase Security Holdings statistics for bank and non-bank financial institutions and their investment behavior in debt securities.[1] The holdings include both foreign and domestic as well as government and corporate securities. I contrast the buying behavior of the three largest groups of institutional investors: banks; investment funds; and insurance companies and pension funds. By examining the three sectors jointly, I can investigate the investment behavior of banks, investment funds and insurance companies and pension funds in the same security at a given point in time.

Theory yields a variety of predictions about the buying behavior of capital market participants. The standard efficient market hypothesis claims that asset prices must reflect all available information due to the existence of arbitrageurs (Fama, 1965; Friedman, 1953). While banks may be forced to sell undervalued assets due to margin calls, non-levered institutional investors may stabilize the market by buying up fire-sold assets in order to benefit from future price gains (Shleifer and Vishny, 1992). In contrast, it might also be rational to speculate on price increases so that prices can be pushed away from fundamentals (DeLong et al., 1990b; Abreu and Brunnermeier, 2003). However, despite its importance for macro-prudential policy and financial stability, empirical evidence on who is buying and selling as a response to price changes has been elusive due to a lack of granular data.

One contribution of this paper is to identify insurance companies and pension funds as counter-cyclical investors who "lean against the wind" by buying securities when prices are falling and selling them when prices are rising.[2] Due to the market clearing condition, for every pro-cyclical investor there needs to be a counter-cyclical investor who takes the other side of the trade. Said differently, for every buyer there needs to be a seller, and vice versa. Although the theoretical literature predicts rational arbitrageurs with "deep pockets" to behave counter-cyclically, empirical studies have failed to identify them.

The closest paper to this one is Abbassi et al. (2016), which shows that banks with trading expertise increased their holdings of debt securities with falling prices during the crisis relatively more than banks without trading expertise. In contrast to their paper, I distinguish the investment behavior of the entire banking sector to non-bank financial institutions, i.e. the investment fund industry and the insurance company and pension fund sector.

In addition, their analysis only sheds light on the relative investment behavior of trading banks versus non-trading banks, but remains silent about whether these institutions *actually* buy when prices fall. In contrast to Abbassi et al. (2016), I show not only whether certain sectors act relatively *more* counter-cyclically than do others, but also that insurance companies and pension funds *actually* buy securities when prices fall and sell securities when prices rise. In addition, instead of concentrating only on times of stress, I aim to generalize the cyclical investment behavior across time periods, verifying that it is robust during the crisis. While periods of high stress are certainly crucial for financial stability, normal periods are also important to consider as these are times when systemic

[1] Abbassi et al. (2016) and Buch et al. (2016) focus on banks' investment behavior in debt securities. Domanski et al. (2017) use aggregate data for German insurance companies and pension funds.

[2] I am not the first who uses the term in this context. Weill (2007) shows theoretically that market makers are "leaning against the wind" by providing liquidity in times of market stress.

risk builds up.

Security holdings of banks have received much attention recently.[3] However, there is little evidence on their trading behavior at the micro-level due to a lack of security-level holdings data. Micro-level evidence is crucial due to the heterogeneity in price dynamics of bonds depending on their security-level characteristics, such as the country and sector of issue, the maturity, or the credit rating.[4] In addition to showing that the banking sector as a whole acts pro-cyclically, I also exploit cross-sectional variation and show that the pro-cyclical behavior is stronger for banks that are relatively less capitalized. These results are consistent with models of limits to arbitrage due to capital constraints (Gromb and Vayanos, 2002; Shleifer and Vishny, 1997). However, it is at odds with Hanson et al. (2015) who model banks as patient fixed-income investors.

This paper also contributes to the investment fund literature. Fund managers may act with a short-term horizon due to agency frictions as they are exposed to injections and redemptions from investors (Chevalier and Ellison, 1997; Morris and Shin, 2015; Chen et al., 2010; Goldstein et al., 2015). While most papers focus on the relationship between performance and inflows, I investigate the investment behavior of investment funds. Many investment funds are measured on monthly or quarterly performance, which adds pressure to chase the market higher as it moves. Since fund managers may not be able to coordinate their selling behavior and have an incentive to time the market, it may be rational for them to trade pro-cyclically (Abreu and Brunnermeier, 2003). Consistent with this prediction, I provide empirical evidence that investment funds respond pro-cyclically to price changes. I also show that investment funds that face more outflows act relatively more pro-cyclically relative to other investment funds. Brunnermeier and Nagel (2004) similarly show that hedge funds that were not riding the tech bubble underperformed and suffered significant investor redemptions. My findings are also in line with the findings of Feroli et al. (2014) who show that a feedback loop between prices and sales of investment funds managers can emerge.[5] Since the pro-cyclicality seems to be existent in both upswings and downturns, delegated portfolio managers may generally increase market volatility and distort asset prices (Guerrieri and Kondor, 2012).

In contrast to the pro-cyclical investment behavior of banks and investment funds, I find that insurance companies and pension funds act counter-cyclically with respect to price changes. While this is consistent with the view that long-term investors should stabilize the market by acting in a contrarian way, this has not been shown empirically.[6] Most studies even point to pro-cyclical behavior of insurance companies and pension funds. The reason for that may be that most studies focus on how credit ratings affect the investment behavior of investment funds, and failing to specifically ask the question

[3]See e.g. Acharya et al. (2014), Acharya and Steffen (2015), Battistini et al. (2014), Gennaioli et al. (2014) and references therein.

[4]Again, a notable exception that uses security-level holdings data is Abbassi et al. (2016). While they do not show how the whole banking sector responds to price changes, my findings show that banks generally respond pro-cyclically to price changes.

[5]In addition, Shek et al. (2015) show that investment funds sell more when they face outflows. Raddatz and Schmukler (2012) also show that mutual funds' investment behavior tends to be pro-cyclical and thus not stabilizing; they reduce their exposure to countries in bad times and increase it during good times.

[6]My findings are consistent with an asset insulator model like in Chodorow-Reich et al. (2016). They show that usually stock prices of insurance companies do not drop when they suffer losses on their security holdings.

of whether they actually act pro or counter-cyclically (Ellul et al., 2011, 2015; Merrill et al., 2012). Becker and Ivashina (2015) show that insurance companies buy corporate bonds that are the highest yielding within each rating group as they are reluctant to hold more capital when they hold worse-rated bonds.[7] I find that counter-cyclical investment behavior is weaker in times when insurance companies' and pension funds' negative duration gap is larger. This suggests that a low interest rate environment may weaken the counter-cyclical behavior as it can result in larger duration gaps for insurance companies and pension funds. In addition, I present evidence that insurance companies and pension funds buy bonds whose excess bond yields rise. This supports the hypothesis that they are buy-and-hold investors and not averse to liquidity risk. In general, my results suggest that the investment behavior of insurance companies and pension funds can be a stabilizing force on the capital markets.

My results are consistent with intermediary asset pricing models. While in standard asset pricing models, households are the marginal investors and determine asset prices, see e.g. Campbell and Cochrane (1999), my results suggest that financial intermediaries can have asset pricing effects. My results are therefore consistent with frameworks where the marginal investors are financial intermediaries (Adrian and Boyarchenko, 2012; Brunnermeier and Pedersen, 2009; He and Krishnamurthy, 2013). These models have been, for example, tested by Adrian et al. (2011) and Adrian et al. (2010a).

However, my results also suggest that direct empirical tests of intermediary asset pricing models should not only take into account financial constraints of broker dealers but also of other financial intermediaries, such as investment funds and insurance companies and pension funds. For these institutions it is important that it is not necessarily the leverage ratio that determines asset prices. My results suggest that net outflows of investment funds and the duration mismatch of insurance companies and pension funds are potential risk factors that can be used for testing intermediary asset pricing models.

My results are also consistent with leverage cycle theories in the spirit of Adrian and Shin (2010, 2014). In particular, my finding that banks act pro-cyclically and even more so when they are more capital constrained is in line with these leverage cycle theories. When banks suffer losses on their security holdings, this tightens their constraints and induces them to sell securities whose prices have fallen. On the other side, when banks experience gains on their security holdings, their constraints loosen which makes them buy securities whose prices have increased. This investment behavior can again have an impact on prices and therefore their constraints.[8]

Lastly, my results are also consistent with models of limits to arbitrage due to capital constraints (Gromb and Vayanos, 2002; Shleifer and Vishny, 1997) and theories where banks are acting pro-cyclically (Hanson and Stein, 2015; Shleifer and Vishny, 2010). In contrast, my results are at odds with models where banks are risk absorbers, see for example Hanson et al. (2015), where banks are modelled as patient fixed-income investors.[9] My findings are also inconsistent with theories that model less levered institutions as stabilizing (Shleifer and Vishny, 1992). I find that that less levered institutions do not

[7]Other studies that indicate that insurance companies and pension funds act pro-cyclically are Acharya and Morales (2015); Domanski et al. (2017); Duijm and Steins Bisschop (2015); Haldane (2014).

[8]The framework by Geanakoplos (2010) is also consistent with my findings.

[9]However, one difference to Hanson et al. (2015) is that they focus on the holdings of securities by financial institutions while I investigate their trading behavior.

necessarily act as a stabilizing force. While even non-levered institutions such as mutual funds can exacerbate price dynamics and amplify financial cycle dynamics, insurance companies and pension funds act in a stabilizing fashion.

The paper is structured as follows. In section 2, I describe the data. Section 3 presents the main empirical findings on the heterogeneous investment responses of financial institutions to price changes. Section 4 shows that a balance sheet channel is at work by showing heterogeneous responses within each sector dependent on the institutions' balance sheet constraints. Section 5 discusses the dynamics of price changes. In section 6, I conduct additional robustness tests. Section 7 concludes.

2 Data

2.1 Data Description

The Microdatabase Securities Holding Statistics of the Deutsche Bundesbank's Research Data and Service Centre of the Deutsche Bundesbank provides quarterly security-by-security-level holdings data of all investors based in Germany from 2005 Q4 onwards. The data includes the raw, nominal and market value of each security. The institutions report the raw value of the security holdings to the Deutsche Bundesbank, which subsequently calculates the nominal and market value. The raw value is the nominal value held in the currency of denomination. The nominal value is the notional amount of security holdings and does not reflect price movements. The market value is the number of securities held multiplied by the price.[10] The price that is used to calculate the market value of the security is gathered from the Centralised Securities Database (CSDB) and reflects the market price of the security at the end of the quarter. I use this price for the rest of my analysis. ΔPrice is calculated by taking the difference of the log of the price.

The security is identified with the International Security Identification Number (ISIN). Information about the currency of denomination, the security classification and the issuing sector of the security is also available. The holdings are further split up by the sector that is holding the security. The largest holding sectors are banks, investment funds and insurance companies and pension funds, followed by non-financial corporates and households. While this dataset contains information about the sector that is holding the security, it does not specify which institution within the sector is holding it.

However, I also use the institution-level security-level holdings data and balance sheet information for all banks in Germany for the same time period from the Microdatabase Securities Holding Statistics and the monthly bank balance sheet statistics, respectively. For investment funds, I use institution-level security-holdings data and balance sheet data from the investment fund statistics of the Deutsche Bundesbank. However, the institution-level security-holdings data is only available from the end of 2009. For insurance companies and pension funds the institution-level security-holdings data is not available. For a detailed data description of the Microdatabase Securities Holding Statistic see Amann et al. (2012) and Bade et al. (2016).

In order to harmonize the analysis for all three sectors, I use sector-level data for my main analysis. In addition, I only consider the three largest sectors: banks; investment

[10] The nominal value needs to be adjusted to reflect only investment decisions (see Appendix).

funds; and insurance companies and pension funds. I also restrict my analysis to debt securities and discard any equity security holdings.

I download additional security-specific characteristics from Bloomberg and Datastream. The yield refers to the yield-to-maturity. The credit rating is the S&P rating if available and the Fitch rating otherwise. Investment grade rating is defined as a rating better than BB+. For parts of the analysis, the data provided by the Deutsche Bundesbank is merged with publicly available data. The country-specific 10-year generic government bond yield, the consumer price index and GDP are from the IMF. I obtain GDP growth and the inflation rate by taking the natural log change of GDP and the consumer price index. If GDP is not available quarterly, I interpolate the annual value linearly. The VIX is the log of the implied volatility for S&P 500 stock options and is obtained from the Chicago Board Options Exchange and downloaded through Datastream. The EONIA is from the ECB. The country-specific variables are merged with the first two characters of the ISIN code. This is consistent with the nationality and not the residence principle and accounts for offshore issuance of securities.

2.2 Summary Statistics and Stylized Facts

Table 1 shows the summary statistics of the main variables. The average value of a security held is 22.6 million Euros for insurance companies and pension funds, 31.8 million Euros for investment funds and 57.6 million for banks. Insurance companies and pension funds, which hold a significantly smaller quantity of securities, are the smallest group of debt security holders among the three sectors. Insurance companies and pension funds not only hold fewer securities, but they also trade less. However, when they do trade, they transact larger volumes than do investment funds. Investment funds are the most active traders among the three; the number of observations for buy and sell outstrip those for banks and insurance companies and pension funds. On average, the amounts they trade are smaller than those of banks and insurance companies and pension funds. This is also true for the percentage changes in their holdings. When investment funds trade, they increase their holdings on average by 22 percent and reduce their holdings on average by 21 percent. The numbers for banks and insurance companies and pension funds are larger. Banks increase their holdings on average by 37 percent and reduce their holdings by 41 percent. Insurance companies and pension funds change their holdings on average by 31 percent. The standard deviation of the netbuy variable also suggests that investment funds transact smaller amounts than do banks and insurance companies and pension funds. The standard deviation is 43 percent for for investment funds compared to 67 percent for insurance companies and pension funds and 81 percent for banks. Lastly, while the average price change is close to zero, the standard deviation of the price change is 4 percent.

Figure 1, Figure 2 and Figure 3 show the holdings of debt securities of the three sectors over time. Banks are the largest holder of debt securities, followed by investment funds and insurance companies and pension funds. While banks increased their security holdings before the beginning of the financial crisis, they have since reduced their security holdings significantly (Figure 1). In contrast, non-bank financial institutions such as investment funds and insurance companies gained more importance in the provision of market-based funding. Although investment funds built up their security holdings over time they were selling securities during the sovereign debt crisis (Figure 2). In contrast, insurance companies and pension funds were building up debt securities even between 2010 and 2012 (Figure 3).[11]

The active selling behavior of banks and investment funds in the crisis paid off in the short run, as can be seen from Figure 4. The capital gains on their debt security portfolios were positive before dropping into negative territory in mid-2010, but still without major losses. Insurance companies and pension funds, however, suffered severely when their bonds fell in value during the crisis, but their medium-term strategy paid off when prices began to recover. Between mid-2011 and the end of 2014 capital gains on their debt securities have been nearly 30 percent. They have outperformed banks and investment funds not only since mid-2010, but also since the beginning of the financial crisis. While insurance companies and pension funds kept buying securities during the crisis, temporarily suffering losses, they outperformed the other two sectors in the medium run. This is in line with the statement by Matteo Renzi, at that time Italy's prime minister, to the Italian Senate on February 17, 2016:

> "Let me say that if some northern European lenders had kept their Italian government debt in 2011-2012, they would be earning much more."

However, holding or even increasing the holdings of securities that have performed poorly can be a risky strategy as bond prices tend to continue their trend for several quarters before price trends reverse (Cutler et al., 1991, 1990; Moskowitz et al., 2012). Although the selling behavior that Matteo Renzi stresses has been formally rationalized by DeLong et al. (1990b), not every investor can take the same side of a trade. Due to the adding-up constraint, someone has to buy the securities when their prices fall and others are selling them.[12] The above results suggest that insurance companies and pension funds have been the institutions that tried to "catch the falling knife". However, these stylized facts only show simple aggregated numbers that can be influenced by other factors. In the next section I turn to a security-by-security analysis to test the systematic investment behavior of the different sectors more formally.

3 Main Results

I attempt to shed light on the question of which institutions act pro-cyclically or counter-cyclically by investigating how their investment decisions depend on price changes. My regression is in the spirit of Abbassi et al. (2016), but instead of comparing trading banks to non-trading banks, I compare insurance companies and pension funds to banks and investment funds. I treat insurance companies and pension funds as my benchmark and define a dummy *Banks* that equals one for banks and zero otherwise. The second dummy *Funds* takes a value of one for investment funds and zero otherwise. I regress the percentage increase in the nominal amount held by each institution on the interaction of the respective dummies with the price changes. The coefficients on the interaction terms show how much more pro-cyclically banks and investment funds act compared to insurance companies and pension funds. I estimate the following specification:

[11] For the portfolio composition of the three sectors see Table A1.

[12] DeLong et al. (1990b) call them "passive investors".

$$Netbuy_{i,s,t} = \beta_1 \Delta Price_{s,t-1} * Funds_i + \beta_2 \Delta Price_{s,t-1} * Banks_i + \alpha_{s,t} + \alpha_{i,t} + \alpha_{i,s} + \epsilon_{i,s,t} \quad (1)$$

The results are shown in column (6) of Table 2. Netbuy is the change in the log of the nominal amount held of security s at quarter t given the institution trades.[13] ΔPrice is the change of the log price of the security.[14] The price change at time t reflects the change in the price from the end of quarter $t-1$ until the end of quarter t. I lag ΔPrice by one quarter in order prevent contamination of my results by the possibility that trading decisions have a price impact.[15] In addition, this allows me to rule out the possibility that trading decisions are executed before the institution observes the reported price.[16]

In this specification I also include security∗time, sector∗time and security∗sector fixed effects. The inclusion of security∗time fixed effects controls for all time-variant and time-invariant security-specific characteristics so that a separate security fixed effect is spanned by the security∗time fixed effect. This specification allows me to draw conclusions about the investment behavior in one specific security at a given point in time. For instance, a positive correlation between the error term and the change in the price leads to an overestimation of the price change coefficient. Comparing banks and investment funds to insurance companies and pension funds allows me to control for unobserved and observed time-varying security characteristics. The additional inclusion of sector∗time fixed effects controls for time-variant and time-invariant sector-specific characteristics. By controlling for sector∗time fixed effects, I can confirm that results hold if I control for the amount invested by the specific sector at a given time. Lastly, I saturate the specification with security∗sector fixed effects to control for observed and unobserved preference of the three sectors for specific securities.

Column (6) shows that both banks and investment funds invest more pro-cyclically in response to price changes than do insurance companies and pension funds (Table 2). A 10 percent price increase of a security is associated with a 8.6 percentage point stronger increase by banks and a 4.3 percentage point stronger increase of the nominal position by investment funds relative to insurance companies and pension funds. As can already be seen from the interpretation of the results, the disadvantage of including security∗time fixed effects is that I can only make statements about whether the sectors trade more or less pro or counter-cyclically to price changes relative to insurance companies and pension funds and not whether they actually buy or sell.

Columns (1)-(3) exclude the security∗time fixed effects. Excluding security∗time from the specification relaxes the restrictions that at least two sectors need to trade the se-

[13]The netbuy measure reflects only buy and sell decisions and no valuation effects. The results are robust to the use of other netbuy measures. For instance, the results do not change qualitatively whether I use the log of the amount bought minus the log of the amount sold or the amount in Euros. The results are also robust when I use buy and sell separately instead of using a netbuy measure. The results are also robust when hold decisions are included.

[14]The results are robust to the inclusion of higher lags of the price change as well as price changes of a lower frequency.

[15]In this case the change in the price and the decision to buy or sell may be jointly determined.

[16]If I included the contemporaneous price change, trading decision could have been executed any time during the quarter t, although the price change I am using in my regression has not been observed as it is the price change from the end of quarter $t-1$ until the end of quarter t. Therefore, unless the trading decision is always executed at the last point of the quarter, the contemporaneous independent variables may be observed only after the decision to transact is taken.

curity at a given point in time. The exclusion of the security$*$time fixed effect implies that the level of the price change is identified as it is no longer collinear with the fixed effects. The interpretation of the level of the price change coefficient is the response of insurance companies and pension funds to price changes. Column (3) of Table 2 shows that a 10 percent increase in the price is associated with a 4.3 percent decrease of the nominal amount held by insurance companies and pension funds. The interaction of the price change with the dummy *Funds* shows that investment funds increase their nominal holdings by 5.7 percentage points percentage more, i.e. they increase their holdings by 1.4 percent. The interaction of the price change with the dummy *Banks* shows that banks increase their holdings by 7.9 percentage points more than insurance companies and pension funds, i.e. they increase their holdings by 3.6 percent. Column (2) and (3) are equivalent to splitting the sample and estimating the equation separately for banks, investment funds and insurance companies and pension funds. This also allows testing the null hypothesis whether institutions do not respond to price change against the alternative hypothesis that they change their holdings in response to price changes. This is in contrast to Table 2 where I test whether institutions change their holdings differentially in response to price changes.

Therefore, the following specification can be estimated:

$$Netbuy^{X}_{s,t} = \beta_1 \Delta Price_{s,t-1} + \alpha_s + \alpha_t + \epsilon_{s,t} \tag{2}$$

X represents investment funds, banks or insurance companies and pension funds. Columns (1) and (2) show the results for when X equals investment funds; columns (2) and (3) are for insurance companies and pension funds; columns (5) and (6) show the results for banks. Again, α_s is a security fixed effect that controls for security-specific characteristics that are time-invariant. The inclusion of security fixed effects controls for the fact that different securities have different time-invariant characteristics, such as the expiration date or the coupon. It also enables me to analyze the investment behavior in a specific security over time, which circumvents the issue that the number of securities outstanding in the economy can change.[17] α_t is a time fixed effect that controls for market-wide development. As I split the equation into three parts the security fixed effect as well as the time fixed effects are sector-specific. This is equivalent to the sector$*$time and sector$*$security fixed effect in Table 2.

Table 3 shows the estimation of equation (2) sector by sector. Investment funds and banks buy securities whose prices have risen and sell securities that have lost value, i.e. they have an upward sloping demand curve. In contrast, insurance companies and pension funds buy when prices have fallen and sell when prices have risen.[18] The inclusion of time fixed effects implies that aggregate time-specific characteristics that affect the investment behavior are discarded. For instance, when banks sell securities when prices fall, if this is also the time when their funding dries up or they have to de-lever, this would not capture pro-cyclical behavior due to the time fixed effects. On the other side, when insurance companies and pension funds increase their holdings in general in times when prices fall, this would not be captured in a specification with time fixed effects. Including time fixed effects might somewhat overcontrol some of the effects. Instead of showing how much

[17]See appendix for details.

[18]In the working paper version of the paper I show the response of the various institutions to macro-financial variables, see Timmer (2016).

insurance companies and pension funds actually buy when prices fall, it rather shows how much is bought of securities whose prices decreased relatively more than those of other securities.

Therefore, Table 3 also shows the results without time fixed effects. The effects are again statistically and economically highly significant. A two standard deviation increase in the price (7.4 percent) is associated with 2.52 percent increase in the nominal holdings for banks, 0.78 percent for investment funds and a 6.29 percent decrease for insurance companies and pension funds. These magnitudes add up to an increase of 1.45 million Euros for banks, 0.25 million for investment funds and 1.42 million decrease for insurance companies and pension funds.[19] The counter-cyclical investment behavior of insurance companies and pension funds offsets almost completely the pro-cyclical investment behavior of banks and investment funds, although the security holdings of banks and investment funds are significantly larger than those of insurance companies and pension funds.

The results above indicate that banks and investment funds act like positive feedback investors who "buy securities when prices rise and sell when prices fall" (DeLong et al., 1990b). Since insurance companies and pension funds have "deep pockets" they may be able to trade against them (DeLong et al., 1990a).[20] The investment behavior of banks and investment funds might be rational for several reasons. In the next section, I empirically investigate one potential channel that could generate these findings, a balance sheet channel.

4 Balance Sheet Constraints

4.1 Balance Sheets and Investment Behavior

The pro-cyclical investment behavior of banks and investment funds could be explained by their unstable balance sheet composition. I test this channel by exploiting cross-sectional heterogeneity within the banking and investment fund sector. This within-sector heterogeneity confirms that institutions with tighter constraints act in a more pro-cyclical way to price changes. In particular, banks with tighter capital constraints and investment funds with more outflows act relatively more pro-cyclically. The constraints of banks and investment funds also tighten when the institutions suffer losses on their security holdings. Since price changes exhibit a momentum factor at short horizons and banks and investment funds are averse to short-term losses, the pro-cyclical investment behavior of banks and investment funds may be rational.

In contrast, insurance companies and pension funds have long-term liabilities so that they are not exposed to redemption pressure. While insurance companies and pension funds act relatively less counter-cyclically in times when their negative duration gap rises, the duration gap does not seem to be related to losses on their security holdings.[21] The benefit of a more stable balance sheet may explain why insurance companies and pension

[19] It is important to stress that these numbers are for a single security. Given that the institutions hold several thousands of securities, the results sum up to even larger aggregate numbers.

[20] Insurance companies' and pension funds' investment behavior is consistent with passive investors in DeLong et al. (1990b).

[21] Chodorow-Reich et al. (2016) show that stock prices of insurance companies in the US are usually not sensitive to losses on their security holdings.

funds are acting in a counter-cyclical manner and can benefit from buying securities whose values have fallen.

Before I empirically link the institution's balance sheet constraints to their investment behavior, I lay out the balance sheet structure of the institutions under investigation and discuss the balance sheet channel hypothesis in greater detail.[22]

4.1.1 Banks

Figure 5 shows different categories of the aggregated balance sheet of German banks proportionally. The total size of the balance sheets amounted to 7.85 trillion Euros in 2014, which is around 270 percent of Germany's GDP (2.9 trillion Euros in 2014). The liability side mainly consists of retail and wholesale deposits. Only 382 billion Euros, approximately 5 percent, are equity capital. Both retail and interbank borrowing are short-term liabilities that can be withdrawn without an extended period of notice.[23]

When creditors refuse to roll over their debt or actively withdraw their funds, the asset side needs to be reduced in order to service the liabilities. The asset side of banks mainly consists of longer-term assets, such as debt securities and loans. When funding liquidity dries up, banks start by reducing their most liquid assets, such as cash and excess reserves at the central bank. As these contribute only a small amount to the aggregate balance sheet and banks are unable to call in loans, debt securities need to be sold. If the liquidity dryup is systemic and non-specific to a single bank, banks may have trouble finding a buyer for the securities, forcing them to sell them below their fundamental value, what is known as a "fire sale".

The small amount of equity capital exacerbates their unstable balance sheet structure. The poorer capitalized a bank is, the more leverage increases when the value of the assets declines. In order to keep leverage constant, banks need to sell securities which can lead to a spiral between lower asset prices and weaker balance sheets (Adrian and Shin, 2010, 2014; Brunnermeier, 2009; Brunnermeier and Pedersen, 2009; Greenwood et al., 2015).[24]

The ability of banks to take on additional exposure is therefore limited by their capital cushion (Danielsson et al., 2012). In particular, a better capitalized bank may be able to act in a counter-cyclical fashion, a strategy that pays off only at longer horizons, as it is relatively less sensitive to losses on their security holdings in the short run.[25] In contrast, a bank with a lower capital ratio is more sensitive to losses on their securities. Therefore, it may be rational for these banks to act pro-cyclically, as this is a relatively less risky

[22] See also Hanson et al. (2015) for a discussion of the balance sheets of various financial intermediaries.

[23] While in the banking crisis as described in Diamond and Dybvig (1983) retail deposits were withdrawn, the most recent financial crisis was characterized by a withdrawal of wholesale funding and money market fund shares.

[24] This is not only the case for banks that mark-to-market. Geanakoplos (2003) and Fostel and Geanakoplos (2008) stress the importance of collateral constraints for balance sheet dynamics. For instance, a higher levered bank is more sensitive to price changes as it alters the collateral value a bank can borrow against. This is independent whether the bank marks-to-market their security holdings. In addition, lower capitalized banks are more vulnerable as they mechanically have a larger share of unstable funding. Adrian et al. (2015) also point out that accounting rules are unlikely the reason for balance sheet dynamics. Laux and Leuz (2010), Allen and Carletti (2008) and Plantin et al. (2008) describe the mark-to-market behavior of banks in more detail.

[25] See Abbassi et al. (2016).

strategy due to the short-term momentum component of bond prices.[26] In order to shed light on the question of whether a balance sheet channel is actually at work, I test whether there is heterogeneity in the cyclical investment behavior across banks depending on their degree of capitalization.

Hypothesis 1 *Banks with tighter capital constraints act relatively more pro-cyclically.*

In order to test **Hypothesis 1**, I obtain data on bank-level security holdings. The dataset covers every bank in Germany and their security holdings from 2005 Q4 through 2014 Q4. For all 1954 banks in my sample I define the capital ratio of the bank as the ratio of equity to total assets. I fix the capital ratio at the beginning of the sample to assure that changes in the capital ratio are not driven by active balance sheet management, see e.g. Adrian and Shin (2010).[27] The empirical strategy uses the bank's capital ratio and interacts it with the price change of the security. I expect a negative coefficient for the interaction term of the price change with the capitalization measure, i.e. poorer capitalized banks act relatively more pro-cyclically.

The empirical specification for column (4) in Table 4 is as follows:

$$Netbuy_{i,s,t} = \beta_1 \Delta Price_{s,t-1} * Capital_i + \alpha_{s,t} + \alpha_{i,t} + \epsilon_{i,s,t} \tag{3}$$

This is the most conservative specification and includes security∗time fixed effects and institution∗time fixed effects. This allows me to control for all unobserved time-varying institution and security-specific characteristics. The separate inclusion of security fixed effects, time fixed effects and institution fixed effects is not possible as they are spanned by the inclusion of security∗time and institution∗time fixed effects. In addition, the inclusion of the level of the price change and the capital ratio is not possible due to collinearity with the fixed effects. Standard errors are double clustered at the security and institution-level to account for serial correlation between observations of the same security and institution across time.[28]

Table 4 shows that the coefficient of the interaction between the price change and the capital ratio is negative and statistically significant. A one percentage point lower capital ratio is associated with a 3.1 percentage point more pro-cyclical investment behavior for a 10 percent price change. This result provides evidence in support of **Hypothesis 1**. Since the price change is collinear with the security∗time fixed effect, the price change coefficient is not identified in equation (3). Columns (1)-(2) relax this restriction so that the level of the price change can be included in the regression specification. The results also hold when I exclude institution∗time fixed effects and security∗time fixed effects. For instance, column (2) shows the specification with security and institution∗time fixed effects separately. Since the capital ratio is demeaned by the sample average, the level coefficient can be interpreted as a response of a bank with an average capital ratio, which

[26] While I pose the assumption here that pro-cyclical investment behavior is relatively less risky at short horizons than counter-cyclical investment behavior, I test this more formally in section 5.

[27] In this regression, I am only interested in the cross-sectional variation of the cyclical investment behavior across banks. If I used the contemporaneous capital ratio instead, the coefficient could be driven by both changes in the capital ratio over time and the cross-sectional component. The capital is the book value and not the market value of equity.

[28] The results are even stronger when I cluster either on the security, on the institution or on the security-institution level. The results also hold when I include security∗institution fixed effects.

is approximately 5 percent. A bank with a capital ratio of 5 percent increases the nominal holdings by 6.5 percent in response to a 10 percent price increase. For every one percentage point lower capital ratio, the response is 2.5 percentage points stronger. For instance, a bank with a capital ratio of 4 percent increases its holdings by 9 percent instead of 6.5 percent.

Table 5 splits the sample into a pre-crisis, crisis, post-crisis, and a post-regulatory reform implementation period. This follows the difference-in-difference approach in Adrian et al. (2017), who investigate the impact of dealer balance sheets on bond liquidity provision and show that while bonds traded by more levered institutions have been more liquid prior to the crisis, this relation reverses post-crisis. The impact of the capital ratio on the cyclical investment behavior should become stronger when overall constraints are tighter if a causal mechanism between the tightness of the capital constraint and the pro-cyclical investment behavior is at work. When banks' capital ratios rise, they are pushed away from their financial constraint, which should weaken the impact of the capital ratio on the pro-cyclical investment behavior. Table 5 splits the sample into a pre-crisis, crisis, post-crisis, and a post-regulatory reform implementation period. This follows the difference-in-difference approach in Adrian et al. (2017), who investigate the impact of dealer balance sheets on bond liquidity provision and show that while bonds traded by more levered institutions have been more liquid prior to the crisis, this relation reverses post-crisis. The impact of the capital ratio on the cyclical investment behavior should become stronger when overall constraints are tighter if a causal mechanism between the tightness of the capital constraint and the pro-cyclical investment behavior is at work. When banks' capital ratios rise, they are pushed away from their financial constraint, which should weaken the impact of the capital ratio on the pro-cyclical investment behavior.

Table 5 indeed shows that the coefficient is strongest in the crisis period when banks suffered losses and capital constraints became tighter. The impact is also negative in the pre-crisis period, at the peak of the leverage cycle, when capital constraints were close to being binding. When security prices started to recover after Draghi's announcement to do "whatever it takes to preserve the Euro" capital positions of banks improved again. This distanced banks from their financial constraint, which arguably led to the weakening of the impact of capital ratios on the pro-cyclical investment behavior in the post-crisis period.[29] Lastly, in 2014 new capital requirement for banks were introduced (European Commission, 2013). The results show that the impact of the capital ratio on the pro-cyclical investment behavior is weakest in the post-regulatory reform implementation period and if anything, the relation reversed. This result suggests that that the implementation of regulatory reforms had a mitigating effect on the pro-cyclical investment behavior of banks.[30]

4.1.2 Investment Funds

The investment fund industry in Germany is a significant sector, with an aggregate balance sheet of 1.7 trillion Euros in 2014 (more than 50 percent of Germany's GDP). In Germany, the sector consists almost exclusively of open-end mutual funds, such as bond and mixed

[29] See Acharya et al. (2017) for the real effects of the "whatever it takes" announcement.

[30] Note that in this table the price coefficient as well as the capital coefficient are absorbed by the security∗time fixed effect as well as the institution∗time fixed effect, respectively.

funds.[31] The leverage of these investment funds is limited. Figure 6 shows that only 2 percent of their liability side consists of loans. At first glance, the fact that investment funds are not vulnerable to runs on their debt liabilities may raise doubts about their contribution to systemic risk. As their investors provide equity capital, this suggests that investment funds can be seen as benign with respect to financial stability.

However, investors in open-end mutual funds can draw down their capital quickly. This changes the assets under management of the fund, which is the fund's equity capital. In other words, investment funds' capital is not permanent, unlike the equity capital of non-financial corporations. As investment fund shares issued make up the lion's share of investment funds' liabilities, simple metrics like the total assets to equity ratio can lead to misleading conclusions when it comes to identifying financial vulnerabilities. Once investors start redeeming assets, a feedback loop between redemptions by investors and sales of portfolio managers can emerge, as the redemptions of investors are usually not orthogonal to the performance of the investment fund.[32] In particular, losses on security holdings are associated with investor redemptions; since investment funds are averse to redemptions from investors, they may have incentives to limit short-term losses. This is particularly strong when investment funds already suffered outflows, as higher outflows make them more vulnerable to falling prices.[33] From this the following hypothesis arises:

Hypothesis 2 *Investment funds with more net outflows act relatively more pro-cyclically.*

In order to test **Hypothesis 2**, I use data on all investment funds and their security-level holdings. However, in contrast to the bank-level security-level holdings data, the data on investment funds is only available from 2009 Q4 onwards. First, I define the net outflow of a fund as

$$NetOutflow_{i,t} = -(\frac{Shares_{i,t} - Shares_{i,t-1}}{NAV_{i,t-1}}) \tag{4}$$

Shares are the investment fund's shares outstanding at face value to control for outflows to be driven mechanically by the price of the investment fund. NAV is the net asset value, used to scale for how large the outflows are relative to the size of the investment fund.

I estimate the following specification to test whether investment funds that suffered more outflows indeed rebalance their portfolio towards securities that have been risen versus those that have been fallen:

$$Netbuy_{i,s,t} = \beta_1 \Delta Price_{s,t-1} * NetOutflow_{i,t-1} + \alpha_{s,t} + \alpha_{i,t} + \epsilon_{i,s,t} \tag{5}$$

Column (4) of Table 6 shows the results with double clustered standard errors at the security and institution-level to account for serial correlation between observations of

[31] In 2014 there have been 5,923 investment funds in Germany of which 57.2 percent are mixed mutual funds and 15 percent are bond mutual funds. Only 0.5 percent are hedge funds.

[32] See e.g. Chevalier and Ellison (1997) and Chen et al. (2010) for the relationship between fund outflows and performance.

[33] See also Goldstein et al. (2015), Feroli et al. (2014) and Morris and Shin (2015) for empirical and theoretical evidence on this channel.

the same security and institution across time.[34] A 10 percent net outflow is associated with a 1.8 percentage point stronger pro-cyclical investment behavior for a 10 percent price change. Column (2) shows the results without security∗time fixed effects but with institution∗time and security fixed effects so that the price change coefficient is identified. The results can be interpreted as follows: an investment funds without outflows increases its security holdings by 1.8 percent to a 10 percent price increase, while a fund that suffers 10 percent net outflows increases the amount by 3.1 percent.[35]

4.1.3 Insurance Companies and Pension Funds

The total size of the insurance companies' and pension funds' balance sheet in Germany in 2014 was 2.4 trillion Euros (more than 80 percent of Germany's GDP). On the asset side, cash and deposit holdings are much larger than for banks and contribute 21 percent to total assets, while almost 60 percent are securities (Figure 7). The leverage ratio of insurance companies is much smaller compared to banks. The lion's share of liabilities is represented by insurance technical reserves; these are net equity of households in life insurance and pension fund reserves or prepayments of insurance premiums and reserves for outstanding claims. These long-term liabilities are mostly contingent and their payouts are relatively independent of the state of the real economy and overall financial conditions. This predictable liability structure may give insurance companies and pension funds more autonomy in their portfolio choice as compared to banks or investment funds. For instance, an accident with an insured car, a damage to an insured building or a death of a person are events that could be covered by insurance companies and cause payouts. As the structure of the liability side of insurance companies' and pension funds' balance sheet is relatively persistent, this keeps their funding and rollover risk relatively moderate and leaves them with more "skin in the game".[36] In addition, insurance companies and pension funds in Germany do not have to mark-to-market their security holdings during my sample period (Fabozzi, 2012).[37] This may enable "deep pocket investors", such as insurance companies and pension funds, to buy securities when prices have dropped when other actors, such as banks and investment funds, may sell these securities. When prices have decreased, insurance companies and pension funds can benefit from a reversal of the price if they hold on to the security. Therefore, insurance companies and pension funds may act counter-cyclically due to their more stable balance sheet as compared to those of banks and investment funds.

However, while insurance companies and pension funds are less sensitive to losses on their security holdings than banks and investment funds, they are unlikely to be totally unconstrained investors. While their long-term liabilities relative to their assets are

[34] The results are even stronger when I cluster either on the security, on the institution or on the security-institution level. The results also hold when I include security∗institution fixed effects.

[35] Although the price change coefficient is economically large and significant, it is not statistically significant. The standard error suggests that there is large heterogeneity in the cyclical investment behavior across investment funds which is exploited by the interaction with the net outflow variable. However, other kinds of heterogeneities are worth exploring in future research.

[36] Acharya et al. (2011) discuss the systemic importance of insurance companies for the global economy in more detail. Manconi et al. (2016) document their selling behavior when they face a large outflow.

[37] With the introduction of Solvency II in January 2016, insurance companies and pension have to mark-to-market their security holdings.

usually an advantage, the duration mismatch of assets and liabilities can also become problematic. Insurance companies and pension funds discount their liabilities with the risk-free rate. When the risk-free rate falls, insurance companies' and pension funds' liabilities increase relatively more than their assets due to their negative duration gap. In order to prevent having a duration mismatch that is too large, insurance companies and pension funds may engage in duration matching by buying long-term bonds, independent of the price change. While it is usually the case that insurance companies and pension funds buy securities whose value dropped most, this may change when the duration mismatch increases. When interest rates fall, the prices of long-term bonds rise and the duration mismatch of insurance companies and pension funds increases. In order to investigate whether the duration mismatch is indeed a balance sheet constraint that affects the investment behavior of insurance companies and pension funds, I test the following hypothesis:

Hypothesis 3 *Insurance companies and pension funds act relatively less counter-cyclically when their duration mismatch increases.*

Security holdings data is not available on the institution-level for insurance companies and pension funds. In order to test the hypothesis, I instead use balance sheet data for the insurance company and pension fund sector in Germany provided by the Deutsche Bundesbank and proxy the duration mismatch by constructing a maturity mismatch measure by dividing insurance companies' and pension funds' long-term liabilities by their long-term assets. A higher ratio of long-term liabilities to long-term assets is associated with a higher on-balance sheet maturity mismatch. Since the duration of an asset is closely linked to its maturity, the maturity mismatch can be seen as a proxy for the duration mismatch.[38]

In order to test this hypothesis, I estimate the following specification:

$$Netbuy_{s,t} = \beta_1 \Delta Price_{s,t-1} + \beta_2 \Delta Mismatch_{t-1} * \Delta Price_{s,t-1} + \alpha_t + \alpha_s + \epsilon_{s,t} \quad (6)$$

The results are shown in column (2) of Table 7. The specification includes security fixed effects to control for time-invariant security-specific characteristics. Time fixed effects control for observed and unobserved time-specific characteristics. As this regression is on the sector-level, all sector-specific time trends are also controlled for. If **Hypothesis 3** is true, I would expect a positive sign for the interaction of the change in the maturity mismatch and the change in the price. The larger the mismatch, the more pro-cyclically (less counter-cyclically) insurance companies and pension funds act on the capital markets with respect to price changes.[39]

Column (2) of Table 7 shows that a one percentage point increase in the mismatch ratio is indeed associated with a 3.5 percentage point weaker counter-cyclical investment behavior for a 10 percent price change. Column (1) shows that this pattern holds when time fixed effects are not included in the regression. In this case counter-cyclical investment behavior is even stronger as insurance companies and pension funds seem to buy

[38] Of course, insurance companies and pension funds can use interest swaps to hedge their interest rate exposure. However, since hedging is expensive, insurance companies and pension funds may not fully hedge their exposure.

[39] In recent work Domanski et al. (2017) provide a theoretical framework for this behavior. They also provide consistent evidence with aggregate data.

more in general when prices fall. This also holds when I include macro-economic controls in the regression instead of using time fixed effects, seen in column (4). Column (5) is the most conservative specification. In order to rule out that the duration mismatch is correlated with other macro-economic variables and that the mismatch only picks up this correlation, I control for the interaction between several macro-economic variables, such as German GDP growth, inflation, the 10-year government bond yield, the EONIA and the VIX and the price change. Even controlling for these other interaction terms, the interaction of the price change with the mismatch ratio is still highly significant.
After having shown that insurance companies and pension funds act relatively less counter-cyclically in times when the duration mismatch increases, this still poses the question what drives the aggregate pattern of section 2, i.e. that insurance companies and pension funds act counter-cyclically on average. One mechanism that could explain these findings is the correlation of the tightness of their constraints with gains and losses on the portfolio holdings. In contrast to investment funds and banks, whose constraints tighten when they suffer losses on their security holdings, the duration mismatch of insurance companies and pension funds should, if anything, decrease when prices fall due to their negative duration gap.[40] Therefore, insurance companies and pension funds may use this comparative advantage to act counter-cyclically. I test the link between capital gains and the tightness of the balance sheet constraint more formally in the next section.

4.2 Balance Sheet Constraints and Capital Gains

The above hypotheses and results suggest that there is a link between capital gains and losses on their portfolio holdings of different investor types and the tightness of their constraints. As shown in the previous section, poorer capitalized banks and investment funds with more outflows act relatively more pro-cyclically. When insurance companies' and pension funds' duration mismatch increases, they also tend to act relatively less counter-cyclically.

In order to align the findings of section 2 with the overall pattern that insurance companies and pension act counter-cyclically and the banking and investment fund sector acts pro-cyclically, I test whether losses on portfolio holdings are affecting the constraints of the various institutions. When prices fall and losses on their security holdings lead to tighter constraints, institutions may (i) be forced to sell securities or (ii) sell securities in order to avoid further price falls tightening constraints even more. This may be the case because pro-cyclical investment behavior is profitable in the short run. In order to test whether the tightness of the constraint is related to the losses on the security holdings, I estimate the following specification:

$$Constraint_t^X = \alpha + \beta_1 Netgains_{t-1} + \epsilon_t \tag{7}$$

where X is either (i) investment funds, (ii) banks or (iii) insurance companies and pension funds. For investment funds, I again use net outflows of a fund as defined in the last section as a constraint; for banks I use capital over total assets at the beginning of the sample and for insurance companies and pension funds I use the change in the maturity mismatch.[41]

[40] When interest rates fall and security prices rise, assets of insurance companies and pension funds may rise relatively less than their liabilities due to their larger sensitivity to interest rate changes.

[41] I fix total assets at the beginning of the period to prevent the capital ratio to be driven by active

These simple correlations in column (1), (2) and (4) of Table 8 confirm that banks' and investment funds' constraints tighten when they suffer losses on their security holdings and insurance companies' and pension funds' constraints, if anything, loosen.

In order to test this correlation more structurally, I can use institution-level data for banks and investment funds to estimate the following equation:

$$Constraint^X_{i,t} = \beta_1 Netgains_{i,t-1} + \alpha_i + \alpha_t + \epsilon_{i,t} \tag{8}$$

where X can be either investment funds or banks. The specification includes institution fixed effects to control for unobserved and observed time-invariant heterogeneity in the cross-section of investment funds or banks, e.g. some banks may be structurally better capitalized than others. The specification also includes time fixed effects to control for institution-invariant time trends. The results from the simple correlation can be confirmed in columns (3) and (5) of Table 8. When banks suffer losses on their security holdings it tightens their constraints by reducing their capital. Losses on investment funds' balance sheets are associated with redemptions from investors.

5 Price Change Dynamics

5.1 Investment Behavior and Future Price Changes

In order to test how prices of securities move after various institutions have bought them, I regress the difference of the k period ahead log of the price and the current log of the price, $\Delta Price_{s,t+k}$, on the netbuy variable for each institution type X for security s as follows:

$$\Delta Price_{s,t+k} = \beta_1 Netbuy^X_{s,t} + \alpha_t + \epsilon_{s,t+k} \tag{9}$$

where

$$\Delta Price_{s,t+k} = Price_{s,t+k} - Price_{s,t} \tag{10}$$

and the price is expressed in logs and time fixed effects, α_t, control for market-wide developments. Column (1) of Table 9, Table 10 and Table 11 report results for k=1. The results show that the price of a security increases after banks and investment funds have acquired the security. These results are in line with Adrian et al. (2010a,b, 2011) who show that the investment behavior of banks can predict price changes and can even stimulate the economy. A doubling in the nominal amount held is associated with a 0.12 percent increase in the bond price in the next quarter for banks and 0.2 percent for investment funds.

In contrast to the prices of securities that have been bought by banks and investment funds, the prices of securities that have been bought by insurance companies and pension funds do not increase significantly. Columns (2) and (3) of Table 11 show that prices decrease two and three quarters after insurance companies and pension funds have bought them. A doubling in the amount bought by insurance companies and pension funds result

balance sheet management. However, here I am interested in the changes in capital over time. Therefore, I only fix total assets at the beginning of the period so that changes in the capital ratio are only driven by mark-to-market activities as well as equity issuance.

on average in 0.2 percent lower bond prices after two and three quarters. However, after ten quarters the results are reversed. For k=10, the prices of bonds have increased after insurance companies and pension funds have bought them and decreased when banks and investment funds have bought them. After twelve quarters bond prices are 1.7 percent higher when insurance companies and pension funds have doubled their position. These findings are consistent with the impression given by Figure 4 that the counter-cyclical strategy of insurance companies and pension funds is not profitable at short horizons but outperforms pro-cyclical investment behavior in the medium run.

5.2 Momentum and Reversal of Prices

Prior evidence suggests that price changes are positively auto-correlated at short horizons but negatively correlated at longer horizons (Cutler et al., 1990, 1991; Moskowitz et al., 2012).[42] This would support the results of section 5.1 that pro-cyclical investment behavior is profitable at short horizons while counter-cyclical investment behavior pays off at longer horizons. According to Cutler et al. (1990) price changes reflect a fundamental and a transitory component. While the fundamental component follows a random walk, the transitory component follows a first-order autoregressive process that is likely driven by a dominance of noise traders who overreact to fundamental news. In the absence of noise traders, investors are not expected to change their security holdings as a response to price changes (Milgrom and Stokey, 1982). After rejecting this hypothesis in section 3, this section delivers complementary evidence on the possible channel. Positive feedback investing may be rational when the investment horizon is short and one has a strong loss aversion at short horizons. In this case, it may be rational to have a positive demand elasticity to price changes. In contrast, counter-cyclical investors, who have a negative demand elasticity to price changes, may have a low short-term loss aversion but instead aim to maximize their profits at long horizons.

Although the positive auto-correlation at short horizons and the negative auto-correlation at longer horizons has been pointed out by previous papers, I study whether the same pattern also holds in my data. Therefore, I estimate the following specification:

$$\Delta Price_{s,t+k} = \alpha_{t+k} + \beta_1 \Delta Price_{s,t} + \epsilon_{i,t+k} \tag{11}$$

Table 12 shows that banks and investment funds can indeed avoid short-term losses by acting pro-cyclically, as price changes are positively auto-correlated at short horizons. In contrast, as insurance companies' and pension funds' constraints do not tighten when they suffer losses on their security holdings, this may enable them to step in when bonds are cheap. That this counter-cyclical investment strategy can be profitable when prices revert can be seen in Table 12. Given that insurance companies and pension funds act on longer horizons, one would expect them to buy potentially undervalued securities as they have the comparative advantage to wait until the prices revert. I turn to this topic in the next section.

[42] Vayanos and Woolley (2013) propose a model of momentum and reversal.

6 Additional Tests

6.1 Investment Behavior and Excess Bond Yields

As shown above, banks and investment funds act in a pro-cyclical manner to price changes. This behavior can be profitable in the short run but is less profitable than the investment behavior of insurance companies and pension funds in the medium run. Since banks and investment funds trade on shorter horizons than do insurance companies and pension funds, they might be more averse to liquidity risk. In this section, I define an excess bond yield; the yield spread of a security that cannot be justified by credit risk, to test this hypothesis. An increase in the excess bond yield reflects an increase in returns without an increase in credit risk. That the excess bond yield increases might be due to lower liquidity, which may not be part of the fundamental value. Therefore, changes in the excess bond yield could arguably be interpreted as variation of the non-fundamental component of the bond.

My approach is similar to the one of Gilchrist and Zakrajšek (2012). First, I define a risk-free yield for five maturity buckets, i.e. for 1-3 years, 3-5 years, 5-7 years, 10-20 years, above 20 years.[43] I define the risk-free yield as the yield of a German government security in each benchmark. In order to define an excess bond yield, I regress the security-specific yield-to-maturity on the risk-free yield of its maturity bucket, a categorial credit rating variable and a security fixed effect to control for time-invariant security-specific characteristics such as exchange rate risk if the security is denominated in foreign currency. I estimate the following regression:

$$Yield_{s,t} = \beta_1 Yield^{rf}_{m,t} + \gamma' \mathbf{Rating}_{s,t} + \alpha_s + \epsilon_{s,t} \tag{12}$$

where **Rating** is a vector of dummies for each rating category. I take the residual of this regression and define:

$$ExcessBondYield = \epsilon_{s,t} \tag{13}$$

Yields may be higher for bonds that are more difficult to sell, especially in times of market turmoil. Illiquidity is only a risk for short-term investors that need to sell securities at short horizons. Investors that hold securities until maturity should not be reluctant to hold these securities. In contrast, these investors should even buy these securities when the liquidity premium goes up when these also yield higher expected future returns.

Therefore, I investigate which investors are buying and selling bonds whose excess bond yields rise as follows:

$$Netbuy^{X}_{s,t} = \beta_1 \Delta ExcessBondYield + \alpha_s + \alpha_t + \epsilon_{s,t} \tag{14}$$

Table 13 shows the results of a regression of the netbuy variable on the excess bond yield.[44] Insurance companies and pension funds buy securities whose excess bond yields increase and sell them when the excess bond yield decreases. In particular, column (3) shows that a one percentage point increase in the excess bond yield is associated with a 2.3

[43] I follow Ellul et al. (2011) for the choice of the maturity groups.

[44] Since the variable Excess Bond Yield is estimated, I bootstrap the standard errors.

percent increase in the nominal amount held. This might be the case because insurance companies and pension funds often hold bonds until maturity and do not have to sell at short notice. In contrast, banks and investment funds buy when the excess bond yield falls and sell when the excess bond yield increases.

If changes in the excess bond yield are interpreted as changes away from their fundamental value, these results suggest that banks and investment funds are pushing away prices from fundamentals and insurance companies and pension funds stabilize prices and push them towards fundamentals. Since banks and investment funds trade more frequently than do insurance companies and pension funds, it may be rational for them to consciously buy securities that are overvalued. Speculating on further price rises indicates that investors attempt to ride the bubble and time the market by selling the security when the price is at the inflection point (Brunnermeier and Nagel, 2004). The behavior of banks to buy securities whose excess bond yield falls is consistent with the model of Shleifer and Vishny (2010) who show that if banks believe that security prices will increase further, they lever up and buy securities.[45] However, once prices start to fall, banks cannot roll over funding and may have to sell securities in order to de-lever again. Alternatively, banks and investment funds may sell securities that trade below their fundamental value if they expect the downward trend to continue further at short horizons, as shown in Table 12.

In contrast, return-oriented investors who have a long-term investment horizon and potentially hold securities until maturity may be buying up troubled assets when they believe the security is undervalued in order to benefit from future price increases (Hanson and Stein, 2015). In line with the typical behavior of return-oriented investors, insurance companies and pension funds, who may be more risk tolerant due to their long-term liabilities, buy assets whose excess bond yield has risen.This behavior can act as a stabilizing force in bad times and prevent prices from falling by as much as they would otherwise. Selling securities whose excess bond yields are falling and whose prices are potentially rising above their fundamental value on the other side can also prevent bubbles from growing. These types of investors have received rather less attention but are certainly important actors who can prevent the buildup of systemic risk that could materialize in a crisis (Brunnermeier and Sannikov, 2014).

6.2 Cyclical Investment Behavior and Risk

6.2.1 Credit Risk

While in the previous section I have used the credit rating in order to construct an excess bond yield, I have neither used the credit rating unconditionally in order to test whether the rating of the bond affects their investment behavior, nor have I investigated whether the cyclical investment behavior is different across rating categories. In order to do so, I first construct a dummy that equals one if the security is rated investment grade and zero otherwise. I interact the dummy, IG, with the price change. A positive coefficient shows that institutions act relatively more pro-cyclically with respect to investment grade bonds. Table 14 shows that the counter-cyclical investment behavior of insurance companies and

[45]This behavior is also consistent with models that predict myopic behavior due to short-term incentives (Stein, 1989).

pension funds is more pronounced for non-investment grade bonds. It also shows that the results are robust along two additional dimensions. First, the price change coefficient is still highly significant even after controlling for the rating category. This allows me to rule out the possibility that price changes due to rating category changes are driving the results, see e.g. Ellul et al. (2011, 2015) and Merrill et al. (2012). Second, cyclical investment bevavior is robust across rating types. For instance, while for insurance companies and pension funds the cyclical investment behavior is different in magnitude for investment grade bonds and non-investment grade bonds, insurance companies and pension funds act counter-cyclically both with respect to investment grade bonds and non-investment grade bonds. On the other side, banks and investment funds act pro-cyclically for both types of categories.

6.2.2 Foreign Exchange Rate Risk

Table 15 looks at whether the cyclical investment behavior is different for bonds that are denominated in foreign currency. I define a dummy that is equal to one if the bond is denominated in foreign currency and zero otherwise. I interact the dummy FC with the price change coefficient. A positive coefficient indicates that institutions act relatively more pro-cyclically with respect to foreign currency bonds. Table 15 shows that the results hold for both domestic currency and foreign currency bonds. The results are, if anything, stronger for foreign currency bonds. This finding underlines the results by Cerutti et al. (2015). They find that emerging markets that rely on investment funds and banks as their main creditors, exhibit relatively higher volatility of their capital inflows. They argue that it is important for emerging markets to monitor their investor base. My results support their hypothesis and do not only apply to cross-border inflows into emerging market countries, but also more generally to both domestic and foreign investors as well as corporates and governments.[46]

6.2.3 Market Risk

While the above measures focus on credit and foreign exchange rate risk, I have thus far neglected the interaction between market risk and the price change. To address this, I define a β_{dax} in relation to the German stockmarket index by estimating the following specification for each security s:

$$\Delta Price_t = \alpha + \beta_{dax} \Delta Dax_t + \epsilon_t \tag{15}$$

where Dax is the log of the German stockmarket index. Then, I obtain the beta coefficient for each security, β_{dax}, which reflects the relation of the price change with the stockmarket. A positive and large β_{dax} indicates high systematic risk with respect to the stockmarket. A coefficient of one reflects that the price of the security moves in tandem with the stockmarket, on average. An investor whose benchmark portfolio is on average highly correlated with the German stockmarket can buy securities with a low or even negative β_{dax} in order to hedge exposure to the stockmarket. Table 16 shows whether the cyclical investment behavior of the various institutions differs depending on the beta of the security in question. For this, I interact the β_{dax} with the price change of the security. A positive

[46] Table A2 shows the results for German and foreign bonds.

coefficient on the interaction term shows that institutions act relatively more pro-cyclically or less counter-cyclically with respect to bonds that reflect a higher systematic risk with respect to the stockmarket. Column (4) shows that insurance companies and pension funds act relatively more counter-cyclically with respect to bonds that have a larger beta. In contrast, banks act relatively more pro-cyclically with respect to these bonds.[47]

Table A4 shows the same analysis but instead of using the price change of the security and the percentage increase in the stockmarket index. I use the security-specific yield and the risk-free yield (rf) to define β_{rf}.[48] Securities that have a large β_{rf} move in tandem with the risk-free securities and can be considered less risky. Table A4 shows that the beta with respect to the risk-free yield does not seem to be important in determining the cyclical investment behavior.[49]

One other dimension of risk is the volatility of the bond. I define the volatility of the bond as its sample standard deviation and interact it with the price change. A positive coefficient shows that institutions act relatively more pro-cyclically with respect to more volatile bonds. Table A6 shows that banks seem to act relatively more pro-cyclically with respect to less volatile bonds.

In order to investigate further whether the cyclical investment behavior changes over the financial cycle, I look at times of a high VIX in the next step. When market liquidity is low, pro-cyclical investment behavior can lead to strong market distortions and investors may be forced to sell at fire-sale prices because they have to meet margin calls or they cannot roll over their liabilities. If prices fall and investors act pro-cyclically during volatile times, their redemption can trigger a spiral of market and funding liquidity (Brunnermeier and Pedersen, 2009). Amihud et al. (2006) and Amihud and Mendelson (1986), show that short-term investors avoid illiquid securities in times of high expected volatility. The probability that illiquid assets will have to be sold at fire-sale prices increases when volatility increases. Hence, funds with daily reception notice should not hold illiquid assets in volatile times if they want to avoid selling off assets at fire-sale prices. In contrast, long-term investors can benefit from a liquidity premium as short-term investors avoid illiquid securities in times of high expected volatility.

In order to test whether the cyclical behavior of financial institutions intensifies in volatile times, I interact the VIX with the change in the price. Column (1) of Table A7 shows that as soon as the VIX increases, investment funds exacerbate the pro-cyclicality, which is in favor of the hypothesis that investment funds act relatively more pro-cyclically in times when asset prices are down. However, once time fixed effects are included, the result diminishes. When the market in general is more volatile, measured by a high VIX, investment funds and insurance companies and pension funds act relatively less counter-cyclically (Table A7). However, even large movements in the VIX, e.g. a 100 percent increase in the VIX, does not make insurance companies and pension funds act pro-cyclically. In addition, the result also diminishes when time fixed effects are included.

This suggests that the results are not driven by specific time periods, which I test more formally in the next section.

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[47] Table A3 show the results when the covariance instead of the β_{dax} is used.

[48] I again use the German government bond in the respective maturity bucket as the risk-free yield.

[49] Table A5 shows the results for the covariance instead of the beta.

6.3 Crisis Split

In Table A8, Table A9 and Table A10 I divide the sample into three subsamples: pre-crisis (2006 Q1:2008 Q1), crisis (2008 Q2:2012 Q3), and post-crisis (2012 Q4:2014 Q4).[50] Even in this very conservative specification with period-specific security fixed effects, the results are remarkably stable. Table A8 show the results for investment funds. In the pre-crisis period, a 10 percent increase in the price is associated with a 1.3 percent increase in the nominal holdings of the security when security fixed effects are included and an increase of 0.5 percent when both security and time fixed effects are included. In the crisis they increase the nominal amount both with and without time fixed effects by 1.1 percent. In the post-crisis period the response changes to 0.9 percent and 1.7 percent, respectively.

Table A9 shows that insurance companies and pension funds acted relatively more counter-cyclically before the crisis. However, the counter-cyclical investment behavior is still strong in the crisis and post-crisis period with elasticities between 0.16 and 0.53 depending on the specification.

For banks, the pro-cyclical investment behavior has been more pronounced before and after the crisis with magnitudes of 0.5 to 0.8. During the crisis, the response was lower in magnitude but still highly significant at the 1 percent significance level (Table A10). Banks reduced their holdings by 2.5 percent and 3 percent as a response to a 10 percent price decrease, depending on the specification.

6.4 Further Robustness

Additionally, I test whether the response is robust for both buying and selling behavior. This can be confirmed in Table A11. Investment funds and banks buy when price rise and sell when they fall. In contrast, insurance companies and pension funds buy when prices fall and sell when prices rise.

Until now I have assumed that the coefficient is the same for corporate and government bonds. In Table A12, I relax this assumption and allow the coefficient to vary by issuing sector. In particular, I define a dummy for each of the three issuing sectors: government, banks and other-financial corporates (ofc). I interact the price change with the respective dummies. A positive coefficient can be interpreted as evidence for relatively more pro-cyclical investment behavior compared to the benchmark of non-financial corporate bonds (nfc). In general, I confirm my previous findings. In most cases, the highest quantitative responses to price changes are with respect to non-financial corporate bonds. A 10 percent increase in the price is associated with a 1.2 percent and 8.6 percent increase in the amount held for investment funds and banks, respectively, but a 31 percent decrease by insurance companies and pension funds. While the sign of the coefficients is still in line with the benchmark model, the magnitude of the cyclical investment behavior varies depending on the issuer type. Insurance companies and pension funds act relatively less counter-cyclically with respect to bank, other-financial corporate and government bonds. Banks and investment funds act relatively less pro-cyclically with respect to government bonds but not significantly different with respect to other-financial corporate and bank bonds.

[50] 2008 Q2 is the first quarter in which Germany's seasonally adjusted quarterly GDP dropped the first time in my sample. The end of the crisis period is defined as the quarter after Mario Draghi's announcement to do "whatever it takes to preserve the Euro", which happened in 2012 Q3.

To test the sensitivity of the price change coefficient to the inclusion of further controls, Table A13 shows a summary of the lagged price change coefficients for various specifications. Controlling for more unobserved and observed characteristics also indicates whether the sectors respond to relative price changes of the debt securities or whether the investment decision is driven by broad market valuations. Creating a more coherent sample across the sectors sheds light on the question of whether the coefficients are driven by a sample selection bias. The coefficient is consistently positive for investment funds and banks and negative for insurance companies and pension funds. Row (1) is the result of a simple regression of the netbuy variable on the lagged price change excluding any controls. While the inclusion of security fixed effects allows to make judgement about the investment behavior in a specific security over time, excluding security fixed effects does not only capture the time-series variation but also the cross-sectional variation. Including security fixed effects controls for all time-invariant security-specific characteristics, such as the coupon or the maturity date, but of course also for the issuing country of the security. The approach using security fixed effects focuses on one specific security and attempts to explain the buying and selling behavior over time.[51] Both regressions show that, unconditional and conditional on time-invariant security characteristics, banks and investment funds respond pro-cyclically to price changes, while insurance companies and pension funds act counter-cyclically.

Row (3) includes macro controls for Germany, i.e. German GDP growth, inflation, the 10-year government bond yield, the EONIA and the VIX. Row (4) assigns country-specific controls to the country of issue. Row (5) absorbs observed and unobserved country-specific time-varying characteristics. In order to examine how financial institutions invest in specific securities, compared to other securities that were issued in the same sector of the same country, the specification is also saturated with sector∗country∗time fixed effects. This controls for unobserved and observed time-varying heterogeneity, such as the time-varying common component of a specific asset class. In particular, it adds the issuing sector dimension for banks, other-financial corporations, non-financial corporations, and governments in their capacity as issuing sectors. Hence, for each issuing sector of a given country I control for the average amount bought or sold at a given point in time, which controls for broad market valuations of this index. Even within this benchmark, banks and investment funds buy securities that have increased in value. However, while for investment funds and banks the coefficients are even higher than in specification (5), the coefficient for insurance companies and pension funds is relatively lower. This indicates that insurance companies and pension funds tend to buy securities that are included in a falling index. In contrast, banks' and investment funds' pro-cyclical investment behavior is also driven by idiosyncratic movements of the security compared to its benchmark.[52] To make the sample of securities held more comparable, row (7) restricts the security sample to all securities that have been held by insurance companies and pension funds, investment funds and banks at least once throughout the sample.

[51]The coefficients vary slightly from Table 3 as the sample is harmonized in Table A13 to make coefficients better comparable.

[52]In Table A14, I decompose the price change is into a broad market valuation of the issuing sector-country index and an idiosyncratic part. For insurance companies and pension funds and banks the broad price change movement is more important than the relative one. In contrast, for investment funds the relative price change is more important than the broad index.

7 Conclusion

This paper analyzes the cyclical investment behavior of investment funds, banks and insurance companies and pension funds. I show that banks and investment funds are pro-cyclical investors with respect to price changes. In contrast, insurance companies and pension funds respond counter-cyclically to price changes: they buy when prices have fallen and sell when prices have gone up.

One channel that could generate the heterogeneity in the cyclical investment behavior is based on the investors' balance sheet dynamics. I provide evidence that is consistent with this channel by exploiting cross-sectional heterogeneity between institutions for banks and investment funds. The pro-cyclical investment behavior is stronger for banks that are relatively weaker capitalized and investment funds that face relatively more outflows. Although investment funds use almost no leverage, both investment funds and banks are sensitive to short-term losses on their security holdings. In order to avoid these losses, they act pro-cyclically as prices exhibit a short-term momentum factor. Since insurance companies' and pension funds' balance sheets are more resilient to short-term losses, they can act in a counter-cyclical manner.

The pro-cyclical investment behavior of investment funds and banks resulted in relatively mild losses during the European sovereign debt crisis. Although insurance companies and pension funds suffered severe losses during the crisis, they outperformed banks and investment funds in the medium run.

The results suggest that the investment behavior of insurance companies and pension funds can be a stabilizing force on capital markets. In contrast, the investment behavior of banks and investment funds can exacerbate price dynamics and lead to excessive volatility in capital markets. These results underline the findings of Cerutti et al. (2015) who argue that it can be hazardous for countries to rely on investment funds and banks as their main investors.

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Table 1: Summary Statistics

Panel A: Insurance Companies and Pension Funds

	Holdings	Buy	Sell	Netbuy	Buy %	Sell %	ΔPrice
Mean	22.634	11.021	9.768	-0.003	0.311	-0.305	0.001
Std.	78.122	35.295	33.349	0.670	0.577	0.612	0.037
Obs.	136954	14665	15183	29848	14665	15183	734517

Panel B: Investment Funds

	Holdings	Buy	Sell	Netbuy	Buy %	Sell %	ΔPrice
Mean	31.842	5.887	6.192	-0.012	0.218	-0.212	0.001
Std.	115.805	26.240	24.487	0.438	0.389	0.377	0.037
Obs.	383521	107737	124584	232321	107737	124584	734517

Panel C: Banks

	Holdings	Buy	Sell	Netbuy	Buy %	Sell %	ΔPrice
Mean	57.641	12.749	15.800	-0.002	0.372	-0.407	0.001
Std.	167.278	47.811	58.529	0.812	0.669	0.758	0.037
Obs.	475782	62553	57783	120336	62553	57783	734517

Holdings is the nominal value held if a security is held (in million Euros). Buy and sell refers to the amount bought and sold in million Euros. Netbuy is the change in the log of the nominal amount held. Buy % (Sell %) is the change in the log of the nominal amount held if positive (negative). ΔPrice is the change in the log of the price. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2004 Q4 - 2014 Q4; author's calculations.

Table 2: Heterogeneity in Cyclical Investment Behavior − Interactions

	Dependent variable: Netbuy					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	-0.576***	-0.850***	-0.429***			
	(0.115)	(0.116)	(0.132)			
ΔPrice ∗ Funds	0.718***	0.955***	0.565***	0.647***	0.861***	0.428**
	(0.117)	(0.118)	(0.134)	(0.145)	(0.159)	(0.186)
ΔPrice ∗ Banks	0.912***	1.191***	0.789***	0.993***	1.359***	0.855***
	(0.140)	(0.143)	(0.158)	(0.176)	(0.186)	(0.217)
R-squared	0.0834	0.119	0.123	0.453	0.529	0.532
Observations	386618	382505	382505	147449	147449	147449
Security FE	Yes	-	-	-	-	-
Time FE	Yes	No	-	-	-	-
Security∗Time FE	No	No	No	Yes	Yes	Yes
Sector∗Time FE	No	No	Yes	No	No	Yes
Security∗Sector FE	No	Yes	Yes	No	Yes	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *Banks* is a dummy that equals one for banks and zero otherwise. *Funds* is a dummy that equals one for investment funds and zero otherwise. The benchmark is insurance companies and pension funds. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 3: Heterogeneity in Cyclical Investment Behavior − Sample Split

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.105***	0.136***	-0.850***	-0.429***	0.341***	0.361***
	(0.024)	(0.026)	(0.116)	(0.132)	(0.084)	(0.088)
R-squared	0.120	0.126	0.161	0.173	0.112	0.114
Observations	232321	232321	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 4: Bank Heterogeneity

	Dependent variable: Netbuy			
	(1)	(2)	(3)	(4)
ΔPrice	0.584**	0.647**		
	(0.232)	(0.271)		
ΔPrice ∗ Capital	-10.44**	-24.52*	-18.67***	-31.49**
	(4.300)	(12.952)	(6.833)	(14.146)
R-squared	0.116	0.126	0.236	0.247
Observations	1643361	1643361	1643361	1643361
Security FE	Yes	Yes	-	-
Institution FE	Yes	-	Yes	-
Time FE	Yes	-	-	-
Institution∗Time FE	No	Yes	No	Yes
Security∗Time FE	No	No	Yes	Yes

The dependent variable is the change in the log of the nominal amount held for banks on the institution-level. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *Capital* is equity as a ratio of its total assets at the beginning of the period. *Capital* is demeaned by the average across banks. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are double clustered at the security and institution-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, monthly bank balance sheet statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 5: Bank Heterogeneity across Time

	Dependent variable: Netbuy			
	(1)	(2)	(3)	(4)
ΔPrice ∗ Capital	-4.021	-52.06***	-7.049	2.197
	(34.382)	(18.561)	(36.442)	(39.385)
R-squared	0.218	0.258	0.289	0.286
Observations	440880	692433	198374	311674
Institution∗Time FE	Yes	Yes	Yes	Yes
Security∗Time FE	Yes	Yes	Yes	Yes
Sample	Pre-Crisis	Crisis	Post-Crisis	Post-Reg. Reform

The dependent variable is the change in the log of the nominal amount held for banks on the institution-level. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *Capital* is equity as a ratio of its total assets at the beginning of the period. *Capital* is demeaned by the average across banks. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). *Pre-Crisis* refers to the period 2006 Q1:2008 Q1, *Crisis* refers to 2008 Q2:2012 Q3, *Post-crisis* refers to 2012 Q4:2013 Q4 and *Post-Reg. Reform* refers to 2014 Q1:2014 Q4. Standard errors are in parentheses. Standard errors are double clustered at the security and institution-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, monthly bank balance sheet statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 6: Investment Fund Heterogeneity

	Dependent variable: Netbuy			
	(1)	(2)	(3)	(4)
ΔPrice	0.0885	0.177		
	(0.302)	(0.277)		
ΔPrice ∗ Net Outflow	1.486**	1.259**	1.920***	1.789***
	(0.722)	(0.572)	(0.608)	(0.584)
R-squared	0.340	0.435	0.422	0.507
Observations	2554558	2554558	2554558	2554558
Security FE	Yes	Yes	-	-
Time FE	Yes	-	Yes	-
Institution FE	Yes	-	-	-
Institution∗Time FE	No	Yes	No	Yes
Security∗Time FE	No	No	Yes	Yes

The dependent variable is the change in the log of the nominal amount held for investment funds on the institution-level. Δ*Price* is the change in the log of the price. *Net Outflow* is the negative of the change in the face value of shares outstanding as a ratio of the lagged Net Asset Value. The level of *Net Outflow* is included in the specification whenever not collinear with the fixed effects. All independent variables are lagged by one quarter. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are double clustered at the security and institution-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, investment fund statistics, 2009 Q4 - 2014 Q4; author's calculations.

Table 7: ICPF Heterogeneity

	Dependent variable: Netbuy				
	(1)	(2)	(3)	(4)	(5)
ΔPrice	-0.831***	-0.416***	-0.926***	-0.926***	-0.602***
	(0.115)	(0.132)	(0.136)	(0.136)	(0.159)
ΔPrice ∗ ΔMismatch	32.26***	34.77***	40.56***	40.56***	37.98***
	(6.822)	(8.447)	(9.022)	(9.022)	(10.102)
R-squared	0.162	0.174	0.168	0.168	0.174
Observations	29848	29848	29848	29848	29848
Security FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	No	Yes
Macro Controls	No	-	Yes	Yes	-
Macro Interactions	No	No	No	Yes	Yes

The dependent variable is the change in the log of the nominal amount held for insurance companies and pension funds. Δ*Price* is the change in the log of the price. Δ*Mismatch* is the change in the ratio of long-term liabilities to long-term assets of insurance companies and pension funds. The level of Δ*Mismatch* is included in the specification whenever not collinear with the fixed effects. Macro controls include the German GDP growth, inflation, the 10-year government bond yield, the EONIA and the VIX. Macro interaction are the respective interaction of the macro controls with the price change. All independent variables are lagged by one quarter. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Deutsche Bundesbank, time series database, banks and other financial institutions, insurance corporations and pension funds, 2005 Q4 - 2014 Q4; author's calculations.

Table 8: Capital Gains and Balance Sheet Constraints

	Δ Mismatch	Capital		Net Outflows	
	(1)	(2)	(3)	(4)	(5)
Net Capital Gains	0.0542	0.0937***	0.257***	-0.217***	-0.0822***
	(0.054)	(0.034)	(0.008)	(0.072)	(0.007)
R-squared	0.0292	0.186	0.807	0.303	0.335
Observations	36	36	59563	36	92870
Time FE	-	-	Yes	-	Yes
Institution FE	-	-	Yes	-	Yes

The dependent variable Δ*Mismatch* is the change in the ratio of long-term liabilities to long-term assets of insurance companies and pension funds; *Capital* is equity as a ratio of its total assets with assets being fixed at the beginning of the period; *Net Outflow* is the negative of the change in the face value of shares outstanding as a ratio of the lagged Net Asset Value. *Net Capital Gains* are sector or institution specific net capital gains on security holdings and lagged by one quarter. Columns (1), (2) & (4) are on the sector sector-level. Columns (3) & (5) are on the institution-level. Fixed effects are either included (Yes), not included (No) or cannot be included (-). Robust standard errors are in parentheses. Standard errors are clustered at the institution-level and robust to heteroskedasticity and autocorrelation in column (3) and (5). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Deutsche Bundesbank, time series database, banks and other financial institutions, investment fund statistics, monthly balance sheet statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 9: Future Price Changes − Investment Funds

	Dependent variable: $\text{Price}_{t+k} - \text{Price}_t$							
	k=1	k=2	k=3	k=4	k=6	k=8	k=10	k=12
Netbuy_{Funds}	0.201***	0.209	-0.0514	-0.0321	-0.893***	-1.363***	-1.570***	-0.392
	(0.067)	(0.132)	(0.163)	(0.216)	(0.307)	(0.363)	(0.425)	(0.408)
R-squared	0.0253	0.0265	0.0267	0.0314	0.0356	0.0389	0.0471	0.0534
Observations	508645	458306	413195	371909	303699	243732	195595	154294
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the change in the log of the price between quarter t+k and t. $Netbuy_{Funds}$ is the change in the log of the nominal amount held of investment funds. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 10: Future Price Changes − Banks

	Dependent variable: Price_{t+k}-Price_t							
	k=1	k=2	k=3	k=4	k=6	k=8	k=10	k=12
Banks	0.123***	-0.0182	-0.319***	-0.353***	-0.257**	-0.251*	-0.227	-0.736***
	(0.036)	(0.053)	(0.082)	(0.090)	(0.106)	(0.130)	(0.167)	(0.175)
R-squared	0.0253	0.0265	0.0268	0.0315	0.0355	0.0388	0.0469	0.0536
Observations	508645	458306	413195	371909	303699	243732	195595	154294
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the change in the log of the price between quarter t+k and t. $Netbuy_{Banks}$ is the change in the log of the nominal amount held of banks. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 11: Future Price Changes − ICPF

	Dependent variable: Price_{t+k}-Price_t							
	k=1	k=2	k=3	k=4	k=6	k=8	k=10	k=12
Netbuy_{ICPF}	0.0714	-0.213**	-0.233*	-0.188	-0.497**	-0.277	0.761***	1.753***
	(0.056)	(0.097)	(0.126)	(0.169)	(0.243)	(0.255)	(0.260)	(0.268)
R-squared	0.0253	0.0265	0.0267	0.0314	0.0355	0.0387	0.0470	0.0536
Observations	508645	458306	413195	371909	303699	243732	195595	154294
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the change in the log of the price between quarter t+k and t. $Netbuy_{ICPF}$ is the change in the log of the nominal amount held of insurance companies and pension funds. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 12: Momentum and Reversal in Prices

	Dependent variable: $\text{Price}_{t+k} - \text{Price}_t$							
	k=1	k=2	k=3	k=4	k=6	k=8	k=10	k=12
ΔPrice	0.0460***	0.0358***	-0.0173***	0.00378	0.00332	-0.0162	-0.122***	-0.0741***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)	(0.011)	(0.014)	(0.018)
R-squared	0.191	0.193	0.182	0.177	0.158	0.115	0.0479	0.0420
Observations	445056	394264	352757	314980	247176	193422	147924	113408
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable is the change in the log of the price between quarter t+k and t. $\Delta Price$ is the change in the log of the price between quarter t and t-1. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 13: Excess Bond Yield

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔExcess Yield	-0.00225*	-0.00259*	0.0225***	0.0110*	-0.0222***	-0.0205***
	(0.001)	(0.001)	(0.005)	(0.007)	(0.004)	(0.003)
R-squared	0.160	0.165	0.336	0.346	0.201	0.203
Observations	190824	190824	24882	24882	90967	90967
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. Δ *Excess Yield* is the lagged change in the residual of a regression of the yield-to-maturity on the risk-free yield within its maturity bucket, an indicator variable for the credit rating and a security fixed effect. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 14: Credit Rating

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0800***	0.0989***	-1.253***	-0.921***	0.262**	0.271**
	(0.028)	(0.030)	(0.198)	(0.196)	(0.120)	(0.120)
IG	0.000435	-0.0164	0.137**	0.0400	0.0398	0.0121
	(0.019)	(0.019)	(0.061)	(0.066)	(0.035)	(0.035)
ΔPrice ∗ IG	0.0988*	0.149***	0.683***	0.859***	0.184	0.212
	(0.051)	(0.052)	(0.247)	(0.248)	(0.167)	(0.169)
R-squared	0.120	0.126	0.161	0.174	0.112	0.114
Observations	232321	232321	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *IG* is a dummy that equals one if the security is rated investment grade and zero otherwise and is lagged by one quarter. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table 15: Foreign Currency Bonds

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.101**	0.212***	-0.709***	-0.243	0.165*	0.198*
	(0.050)	(0.053)	(0.131)	(0.151)	(0.099)	(0.105)
ΔPrice ∗ FC	0.00445	-0.0921	-0.588**	-0.763***	0.509***	0.452**
	(0.057)	(0.059)	(0.284)	(0.281)	(0.184)	(0.185)
R-squared	0.120	0.126	0.161	0.173	0.112	0.114
Observations	232314	232314	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

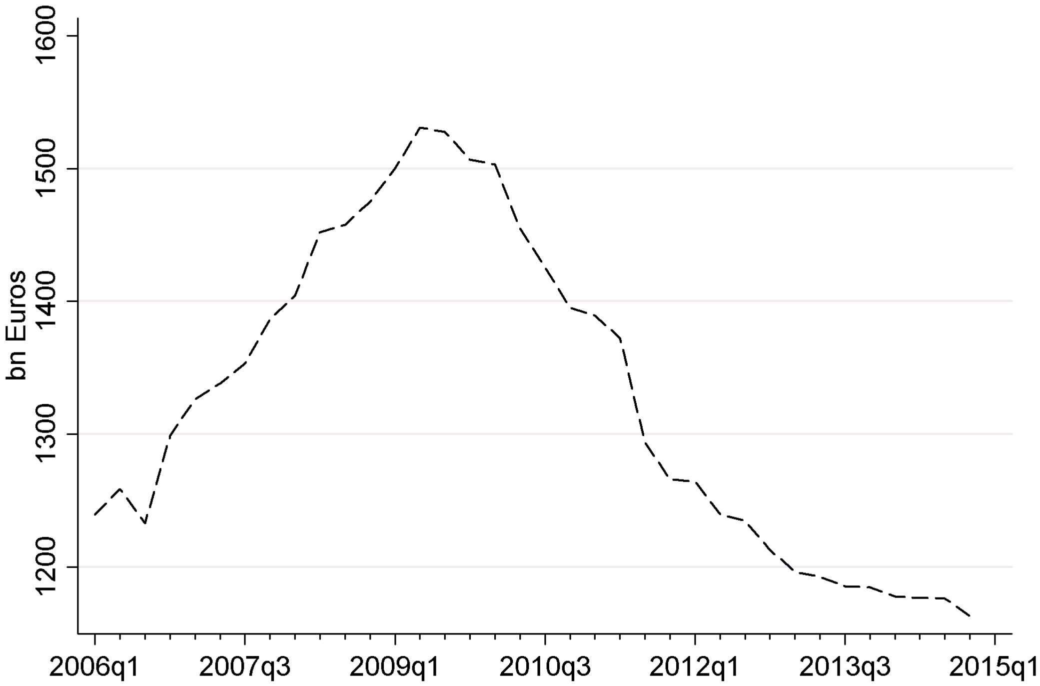
The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *FC* is a dummy that equals one if the security is denominated in foreign currency and zero otherwise. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table 16: β Stockmarket

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.122***	0.162***	-0.841***	-0.342**	0.275***	0.300***
	(0.032)	(0.036)	(0.144)	(0.147)	(0.099)	(0.095)
ΔPrice $* \beta_{Dax}$	-0.135	-0.210	-0.651	-1.551**	0.841**	0.670**
	(0.141)	(0.188)	(0.509)	(0.725)	(0.353)	(0.326)
R-squared	0.116	0.122	0.160	0.172	0.109	0.110
Observations	230374	230374	29609	29609	117616	117616
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

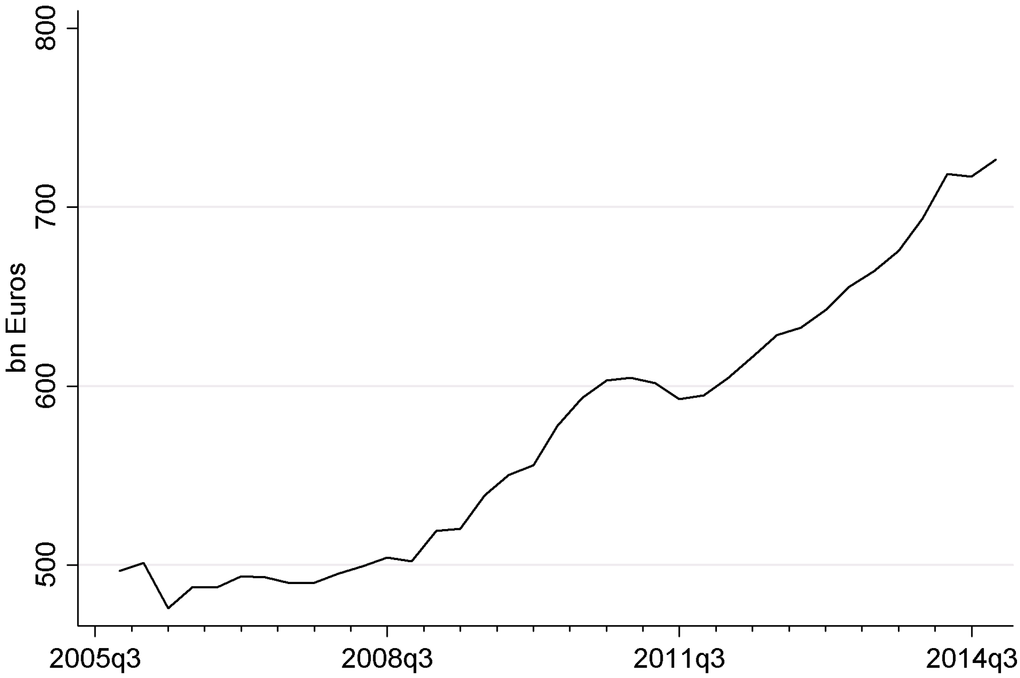
The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. β_{Dax} is the coefficient obtained from a regression of the price change of the security on the percentage change of the German stockmarket index (Dax). β_{Dax} is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Figure 1: Nominal Debt Security Holdings of Banks



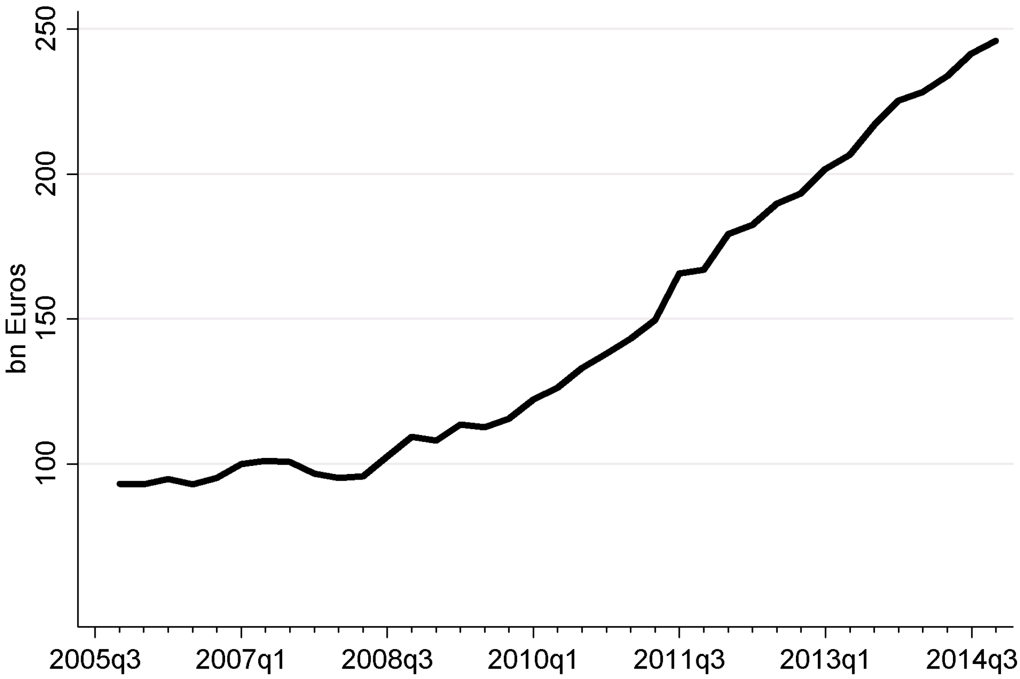
Note: The Figure shows the nominal value of debt securities held by banks. Source: Author's calculations; Data: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4.

Figure 2: Nominal Debt Security Holdings of Investment Funds



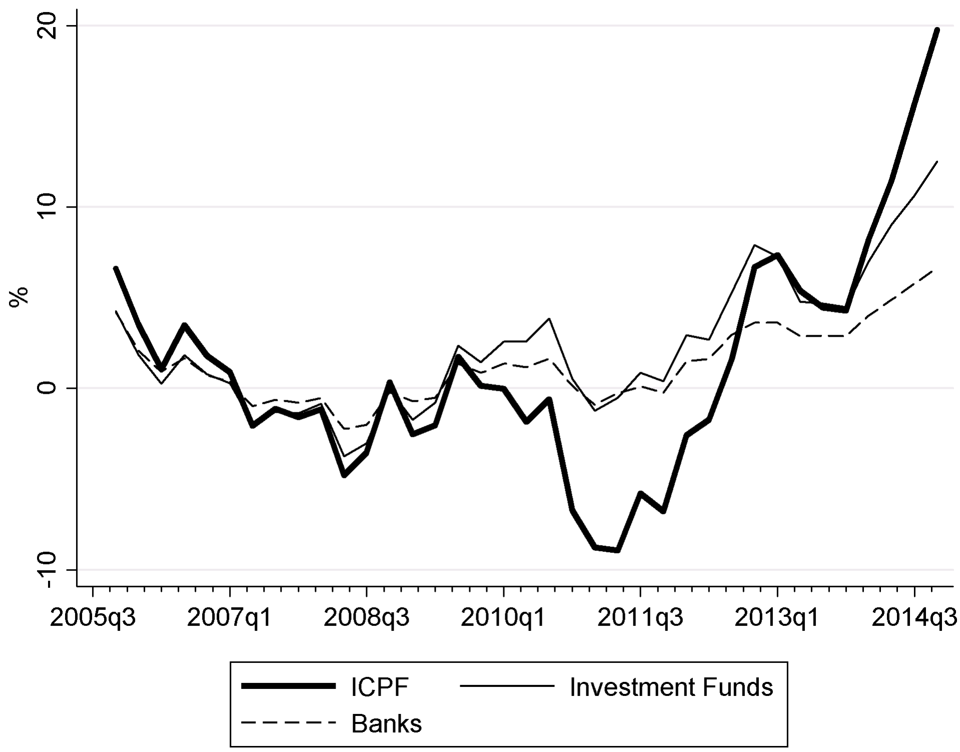
Note: The Figure shows the nominal value of debt securities held by investment funds. Source: Author's calculations; Data: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4.

Figure 3: Nominal Debt Security Holdings of Insurance Companies and Pension Funds



Note: The Figure shows the nominal value of debt securities held by insurance companies and pension funds. Source: Author's calculations; Data: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4.

Figure 4: Capital Gains on Security Holdings

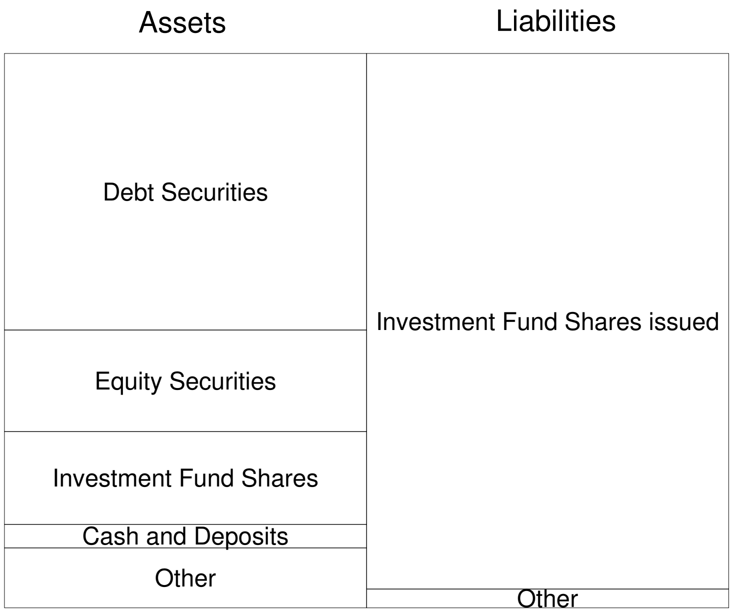


Note: The Figure shows the capital gains of *Banks*, *Investment Funds* and insurance companies and pension funds (*ICPF*). The capital gains are calculated as the difference between the total market value of all securities and the total nominal value of all securities divided by the total nominal value of all securities. Source: Author's calculations; Data: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4.

Figure 5: Balance Sheet of Banks in Germany

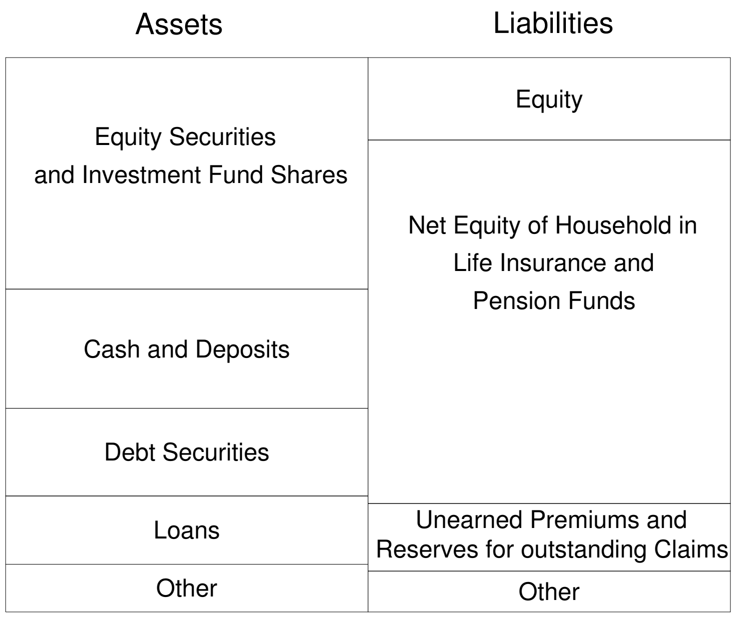
Note: Assets (in EUR billions, share of total assets): Loans to Non-Banks (3127, 40%), Loans to Banks (1950, 25%), Debt Securities (1176, 15%), Others (1599, 20%); Liabilities (in EUR billions, share of total liabilities): Capital (382, 5%), Retail Deposits (3299, 42%), Interbank Borrowing (1717, 22%), Debt Securities issued (1115, 14%), Other (1341, 17%); Total: EUR 7853 billion. Source: Author's calculations; Data: Deutsche Bundesbank, time series database, banks and other financial institutions, banks.

Figure 6: Balance Sheet of Investment Funds in Germany



Note: Assets (in EUR billions, share of total assets): Debt Securities (825, 50%), Equity Securities (303, 18%), Investment Fund Shares (277, 17%), Cash and Deposits (70, 4%), Other (179, 11%); Liabilities (in EUR billions, share of total liabilities): Investment Fund Shares issued (1597, 97%), Other (56, 3%); Total: EUR 1653 billion. Source: Author's calculations; Data: Deutsche Bundesbank, time series database, banks and other financial institutions, investment companies

Figure 7: Balance Sheet of Insurance Companies and Pension Funds in Germany



Note: Assets (in EUR billions, share of total assets): Investment Fund Shares and Equity Securities (1014, 42%), Cash and Deposits (384, 21%), Debt Securities (384, 16%), Loans (299, 12%), Other (209, 9%); Liabilities (in EUR billions, share of total liabilities): Equity (361, 15%), Net Equity of Household in Life Insurance and Pension Funds (1592, 66%), Unearned Premiums and Reserves for outstanding Claims (296, 12%), Other (90, 3%) Total: EUR 2428 billion. Source: Author's calculations; Data: Deutsche Bundesbank, time series database, banks and other financial institutions, insurance corporations and pension funds.

Appendix

While most securities have a constant amount outstanding over time, the supply of some securities can change. The actual amount outstanding can change if the bond is callable or when for asset-backed securities a part of the amount issued is returned to investors early. The effective amount outstanding (the tradable amount) of securities can for instance be altered when securities are bought under asset-purchase programs. While if the total amount outstanding diminishes, the security is not included in the sample, the security is included when the amount outstanding is not reduced to zero. In order to make sure that the changed amount outstanding does not appear as a transaction, I adjust by the pool-factor.[53]

The nominal value is

$$NominalValue = RawValue * e * Poolfactor \tag{16}$$

where e is the domestic price of foreign currency. The pool factor adjusts the nominal value of the specific security by partial or special redemptions. If no redemption has occurred, the poolfactor is one. It gives the amount that is left to be distributed.

In order to obtain a nominal value that moves only when a security is actually bought or sold, the nominal value needs to be adjusted by exchange rate changes and the pool factor.

$$AdjustedNominalValue_t = \frac{NominalValue_t}{Poolfactor_t} * \frac{e_{t-1}}{e_t} \tag{17}$$

$\frac{e_{t-1}}{e_t} - 1$ is the percentage appreciation of the Euro. If the Euro appreciates and the foreign currencies depreciate, this reduces the nominal value of securities in Euros if these securities are denominated in foreign currency and these movements do not reflect buy decisions. By multiplying by the poolfactor, I adjust for partial or special redemptions. In the text, I always refer to the adjusted nominal value in order to adjust for the movements that do not reflect investment decisions. The netbuy variable is obtained by taking the natural log change of the adjusted nominal value given they trade.

[53]This changed supply can still have effects that are not captured by the security fixed effects. However, I can control for this security-specific amount outstanding by including security∗time fixed effects.

Table A1: Bond Holdings of German Investors (in %)

Variable	Funds	ICPF	Banks
Government	54.9	53.2	33.1
OFC	7.5	7.3	9.8
NFC	8.3	3.9	1.5
Banks	29.3	35.5	55.5
Euro	84.2	92.2	95.1
USD	11.8	2.4	3.4
Other Currency	4.2	5.6	1.8
Domestic	39.6	39.5	73.6
Foreign	60.7	60.7	26.7

Percentage debt securities holdings of investment funds (*Funds*), insurance companies and pension funds (*ICPF*) and *Banks* issued by the Government, Other-Financial Corporations (OFC), Non-Financial Corporations (NFC), Banks, in Euros, US Dollars (USD), other currency and by domestic or foreign residents. Values are averages over the sample period. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2004 Q4 - 2014 Q4; author's calculations.

Table A2: German vs. Foreign Bonds

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.114***	0.142***	-0.941***	-0.509***	0.383***	0.406***
	(0.025)	(0.027)	(0.149)	(0.157)	(0.103)	(0.104)
ΔPrice $*$ German	-0.161*	-0.107	0.293	0.279	-0.129	-0.142
	(0.088)	(0.089)	(0.229)	(0.239)	(0.179)	(0.182)
R-squared	0.120	0.126	0.161	0.173	0.112	0.114
Observations	232321	232321	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *German* is a dummy that equals one if the country of issue is Germany and zero otherwise. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table A3: Covariance Stockmarket

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0850***	0.119***	-0.934***	-0.519***	0.255***	0.269**
	(0.033)	(0.039)	(0.154)	(0.160)	(0.096)	(0.110)
ΔPrice$*cov_{\Delta Price,Dax}$	0.0104	0.00887	0.0793	0.0536	0.106*	0.0979*
	(0.015)	(0.017)	(0.087)	(0.082)	(0.056)	(0.056)
R-squared	0.120	0.126	0.159	0.171	0.111	0.113
Observations	226614	226614	29432	29432	119032	119032
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. $cov_{\Delta Price,Dax}$ is the covariance of the price change of the security and the percentage change of the German stockmarket index (Dax). $cov_{\Delta Price,Dax}$ is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table A4: β Risk-free Yield

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0964***	0.131***	-0.859***	-0.442***	0.349***	0.364***
	(0.027)	(0.036)	(0.143)	(0.152)	(0.091)	(0.111)
ΔPrice $*\ \beta_{rf}$	0.00803	0.00553	0.162	0.118	-0.0136	-0.00962
	(0.020)	(0.016)	(0.128)	(0.107)	(0.049)	(0.066)
R-squared	0.111	0.117	0.158	0.170	0.106	0.108
Observations	221671	221671	28844	28844	112615	112615
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. β_{rf} is the coefficient obtained from a regression of the yield of the security on on the risk-free yield within its maturity bucket. β_{rf} is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table A5: Covariance Risk-free Yield

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0991***	0.133***	-0.894***	-0.488***	0.346***	0.364***
	(0.025)	(0.034)	(0.165)	(0.138)	(0.122)	(0.101)
ΔPrice$*cov_{yield,rf}$	-0.0263	-0.0396**	0.0643	0.0723	0.00779	0.0168
	(0.024)	(0.018)	(0.106)	(0.125)	(0.057)	(0.054)
R-squared	0.113	0.119	0.159	0.171	0.106	0.108
Observations	217641	217641	28829	28829	112092	112092
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. $cov_{yield,rf}$ is the covariance of the yield of the security and the risk-free yield within its maturity bucket. $cov_{yield,rf}$ is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Bloomberg, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table A6: Volatility

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.109***	0.153***	-0.928***	-0.363	0.539***	0.594***
	(0.035)	(0.040)	(0.174)	(0.233)	(0.126)	(0.137)
ΔPrice $*$ vol	-0.00240	-0.00925	0.0600	-0.0414	-0.121**	-0.130**
	(0.018)	(0.017)	(0.090)	(0.099)	(0.057)	(0.058)
R-squared	0.120	0.126	0.161	0.173	0.112	0.114
Observations	232321	232321	29848	29848	120336	120336
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *vol* is the standard deviation of $\Delta Price$. *vol* is demeaned and standardized by the sample standard deviation. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Bootstrapped standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table A7: VIX

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.0719***	0.133***	-1.003***	-0.463***	0.328***	0.346***
	(0.027)	(0.031)	(0.127)	(0.146)	(0.096)	(0.102)
VIX	0.00492		0.0464***		-0.00293	
	(0.003)		(0.012)		(0.007)	
ΔPrice ∗ VIX	0.140**	0.00936	0.623**	0.207	0.0888	0.0856
	(0.056)	(0.060)	(0.282)	(0.347)	(0.202)	(0.214)
R-squared	0.120	0.126	0.162	0.173	0.112	0.114
Observations	232041	232041	29848	29848	120283	120283
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. Δ*Price* is the change in the log of the price and is lagged by one quarter. *VIX* is the log of the implied volatility for S&P 500 stock options and demeaned by the sample average. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, Datastream, 2005 Q4 - 2014 Q4; author's calculations.

Table A8: Crisis Split for Funds

	Dependent variable: Netbuy					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.131*	0.0540	0.109***	0.106***	0.0946*	0.172***
	(0.078)	(0.085)	(0.029)	(0.032)	(0.054)	(0.064)
R-squared	0.190	0.196	0.164	0.168	0.183	0.191
Observations	42186	42186	99962	99962	86831	86831
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Period	Pre-Crisis	Pre-Crisis	Crisis	Crisis	Post-Crisis	Post-Crisis

The dependent variable is the change in the log of the nominal amount held for investment funds. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Pre-Crisis* refers to the period 2006 Q1:2008 Q1, *Crisis* refers to 2008 Q2:2012 Q3 and *Post-crisis* refers to 2012 Q4:2014 Q4. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table A9: Crisis Split for ICPF

	Dependent variable: Netbuy					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	-3.383***	-2.335***	-0.502***	-0.168	-0.466*	-0.531*
	(0.486)	(0.573)	(0.155)	(0.180)	(0.252)	(0.296)
R-squared	0.258	0.268	0.181	0.194	0.235	0.246
Observations	7776	7776	13225	13225	7877	7877
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Period	Pre-Crisis	Pre-Crisis	Crisis	Crisis	Post-Crisis	Post-Crisis

The dependent variable is the change in the log of the nominal amount held for insurance companies and pension funds. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Pre-Crisis* refers to the period 2006 Q1:2008 Q1, *Crisis* refers to 2008 Q2:2012 Q3 and *Post-crisis* refers to 2012 Q4:2014 Q4. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table A10: Crisis Split for Banks

	Dependent variable: Netbuy					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	0.615**	0.664**	0.256**	0.302***	0.761***	0.569**
	(0.282)	(0.297)	(0.104)	(0.110)	(0.250)	(0.267)
R-squared	0.146	0.147	0.151	0.153	0.167	0.170
Observations	30665	30665	53165	53165	33314	33314
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Period	Pre-Crisis	Pre-Crisis	Crisis	Crisis	Post-Crisis	Post-Crisis

The dependent variable is the change in the log of the nominal amount held for banks. Δ*Price* is the change in the log of the price and is lagged by one quarter. *Pre-Crisis* refers to the period 2006 Q1:2008 Q1, *Crisis* refers to 2008 Q2:2012 Q3 and *Post-crisis* refers to 2012 Q4:2014 Q4. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table A11: Buy and Sell

	Funds		ICPF		Banks	
Dependent variable:	Buy	Sell	Buy	Sell	Buy	Sell
	(1)	(2)	(3)	(4)	(5)	(6)
ΔPrice	1.592***	-0.524**	-0.865*	4.235***	1.825***	-1.232***
	(0.237)	(0.247)	(0.443)	(0.402)	(0.270)	(0.280)
R-squared	0.238	0.272	0.254	0.286	0.378	0.338
Observations	333827	336908	116917	119234	405185	408853
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

The dependent variable *Buy* is the log of the nominal amount bought. The dependent variable *Sell* is the log of the nominal amount sold. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table A12: Issuer Sector Heterogeneity

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Price$	0.121***	0.137***	-3.096***	-2.712***	0.875***	0.828***
	(0.037)	(0.039)	(0.682)	(0.662)	(0.276)	(0.276)
$\Delta Price*$ gov	-0.146**	-0.124*	2.442***	2.437***	-0.770**	-0.650**
	(0.069)	(0.070)	(0.698)	(0.673)	(0.310)	(0.309)
$\Delta Price *$ banks	0.0844	0.123*	2.406***	2.653***	-0.468	-0.446
	(0.069)	(0.071)	(0.718)	(0.695)	(0.300)	(0.299)
$\Delta Price *$ ofc	-0.0379	-0.0122	2.196***	2.246***	-0.293	-0.267
	(0.062)	(0.063)	(0.748)	(0.719)	(0.357)	(0.357)
R-squared	0.121	0.127	0.161	0.173	0.113	0.115
Observations	226726	226726	29556	29556	119033	119033
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price$ is the change in the log of the price and is lagged by one quarter. *gov* is a dummy that equals one if the security is a government bond and zero otherwise. *banks* is a dummy that equals one if the security is a bank bond and zero otherwise. *ofc* is a dummy that equals one if the security is a bond issued by an other-financial institution and zero otherwise. The level coefficient reflects the response to non-financial corporate bonds. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.

Table A13: Summary Table

	Dependent variable: Netbuy		
	(1)	(2)	(3)
Specification	Funds	ICPF	Banks
(1) No Controls	0.156***	-0.461***	0.343***
	(0.021)	(0.113)	(0.070)
(2) Security FE	0.106***	-0.900***	0.351***
	(0.024)	(0.115)	(0.085)
(3) Macro Controls	0.140***	-0.792***	0.368***
	(0.024)	(0.116)	(0.085)
(4) Country Controls	0.172***	-0.828***	0.366***
	(0.024)	(0.121)	(0.087)
(5) Country∗Time FE	0.126***	-0.480***	0.345***
	(0.028)	(0.155)	(0.095)
(6) Country∗Sector∗Time FE	0.155***	-0.341**	0.387***
	(0.029)	(0.167)	(0.098)
(7) Sample of securities held by all	0.105***	-0.850***	0.341***
	(0.024)	(0.116)	(0.084)

The dependent variable is the change in the log of the nominal amount held. The coefficients are the estimated effect of ΔPrice. ΔPrice is the change in the log of the price and is lagged by one quarter. For each sector the number of observations are the same in specifications (1)-(6). *Macro Controls* include German GDP growth, inflation, the 10-year government bond yield for Germany and the EONIA as well as the VIX. *Country Controls* include country-specific GDP growth, inflation, the 10-year government bond yield for Germany and the EONIA as well as the VIX. Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, IMF, ECB, 2005 Q4 - 2014 Q4; author's calculations.

Table A14: Broad and Relative Price Changes

	Dependent variable: Netbuy					
	Funds		ICPF		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \text{Price}_{broad}$	-0.0142	0.0180	-1.125***	-0.463*	0.423***	0.537***
	(0.038)	(0.050)	(0.208)	(0.243)	(0.136)	(0.154)
$\Delta \text{Price}_{relative}$	0.127***	0.132***	-0.464***	-0.269*	0.342***	0.349***
	(0.028)	(0.029)	(0.148)	(0.152)	(0.096)	(0.097)
R-squared	0.116	0.122	0.162	0.173	0.109	0.111
Observations	207761	207761	27449	27449	108468	108468
Security FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

The dependent variable is the change in the log of the nominal amount held. $\Delta Price_{broad}$ is the price change of the index for the issuing sector in the specific country. $\Delta Price_{relative}$ is the deviation of the security-specific price change from the price change of the country-issuing sector index. All independent variables are lagged by one quarter. Column (1)-(2) estimate the specification for the investment fund sector. Column (3)-(4) estimate the specification for the insurance companies and pension fund sector. Column (5)-(6) estimate the specification for the banking sector. Fixed effects are either included (Yes), not included (No) or spanned by other fixed effects (-). Standard errors are in parentheses. Standard errors are clustered at the security-level and robust to heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Research Data and Service Centre of the Deutsche Bundesbank, Microdatabase Securities Holdings Statistics, 2005 Q4 - 2014 Q4; author's calculations.