Real Estate Investments, Regulation, and Financial Intermediation

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

Real estate as an asset class can deliver high risk-adjusted returns, which are also low-correlated to the returns of other asset classes, such as stocks and bonds. According to the literature, a well-diversified mixed-asset portfolio should therefore comprise between 10% and 30% of real estate.[1] This holds true for large and medium-sized institutional investors, but also for small retail investors (private investors). However, direct real estate proves to be an unsuitable investment for the vast majority of private investors. The reasons for this include high transaction costs and long transaction periods (leading to low liquidity), the heterogeneity of the assets themselves and the absence of an efficient marketplace (resulting in high due diligence costs) and, above all, the large lot sizes of the individual assets.[2] The large lot sizes and the indivisibility of direct real estate make it impossible for small investors to create a well-diversified portfolio, consisting of a variety of different real estate assets. Even one single direct investment typically exceeds the above-mentioned optimal portfolio weight of 10% to 30% for the vast majority of private investors, leaving them with an unbalanced portfolio containing lump risks.[3] Furthermore, a direct investment would leave the unspecialized private investor with rather high due diligence costs. To sum up, direct real estate involves risks that are not compensated with a risk premium, since they can be diversified and mitigated by increasing portfolio size.

In order to nevertheless profit from the favorable risk-return profile and the diversification benefits of real estate, private investors can invest indirectly. By doing so, the investor acquires claims against a financial intermediary (usually in form of fund shares, certificates or policies). The financial intermediary for its part invests in direct physical real estate.

Due to its portfolio size, the financial intermediary is able to invest in a large di-

[1] Studies examining the optimal real estate quota include Ziobrowski and Ziobrowski (1997), Chun et al. (2000), Brounen and Eichholtz (2003), Hoesli et al. (2004), Bond et al. (2006), Lee and Stevenson (2006), Hoesli and Lizieri (2007), Brounen et al. (2010) and Rehring (2012).

[2] For a more comprehensive overview of the shortfalls of direct real estate as an asset class, see, for example, Sebastian et al. (2012).

[3] According to the literature, at least 20 to 50 different assets are required to diversify most of the idiosyncratic asset specific risk, see, for example, Brown and Matysiak (2000).

versified real estate portfolio on the one hand, but to issue very small shares on the other hand, thus transforming the lot size substantially.[4] Furthermore, the intermediary is able to transform risk, return and liquidity. Open-end real estate funds in Germany, for example, issue and redeem shares on a daily basis, whereas trading the actual underlying real estate assets usually takes several months. Moreover, the funds issue and redeem shares at the valuation-based net asset value of the underlying properties, instead of at their more volatile market transaction price.[5]

Another example of the transformation of risk, return and liquidity are life insurance policies, also known as life endowment policies. As a private retirement scheme, life insurance policies are illiquid and have a term to maturity of usually more than 20 years. In return, the policies offer a guaranteed minimum return rate, independent of the more volatile and uncertain returns of the underlying assets (i.e. bonds, stocks and real estate).

Both of the aforementioned types of financial intermediation are popular amongst private investors in Germany. According to GDV (2006), the market for life insurance policies has a volume of more than EUR 1.000 billion in Germany alone. With an invested capital of EUR 145 billion, the German open-end real estate fund industry is the predominant indirect German real estate investment vehicle and the largest market for open-end real estate funds worldwide.[6] One reason for the tendency towards non-listed indirect investments in Germany can be seen in the widely-held aversion to market volatility and stock ownership amongst German retail investors.[7]

However, financial intermediaries cannot eliminate but only transform illiquidity and market volatility. Therefore, financial intermediaries are usually exposed to structural risks in exchange for delivering more stable returns and/or increased liquidity.

[4] According to BVI (2017), the portfolio volume of German open-end real estate funds average out at more than EUR 150 million. The share prices usually range from EUR 50 to EUR 100.

[5] See Barkham and Geltner (1994) for an examination of the dynamic of prices and valuations.

[6] See Downs et al. (2016).

[7] According to the 2016 shareholding statistics of Deutsches Aktieninstitut (DAI), the number of shareholders and investors in equity funds in Germany amounted to only 9 million in 2016. This equals 14 percent of the German population over the age of 14 years.

Since direct real estate assets cannot be traded on a daily basis, an open-end real estate fund can become insolvent if the volume of its redeemed shares exceeds the sum of its newly issued shares and its cash reserve at any point in time. In this case the fund must immediately suspend the redemption of its shares and may eventually even be forced to liquidate its portfolio, both of which are very unpleasant for the funds investors.[8] A life insurance company faces insolvency if the guaranteed rates sustainably exceed the return of its portfolios assets. Anticipating this might cause life insurance companies to rethink their asset allocations and shift portfolio weights away from government bonds towards higher yielding asset classes, such as real estate. This in turn may lead to more portfolio risk and regulatory intervention.

This dissertation analyzes the structural risks of open-end real estate funds in Germany and of life insurance companies in Europe. Both intermediaries have been exposed to economic uncertainty, low interest rates and regulatory intervention in the aftermath of the great financial crisis in 2007/2008.

Chapter 2 examines the impact of a new risk-based regulatory framework (Solvency II) on the attainability of target returns, the attainability of portfolio efficiency and the asset allocation of European life endowment insurers. The chapter starts with a brief introduction to the Solvency II Directive, focusing on the rules for calculating solvency capital requirements (SCR) according to the Solvency II standard formula. The subsequent numerical analysis includes several portfolio optimizations focusing on six relevant asset classes for the 1993 to 2017 time period. Optimal portfolios with respect to the Solvency II capital requirements, with respect to conventional risk measures, and a combination of both optimization problems were derived. The results show that the capital requirements according to Solvency II are not adequately calibrated. Nevertheless, due to a solid equity base, the majority of European insurers are still able to attain high target returns and mean-variance-efficiency. However, undercapitalized insurers are not able to hold risk-optimal allocations of

[8] Chapter 4.2 provides some regulatory background on the liquidation regime of German open-end real estate funds and an overview of the recent crisis.

equities, real estate and hedge funds any longer. In an environment of very low interest rates, these insurers may also face difficulties obtaining their target returns. This is the first study to explicitly incorporate the solvency capital requirement as a numerical constraint into the insurers' portfolio optimization problem. As a result, the approach shown in this chapter first provides insights into the attainable target return and the asset weights as a direct function of insurers' equity.

Chapter 3 examines the factors that cause the closing (i.e. the redemption of shares) of open-end real estate funds. During the October 2008 fund crisis, approximately one-third of German open-end real estate retail funds, with total assets under management of about EUR 30 billion, were forced to suspend the redemption of their shares. A fund closure generally leads to fund liquidation, which is a severe issue for management and investors. Subsequent to a closure, the fund management is forced to liquidate the fund by selling the real estate assets. The liquidation often occurs under high selling pressure, and may involve significant fees. Moreover, in the event of a fund closure, the fund investors' capital is totally constrained. Investors can no longer redeem their shares but only sell them on the secondary market, often at significantly discounted prices. Thus, knowing the determinants of fund closures could help the fund management to adjust investment strategies and diminish the closure risk. The monthly panel dataset contains fund-specific information such as the liquidity ratio, capital net inflows, leverage ratios and management fees for the entire population of German open-end real estate retail funds over the August 2002 to June 2016 time period. The results of the logit model suggest a significantly positive influence of fund run risk and industry-wide spillover effects on fund closure probability. The results also indicate that a greater share of institutional investors tends to increase the probability of fund closure. On the other hand, economies of scale and scope decreased the probability of fund closures.

Chapter 4 examines the discount to net asset value (NAV) of closed open-end real estate funds in Germany. During the global financial crisis, the German open-end real estate fund industry experienced massive share redemptions. A total of ten

retail funds with cumulative assets under management of over EUR 30 billion, were forced to suspend share redemptions, and nine funds ultimately liquidated their entire portfolios. Investors of these funds could await the stepwise liquidation of the funds' assets (which usually takes several years) or they could sell their shares on the secondary market, often at a notable discount to net asset value (NAV). This chapter analyzes the discount to NAV of distressed German open-end real estate funds. The hand-collected dataset covers the entire crisis and post-crisis period from October 2008 to June 2016. The analysis shows that the discount to NAV is driven by fundamental risks: It is positively correlated with the fund's leverage ratio and decreases with the share of liquid assets. Moreover, the NAV discounts are related to potential conflicts of interest between investors and fund management (TER and extraordinary payouts). The findings also include that NAV discounts are driven by spillover effects from the announcement of other fund liquidations, as well as by investor sentiment, which is approximated by the aggregate level of capital inflows into the industry and by the degree of macroeconomic uncertainty.

The dissertation ends with a conclusion in Chapter 5.

Chapter 2

The Impact of Risk-Based Regulation on European Insurers' Investment Strategy

Michael Heinrich, Daniel Wurstbauer

2.1 Introduction

Short-term and long-term interest rates are currently close to their historical lows, as are yields on top-rated government bonds. For example, the annual yield on new issue 10-year German government bonds was just 0.467% in July 2017, with no sustainable interest rate turnaround foreseeable anytime soon. According to a recent publication by the European Central Bank (ECB), more than half the investments of insurance companies in Europe are in fixed-interest securities. Hence, this politically motivated low-interest phase poses a major challenge to the largest institutional investors in Europe, which together hold almost EUR 7.8 trillion of assets.[1] More precisely, the combination of low bond yields and high interest rate guarantees on existing life insurance policies can result in severe undercoverage for insurers.[2] The pressure on insurance companies to take action is growing even stronger because the high yielding bonds from the pre-low-interest phase that insurers still hold in their portfolios will mature sooner than the "high rate" insurance policies. Insurers will therefore be forced to move their investments out of top-rated government bonds into asset classes offering higher returns, such as corporate bonds, equities or alternative investments like real estate or hedge funds.

Several practitioner studies report that European insurers have already expanded their quotas for alternative investments in recent years.[3] However, the introduction of a new risk-based regulatory framework in 2016 (Solvency II) could have significant implications on insurers' investment strategy and could even counteract this trend in the months and years ahead. In order to limit their insolvency risk, insurers must now underpin all risky balance sheet items (including investments) pro rata with equity capital. The required amount of equity — the solvency capital requirement or SCR — varies considerably depending on the respective asset class. From an

[1] See ECB (2017).

[2] According to an analysis by Assekurata (2016), for example, the average guaranteed interest rate on existing policies among German life insurance companies amounted to 2.97% in 2016.

[3] Blackrock (2013), Preqin (2013), Preqin (2015), Insurance Europe and Oliver Wyman (2013), Towers Watson (2013), EY (2016), EY (2017).

economic perspective, the regulator has introduced a new constraint into the portfolio optimization problem: The aggregate of the SCR for all risk positions must be less than the insurer's amount of equity capital (the basic own funds or BOF). If this constraint is binding, a shift in the portfolio weights is foreseeable. Since the optimized portfolios without the constraint are efficient, the constrained portfolios must exhibit either more risk or less return. Both effects are highly undesirable, considering that the original purpose of the regulation is the mitigation of risk, and that insurers are already facing undercoverage in terms of return.[4]

Most of the existing literature on the effects of Solvency II on insurers' investment policy only deals with specific details of the framework, such as the calibration of the SCR for certain asset classes, for example.[5] There are, however, two very comprehensive and seminal contributions by Hoering (2013) and Braun et al. (2015), entitled "Will Solvency II Market Risk Requirements Bite? The Impact of Solvency II on Insurers' Asset Allocation" and "Portfolio Optimization Under Solvency II: Implicit Constraints Imposed by the Market Risk Standard Formula", respectively. Hoering (2013) states that the aforementioned constraint imposed by the Solvency II standard formula's market risk module is not binding for many European insurers. He notes that the widely-used Standard & Poor's (S&P) rating model requires even more equity capital than Solvency II for most S&P rating classes. He concludes that insurers with a credit rating of BBB or better will most likely not alter their asset allocation after the introduction of Solvency II. However, Hoering is not examining efficient portfolios in an environment of extremely low interest rates, but rather the investment portfolio of a representative European-based life insurer in 2012. Braun et al. (2015), on the other hand, consider the issue of optimizing an insurance company's asset allocation when the firm needs to adhere to the capital requirements of Solvency II in the context of modern portfolio theory. They run a quadratic

[4]Besides the effects on portfolio efficiency, a reallocation of insurers' assets could lead to fundamental shifts in demand and pricing for several asset classes, as Fitch Ratings (2011) has already pointed out.

[5]See, for example, Braun et al. (2014), Gatzert and Kosub (2013), Gatzert and Martin (2012), Severinson and Yermo (2012), Fischer and Schlüter (2012), Al-Darwish et al. (2011), Rudschuck et al. (2010) and Van Bragt et al. (2010).

portfolio optimization program, and subsequently compute the capital charges for the respective portfolios according to Solvency II. They find that most of the efficient portfolios are not admissible if the insurer's amount of equity capital is limited to the industry average of 12%. In contrast to Hoering, Braun et al. therefore conclude that Solvency II might cause severe asset management biases in the European insurance sector.

This paper fills the gap between the two aforementioned studies: Depending on insurers' equity capital and investment objectives, Solvency II might render certain target returns unattainable, cause portfolio inefficiency or lead to no restrictions on insurers' asset allocation at all. To the best of our knowledge, there exists no previous study that has explicitly incorporated the solvency capital requirement as a numerical constraint into the insurers' portfolio optimization problem. As a result, our approach first provides insights into the attainability of different target returns as a direct function of insurers' basic own funds.[6] Furthermore, we calculate the critical threshold for the basic own funds needed to attain portfolio efficiency at the respective target returns. Ultimately, our analysis provides an in-depth look at how the optimal portfolio weights for individual asset classes will respond to a restriction on insurers' equity capital.

The paper is structured as follows. Section 2.2 presents the market risk standard formula of Solvency II. Section 2.3 introduces the dataset used within the portfolio optimization, as well as the specific calibration of the Solvency II standard formula according to the dataset. In Section 2.4, we run different portfolio optimization programs with the solvency capital requirement as an explicit constraint, and present the results. Finally, Section 2.5 concludes.

[6]Note that the attainability of a certain target return is necessary to fulfill the interest rate guarantees on existing life insurance policies, as already pointed out.

2.2 The Solvency II Standard Formula

Solvency II codifies and harmonizes the insurance regulation inside the European Union (EU). Its primary concern is the amount of equity capital that insurance companies must hold to reduce their risk of insolvency. For this purpose, Solvency II introduced risk-based capital requirements across all EU Member States for the first time. The solvency capital requirement (the SCR) for an individual insurer can be determined either by using a standard formula imposed by the regulator, or by implementing an insurance internal model. The focus of this paper will be on the Solvency II standard formula, which serves as a reference point for any further analysis.

The Solvency II standard formula refers to basic actuarial principles, and it is calibrated according to historical data. The standard formula consists of separate risk modules (i.e., risk categories), including market risk, counterparty default risk, life underwriting risk, non-life underwriting risk, health underwriting risk and intangible asset risk. Each of these modules consists of further sub-modules (see EIOPA, 2012). In order to determine a company's overall capital requirement, the capital requirements for all risk modules (and sub-modules) are determined first, and aggregated subsequently by taking into account diversification effects.

The further analysis is focused on the market risk module, which is of particular importance as its capital requirements depend directly on the insurers' asset allocation. In addition, according to the "EIOPA Report on the fifth Quantitative Impact Study (QIS5) for Solvency II" (see EIOPA, 2011), and according to a study by Fitch Ratings (2011), the market risk module plays the predominant role in determining a company's overall SCR.

The market risk module (SCR_{mkt}) consists of seven sub-modules: interest rate risk, equity risk, property risk, spread risk, concentration risk, illiquidity risk and exchange rate risk. In line with previous studies (see Gatzert and Martin, 2012 or

Braun et al., 2015, for example), the further analysis is limited to the most important sub-modules, which are interest rate risk, equity risk, property risk and spread risk. Generally, the SCR for each sub-module refers to the change in the basic own funds ΔBOF that results due to a shock or stress in the financial markets, related to the module's risk category (e.g., a real estate crisis, a shift in the term structure of interest rates, etc.). BOF is defined as the difference between the market values of assets and liabilities. Without loss of generality, BOF is assumed to equal the equity capital position on the insurer's balance sheet. All specifications presented next are taken from the "Revised Technical Specifications for the Solvency II valuation and Solvency Capital Requirements calculations" released by EIOPA (2012).[7] This document defines the Solvency II standard formula.

The interest rate risk sub-module (Mkt_{int}) accounts for the fact that both assets and liabilities react to changes in the term structure of interest rates. As the assets' and the liabilities' interest rate sensitivities are typically not perfectly matched, both upward and downward shocks to the yield curve could theoretically have a negative effect on the BOF. Hence, the capital requirement for interest rate risk depends on two possible states,

$$Mkt_{int}^{up} = BOF|_{up} \tag{2.1}$$

$$Mkt_{int}^{down} = \Delta BOF|_{down} \tag{2.2}$$

where $\Delta BOF|_{up}$ and $\Delta BOF|_{down}$ are the changes in the market value of assets minus liabilities caused by an upward or downward change in the interest rate, respectively. The altered interest rate structures for the two stress scenarios ("up" and "down") are derived by multiplying the current interest rate for any given maturity (r_t) by predefined upward and downward stress factors (s_t^{up} and s_t^{down}), which are specified and tabulated by the regulator (see EIOPA, 2012):

$$r_{t\_stressed}^{up} = r_t * (1 + s_t^{up}) \tag{2.3}$$

[7] The European Insurance and Occupational Pensions Authority (EIOPA) is part of a European System of Financial Supervisors that comprises three European Supervisory Authorities.

$$r^{down}_{t\_stressed} = r_t * \left(1 + s^{down}_t\right) \tag{2.4}$$

In any case, the absolute change in the interest rate for a stress scenario must be at least 1 percentage point, according to EIOPA. In practice, the downward stress scenario is of much greater relevance, especially for life insurance companies. This is due to the typically higher duration of insurers' liabilities compared to assets, causing the market values of liabilities to rise more than those of assets in case of a downward interest rate shock. Moreover, the absolute value of liabilities usually exceeds the absolute value of interest rate-sensitive assets. Hence, only a downward shift of the yield curve has a negative impact on the BOF in the vast majority of cases.

The equity risk sub-module refers to volatility in the market value of equities and its impact on the BOF. Generally, EIOPA distinguishes between two types of equities: The "type 1" equities include all equities listed in countries of the EEA or OECD, while the "type 2" equities include all those listed in other countries. Moreover, all non-listed equity investments, such as private equity, hedge funds, commodities and other alternative investments, are also considered "type 2" equities. The capital requirement for the equity risk sub-module is determined in two steps. First, the individual capital requirement ($Mkt_{eq,i}$) for each type of equities (i) is determined by the predefined stress factors:

$$Mkt_{eq,i} = \max(\Delta BOF|\text{equity shock}_i; 0) \tag{2.5}$$

The stress factors for "type 1" and "type 2" equities are 39% and 49%, respectively. These figures are based on historical total return data, and refer to the value at risk (VaR) with a confidence level of 99.5% on an annual basis. Second, the resulting overall equity risk SCR is calculated using a preset correlation matrix imposed by

the EIOPA,

$$Mkt_{eq} = \sqrt{\sum_i \sum_j CorrIndex_{i,j} * Mkt_{eq,i} * Mkt_{eq,j}} \tag{2.6}$$

where $CorrIndex_{i,j}$ is the predefined correlation coefficient of 0.75 between "type 1" and "type 2" equities.

Similarly, the property risk sub-module accounts for risks arising from volatility in the real estate markets. This sub-module applies to direct investments (land, buildings and immovable property rights) and to real estate funds, if it is possible to assess and evaluate the risk of the funds' underlying assets (look-through approach). The capital requirement for property risk (Mkt_{prop}) is again determined by the 99.5% VaR on historical total return data, and amounts to 25%:

$$Mkt_{prop} = \max(\Delta BOF|\text{property shock}; 0) \tag{2.7}$$

The spread risk sub-module accounts for risks that occur due to changes in the level or in the volatility of credit spreads over the risk-free interest rate structure. In particular, it applies to traditional fixed-income products (e.g., corporate bonds), asset-backed securities and other structured credit products, as well as credit derivatives. Depending on the type of product, the individual spread shock on bonds is determined as follows:

$$\text{spread shock on bonds} = \sum_i MV_i * F(rating_i; duration_i) \tag{2.8}$$

where MV_i is the market value of the credit risk exposure of bond i and $F(rating_i; duration_i)$ is a function of the individual credit quality and duration of each bond or loan. The actual factors $F(\cdot)$ can be found in a table published by the regulator (see EIOPA, 2012). In this paper, we limit our analysis to traditional corporate bonds. Hence, the capital requirement for credit spread (Mkt_{spread})

simply refers to the spread shock on bonds as calculated according to Formula 2.8.

$$Mkt_{spread} = \max(\Delta BOF|\text{spread shock on bonds}; 0) \tag{2.9}$$

Finally, the total capital requirement for the insurer's market risk exposure (SCR_{mkt}) is an aggregation of all sub-risks using the predefined regulatory correlation matrix (see EIOPA, 2012 or Section 2.3) as follows:

$$\begin{aligned} SCR_{mkt} \quad = \quad \max \Bigg\{ & \sqrt{\sum_i \sum_j CorrMkt_{i,j}^{up} * Mkt_i^{up} * Mkt_j^{up}} \; ; \\ & \sqrt{\sum_i \sum_j CorrMkt_{i,j}^{down} * Mkt_i^{down} * Mkt_j^{down}} \Bigg\} \end{aligned} \tag{2.10}$$

where $i, j \in \{$interest risk, equity risk, property risk, spread risk$\}$ and "up" and "down" indicate whether the upward or downward stress scenario for interest rate risk is applied. The correlation coefficients differ slightly depending on the "up" or "down" scenario. The exact calibration of the standard formula and the descriptive statistics according to the dataset will be presented in Section 2.3.

2.3 Data and Calibration

2.3.1 Data

In this section, we introduce the dataset used for the portfolio optimization and for the exact calibration of the Solvency II standard formula. Common benchmark indices are used as proxies for the respective asset classes. We therefore assume that each asset class's sub-portfolio has already been diversified prior to the overall asset allocation process. The dataset includes the six most common asset classes: government bonds, corporate bonds, stocks, real estate, hedge funds and money market instruments.

We use quarterly total return data for the last 25 years (Q1 1993 to Q2 2017).[8]

European government bonds are represented by the Citigroup European World Government Bond Index with mixed maturities. The index covers government bonds from 16 European countries and is frequently used as a benchmark index. Corporate bonds are represented by the Barclays U.S. Corporate Bonds Market Index, since there is no European benchmark index with a sufficiently long time series for corporate bonds.[9] This index consists of various investment-grade bonds with different maturities, which is in line with the actual bond portfolios held by European insurers. Stocks are represented by the MSCI Europe Total Return Index. Short-term money market investments are represented by the JP Morgan Euro 1M Cash Total Return Index. Direct real estate is represented by the IPD U.K. Property Total Return Index, which is also used by EIOPA for the overall calibration of the standard formula's property risk sub-module (see EIOPA, 2012). Since the index is based on valuations rather than on the actual transaction prices of properties, the capital return component is subject to the so-called appraisal smoothing bias. Hence, we follow Rehring (2012) and correct the capital returns by using the unsmoothing approach of Barkham and Geltner (1994). In addition, direct real estate investments entail high transaction costs. Therefore, we correct the total returns for overall transaction costs of 7%, as proposed by Collet et al. (2003), Marcato and Key (2005) and Rehring (2012). Finally, hedge fund investments are represented by the HFRI Fund Weighted Composite Index, which is a commonly used industry-level performance benchmark.

2.3.2 Calibration of the Solvency II Standard Formula

To calculate the individual SCR for each of the six asset classes, as well as the aggregated SCR for the resulting portfolio (i.e., SRC_{mkt}), we apply the EIOPA

[8] All data is obtained from Thomson Reuters Datastream.

[9] The BofA Merrill Lynch (Code: MLEX-PEE) European corporate bond index only dates back to 1996. The index shows a very similar risk-return profile and correlation patterns. Therefore, our results are unlikely to be affected by the choice of this index.

specifications as presented in Section 2.2, taking into consideration the characteristics of the aforementioned benchmark indices. For direct real estate, a 25% SCR must be applied. While the MSCI Europe Index is classified as "type 1" equities with a 39% SCR, the HFRI Fund Weighted Composite Index is classified as "type 2" equities, and thus requires a 49% SCR. The capital charges for both types of equities are aggregated, using the regulatory prescribed correlation of 0.75 as described in Formula 2.6. Government bonds and money market instruments are not subject to capital charges, and therefore do not enter the SCR calculations directly. However, the overall portfolio's SCR also depends on the allocation of government bonds, as the allocation of government bonds affects the duration of the portfolio and therefore the SCR for interest rate risk. The interest rate sensitivity of government bonds is given by the modified duration of the Citigroup European World Government Bond Index (5.03 as of 02/2017).

To determine the SCR for the spread risk module, Formula 2.8 from Section 2.2 is applied. The respective duration and rating of the corporate bond portfolio determines the exact SCR. We use the modified duration of the Barclays U.S. Corporate Bond Market Index as of 02/2017, which is 7.16. Since the index represents a bucket of investment-grade fixed-income securities, we average the spread shocks across several credit quality buckets for the aforementioned duration of 7.16, using the prescribed formulas taken from the EIOPA specifications for the Solvency II standard formula (see EIOPA, 2012). As a result, we obtain an 8.9% SCR for the spread risk module.

For the interest rate risk module, we use a simplified approach suggested by Hoering (2013), who determines the capital requirement based on the total duration gap between assets and liabilities. The duration gap is calculated as the difference between the duration of the asset side and the duration of the liability side of the balance sheet, and hence indicates the interest rate sensitivity of the basic own funds (BOF) of the insurer. The duration of the asset side is determined by the actual portfolio allocation, or, more precisely, by the relative weights of the government bonds and

corporate bonds and by their respective durations. In contrast, the duration of the liability side is given exogenously. We use the information provided by the "CEIOP's Report on its fourth Quantitative Impact Study (QIS4) for Solvency II" (CEIOPS, 2008), according to which the median duration of the liabilities of life insurers in Europe is 8.9. Moreover, Braun et al. (2014) set the duration of representative life insurers' liabilities to 10.0, based on several practitioner studies for the German life insurance market. We use the average, and set the duration of the liability side to 9.5 in this study.

Following Braun et al. (2014) and Hoering (2013), the interest rate shock is approximated by parallel upward and downward shifts of the interest rate structure curve. As a result of the low interest rate environment, the respective upward and downward shock factors are currently extremely small (see Formula 2.3 and Formula 2.4). However, as per the EIOPA framework, we consider the minimum shock factor of 1 percentage point for the further analysis. In addition, given the presented calibration, the duration of liabilities exceeds the duration of assets for every possible portfolio composition, so we limit the further analysis to the downward shock scenario. To summarize, we model the risk of interest rate changes as a -1 percentage point parallel shift in the interest rate structure curve. The actual SCR for interest rate risk is therefore determined by multiplying the downward interest rate shock of -1 percentage point by the duration gap, which in turn is determined by the respective portfolio allocation. For example, a duration gap of 6.0 would require capital charges for the interest rate risk of 6.0%.

2.3.3 Descriptive Statistics

Table 2.1 depicts the empirical risk and return profiles for the benchmark indices, as well as the empirical and regulatory correlation matrices and the SCR. The upper figures in the first section of the table show the empirical correlations between the returns of the benchmark indices. The figures in parentheses below show the reg-

Table 2.1: Descriptive Statistics and Solvency II Standard Formula Calibration

	Direct Real Estate	Hedge Funds	Money Market	Corp. Bonds	Stocks (Europe)	Govt. Bonds	Interest Rate Risk
Direct Real Estate	1.00 (1.00)						
Hedge Funds	0.14 (0.75)	1.00 (1.00)					
Money Market	0.03 -	0.05 -	1.00 -				
Corp Bonds	0.19 (0.50)	-0.04 (0.75)	0.52 -	1.00 (1.00)			
Stocks (Europe)	0.47 (0.75)	0.18 (0.75/1.00)	0.06 -	0.14 (0.75)	1.00 (1.00)		
Govt. Bonds	-0.13 -	0.37 -	0.29 -	0.07 -	-0.02 -	1.00 -	
Interest Rate Risk	- (0.50)	- (0.50)	- -	- (0.50)	- (0.50)	- -	- (1.00)
Mean	1.90%	2.62%	0.75%	1.83%	2.45 %	1.33%	-
STD(σ)	5.08%	5.32%	0.62%	3.17%	9.51 %	1.89%	-
SCR	25.00%	49.00%	-	8.86%	39.00 %	-	1% $\times$ DG
99.5% VaR	18.38%	16.50%	0.15%	8.82%	38.84 %	4.31%	-
Duration	-	-	-	7.16	-	5.03	-

The upper division of the table shows the empirical correlation coefficients and the regulatory correlation coefficients (in parentheses below). All correlations refer to the downward interest rate shock scenario. Stocks and hedge funds are aggregated first with a 0.75 correlation. The lower division of the table shows the mean quarterly returns of the assets and the corresponding standard deviations (σ). Moreover, the capital requirements (SCR) and the values at risk (VaR) as their empirical counterparts are presented. The interest rate risk's SCR must be calculated depending on the actual duration gap (DG). The respective durations for the assets are outlined in the last row.

ulatory correlations as imposed by EIOPA (2012). The second section of the table provides information on the mean quarterly returns, the standard deviations, the empirical VaR (on an annual basis) as well as the corresponding SCR, as already outlined in Section 3.2.

The descriptive statistics show the expected risk-return relationship for the benchmark indices: Short-term money market instruments yield the lowest returns and also exhibit the lowest risk in terms of standard deviation. At the other extreme are stocks with a mean quarterly return of 2.45% and a standard deviation of 9.51%, thus representing the riskiest and best-yielding asset class, except for hedge funds. The rather high capital requirements for high yielding assets (stocks, hedge funds and real estate) indicate that certain target returns may no longer be attainable for insurers with a low equity base, as already conjectured in the introduction. Moreover, the SCR calculated by EIOPA in 2012 does not seem to be in line with its empirical counterpart any longer. The indices we use show a value at risk of only

18.38% for real estate and only 16.50% for hedge funds, as opposed to 25% SCR and 49% SCR, respectively.[10] Similarly, the correlation figures imposed by the Solvency II standard formula severely overestimate the empirical correlations, which undermines the incentive for a thorough portfolio diversification. The parameterization of the standard formula may therefore not only render certain target returns unattainable, but may also lead to inefficient portfolio allocations and increase investment risk, instead of mitigating risk.

In the next section, we further analyze the effects of the potentially incorrectly parameterized capital requirements of the Solvency II standard formula in a dynamic portfolio optimization context.

2.4 Portfolio Optimization

2.4.1 Attainability of Target Returns and Portfolio Efficiency

The attainable target return as a function of insurers' basic own funds is obtained by solving the well-known quadratic portfolio optimization program, as first introduced by Markowitz (1952). The covariance matrix ($\mathbf{\Sigma}_{reg}$) is comprised of capital requirements (SCR) and regulatory-imposed correlations, instead of empirical stan-

[10] In accordance with the EIOPA framework, the value at risk was calculated on an annual basis for the 99.5% level.

dard deviations (σ) and empirical correlations.[11] The optimization program can be stated as follows:

$$\min_{w} : \; SCR_{mkt} = \sqrt{\mathbf{w}'\mathbf{\Sigma}_{reg}\mathbf{w}}, \tag{2.11}$$

$$\text{subject to} \quad \mathbf{w}'\mathbf{M} = \mu_{target}, \tag{2.12}$$

$$w_i \geq 0, \tag{2.13}$$

$$\mathbf{w}'\mathbf{1} = 1, \tag{2.14}$$

$$\text{and} \quad w_i \leq u_i \quad i \in \{1, 2, \ldots, 6\}, \tag{2.15}$$

where:

- w_i is the weight of asset class i,
- $\mathbf{w}$ is the column vector of portfolio weights,
- $\mathbf{M}$ is the column vector of mean returns, and
- u_i is the upper limit for the weight of asset class i.

The optimization objective is to minimize the portfolio's SCR with respect to a given target return (Equations 2.11 and 2.12). Equation 2.13 excludes short positions, and Equation 2.14 constrains the budget. In addition, Equation 2.15 introduces

[11] The Solvency II covariance matrix is calculated as the outer product of the regulatory correlation matrix ($\mathbf{R}_{reg}$) and the column vector of capital requirements ($\mathbf{SCR}$), both as shown in Table 2.1 ($\mathbf{\Sigma}_{reg} = \mathbf{SCR} \otimes \mathbf{R}_{reg} \otimes \mathbf{SCR}'$). The resulting matrix is not positive semi-definite, which may cause a discontinuity in the quadratic objective function (Equation 2.11). We therefore apply the algorithm of Higham (2002) in order to obtain the nearest positive semi-definite matrix. Furthermore, there are circularity issues: Both the equity SCR and the interest rate SCR are a function of the portfolio weights themselves (i.e., a function of the solution vector of the optimization program). While the equity SCR accounts for diversification within the equity sub-module, the interest rate SCR is determined by the duration gap, which in turn depends on the weights of corporate bonds and government bonds. To overcome these issues, all N permissible combinations of hedge funds, stocks, corporate bonds and government bonds are enumerated up to the fourth decimal place. For any given target return, the original problem is now solved N times. Each of the N optimizations uses the corresponding preset asset weights as additional constraints (i.e., the weights of the four asset classes with circularity issues are held constant). Hence, the covariance matrix no longer exhibits circular references. Finally, the portfolio allocation with the lowest SCR of all the N optimization results is chosen as the global optimum for the respective target return.

investment limits to ensure that only realistic portfolios are obtained. The limits are derived from previous European regulatory standards, which are still reflected in the actual portfolios of European insurers.[12] Specifically, real estate weights are capped at 25%, hedge fund weights at 5%, stocks at 35% and equities (hedge funds and stocks together) are not allowed to exceed 35% of total assets.

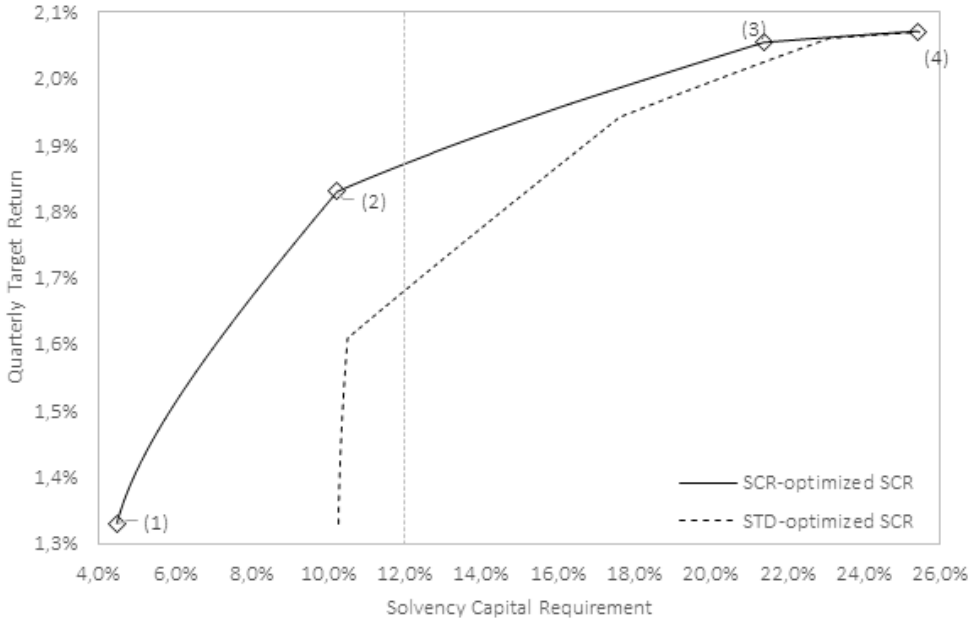
The optimization program is solved for all achievable target returns.[13] The resulting portfolios exhibit the lowest possible capital charges for any given target return. The results likewise show the maximum attainable target return for any given SCR (i.e., any exogenously given amount of basic own funds). The attainability of portfolio efficiency depending on the insurers' basic own funds is derived in a straightforward way. We run the portfolio optimization program as described by Equations 2.11 to 2.15, replacing the regulatory covariance matrix ($\mathbf{\Sigma}_{reg}$) with the empirical covariance matrix ($\mathbf{\Sigma}_{emp}$) in order to obtain the set of mean-variance-efficient portfolios. Subsequently, we calculate the SCR induced by the mean-variance-efficient portfolios, using Formula 2.10.

Figure 2.1 illustrates the results of both optimization programs in the μ-SCR-space. The SCR-optimal frontier is plotted as a solid line, while the mean-variance-efficient portfolios are plotted as a dashed line. It is obvious that the SCR-optimal portfolios lead to much lower capital requirements than the mean-variance-efficient portfolios. In other words, almost any target return is attainable with a much lower amount of basic own funds if the insurer strictly adheres to the Solvency II standard formula instead of minimizing investment risk. This first result already shows the incompatibility between actual investment risk and the market risk capital requirements according to Solvency II. Moreover, the asset allocations and the investment risk differ decisively between the results of both optimization programs. The SCR-optimal

[12] The investment limits we use are particularly inspired by the German "Regulation on the Investment of Restricted Assets of Insurance Undertakings" (Investment Regulation; German: Anlageverordnung).

[13] The lowest portfolio target return is determined by the asset class with the lowest expected return, i.e., money market. At the other extreme, the highest portfolio target return is achieved by sequentially increasing the weights of the assets with higher expected returns, until the individual investment limits are reached.

Figure 2.1: Optimized Portfolios in the μ-SCR-Space



See text for explanations.

frontier is characterized by four points, which are depicted in Figure 2.1: The Min-SCR-portfolio at the lower left end of the curve consists of 100% government bonds. This is not surprising, since government bonds have no SCR as such, but they have a duration of 5.03, which enables them to hedge insurers' liabilities against interest rate shocks. The portfolio at point 2 consists of 100% corporate bonds. Corporate bonds have comparably low capital requirements, but also have very good abilities to hedge liabilities against interest rate shocks (a duration of 7.16). At point 3, the portfolio consists of 65% corporate bonds, 30% stocks and 5% hedge funds. This portfolio at point 4 has the maximum achievable target return given the investment limits (μ = 2.07%, SCR = 25.42). The portfolio consists of 40% corporate bonds, 30% stocks, 5% hedge funds and 25% direct real estate. The concave curvature between the four knit points indicates that the Solvency II standard formula accounts for some diversification in terms of capital charges. However, compared to the common Markowitz optimization, the diversification effect is negligible, and clearly does not govern the allocation process. The allocation is clearly driven by the asset classes' capital charges and durations. The asset classes are allocated sequentially

without noteworthy diversification. Asset classes with high capital requirements are allocated only when required by the target return.

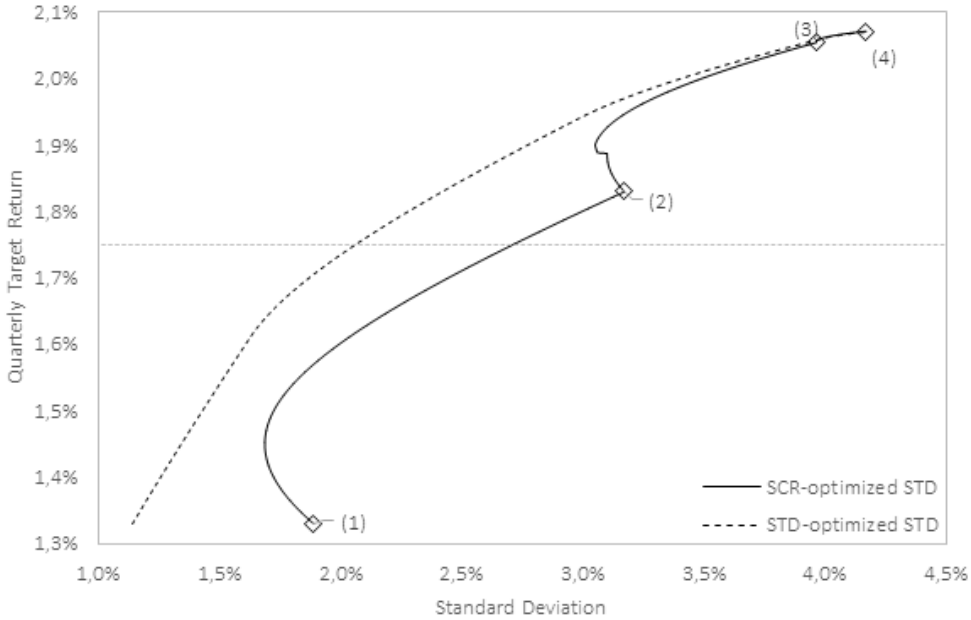
The mean-variance-efficient portfolios also consist of government bonds and corporate bonds to a large extent, as the returns of these asset classes exhibit low volatility. However, stocks, hedge funds and real estate are now allocated across the entire spectrum of target returns. In contrast to the SCR-optimal portfolios, the asset classes are now allocated simultaneously, not sequentially. The allocation is governed by the diversification effect instead of the duration gap. Appendix 1 shows the asset allocations for both optimization programs' results in detail. Figure 2.2 illustrates the results of both optimization programs in the $\mu - \sigma$-space and manifests the deadweight loss caused by the Solvency II standard formula: Given a target return of 1.75%, the standard deviation of the mean-variance-efficient portfolio is 75 basis points below the corresponding standard deviation of the SCR-optimal portfolio. Using two standard deviations as the relevant measure for quantifying risk, the shortfall risk of the portfolio would increase decisively by 150 basis points per quarter![14] As Figure 2.2 shows, the dead weight loss becomes even larger for higher target returns.

According to the information provided by the German Federal Financial Supervisory Authority (BaFin) and the results of QIS5 released by EIOPA (2011), the average European insurer's basic own funds amount to approximately 10%-12%. In the spirit of Braun et al. (2015) and Hoering (2013), we use 12% as a reference point for the further analysis. Considering the average European insurer's asset allocation in the past (see, e.g., Fitch Ratings, 2011; Insurance Europe and Oliver Wyman, 2013), as well as the past performance of the asset classes, the quarterly target return used to be approximately 1.75% (or 7% p.a.). This is sufficient to cover the high interest rate guarantees on existing insurance policies and additional overhead costs.

As the vertical gridline in Figure 2.1 shows, quarterly returns of up to 1.88% are at-

[14] This corresponds to a value at risk of approximately 95%, assuming returns are normally, identically and independently distributed.

Figure 2.2: Optimized Portfolios in the μ-σ-Space



See text for explanations.

tainable with basic own funds of 12%. However, only 1.68% are efficiently attainable. The efficient portfolio with a 1.75% quarterly return induces an SCR of 13.45%. This result shows that average and overcapitalized European insurers are well equipped to fulfill the capital requirements according to the Solvency II standard formula and minimize their portfolios' investment risk at the same time. However, the situation turns out differently for undercapitalized market participants. According to the QIS5 results of EIOPA (2011), one-quarter of all European insurers are at risk of not meeting the capital requirements imposed by Solvency II. Putting aside operational risks (e.g., insufficient reinsurance or high concentration risk), it is likely that these insurers' basic own funds amount to less than 12%. As Figure 2.1 shows, the attainable target return decreases sharply for insurers with basic own funds below 10%. The efficiently attainable target return decreases even more rapidly. Portfolio efficiency is not attainable at all for insurers with basic own funds below 10%. Undercapitalized insurers will not be able to increase their allocations of equities and alternative assets in the search for higher returns and portfolio diversification. On the contrary, undercapitalized insurers might be forced to reduce these asset classes

in order to match their portfolio's capital requirement with their basic own funds.

In the next section, we analyze how the optimal portfolio weights for the individual asset classes respond to a restriction on insurers' basic own funds.

2.4.2 Effects on the Allocations of Individual Asset Classes

The optimization programs run in Section 4.1 can be considered as extreme points. No insurer will strictly adhere to only one of the optimization objectives (SCR or standard deviation). Rather, in practice, it is the combination of both optimizations that is of particular relevance. We therefore include the insurers' basic own funds as an additional constraint into the standard mean-variance optimization. The optimization program is now formulated as follows:

$$\min_{w} : \sigma = \sqrt{\mathbf{w}'\mathbf{\Sigma}_{emp}\mathbf{w}}, \tag{2.16}$$

$$\text{subject to} \quad \mathbf{w}'\mathbf{M} = \mu_{target}, \tag{2.17}$$

$$w_i \geq 0, \tag{2.18}$$

$$\mathbf{w}'\mathbf{1} = 1, \tag{2.19}$$

$$w_i \leq u_i \quad i \in \{1, 2, \ldots, 6\}, \tag{2.20}$$

$$\text{and} \quad BOF = \sqrt{\mathbf{w}'\mathbf{\Sigma}_{reg}\mathbf{w}}, \tag{2.21}$$

where:

- BOF is the basic own funds of the insurer.

Equation 2.21 ensures that the resulting SCR (right-hand side) stays below the insurer's basic own funds (left-hand side), while the portfolios are optimized with regard to investment risk (Equation 2.16). The BOF serves as an upper boundary,

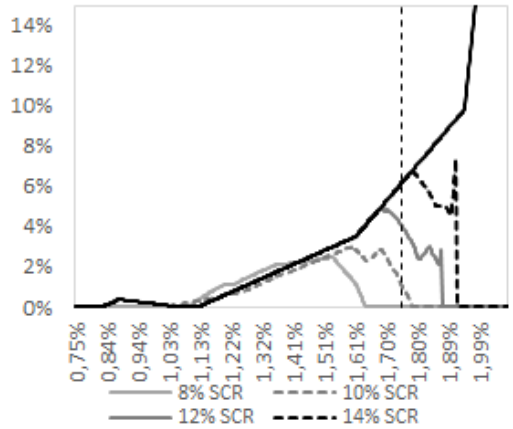
and is given exogenously by the equity capital of the individual insurer. By varying the BOF, it is now possible to derive the optimal portfolio allocation for any given combination of capital budget and target return.

The optimization program is solved for all achievable target returns and for four different levels of BOF (8%, 10%, 12% and 14%). The six panels depicted in Figure 2.3 show the target returns on the horizontal axis, and the respective asset weights on the vertical axis. The four levels of basic own funds are indicated by the legends underneath the respective panels. In addition, the unrestricted portfolio weights are shown as solid black lines and the quarterly target return of 1.75% is indicated by the vertical grid line.

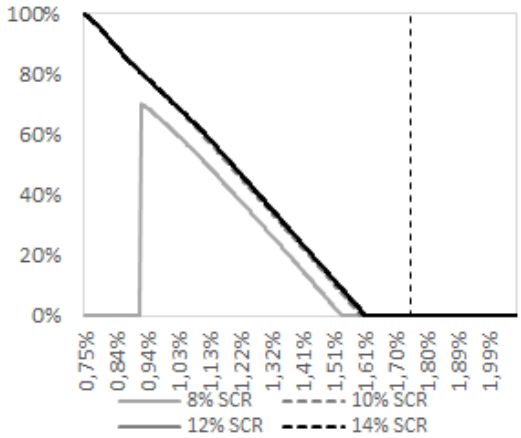
When interpreting the results for a quarterly target return of 1.75%, it becomes evident that stocks, hedge funds and real estate allocations react extremely sensitively to a restriction on insurers' basic own funds. Government bonds are robust to variations in the BOF, and corporate bond allocations do even increase after the basic own funds have been restricted. For high target returns, money market instruments are not a part of the efficient portfolios at all. The results show that the introduction of Solvency II will indeed reverse the trend towards higher quotas for stocks and alternative investments, especially for insurers with a weak equity base. Insurers with basic own funds below 10%, for example, are forced into real estate quotas below 5% and hedge fund allocations below 2%.

Figure 2.3: Optimal Portfolio Allocations for Different Levels of Basic Own Funds

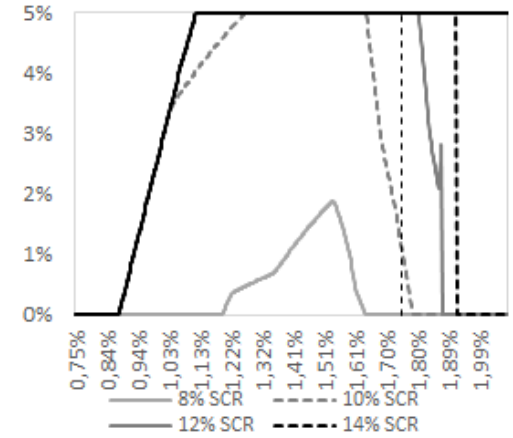
Panel a: Allocation of Stocks



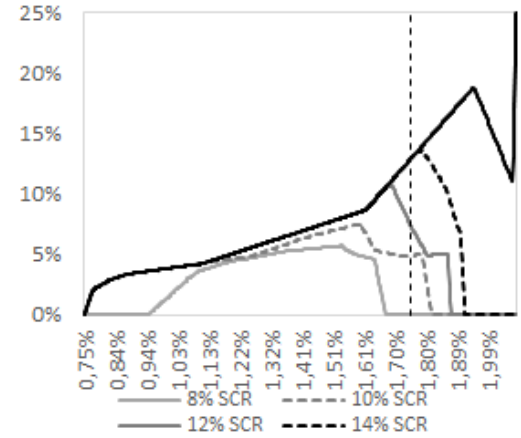
Panel b: Allocation of Money Market Instruments



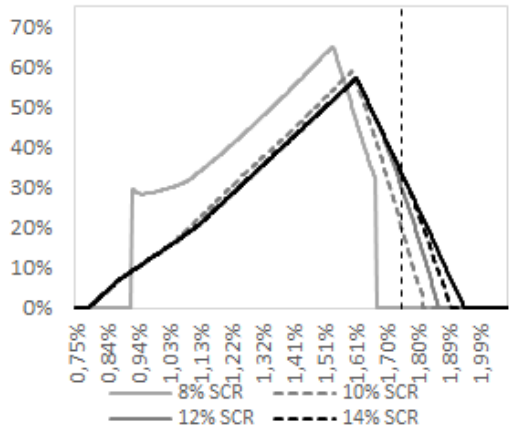
Panel c: Allocation of Hedge Funds



Panel d: Allocation of Direct Real Estate



Panel e: Allocation of Government Bonds



Panel f: Allocation of Corporate Bonds

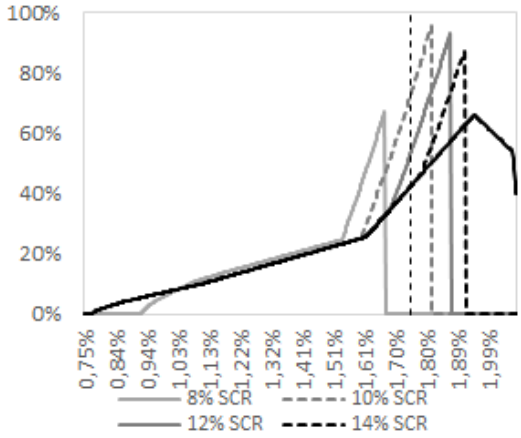


Figure 2.3 illustrates the STD-optimal portfolio weights for the six asset classes for different given levels of basic own funds. The unrestricted portfolio weights are shown as the solid black line, and the quarterly target return of 1.75% is indicated by the dot-dashed vertical gridline.

2.5 Conclusion

In 2016, the EIOPA introduced a risk-based capital model for European insurers (Solvency II), and thereby changed the set of rules that had prevailed for previous decades. To analyze the effects of the new regulatory standard on insurers' investment strategy, we conducted several portfolio optimization programs with respect to the capital requirements of the Solvency II standard formula.

Our results show that the Solvency II capital requirements impede the construction of mean-variance-efficient portfolios. There are three main reasons for this: (1) The Solvency II standard formula presets very high correlations between the asset classes, and therefore does not reward risk reduction through diversification, (2) the solvency capital requirements for equities and for alternative asset classes are set too high, and (3) Solvency II focuses on the mitigation of interest rate risk, in contrast to the classical mean-variance optimization. While the latter can be deemed economically meaningful, the first two issues must be considered as misspecifications of the Solvency II standard formula. The high regulatory correlation figures and capital requirements for real estate and equities (including hedge funds) may be the result of a principle of prudence, which is reasonable when viewed in isolation. However, with a holistic view, unbalanced and inefficient portfolios are the consequence.

As a consequence, Solvency II increases the portfolios' investment risk and decreases the attainable target return for insurers with a weak equity base. Given that the primary purpose of the regulation is the mitigation of risk, and given that some insurers are already facing an undercoverage in terms of returns, those effects are highly undesirable. However, insurers with above-average amounts of basic own funds (12% or higher) are able to fulfill the Solvency II capital requirements, attain high target returns and attain mean-variance-efficiency at the same time (see Figure 2.1). Those insurers do not face a binding constraint with the introduction of the Solvency II capital requirements, as Hoering (2013) stated. On the other hand, insurers with below-average basic own funds (10% or lower) are limited in

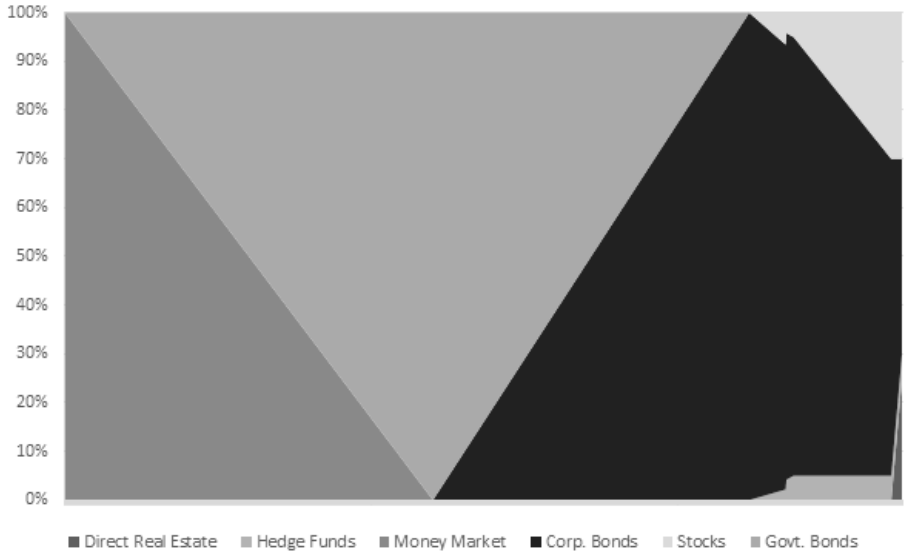
their attainable target returns. Furthermore, those insurers are not able to attain mean-variance-efficiency irrespective of the target return (see Figure 2.1). Undercapitalized insurers are forced to strictly minimize the SCR according to the Solvency II standard formula when constructing their portfolios. As Figure 2.2 illustrates, this increases investment risk in the classical sense and might cause severe asset management biases, as stated by Braun et al. (2015).

Technically, the Solvency II standard formula forces insurers with a weak equity base to reduce assets with a high SCR and no interest rate sensitivity, namely stocks, direct real estate and hedge funds (and presumably all other investments in the equity risk sub-module, in particular "type 2" equities). Small and mid-size insurers with a weak equity base are not able to develop and audit a cost-intensive insurance internal solvency model to evade the standard formula. The regulator could mitigate this issue in the future by allowing for more flexibility when considering revisions to the standard formula.

2.6 Appendix 1

Figure 2.4: Optimal Portfolio Allocations

Panel a: Optimal Allocations for SCR-optimized Portfolios



Panel b: Optimal Allocations for STD-optimized Portfolios

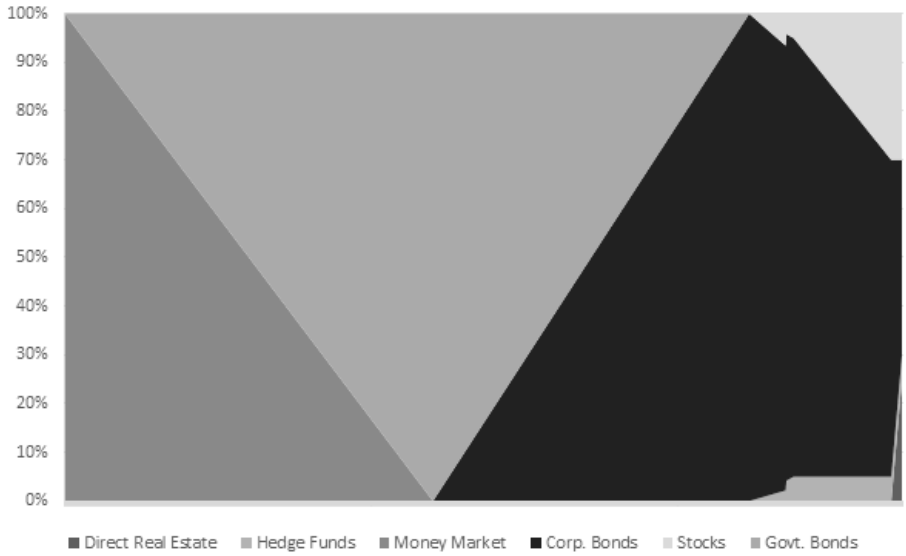


Figure 2.4 shows the resulting asset allocation for both optimization programs as stated in Section 2.4.1.

Chapter 3

The Determinants of Real Estate Fund Closures

Sebastian Schnejdar, Michael Heinrich, Rene-Ojas Woltering, Steffen Sebastian

3.1 Introduction

With invested capital of EUR 145 billion, the German open-end real estate fund industry is the predominant indirect German real estate investment vehicle and the largest market for open-end real estate funds worldwide.[1]

Investors in open-end real estate funds trade with the fund's investment company, which sells and redeems shares at net asset value (NAV) on a regular basis. The open-end structure is associated with considerable "bank run" risk (i.e., fund run risk), because of the long-term direct real estate investments and daily share redemptions (Bannier et al., 2008; Weistroffer and Sebastian, 2015; Fecht and Wedow, 2014). Therefore, German regulation demands a minimum liquidity reserve of 5% of a fund's NAV. In practice, average liquidity ratios range from 20%-30% (see Downs et al., 2016). Nevertheless, these liquidity ratios occasionally prove insufficient, especially during times of high volatility.

The German open-end fund industry was hit severely in the aftermath of the global financial crisis. As of October 2008, ten public German open-end real estate funds with total assets under management of about EUR 28 billion were forced to suspend share redemption.[2]

We use a panel logit model to explain fund closure probability. Our empirical study is based on a monthly panel dataset that consists of twenty-four open-end German real estate retail funds, and which covers all closure events in the history of the asset class.[3]

We find that fund closure probability increases with increasing fund run risk, which is represented by a fund's liquidity ratio and net capital inflows. Economies of scale and

[1] Downs et al. (2016).

[2] The regulatory regime was modified in succession of the fund crisis. Nevertheless, our analysis is unaffected by those changes, since fund closure events occurred under the prior investment law (InvG, effective from January 1, 2004-July 22, 2013).

[3] In our sample, we focus on retail funds. We exclude semi-institutional funds, which are primarily intended for institutional investors. Semi-institutional funds are legally classified as retail funds, but the minimum investment ranges from EUR 10,000 to EUR 1 million.

scope, proxied by fund size, age, and the presence of a distribution network for fund shares, help prevent fund closures. Moreover, we find evidence that industrywide spillover effects from the closure of other open-end real estate funds tend to increase fund closure probability. Lastly, we find evidence that a larger share of institutional investors increases fund closure probability.

Identifying fund closure determinants helps diminish uncertainty about the overall asset class, while restoring trust in the remaining funds.

The most recent example of a fund crisis was the massive share redemptions from U.K. open-end real estate funds that took place in the aftermath of the Brexit referendum on June 23, 2016. Seven public open-end funds from the U.K. closed, which represented one-half the total assets under management of the U.K. market.[4] Hence, open-end fund participants in foreign countries like the U.K. could learn from the German experience.

The paper is structured as follows. The next section (Section 3.2) gives an overview of the German open-end fund crisis. Section 3.3 describes the used variables, which are mainly derived from the existing literature of business failure prediction models. Section 3.4 illustrates the dataset, while the regression results are presented in section 3.5. The last section exhibits our conclusion.

3.2 The German Open-End Fund Crisis

German open-end real estate funds are required by law to close (i.e., suspend share redemptions) if liquidity ratios fall below 5%. A shortfall in the fund liquidity ratio is very serious because open-end real estate funds are obliged to sell their real estate assets within the first six months of closure without a discount to the last appraisal

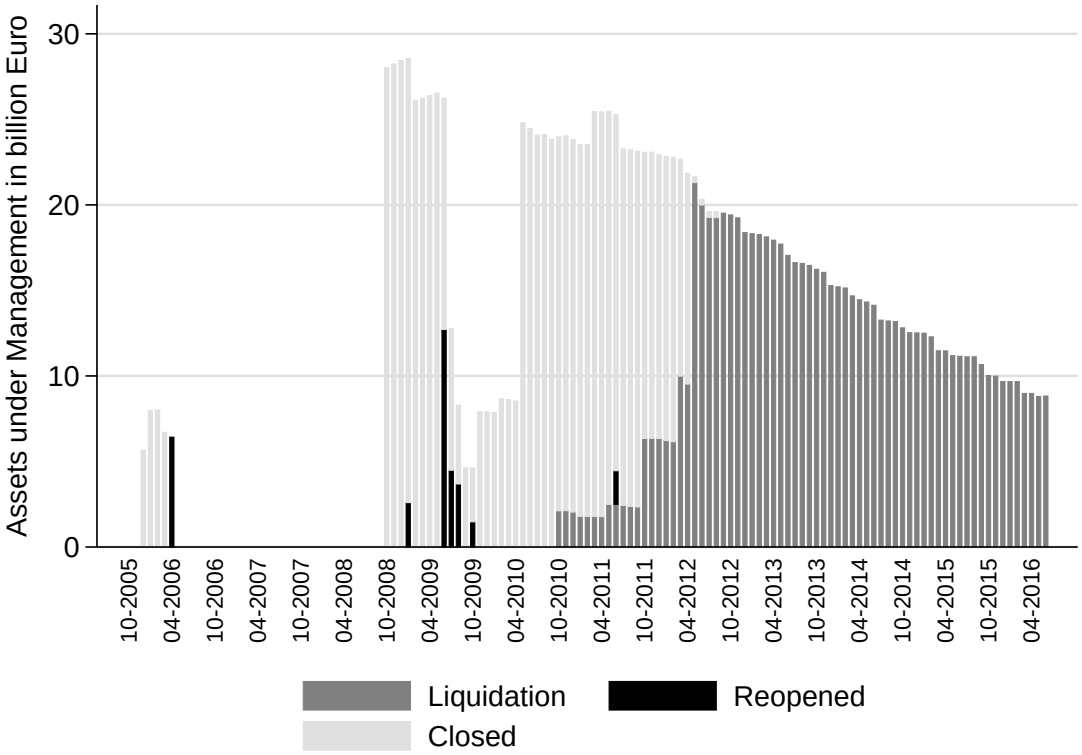
[4] M&G Property Portfolio, Henderson UK Property PAIF, Standard Life UK Real Estate Fund, Aviva Investors Property Trust, Columbia Threadneedle UK Property Authorised Investment Fund (PAIF), Canada Life UK Property Fund, and Aberdeen UK Property Fund.

value. Closed funds must sell sufficient assets to raise their cash reserves and fulfill share redemptions (i.e., reopen).

After a twenty-four-month period, funds are forced to sell off their entire real estate portfolios and pay out the proceeds to investors. However, selling properties during times of market turmoil, especially in the first months of closure, is almost impossible. Hence, all the funds that closed in October 2008 were ultimately forced to liquidate after the twenty-four-month period. Nevertheless, seven of these funds reopened subsequent to their first close in October 2008, but all were forced to close for good for a second time.

Figure 3.1 shows the size of closed German open-end real estate funds (grey bars), as well as the size of funds in liquidation (dark grey bars). The graph also illustrates the size of fund reopenings (black bars). During the first fund crisis in 2005/2006, two open-end real estate retail funds with total fund volume of EUR 8 billion, closed. These closures were caused by short-term uncertainty about the funds' property valuations. After a short period of time, both funds reopened. The second, and larger, crisis began in October 2008, with the closure of ten funds, with assets under management of about EUR 28 billion. The reopening of several funds over the following twelve months suggested an upward trend. Nevertheless all of these funds were forced to close again. As of May 2010, the total fund size of distressed funds was equal to earlier levels of around EUR 27 billion. Following the first fund liquidation announcement in October 2010, and through August 2012, all previously closed funds were forced to announce their liquidations. The decreasing fund size over the sample period, as shown in Figure 3.1, is due to two primary effects: 1) The proceeds from distressed funds' sold properties were distributed to investors, and 2) a decrease in property appraisal values. As of June 2016, about EUR 10 billion of invested capital remained inaccessible to investors.

Figure 3.1: Overview Open-End Fund Crises



This figure shows the total fund size of German open-end real estate funds that either suspended share redemptions (grey bars) or were already in the process of fund liquidation (dark grey bars). The graph also indicates the total fund size of reopenings (black bars).

Table 3.1 gives a clear overview of the fund closure and liquidation dates.[5]

3.3 Related Literature and Hypotheses

Our theoretical framework on fund closures is based on the literature on business failures. Business failure prediction models generally focus on identifying an imminent financial crisis by predicting individual firm insolvencies. Several firm bankruptcies can cause considerable negative economic effects (i.e., high unemployment rates and reduced stability of the financial market in case of bank failures). Kupiec and Ramirez (2013) find that U.S. bank insolvencies cause a significant drop in the over-

[5]The HansaImmobilia fund was ultimately forced to close and liquidate in 2012 without a twenty-four-month closing period. Furthermore, the UniImmo global fund closed in 2011 for three months due to uncertainty about its Japanese property reappraisals following the Tohoku earthquake. The UniImmo global fund was able to reopen.

Table 3.1: Overview Open-End Fund Closures and Liquidations

fund	1. crisis	2. crisis	last closure	notice liquidation
AXA Immoselect	-	10/08 - 08/09	11/09	10/11
CS Eur.	-	10/08 - 06/09	05/10	05/12
DEGI Eur.	-	10/08	10/08	10/10
DEGI Int.	-	10/08 - 01/09	11/09	10/11
HansaImmobilia	-	-	10/12	10/12
KanAm Grund.	01/06 - 03/06	10/08 - 07/09	05/10	03/12
MS P2 Value	-	10/08	10/08	10/10
UBS 3 Sector RE	-	10/08 - 10/09	10/10	09/12
SEB ImmoInvest	-	10/08 - 06/09	05/10	05/12
TMW Immobilien	-	10/08 - 10/09	02/10	05/11
DEKA Immo. Global	-	-	-	-
DEKA Immo.Fonds	-	-	-	-
DEKA Immo. Eur.	-	-	-	-
EURO ImmoProfil	-	-	-	-
Inter ImmoProfil	-	-	-	-
Grundbesitz Eur.	12/05 - 03/06	-	-	-
Grundbesitz Global	-	-	-	-
HausInvest Eur.	-	-	-	-
HausInvest Global	-	-	-	-
UniImmo D.	-	-	-	-
UniImmo EUR.	-	-	-	-
UniImmo Global	-	03/11 - 06/11	-	-
WestInvest 1	-	-	-	-
WestInvest Inter.	-	-	-	-

This table provides an overview of all open-end real estate retail funds. It gives the date of the first closure of each fund during the first fund crisis in 2005/2006. Nine funds closed in the second fund crisis in October 2008; seven of these reopened for a certain period of time. Those funds show a second closing date. After twenty-four months of closing, all nine funds were required to announce their liquidations. Column 5 gives the liquidation date.

all economic development in the 1900 to 1930 period. Because of the importance of these issues, the literature on failure prediction models covers a plethora of scientific work over the past fifty years, beginning with Beaver (1966). Following Balcaen and Ooghe (2006), Zavgren (1985), Sheppard (1994), Zmijewski (1984), Swanson and Tybout (1988), and Becchetti and Sierra (2003), we focus on conditional probability models, especially logit models. Zhao (2004) for example apply a logit model to derive the determinants of fund closings for U.S. open-end mutual funds in the 1992 to 2001 period.

One common problem of failure prediction models is that the balance sheet items are inconsistently defined. However, the fund-specific variables are regulated by law, so they are identically defined for all funds. Real estate fund closures are therefore

somewhat predestined for use in failure predicting models.

According to Balcaen and Ooghe (2006), another important problem is how to precisely define failure. Most studies use a change in corporate legal status as the definition of a failure, although the closure of a fund does not immediately imply a loss for investors. Nevertheless, at the time of closure, the open-end fund structure dissolves, which does change the intrinsic nature of the fund. Therefore, we use the legal event of "fund closure" to mean failure in an effort to avoid the problem of poorly defining the dichotomy of the dependent variable.

Failing to capture corporate failures in a sample time period is another issue for failure prediction models. As a result, we find that the corporate qualities that may lead to a subsequent failure are assigned to the group of non-failing individuals. Moreover, most studies on failure prediction are non-random regarding particular industries or size classes. To avoid a distortion, we include the entire relevant time frame, including all fund closures independent of age, size, or investment focus.[6]

3.3.1 Fund Run Risk

Whenever fund investors observe increasing share redemptions that threaten to exceed a fund's liquidity ratios, they have an incentive to redeem their own shares. In the worst case, this "vicious cycle" leads to a fund closure. The mechanism is similar to a bank run, and is a serious shortfall of the open-end structure. Therefore, sufficiently large liquidity ratios are required. During times of economic uncertainty, this safety buffer can diminish the harmful impact of share redemptions.

Hill et al. (2011) find that a higher liquidity ratio, calculated as cash to total assets, leads to a lower probability of business failure. Gilbert et al. (1990) study the bankruptcies of seventy-six U.S. firms from 1974 through 1983, and find that larger liquidity ratios decrease the probability of a bankruptcy. Therefore, we expect a

[6] Balcaen & Ooghe (2006).

negative relationship between liquidity ratio and closure probability.

Large capital outflows that exceed a fund‘s cash reserves generally lead to fund closure. Individual fund net flows can be a consequence of poor fundamentals, such as, e.g., low liquidity ratios, high leverage ratios, or excessive management fees. If investors lose trust in their investments, they may opt to redeem shares.

On the other hand, fund net flows could affect fund closure probability independent of fund-specific variables. Bannier et al. (2008), for example, find that investors redeem shares only because of expected share redemptions by other investors. Those expectations could be a result of reported capital outflows, which by themselves do not allow for any direct conclusions about a fund‘s economic situation. Therefore, capital outflows may be a crucial element of a “self-fulfilling prophecy” that leads to fund closures. Hence, individual fund net flows could serve as an additional proxy for fund run risk.

The potential impact of a fund run leads us to Hypothesis 1:

Hypothesis 1: *Fund closure probability increases with increasing fund run risk.*

3.3.2 Economies of Scale and Scope

According to Laitinen (1992), Hill et al. (2011), and Assadian and Ford (1997), corporate size plays an important explanatory role in business failures. Size is a proxy for potential economies of scale and scope, as well as for learning effects. Hence, larger companies should exhibit lower failure probability.[7] Moreover, large open-end real estate funds that show significant growth in prior periods are more likely to attract different, and therefore sufficiently uncorrelated, target groups. In contrast, smaller funds are more likely to depend on only a few investors. On the contrary, Laitinen (1992) finds that newly founded and fast growing companies (i.e., growth in net sales) that exhibit high leverage ratios also tend to exhibit higher bankruptcy

[7] Hill et al. (2011).

risk. Moreover, Assadian and Ford's (1997) study on U.S. corporate bankruptcies from 1964 through 1991 finds that larger firms exhibit a higher probability of failure.

Although the literature is generally ambivalent about the sign of the influence on firm size, we include fund size as an additional explanatory factor. We suspect that the diminishing effect of size due to economies of scale and scope is dominant over the increasing effect of rapid growth on closure probability. Hence, we expect a negative overall influence of fund size on closure probability.

Company age is also a significant factor in business failures.[8] Young companies have a higher probability of failure than older ones. Analyzing Canadian corporate bankruptcies in 1996, Thornhill and Amit (2003) state that age indicates economies of scope in the organizational process. Therefore, we include fund age as a further fund-specific variable.

We note that eight of the twenty-four open-end real estate funds belong to large German banks.[9] Fund shares are sold by the retail distribution networks of these banks, which are actively advertised by bank advisors. Therefore, bank-owned funds have direct access to a plethora of bank customers. In addition, the purchase of open-end real estate fund shares is often part of clients' pension provision solutions, which are directly sold by the fund's sponsor (bank). Therefore, these funds have a wider target group and larger economies of scope than funds without such a distribution network.

Maurer et al. (2004) state that fund sponsors can buy a sufficient amount of their own fund shares during times of high share redemptions to stabilize liquidity ratios. Hence, the financial power of the fund sponsor may serve as an additional element to prevent fund closures.[10] The open-end real estate funds that use a distribution network belong to the largest German banks and financial syndicates. Hence, we

[8] Thornhill & Amit (2003).

[9] Hausinvest funds, DEGI funds, Grundbesitz funds, DEKA funds.

[10] However, in December 2005, when the Grundbesitz investment fund experienced a liquidity shortage, Bannier et al. (2008) note that the fund sponsor Deutsche Bank was not willing to pay for its "own" fund shares.

use the existence of a distribution network as an additional proxy for economies of scale and scope.

The possible influence of economies of scale and scope are the basis of our second hypothesis:

Hypothesis 2: *Fund closure probability decreases with increasing economies of scale and scope.*

3.3.3 Industrywide Spillover Effects

Although fund specifics are suitable to describe a fund‘s economic situation, Zavgren (1985) and Maltz et al. (2003) find they are not sufficient to fully explain the probability of fund closure.

According to Aharony and Swary (1983) large-scale bank insolvencies lower the stock market value of the remaining solvent banks. Moreover, Bannier et al. (2008) analyze the first German open-end fund crisis in 2005/2006, and find that the closure of a particular fund can result in significant contagion effects to the overall industry. Closed funds could be forced to sell assets to reopen again, or, in the case of a subsequent liquidation, must sell their entire portfolio. Because total assets under management often amount to several billion euros, fire sales could lead to lower real estate prices for a fund‘s portfolio properties. Furthermore, open-end real estate funds often share the same investment focus (e.g., asset class, investment volume, country share), so a significant price drop could affect the overall property prices of the remaining funds. These funds sell parts of their real estate properties on a regular basis, and, therefore, could be directly affected by lower overall property prices, especially during liquidity shortages. Our third hypothesis accounts for these potential negative externalities.

Hypothesis 3: *Negative spillover effects from the closure of other funds may increase fund closure probability.*

3.3.4 Institutional Investors

On average, 98% of all fund shares are held by retail investors. Thus, our research design focuses solely on retail funds. Nevertheless, some funds have a considerably larger share of institutional investors than others (the range is typically from 0% to 30%). These professionals exploit stable, valuation-based fund returns, and regard them as a high-yielding alternative to money market investments.

Prior to the crisis, when interest rates were low, institutional investors used the open-end fund structure to "park" their capital in higher-yielding open-end real estate funds. As the crisis deepened, professionals have to decide if their investment in open-end real estate funds is still favorable regarding the current risk-return profile. In consequence, they could even be forced to sell their shares, which could come as a surprise to the remaining retail investors. This effect increases with the share of professional investors.

According to Larrain et al. (2017), legal restrictions for pension funds led to distressed sales of Chilean stock holdings, which caused a significant higher loss for these stocks than for others. Hence, retail investors should consider the prevailing blockholder risk, which could create additional selling pressure and decrease a fund‘s liquidity ratios. Our fourth hypothesis reflects the risk associated with potentially fast-moving "smart money."

Hypothesis 4: *Fund closure probability increases with the share of institutional investors.*

3.3.5 Control Variables

Our control variables include management costs as an additional fund-specific factor. Fund investors, as well as potential new investors, may consider management fees as too high, which could lead to selling pressure or a lack of inflows. In particular, we use the fund-specific total expense ratio (TER), and we expect an increasing effect

on fund closure probability.

We also control for funds‘ annual total returns as a measure of fund performance. While large returns indicate funds high quality, there is also the possibility, especially in times of financial crisis, that these funds did not fully reappraise their portfolio to current, hence lower, values. This uncertainty about the current valuation could increase the funds closure probability.

Total return also includes the entire history of dividend fund payouts. Flagg et al. (1991) use COMPUSTAT data for the 1975-1981 time frame, and find that the reduction of dividends is a significant predictor of business failure.[11] We expect funds with higher dividend payouts to exhibit a lower closure probability.

Hill et al. (2011), Dimitras et al. (1996), and Zavgren (1985) find that a higher ratio of total liabilities to total assets increases the probability of bankruptcy. Therefore, we use funds' leverage ratios as an additional control variable affecting the probability of fund closure, and we expect a positive sign.

To strengthen our regression results, we also control for the macroeconomic environment by considering macroeconomic uncertainty and the returns of competing asset classes. The macroeconomic development of the national economy, especially during downturns, has a significant impact on business failure probability.[12] We use two popular uncertainty indices to control for macroeconomic influence. First, the Policy Uncertainty Index Europe from Baker et al. (2017) for macroeconomic uncertainty. Moreover, we use one of several implied volatility indices (shortened VIX), which are widely used to account for stock market uncertainty (e.g., Bekaert et al. (2013)). In detail, we use the VIX Europe volatility index based on the Eurostoxx 50. Ben-Rephael (2017) use a similar implied volatility index based on the S&P100 as a measure of uncertainty in his study to test the impact of uncertainty on fund management decision to sell assets in U.S. equity mutual funds from 1986 to 2009.

[11] Flagg et al. (1991).
[12] Bhattacharjee et al. (2009).

According to Zavgren (1983), higher interest rates can strongly affect bankruptcy rates. Moreover, Swanson and Tybout (1988) identify the interest rate as one of the two most important explanatory factors for business failures. Hence, we control for the external environment by using the one-year German government bond yield to account for the German interest rate level, and the dividend yield of the German blue-chip stock market index (DAX30) to control for the return potential of the competing stock market. We also control for the development of the fund's target real estate markets by using the country-specific EPRA total return.

3.4 Data, Methodology, and Sample Description

3.4.1 Data

We use a panel logit framework to analyze fund closure probability for twenty-four open-end real estate funds over a 167-month period from August 2002 through June 2016. These twenty-four funds represent the population of both distressed and healthy open-end German real estate retail funds. Ten of the twenty-four funds were issued in the 2000s, five after August 2002. Therefore, our dataset begins in August 2002 in order to ensure a strongly balanced panel framework. Note further that a new investment law (InvG) was decided on in January 2002, based on an EU directive. This new regime had a significant effect on the legal environment for open-end real estate funds. The use of annual accounting information is also common in failure prediction models.[13] Hence, our data consists of monthly, semiannual, and annual fund reports provided by individual fund management to estimate the impact of fund-specific variables such as liquidity, leverage, and management fees on closure probability.[14] Furthermore, we use data about professional investors from

[13]See, e.g., Balcaen & Ooghe (2006) and Dimitras et al. (1996).

[14]Asset Management Deutschland, AXA Investment Managers Deutschland, Credit Suisse, KanAm Grund Kapitalanlagegesellschaft, Morgan Stanley Real Estate Investing, Pramerica Property Investment, SEB Asset Management, UBS Real Estate.

MorningStar Direct.

3.4.2 Research Design and Variable Definitions

Our key variable of interest is the closure probability of fund i at the end of month t, which is calculated as a 0/1 indicator variable. In a fund closure month, the dummy variable is set to 1. In the following month, the distressed fund is excluded from the panel regression model. Hence, the closure events are captured solely in the panel logit framework.

For the purposes of our empirical tests, we estimate the following panel regression model:

$$\begin{aligned} Closure_{i,t} = \alpha &+ \beta_1\ Liquidity_{i,t-1} + \beta_2\ Individual\ Fund\ Flows_{i,t} \\ &+ \beta_3\ ln\ Fund\ Size_{i,t-1} + \beta_4\ ln\ Age_{i,t} + \beta_5\ Sale\ by\ bank_{i,t} \\ &+ \beta_6\ TER_{i,t-1} + \beta_7\ Total\ Return_{i,t-1} + \beta_8\ \Delta\ Leverage_{i,t-1} \\ &+ \beta_9\ Institutional_{i,t-1} + \beta_{10}\ Fund\ Closure_{i,t} \\ &+ \beta_{11}\ Policy\ Uncertainty\ Index\ Europe_{i,t} + \beta_{12}\ VIX\ Europe_{i,t} \\ &+ \beta_{13}\ German\ Bond\ 1Y_{i,t} + \beta_{14}\ DAX\ 30\ Dividend\ Yield_{i,t} \\ &+ \beta_{15}\ Individual\ EPRA\ TR_{i,t} + v_{i,t} \end{aligned} \tag{3.1}$$

Our regression results are estimated using a panel logit model with heteroscedasticity robust standard errors.

Since the provided fund-specific data is published with a significant time lag, we include a one-month time lag for these variables. In contrast, the individual fund flow variable, age, sale by bank, fund closure indicators, uncertainty indicators, and macroeconomic control indicators, are included without any time lag.

Due to the large assets under management of open-end real estate funds, a closure of

one or more of these funds will be recognized by both institutional, as well as retail investors. As a consequence, fund investors will adjust their fund investment strategy within one month after the closure event occurs. The current market uncertainty and economic situation are also known by investors at present day. Hence, we do not include any time lag for the variables.

We use the following two variables as proxies for fund run risk.
Liquidity denotes the liquidity ratio, which is calculated as the ratio of a fund‘s cash reserves to gross asset value (GAV).
Individual Fund Flows denotes capital net flows into the specific open-end real estate fund. This variable is calculated as the monthly percentage change of net capital fund flows proportional to the respective fund size.

We use three variables to test for the impact of economies of scale and scope on fund closure probability.
Fund Size is the overall logarithmic fund volume measured in billions of euros.
Age represents the logarithmic monthly fund age.
Sale by Bank is a 0/1 indicator variable that is set to 1 if the shares of a particular fund are sold by the distribution network of the fund sponsor (bank).

We proxy for the effect of potential spillover effects on fund closure probability by using the closure announcements of other funds.
Fund Closure is a counting variable that captures the effect of other fund closure announcements. Thus, we test for the impact of industrywide spillover effects.

We also test for a relationship between the share of institutional investors and fund closure probability.
Institutional represents the percentage share of institutional fund investors. It is calculated as the ratio of a fund's market value held by institutional shareholders to its overall market value.

We use the following fund-specific control variables.

TER represents the annual management costs, calculated in percentage of the overall fund size.
Total Return denotes annual NAV performance measured as the percentage change in net asset value. Total Return also includes all extraordinary payouts, which are defined as total fund-specific payouts in a given month relative to a fund's NAV.
Leverage is the absolute difference (Δ) of the fund's debt compared to its GAV. In detail, we use the first differences of the leverage ratio to correct for non-stationarity.

Furthermore, we use the general macroeconomic environment to validate our estimation results. First, we include two variables for market uncertainty. Second, we consider the impact of bond and stock market returns as alternative investments. We also control for the country-specific market return of the fund's target markets.
Policy Uncertainty Index Europe is a measurement of overall political uncertainty in the European market. In detail, Baker et al. (2017) use major newspapers from several European countries and count the number of articles, which include simultaneously the items "uncertainty", "economic", as well as items related to the political situation.[15]

VIX Europe is the Euro Stoxx 50 Volatility Index (VSTOXX), which represents our second proxy for macroeconomic uncertainty. The index measures implied stock market risk. Furthermore, we normalize both indices to make the comparison of the magnitude of both coefficients in the model framework more easier.

German Bond 1Y illustrates the German interest level for bond investments. The interest rate of short-term German government bonds is considered the benchmark for bond investments. This variable serves as a proxy for the opportunity costs for an investment in open-end real estate funds.

DAX 30 Dividend Yield captures the return potential of the German stock market. The DAX 30 consists of the largest thirty companies in Germany. We use the dividend yield instead of stock market performance in order to find a more suitable

[15] A full list is available at: www.policyuncertainty.com.

Table 3.2: Overview Summary Statistics

	Mean	Std. Dev.	Min	Max	Obs
Closure	0.006	0.08	0	1	2931
Fund Specifics					
Liquidity	0.253	0.122	0.007	0.814	2820
Individual Fund Flows	0.002	0.036	-0.566	0.77	3091
Fund Size	36.118	32.772	0.69	136.896	3226
Age	242.927	173.67	25	599	3121
Sale by Bank	0.392	0.488	0	1	3173
Institutional	0.02	0.048	0	0.319	2144
TER	0.008	0.002	0	0.015	2554
Total Return	0.012	0.078	-0.579	0.489	2485
Leverage	0.222	0.113	0	0.641	2797
Industrywide Spillover					
Fund Closure	0.195	0.926	0	9	3246
Macroeconomic Control Variables					
Policy Uncertainty	138.466	55.911	47.694	394.635	3246
VIX Europe	24.939	9.920	11.938	60.677	3246
German bond 1Y	0.016	0.015	-0.006	0.047	3087
DAX 30 Dividend Yield	0.03	0.007	0.019	0.053	3246
Individual EPRA TR	0.005	0.052	-0.274	0.387	2899

This table provides an overview of the mean, standard deviation, minimum, maximum, and number of observations for all variables.

measure of the return potential of stocks versus fund investments, and bond market returns without speculative gains.

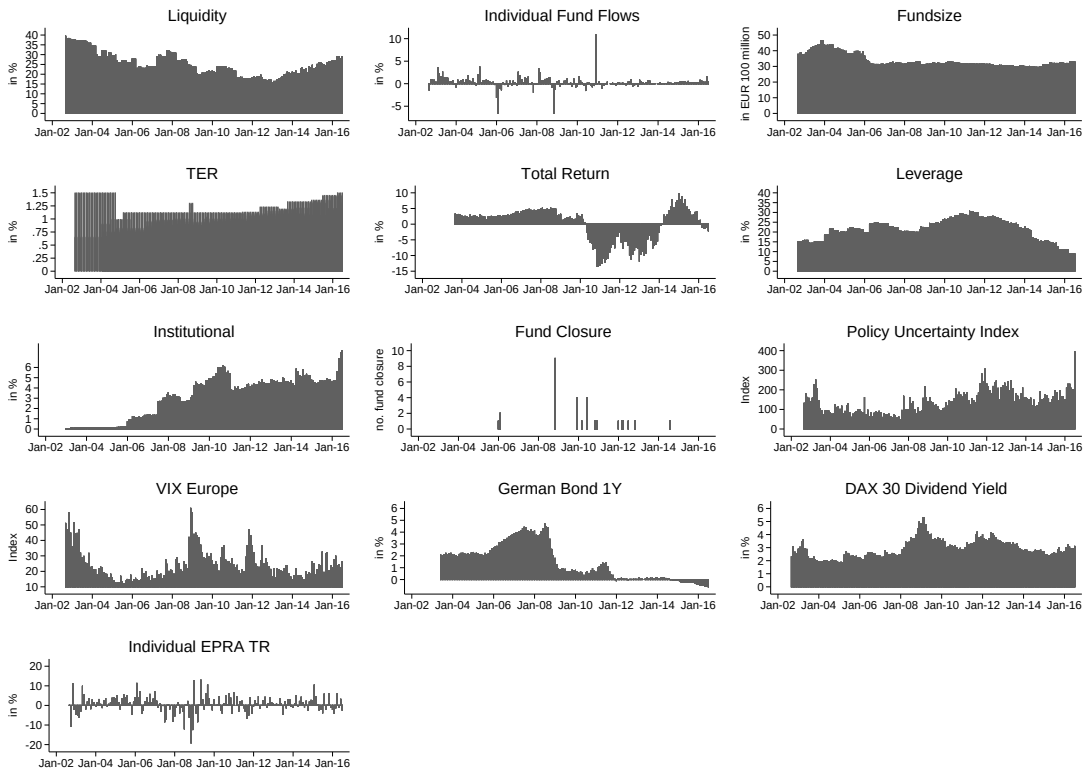
Individual EPRA TR is calculated as the weighted monthly EPRA total return of a fund's target real estate market returns. This variable captures the development of the overall real estate markets, and serves as a proxy for the business cycle.

3.4.3 Descriptive Statistics

Table 3.2 shows the summary statistics for the explanatory variables.

The liquidity ratios show significant heterogeneity over time as well as across funds. The average liquidity ratio is 25.03%, with a range from 0.7% to 81.4%. Several funds were issued within the sample period. A fund opening is accompanied by a liquidity ratio of almost 100% because the accumulated capital has not yet been invested. Thus, we first consider newly issued funds after a twenty-four-month

Figure 3.2: Summary Statistics



This figure illustrates the average progression of fund-specific, industrywide spillover effects and macroeconomic control variables from 2002:8 through 2016:6.

period. The liquidity ratios increase significantly from 2012 due to the progressing liquidation of ten funds in the dataset that were forced to sell their entire real estate property portfolios and transfer the earnings to investors. Figure 3.2 illustrates the considerable increase in average liquidity ratios due to property sales beginning in Q3 2012.

The funds show average monthly fund flows of about 0.2% relative to respective fund volume. Newly issued funds show strong capital inflows within the first two years, which could distort the regression results (note again that we only include funds if they are at least twenty-five months old). Moreover, several funds within the same fund family merged within the sample period.

For example, the WestInvest 1 fund had monthly capital outflows of 100% (purely arithmetical) in October 2009 due to a fund merge with the WestInvest Interselect fund, which had tremendous capital inflows over the same period. For the same

reason, the Inter Immoprofil fund displayed a 248% capital inflow in November 2010. We control for fund merges by excluding these special events from our dataset (n = 5) in order to avoid distortions. Subsequently, the Euro ImmoProfil fund now shows the maximum capital inflows of 77.0% at the beginning of 2005, while the Inter ImmoProfil fund has -56.6% capital outflows in October 2009.

Fund size ranges from EUR 69 million to EUR 13.6 billion, with an average size of EUR 3.6 billion and a median of EUR 2.5 billion. Fund size is measured in EUR 100 million. The Deka Immobilien Europa fund is the largest open-end real estate fund, with an average of EUR 9.87 billion and a maximum of EUR 13.6 billion. In contrast, distressed funds show a significantly negative trend in fund size. For example, the Morgan Stanley P2 value fund had a minimum of only EUR 69 million as of June 2016, due to advanced fund liquidations. But the remaining funds ultimately boosted their fund volumes due to the increased demand for open-end fund shares in Germany since 2014.

Figure 3.2 shows that average fund size decreased from EUR 4.5 billion in January 2004, due to newly issued funds (i.e., low fund volume), to the lowest levels over the 2006-January 2011 period of about EUR 3 billion. Since then, average fund size has risen, despite the fact that several funds were forced to liquidate. Significant capital inflows into the remaining funds led to an average fund volume of about EUR 3.5 billion as of June 2016.

Several funds were issued after August 2002, but within our sample period. The oldest fund at the beginning of the dataset was the UniImmo global fund at thirty-six years (433 months).

The Sale by Bank variable displays a mean of 0.39. This is because the vast majority of open-end real estate funds never switched from using a distribution network to sell fund shares to a system without a direct selling feature, or vice versa. Since October 2012, the DEGI fund family was the sole fund choosing to use a distribution network. Hence, about 40% of all funds sell shares via a distribution network.

Institutional shareholders on average represent 2% of all fund investors. The UBS 3 Sector Real Estate fund reports an institutional share of up to 31.9%, while DEGI Europa has a 0.00% minimum share and never exceeds 0.30%. According to Figure 3.2, the average share of institutional investors significantly increased to about 6% from August 2002 through Q1 2011. It subsequently decreased dramatically through June 2016. Nevertheless, the graph may be biased due to the quality of the data provided.

For example, the Morningstar Direct data is not fully available, because they only report data from seventeen of the twenty-four open-end real estate funds. Furthermore, at the end of the dataset, open-end funds with generally larger shares of institutional investors (such as the UBS 3 Sector Real Estate fund and the TMW Immobilien Welt fund) had provided insufficient information. Therefore, the sharp decline in the average share of institutional investors reported appears excessive.

Closure announcements are clustered in a few months over the sample period. The mean of the counting variable is 0.195. In October 2008, nine funds suspended share redemptions, and four funds had been forced to close as of November 2009 and May 2010. All nine funds that closed in October 2008 reopened, but were ultimately forced to close again from November 2009 through October 2010. Hence, the counting variable, which captures every fund closure event, includes some duplicates.

TER denotes annual management costs for each investor as a percent of fund volume. Funds‘ expense ratios range from 0% to 1.5% of average annual fund volume. The average total expense ratio is 0.8%. Funds' total expense ratios generally increase over time. The CS Euroreal fund shows the largest management fees at the beginning of the sample period in 2002, with a 1.5% expense ratio.

Total Return is defined as the annual change in net asset value. Extraordinary payouts to investors, due to the selling off of real estate portfolios, are considered in the calculation of total return for all distressed funds, as well as in the regular dividend payout for both healthy and distressed funds. Average annual total return

is 1%. Table 3.2 shows a minimum annual total return of -57.90% for the MS P2 value fund in October 2010, and a maximum of +48.9% for the Inter ImmoProfil fund in January 2016.

Leverage ratios also differ dramatically across funds. Five distressed funds (DEGI International, DEGI Europa, TMW Immobilien Welt, MS P2 Value, and UBS 3 Sector Real Estate) report leverage ratios of zero as of the end of the sample period. The Grundbesitz Europa fund exhibited a leverage ratio of 64.1% in Q3 2006 and Q1 2007. The average for all funds is 22.2%. In addition, the KanAM Grundinvest fund, which was forced to close in October 2008, exhibited an average leverage ratio of 38.66%, while the healthy Deka Immobilien global fund had only 18.48%.

Figure 3.2 shows that the average leverage ratio tended to rise through 2012. Afterward, it decreased consistently and significantly to the end of the sample period, largely because distressed funds repay their property-related loans. In contrast, healthy funds show stable leverage ratios across time.

According to Table 3.2, our first uncertainty indicator, the Policy Uncertainty Index, displays an average index value of 138.46, with the lowest value of 47.69 in Q4 2007. In contrast, the Brexit referendum in June 2016 caused tremendous uncertainty (maximum of 394.63) in the overall European economy.

Our second uncertainty indicator is the Euro Stoxx 50 Volatility Index (VSTOXX) (commonly referred to as VIX). The VIX displays an average value of 24.94. The highest stock market uncertainty, at 60.67, is measured in Q1 2009; the lowest value of 11.93 was recorded in July 2005.

The interest rate of German government bonds with one-year maturity ranges from -0.6% in June 2016 to +4.7% in June 2008. The average interest rate is 1.6%. Figure 3.2 shows that government bond yields increase over 2002-2008. Due to the expansive monetary policy in the wake of the global financial crisis, interest rates decreased considerably and even reached negative values toward the end of the

sample period.

On average, the thirty largest German companies distribute 3% annual payouts. The variable shows a minimum dividend of 1.9% in December 2004 and a maximum of 5.3% in February 2009. According to Figure 3.2, the DAX 30 exhibited relatively low dividend yields from 2004 through 2005. Afterward, dividends increased. In summary, the DAX 30 companies distributed significant and relatively stable annual dividend payments of about 2% to 4%.

Individual EPRA total returns ranged from -27.4% to 38.7%, with an average of 0.5%. Figure 3.2 shows a rather volatile development of the weighted funds' target real estate markets. The figure shows that the minimum was reached in Autumn 2008 during the financial market turmoil of the global financial crisis. In subsequent years, we observe a significant recovery of the funds' target real estate markets, with mainly positive total returns.

3.5 Results

Table 3.3 contains the results of four panel logit regression models (I-IV). The first model includes only fund-specific explanatory variables (I), while the second specification also includes the industrywide spillover variable (II). The third model (III) is estimated using fund-specific, industrywide spillover, and macroeconomic control variables.[16]

Model IV further includes the share of institutional investors. Unfortunately, Morningstar Direct provides data on fund ownership structure for only seventeen of the twenty-four funds. Hence, we lose 420 observations from model IV versus model III (N = 2,037). The standard errors of the regression coefficients are in parentheses.

[16] We control for the legal fund environment (e.g., the selling restrictions on the properties) and do not confirm a significant influence on fund closure probability; According to Sheppard (1994) and Hall (1994), the level of diversification has a significant influence on business failures, but we find no influence of regional or sectoral diversification (Herfindahl index) on the probability of a fund closure.

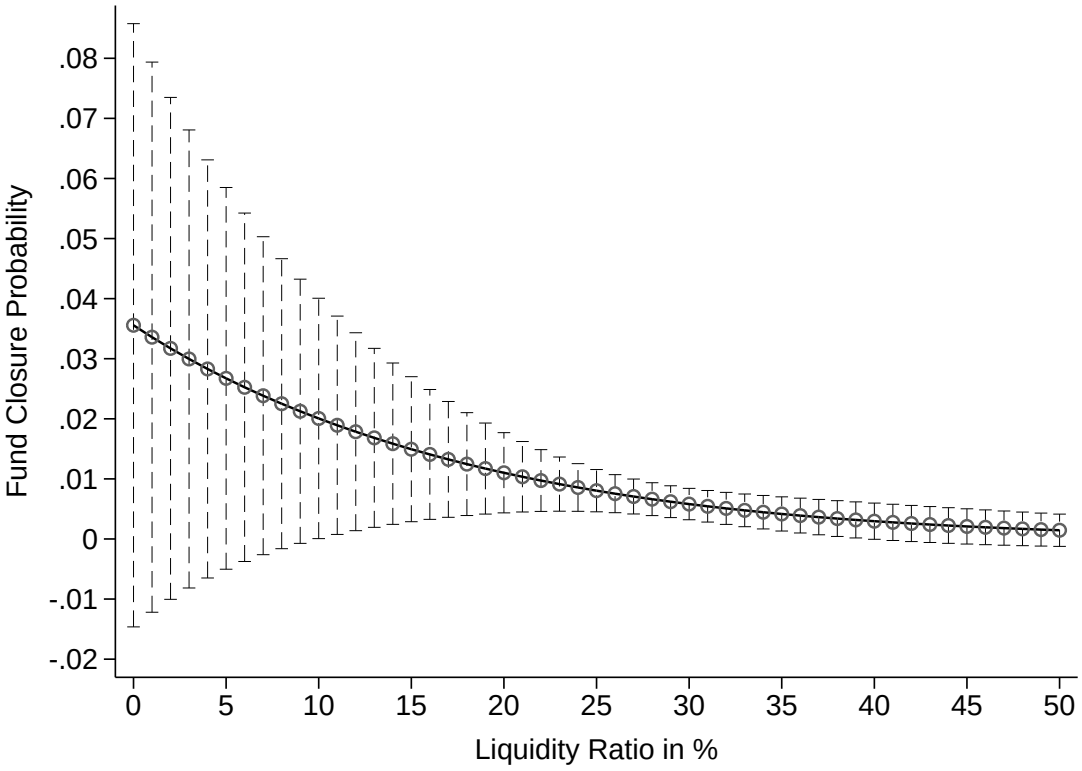
Table 3.3: Explaining Fund Closure Probability

	(I)	(II)	(III)	(IV)
Fund Specifics				
$Liquidity_{i,t-1}$	-0.0583**	-0.0861**	-0.107*	-0.221**
	(0.0249)	(0.0378)	(0.0610)	(0.0981)
$Individual\ Fund\ Flowsi,t$	-0.177**	-0.125***	-0.143***	-0.310***
	(0.0781)	(0.0349)	(0.0386)	(0.118)
ln $Fund\ Size_{i,t-1}$	0.950*	0.800*	0.709*	2.134*
	(0.560)	(0.461)	(0.405)	(1.285)
$ln\ Age\ i,t$	-1.271***	-0.772	-1.018*	-1.704**
	(0.480)	(0.503)	(0.578)	(0.830)
$Sale\ by\ Bank_{i,t}$	-1.287	-2.062**	-1.666*	-1.146
	(0.796)	(0.922)	(0.864)	(0.965)
$Institutional_{i,t-1}$				0.234***
				(0.0868)
$TER_{i,t-1}$	3.485***	5.100***	5.032**	7.212
	(1.236)	(1.571)	(2.309)	(4.406)
$Total\ Return_{i,t-1}$	0.103***	0.0557	0.0392	-0.0176
	(0.0387)	(0.0668)	(0.0889)	(0.278)
$\Delta\ Leverage_{i,t-1}$	0.184***	0.189***	0.168**	0.112
	(0.0511)	(0.0556)	(0.0675)	(0.0726)
Industrywide Spillover				
$Fund\ Closure_{i,t}$		0.620***	1.063***	1.120**
		(0.107)	(0.408)	(0.475)
Macroeconomic Control Variables				
$Policy\ Uncertainty\ Index\ Europe_{i,t}$			-0.383	-0.318
			(0.626)	(0.798)
$VIX\ Europe_{i,t}$			-0.212	-0.475
			(0.621)	(1.065)
$German\ Bond\ 1Y_{i,t}$			-0.727*	-0.394
			(0.387)	(0.457)
$DAX30\ Dividend\ Yield_{i,t}$			-1.978	-2.578**
			(1.234)	(1.224)
$Individual\ EPRA\ TR_{i,t}$			-0.0521	-0.135
			(0.0826)	(0.0928)
Constant	-3.607	-7.021**	1.124	0.168
	(2.359)	(3.201)	(4.275)	(4.628)
Observations	2,046	2,046	2,037	1,617
McFadden R-squared	0.287	0.530	0.568	0.675

This table gives the results of the panel logit model regression. Model I shows the influence of the fundamentals that explain the probability of fund closure. Model II further includes, besides the fund-specific variables, the industry-wide spillover effects. Model III, our preferred model, includes further the macroeconomic control variables. Model IV adds the share of institutional investors. The Policy Uncertainty and VIX Europe variables are standardized with zero mean and a standard deviation of one. Robust standard errors are in parentheses. Stars denote significance as follows: *** p<0.01, ** p<0.05, * p<0.1.

Due to the non-linear relationship, the interpretation of regression coefficients in panel logit models is not intuitive. While our empirical tests are based on the statis-

Figure 3.3: Effects of the Liquidity Ratio on the Fund Closure Probability



This figure compares how fund closure probability reacts to changes in fund run risk as represented by the liquidity ratio. The dashed lines denote the 95% confidence interval.

tical significance of the coefficients, we use graphical analyses to judge the economic significance of our results.[17] Figures 3.3 to 3.9 show the mean marginal effect of a variation of the respective independent variable over all considered combinations with the other independent variables. We derive these figures from our preferred regression model (III), and the marginal effects of the share of institutional investors from model IV.

We first focus on testing Hypothesis 1, to determine whether higher fund run risk causes higher fund closure probability. Fund run risk is represented by the fund liquidity ratio, as well as by individual fund capital inflows. Both variables show the expected negative influence on closure probability. A larger liquidity ratio c.p. significantly reduces closure probability in the next month. This negative effect is robust for all four model specifications.

[17] Greene (2010), Downs et al. (2016).

Figure 3.3 illustrates that closure probability increases if a fund exhibits a liquidity ratio of less than 5%, because, under German law, these funds are forced to close. Funds with liquidity ratios at 5% exhibit closure probabilities of about 2.5%. Under a liquidity ratio of 10%, the probability decreases to 2%. Average liquidity ratios of 25%, as well as higher ratios of up to 50%, are associated with closure probabilities of around 1%. These results are in line with unconditional closure probabilities. Our dataset contains about twenty fund closure events, which equates to a 1% closure probability over 2,037 total observations. A larger share of cash and short-term money market positions serve as a safety buffer for investors. Hence, a higher liquidity ratio decreases the risk of beginning a vicious cycle. Especially if the liquidity ratio is already low, the decreasing impact on closure probability of a 1% increase in the liquidity ratio is more than proportional.

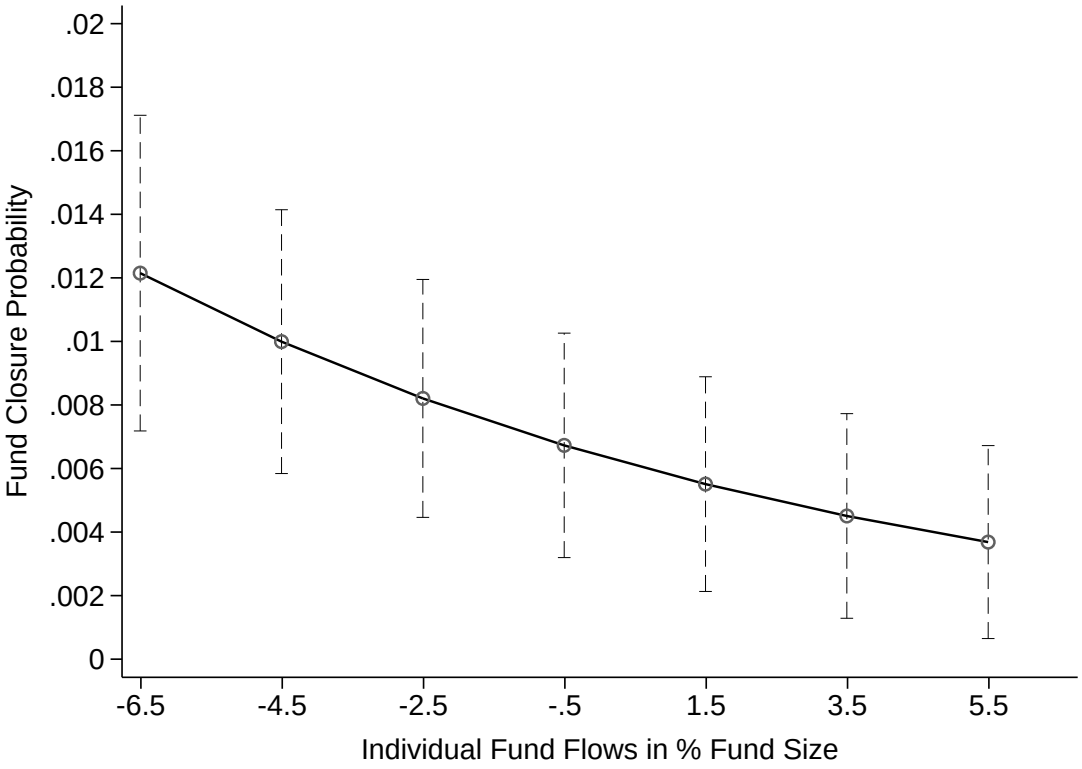
In addition, fund capital inflows exhibit a significant and robust negative effect on closure probability across all four model specifications. Capital inflows into a particular fund reduce closure probability c.p., while large contemporaneous capital outflows significantly increase it. Figure 3.4 illustrates the marginal impacts. Large capital outflows of about 6.5% lead to a 1.2% closure probability, while capital outflows of 4.5% exhibit a 1% closure probability. Positive capital flows lead to a significantly lower closure probability of 0.7% to 0.5%.

In summary, both proxies are consistent with Hypothesis 1. Fund closure probability rises during times of higher fund run risk.

Next, we examine Hypothesis 2, whether fund closure probability is driven by economies of scale and scope. Our three proxy variables are age, the sale by bank dummy variable, and fund size.

We use the logarithm of fund age as an additional influential factor that affects fund closure probability. Older funds exhibit c.p. lower closure probability. The negative effect is significant in models I, III, and IV. The negative sign on the regression coefficient is in line with the literature. Older companies or funds are likely to

Figure 3.4: Effects of Individual Fund Flows on Fund Closure Probability



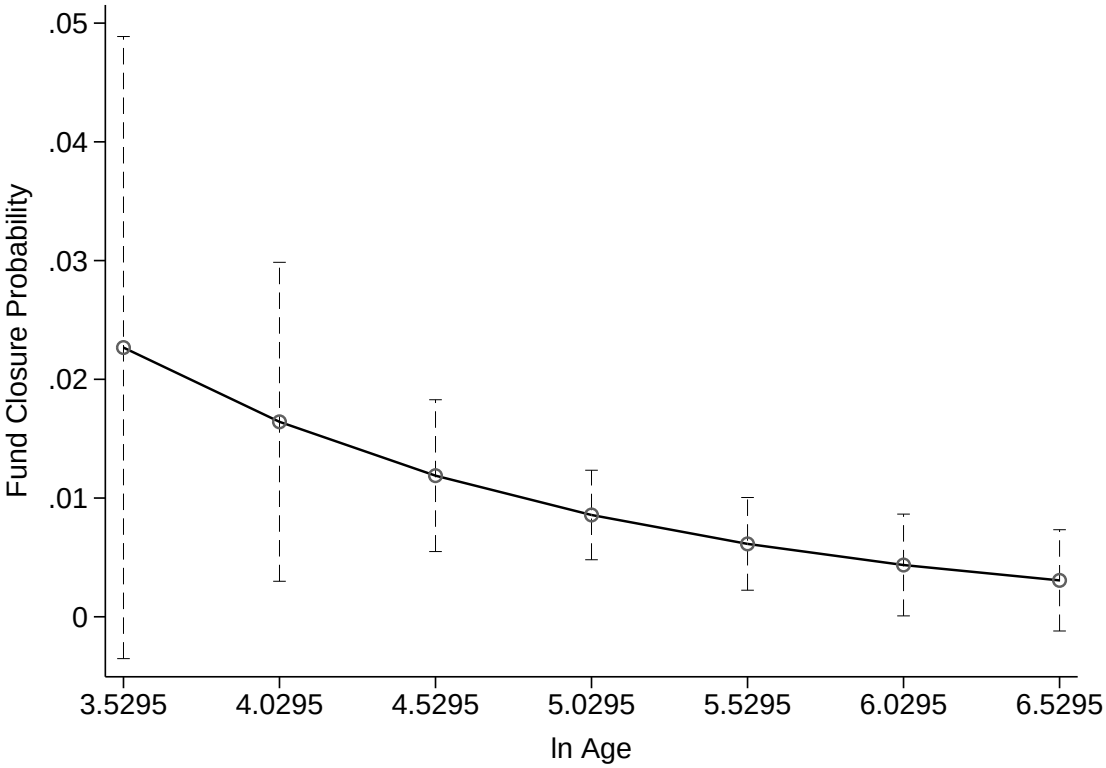
This figure compares how fund closure probability reacts to changes in fund run risk as proxied for by individual fund flows. The dashed lines denote the 95% confidence interval.

obtain larger economies of scope in the organizational process because they have had more time to establish efficient processes and structures.

Figure 3.5 shows how the marginal effects of logarithmic age affect fund closure probability. Age is varied over two standard deviations below and above the mean. Average fund age is about twenty years. A logarithmic fund age of 3.52 (i.e., two standard deviations below the mean) is associated with a closure probability of about 2%. In the case of a two-standard deviation variation above the mean (6.52), the closure probability decreases considerably to 0.5%.

Open-end real estate funds that use the retail distribution network of their issuing sponsor (bank) show c.p. lower fund closure probability. The negative sign is robust among all four model specifications. Nevertheless, we find a significant influence only in models II and III.

Figure 3.5: Effects of Fund Age on Fund Closure Probability



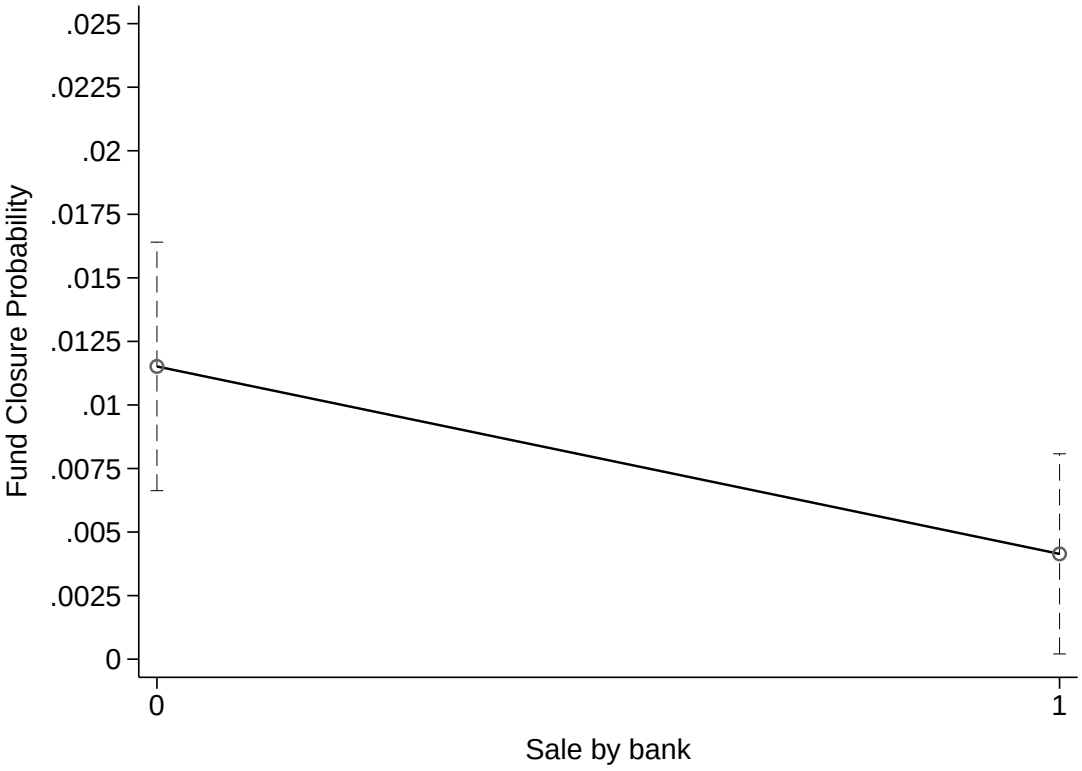
This figure compares how fund closure probability reacts to changes in the economy of scope and scale variable as proxied for by fund age. The dashed lines denote the 95% confidence interval.

Figure 3.6 illustrates that funds without a distribution network exhibit a closure probability of about 1.25%. Those with a distribution network exhibit a considerably lower closure probability of 0.5%.

Interestingly, larger funds exhibit c.p. a higher fund closure probability. This positive effect is significant for all four model specifications. Figure 3.7 illustrates the marginal effects of a variation in fund size on closure probability. We use the logarithm of fund size in the model specification. For example, for a logarithmic fund size of 0.88, the fund closure probability is about 0.25%; for a larger fund size of 4.88, the probability would be about 1.5%.

In summary, we find significant influence in two of our three proxies for economies of scope and scale on fund closure probability. Fund age and the sale by bank variables show the expected negative signs, and are statistically significant in the third model (III).

Figure 3.6: Effects of the Sale by Bank Variable on Fund Closure Probability



This figure compares how fund closure probability reacts to changes in the economy of scope and scale variable, as represented by the sale by bank variable. The dashed lines denote the 95% confidence interval.

Next, to test for the presence of negative spillover effects from other fund closures (Hypothesis 3), we use the number of closures in each month of our sample period. The coefficient on the fund closure variable is positive and significant across all model specifications. As illustrated in Figure 3.8, the probability is almost zero if there are zero to three fund closures of other funds in the respective month. In months with more than three closures, the probability increases substantially by about 10% with every additional event. In October 2008, when nine funds were forced to close, the closure probability of the remaining funds was approximately 70%.

According to Table 3.4, the dependent variable is relatively strongly correlated with the fund closure variable at about +0.42. In summary, we find evidence that spillover effects affect closure probability.

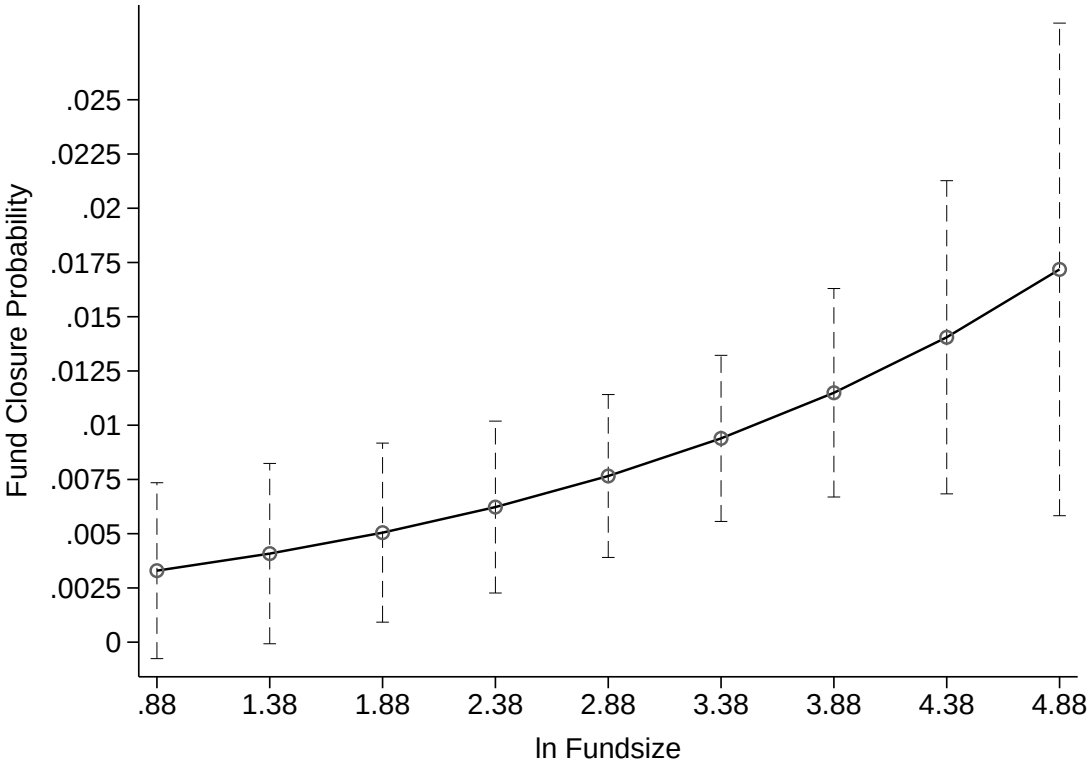
We also test whether the share of institutional investors affects the closure probabil-

Table 3.4: Correlation Matrix: Fund Specifics, Spillover, and Macroeconomic Variables

	Closure	$Liquidity_{i,t-1}$	$Individual\ Fund\ Flows_{i,t}$	$ln\ Fundsize_{i,t-1}$	$ln\ Age_{i,t}$	$Sale\ by\ bank_{i,t}$	$Institutional_{i,t-1}$	$TER_{i,t-1}$	$Total\ Return_{i,t-1}$	$\Delta\ Leverage_{i,t-1}$	$Fund\ Closure_{i,t}$	$Policy\ Uncertainty_{i,t}$	$VIX\ Europe_{i,t}$	$German\ bond\ 1Y_{i,t}$	$DAX30\ Dividend\ Yield_{i,t}$	$Individual\ EPRA\ TR_{i,t}$
Closure	1.00															
$Liquidity_{i,t-1}$	-0.04	1.00														
$Individual\ Fund\ Flows_{i,t}$	-0.17	0.09	1.00													
$ln\ Fundsize_{i,t-1}$	-0.02	-0.01	0.00	1.00												
$ln\ Age_{i,t}$	-0.05	-0.27	-0.14	0.39	1.00											
$Sale\ by\ bank_{i,t}$	-0.05	0.11	-0.05	0.34	0.11	1.00										
$Institutional_{i,t-1}$	0.14	-0.16	0.04	-0.55	-0.39	-0.29	1.00									
$TER_{i,t-1}$	0.03	0.04	0.08	-0.15	-0.20	0.14	0.15	1.00								
$Total\ Return_{i,t-1}$	0.05	0.24	0.04	0.13	0.06	0.10	-0.37	-0.14	1.00							
$\Delta\ Leverage_{i,t-1}$	0.08	-0.07	-0.02	-0.02	-0.02	-0.01	0.04	-0.04	-0.03	1.00						
$Fund\ Closure_{i,t}$	0.42	-0.03	-0.19	-0.03	-0.01	-0.01	0.06	0.02	0.00	0.05	1.00					
$Policy\ Uncertainty_{i,t}$	0.06	-0.13	-0.01	0.05	0.18	0.02	0.03	0.22	-0.17	-0.01	0.15	1.00				
$VIX\ Europe_{i,t}$	0.07	0.03	-0.01	-0.03	0.02	-0.05	0.11	0.02	-0.05	0.02	0.14	0.43	1.00			
$German\ bond\ 1Y_{i,t}$	-0.00	0.26	0.03	-0.08	-0.25	-0.03	-0.01	-0.20	0.22	-0.00	-0.03	-0.68	-0.27	1.00		
$DAX30\ Dividend\ Yield_{i,t}$	0.09	-0.19	-0.05	-0.08	0.05	-0.05	0.18	0.15	-0.08	0.03	0.18	0.46	0.62	-0.31	1.00	
$Individual\ EPRA\ TR_{i,t}$	-0.14	-0.05	0.03	0.02	0.00	-0.00	-0.01	-0.02	-0.07	-0.03	-0.28	-0.14	-0.11	-0.17	-0.21	1.00

This table shows the correlation coefficients between the dependent and independent variables of the panel regression model.

Figure 3.7: Effects of Fund Size on Fund Closure Probability



This figure compares how fund closure probability reacts to changes in the economy of scope and scale variable as proxied for by fund size. The dashed lines denote the 95% confidence interval.

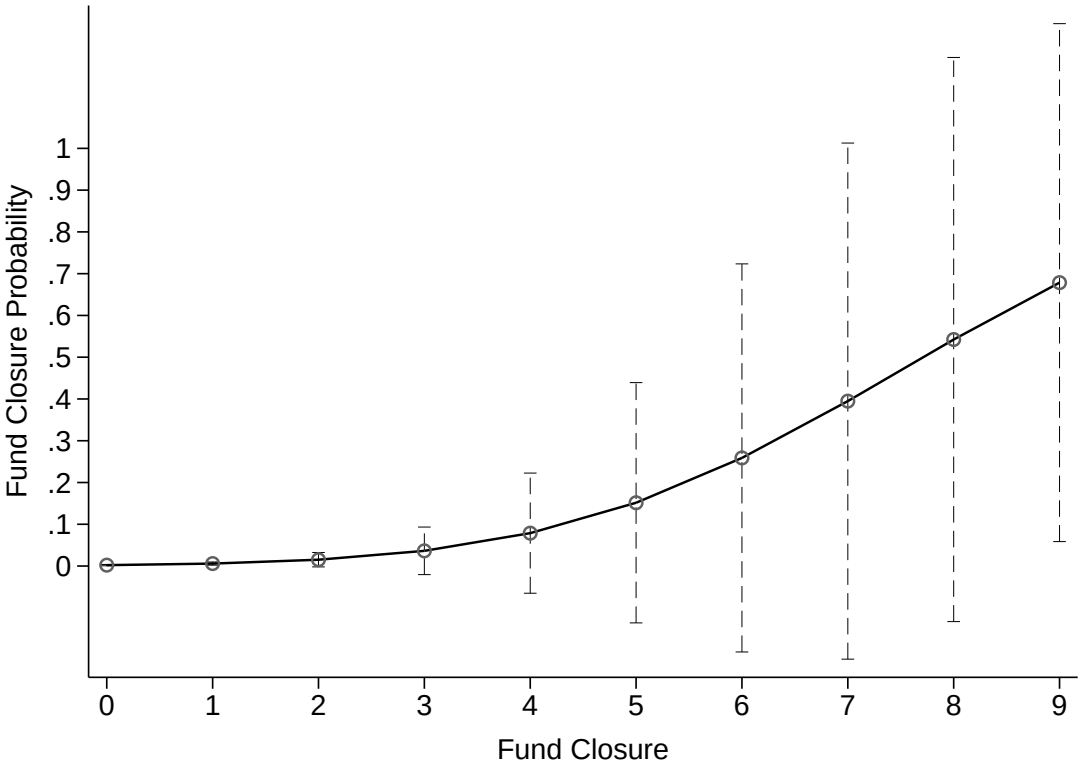
ity of open-end real estate funds (Hypothesis 4). Model IV in Table 3.3 shows that a larger share of institutional investors significantly increases c.p. closure probability in the next month.

Figure 3.9 illustrates that a 0% share of institutional investors leads to a 0.75% fund closure probability, while an 11.5% share, which represents a two-standard deviation increase above the mean, exhibits a 2.5% closure probability.

Our regression results are in line with the general notion that having a higher share of institutional investors is tied to significant blockholder risk for the remaining retail investors. Professional fund investors hold and are able to redeem a high proportion of fund shares. This can lead to additional selling pressure on fund management, which can also increase closure probability due to decreasing liquidity ratios.

This fundamental effect becomes even stronger because institutional investors can

Figure 3.8: Effects of the Number of Fund Closures on Fund Closure Probability

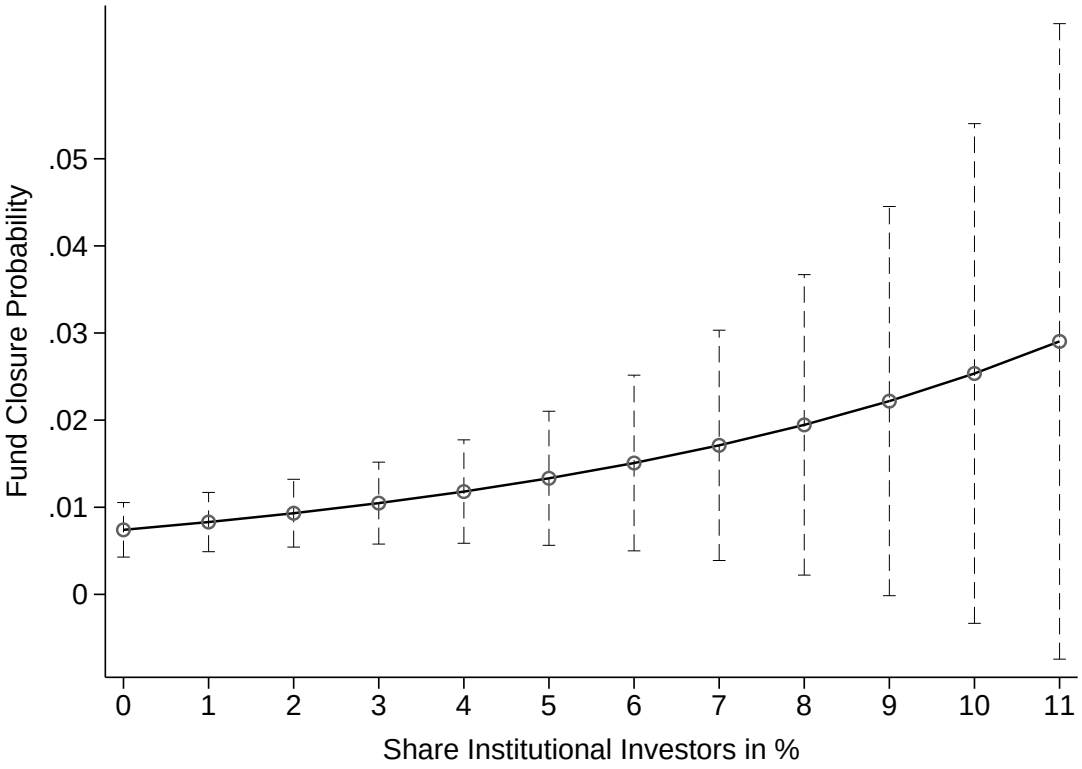


This figure compares how fund closure probability reacts to changes in the spillover variable as represented by the number of fund closures. The dashed lines denote the 95% confidence interval.

redeem their shares suddenly regardless of fund performance. This could come as a surprise for remaining investors due to their short-term investment horizons. Retail investors who take this potential blockholder risk into account may be inclined to sell their own shares more rapidly compared to those in funds held mainly by private investors. Given that we lose 420 observations due to unavailable data, we test the influence of institutional share based on only 1,617 observations. Thus, although the results are relatively robust, they should be interpreted with caution.

Furthermore, we use a set of fund-specific and macroeconomic control variables. We include TER, fund total return, and fund leverage ratio as fund-specific control variables in all model specifications (I-IV). Consistent with the literature, management fees (TER), as well as the leverage ratio, exhibit a significant and robust positive effect on closure probability across the model specifications. Note that higher leverage ratios amplify the effect of potentially negative property reappraisals, and could

Figure 3.9: Effects of the Share of Institutional Investors on Fund Closure Probability



This figure compares how fund closure probability reacts to changes in the share of institutional investors. The dashed lines denote the 95% confidence interval. The figure is based on the results of the fourth model specification (model IV).

cause additional selling pressure on fund management. Moreover, if investors consider management fees too high, they are more likely to redeem their shares. The total return variable shows no consistent regression results across the model specification.

In models III and IV, we control further for macroeconomic environment. In particular, we test for the impact of two widely used uncertainty indicators, the VIX Europe and the Policy Uncertainty Index Europe, to capture prevailing macroeconomic uncertainty. We also use short-term German government bond yields and the DAX 30 dividend yield to control for the return potential of alternative asset classes (i.e., bonds and stocks).

We then control for the total return of funds' target real estate markets. The control variables show no consistent or significant results across the different model speci-

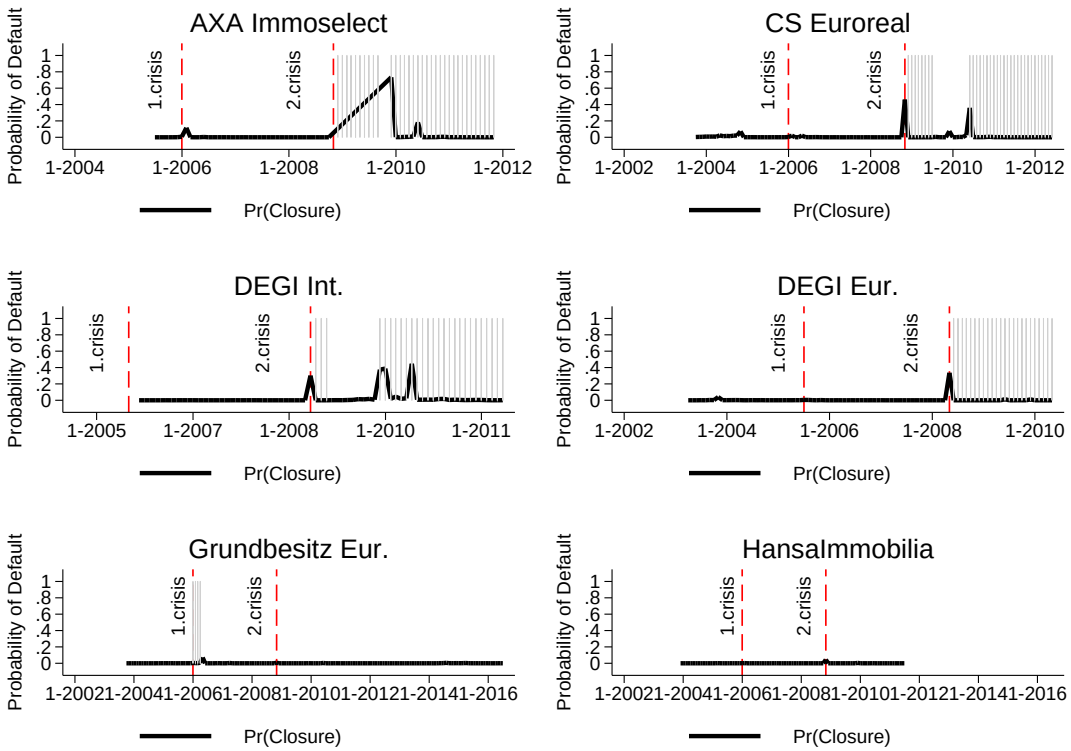
fications. This is potentially due to the considerable cross-correlation the variables exhibit with each other.

Table 3.4 shows that economic uncertainty is strongly correlated with the DAX 30 dividend yield (+0.46), and negatively correlated with the government bond interest rate (-0.68). In addition, stock market uncertainty shows a similar relationship with the DAX 30 dividend yield (+0.61) and the interest rate level (-0.22). The individual EPRA total return shows no strong correlation with any other macroeconomic control variables.

The regression results for the four model specifications are relatively robust. Model I, which includes solely fund-specific factors, shows a McFadden R-squared of 28.7%. The model fit significantly increases by adding the counting variable for the number of fund closures in the respective month. Hence, model II exhibits a McFadden R-squared of 53.0%. Model III further includes macroeconomic control variables in order to validate the regression results, which increases the model fit of about 4% to a McFadden R-squared of 56.8%. Model IV adds the share of institutional investors, and exhibits a McFadden R-squared of 67.5%.

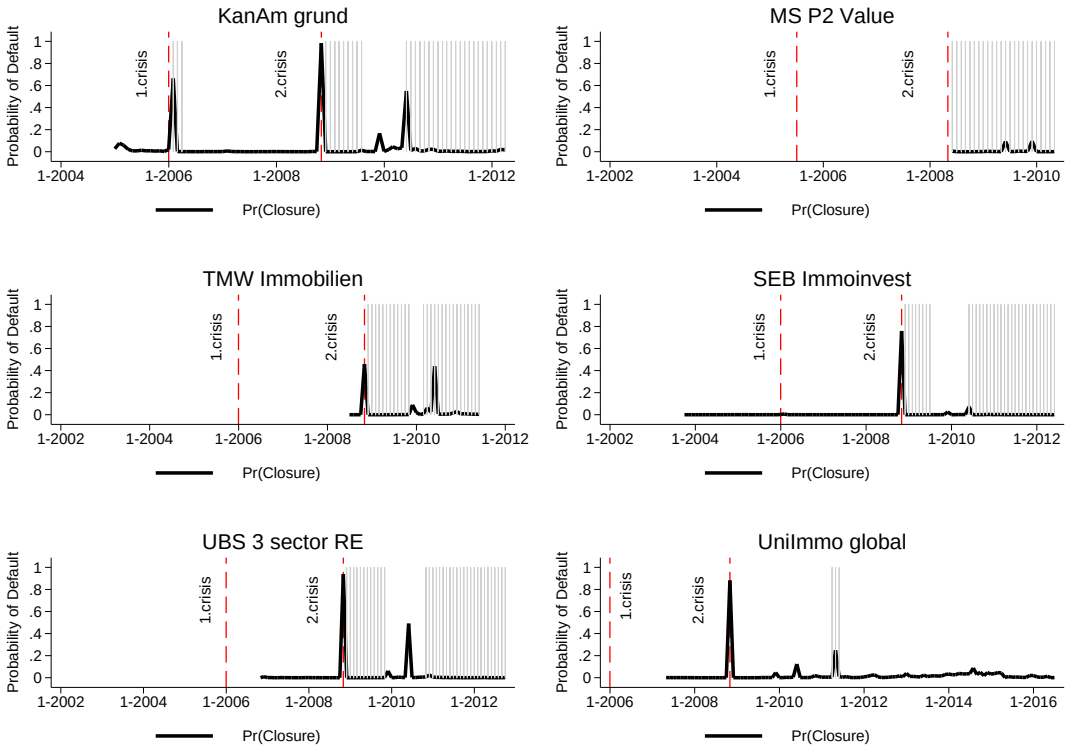
We illustrate the model fit of our preferred model (III) by conducting an in-sample prediction of closure probability for all twenty-four funds. Figures 3.10 to 3.13 show the results for all distressed funds and for the remaining healthy funds, respectively. According to Figures 3.10 and 3.11, eight of the twelve distressed funds exhibited considerable predictive closure probability in October 2008, at the peak of the second fund crisis. The graphs show the prediction for every month in the sample period. Hence, we mark the periods after the actual fund closure event, because these predictions are only theoretical.

Figure 3.10: The Predicted Fund Closure Probability of Distressed Funds I



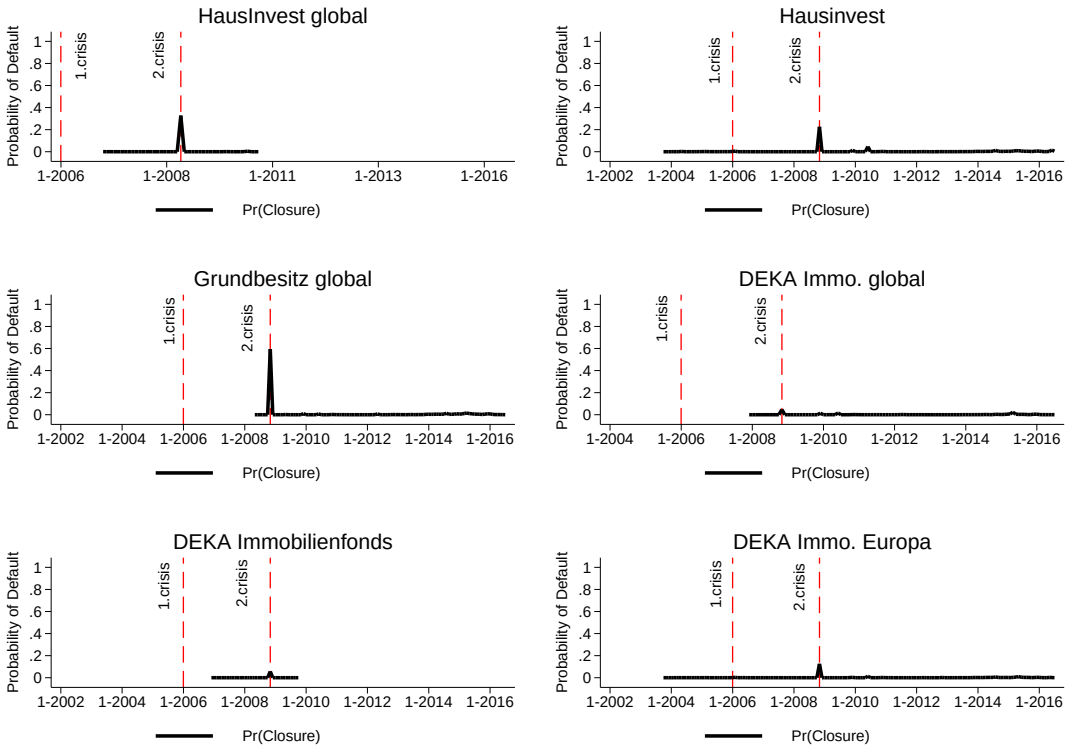
This figure shows the predicted fund closure probability of all distressed open-end real estate funds. It validates the predictive power of the panel logit regression. Most funds show their highest closure probability at the date of actual closure. Predicted fund closure probability after the actual closure date is only theoretical, and is therefore denoted as a dashed line.

Figure 3.11: The Predicted Fund Closure Probability of Distressed Funds II



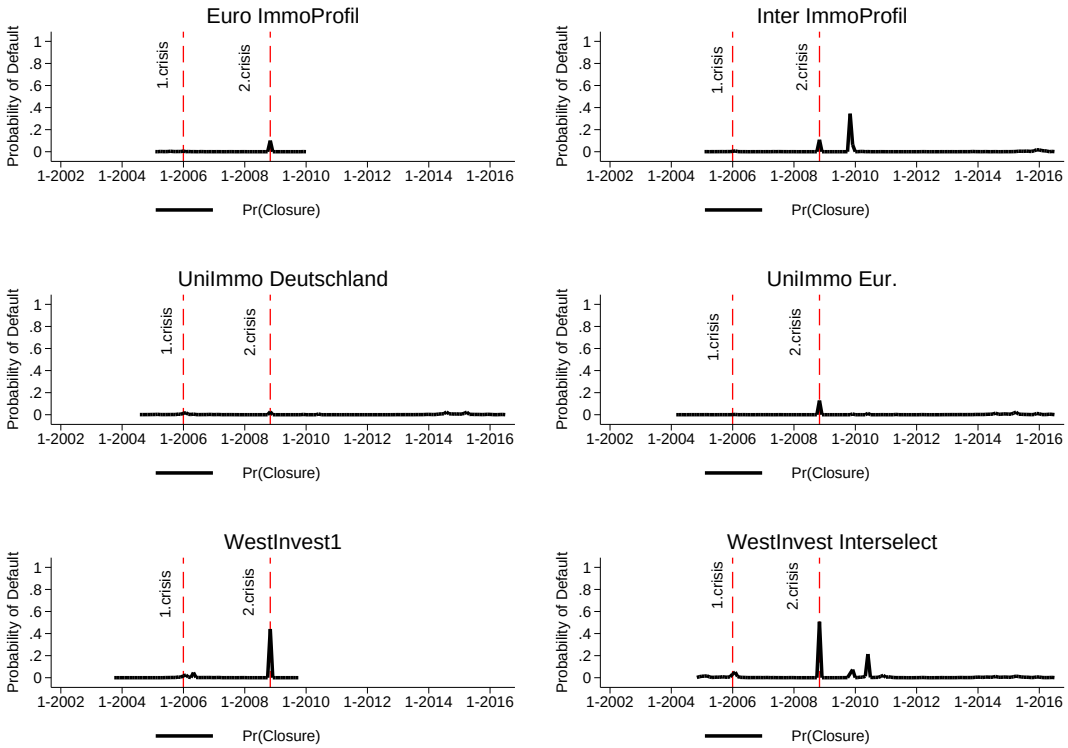
This figure shows the predicted fund closure probability of all distressed open-end real estate funds. It validates the predictive power of the panel logit regression. Most funds show their highest closure probability at the date of actual closure. The predicted fund closure probability after the actual closure date is only theoretical, and is therefore denoted as a dashed line.

Figure 3.12: The Predicted Fund Closure Probability of the Remaining Healthy Funds I



This figure shows the predicted fund closure probability of all healthy open-end real estate funds. It validates the predictive power of the panel logit regression.

Figure 3.13: The Predicted Fund Closure Probability of the Remaining Healthy Funds II



This figure shows the predicted fund closure probability of all healthy open-end real estate funds. It validates the predictive power of the panel logit regression.

Figures 3.12 and 3.13 illustrate the significant closure probability of the remaining healthy funds. At the height of the crisis, in October 2008, half of all the healthy funds exhibited low closure probability. Only one of the twelve funds showed a closure probability higher than 50%.

Overall, the model possesses high predictive power. Nevertheless, some funds that exhibit all the determinants of distressed funds remain open in the aftermath of a global financial crisis. This may indicate that simple bad luck sometimes plays a part in fund closures.

3.6 Conclusion

This paper contributes to the literature on failure prediction models and liquidity transformation risk in several ways. We began by noting that about one-third of all open-end German real estate funds were forced to close during the first and second fund crises, in 2005/2006 and October 2008, respectively. This led to significant lower demand for fund shares by retail investors from 2008 through 2015. Second, we use fund-specifics, industrywide spillover effects, as well as macroeconomic control variables to analyze the most important factors driving fund closure probability. On the fund-specific side, we find that fund closure probability is driven by the degree of fund run risk. Funds with low liquidity ratios and capital outflows exhibit higher probability of closure. Fund management could reduce capital outflows by marketing the funds to a more diverse group of investors (i.e., focus on retail investors by using a bank to distribute their shares). It may also be possible to reduce the risk of fund closure by using a more conservative investment strategy with larger liquidity ratios. However, higher shares of cash and money market deposits come at the expense of lower returns. We also document that economies of scale and scope help decrease fund closure probability. We find evidence of negative spillover effects from the closure announcements of other funds. These effects are outside the control of fund management. We further find that having a larger share of institutional investors significantly increases fund closure probability. Ultimately, we find that fund management can prevent closures in part by following a more conservative fund strategy and by focusing on well-established funds that use distribution networks to sell shares. Nevertheless, systematic closure risk is a somewhat inherent feature of the open-end structure.

Chapter 4

The Discount to NAV of Distressed Real Estate Funds

Sebastian Schnejdar, Michael Heinrich, Rene-Ojas Woltering, Steffen Sebastian

4.1 Introduction

Open-end real estate funds, besides REITs and closed-end funds, represent one of the most significant real estate investment vehicles worldwide[1], with Germany being the largest market. As of December 2016, this asset class had investments totalling about EUR 145 billion.

Investors in these funds trade directly with the fund or its sponsor, which sells and redeems shares on a regular basis. Price per share is determined by the sponsor, and is based on the market value of all assets and liabilities. Each month, independent appraisers reappraise one-twelfth of the entire portfolio.[2] Due to their NAV-based pricing system, open-end real estate funds are usually less volatile than REITs or real estate stocks, which are subject to stock market risk. This, however, comes at the cost of increased liquidity risk. The discrepancy between the daily liquidity of fund shares and the illiquidity of the underlying direct property investments is referred to as "bank run" risk (Bannier et al., 2008; Weistroffer and Sebastian, 2015). To maintain the "buy-back" guarantee, open-end real estate funds tend to hold high cash reserves. In Germany, at least 5% of a fund's NAV must be held in cash or liquid assets. In practice, average liquidity ratios tend to fluctuate between 20% and 30% (see Downs et al., 2016a), although these reserves may prove inadequate during times of market turmoil.

A recent example of what havoc market turmoil can wreak can be seen with the Brexit Referendum in the U.K. on June 23, 2016. The decision to leave the European Union came as a surprise to many investors, and led to massive redemptions from U.K. open-end real estate funds. As a result, seven public U.K. funds, representing half the total open-end real estate fund assets under management, were forced to

[1] See Downs et al. (2016b) for a recent overview.
[2] See Weistroffer and Sebastian (2015) and Fecht and Wedow (2014).

suspend share redemptions.[3]

However, the German open-end fund industry was hit even harder in the aftermath of the 2008 global financial crisis. Between October 2008, the month after the Lehman Brothers bankruptcy, and October 2010, ten public German open-end real estate funds had to suspend share redemptions.[4] None of these funds could raise enough liquidity to reopen and fulfill all the redemption requests. Thus, each one had to liquidate its portfolio and pay out the proceeds to investors.[5]

Besides waiting for the stepwise liquidation of fund assets, German open-end real estate fund investors have the option of selling their shares on the secondary market. This option is available both for funds in a liquidation phase, as well as those under share redemption suspensions. In this paper, we refer to both types as "distressed" open-end real estate funds. Although the fund companies continue to regularly publish NAVs per share, the price per share on the secondary market becomes a function of supply and demand.

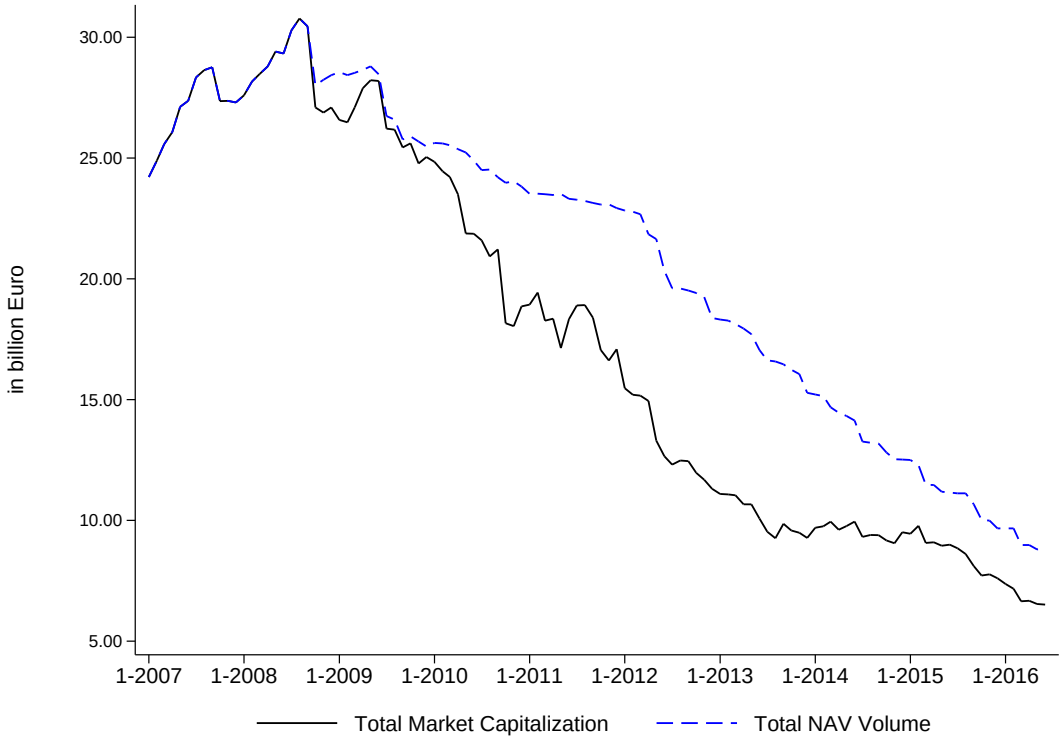
The principles of supply and demand suggest that secondary market prices should be lower than NAV if a large number of investors choose not to wait for the liquidation process to proceed. Due to the increasing supply of fund shares, market prices must fall below NAV to realign supply and demand. Furthermore, the loss of the "buy-back" guarantee, as well as the shift from a relatively stable appraisal-based pricing system to more volatile transaction-based share prices, justifies a risk premium. Figure 4.1 confirms this intuition. A comparison of the NAV-based total fund size

[3] M&G Property Portfolio, Henderson UK Property PAIF, Standard Life UK Real Estate Fund, Aviva Investors Property trust, Columbia Threadneedle UK Property Authorised Investment Fund (PAIF), Pramerica Property Investment, Canada Life UK Property Fund, and Aberdeen UK Property Fund.

[4] This paper focuses solely on retail funds. We exclude semi-institutional funds, which are primarily intended for institutional investors. They are legally classified as retail funds, but the minimum investment begins at EUR 1 million. Consequently, semi-institutional funds do not fit our framework, where the supply and demand of fund shares on the secondary market, and, hence, ultimately the discount to NAV per share, is determined by the unwillingness of retail investors to go through the liquidation process. Moreover, we exclude the UniImmoGlobal fund, which was forced to close only from March to June 2011 due to devaluations of real estate assets in Japan after the Tohoku earthquake and tsunami.

[5] The next section provides some regulatory background on the liquidation regime of German open-end real estate funds and an overview of the recent crisis.

Figure 4.1: Total NAV Volume and Total Market Capitalization



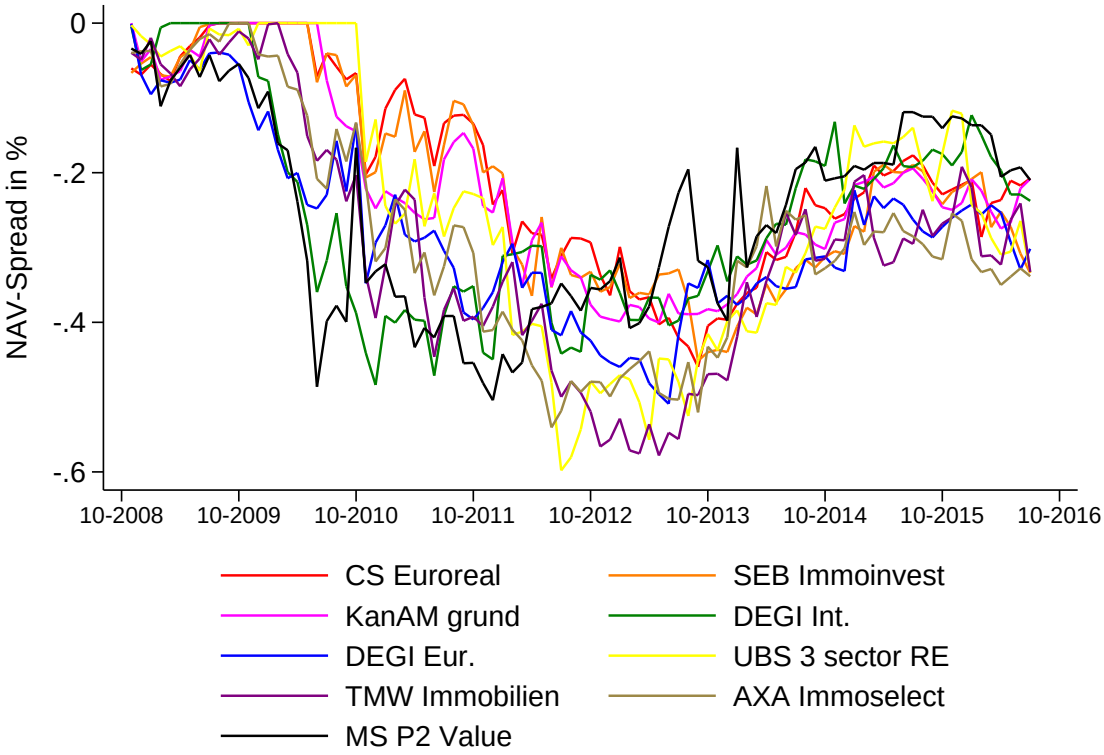
This figure shows total NAV volume and total market capitalization of all distressed open-end real estate funds from 2007:1 to 2016:6. The above figure illustrates the absolute deviation between NAV and market prices, while the below figure shows the relative deviation. Total market capitalization is defined as the sum of the fund-specific stock market prices weighted by the total number of shares of each fund. Total fund volume is calculated as the sum of the total number of fund shares multiplied by the NAV of each fund.

of all distressed real estate funds (blue line) and their total market capitalization based on secondary market share prices (black line) reveals that investors engaging in secondary market trading on average accept substantial discounts to NAV.

Beyond these general considerations, however, little is known about the specific factors that explain the discount to NAV of distressed open-end real estate funds. Figure 4.2 shows that the discounts of distressed real estate funds differ substantially across funds. Therefore, we aim to identify the fund-specific factors behind the heterogeneity of NAV spreads across funds. In addition, and despite the different closing dates, the individual discounts to NAV tend to be highly correlated between funds. Thus, we explore whether the correlations of NAV discounts are driven by marketwide sentiment.

Our goal is to answer these questions by providing a comprehensive analysis of the

Figure 4.2: Discount to NAV



This figure shows the development of the discount to NAV for each fund from 2007:1 to 2016:6. The discount to NAV indicates the negative deviation between the fund's NAV and the secondary market price in percent.

factors that explain discounts to NAV of distressed open-end real estate funds. NAV discounts have already been extensively studied in the context of closed-end funds (e.g., Lee et al., 1991; Pontiff, 1996; Chay and Trzcinka, 1999) and of publicly traded REITs or real estate operating companies (REOCs) (e.g., Barkham and Ward, 1999; Brounen and ter Laak, 2005; Patel et al., 2009). The major difference between these strands of the literature and our paper is that the discounts to NAV of closed-end funds or REITs may theoretically persist forever. In contrast, the forced liquidation of the funds in our sample ensures investors actually receive payouts. This enables us to study NAV discounts in a new setting. On the one hand, it is an advantage that funds are liquidated and investors are paid. However, on the other hand, a "forced liquidation" may result in a poorer bargaining position for selling property, which by itself may justify a discount to NAV.

Understanding what drives NAV discounts of distressed open-end real estate funds

is relevant for all market participants. The magnitude of the discount to NAV is not only relevant for existing investors, for whom it represents a loss of shareholder value, but also for potential new investors, for whom it may represent an investment opportunity. Fund families may also be concerned about discounts to NAV. Their prestige may be damaged if investors not only suffer liquidity constraints, but also high discounts to NAV on the secondary market. Moreover, regulators may be interested in fostering an environment where discounts to NAV are as small as possible. Finally, market participants from other countries with established open-end real estate fund structures may be able to learn from the German experience.

Our empirical study is based on a monthly panel of nine distressed open-end real estate funds in Germany. It covers the complete crisis and post-crisis periods, from October 2008, when the first funds suspended share redemptions, through June 2016.[6]

Our set of explanatory variables is comprised of fund-specific, external variables and control variables. We use the leverage ratio, the liquidity ratio, management fees, extraordinary payouts, economic growth of target markets, and tenancy of fund properties to explain the fund-specific, or idiosyncratic, part of the NAV discount. External variables are used to capture the systematic component. Here, we use closures of other funds and total number of funds in liquidation. Both variables can also be interpreted as spillover effects from other real estate funds. Moreover, we control for the total amount of net fund flows to all real estate funds that continue to sell and redeem shares. We also include macroeconomic uncertainty indices, which have become increasingly popular as a means to account for the rising degree of economic uncertainty in the aftermath of the global financial crisis. We control for funds' past performance, size, and share of institutional holdings.

Using fixed-effects panel regressions to explain the discount to NAV, we provide evi-

[6]Nine of the ten closed retail funds were relatively comparable to each other. However, the HansaImmobilia Fund was liquidated without adhering to the closing period of twenty-four months. We exclude that fund from our dataset.

dence that fundamental, fund-specific variables play a substantial role. In particular, we find that the discount to NAV increases with rising leverage ratios, and decreases with the ratio of cash holdings. This is consistent with the idea that the risk of distressed real estate funds depends primarily on whether appraisal values are reliable. This risk increases (decreases) with rising leverage (liquidity). We also find that the discount to NAV is related to potential conflicts of interest between investors and fund management. It increases concurrent with management fees, and is smaller for funds with higher extraordinary payouts, suggesting the benefit of investor-friendly behavior. We find evidence of industrywide spillover effects because the discount to NAV increases when other funds announce liquidations. Finally, we provide evidence that the discount to NAV is related to our proxies for investor sentiment. We find that discounts to NAV decrease with the total level of capital flows into the open-end fund industry, and increase with the degree of macroeconomic uncertainty.

The reminder of this paper is organized as follows. Section 4.2 provides an overview of the German open-end fund crisis and some regulatory details. Section 4.3 describes our set of explanatory variables and how they relate to the extant literature. Section 4.4 describes our data, while our regression results are in section 4.5. Section 4.6 concludes.

4.2 The German Open-End Fund Crisis and Regulatory Background

When a German open-end real estate fund suspends share redemptions, it tries to sell enough properties to increase its liquidity reserves, and reopen and ultimately fulfil all redemption requests. Funds that fail to reopen within twenty-four months are forced to liquidate their portfolios and pay out the proceeds to investors.

Selling properties within a particular time frame can be difficult, however, especially

during, e.g., times of low transaction activity in the real estate markets, such as during the aftermath of the 2008 global financial crisis. Lower asking prices can help increase the probability of a sale. However, in order to avoid "fire sales", the German legislature enacted sale price restrictions tied to appraisal values. During the first twelve months following share redemption suspensions, funds are thus not permitted to sell properties below their most recent appraised values. After the first twelve months, the funds may sell properties at a discount of up to 10% relative to the last appraised value.

These legal restrictions may be viewed as overly burdensome for distressed real estate funds that are attempting to reopen. However, funds are allowed to reappraise their properties prior to transactions, which effectively enables fire sale prices. However, large discounts of transaction prices relative to previous appraisal values can destroy trust in a fund's appraisal values. And a "vicious circle" may result if a lack of confidence in a fund's published NAVs leads to higher redemption requests when the fund attempts to reopen.

The liquidation process is overseen by the Federal Financial Supervisory Authority (BaFin), which determines an individual time line for every fund (typically between three and five years). Subsequently, the investment company is no longer in charge of managing further liquidations. Rather, a third-party depository bank is tasked with selling the entire real estate portfolio.[7] Funds in liquidation may sell properties at discounts of up to 20% during the first twelve months of the liquidation process. Twelve months later, discounts of up to 30% are authorized. After the determined liquidation date, the fund's management is transferred to a depository bank, which can sell the assets without restrictions. This event also leads to an extraordinary tax burden for all investors, because a land transfer tax applies.

Figure 4.3 provides a detailed overview of the number and total fund size of German

[7] As a consequence of the open-end real estate fund crisis, the regulatory regime was modified several times. However, our analysis is unaffected by these changes because all the funds in our analysis were liquidated under the prior investment laws (InvG, effective from 1/1/2004 - 7/22/2013).

Table 4.1: Overview of Distressed Open-End Real Estate Funds

fund	first closure	second closure	notice liquidation	depository bank
CS Euroreal A	10/30/08 - 06/29/09	05/20/10	05/21/12	04/30/17
SEB ImmoInvest	10/29/08 - 06/02/09	05/06/10	05/07/12	04/30/17
KanAm Grundinvest	10/28/08 - 07/08/09	05/06/10	03/01/12	12/31/16
AXA Immoselect	10/28/08 - 08/28/09	11/19/09	10/20/11	10/20/14
DEGI International	10/31/08 - 01/31/09	11/17/09	10/25/11	10/15/14
DEGI Europa	-	10/31/08	10/01/10	09/30/13
UBS (D) 3 Sector RE	10/31/08 - 10/31/09	10/06/10	09/05/12	09/05/15
TMW Immobilien	10/28/08 - 10/31/09	02/08/10	05/31/11	05/31/14
Morgan Stanley P2 Value	-	10/30/08	10/26/10	09/30/13

This table provides an overview of the relevant events for all distressed public open-end real estate funds, particularly date of first closure, reopening date, date of their second closure, date of liquidation announcement, and date of the depository bank taking control of the liquidation process.

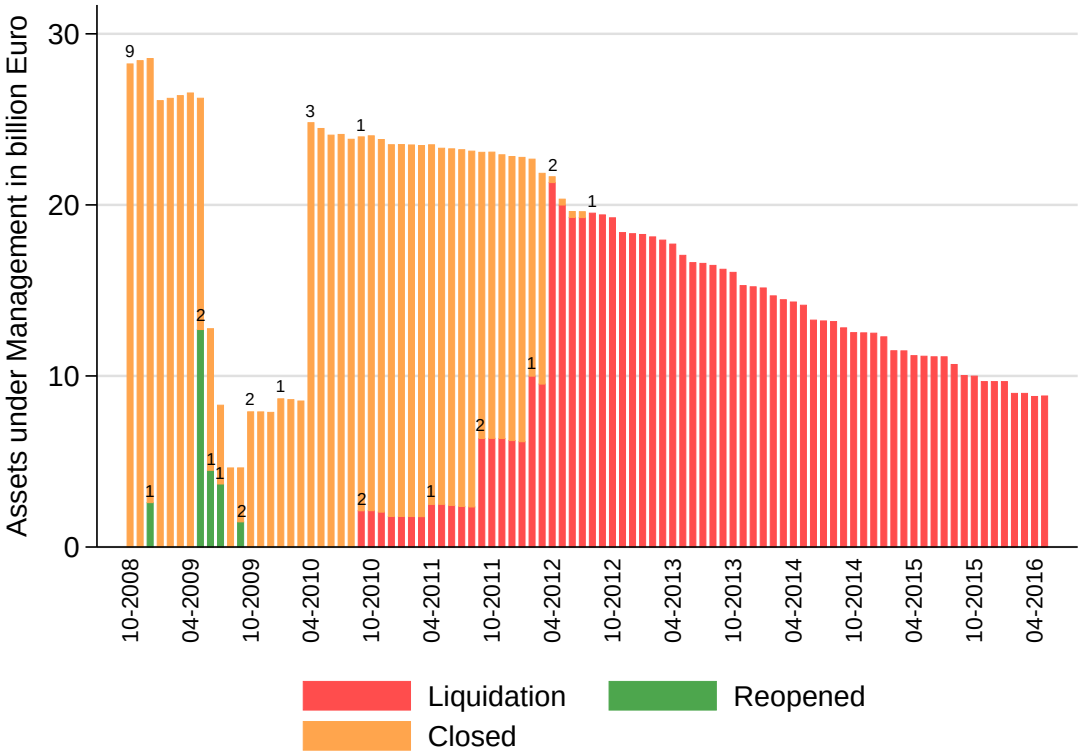
open-end real estate funds that either suspended share redemptions (orange bars), or were already in the process of fund liquidation (red bars). The graph also shows the number and total fund size of reopenings (green bars). The crisis began in October 2008, when nine funds with total assets under management of EUR 28 billion suspended share redemptions. The reopening of seven of these funds over the following twelve months indicated a recovery. However, these reopenings proved unsustainable. Through May 2010, the total fund size of funds that had suspended share redemptions had returned to previous levels of around EUR 27 billion, but the first fund liquidations were announced in October 2010. As of August 2012, all previously suspended funds had entered the liquidation phase.[8] The shrinking fund volume over time shown in Figure 4.3 is due to two effects: 1) distributions to investors facilitated by property disposals, and 2) falling property appraisal values following impairments. As of June 2016, EUR 10 billion of invested capital was yet to be distributed to shareholders under liquidation.

4.3 Related Literature and Hypotheses

To the best of our knowledge, this is the first paper to address NAV discounts of distressed funds in general, and distressed real estate funds in particular. While

[8] Table 4.1 provides the exact dates of all the major events for the distressed real estate funds in our sample.

Figure 4.3: Overview Open-End Fund Crisis



This figure shows the number and the total fund size of the German open-end real estate funds, that either suspended share redemptions (orange bars) or were in the process of fund liquidation (red bars). The graph also shows the number and the total fund size of any reopenings (green bars).

there is no extant literature that relates directly to our work, our research questions are related to the literature on the closed-end fund puzzle.

In essence, the basket of stocks held by these funds trades for less than the combined market value of the individual stocks held in the portfolio (Cherkes, 2003). Thus, even in the presence of professional fund management, the pooling appears to reduce the portfolio's worth. According to Lee et al. (1991), closed-end fund discounts are the result of private investor sentiment, or what are referred to as noise traders. An irrational downturn in investor sentiment leads to larger discounts. Therefore, holding a closed-end mutual fund portfolio can result in larger risk, or uncertainty, than holding the underlying fund's assets.

Our research is also related to the literature on the discounts (or premia) to NAV

of publicly traded REITs or REOCs.[9] It is not uncommon for REITs to trade at a premium to their NAV, but they also frequently trade at discounts to NAV. Similarly to closed-end funds, Barkham and Ward (1999) find evidence that supports the noise trader hypothesis for listed property companies in the U.K.

The difference between these two strands of the literature and our paper is that distressed real estate funds are forced to sell off their property portfolios and pay out the proceeds to investors. Open-end real estate funds can be seen as a mixed form between listed and direct real estate. While REITs are as liquid as common stocks, open-end real estate funds are only liquid as long as investors can redeem their shares to the fund or the sponsor of the fund. On the other hand, the shares of "closed" open-end real estate fund can be traded on the secondary markets, often at substantial discounts. In this context, the discount to NAV of distressed open-end real estate funds can be interpreted as the price of reduced liquidity and uncertainty regarding the appraisal values of the fund's properties.[10] This enables us to study how investors price the risks associated with the forced liquidation of a direct-property portfolio.

Figure 4.2 shows that the discounts to NAV of distressed real estate funds are heterogeneous across funds, which suggests they are driven by fund-specific, or idiosyncratic, variables. Our first three hypotheses and the respective proxy variables reflect these potential internal factors. Figure 4.2 also reveals that the discounts to NAV are correlated between the funds over time. Lee et al. (1991) document that this is true of closed-end funds as well, which indicates that NAV discounts may be affected by either industrywide or macroeconomic sentiment. Hypotheses 4 and 5 reflect these potential external factors.

[9] In contrast to common stocks and mutual funds, there is no public market for the real estate assets alone.

[10] Schweizer et al. (2013).

4.3.1 Financial Leverage

The anticipation of lower transaction prices compared to current appraisal values is a potential rational explanation for substantial discounts to NAV. The effect of lower appraisal values or transaction prices on a fund's NAV is amplified further by the amount of financial leverage used by a fund. For example, if investors anticipate that the next appraisal round will reveal a 10% decrease in property values, then a leverage ratio of 50% would justify a 20% discount to NAV, assuming all the fund's assets are invested in real estate. Thus, the leverage ratio risk may be reflected in a lower market price relative to the NAV per share. Bond and Shilling (2004) and Brounen and ter Laak (2005), using data on European public property companies, find that leverage is positively correlated with NAV discounts. Likewise, the discount to NAV of distressed open-end real estate funds may also increase with the leverage ratio.

Mirroring this principle, we find that the opposite effect may occur when a fund has high cash reserves. Because distressed real estate funds may be forced to sell their portfolios, they tend to exhibit rising liquidity ratios until they pay out proceeds to investors. In contrast to the appraisal values of the properties, a fund's liquid assets generally have little to zero market or appraisal risk, and can be considered safe for investors. Consistent with the idea that investors appreciate higher liquidity ratios, Fecht and Wedow (2014) find that lower liquidity ratios are associated with higher redemptions. Therefore, we expect a negative relationship between the liquidity ratio of a fund and its discount to NAV. The potential impact of the fundamental risk associated with the degree of financial leverage employed by a fund leads to Hypothesis 1:

Hypothesis 1: *The discount to NAV increases (decreases) with the leverage (liquidity) ratio of a fund.*

4.3.2 Conflicts of Interest

According to the closed-end fund literature, management costs are an important, but ambivalent, determinant of NAV discounts. For example, if the expected return on the equity portfolio of a closed-end fund is 7%, fund fees of 1.5% per year can considerably reduce that return after fees. Gemmill and Thomas (2002) document that small closed-end funds, which often display large management costs, exhibit larger discounts to NAV. On the other hand, Lenkey (2015) shows that the relation between NAV discounts and management fees is not stable due to two opposing effects 1) larger fees reduce shareholder value 2) larger fees increase management abilities.

During normal times, investors in open-end real estate funds can "vote with their feet," and sell their shares back to the fund if they believe management's fees are excessive. This would decrease assets under management and hence fee income, thereby incentivizing fund managers to act in line with investor interests. In contrast, investors in distressed real estate funds do not have the option to redeem their shares to the fund, and are fully exposed to the fees set by management. They can only choose to sell their shares on the secondary market, where assets under management remain unaffected. This potential conflict of interest between fund management and investors can have an effect on NAV discounts if investors in expensive funds are more inclined to sell their shares on the secondary market.

A similar conflict of interest arises because fund managers of distressed real estate funds maximize fee income by delaying the liquidation process. During normal times, investors in open-end real estate funds receive an annual dividend. When a distressed fund is in the process of liquidating, however, investors receive additional "extraordinary" payouts from the stepwise liquidation of the fund's real estate assets, often on a semiannual basis. Here, large payouts may signal that fund management is acting in the interest of investors, and is interested in a speedy liquidation process. Accordingly, distressed funds with higher payout ratios are expected to trade at lower

discounts to NAV compared to their peers with smaller payout ratios. Furthermore, investors in funds with large NAV discounts may appreciate payouts, because the dividend yields are considerably higher when calculated with respect to discounted share prices rather than NAVs. Consistent with this idea, the literature on the closed-end fund puzzle finds that low dividend payouts lead to larger discounts to NAV (Pontiff, 1996; Gemmill and Thomas, 2002; Cherkes, 2003; and Malkiel and Xu, 2005). The potential conflict of interest between fund management and investors leads to our second hypothesis concerning the discount to NAV of distressed real estate funds:

Hypothesis 2: *The discount to NAV increases when the fund management does not act in the interest of fund investors.*

4.3.3 Portfolio Quality

The anticipation of lower transaction prices than current appraisal values is a potentially rational explanation for substantial discounts to NAV. Recent research suggests that GDP may be a useful variable to forecast future direct real estate prices. Using a global sample of office property prices, De Wit and van Dijk (2003) find that GDP positively influences direct real estate prices. Accordingly, NAV discounts may be smaller if the fund's assets are located in countries with positive GDP developments.

Another measure of the quality of a fund's property portfolio is average tenancy rate. Wurtzebach et al. (1991) find that high office vacancy rates (or low tenancy rates) are associated with decreasing commercial real estate returns in the U.S. Hence, higher tenancy rates may be perceived as a signal of the quality of a fund's property portfolio, as well as more stable cash flows and property values. In other words, we posit that funds with higher tenancy rates are less likely to devalue their properties in the near future. We thus expect a negative relationship between a fund's tenancy

rate and its discount to NAV. Taken together, our two proxies for fund portfolio quality lead to Hypothesis 3:

Hypothesis 3: *The discount to NAV decreases with a fund's property portfolio quality.*

4.3.4 Spillover Effects

Figure 4.2 shows the correlation of NAV discounts between funds over time, and suggests the presence of a systematic component simultaneously affecting the NAV discounts of all funds. The financial fragility of open-end real estate funds exhibits some striking similarities to the banking sector. Spillover risk (where problems from one bank can spread to others within the system) is a prime concern for authorities and a rationale for regulating the financial system. For example, Aharony and Swary (1983) find that large bank failures can lead to falling prices for solvent bank stocks if the failures are caused by systemwide banking problems.

In the context of distressed real estate funds, negative spillover effects may arise from the announcement of another fund's closure or liquidation. Such an announcement by other funds may increase doubts over the future development of the overall asset class. Investors in distressed real estate funds who speculated on a successful reopening may see their hopes vanish with the announcement of another fund's suspensions of share redemptions. Similarly, the announcement of another distressed real estate fund entering the liquidation phase may imply that the last chance for a successful reopening has passed. As a result of negative industry news, the share prices of distressed funds may fall even further, thereby increasing the discount to NAV. This leads us to Hypothesis 4:

Hypothesis 4: *The discount to NAV increases due to negative spillover effects from the announcement of other fund's closures or liquidations.*

4.3.5 Sentiment

Our next hypothesis aiming to explain the systematic component of NAV discounts relates to industrywide or macroeconomic sentiment. In particular, we focus on variables that proxy for industrywide sentiment toward the asset class. If investor sentiment reflects investor behavior toward an asset class, we expect there to be an effect on the returns of the underlying securities. The returns on the secondary market may then directly impact a widening or a compression of the discount to NAV.

Indro (2004) finds a high correlation between aggregate equity fund flows and other measures of investor sentiment, such as the bullishness of individual investors or newsletter writers. This suggests that fund flows can be a useful proxy for investor sentiment. Consistent with the hypothesis that investor sentiment affects returns, Warther (1995) finds a strong relationship between aggregate flows into equity mutual funds and contemporaneous returns of the securities held by these funds. Similarly, Ben-Rephael et al. (2012) find that monthly aggregate shifts between bond funds and equity funds are positively correlated with contemporaneous aggregate stock market excess returns.

In addition to industry-specific sentiment, the returns and NAV discounts of distressed real estate funds may also be driven by macroeconomic sentiment. Two popular uncertainty indices are used commonly in the literature. First, the Economic Policy Uncertainty Index of Baker et al. (2015) features prominently in a plethora of research (e.g., European Central Bank, 2013, European Commission, 2013, and International Monetary Fund, 2014).[11] Second, the implied volatility index (VIX), which proxy for stock market uncertainty, measure anticipated (implied) stock market risk based on the difference between stock prices and stock price futures (e.g., Baker et al., 2015; Bekaert et al., 2013). This measure is important because the funds are subject to common stock market risk after the event of clos-

[11] The full list can be found at: www.policyuncertainty.com/research.

ing. The expected impact of sentiment on the discount to NAV of distressed funds is summarized in Hypothesis 5:

Hypothesis 5: *The discount to NAV increases with improving investor sentiment.*

4.4 Data, Methodology and Sample Description

4.4.1 Data

Our sample consists of the population of all nine distressed German open-end real estate funds.[12] Table 4.1 provides an overview of the funds, as well as their closure, reopening, and liquidation dates.

Our panel dataset covers the October 2008 through June 2016 period. The starting point coincides with the closure of the nine funds. Subsequently, substantial divergences between secondary market prices and NAVs emerged, which led to the NAV spreads examined in this paper.

Following Lee et al. (1991) and Barkham and Ward (1999), we calculate the discount to NAV as the difference between current NAV and the contemporary fund's market price divided by current NAV. NAVs are published daily for each fund by the fund management (KVG); market prices are provided by the Hamburg-Hannover stock exchange.

Our fund-specific variables are hand-collected from the monthly fact sheets found on the individual fund websites, as well as from funds' semiannual and annual reports. Note that several funds are managed by depository banks that no longer provide monthly fact sheets. Their annual and semiannual reports are also less detailed. Hence, our explanatory variables are somewhat less up-to-date toward the end of the sample.

[12] As noted earlier, we exclude the HansaImmobilia fund and the UniImmoGlobal fund.

The share of institutional owners per fund comes from Morningstar Direct. We also collect industrywide data on fund flows from the German Investment and Asset Management Association (BVI), which collects data about net flows directly from its members and represents the vast majority of the German mutual fund industry. The dataset includes the monthly net flows of forty-eight public and semi-institutional German open-end real estate funds in our sample period.[13] Data on GDP come from the OECD.

4.4.2 Research Design and Definition of Variables

We use a panel regression model to examine the determinants of NAV discounts for distressed real estate funds. Our unbalanced panel consists of 708 fund-month observations. The key variable of interest is the discount to NAV of fund i at the end of month t, which is calculated as follows:

$$Discount\ to\ NAV_{i,t} = \frac{Stock\ market\ price_{i,t}}{NAV\ per\ share_{i,t}} - 1 \tag{4.1}$$

For the purpose of our empirical tests, we estimate the following panel regression

[13]Since 2013, according to the German Central Bank, extraordinary payouts of distressed funds have been considered as capital outflows (BVI, 2016). In contrast, all extraordinary payouts of distressed funds are set equal to zero in order to standardize the calculations for both healthy and distressed funds.

model:

$$
\begin{aligned}
Discount\ to\ NAV_{i,t} = \alpha &+ \beta_1\ \Delta\ Leverage_{i,t-1} + \beta_2\ \Delta\ Liquidity_{i,t-1} + \beta_3\ \Delta\ TER_{i,t-1} \\
&+ \beta_4\ Extraordinary\ Payouts_{i,t} \\
&+ \beta_5\ Economic\ Growth\ Target\ Markets_{i,t-1} + \beta_6\ \Delta\ Tenancy_{i,t-1} \\
&+ \beta_7\ Flows\ Asset\ Class_t + \beta_8\ Event\ Fund\ Liquidation_t \\
&+ \beta_9\ Event\ Fund\ Closure_t \\
&+ \beta_{10}\ Policy\ Uncertainty\ Index\ Europe_t + \beta_{11}\ VIX\ Europe_t \\
&+ \beta_{12}\ \Delta\ Perform_{i,t-1} + \beta_{13}\ \Delta\ Fund\ Size_{i,t-1} \\
&\beta_{14}\ \Delta\ Institutional_{i,t-1} + \beta_{15}\ Fund\ Reopening_{i,t} \\
&+ v_{i,t}
\end{aligned}
\tag{4.2}
$$

We separate our key explanatory variables into fund-specific, external, and control variables, as follows.

Leverage is the leverage ratio of the fund, calculated as the ratio of the fund's debt relative to it's gross asset value (GAV).

Liquidity is the liquidity ratio, measured as the ratio of the fund's cash equivalents to GAV.

TER represents annual management costs as a percent of fund volume. Because investors can no longer "vote with their feet," we expect to find higher fees associated with higher NAV discounts.

Extraordinary payouts are defined as total fund-specific payouts in a given month relative to a fund's NAV. Similarly to the TER ratio, this variable aims to capture the degree of investor friendliness of a fund's management. A negative correlation between this variable and the discount to NAV would indicate a lower degree of conflicts of interest between investors and fund managers, leading to a smaller NAV

discount.

Economic Growth Target Markets is a fund-specific GDP growth measure. This variable aims to capture the anticipated price development of a fund's real estate portfolio. It is calculated as the weighted sum of monthly GDP growth in the individual funds' target country markets.

Tenancy represents the proportion of rented to overall space of the real estate fund's assets. This variable is used to proxy for a fund's portfolio quality. As with the previous variable, which captures the GDP development of the fund's underlying property markets, a higher portfolio quality or better outlook is expected to lead to a smaller discount to NAV.

Event Fund Closure is a 0/1 indicator variable that captures the announcement that at least one other real estate fund has suspended share redemptions.

Event Fund Liquidation is a dummy variable that indicates another fund is unable to reopen and has begun the liquidation process. Both events may lead to a deterioration in investor sentiment. A positive relationship between these events and the discount to NAV would generally confirm the spillover hypothesis. We also include closure or liquidation announcements from semi-institutional funds.

Flows Asset Class are the total net fund flows (newly bought fund shares less redemptions) into all healthy open-end real estate funds. Here, we also include flows into semi-institutional funds. While only normally functioning open-end real estate funds can have net flows, we use this variable to capture general investor sentiment toward the asset class.

Policy Uncertainty Index Europe aims to capture the degree of political uncertainty in Europe. To construct this Index, Baker et al. (2015) first select two influential newspapers for each European country, such as, e.g., "Le Monde" and "Le Figaro" for France, or "Handelsblatt" and "Frankfurter Allgemeine Zeitung" for Germany, etc. Next, the authors count the number of articles that include the terms "uncertain,"

"uncertainty," "economic," or "economy," and at least one policy-relevant item. The count is scaled by the overall number of articles in each newspaper.

VIX Europe is the Euro Stoxx 50 Volatility Index (VSTOXX), commonly referred to as VIX. This is our second measure of macroeconomic uncertainty. This index measures the anticipated (implied) stock market risk based on the difference between stock prices and stock price futures. Both macroeconomic indices are normalized (i.e., the mean was subtracted, and all values subsequently divided by their standard deviations). This transformation allows us to not only interpret the sign and statistical significance of the respective regression coefficients, but also to compare the magnitudes of both coefficients. Our set of control variables consists of a fund's past performance, fund size, and share of institutional owners, as well as a dummy variable indicating whether the distressed real estate fund of interest already experienced a suspension of share redemptions and subsequent reopening.

Performance is the appraisal-based rolling twelve-month performance according to BVI. This variable basically reflects the NAV performance. On the one hand, high returns are indicative of solid fund performance. On the other hand, it may signal that the fund has not yet adjusted its appraisal values to reflect lower market values. This would imply that NAV per share is expected to fall in the future, thereby justifying a larger discount.

Fund Size is measured in billions of Euros. The Federal Financial Supervisory Authority (BaFin) of Germany determines an individual liquidation horizon for each fund. Larger funds tend to receive more time to liquidate their portfolio compared to smaller ones. Therefore, on the one hand, fund size could be interpreted as a proxy for expected liquidation time. Hence, we would expect a positive relationship between fund size and NAV discounts. On the other hand, larger funds with longer liquidation horizons might use an optimized market timing strategy for their property disposals, and could enjoy better bargaining positions.

Institutional shareholders represents the share of institutional shareholders as pro-

vided by Morningstar Direct. Here, too, the expected effect is ambivalent. German open-end real estate funds are predominantly held by retail investors. Thus, due to their low price volatility and relatively high and stable yields compared to money market interest rates, conventional wisdom suggests that institutional investors exploited open-end funds as a cash substitute prior to the fund crisis. We use share of institutional ownership to test whether it has an effect on the discount to NAV. Once open-end real estate funds become distressed, their share prices on the secondary market show substantial price volatility. Therefore, investors are likely to reevaluate their optimal risk exposure to the asset class, and could potentially decide to sell their shares. This could lead to further price pressure on the secondary market, and hence larger discounts to NAV. Consistent with this idea, Larrain et al. (2017) examine the effect of a regulatory constraint, which forced pension funds to fire sale their Chilean stock holdings. The authors find that those stocks with the highest selling pressure lost 4% compared to other stocks. Alternatively, a large percent of well-informed institutional investors may signal high fund quality, and could be associated with lower discounts to NAV. Evidence in the related literature is mixed. Barclay et al. (1993) find that closed-end funds with large blockholders display larger discounts. In contrast, Morri and Benedetto (2009) find that Italian closed-end real estate funds with large blockholders tend to exhibit smaller discounts to NAV.

Fund Reopening is a dummy variable that indicates whether a distressed real estate fund has already reopened previously, and hence suspended share redemptions for a second time. Investors may perceive such funds as less likely to achieve another reopening, thus leading to larger discounts to NAV.

Our regression results are estimated using cross-sectional fixed effects and heteroscedasticity-robust standard errors.

Fund-specific variables generally enter the regression model with one lag, because the monthly fact sheets are published with a time lag. Also, investors need time to

adjust their decision making process subsequent to changes in key fund indicators. However, we include extraordinary payouts, net capital inflows, dummy variables, and uncertainty indicators without any lag. Extraordinary Payouts, the closure or liquidation of one or more specific open-end real estate funds, is generally a comprehensive event that would be extensively reported in the media. Therefore, we would expect both institutional and private investors to recognize the enormity of such an event, and adjust their investment strategies within one month. Moreover, uncertainty is a prevalent condition. In addition to the economic interpretation, the statistical significance of the coefficients, as well as the overall fitness measures like the AIC criteria, support the chosen lag structure as explained above.

Due to the non-stationarity of the leverage ratio, the liquidity ratio, TER, the tenancy rate, performance, fund size, and the share of institutional investors, these variables enter the regression with their first differences (Δ).

4.4.3 Descriptive Statistics

Table 4.2 shows some descriptive statistics on the dependent and explanatory variables. Table 4.2 reveals that the average discount to NAV of distressed real estate funds is 25% with a standard deviation of 13.3%.

The independent variables in Table 4.2 are separated into three categories: fund-specific, external variables, and control variables.

The average leverage ratio of all funds is 24.8%. Figure 4.4 shows that the average leverage ratio diminishes considerably over time. This effect is to be expected, because funds repay their loans from the proceeds from property disposals. There is also a substantial heterogeneity of leverage ratios across funds. The DEGI International fund reports a leverage ratio of 0% in June 2014, the Morgan Stanley P2 value fund exhibits a leverage ratio of 69% at the beginning of 2014.

The liquidity ratios also show considerable heterogeneity. The TMW Immobilien

Figure 4.4: Discount to NAV, Fund Specifics, External and Control Variables

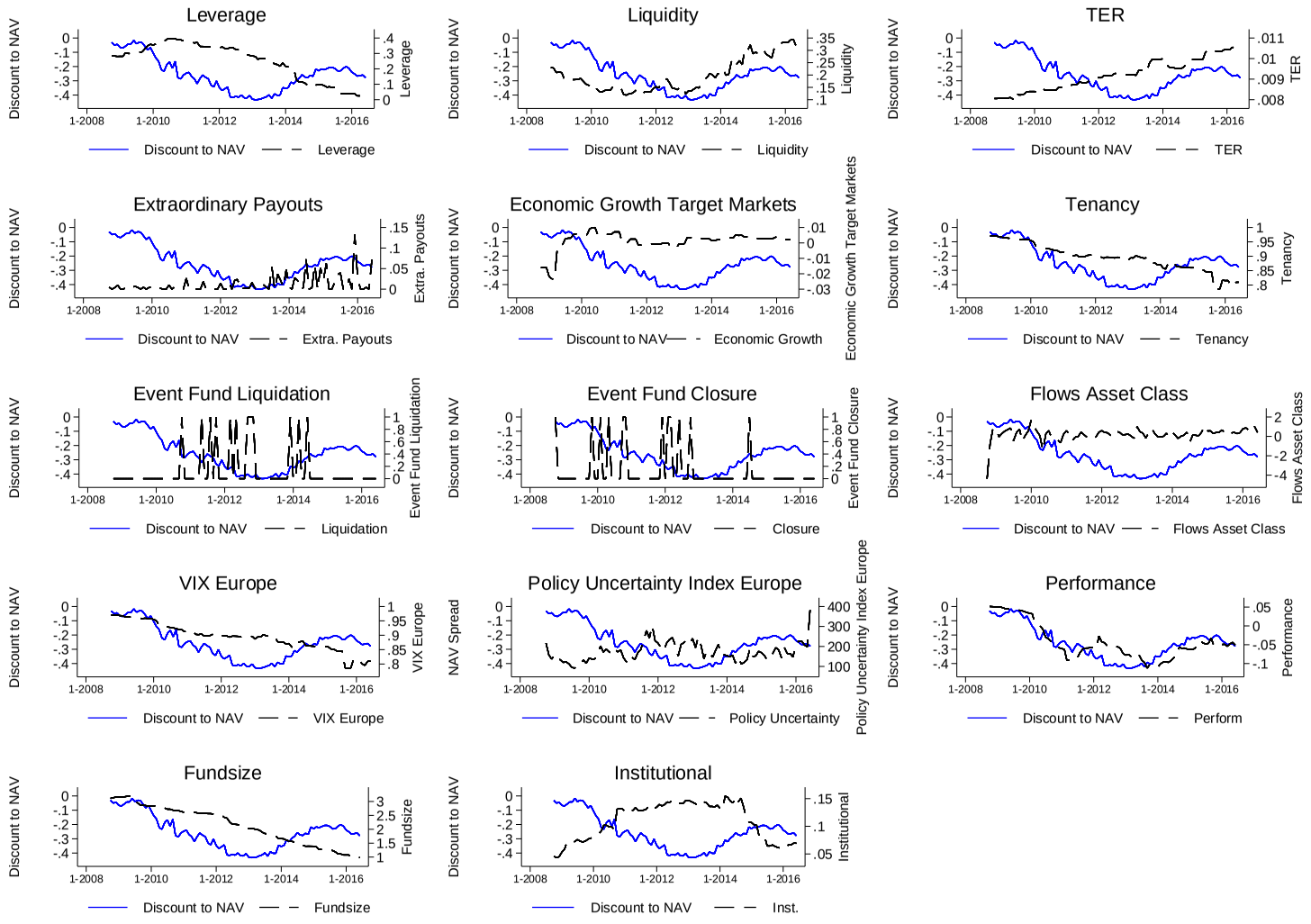


Figure 4.4 illustrates the average progression of the fund-specific, external and control variables for all distressed real estate funds in contrast to the average course of the discount to NAV from 2008:10 to 2016:6. The first two rows show the development of the fund-specific factors. The third row shows the three industry-wide spillover variables. The fourth row includes the two macroeconomic uncertainty indicators. The control variables are displayed afterwards.

Table 4.2: Overview Summary Statistics

	Mean	Std.Dev.	Min	Max	Obs
Discount to NAV	0.267	0.133	0.000	0.598	783
Fund Specific Variables					
Leverage	0.248	0.157	0.000	0.690	837
Liquidity	0.200	0.142	0.003	0.828	837
TER	0.009	0.002	0.003	0.015	837
Extraordinary Payouts	0.012	0.05	0.000	0.565	837
Economic Growth Target Markets	0.001	0.006	-0.031	0.013	836
Tenancy	0.893	0.077	0.595	1.000	815
External Variables					
Event Fund Liquidation	0.129	0.335	0.000	1.000	837
Event Fund Closure	0.129	0.335	0.000	1.000	837
Flows Asset Class	0.215	0.651	-4.358	1.693	837
Policy Uncertainty Index Europe	174.315	47.613	91.379	394.635	837
VIX Europe	26.400	8.832	14.392	60.677	837
Control Variables					
Perform	-0.045	0.086	-0.389	0.086	816
Fund Size	2.140	1.970	0.069	6.598	837
Institutional	0.111	0.092	0.003	0.368	792
Fund Reopening	0.671	0.470	0.000	1.000	837

This table provides an overview of the mean, standard deviation, minimum, maximum, and the number of observations for all variables.

Weltfonds fund displays a liquidity ratio of 0.3% in May 2016, which is below the regulatory threshold of 5.0% and is allowed for only a short period of time. However, this fund exhibit a significantly low liquidity ratio over the entire sample period. In contrast, the UBS 3 Sector Real Estate fund has a liquidity ratio of 21.6% at the closing date, which rises as high as 82.8% by September 2015. Note that fund strategies partially cause these substantial differences. During the sample period, DEGI International fund liquidated a significant portion of its assets without substantial extraordinary payouts until October 2014. On average, the liquidity ratio amounts to about 20.0%. Figure 4.4 illustrates the considerable increase in average liquidity ratios over time due to high sales proceeds beginning in Q3 2012.

The average total expense ratio is 0.9%. The KanAm Grundinvest fund has the highest management fees at the end of the sample period in 2016 with 1.5%, while the AXA Immoselect fund exhibits the lowest fees at 0.3% in October 2008.

The average payout ratio is only 1.2%. The UBS 3 Sector Real Estate fund made an extraordinary payment of about 56.5% of its respective market value in December 2015. Other funds distributed their payouts more evenly over the sample period, however, the management of AXA Immoselect fund continuously distributed about 3%-4% of its respective market value per share from 2008 through 2013. Figure 4.4 illustrates the significant increase in extraordinary payouts due to the accelerating liquidation process, which began in Q3 2012.

The average GDP growth rate of the fund's target markets is 0.1% and it ranges from -3.1% to +1.3%. While there is little heterogeneity across funds regarding this measure, Figure 4.4 shows a substantial time variation that is attributable to the economic rebound following the global financial crisis.

The average tenancy rate is 89.3%. Table 4.2 shows that the Morgan Stanley P2 Value fund exhibited a tenancy rate of 100% over the June-December 2013 period, while TMW Immobilien Weltfonds fund reported only 76% to 69% during the same period.

On average, a closure or a liquidation occurred in 12.9% of the periods. Consistent with the spillover hypothesis, Figure 4.4 shows that closures and liquidations tend to cluster together over time.

The average asset class capital inflows are EUR 215 million per month. The funds experienced strong capital inflows of about EUR 1.69 billion in January 2010, and rather extreme capital outflows of EUR 4.36 billion in October 2008.

Figure 4.4 shows that the implied stock market volatility, as measured by VIX Europe, tends to decline over time. In contrast, the Political Uncertainty Index increases during the middle of our sample period, when many funds entered the liquidation phase.

Table 4.3 shows a positive correlation on an aggregate level between the absolute level of the NAV discount and the European Policy Uncertainty Index (general un-

certainty) of (+0.36). However, on the other hand, we observe an inverse relationship between the absolute level of the discount to NAV and the VIX (stock market uncertainty) of (-0.45). Although both uncertainty indices share two peaks, in 2008 (global financial crisis) and 2012 (European debt crisis), they appear uncorrelated in general.

The rolling twelve-month performance of the funds (based on NAVs) averages -4.5%, and it ranges from -38.9% to +8.6%. Just as with overall economic development, the variance of this variable is driven mainly by the time dimension, namely, the global financial crisis.

Fund size ranges from EUR 69 million to EUR 6.6 billion. The UBS 3 Sector Real Estate fund is the smallest fund, with an average size over the entire sample period of EUR 321.0 million. The CS Euroreal A fund is the largest, with an average of EUR 5.0 billion. Despite the negative time trend, the time dimension explains only a small part of the overall variance of the fund size variable. Institutional shareholders on average represent 11.1% of all fund investors. The UBS 3 Sector Real Estate fund reports an institutional share of up to 37%, while the DEGI Europa never exceeds more than 5%.

According to Table 4.3, the discount to NAV shows a relatively strong negative correlation with the fund size (-0.25) and fund performance (-0.56) variables. Furthermore, the NAV discounts show a relatively strong positive correlation with the share of institutional investors (0.35).

4.5 Results

Table 4.4 contains the panel regression results, which are estimated using cross-sectional and time-fixed effects, as well as the heteroscedasticity-robust standard

Table 4.3: Correlation Matrix: Fund-Specifics, External Variables, and Control Variables

	Discount to NAV	Leverage	Liquidity	TER	Extra- payouts	Economic Growth	Tenancy	Event Fund Liq.	Event Fund Closure	Flows Asset Class	Policy Uncertainty	VIX Eur.	Perform	Fund Size	Inst.	Fund Reopening
Discount to NAV	1.000															
Leverage	0.072	1.000														
Liquidity	-0.210	-0.473	1.000													
TER	0.155	-0.108	0.097	1.000												
Extra- payouts	-0.041	-0.143	0.199	0.071	1.000											
Economic Growth	0.219	-0.052	0.030	0.050	0.049	1.000										
Tenancy	-0.261	0.477	-0.132	-0.031	-0.127	-0.163	1.000									
Event Fund Liq.	0.236	0.129	-0.090	-0.006	-0.032	-0.042	-0.000	1.000								
Event Fund Closure	0.036	0.195	-0.096	-0.070	-0.021	-0.000	0.118	0.246	1.000							
Flows Asset Class	0.058	-0.153	0.071	0.081	0.018	0.157	-0.124	-0.103	-0.343	1.000						
Policy Uncertainty	0.367	-0.050	0.012	0.101	0.036	-0.037	-0.190	0.136	0.094	-0.065	1.000					
VIX Eur.	-0.457	0.202	-0.050	-0.166	-0.101	-0.564	0.272	-0.107	0.074	-0.117	0.097	1.000				
Perform	-0.560	0.095	0.041	-0.148	-0.098	-0.180	0.446	-0.102	0.074	-0.014	-0.149	0.340	1.000			
Fund Size	-0.253	0.154	-0.246	-0.492	-0.121	-0.066	0.191	0.015	0.077	-0.078	-0.075	0.190	0.397	1.000		
Inst.	0.358	0.237	-0.040	0.210	0.020	0.037	0.027	0.123	0.037	-0.018	0.069	-0.184	-0.291	-0.565	1.000	
Fund Reopening	0.325	-0.031	-0.206	0.143	0.005	0.347	-0.238	-0.004	-0.067	0.100	0.158	-0.336	-0.015	0.221	0.054	1.000

This table shows the correlation coefficients between all variables of the panel regression model.

errors.[14] Model I employs only fund-specific explanatory variables, which are used to test Hypotheses 1-3. The control variables, used in all models, are also fund-specific. In models II and III, we subsequently introduce further explanatory variables that are external to the funds. Model II includes two industrywide variables, which enables us to test the spillover hypothesis (Hypothesis 4). Finally, model III also incorporates macroeconomic variables in order to test Hypothesis 5.[15] The standard errors of the regression coefficients are in parentheses.

Our initial analysis focuses on the impact of a fund's financial leverage on its discount to NAV. We find that the discount to NAV increases with the leverage ratio. An increase in the absolute difference of the leverage ratio by 1% leads on average and c.p. to a 0.089% larger discount to NAV in the next period. Mirroring this principle, the liquidity ratio has a negative effect on the discount to NAV. A rise in the lagged absolute difference of the liquidity ratio by 1% leads on average and c.p. to a 0.139% lower discount to NAV. This is plausible, given that a larger share of cash and short-term money market positions represents money saved for fund investors. Therefore, larger liquidity ratios diminish risk, which is primarily related to the appraisal values of the real estate portion of the fund. In summary, both of our proxies are consistent with Hypothesis 1. The discount to NAV is driven by a fund's financial leverage, since it increases (decreases) with its leverage (liquidity) ratio.

Next, we examine whether NAV discounts are related to potential conflicts of interest between fund management and investors. We find no significant influence of management costs (TER) on the NAV discount. Extraordinary payouts, on the other hand, play an important role. A 1% higher payout leads on average and c.p. to a 0.273% lower discount. This result is consistent with Hypothesis 2. If

[14] Time-fixed effects enable us to control for any unobserved time effects. However, the time dummies also cause identical regression coefficients for the fund-specific variables across all three specifications. In the next chapter, we describe a possible method by which to confirm the goodness of fit for each model specification.

[15] In untabulated results, we also control for the time to liquidation date and the legal fund environment, e.g., the selling restrictions of the real estate properties. We find no significant influence of these regulatory variables on the discount to NAV. We also find no significant influence of regional or sectoral diversification (Herfindahl index) on the discount to NAV.

Table 4.4: Explaining the Discount to NAV

	(I)	(II)	(III)
Fund Specific Variables			
Δ $Leverage_{i,t-1}$	0.0898*	0.0898*	0.0898*
	(0.0475)	(0.0475)	(0.0475)
Δ $Liquidity_{i,t-1}$	-0.139**	-0.139**	-0.139**
	(0.0588)	(0.0588)	(0.0588)
Δ $TER_{i,t-1}$	-1.702	-1.702	-1.702
	(5.059)	(5.059)	(5.059)
$Extraordinary\ Payouts_{i,t}$	-0.273***	-0.273***	-0.273***
	(0.0643)	(0.0643)	(0.0643)
$Economic\ Growth\ Target\ Markets_{i,t-1}$	0.193	0.193	0.193
	(1.936)	(1.936)	(1.936)
Δ $Tenancy_{i,t-1}$	-0.116	-0.116	-0.116
	(0.0919)	(0.0919)	(0.0919)
External Variables			
$Event\ Fund\ Liquidation_{i,t}$	-	0.249***	0.148***
	-	(0.045)	(0.0343)
$Event\ Fund\ Closure_{i,t}$	-	0.028	0.00218
	-	(0.034)	(0.0682)
$Flows\ Asset\ Class_{i,t}$	-	-	-0.0308*
	-	-	(0.0142)
$Policy\ Uncertainty\ Index\ Europe_{i,t}$*	-	-	0.0377***
	-	-	(0.00727)
$VIX\ Europe_{i,t}$*	-	-	-0.0133
	-	-	(0.0142)
Control Variables			
Δ $Perform_{i,t-1}$	-0.0788	-0.0788	-0.0788
	(0.127)	(0.127)	(0.127)
Δ $Fund\ Size_{i,t-1}$	0.00239	0.00239	0.00239
	(0.0377)	(0.0377)	(0.0377)
Δ $Institutional_{i,t-1}$	0.478**	0.478**	0.478**
	(0.167)	(0.167)	(0.167)
$Fund\ Reopening_{i,t}$	0.0283	0.0283	0.0283
	(0.0361)	(0.0361)	(0.0361)
Constant	0.0540**	0.0908***	0.129**
	(0.0198)	(0.0263)	(0.0408)
Observations	708	708	708
R-squared	0.735	0.735	0.735
Number of funds	9	9	9

This table shows the fixed-effects panel regression results. Model (I) contains the particular influence of the fund-specific variables. Model (II) adds the industry-wide variables to test the spillover hypothesis. Model (III) is the main model, which also includes industry-wide and macroeconomic proxies for investor sentiment. Policy Uncertainty and VIX Europe Variables are standardized with zero mean and a standard deviation of one. Robust standard errors are in parentheses, *** p<0.01, ** p<0.05 and * p<0.1.

fund management regularly pays out high amounts of liquidity, rather than holding cash or properties to maximize their fee income, this signals a certain amount of investor friendliness. The practice of extraordinary payouts at time of closing, however, differs considerably among funds in the dataset. Some closed funds effect constant substantial payments on a semiannual or annual basis. Others pay more irregularly or infrequently. A history of regular distributions increases trust in fund management, and could influence investors to remain invested.

To test Hypothesis 3, we have two variables that proxy for a fund's portfolio quality. First, real estate funds are more likely to be able to sell assets for reasonable prices in good-performing countries than in countries locked in recession. Investors are informed about the target market mix through monthly, semiannual, and annual fund reports. Moreover, investors receive continuous information about economic development via the media. Both sources of information should theoretically lead to higher demand on the secondary market for funds invested in more prosperous markets. Nevertheless, we find no significant influence of the Economic Growth variable on the discount to NAV. Our second proxy for fund portfolio quality is average tenancy rate. On average, higher quality properties should be associated with larger tenancy rates, and vice versa. However, the coefficient on the tenancy rate is not statistically significantly different from zero. Hence, we find no evidence for Hypothesis 3, i.e., NAV discounts do not appear to be driven by a fund's portfolio quality. A possible explanation for this result could be that a fund's portfolio quality is already sufficiently reflected in its NAV. Hence, investors would not need an additional risk premium, and this would be reflected in lower share prices.

Our regression results in model II provide support for the spillover hypothesis. In the case of another distressed real estate fund failing to reopen and subsequently announcing its liquidation, the discount to NAV for all distressed funds rises c.p. and on average by 0.249%. This effect remains significant, although somewhat weaker, in model III, when further external variables are included in the regression model. The announcement of other fund liquidations may lead to diminished hope, and is

likely to further deteriorate investor trust in this asset class. The announcement of other fund closures, on the other hand, does not appear to significantly impact the NAV discount.

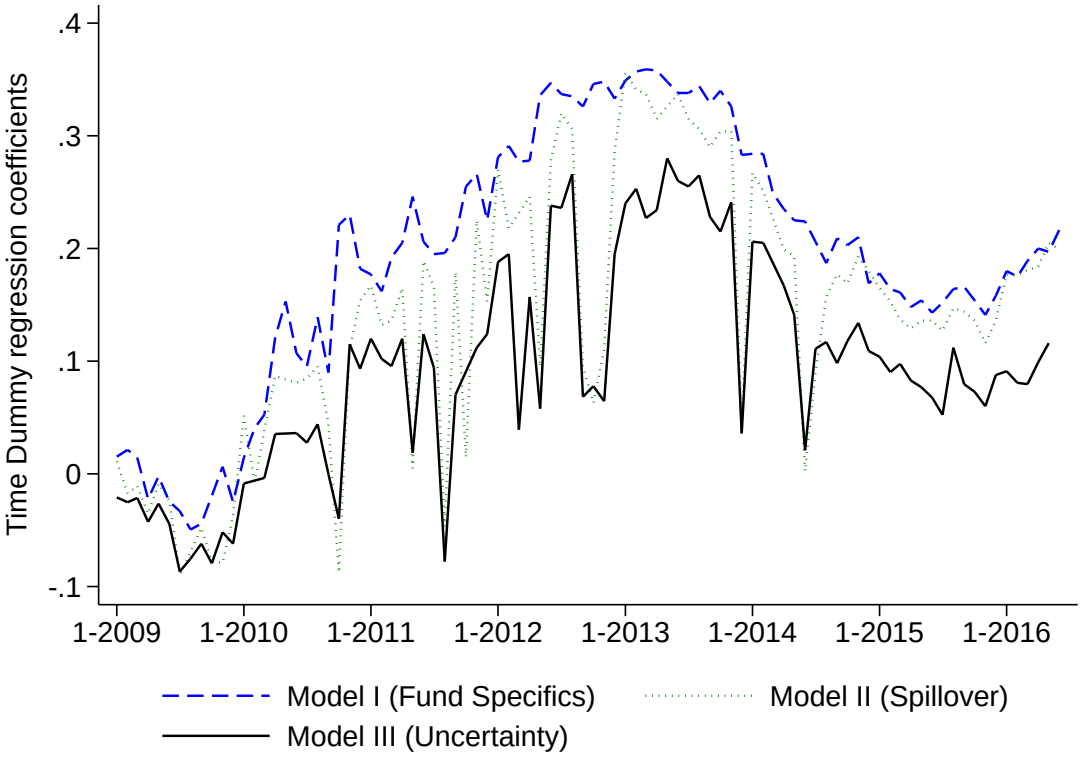
We have three proxy variables to test whether NAV discounts are driven by investor sentiment. First, we use capital inflows into all open-end real estate funds to examine the impact of investor sentiment toward the specific asset class on NAV discounts. Model III documents a significant relationship between asset class net flows and the discount to NAV. Larger fund flows into the overall asset class c.p. and on average diminish the discount to NAV. Second, we use the European Policy Uncertainty index, which measures overall macroeconomic uncertainty. An increase in this Index leads c.p. and on average to a larger NAV discount. In contrast, when we use the VIX to measure specific stock market risk, we find no significant effect between the VIX Europe and the NAV discount.[16] In conclusion, we find evidence for Hypothesis 5, when our proxy for investor sentiment is based on fund flows and political uncertainty.

Regarding our control variables, we find a positive relationship between the share of institutional investors and the discount to NAV. An increase in the absolute difference of the share of institutional investors by 1% leads on average and c.p. to a 0.478% larger discount in the next period. Past performance, fund size, and the dummy variable indicating a former fund closure are all statistically insignificant.

In order to determine the goodness of fit of our models, we use the time dummy coefficients of the three model specifications (I-III). Because the dummy variables have no economic interpretation, we consider the coefficients to be the unexplained, yet time-specific, components of the discount to NAV. Figure 4.5 illustrates how the unexplained (unsystematic) time effects diminish after we incorporate additional time-dependent variables into the model. The figure shows the progression of the time dummy coefficients over ninety periods from January 2009 to June 2016 (ninety-

[16] In untabulated results, we find a positive relationship between the VIX Europe and discounts to NAV when we run the regression without the Political Uncertainty Index.

Figure 4.5: Development of Time Dummies



This figure shows the regression coefficients of the time dummies for the ninety periods from January 2009 through June 2016 (note there is a loss of three periods at the beginning due to the preferred lag structure). The regression coefficients of these dummy variables represent the unexplained but time-specific component of the discount to NAV. The progression of each line near zero indicates a better fit of the model compared to the other model specifications, as there is less unexplained variance left.

three periods in total, minus three periods for the lag structure). The time dummy coefficients of model I exhibit considerably positive signs over time. Moreover, the parabolic progression indicates a time trend that we can account for by using the monthly time dummies in the regression model. This parabolic progression can also be seen in the development of the discount to NAV, which increases after the individual closure dates for each fund to a maximum in mid-2012, and significantly decreases thereafter by about 20%-30% until June 2016. Model II exhibits a less distinct time trend. Model III, which includes all variables, has the best fit and, therefore, the least distinct time trend of the dummy regression coefficients.

4.6 Conclusion

This paper examines the discounts to NAV of distressed open-end real estate funds. The stock market prices of distressed real estate funds are up to 60% lower than their NAVs. These discounts can be interpreted as a compensation for the valuation risk associated with the fund liquidation process and a sudden decrease in liquidity.

Open-end real estate funds differ fundamentally from mutual funds, because the underlying properties are not traded on a stand-alone basis in public markets as in the case of stocks. Accounting for the specific environment of open-end real estate funds, this paper contributes to the literature on NAV discounts, as well as to the empirical literature on liquidity crises of open-end real estate funds in general.

To explain the major factors driving the NAV discounts of distressed real estate funds, we categorize the explanatory variables into internal or fund-specific variables, and into industrywide or macroeconomic variables that are external to the funds. Overall, we find notable differences between the individual funds (cross-sectional heterogeneity), but the variance of the discount is also driven considerably by time-dependent factors. On the fund-specific side, we provide evidence that the discount to NAV is related to the degree of financial leverage employed by the funds. Funds with high liquidity ratios and/or low leverage ratios tend to be associated with lower NAV discounts. This suggests that a more conservative strategy by fund management may help decrease the discounts. Moreover, we find that funds with higher payout ratios trade at lower NAV discounts. This is consistent with our hypothesis that funds paying out more to investors are signaling greater investor friendliness. However, some factors are not under the control of fund management. For example, we find evidence of negative spillover effects from the liquidation announcements of other funds. Furthermore, we find evidence that NAV discounts are driven by investor sentiment, as evidenced by the impact from fund flows into the asset class and the degree of macroeconomic uncertainty.

Chapter 5

Conclusion

This dissertation aims to analyze the structural risks of financial intermediation associated with real estate investments. In particular, I analyze how life insurance companies in Europe and open-end real estate funds in Germany have reacted to the economic turmoil in the aftermath of the great financial crisis after 2007/2008. The analyzed time period has been characterized by historically high economic uncertainty and historically low interest rates. Both factors serve as unique conditions for stress testing the aforementioned vehicles and for drawing conclusions about the structural risks involved with the respective transformation of risk, return and liquidity.

Chapter 1 provides a general rationale for financial intermediation in association with real estate investments. The chapter also briefly touches on the structural risks analyzed later in the dissertation (i.e., insolvency of a life insurance company due to sustainably low interest rates and insolvency of open-end real estate funds due to sustainably negative fund flows).

In Part 1 of the dissertation (Chapter 2), I examine the impact of a new risk-based regulatory framework (Solvency II) on the attainability of target returns and portfolio efficiency of European life endowment insurers. Initially, the combination of very low yields on government bonds and high interest rate guarantees on existing life endowment policies results in a severe undercoverage for life endowment insurers. Beyond that, higher-yielding asset classes have high capital requirements according to Solvency II. Solvency II therefore prevents the insurers from reallocating their portfolios towards higher target returns and thus prevents them from earning their required returns and fulfilling their interest rate guarantees. To some extent, Solvency's high capital charges are economically reasonable, since higher-yielding assets are generally subject to more market risk. However, my results show that the regulator misunderstands real estate as an asset class and does not account for its heterogeneity, its diversification potential in a mixed asset portfolio and its interest rate sensitivity in an asset liability context. Due to these misspecifications, many insurers will neither be able to earn their target returns with their currently

bond-based portfolio, nor will they be able to increase their portfolio weights for real estate in order to earn higher returns and diversify their portfolios.

In Part 2 of the dissertation (Chapter 3 and Chapter 4), I analyze the crisis of open-end real estate funds in Germany. During the fund crisis starting in October 2008, almost one-third of all German open-end real estate retail funds were forced to suspend their share redemptions. As a consequence, the funds' management was forced to liquidate the funds by selling the real estate assets. Nine funds were even forced to ultimately liquidate their entire portfolios. The results of Chapter 3 show that, above all, fund run risk (i.e., substantial negative fund flows) and industrywide spillover effects can cause a fund to suspend share redemptions. Economies of scale and scope (i.e., fund size, age, and the presence of a distribution network for fund shares) reduce the probability of fund closures. A greater share of institutional investors increases the probability of fund closures. Once a fund has closed, investors could either await the stepwise liquidation of funds' assets or sell their shares on the secondary market, often at a substantial discount to net asset value of up to 60%. The discount to NAV is positively correlated with the fund's leverage ratio and negatively with the share of liquid assets. The results also show that the NAV discounts are driven by spillover effects from the announcement of other fund liquidations and by investor sentiment, which is represented by the aggregate level of fund inflows into the industry (i.e., all analyzed funds) and by the degree of macroeconomic uncertainty. The most critical factor for both funds closures and subsequent discounts to NAV prove to be the fund flows from and into the individual funds as well as those on industry level. This result suggests that open-end real estate funds are misspecified in the sense that they provide too much liquidity and don't limit fund flows before the funds are forced to suspend share redemptions.

As an overall conclusion, the functioning of an indirect investment vehicle, especially in times of economic turmoil, depends on its structure, which is defined by a regulatory framework. Life endowment insurers turned out to be regulated too strictly and in an undifferentiated manner when it comes to real estate investments.

This makes real estate an unattractive and expensive asset class from an economic capital perspective and prevents life insurers from further expanding their real estate quotas. On the other hand, open-end real estate funds turned out to be regulated insufficiently when it comes to liquidity transformation. During the analyzed time period, the funds allowed investors to purchase and redeem shares on a daily basis, thus providing almost unrestricted liquidity, which led to massive negative fund flows, fund closings and high NAV discounts. In the case of life endowment insurers, the EIOPA does not intend to adjust the property risk module of the Solvency II framework. In the case of open-end real estate funds, the KAGB framework was already subject to a series of changes in order to readjust the liquidity of open-end real estate funds. Those changes include a minimum holding period of 24 months for new investors and a notice period for share redemptions of 12 months.

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