Published first online in Journal of Real Estate Research, 2022, vol. xx, no. xx, pp. xx-xx, which should be cited to refer to this work.
DOI : 10.1080/08965803.2022.2033392

Fund Closure Risks of Open-end Real Estate Funds

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19 May 2020

Abstract

Over the past decades, numerous open-end real estate funds (OEREFs) in several countries became unable to maintain the liquidity provision and had to suspend the redemption of fund shares. This paper examines OEREF closures in Germany, the worlds largest OEREF market. We find that funds with a larger share of institutional investors had a higher closure probability. This is consistent with the assertion that well-informed investors are able to move quickly, as well as the notion that some institutional investors misused OEREFs as a short term substitute for lower-yielding money market investments. By contrast, economies of scale and scope appear to prevent closures. Older funds and those sold through physical bank branch networks are less likely to close. Among the factors beyond the control of fund managers are negative spillover-effects resulting from closures of other OEREFs.

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Keywords: Fund Closure, Open-End Real Estate Funds, Liquidity Crisis, Spillover Effects

JEL classification: G230, L85, G33

[0] This is the original author manuscript. The final version of this article has been published in Journal of Real Estate Research on 07 April 2022.

1 Introduction

OEREFs are a popular form of real estate ownership in major capital markets such as the US, UK, Germany and Switzerland (see Downs et al., 2017 for a recent overview). A key benefit of OEREFs is that they provide exposure to direct-property as an asset class, but without the stock market volatility of Real Estate Investment Trusts (REITs), which often resembles the general stock market in this respect. While Private Equity Real Estate Funds (PEREFs) are not subject to stock market volatility, they are notorious for being illiquid as investors are typically locked-in for the fund's lifetime. Shares in OEREFs on the other hand, are tradable on a regular basis. The transformation of direct-property into fund shares is performed by the OEREFs themselves. The fund, or its sponsor, issues and redeems fund shares based on the fund's current NAV per share, in some instances even on a daily basis. To maintain the buyback guarantee, OEREFs have to hold sufficient liquidity reserves. This enables them to maintain their ability to cope even with large waves of investor redemptions.

The suitability of the open-end fund structure as an investment vehicle for an inherently illiquid asset such as direct-property has long been debated (see for example Rosenberg and Sack (1975), Fecht and Wedow (2014), Weistroffer and Sebastian (2015)). At the core of the critique is the duration mismatch between the long term nature of direct-property investments that are financed with equity which is redeemable on a short term basis. When investors sell back a substantial number of shares to the fund, OEREFs may run into liquidity problems. While initial redemptions can be met using the fund's cash reserves, any further share redemptions have to be financed from property sales. Due to the illiquidity of direct-property, this process is typically time-consuming. As a result, OEREFs with such liquidity problems are often forced to close temporarily by suspending the redemption of fund shares until sufficient liquidity is created from selling off property.

Among the first examples of OEREFs with liquidity problems are the Prudential PUT and the Legal & General in the early 1980s in the UK (Lee, 2000). Australian OEREFs experienced a severe crisis in the early 1990s, following the property market crash in 1990

(Little, 1992). Also in the early 1990s, the Dutch Rodamco OEREF managed to prevent liquidation only by terminating its open-end fund structure and instead listing on the stock exchange (Kynoch, 1990; De Wit (1993)). The most recent OEREF liquidity crises occurred in the UK. During the COVID-19 pandemic several open-end OEREFs in the UK were forced to close due to large uncertainty about the valuation of their properties. Moreover, following the surprise Brexit Referendum on June 23, 2016, investors reacted with substantial capital outflows from UK OEREFs. As a consequence, seven UK OEREFs were forced to suspend share redemptions (Schnejdar et al., 2019).

Despite being the largest and one of the oldest OEREF markets, it was not until 2005 that Germany experienced its first OEREF crisis. In 2005 and 2006, two German OEREFs closed due to short term valuation uncertainties, but successfully reopened soon thereafter. Only two years later, the German OEREF industry was severely hit by the global financial crisis. In October 2008, ten German OEREFs with a total fund size of about EUR 28 billion were forced to close and suspend share redemptions. In most cases, the initial fund closure was only the beginning of a vicious circle. As the funds finally attempted to re-open, many were then confronted with even larger redemption requests and had to abandon the re-opening. In the years following the financial crisis, a total of ten German OEREFs were eventually forced to liquidate as the solution of last resort. Schnejdar et al. (2019) find that OEREF liquidations are associated with substantial shareholder value losses. Fund closures however not only hurt individual investors, but also the German OEREF industry as a whole, and in particular the reputation of the affected fund families.

The closure wave during the financial crisis suggests that systemic factors are at the core of the vulnerability of the OEREF industry. On the other hand, a majority of German OEREFs were able to maintain liquidity provision throughout all periods, indicating the prevalence of idiosyncratic, or fund-specific impact factors. This raises the following question: Which systemic and idiosyncratic factors explain why some OEREFs fail while others survive? To the best of our knowledge, the real estate literature does not address these issues. With this paper we intend to close this gap by providing an empirical analysis of the determinants of OEREF closures.

We model fund closure probability using panel logit regression models. OEREFs are forced to close when they are no longer able to meet share redemptions. Fund closures result technically from a combination of low fund-level liquidity and ongoing capital outflows as investors sell back their shares. Resembling a classic bank run, the mere fear of a fund closure may cause investors to sell, sothat we refer to this scenario as fund run risk in our context. Ensuring that our model controls for fund-run risk, our hypotheses and key explanatory variables however, rather tend to center on those factors which have contributed to this critical scenario.

Our empirical study is based on the entire population of German OEREFs over the period August 2002 to June 2016 and covers all closure events in the history of the asset class. Our monthly panel dataset, which is in large part hand-collected, contains not only fund-specific, but also sector-wide explanatory variables.

Our empirical results suggest that fund closures are driven by both, fund-specific, as well as industry-wide factors. We find that fund closures are related to the level of a fund's liquidity reserves and fund-level outflows of capital triggered by investor redemptions, leading us to confirm that fund closures are related to fund run risk. However, fund closures are far from deterministically dependent on these two factors alone. We provide evidence that economies of scale and scope can help reduce the fund closure probability. Older funds are less likely to close. Moreover, funds managed and distributed by the same bank have a lower closure probability. The presence of a physical distribution network allows for a more direct relationship with the customer which can help coordinate investor behavior in a less damaging manner.

In contrast, funds with a larger share of institutional shareholders are more likely to close. This finding may be explained by the ability of institutional investors to act more rapidly than retail fund investors. It is also consistent with the assertion that at least some institutional investors used OEREFs as a short term substitute for lower yielding cash holdings and then switched back as interest rates began to rise again. This tactical investment behavior is not compatible with the long term nature of the assets held by OEREFs. Our analysis of systemic, or industry-wide, factors reveals that fund closures are driven by negative spillover effects from other funds. In particular, we document a significant spillover-effect from the announcement of other fund closures.

This work contributes to an improved understanding of the vulnerability of OEREFs. Our identification of fund closure determinants can help reduce uncertainty about the overall asset class, thus restoring trust in the remaining funds. The fund-specific impact factors we identify, are largely controllable by the fund. We provide suggestions regarding how fund management can adjust investment strategies and marketing to minimize closure risk. On the other hand, the systemic risk factors contributing to fund closure probability are beyond the control of individual fund managers or fund families. The German legislator has responded by introducing a minum holding period of two years and a notice period of one year before fund shares can be redeemed. This change reduces the degree of liquidity transformation provided by German OEREFs, and improves the cash management, thereby reducing not only individual fund run risk, but also the potential for negative spillover effects. Indeed, since the introduction of the new regime, German OEREFs have not suffered another liquidity crisis. The OEREF crises in the UK suggests that other countries too, may learn from the German experience.

The remainder of this paper is structured as follows. The following Section 2 gives an overview of the German open-end fund crisis. Section 3 describes this study's variables, which are mainly derived from the literature on business failure prediction models. Section 4 describes the dataset, while the regression results are presented in Section 5. The final section concludes.

2 The German Open-End Fund Crisis

With a total fund size of EUR 205 billion by mid-November 2019, OEREFs are more than ever the predominant real estate investment vehicle in Germany and the largest market for OEREFs worldwide (see Downs et al., 2017).

German OEREFs hold substantial cash reserves to maintain the liquidity provision. UN-der German investment law, OEREFs are required to hold a minimum liquidity reserve of 5% of a funds NAV (Schweizer et al., 2013). During normal market phases, liquidity ratios tend to range from 20%-30% (see Downs et al., 2016). Nevertheless, these liquidity ratios occasionally prove insufficient, especially during financial crises. If the liquidity ratio falls below 5%, German OEREFs must close (i.e. suspend share redemptions). In practice, however, many German OEREFs choose to close before liquidity falls below this threshold.

In the past, some German OEREFs have closed not because of liquidity problems, but in order to protect investors. During the first German OEREF crisis in 2005/2006 two funds with total fund volume of eight billion EUR closed. These closures were caused by short term uncertainty about the funds' property valuations. After a brief period, both funds reopened. Similarly, in 2011, the UniImmo Global fund closed due to uncertainties about the values of its Japanese properties following the Tohoku earthquake. After all Japanese properties had been reappraised, the fund was able to reopen successfully after three months.

In contrast to these appraisal-related fund closures, experiences with liquidity-related fund closures has been more severe. In theory, a temporary closure enables the funds to generate sufficient liquidity reserves for a reopening. In practice, however, this can prove problematic. First of all, in order to protect fund investors, German OEREFs are not allowed to sell properties below the most recent appraisal value within the first twelve months of closure. This rule can prove to be a serious barrier to liquidity generation, especially if the closure coincides with a financial crisis in which property prices in general are on a strong downward trend. Secondly, the negative investor experience during a fund closure can lead to an even more and larger requests for share redemptions once the fund attempts to reopen.

Investors are only able to sell their fund shares on the secondary market during these periods often at substantial discounts to NAV (see Schnejdar et al., 2019). If a German OEREF was unable to reopen successfully within twenty-four months of closure, these funds would have to sell off their entire real estate portfolios and pay out the proceeds to fund investors.

Figure 1 shows the total size of closed German OEREFs (light grey bars), as well as the size of funds in liquidation (dark grey bars). The graph also illustrates the total volume of fund reopenings (black bars). A detailed overview of all fund closure and liquidation dates within the German OEREF industry is provided in Table 1.[1] In October 2008, ten German OEREFs with a total fund size of about EUR 28 billion were forced to close due to liquidity problems. Seven of these funds reopened subsequent to their first closure in October 2008, but all were ultimately forced to close for a second time. As of May 2010, the total fund size of distressed funds returned to earlier levels. By August 2012, all closed funds were forced to announce their liquidations. Generally, as shown in Figure 1, the average fund size decreases over time due to the payouts to investors from the funds sold properties as well as due to a decrease in property appraisal values. At the end of the sample period in June 2016, about ten billion EUR remained inaccessible to current fund investors.

3 Related Literature and Hypotheses

Our theoretical framework for explaining OEREF closures is derived from the literature on business failures. Business failure prediction models generally focus on identifying an imminent financial crisis by predicting individual firm insolvencies. Kupiec and Ramirez (2013) find that U.S. bank insolvencies caused a significant drop in overall economic development in the period 1900 to 1930. Because of the importance of these issues, the literature on failure prediction models constitutes a plethora of scientific work over the past fifty years, beginning with Beaver (1966). Following Balcaen and Ooghe (2006), Zavgren (1985), Sheppard

[1] The HansaImmobilia fund was ultimately forced to close and liquidate in 2012 without a 24-month closing period.

(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 employs a logit model to derive the determinants of fund closures 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, our fund-specific variables are regulated by investment law, so that they are defined identically for all funds. According to Balcaen and Ooghe (2006), another important problem is how to precisely define failure. We use the legal event of a "fund closure" to measure failures in an effort to avoid the problem of poorly defining the dichotomy of the dependent variable. Inability to capture corporate bnkruptcies in a sample time period is another issue for failure prediction models. To avoid a distortion, we include the entire relevant time frame, including all fund closures regardless of age, size, or investment focus.

3.1 Fund Run Risk

Whenever fund investors observe increasing share redemptions that threaten to exceed a fund's liquidity ratio, they have an incentive to redeem their own shares. In the worst case, this "vicious circle" leads to a fund closure. The mechanism is similar to a bank run, and it is a serious shortfall of the open-end structure. Therefore, sufficiently large liquidity ratios are required. During phases of economic uncertainty, this safety buffer can reduce 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 bankruptcy. Therefore, we expect a negative relationship between liquidity ratio and closure probability.

Fund closures are technically caused by capital outflows that exceed a fund's cash reserves. An individual fund's negative net flows can be a consequence of poor fundamentals, such as 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 the fund closure probability independent of fund-specific variables. Bannier et al. (2008), for example, state that investors may redeem shares only because of expected share redemptions by other investors. Such expectations could be a result of reported capital outflows, which 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" which leads to fund closures. Hence, we use the individual fund's net flows as an additional proxy for the risk that there will be a run on the fund (fun run risk).

Fund closures are technically caused by a combination of substantial capital outflows in combination with insufficient liquidity ratios. While it is clearly important to control for these factors in our model, the underlying reasons for a fund closure are more complex. Our primary interest is in the fundamental and systemic impact factors potentially leading to fund closures, as captured in the following hypotheses.

3.2 Economies of Scale and Scope

One strand of the literature supports the notion that economies of scale and scope can help prevent business failures. Using size as a proxy for potential economies of scale and scope, as well as for learning effects, Hill et al. (2011) find that larger companies exhibit a lower failure probability. Also suggesting scale advantages, Laitinen (1992) finds that newly founded and fast growing companies (i.e., growth in net sales) which exhibit high leverage ratios also tend to exhibit higher bankruptcy risk. On the other hand, 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 somewhat ambivalent about the relatiship between firm size and business failures, we expect economies of scale and scope, in addition to fund size, to diminish the probability of fund closure. Hence, we expect a negative overall influence of fund size on closure probability. In the context of OEREFs, larger funds are also more likely to have a broader, more diversified investor base. By contrast, smaller funds tend to be dependent on only a few investors.

The literature also suggests that company age is a significant factor in business failures. Analyzing Canadian corporate bankruptcies in 1996, Thornhill and Amit (2003) find that young companies have a higher probability of failure than older ones. The authors argue that firm age indicates the presence of economies of scope in the organizational process. Therefore, we include fund age as a further fund-specific variable to proxy for economies of scale and scope.

Our third proxy for economies of scale and scope in the context of fund closures is related to the distribution network. In our sample we observe that the fund families of eight of twenty-four OEREFs are associated with large German banks.[2] Fund shares are sold by the retail distribution networks of these banks, where they are actively promoted by bank advisors. Therefore, bank-owned funds have direct access to a large base of bank customers. In addition, the purchase of OEREF shares is often part of clients pension provision solutions, which are also directly sold by the fund's sponsor (bank). Moreover, the direct customer relationship can help convince customers not to sell their fund shares during a liquidity crisis.

Another potential advantage of funds which are managed and distributed by the same bank is expressed by Maurer et al. (2004), who state that fund sponsors can buy a sufficient amount of their own fund's shares during periods 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.[3] Due to their wide customer base and direct customer relationship, we argue that bank-owned funds benefit from economies of scope related to their distribution network. Hence, we use bank-ownership and the associated existence of

[2] Hausinvest and DEGI funds are associated with Commerzbank (formerly with Dresdner Bank), Grundbesitz funds are associated with Deutsche Bank, and DEKA funds with Sparkassen, and Union Investment funds with Volksbanken/Raiffeisenbanken.

[3] 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 invest themselves in ist own fund.

a distribution network as a third proxy for economies of scale and scope. Hypothesis 1 summarizes the possibly preventative impact of economies of scale and scope on the fund closure probability.

Hypothesis 1: *The fund closure probability decreases with increasing economies of scale and scope.*

3.3 Spillover Effects

Zavgren (1985) suggest that firm-specific impact factors are not sufficient to fully explain the probability of business failures. According to Aharony and Swary (1983), large-scale bank insolvencies lower the stock market value of the remaining solvent banks, thus indicating industry-wide spillover effects.

Analyzing the first German open-end fund crisis in 2005/2006, Bannier et al. (2008) argue that the closure of a particular fund can result in significant contagion effects for the industry as a whole. Closed funds are typically forced to sell assets in their attempt to reopen again. In the case of a subsequent fund liquidation, their entire property portfolio has to be sold. As total assets under management of OEREFs often amount to several billion euros, fire sales may not only lead to distressed transaction prices from sales of the affected fund portfolios themselves, but potentially for the whole property market. This is because OEREFs often share similar investment foci (e.g., property sector, investment volume, international diversification). Therefore, a significant price drop could affect the overall property values of other funds, thus directly affecting them, especially during liquidity shortages. We account for the potential of such negative spillover effects by using the number of industry-wide fund closures as a proxy variable.

Industry-wide fund flows can serve as an additional indicator of the current level of trust or uncertainty towards the OEREF industry. As the whole asset class suffers negative fund flows, the probability increases that the issue becomes a hot topic among industry participants, potentially even leading to negative headlines in the financial press. This may trigger further uncertainties regarding the asset class and cause dynamics similar to the fund-level vicious circle dynamics described above.Therefore, we use industry-wide fund flows into the OEREF sector as a second proxy variable for negative spillover effects. Hypothesis 2 summarizes the potentially negative externalities on the fund closure probability.

Hypothesis 2: *The fund closure probability is related to negative spillover effects from other fund closures.*

3.4 Institutional Investors

The financial literature suggests that the investment behavior of institutional investors can have an impact on stock returns. Gompers and Metrick (2001) find that large institutional investors almost doubled their share of the stock market from 1980 to 1996. These investors tend to pour their money into larger rather than smaller companies. The authors argue that the associated shift in the stock market has potentially contributed to the disappearance of the small-cap stock premium. Larrain et al. (2017) analyze fire sales in the Chilean stock market triggered by a regulatory restriction on pension funds wishing to invest in these assets. Stocks subject to the selling pressure showed significantly more negative returns.

Table 2 shows that, on average, 98% of all OEREF shares in our sample are held by retail investors. There is however considerable dispersion among the institutional investor share of individual funds, ranging from 0% for most funds to up to 31.9%. It can be argued that institutional investors possess an informational advantage over retail investors. In particular, they might be able to sell quicker and more decisively in the presence of significant fund run risk. Such investment behavior would trigger additional selling pressure, thereby further decreasing a fund's liquidity ratio and hence increasing the closure probability.

Institutional investors may increase the fund closure risk for another reason. According to Bannier et al. (2008), institutional investors were not always required to pay the front-end load of 5%. These built-in transaction costs need to be paid by all retail investors, which according to Maurer and Sebastian (2002) help to avoid speculative recurrent share transactions. The lack of an upfront fee however combined with the historical share price stability and stable yields from rental income, positions OEREFs as an attractive short term substitute for money market investments. In fact, Figure 2 shows that, as interest rates fell to record lows in 2008 due to the financial crisis, the share of institutional investors increased significantly. When interest rates were rising again between 2011 and 2012, the average share of institutional investors dropped again. The reallocation to cash, may have contributed to the deepening of the OEREF crisis. Our third hypothesis reflects the risks associated with the fast-moving “smart money” mindset of institutional investors.

Hypothesis 3: *The fund closure probability increases an increase in the share of institutional investors.*

3.5 Control Variables

We control for a number of other fund-specific variables that may have an impact on fund closure probability. First of all, we control for a fund’s total expense ratio (TER). During economic crises, fund investors may cast a more critical eye on expensive fund management fees, leading to a higher fund closure probability.

Secondly, we control for a fund’s leverage ratio. Zavgren (1985), Dimitras et al. (1996), and Hill et al. (2011) find that a higher ratio of total liabilities to total assets increases the probability of bankruptcy. For REITs Chaudhry et. al (2004) argue that a larger leverage ratio tend to increase bankruptcy risks. Another advantage of a low leverage ratio is provided by Downs et al. (2016), who describe how OEREFs with less debt possess a larger debt capacity, which may serve as a short term liquidity source to finance redemptions.

Lastly, we control for a funds’ total returns over the previous twelve months. The potential impact of past returns on the fund closure probability is ambiguous. On the one hand, higher returns may indicate higher fund quality, thus leading to a lower closure probability. On the other hand, high returns may signal that the fund has appraised its properties too aggressively, leading to lower future return expectations, especially during financial crises.

4 Data, Methodology, and Sample Description

4.1 Data Sources

Our empirical analysis is based on twenty-four OEREFs over the 167-month period from August 2002 through June 2016. These twenty-four funds represent the population of both distressed and healthy German OEREFs. 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 well-balanced panel framework. Note further that a new investment law (InvG) was passed on in January 2002, based on an EU directive. This new regime had a significant effect on the legal environment for OEREFs in Germany.

The use of annual accounting information is also common in failure prediction models (see for example Balcaen and Ooghe, 2006, and Dimitras et al., 1996). Fund-specific variables such as liquidity, leverage, and management fees are retrieved from data provided in the fund's annual and half-year reports. Moreover, we retrieve information on some key variables from monthly updated fact sheets provided by the funds. Our dataset also includes information provided by MorningStar Direct.

4.2 Research Design and Definition of Variables

We use a panel logit framework to analyze the fund closure probability of fund i at the end of month t, which is measured 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. For the purposes of our empirical tests, we estimate several versions of the following model:

$$
\begin{aligned}
Closure_{i,t} = \alpha &+ \beta_1\ Liquidity_{i,t-1} + \beta_2\ Individual\ Fund\ Flows_{i,t-1} \\
&+ \beta_3\ ln\ Fund\ Size_{i,t-1} + \beta_4\ ln\ Age_{i,t} + \beta_5\ Sale\ by\ bank_{i,t} \\
&+ \beta_6\ TER_{i,t-1} + \beta_7\ Total\ Return_{i,t-1} + \beta_8\ \Delta\ Leverage_{i,t-1} \\
&+ \beta_9\ Industry\ wide\ Fund\ Flows_t + \beta_{10}\ Fund\ Closure_t \\
&+ \beta_{11}\ Institutional_{i,t-1}
\end{aligned} \tag{1}
$$

We use a fund's liquidity ratio and individual fund flows to proxy 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 net capital flows into the specific OEREF. This variable is calculated as the monthly percentage change in net capital fund flows relative to the respective fund size.

We use three proxies to capture the effect of potential economies of scale and scope on the fund closure probability. *Fund Size* is the natural logarithm of the fund volume measured in billions of euros. *Age* represents the natural logarithm of the fund's age in months. *Sale by Bank* is a 0/1 indicator variable that is set to 1 if the shares of a particular fund are sold through the distribution network of a bank.

We proxy for the effect of potential spillover effects on the fund closure probability by using industry-wide fund flows and the closure announcements of other funds. *Industry-wide Fund Flows* is calculated as the sum of net capital flows into or out of all German OEREFs. *Fund Closure* is a counting variable that captures the effect of other fund closure announcements on the fund closure probability.

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

We use the following fund-specific control variables. *TER* represents the annual management fees, calculated in percentage relative to 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 funds NAV. *Leverage* is the absolute difference (Δ) of the funds debt relative to its GAV. In our regressions we use the first differences of the leverage ratio to account for non-stationarity in the level of this variable.

Most fund-specific variables are derived from the monthly fact sheets provided by the funds themselves, which are typically reported with a time lag of two to three weeks, so we lag these variables by one month in our model. We do not lag fund age, sale by bank, and our proxy variables for industry-wide spillover-effects, because these variables are public information without a time-lag.

4.3 Descriptive Statistics

Table 2 shows some summary statistics over the sample period. The liquidity ratios display significant heterogeneity over time as well as across funds. The average liquidity ratio is 25.3%, 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 consider newly issued funds only after a 24-month period. The liquidity ratios increase significantly from 2012, due to the progressive liquidation of ten funds in the dataset that were forced to sell their entire property portfolios and transfer the proceeds to investors. Figure 3 illustrates the considerable increase in average liquidity ratios due to property sales beginning in 2012.

The average monthly fund flows relative to fund size are 0.2%. Newly issued funds tend to show strong capital inflows within the first two years, which could distort the regression results, providing another reason to include them only after twenty-four months. 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 merger with the WestInvest Interselect fund, which accordingly had extraordinary capital inflows in the same period. For the same reason, the Inter Immoprofil fund displayed a 248% capital inflow in November 2010. We control for fund mergers by excluding these special events from our dataset (n = 5) in order to avoid distortions. Accordingly, the maximum capital inflows are now from the Euro ImmoProfil fund with 77.0% at the beginning of 2005, while the Inter ImmoProfil fund shows the maximum capital outflows of -56.6% 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 DekaImmobilien Europa fund is the largest OEREF in our sample, with an average fund size of EUR 9.87 billion and a maximum fund size of EUR 13.6 billion. Distressed funds tend to show a declining fund size over time. For example, the Morgan Stanley P2 value fund had a minimum of only EUR 69 million as of June 2016, due to the advanced stage of fund liquidation by then. However, the remaining funds that were not affected by the crisis were able to grow their fund volumes following increasing demand for OEREFs in Germany since 2014.

Figure 3 shows that the average fund size decreased from EUR 4.5 billion in January 2004 to approximately EUR 3.0 billion over the 2006-January 2011 period, due to newly issued funds (i.e., low fund volume), as well as fund outflows in the wake of the financial crisis. Since then, the average fund size has risen again, despite ongoing fund liquidations. Significant capital inflows into the remaining funds led to an average fund volume of over EUR 4 billion as of June 2016.

The average fund age in our sample is 243 months. The oldest fund at the beginning of the dataset was the UniImmo global fund at 36 years (433 months). Several funds were issued following the start of our sample period in August 2002.

The total expense ratio (TER) denotes the annual management costs as a percentage of fund volume. The average total expense ratio is 0.8%. The CS Euroreal fund had the highest management fees at the beginning of the sample period in 2002, with an expense ratio of 1.5%.

Total Returns are based on the annual change in net asset value, including dividend distributions. The average annual total return is 1%, with a minimum 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 tend to differ strongly across funds. Five distressed funds, namely 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 22.1%. For example, the KanAM Grundinvest fund, which was forced to close in October 2008 shows on average a leverage ratio of 38.66%, while the healthy Deka Immobilien global fund has only a leverage ratio of 18.48% over the sample period. Figure 3 shows that the average leverage ratios tended to rise through 2012. Afterwards, it decreased consistently and significantly until the end of the sample period, largely due to distressed funds repaying their property-related loans. In contrast, healthy funds show stable leverage ratios over time.

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%. Figure 3 shows that the average share of institutional investors significantly increased to about 6% from August 2002 through Q1 2011. It subsequently decreased substantially through June 2016. However, the sharp decline in the average share of institutional investors may be exaggerated. The data is based on Morningstar Direct, which only reports data on seventeen of twenty-four OEREFs. Moreover, towards the end of the dataset funds in liquidation tend to provide less extensive information. This affects in particular OEREFs with relatively large shares of institutional investors such as the UBS 3 Sector Real Estate fund and the TMW Immobilien Welt fund.

Industry-wide fund flows average EUR 228 million per month. At the height of the financial crisis in October 2008 investors redeemed over 4.3 billion euros within just one month from the asset class.

Closure announcements are clustered within a few months over the sample period. The mean of the counting variable is 0.198. 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 subsequently reopened, but were ultimately forced to close again from November 2009 through October 2010.

5 Results

Table 4 contains panel logit regression results on the probability of fund closures, using several specifications of the model shown in equation 1. Model (I) uses only the liquidity ratio and individual fund flows, namely those variables which technically cause fund closures. Model (II) uses all fund-specific control variables. Models (III) and (IV) separately introduce our two proxy variables for industry-wide spillover effects. Finally, model (V), includes all fund-specific and industry-wide spillover variables simultaneously. All regressions are estimated using heteroscedasticity robust standard errors (shown in parentheses).

The regression results provided in Table 4 are based on our full sample of observations. They do not include the share of institutional investors as an explanatory variable. Morningstar Direct provides data on the fund's ownership structure for only seventeen out of twenty-four funds. Hence, the inclusion of the share of institutional investors as an explanatory variable would reduce our sample by 428 fund-month observations, or about 20% of potential observations. The respective regression results for the subsample including the share of institutional investors are provided in Table 5.

Due to the non-linearity of parameters, the interpretation of regression coefficients in panel logit regression models is not straightforward. We follow the advice of Greene (2010), and conduct our empirical tests based on the statistical significance of the coefficients, and use graphical analyses to judge the economic significance of our results (see Figures 4 - 10). Our empirical tests regarding hypotheses 1 to 3, as well as the economic interpretation of the determinants of fund closures are based on model (V), our main model.

Model (I) provides the regression results using only the liquidity ratio and individual fund flows as explanatory variables. Both variables are statistically significant and have the expected negative sign. However, the McFadden R-squared is only 3%. This may be surprising, given that these two variables can technically trigger a fund closure if continued outflows drive a fund's liquidity below 5%. The result of model (I) suggest that there is more behind OEREF closures, which is consistent with the observation that many funds even chose to close before they fall below the 5% minimum liquidity ratio. [4] The McFadden R-squared increases to 17% when all fund-specific variables are included (model II). The explanatory power reaches 47.1% when the model takes into account industry-wide fund lows (model III), and even 50.7% when other fund closures in the industry (model IV) are instead used as the proxy for spillover effects. When both industry-wide spillover variables are included (model V), the explanatory power reaches 52%.

First, we examine the impact of fund run risk and the closure probability. Our first proxy for fund run risk is the fund's liquidity ratio. We find the impact of the liquidity ratio on the fund closure probability is negative and statistically significant across all models. A higher liquidity ratio thus significantly reduces the fund closure probability in the next month. Figure 4 illustrates that the fund closure probability is under 1% for liquidity ratios ranging from 25% (0,898%) to 50% (0,2174%), which is in line with the unconditional closure probability in our sample. The closure probability increases to 2,029% as the liquidity ratio drops to 10%, while a liquidity ratio of only 5% is associated with a fund closure probability

[4] The low explanatory power of model (I) may be explained by the one month lag of the explanatory variables. In untabulated results, we model both variables contemporaneously and find the McFadden R-squared increases to 19%.

of 2.673%.

Individual fund flows are our second proxy for fund run risk. All model specifications reveal a negative and statistically significant impact on the fund closure probability. Figure 5 illustrates the marginal impacts. Large capital outflows of 12% (two standard deviation below the mean) are associated with a closure probability of 1.284%, whereas capital inflows of 12% (two standard deviation above the mean) are associated with a closure probability of just 0.578%. Thus, the evidence on both variables suggests that fund closures are related to fund run risk.

Next, we test whether economies of scale and scope can help reduce the fund closure probability (Hypothesis 1). Our first proxy variable is fund age. The natural logarithm of fund age has a negative and statistically significant impact across all models. Older funds thus tend to be associated with a lower closure probability. The negative sign on the regression coefficient is in line with the literature. Older funds are likely to benefit from economies of scope with respect to organizational processes, because they have more time to establish efficient processes and structures. Figure 6 shows how the marginal effects of logarithmic fund age affect the fund closure probability. Age is also varied over two standard deviations below and above the mean. The average fund age is about twenty years. For a logarithmic fund age two standard deviations above the mean (ln 6.89), which represents a fund age of almost 82 years, the closure probability would be around 0.5%. Nevertheless, the oldest fund in the dataset shows a fund age of around 50 years (ln 6.395). For this maximum age the closure probability shows a value of 0.336%. In contrast, for a logarithmic fund age of 3.46 (i.e., two standard deviations below the mean), which represents a fund age of two years and eight months, the associated closure probability increases to 2.492%.

Our second proxy for economies of scale and scope is the sale by bank dummy variable. We find that OEREFs with bank-owned retail distribution networks obtain a lower fund closure probability. The respective coefficient is negative and significant across all model specifications. Figure 7 illustrates that funds without access to a bank-owned distribution network exhibit a closure probability of 1.237%, whereas bank-owned funds exhibit a considerably lower closure probability of only 0.378%.

Fund size is our third and final proxy for economies of scale and scope. Interestingly, larger funds exhibit a higher fund closure probability. In model (V), our main model, the impact is statistically significant. We use the logarithm of fund size in the model specification. For example, for a logarithmic fund size of 1.3 (two standard deviation below the mean) the fund closure probability is 0.369%. For a fund size of 5.3 (two standard deviation above the mean) the probability increases to 2.616%. In summary, two of our three proxy variables are consistent with the hypothesis that economies of scope help lower the fund closure probability. In contrast, economies of scale do not seem to be beneficial. A potential explanation for the positive relationship between fund size and fund closures is that larger funds and their potential liquidity problems could be more likely to receive broad coverage in the financial news, thereby increasing the risk of a fund run.

Next, we test for the presence of negative spillover effects (Hypothesis 2). Although industry-wide fund flows obtain the expected negative sign, the effect is not statistically significant in our preferred model V. On the other hand, the coefficient on the fund closure variable, our second proxy for spillover effects, is positive and statistically significant across all model specifications. Figure 9 illustrates that the fund closure probability is almost zero in periods without other fund closures. However, the fund closure probability for individual funds increases substantially with the number of other fund closures during the period. For one fund closure the probability of closure is 0.368%. In October 2008, when nine funds were forced to close, the closure probability for the remaining funds was 7.132%.

Our fund-specific control variables all have the expected impacts across all model specifications. Consistent with the literature, management fees (TER) are positively related to the fund closure probability. During phases of financial distress, investors may view expensive management fees in a particularly unfavorable light, and thus decide to redeem their shares. The closure probability also increases with a higher leverage ratio. More financial leverage not only reduces a fund's debt capacity and hence its ability to raise short term liquidity, a higher leverage ratio also amplifies the negative impact of property reappraisals during crises. This could, potentially, ratchet up pressure to sell. We find no evidence that the prior total return is significantly related to the fund closure probability. Thus, neither of the two potential effects seems to outweight the other.

The marginal effects of our key explanatory variables on the closure probability shown in Figures 4-9 are relatively small. Note that these marginal effects show the impact of one variable, when all other variables are held fixed at their means. However, a combination of several risk factors may result in substantially higher closure probabilities for individual funds. Table 3 provides the cross correlations between all explanatory variables. For example, industry-wide flows are negatively correlated with industry-wide fund closures (-0.52), suggesting that these two risk factors tend to occur in combination. Similarly, individual fund flows and industry-wide flows are positively correlated (0.29).

We demonstrate the model fit of our preferred model (V) by conducting an in-sample prediction of the closure probability for all twenty-four funds. The predicted closure probabilities are based on the actual combination of risk factors over time. Figures 11 to 14 show the results for all distressed funds and for the remaining healthy ones, respectively. The graphs show the prediction for each month in the sample period. Hence, we mark the periods after the actual fund closure event, because these predictions are only theoretical. According to Figures 11 and 12, ten of the twelve distressed funds exhibited a considerable predicted closure probability in October 2008, the peak of the second fund crisis.

Figures 13 and 14 show the closure probabilities for those funds that never had to close. At the peak of the crisis, in October 2008, most of the healthy funds exhibited relatively low closure probabilities. Only three of the twelve funds had a closure probability that was 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.

Table 5 provides the subsample regression results including the impact of the share of institutional investors on the fund closure probability, in order to test Hypothesis 3. In order to facilitate comparability, model (I) uses the same set of explanatory variables as in Table 4, model (V). Additionally, Model (II) includes the share of institutional investors as an explanatory variable.

Model II in Table 5 indicates that when institutional investors account for a large share of the fund's investors then that fund's probability of closure tends to increase substantially in the next month. This result implies that a higher share of institutional investors is tied to significant blockholder risk for the remaining retail investors. Institutional fund investors hold - and are able to redeem - a high proportion of fund shares. This can lead to additional selling pressure, which increases closure probability via decreasing liquidity ratios. Figure 10 illustrates that a 0% share of institutional investors is associated with a 0.738% fund closure probability. By contrast, a 12% share, which represents a two standard deviation increase above the mean, leads to a closure probability of 4.369%. The introduction of the share of institutional investors increases the McFadden R-squared from 56.1% to 61.9%.

The results in Table 5 are largely consistent with those reported in Table 4. The coefficient on industry-wide fund flows becomes significant in models (I) and (II) of Table 5. However, the coefficient on individual fund flows turns insignificant in model (II). This change may be explained by the correlation between both variables (0.29). Moreover, the statistical significance of the sale by bank indicator variable disappears when controlling for the share of institutional investors. We place more emphasis on Table 4 in those instances, due to the wider sample coverage.

In additional robustness tests, we control for the impact of the fund's legal environment (e.g., the selling restrictions on the properties). We do not find a significant influence on the closure probability. According to Sheppard (1994) and Hall (1994), the level of diversification has a significant influence on business failures. However, we find no influence of regional or sectoral diversification (Herfindahl index) on the probability of a fund closure. Moreover, we control for the macroeconomic environment by using additional variables like the interest rate of German government bonds, two uncertainty indicators (Euro Stoxx 50 Volatility Index, Policy Uncertainty Index), as well as the EPRA total return, which proxies for the underlying portfolio performance in the funds' target real estate markets. Again, we do not find a significant impact of the macroeconomic environment on the fund closure probability.[5]

6 Conclusion

This paper examines the determinants of real estate fund closures in Germany. In total, about one-third of all German OEREFs were forced to close during the first and second fund crises, in 2005/2006 and October 2008, respectively. Our findings reveal that fund closures are driven by fund run risk, a lack of economies of scope, negative spillover-effects from the industry, as well as a larger share of institutional investors.

Our research has two major implications regarding how fund management can attenuate fund closure risks. First of all, by pursuing a conservative investment strategy using sufficient liquidity ratios and only minimal financial leverage. A potential drawback of this strategy is that it probably comes at the expense of future fund returns, which could in turn limit the funds' future ability to attract positive net capital flows, as suggested by Downs et al. (2016). Secondly, fund management can reduce fund closure risks 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).

However, we also provide evidence of risk factors beyond the control of fund management. In particular we find negative spillover effects resulting from the closure announcements of other funds. Individual funds may thus fall victims of a chain reaction triggered by industry peers, which have potentially acted suboptimally. Here, the regulator is required to intervene appropriately.

Since 2013, the German regulator has responded to the crisis by introducing minimum

[5] These results are available from the authors upon request.

holding periods of two years for new fund investors, limiting leverage to 30% rather than 50%, and by introducing notice periods of one year until share redemptions are fulfilled.In combination, these changes have led to a significantly improved plannability regarding the cash management on behalf of the funds, and helped to restore trust in the industry. To date, no further fund closures have occurred in the German OEREF industry. Nevertheless, liquidity risks remain inherent to the OEREF structure. Our research contributes to the literature on business failure prediction models and liquidity transformation risk.We believe that investors, fund managers, and regulators can benefit from the German experience.

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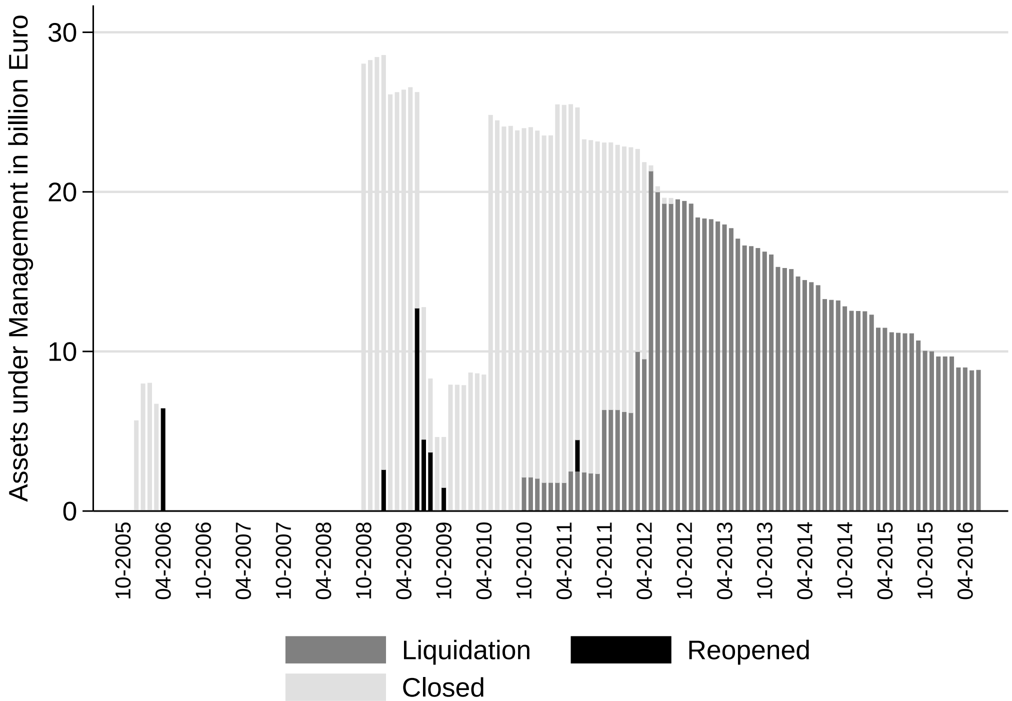
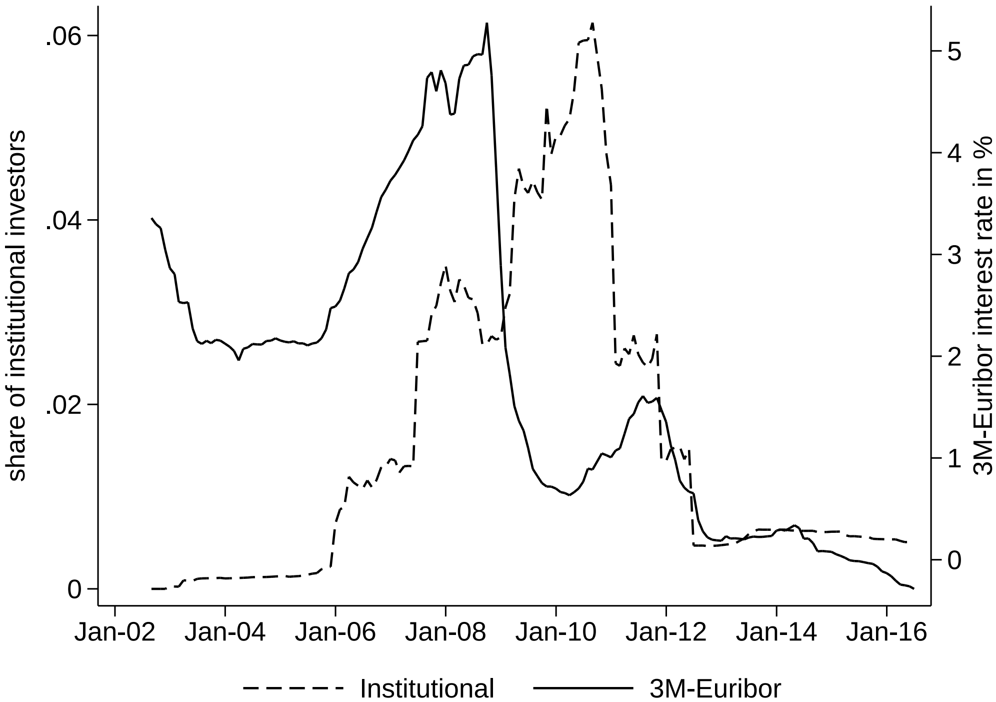
Figures

Figure 1: Overview open-end fund crises



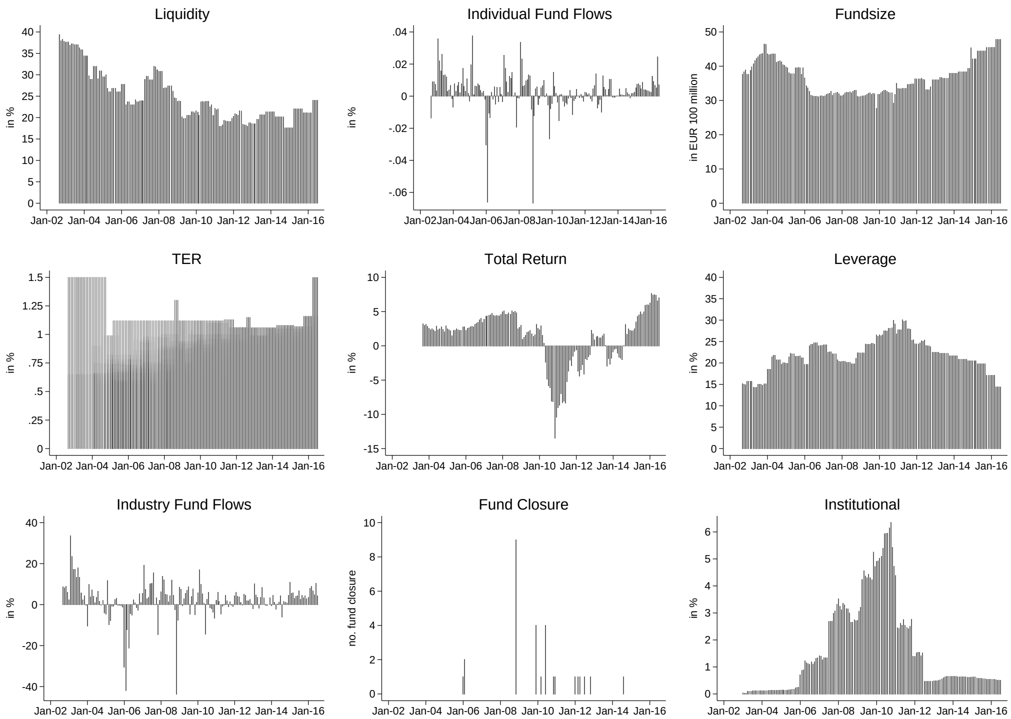
This figure shows the total fund size of German open-end real estate funds that either suspended share redemptions (ligh grey bars) or were already in the process of fund liquidation (dark grey bars). The graph also indicates the total fund size of reopenings (black bars).

Figure 2: Correlation share of institutional investors and Euribor interest rate



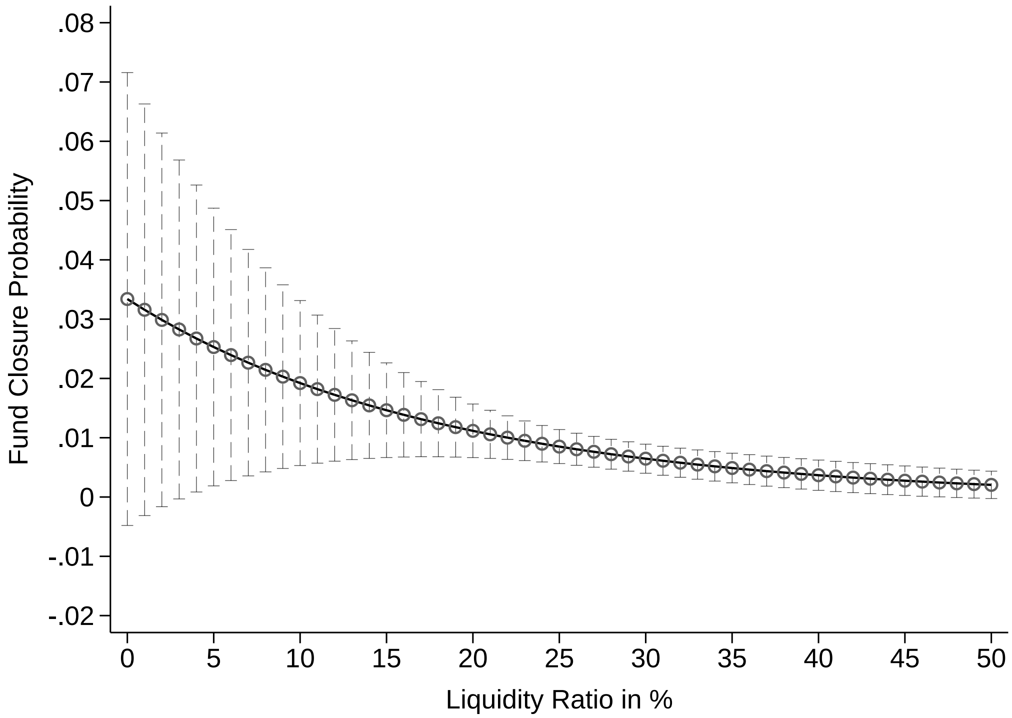
This figure shows the average share of institutional investors in German open-end real estate funds over the sample period as well as the 3M-Euribor interest rate in the same time period.).

Figure 3: Summary statistics



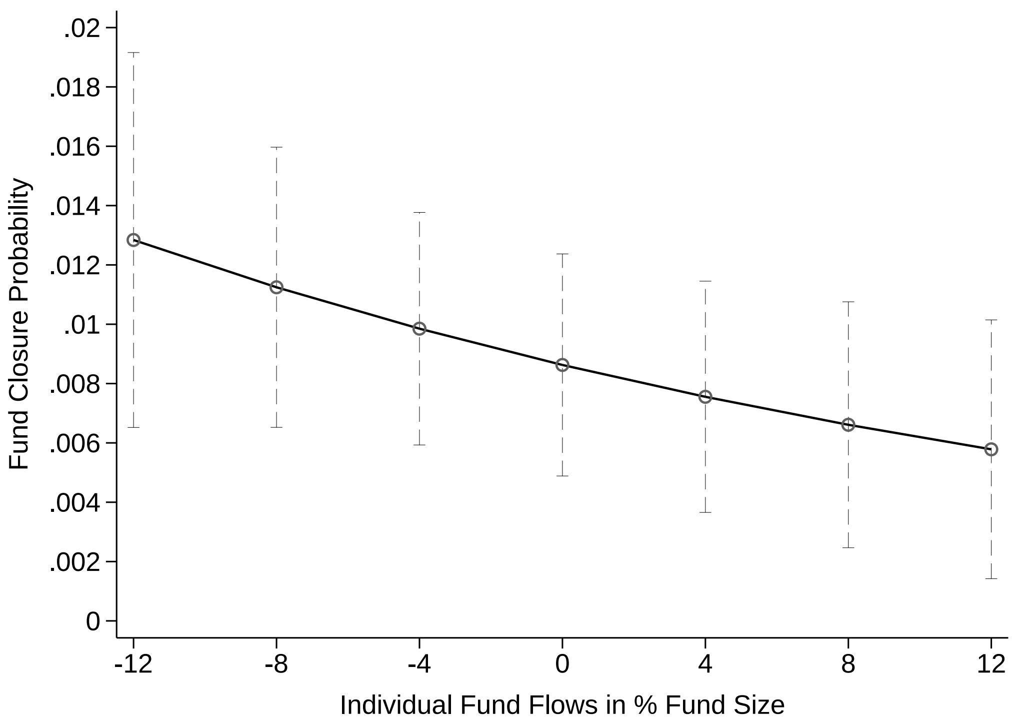
This figure illustrates the average progression of fund-specific and industrywide spillover effects variables from 2002:8 through 2016:6.

Figure 4: Effects of the liquidity ratio on the fund closure probability



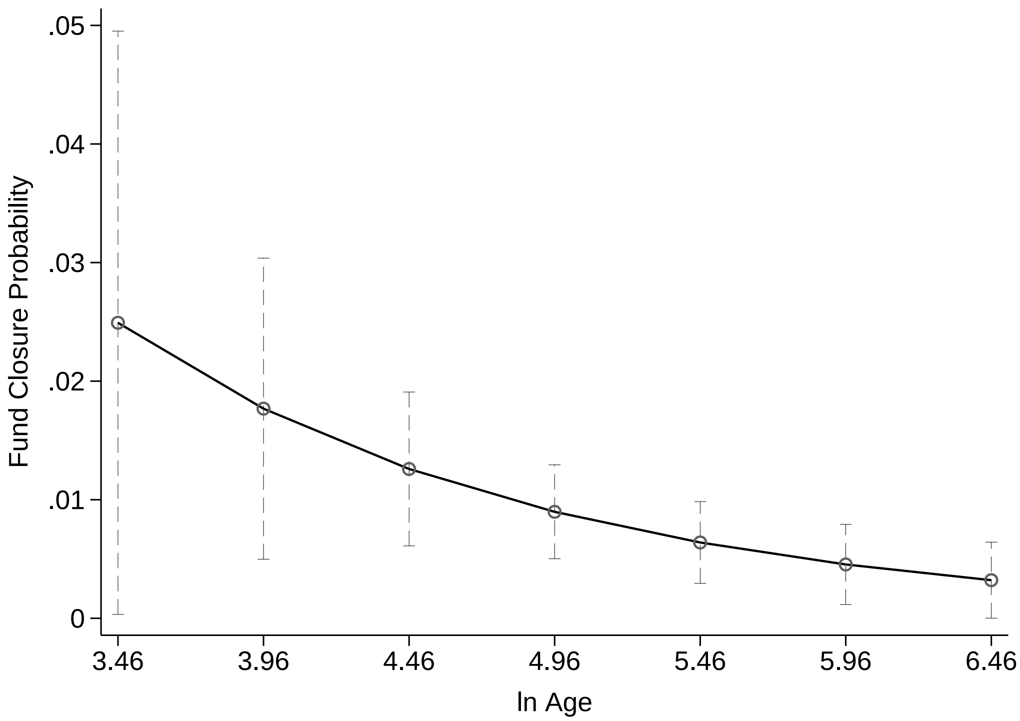
This figure compares how fund closure probability reacts to changes in fund run risk as represented by the liquidity ratio. The dashed lines denote the 95% confidence interval.

Figure 5: Effects of individual fund flows on fund closure probability



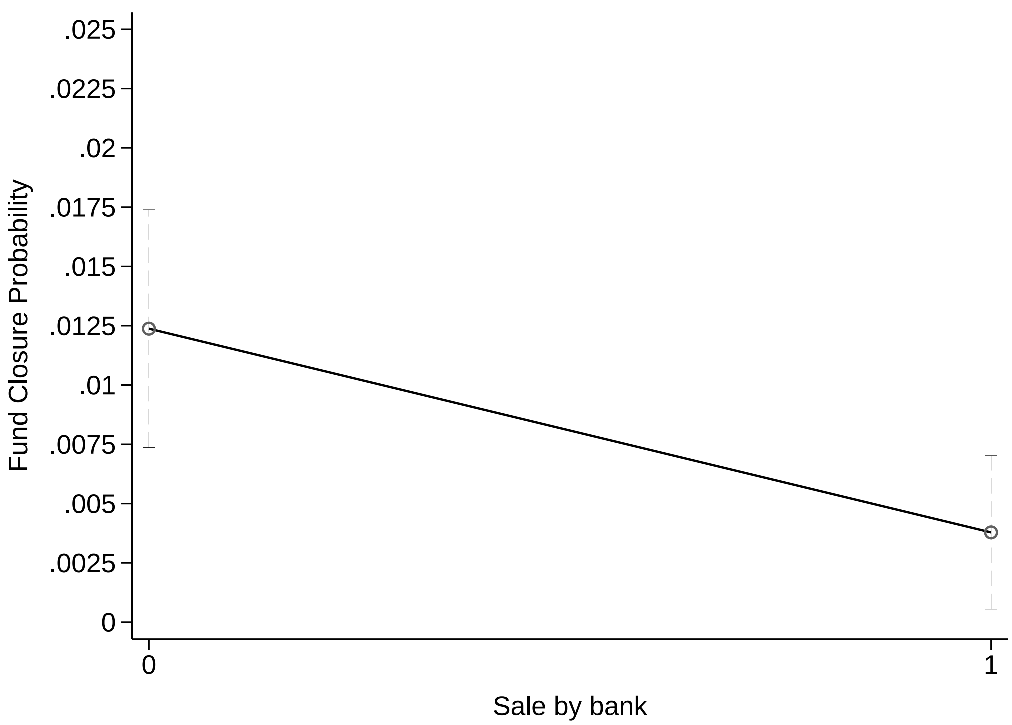
This figure compares how fund closure probability reacts to changes in fund run risk as proxied for by individual fund flows. The dashed lines denote the 95% confidence interval.

Figure 6: Effects of fund age on fund closure probability



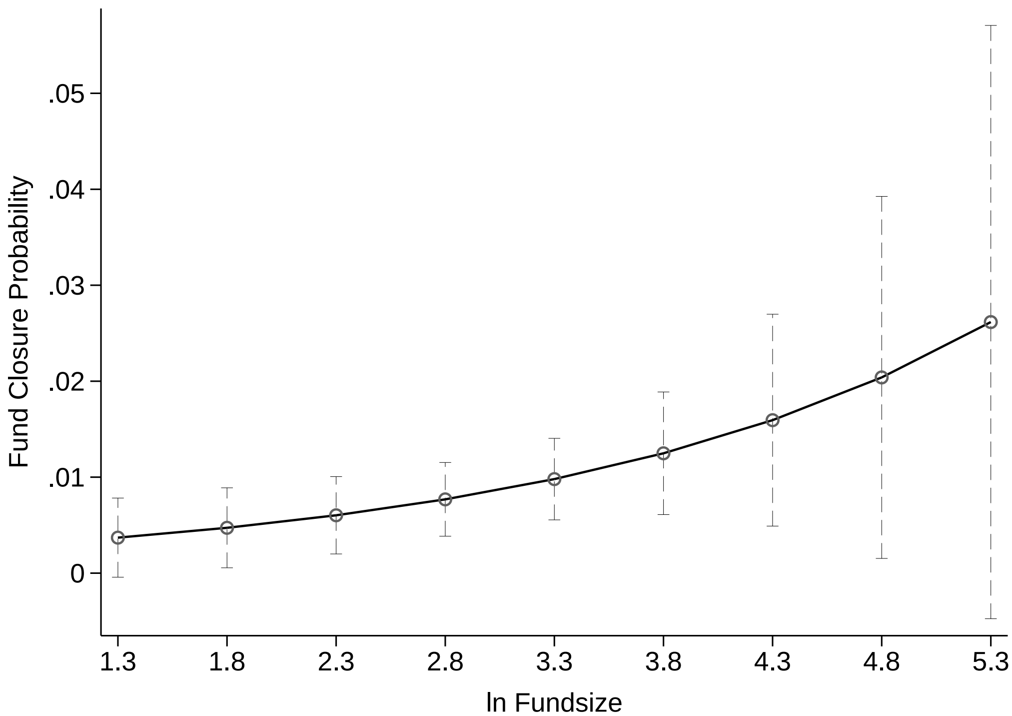
This figure compares how fund closure probability reacts to changes in the economy of scope and scale variable as proxied for by fund age. The dashed lines denote the 95% confidence interval.

Figure 7: Effects of the sale by bank variable on fund closure probability



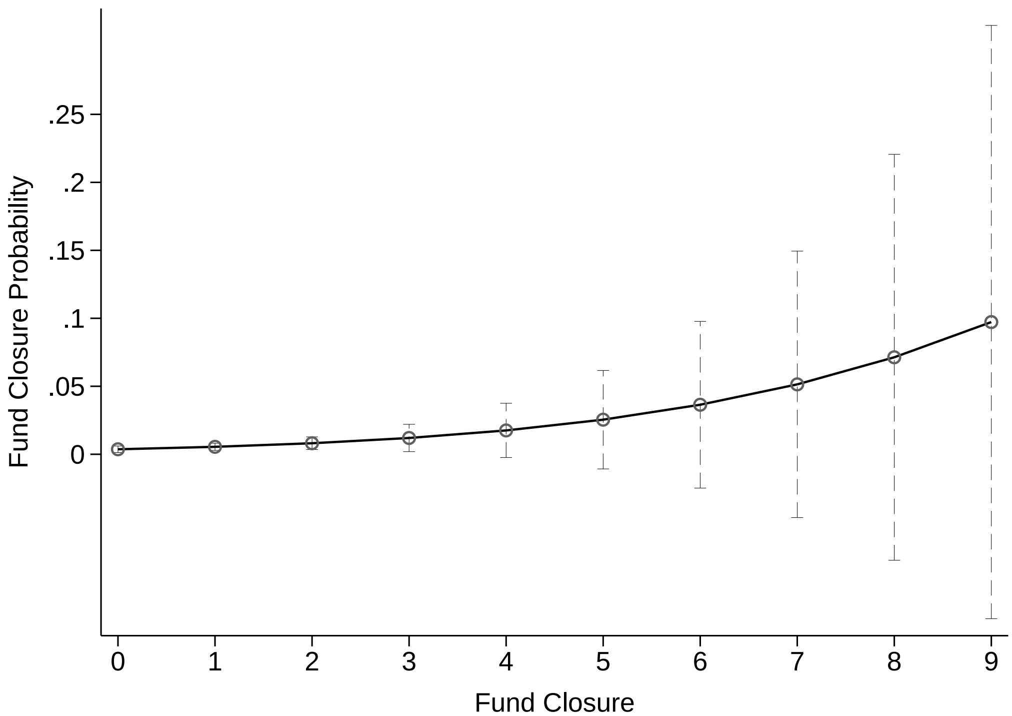
This figure compares how fund closure probability reacts to changes in the economy of scope and scale variable, as represented by the sale by bank variable. The dashed lines denote the 95% confidence interval.

Figure 8: Effects of fund size on fund closure probability



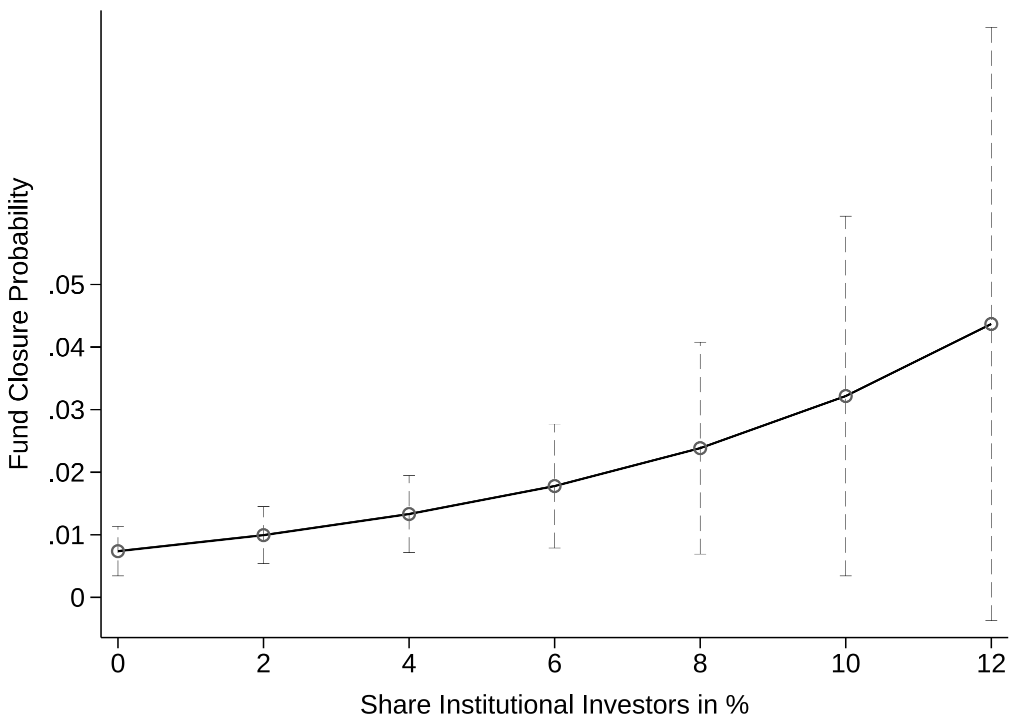
This figure compares how fund closure probability reacts to changes in the economy of scope and scale variable as proxied for by fund size. The dashed lines denote the 95% confidence interval.

Figure 9: Effects of the number of fund closures on fund closure probability



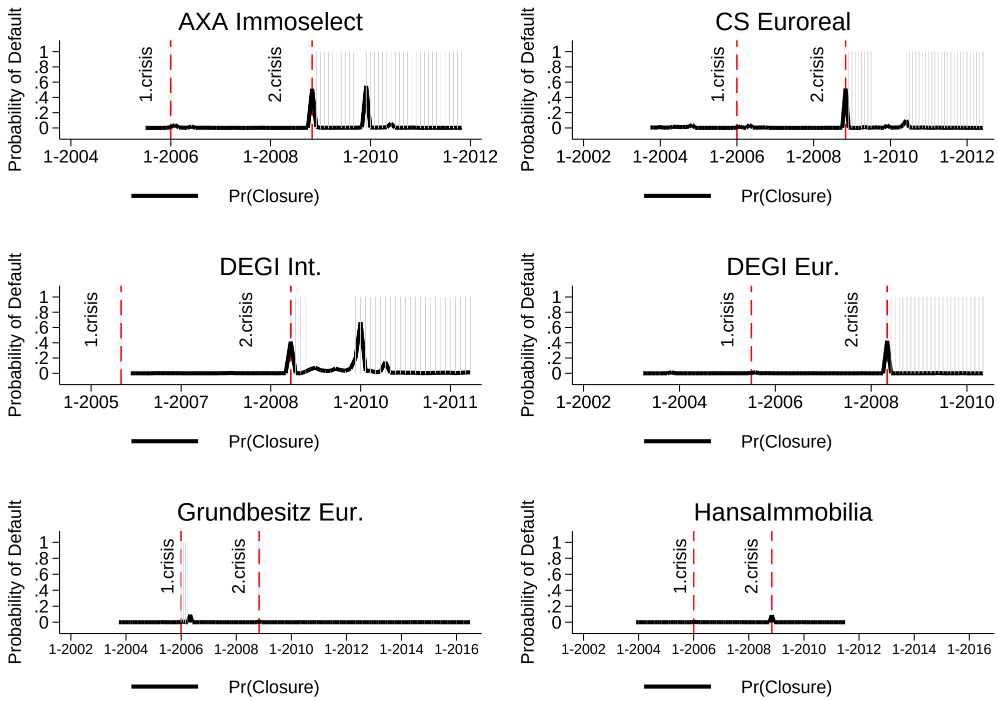
This figure compares how fund closure probability reacts to changes in the spillover variable as represented by the number of fund closures. The dashed lines denote the 95% confidence interval.

Figure 10: Effects of the share of institutional investors on fund closure probability



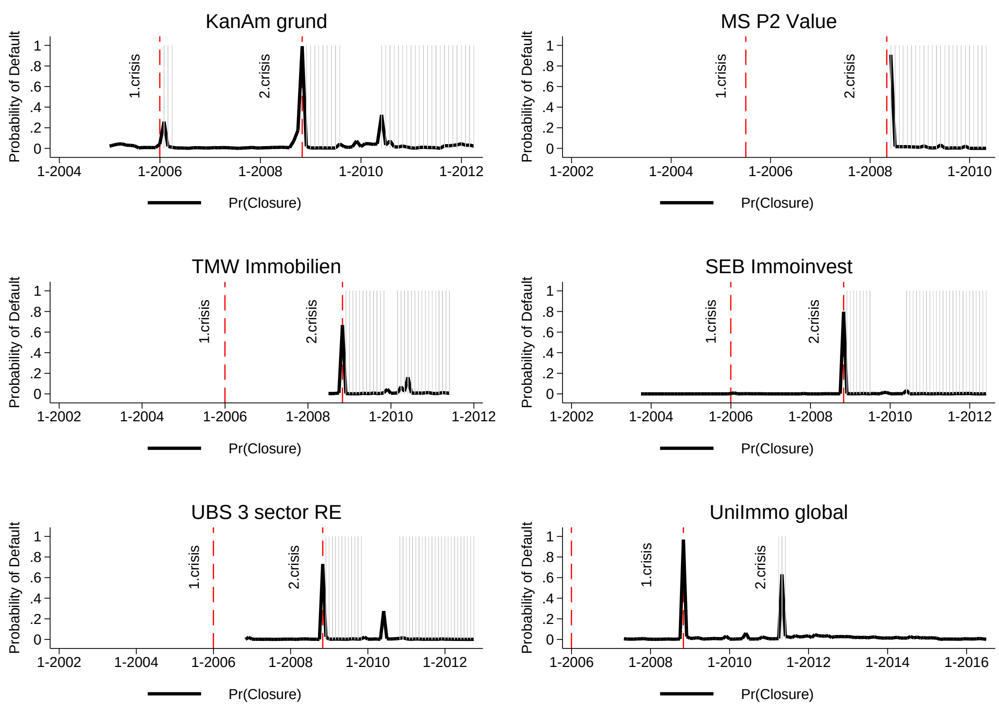
This figure compares how fund closure probability reacts to changes in the share of institutional investors. The dashed lines denote the 95% confidence interval. The figure is based on the results of the reduced model specification including the share of institutional investors.

Figure 11: The predicted fund closure probability of distressed funds I



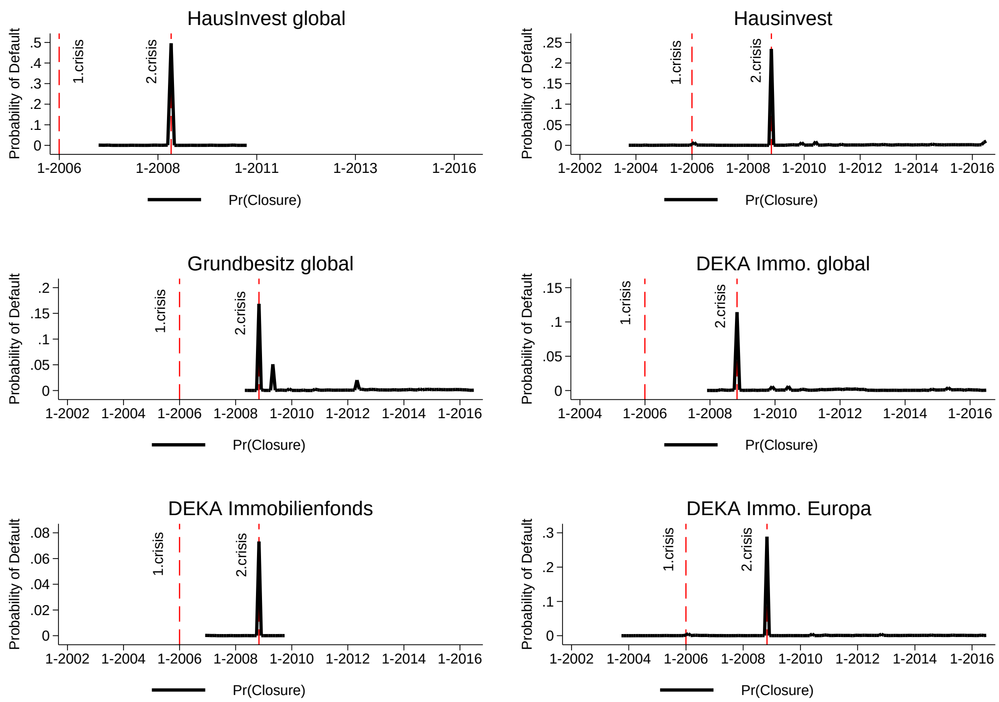
This figure shows the predicted fund closure probability of all distressed open-end real estate funds. It validates the predictive power of the panel logit regression. Most funds show their highest closure probability at the date of actual closure. Predicted fund closure probability after the actual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

Figure 12: The predicted fund closure probability of distressed funds II



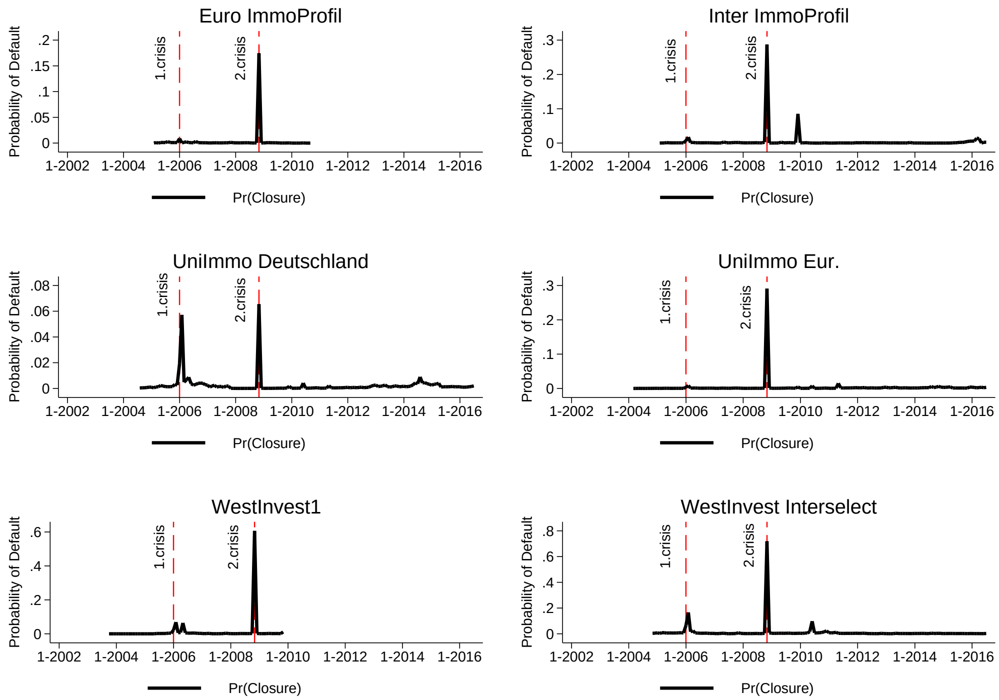
This figure shows the predicted fund closure probability of all distressed open-end real estate funds. It validates the predictive power of the panel logit regression. Most funds show their highest closure probability at the date of actual closure. The predicted fund closure probability after the actual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

Figure 13: 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 14: 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.

Tables

Table 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.

Table 2: Overview summary statistics

	Mean	Std. Dev.	Min	Max	Obs
Closure	0.007	0.082	0	1	2932
Liquidity	0.253	0.122	0.007	0.814	2821
Individual Fund Flows	0.002	0.036	-0.566	0.77	3092
Fund size	36.118	32.767	0.692	136.896	3227
Age	242.873	173.667	25	599	3122
Sale by bank	0.392	0.488	0	1	3174
TER	0.008	0.002	0	0.015	2555
Total Return	0.012	0.078	-0.579	0.489	2497
Leverage	0.221	0.113	0	0.641	2798
Institutional	0.02	0.048	0	0.319	2145
Industry Fund Flows	2.278	8.954	-43.588	33.581	3247
Fund Closure	0.198	0.939	0	9	3247

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

Table 3: Correlation Matrix

Variables	Closure	Liquidity	Ind. Flows	Fund size	Age	Sale by bank	TER	Return	Leverage	Inst.	Industry Flows	Fund Closure
Closure	1.00											
Liquidity	-0.07	1.00										
Ind. Flows	-0.17	0.10	1.00									
Fund size	-0.02	-0.03	0.01	1.00								
Age	-0.05	-0.21	-0.09	0.29	1.00							
Sale by bank	-0.05	0.11	-0.05	0.23	0.17	1.00						
TER	0.01	0.04	0.09	-0.15	-0.12	0.14	1.00					
Return	-0.05	0.23	0.04	0.13	0.07	0.10	-0.13	1.00				
Leverage	0.10	-0.29	-0.03	-0.41	-0.20	-0.18	0.27	-0.28	1.00			
Inst.	0.11	-0.16	0.02	-0.36	-0.33	-0.29	0.15	-0.38	0.35	1.00		
Industry Flows	-0.25	0.07	0.29	0.02	0.03	-0.00	0.00	0.07	-0.06	-0.01	1.00	
Fund Closure	0.44	-0.03	-0.20	-0.02	-0.02	-0.02	0.01	-0.04	0.04	0.06	-0.52	1.00

This table provides the cross-correlation between all variables.

Table 4: Explaining fund closure probability

	(I)	(II)	(III)	(IV)	(V)
VARIABLES	Closure	Closure	Closure	Closure	Closure
Fund-specific Variables					
$Liquidity_{i,t-1}$	-0.0357**	-0.0500**	-0.0950**	-0.0770**	-0.0907**
	(0.0170)	(0.0209)	(0.0385)	(0.0366)	(0.0424)
$Individual\ Fund\ Flows_{i,t-1}$	-0.0685**	-0.0693***	-0.0587	-0.0419*	-0.0526*
	(0.0273)	(0.0253)	(0.0369)	(0.0249)	(0.0289)
$ln\ Fund\ size_{i,t-1}$		0.648*	0.631	0.772*	0.795*
		(0.394)	(0.495)	(0.445)	(0.481)
$ln\ Age_{i,t}$		-1.229***	-0.953*	-1.052**	-1.049**
		(0.373)	(0.489)	(0.503)	(0.501)
$Sale\ by\ bank_{i,t}$		-1.377*	-1.510**	-1.848**	-1.933**
		(0.754)	(0.719)	(0.850)	(0.884)
$TER_{i,t-1}$		2.822**	5.444***	4.372***	4.990***
		(1.164)	(1.610)	(1.557)	(1.559)
$Total\ Return_{i,t-1}$		0.0814**	0.0811	0.0387	0.0552
		(0.0329)	(0.0615)	(0.0937)	(0.0813)
$\Delta\ Leverage_{i,t-1}$		0.169***	0.178***	0.169***	0.172***
		(0.0457)	(0.0638)	(0.0636)	(0.0614)
Industry-wide Variables					
$Industry-wide\ Fund\ Flows_t$			-0.121***		-0.0529
			(0.0159)		(0.0372)
$Fund\ Closure_t$				0.688***	0.446**
				(0.0975)	(0.207)
Constant	-4.004***	-1.984	-5.463*	-4.919*	-5.253*
	(0.486)	(1.964)	(2.867)	(2.745)	(2.811)
Observations	2,529	2,050	2,050	2,050	2,050
McFadden R-squared	0.0300	0.170	0.471	0.507	0.520

This table gives the results of the panel logit model regression. Model I shows the solely influence of fund run risk on fund closure probability. Model II additionally includes further fund-specific variables. In addition, Model III adds the industry-wide fund flows to Model II, whereas Model IV instead includes, besides the fund-specific variables, the fund closure variable. Model V, our preferred model, shows the regressions results of all previous variables combined. Stars denote significance as follows: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Explaining fund closure probability with share of institutional investors

	(I)	(II)
VARIABLES	Closure	Closure
Fund-specific Variables		
$Liquidity_{i,t-1}$	-0.0978***	-0.162***
	(0.0359)	(0.0568)
$Individual\ Fund\ Flows_{i,t-1}$	-0.103*	-0.0539
	(0.0561)	(0.0423)
$ln\ Fund\ size_{i,t-1}$	0.319	2.265***
	(0.591)	(0.841)
$ln\ Age_{i,t}$	-1.006	-1.604**
	(0.615)	(0.660)
$Sale\ by\ bank_{i,t}$	-2.066*	-1.674
	(1.148)	(1.112)
$TER_{i,t-1}$	4.188**	5.154**
	(1.822)	(2.277)
$Total\ Return_{i,t-1}$	0.0876	0.0534
	(0.159)	(0.179)
$\Delta\ Leverage_{i,t-1}$	0.159**	0.191**
	(0.0760)	(0.0800)
$Institutional_{i,t-1}$		0.256***
		(0.0765)
Industry-wide Variables		
$Industry-wide\ Fund\ Flows_t$	-0.0549*	-0.0951***
	(0.0332)	(0.0330)
$Fund\ Closure_t$	0.493***	0.380**
	(0.183)	(0.180)
Constant	-3.135	-7.487**
	(3.187)	(3.589)
Observations	1,622	1,622
McFadden R-squared	0.561	0.619

This table gives the results of our preferred model V without the missing values of institutional investors (I). Model II adds the share of institutional investors to our main model V. Stars denote significance as follows: *** p<0.01, ** p<0.05, * p<0.1.