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Open-ended property funds: Risk and return profile — Diversification benefits and liquidity risks

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ABSTRACT

In addition to the well-established forms of real estate investing (direct and listed), investors can also choose open-ended property funds (OPFs), which are considered a complementary real estate investment option. OPF fund managers generally provide daily liquidity, and these funds must maintain at least 5% liquidity. If liquidity falls below 5%, share redemptions will be temporarily suspended, for a period of up to two years. During this time, investors can only sell shares on the secondary market (exchange), and are thus subject to significant liquidity risk. The objective of this paper is to examine the impact of OPFs as an investment vehicle on the risk and return profile. OPFs in principle have the same underlying as direct and listed real estate investments, but they are subject to a different regulatory regime. Therefore, we analyze the diversification benefits of OPFs in mixed-asset portfolios for various risk measures, investor types, and holding periods. We find that OPFs are ideally suited to reduce portfolio risk. This result holds independent of the holding period and whether in- or out-of-sample Monte Carlo portfolio simulations are used. However, these positive effects come at the cost of increased risk from temporary share redemption suspensions. During these periods, investors may have to accept an average 6% discount in the secondary market compared to the net asset value calculated by OPFs themselves. These discounts can go as high as 20% if investors fear that OPF management will not be able to ensure liquidity within the two-year time limit, and will have to "fire-sell" properties.

1. Introduction

Over the past two decades, investments in real estate have increased dramatically. This growth is at least partially driven by the perceived diversification benefits that real estate offers in multi-asset portfolios. Both direct and listed real estate investments can take advantage of these benefits. However, although the underlying asset is the same, direct and listed real estate investments have very different institutional setups and hence different risk-return profiles (for example, the volatility of respective indices for listed real estate is much higher than for direct real estate — see Table 3). Especially liquidity risk can be very different for varying real estate investments, and can potentially offset diversification benefits.

In this paper, we investigate open-ended property funds (OPFs) as a further means – besides direct and listed real estate investments – to add real estate to institutional and private portfolios. Fund managers invest directly in an internationally diversified real estate portfolio, while holding a cash-equivalent position ranging from 5% to 49% of assets under management for daily liquidity. The resulting historical returns are attractive and quite consistent, with little risk and low correlation with other asset classes. However, the downside is that OPFs must temporarily suspend share redemptions if fund liquidity falls below 5% (see Maurer et al., 2004). Fund managers will then have a maximum of two years to either attract sufficient new asset inflows and/or to liquidate portfolio properties to ensure fund liquidity again. During this time, investors cannot redeem shares, but can sell them in a secondary market. However, market prices can have discounts to the net asset value (NAV) of up to about 20%. Also, there is the risk that fund managers will not have enough liquidity to reopen within the two-year time limit, and may have to sell properties at a loss to ensure liquidity ("fire-sale"). In this case, the realized prices for the sold properties are highly uncertain. Thus, OPF investors bear liquidity risk.

The innovative thrust of this study is threefold. We aim to 1) analyze the impact on the return distributions of OPFs as a further investment option besides direct and listed real estate investments (see Section 4), 2) identify the suitability of German OPFs as an essential building block in private and institutional portfolios (Section 5), and 3) evaluate the severity of any liquidity risk caused by temporary suspensions of

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share redemptions (Section 6). We will thus determine the optimal weights of OPFs in mixed-asset portfolios by considering the trade-off between risk (as measured by standard deviation, lower partial moments, conditional value-at-risk, and maximum drawdown) and return using portfolio optimization.[1]

In our analyses, we consider the special properties of OPFs, especially the positive autocorrelation that results from return-smoothing and the non-normality of the return distribution. Furthermore, we perform several Monte Carlo simulations (in- and out-of-sample) to evaluate OPF characteristics in mixed-asset portfolios for different holding periods.

Ultimately, we find that OPFs can play an important role in a portfolio context for all investor types examined here, regardless of which risk measure is considered or which holding period is chosen. However, there is one condition: that OPF share redemptions not be temporarily suspended.

To investigate potential liquidity risks for OPF investors, we examine short- and long-term valuation effects around the temporary suspension of share redemptions during the only two periods it has occurred (2005/2006 and 2008/2010). We find that investors were not negatively affected if they did not sell their shares in the secondary market (exchange), and if the OPFs provided liquidity before the end of the two-year time limit. Investors who did sell their shares in the secondary market had to accept on average a 6% discount off the NAV calculated by the OPFs themselves.

For OPFs *unlikely* to reopen before the two-year time limit, there is high uncertainty about their NAVs compared to the realized market prices of sold properties. In these cases, investors will be subject to discounts as high as 20% in the secondary market.

The remainder of this paper is structured as follows. Section 2 gives an overview of the related literature. Section 3 introduces OPFs and describes the construction of an appropriate market index. Section 4 provides descriptive statistics for the index and discusses other asset classes. Section 5 introduces the fundamentals of portfolio optimization, and examines how OPFs can impact the risk and return profile of efficient portfolios under several risk measures. It also illustrates the benefits of OPFs for different holding periods. Section 6 evaluates OPF liquidity risk by presenting our examination of fund returns around the temporary suspension of share redemptions. Section 7 summarizes our main results and gives our conclusions.

2. Literature review

Investors' (such as insurance companies, banks, corporations and pension funds) interest in direct and listed real estate investments has increased dramatically in recent years. These instruments seem to provide attractive risk and return profiles, as well as high diversification potential for a mixed-asset portfolio. For that reason many researchers have studied and attempted to model the benefits of establishing diversification strategies for portfolio investments. Within this section we give a comprehensive overview of the evolution in the literature of diversification benefits for direct and listed real estate investments.

Several researchers studied the risk and return characteristics of stocks, bonds, and cash to real estate and analyzed optimal portfolio choice (diversification benefits) of direct real estate investments, including Ross and Webb (1985), Marks (1986), Webb and Rubens (1989) and Ross and Zisler (1991).[2] Ziobrowski and Curcio (1991) extend this literature by exploring potential benefits by adding international real estate investments to a mixed-asset portfolio.

Later studies with direct real estate investments for more countries include Newell and Webb (1994), Quan and Titman (1997), Stevenson (1998), Quan and Titman (1999), Chua (1999), Cheng, Ziobrowski, Caines, and Ziobrowski (1999) and Hoesli, Lekander, and Witkiewicz (2004). All these studies use the classical mean-variance approach and come to the conclusion that direct real estate provides diversification benefits.

More recent studies analyze other issues of investments in direct real estate. Fugazza, Guidolin, and Nicodano (2007) study optimal real estate allocation for long-horizon investors (i.e. considering return predictability). This is of major importance for long run investors, as it is well known that when returns are predictable the mean-variance asset allocation may differ substantially from the long-term one (see Bodie, 1995) while the investor's planning horizon is irrelevant for portfolio choice when returns are independently and identically distributed. Hoevenaars, Molenaar, Schotman, and Steenkamp (2008) study direct real estate investments in an asset-liability framework.

Mixed-asset portfolio studies using listed real estate[3] start with the work by Asabere, Kleiman, and McGowan (1991) and Kleiman and Farragher (1992), who find diversification gains by including REITs in the portfolios. Further evidence on diversification benefits in more countries is given by Eichholtz (1996), Eichholtz and Koedjik (1996), Eichholtz (1997), Mull and Soenen (1997), Gordon, Canter, and Webb (1998), Liu and Mei (1998), Gordon and Canter (1999), Stevenson (1999), Stevenson (2000), Maurer and Reiner (2002), Conover, Swint Friday, and Howton (1998) and Chen, Ho, Lu, and Wu (2005). Another strand of the literature studies real-estate-only portfolios using REITs. The diversification benefits of international investments in REITs are studied in Giliberto (1990), Addae-Dapaah and Kion (1996), Wilson and Okunev (1996), Eichholtz (1997), Pierzak (2001) and Bigman (2002).

Summarizing, these studies suggest that direct and listed investments in real estate are suitable for achieving diversification benefits. However, both investment vehicles have different risk and return profiles, even if the underlying property is equal. This is reflected in a much higher volatility for listed real estate than for direct real estate, which can be interpreted in a way that investment vehicle type also impacts the return distribution for an equal underlying.

As an example, comparable characteristics are found in the option market, where investors can choose to invest in a company share directly or indirectly, with an option based on the same company share as the underlying. Therefore, in this analogy, investment vehicles will significantly impact the risk and return profile because the optional investment alternative reshapes the original return distribution of the underlying.

3. The German OPF market

3.1. Fundamental features

From a legal perspective, an open-ended property fund is a separate special asset, with an investment focus on property initiated and managed by a capital investment company. For investor protection purposes, OPFs are controlled by regulations for identifying, diversifying, and controlling risks, as well as for realizing gains and fund liquidity.[4]

Open-ended property funds were first created in 1959, with the establishment of the "Internationales Immobilien Institut" (the international real estate institute, known as iii-investments). The first German OPF was iii-funds No. 1. Since 1991, there are enough OPFs for a meaningful index formation and statistical evaluation. Especially in recent years the growth of the market has been dramatic. In 1998, there were sixteen OPFs, with assets under management of 43.1 billion Euros. As of February 2009, the market had grown to thirty-five funds managing 82.1 billion Euros. The German OPF market is thus the biggest, and its market capitalization is about one-third of all European Union member countries.[5]

[1] The use of downside risk measures is important to combat potential biases that may result from the violation of the normality assumption for many return distributions (see Sing & Ong, 2000 for a detailed discussion).

[2] For a more detailed overview see the seminal paper by Sirmans and Worzala (2003), Benjamin, Sirmans, and Zietz (1995, 2001) and Hudson-Wilson, Gordon, Fabozzi, and Anson (2005).

[3] For a more detailed overview see also Worzala, Elaine and Sirmans (2003).

[4] See Investmentgesetz (InvG) and Klug (2008) for further details.

[5] According to data from the BVI Bundesverband Investment, Asset Management e.V. (German Asset Management and Investment Association), and Deutsche Bundesbank (German Central Bank).

Table 1
Overview of the German OPF market. This table shows assets under management and the number of included OPFs, generally investable OPFs, and retail-investable OPFs. The number of included OPFs may differ from the number of available OPFs, as funds are only included when covered by BVI and Datastream. The representativeness of included funds is indicated in the "Market Share" column, which gives the ratio of available to reported OPFs. Assets under management are calculated at year-end, except for 2009, which is as of February. The data stem from BVI and Datastream.

Year	Total market of reporting OPFs			Investable OPFs		Retail-investable OPFs	
	Number	In €m	Market share	Number	In €m	Number	In €m
1991	13	10.032	100%	12	10.032	12	10.032
1992	14	13.893	100%	13	13.563	13	13.563
1993	14	21.866	100%	13	21.492	13	21.492
1994	14	25.764	100%	12	25.226	12	25.226
1995	14	29.694	100%	12	29.084	12	29.084
1996	14	37.023	100%	12	36.347	12	36.347
1997	15	40.493	100%	13	39.735	13	39.735
1998	16	43.137	100%	14	42.305	14	42.305
1999	16	49.987	99%	14	49.104	14	49.104
2000	18	47.455	99%	16	46.535	16	46.535
2001	18	54.485	98%	16	54.337	16	54.337
2002	21	69.391	98%	19	69.242	19	69.242
2003	23	83.234	98%	21	83.086	20	81.799
2004	26	85.288	98%	24	84.985	23	83.145
2005	27	80.404	94%	25	80.081	23	77.982
2006	32	73.623	97%	29	72.230	25	69.630
2007	35	80.948	97%	30	78.900	26	75.840
2008	35	81.631	97%	30	79.140	26	75.565
2009	35	82.144	96%	30	79.617	26	75.979

Table 1 provides an overview of the full sample of OPFs from 1991 through February 2009, as well as the subsamples of generally investable funds and retail-investable funds. We form subgroups to examine possible differences in the OPF market based on investability differences. We exclude from the investable OPF subsample any funds that are closed to new investments.[6] Note also that some funds require minimum investments, which can be as much as 350,000 Euros or more. Because these funds are typically not suited for retail investors, we also exclude them from the retail-investable subsample.[7]

For our analysis, we use all OPFs that report their data to the "BVI Bundesverband Investment and Asset Management e.V." (the German Asset Management and Investment Association). To test for consistency, we compare the share prices from BVI with the prices obtained from Datastream. We find twenty-one pricing differences, for an accuracy rate of 99.9%. None of the differences exceeds 1% of the stock price. In the case of a pricing difference, we asked the capital investment company for the price.

For the further analyses, we use all OPFs that are or were covered by both, BVI and Datastream, which ensures the highest possible data accuracy and that the calculated indices are not affected by a survivorship bias. However, our results remain stable when all OPFs are included. This is not surprising, as our sample covers at least 94% of the market.[8] Therefore, we find that the results are not affected from a biased data-generating approach.

In contrast with many other countries, German OPFs are preferred over real estate shares as an alternative investment. OPFs offer three significant advantages, and the regulatory design is similar to the OPF markets in European Union member countries[9]:

(1) The OPF share price is not determined by supply and demand as long as the OPF provides liquidity. Therefore, share prices do not differ from the NAV per share reported by the capital investment companies when there is no temporary redemption suspension. This means that OPF returns tend to be quite smooth, because there is no additional influence from (equity) capital markets.
(2) The number of issued shares varies, which generally ensures high liquidity. As in any investment fund, there is a daily issuance of new shares from buyers and a daily redemption of old shares from sellers.[10]
(3) The rule of risk-spreading governs transactions.[11] This diversification significantly reduces unsystematic risk.

These specific features of OPFs substantially influence their risk-return profile. In general, portfolio returns are determined by rental income, maintenance costs, and value increases or decreases.[12] Rental income and maintenance costs are relatively easy to determine; the primary challenge is gauging changes in value if comparable properties do not trade regularly. Thus, German investment law (§70 para. 2 sentence 2 InvG) mandates that properties be evaluated at least once a year by an independent appraisal board to determine the true market value. The appraisal board members have technical expertise in the area of property market development (§77 para. 2 sentence 1 InvG).

The by law allows the sales comparison approach, the cost approach, and the income approach for the appraisal of fair market value. The income approach is internationally accepted, and is the primary method for valuing OPFs. It appraises a property on the basis of objectively evaluated price and income forecasts, as well as dynamic capitalization rates on the valuation date. Therefore, the daily OPF NAVs are based on the annual expert appraisals since the last valuation date, but do not necessarily represent "true" daily property values.

This valuation approach aims to minimize subjective views about future expectations[13] and to dampen over- and understatements of

[6] The funds Aachener Grund-Fonds Nr. 1, DEGI German Business, DEGI Global Business, KanAm SPEZIAL grundinvest Fonds, and WestInvest ImmoValue are not open to all investors.

[7] The UBS (D) Euroinvest Immobilien fund requires a 350,000 Euro minimum investment; the CS Property Dynamic fund requires a 3 million Euro minimum investment. The SEB ImmoPortfolio Target Return Fund and the SEB Global Property Fund follow the principle "cash on demand only," and are available only to large investors.

[8] Tables and figures are available from the authors upon request.

[9] See, for example, Maurer et al. (2004).

[10] Historically, there have been only two periods when share redemptions were temporarily suspended (2005/2006 and 2008/2010). Both are discussed in detail in Section 5.

[11] At the time of purchase, a property may not constitute more than 15% of the OPF's NAV. Furthermore, the total value of all properties with individual values of more than 10% of a fund's NAV may not constitute more than 50% of the fund's NAV. See InvG § 73 (1).

[12] More than 40% of OPF portfolio properties have leases with residual terms that are longer than January 1, 2014. See BVI Press Release (Attached), 2008.

[13] See Archner (2006) for an extensive analysis.

Table 2
Autocorrelation structure of OPFs. This table shows the autocorrelation coefficient for lags 1 through 12 of the monthly return distributions for the February 1991–December 2008 period for the value-weighted OPF index. Values in bold indicate statistical significance at the 99% confidence level.

Lag	1	2	3	4	5	6	7	8	9	10	11	12
	0.6140	0.5296	0.5192	0.5542	0.5085	0.4613	0.4314	0.4737	0.4839	0.4450	0.3910	0.4244

property values. However, because past appraisal reports are included in the determination of current NAVs, valuation returns are smoothed, an effect known as “appraisal-smoothing.”[14] This smoothing, as well as the less frequent valuations, result in positive autocorrelation of the OPF returns.[15,16] The autocorrelation thus significantly underestimates OPF risk.

Thus, in this paper, we perform an de-smoothing of returns as a correction (see Section 3 for more insights). We use Getmansky et al.'s (2004) method to recompute the return series so that it is free of autocorrelation. This method is based on the estimation of a general moving average process. It can detect arbitrary autocorrelation structures, and can thus cope with annual reappraisals.

A similar problem can also be seen by comparing real estate indices: Those based on expert appraisals at certain valuation dates exhibit less volatility than those based on transactions or new lease agreements.[17] In addition to the positive autocorrelation, we must also consider the non-normality of return distributions for OPFs in our analysis.[18]

3.2. Construction of open-ended property fund indices

To construct an OPF index, we need to first calculate a representative index. We consider all funds covered by the BVI and Datastream[19] beginning in February 1991 (because we have a sufficient number of funds from this date onward), and ending in December 2008. The monthly raw data from the OPFs contain share prices for each month-end. The data are adjusted for share splits and reported net of management fees. Therefore, further analysis is not biased favorably towards OPFs. Dividend payouts are reinvested in the respective fund (before taxes).

For all OPFs, we calculate a monthly pre-tax return based on adjusted share prices. Finally, using the continuous pretax returns of the individual funds, we calculate a value-weighted and an equal-weighted index. Our index can thus be considered a total return index. We use the equal-weighted index to evaluate the robustness of our results because it is not dominated by individual “fund heavyweights.”[20]

4. Portfolio effects from the addition of OPFs — a descriptive analysis

In this section, we examine other asset classes to analyze how integrating OPFs impacts asset allocation. We also discuss the effects of adjusting for “appraisal-smoothing” and illiquidity.

We use the Nikkei 500, the S&P 500, and the DJ Stoxx 600 to represent the equity markets of Japan, the U.S., and Europe, respectively. For fixed income, we use the Japanese, the U.S., the European, and the U.K. Government Bond Index bond indices from J.P. Morgan. We consider the U.K. Government Bond Index separately because the European Government Bond Index excludes U.K. bonds. We also allow LIBOR (London Interbank Offered Rate) investments, which is the short-term money market rate.

We do not consider the German market separately (as represented by the DAX and the REXP) because it is implicitly integrated via the European market.[21] In terms of alternative investments, we use the FTSE EPRA/NAREIT Germany index to represent exchange-listed real estate investment trusts (REITs) as a potential alternative to OPFs.[22] We also consider investments in hedge funds (HFRI Fund of Funds Composite Index) and commodities (S&P GSCI).

For all indices, we use total return indices including reinvested distributions. Note that we convert non-Euro-denominated indices into Euros. Finally, we test all indices for autocorrelation effects. We expected to find a positive first-order autocorrelation in hedge fund return time series due to illiquid trading strategies.[23] However, we find autocorrelation only for the OPF indices (see Table 2).

To adjust for appraisal-smoothing and for illiquidity, we use the Getmansky et al. (2004) method, which incorporates the whole autocorrelation structure of the monthly return distribution (see Table 2). This method improves on Geltner's (1991) approach because the entire lag structure is considered simultaneously. In addition, there is no need for a de-smoothing parameter (see Byrne & Lee, 1995 for the problematic determination of the de-smoothing parameter).

The intuition behind this method is as follows. The measurable return, R_t^o, is not the true return. Rather, it is a combination of the true return in previous periods R_t:

$$R_t^0 = \Theta_0 R_t + \Theta_1 R_{t-1} + \ldots + \Theta_k R_{t-k}$$
$$\Theta_j \in [0,1], j = 0, \ldots, k \text{ and } 1 = \Theta_0 + \Theta_1 + \ldots + \Theta_k. \tag{1}$$

Therefore, the measurable return is the weighted sum of the true returns of the previous periods. It is obvious that the mean of the observable returns is equal to the mean of the true returns. And the standard deviation of the measurable returns is smaller than that of the true returns. Eq. (2) describes the relationship between the standard deviations of the true and observable returns:

$$Std\left[R_t^0\right] = \frac{1}{\Theta_0^2 + \Theta_1^2 + \ldots + \Theta_k^2}\sigma \le \sigma, \tag{2}$$

[14] See Ross and Zisler (1991) and Geltner (1991) for an extensive discussion.
[15] Other, more secondary, reasons are inflation-linked lease contracts and the inclusion of inflation in the appraisal.
[16] Maurer et al. (2004) show in this context that the autocorrelation of real returns is substantially lower.
[17] See McAllister, Baum, Crosby, Gallimore, and Gray (2003) and Pagliari, Scherer, and Monopoli (2004) for more detailed discussions.
[18] See Coleman and Mansour (2005) for further details.
[19] We compute three different indices because not all OPFs are investable, and some funds require a high minimum investment. The first index represents the total OPF market; the second includes only investable funds. The third index includes only funds investable for retail investors. There are only marginal differences between the three indices, and our results do not depend on which one is used. Therefore, we use the total market index in the following analysis. Tables are available upon request from the authors.
[20] Different calculation methods did not lead to any changes in our results. Thus, we use only the value-weighted index as per Maurer, Reiner and Rogalla (2004). Tables are available from the authors upon request.
[21] For robustness, we repeated our analysis including the DAX and the REXP. We found no important effects. Tables are available upon request.
[22] We wanted to include an index of German direct real estate to better analyze the “complementary” role of OPFs to the two established investment types. We considered the DIX (Deutscher Immobilien Index), which is published by the data provider Investment Property Databank GmbH (IPD) and tracks German real estate market performance. However, the DIX is only available on an annual basis. Thus, the data granularity does not match our monthly observations. We also decided against changing our methodology to annual observations because we would lose a great deal of information.
[23] See Avramov, Kosowski, Naik, and Teo (2007) for further details.

Table 3
Descriptive statistics for monthly return distributions. This table gives the mean, standard deviation, skewness, kurtosis, square root of lower partial moment 2 with threshold 0 (LPM), conditional value-at-risk (CVaR) with a 95% confidence level, and maximum drawdown (MaxDD) for the monthly return distribution for the period February 1991–December 2008. All measures are based on monthly data. The assets considered are OPFs before and after an autocorrelation (AC) adjustment (using Getmansky, Lo, and Makarov's (2004) method), equity markets (Nikkei 500, S&P 500, DJ Stoxx 600), bond markets (J.P. Morgan Japan, U.S., Europe, and U.K. Government Bond Indices), money markets (MM) (LIBOR), and alternative investments (S&P GSCI, HFRI Fund of Funds Composite Index, and FTSE EPRA/NAREIT Germany). All indices are total return (or their distributions were reinvested), and all are denominated in Euros. We found no autocorrelation effects for the time series of equity and bond markets or for alternative investments. We use the Jarque and Bera (1980) test to test the assumption of normally distributed monthly returns. All statistics are based on continuous returns.

	Open-ended property funds		Equity markets			Bond markets and money markets					Alternative investments		
	With AC	Without AC	NIKKEI	S&P 500	DJ STOXX 600	JPM Japan	JPM US	JPM Europe	JPM UK	MM	S&P GSCI	HFRI FoHF	REITs
Mean (%)	0.42%	0.42%	−0.01%	0.65%	0.37%	0.57%	0.61%	0.63%	0.57%	0.36%	0.30%	0.53%	0.01%
Std. dev. (%)	0.21%	0.33%	6.67%	5.05%	4.87%	3.54%	2.98%	1.13%	2.47%	0.17%	6.35%	1.53%	7.50%
Kurtosis	4.31	5.33	3.05	3.21	4.08	6.29	3.42	3.23	3.55	3.66	4.07	7.39	7.85
Skewness	0.64	0.21	0.21	−0.26	−0.84	1.09	0.50	−0.32	−0.24	1.26	−0.48	−0.48	−0.26
LPM	0.00%	0.02%	2.66%	1.67%	1.71%	1.01%	0.88%	0.23%	0.71%	0.00%	2.27%	0.34%	2.51%
CVaR	0.05%	−0.30%	−13.14%	−10.52%	−12.66%	−5.50%	−4.54%	−1.85%	−4.98%	0.17%	−14.6%	−3.12%	−19.22%
MaxDD	0.21%	1.07%	73.13%	60.82%	58.20%	40.38%	25.28%	6.71%	19.27%	0.00%	61.11%	15.92%	84.30%
Jarque–Bera statistic	30.2***	50.2***	1.53	2.80**	35.5***	139***	10.5***	4.22*	4.78*	60.91***	18.6***	180***	212***

*** Indicates that the assumption of a normal distribution of monthly returns is rejected at the 1% significance level.
** Indicates that the assumption of a normal distribution of monthly returns is rejected at the 5% significance level.
* Indicates that the assumption of a normal distribution of monthly returns is rejected at the 10% significance level.

where σ represents the standard deviation of the true returns (see Table 3 for the effect on the risk measures after de-smoothing).

In order to calculate the true returns, we can estimate the weighting factors $\theta_k$by using a maximum likelihood estimation. We use the information that the measurable returns can be considered as a moving-average process where the weighting factors are constant. Finally, we can calculate the true returns using the estimated weighting factors.

Table 3 illustrates the influence of the autocorrelation on the OPF descriptive statistics. It also provides descriptive statistics for the various indices over our February 1991–December 2008 sample period.

Equity markets have average monthly returns ranging from −0.01% (NIKKEI) to 0.65% (S&P) 500. Bond markets show returns ranging from 0.57% per month for Japan to 0.63% for Europe over our sample period. The OPF average monthly return of 0.42%[24] is higher than the average money market return of 0.36% per month, and higher than the REIT return of 0.01%.

Equity markets on average have the highest total risk as measured by monthly standard deviations, about 4.87% for Europe and 6.67% for Japan. Only commodities and REITs exhibit similarly high standard deviations.

Bond markets have substantially lower monthly standard deviations, about 1.13% for Europe and 3.54% for Japan. Hedge funds exhibit a comparable risk level, with a standard deviation of 1.53% per month.

Note that even after adjusting for the positive autocorrelation from appraisal-smoothing, OPFs have a very low standard deviation of 0.33% per month. Without the autocorrelation correction, this percentage would be only 0.21%. Only the money market exhibits a lower risk, at 0.17%.

Unlike OPFs, REITs exhibit a comparable risk to equity markets, with a standard deviation of 7.5%. When we consider additional (downside) risk measures like the square root of lower partial moments 2 (LPM), conditional value-at-risk (CVaR), and maximum drawdown (MaxDD), we find that the ranking of asset classes from lowest to highest risk remains the same. We are therefore able to account for the “fat tail” risks explicitly, which is not possible with the standard deviation.

Examining higher moments of the return distribution (skewness and excess kurtosis), we find that OPFs exhibit positive skewness. In contrast, European and U.S. equities, European and U.K. bonds, hedge funds, and REITs all exhibit negative skewness. The return distribution of commodities and hedge funds is almost symmetrical.

However, excess kurtosis is positive for all asset classes, especially for OPFs (2.33) and hedge funds (4.39).[25] This implies that the probability of extreme returns is higher than expected under a normal return distribution. Considering the Jarque–Bera statistic in Table 3, we reject the assumption of a normal distribution of monthly returns for all indices when the entire sample period is considered (except U.S. and Japanese equities).

Table 4 shows the correlations of OPFs with the other asset classes. Note that OPFs have almost no correlation with equity markets and other alternative investments, which implies a high diversification potential. They also have a slightly positive and statistically significant positive correlation with bond markets, and a relatively high significant positive correlation (0.48) with money markets. These positive correlations result from investments in liquid money market instruments and in bond markets to ensure fund liquidity.[26]

5. Efficient asset allocation under different risk measures

5.1. Description of the optimization procedure

Because most return distributions are not normal (see Table 2), we must consider higher moments and downside risk measures. Any skewness effects, such as those measured for REITs, will otherwise be neglected, as well as the effects of extreme returns (positive excess kurtosis) that we can observe for hedge funds and OPFs (see again Table 3). We can thus incorporate into the optimization procedure characteristics such as downside risk that are caused by the higher moments of the return distribution. This will also help to reduce the likelihood of biased and suboptimal portfolio weights.

We consider four different risk measures. The last three are suitable for covering the risk in the tail (downside) of the distribution: 1) Std (Markowitz, 1952) 2) LPM (Harlow, 1991), 3) CVaR (Rockafellar & Uryasev, 2000, 2002), and 4) MaxDD (Grossman & Zhongquan, 1993). Hence, LPM, CVaR, and MaxDD implicitly incorporate higher

[24] As a robustness check, we replicated the OPF index of Maurer et al. (2004) for the January 1975–December 2003 time period, and compared the descriptive statistics (with autocorrelation). We found the same monthly mean (0.50%) and monthly standard deviation (0.20%).

[25] The autocorrelation adjustment for appraisal-smoothing increases the kurtosis of OPFs from 4.31 to 5.33. We explain this increase as follows: As kurtosis increases, the probability of extreme returns also increases, which is interpreted as higher risk.

[26] Typical German OPFs have 25% to 49% of their assets invested in money markets and bond markets (see Maurer et al., 2004).

Table 4
Correlation matrix.This table shows the correlations between the asset classes from Table 3. For OPFs, we use the value-weighted total market index; for equity markets, we use the Nikkei 500, the S&P 500, and DJ Stoxx 600; for bond markets, we use the J.P. Morgan Japan, U.S., Europe, and U.K. Government Bond Indices; for money markets, we use LIBOR; and for alternative investments, we use the S&P GSCI, the HFRI Fund of Funds Composite, and the FTSE EPRA/NAREIT Germany indices. Values in boldface are significantly different from zero at the 5% level.

	OPFs	NIKKEI	S&P 500	DJ STOXX 600	JPM Europe	JPM U.S.	JPM Japan	JPM U.K.	REITs	S&P GSCI	HFRI FoHF	MM
OPFs	**1.00**	−0.01	**0.15**	0.09	**0.39**	**0.29**	**0.22**	**0.29**	−0.03	0.06	0.01	**0.48**
NIKKEI	−0.01	**1.00**	**0.49**	**0.52**	−0.02	**0.22**	**0.38**	**0.14**	**0.16**	**0.30**	0.10	−0.04
S&P 500	**0.15**	**0.49**	**1.00**	**0.82**	0.05	**0.46**	**0.23**	**0.32**	**0.35**	**0.30**	0.12	0.03
DJ STOXX 600	0.09	**0.52**	**0.82**	**1.00**	0.01	**0.15**	0.08	**0.23**	**0.46**	**0.29**	**0.16**	−0.05
JPM Europe	**0.39**	−0.02	0.05	0.01	**1.00**	**0.41**	0.23	**0.51**	−0.12	−0.05	−0.14	**0.18**
JPM U.S.	**0.29**	**0.22**	**0.46**	**0.15**	**0.41**	**1.00**	**0.50**	**0.52**	−0.13	**0.20**	−0.01	**0.14**
JPM Japan	**0.22**	**0.38**	**0.23**	0.08	**0.23**	**0.50**	**1.00**	**0.21**	−0.09	0.03	−0.07	**0.20**
JPM U.K.	**0.29**	**0.14**	**0.32**	**0.23**	**0.51**	**0.52**	**0.21**	**1.00**	−0.10	**0.16**	**0.19**	0.03
REITs	−0.03	**0.16**	**0.35**	**0.46**	−0.12	−0.13	−0.09	−0.10	**1.00**	0.01	0.11	−0.04
S&P GSCI	0.06	**0.30**	**0.30**	**0.29**	−0.05	**0.20**	0.03	**0.16**	0.01	**1.00**	**0.18**	−0.02
HFRI FoHF	0.01	0.10	0.12	**0.16**	−0.14	−0.01	−0.07	**0.19**	0.11	**0.18**	**1.00**	0.02
MM	**0.48**	−0.04	0.03	−0.05	**0.18**	**0.14**	**0.20**	0.03	−0.04	−0.02	0.02	**1.00**

Table 5
Optimal portfolio weights and risk reduction potential of all asset classes (Markowitz approach). This table shows the optimal portfolio weights for the minimum standard deviation (Std) portfolio and the annual Std subject to the weight limits discussed in Section 4.1. We perform both analyses for the traditional and modern retail investors. The period is February 1991–December 2008.

	OPFs	NIKKEI	S&P 500	DJ STOXX 600	JPM Europe	JPM US	JPM Japan	JPM UK	REITs	S&P GSCI	HFRI FoHF	MM	Std
Traditional retail investor													
Without OPFs (%)	0%	3%	6%	5%	55%	0%	0%	0%	0%	0%	0%	30%	3.33%
Traditional retail investor													
With OPFs (%)	25%	0%	7%	3%	45%	0%	0%	0%	0%	0%	0%	20%	2.59%
Modern retail investor													
Without OPFs (%)	0%	5%	14%	6%	45%	0%	0%	0%	0%	0%	15%	15%	4.97%
Modern retail investor													
With OPFs (%)	34%	0%	12%	3%	36%	0%	0%	0%	0%	0%	10%	5%	3.35%

moments due to their calculation methods, and can be regarded as a robustness check on the validity of the results when higher moments are ignored.

Next, we use the four risk measures to calculate efficient mixed-asset portfolios for retail and institutional investors. A portfolio is characterized as efficient when no other combination of assets provides lower risk for the same expected return. For the following portfolio optimizations, we minimize the risk (for every risk measure separately) for the given expected portfolio returns $\mathbb{E}[r_p]$. We formulate the optimization problem as follows:

$$\min_{x} \mathrm{RM}(\tilde{r}) \quad (3)$$

subject to the restrictions

$$\mathbb{E}\left[r_p\right] = r \,\text{and}\, x_1 + \ldots + x_n = 1, \forall i = 1, \ldots, n$$

where r_p is the portfolio return, and x_i is the percentage weight invested in security *i*.

The optimization is restricted by budget constraints (full investment), and by non-negative weights (no short sales). Investments can be made in all assets considered in Table 3.

We differentiate among three investor types. The first two represent retail investors with different risk and return attitudes; the third is a representative institutional investor (life insurer). Depending on the risk and return attitudes (retail investors) and the regulatory framework (institutional investors), we set weight ranges for equities, bonds, and alternative investments or upper bounds (for institutional investors, these are set by German investment law).

The weight ranges for retail investors are set according to the average retail investor portfolio weight in Germany for the respective asset class, and depending on the risk and return attitude published by the BVI. We decided to set these ranges because retail investors tend to maintain their initial portfolio allocations, a phenomenon known as anchoring (see Tversky & Kahneman, 1974). However, the investment restrictions do not strengthen or drive the obtained results for the OPFs. We find that the implied optimal portfolio weights for OPFs are always higher when relaxing the restrictions.[27]

The investment restrictions are as follows:

- For a traditional retail investor, we assume weights of 10% to 20% in equities, 45% to 65% in bonds, 0% to 5% in alternative investments, and 20% to 40% in money markets. This investor's portfolio structure is conservatively defensive.
- For a modern retail investor, we assume a more aggressive portfolio, including weights of 15% to 35% in equities and 10% to 20% in alternative investments. Correspondingly, the weights for bond markets (35% to 55%) and money markets (5% to 25%) are lower.

[27] Tables and figures for the optimization without weight restrictions or different weight ranges are available from the authors upon request.

- For a typical German institutional investor, we assume greater regulatory investment restrictions for life insurers. This implies a maximum investment of 20% in foreign exchange positions and 35% in risky investments (like equities and hedge funds). In addition, non-European equities and indirect commodity investments may not exceed 10%, and hedge funds are limited to 5%. The cumulative REITs and OPFs may not exceed 25%.

We use these three investor types and four different optimization risk measures to find the optimal portfolio within the stipulated investment limits. Initially, we perform the optimization without OPFs, adding them afterwards to evaluate the impact of expanding the universe. We further investigate the influence of the financial crisis on the robustness of the optimal portfolio weights.

5.2. Open-ended property funds in retail investor portfolios

To identify the diversification potential of OPFs for retail investors (traditional and modern), we first apply a classical Markowitz optimization (subject to the weight limits discussed in the prior section). We then determine the portfolio weights of the minimum standard deviation portfolio without OPFs.

In the second step, we allow for OPFs, and compare the risk and the optimal portfolio weights of an identical expected return level portfolio (see Table 5). We also apply two robustness checks, as follows: 1) we use the risk measures LPM, CVaR, and MaxDD to identify the downside protection potential for OPFs (see Fig. 1), and 2) we calculate the results from a U.S. perspective (see Table A1).

Both types of retail investors realize a substantial risk reduction (as measured by the standard deviation of portfolio returns) for the same return level when OPFs are added to the portfolio. Traditional retail investors, with a more defensive portfolio configuration, can lower their portfolio annual standard deviations from 3.33% to 2.59% (see Table 5). This translates to an approximately 20% risk reduction. Modern retail investors can reduce risk by about 32% by adding OPFs. Note from Table 5 that the standard deviation is reduced from 4.97% to 3.35% p.a.[28]

In examining the portfolio composition of the traditional retail investor's optimal portfolio, we find that OPFs add a substantial weight of 25% (see again Table 5). Correspondingly, the weights of money markets and bonds are reduced by about 10 percentage points each.

For the more aggressive retail investor, the addition of OPFs is optimal with a 34% weight. OPF investment leads to a reduction in equity and money market weights of about 10% each, as well as a 5% reduction in hedge fund weights.

Interestingly, the weight of bonds is not reduced, but is actually slightly increased by 1 percentage point. For both investors, we do not consider REIT investments, because this asset class is completely dominated by OPFs. Table 5 provides a detailed breakdown of portfolio weights for all asset classes.

Because most return distributions are not normally distributed, we apply the above described analyses for three additional risk measures (LPM, CVaR, and MaxDD) to incorporate potential tail risks (see Fig. 1). Similarly to the Std risk measure, we find that OPFs have higher portfolio weights in modern retail investor portfolios than in traditional investor portfolios. This is not surprising, however, since the traditional portfolio is already defensive.

However, the importance of OPFs decreases as risk measures focus more on the downside. This can be seen by the lower allocation to the LPM, CVaR, and particularly MaxDD risk measures. Nevertheless, we believe that OPFs should have a significant allocation (at least 9%) in the portfolios of both types of retail investors.

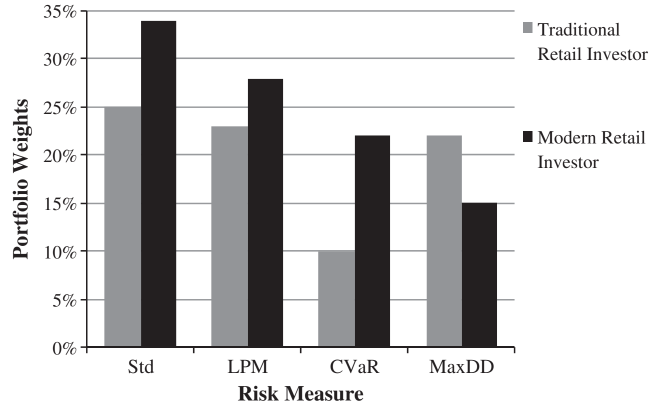

Fig. 1. Optimal portfolio weights for open-ended property funds for different risk measures.This figure shows the optimal portfolio weights subject to the weight limits discussed in Section 5.1 for OPFs in the traditional and modern retail portfolios by applying four different risk measures (Std, LPM, CVaR, and MaxDD). The period is February 1991–December 2008.

To determine whether OPFs significantly enhance portfolio performance, we conduct in- and out-of-sample Sharpe ratio tests according to Jobson and Korkie (1981) and Ledoit and Wolf (2008). For the in-sample test, we use the portfolios constructed above and the historical returns for February 1991–December 2008. We then generate 5000 time series of monthly returns for one year using Efron and Tibshirani's (1994) block-bootstrap method.

For the out-of-sample test, we use the historical returns for February 1991–December 1999 to determine portfolio weights. We then use returns for January 2000–December 2008 to generate 5000 time series of future returns and find that OPFs lead to statistically significant higher Sharpe ratios (see Table 6).

In summary, we tested for the robustness of the obtained optimal portfolio weights for both types of retail investors and applied four risk measures. For downside protection, OPFs decreased in importance, but the optimal holdings were still significant. These results were confirmed by Sharpe ratio tests.

5.3. Open-ended property funds in institutional investor portfolios

Fig. 2 shows the efficient portfolios (efficient frontiers) when we optimize the institutional investor portfolios with and without OPFs, and following the institutional investor constraints described in Section 5.1. The methodology chosen in the previous subsections for retail investors looks different to the presentation here, but it works in the same manner. For retail investors we choose for two types of risk aversion (traditional and modern) weight ranges for different investment types and apply a “point estimator” given the universe of investment opportunities and the restrictions. In comparison we conduct an optimization approach for institutional investors (represented exemplary by life insurers) given their regulatory investment restrictions (see § 88 InvG) and calculate an efficient frontier. When choosing representative optimal portfolios on the efficient frontier both approaches are directly comparable.

Note in Fig. 2 that the efficient frontier is moved upwards by adding OPFs, especially for the defensive portfolios. Hence we find that OPFs improve the risk and return profile significantly.

To verify whether OPFs can also improve the efficient frontier significantly, we conducted a spanning test following Chiang and Lee (2007) and Kan and Zhou (2008). The likelihood ratio test indicates

[28] We repeat our analysis for different time series inception dates. The results show no significant differences. Furthermore, the results hold from a U.S. perspective, and are qualitatively comparable to the EU results (see Table A1).

Table 6
Sharpe ratio test. This table shows the Sharpe ratios for the portfolios of the in- and out-of-sample analyses. Calculations are based on Efron and Tibshirani's (1994) standard block-bootstrap Monte Carlo simulation with five lags and 1000 runs. For the in-sample analysis, we use the periods of February 1991–December 2008 to generate time series of future returns. For the out-of-sample analysis, we use the periods of February 1991–December 1999 to construct the portfolio, and January 2000–December 2008 to construct time series of future returns. For the in-sample analysis, the risk-free return is the average money market rate for February 1991–December 2008 (3.56% p.a.); for the out-of-sample analysis, the period is February 1991–July 1999 (2.69%).

	In-sample	Out-of-sample
Traditional retail investor without OPFs	0.80***	0.23***
Traditional retail investor with OPFs	1.45***	0.38***
Modern retail investor without OPFs	0.87***	−0.13***
Modern retail investor with OPFs	1.23***	0.02***

*** Denotes that the assumption of equal Sharpe ratios is rejected at the 1% significance level, respectively, according to Jobson and Korkie (1981) and Ledoit and Wolf (2008).

a significant increase in the risk and return profile by including OPFs. The exact value of the likelihood ratio is 23.78.

Fig. 3 shows the portfolio composition along the efficient frontier, i.e., the weights of each asset class for the different expected return levels. OPFs are initially included at the regulatory limit of 25%. With an expected return of more than 6.9% p.a., however, their weight gradually decreases as they are replaced by assets with a higher expected return, such as hedge funds. Overall, we conclude that OPFs are important in defensive portfolios geared towards risk reduction, but are also essential in more growth-oriented portfolios.

However, given the non-normality of some return distributions, a central assumption of the Markowitz approach is violated (see Table 2). Therefore, we evaluate the role of OPFs using three downside risk measures (LPM, CVaR, and MaxDD) (see Fig. A1 in the Appendix A). When

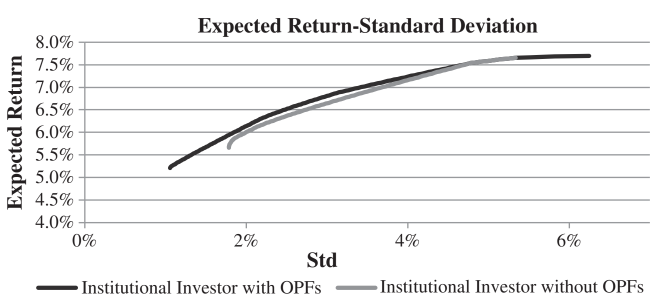

Fig. 2. Efficient portfolios for institutional investors (Markowitz approach).This figure shows the efficient frontiers with and without OPFs using Std as the risk measure and subject to the weight limits discussed in Section 5.1. The observation period is February 1991–December 2008.

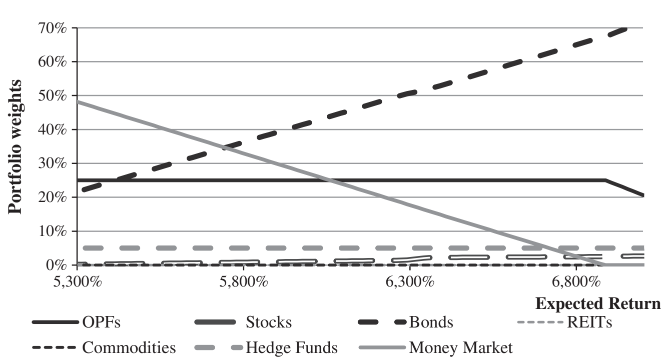

Fig. 3. Composition of efficient portfolios for institutional investors (Markowitz approach).This figure shows the portfolio weights in the portfolios on the efficient frontier for the asset classes we consider. We use Std as the risk measure that depends on the expected return (subject to the weight limits discussed in Section 5.1). The observation period is February 1991–December 2008.

focusing on downside risk, we find that OPFs play a similarly important role as in a Markowitz approach.

5.4. The suitability of open-ended property funds for different holding periods

In the next step, we analyze the influence of OPFs on portfolio returns and risk for different holding periods (this is comparable to Liang, Myer, and Webb's (1996) bootstrap simulation approach). Our starting point is a benchmark portfolio with no OPFs that consists solely of predefined fractions of equities, bonds, and money market investments. Equity and bond allocations are determined by the minimum-variance portfolio for the proxy indices from Table 3 (obtained by a Markowitz portfolio optimization).

From these benchmark portfolios, we successively increase the proportion of OPFs from 0% to 25% in three steps (1%, 10%, and 25%). We simultaneously decrease the other asset class weights uniformly, so that the relative weights of the benchmark portfolio before the inclusion remain constant.

We simulate portfolio returns for the various holding periods (one, five, and ten years) using a bootstrap approach. As a robustness check, we conduct in- and out-of-sample analyses. For the in-sample, we use historical returns from February 1991–December 2008 to determine the allocations of the two asset classes (minimum-variance portfolios for bonds and stocks, respectively) to the benchmark portfolios. Afterward, we construct time series of future returns from the same historical returns.

For the out-of-sample, we use historical returns from February 1991 to July 1999 to construct the benchmark portfolios, and historical returns from August 1999 to December 2008 to construct time series of future returns. We simulate 1000 runs for each holding period.

To gauge how beneficial OPFs are in mixed-asset portfolios for different holding periods, we calculate risk-adjusted performance for every risk measure separately over the three holding periods. We use the same equation: (portfolio return − risk-free return)/risk measure. We calculate the Sharpe ratio (SR) for standard deviation, the Sortino ratio (SoR) for LPM, the return on conditional value-at-risk (RoCVaR) for CVaR, and the Sterling ratio (StR) for MaxDD.

Note from Table A2 that the increase of OPF weights in the benchmark portfolio lowers expected returns in the in-sample analysis for all benchmark portfolios and for all holding periods. However, the successive inclusion of OPFs leads to a steady enhancement of risk-adjusted performance for all risk measures and for all holding periods.[29] For the out-of-sample analysis, we find that OPFs not only

[29] Note that the RoCVaR decreases as the weight of OPFs in the benchmark portfolio increases, in contrast to all other risk-adjusted performance measures. However, this indicates an increase in risk-adjusted performance as well, because a higher CVaR indicates lower risk. The interpretation of the RoCVaR is thus inverse compared to other risk-adjusted performance measures.

enhance risk-adjusted performance, but also increase portfolio returns for all holding periods and initial benchmark compositions.[30]

In summary, we show that the return distribution has favorable risk and return characteristics when OPFs provide daily liquidity. On this basis, OPFs are intensively allocated to investor portfolios (regardless of the optimization method used or the investor type considered). We also demonstrate the validity of our results for different holding periods.

However, as we noted in the introduction, these positive attributes come at a cost: OPF managers must temporarily suspend share redemption if liquidity falls below 5%. We next discuss the primary risk for investors: that they may need to sell their shares on the secondary market during the suspension. Note further that the value of liquidity can be quite large. As Benveniste, Capozza, and Seguin (2001) show, claims on illiquid assets can increase by as much as 12%–22%.

Illiquidity can also have a major impact on portfolio composition. Anglin and Gao (2011) analyze how the liquidity (autocorrelation and trading inability) of an asset can affect an individual's investment decision when that individual has an uncertain need to liquidate. They find that this illiquidity can change the risk profile dramatically.

Furthermore, Lin and Vandell (2007) show that illiquidity creates a difference between ex-ante and ex-post returns. Although the expected returns are equal, ex-post risk is found to be lower than ex-ante risk by a factor dependent on illiquidity. Because this factor can be large even for long holding periods, illiquidity can severely affect portfolio composition.

However, Bond, Soosung, Zhenguo, and Vandell (2007) and Lin, Liu, and Vandell (2009) show that this illiquidity risk can be lowered when holding illiquid assets that have uncorrelated illiquidity risks. Cheng, Lin, and Liu (2010) also study the difference between ex-ante and ex-post risk. They introduce an illiquidity risk metric and integrate it with price risk to make different asset classes comparable. For real estate, they find that using their illiquidity risk metric increases risk significantly and hence reduces optimal real estate exposure in portfolios.

Finally, Bond and Slezak (2010) incorporate illiquidity into a portfolio optimization approach with uncertainty aversion, following Garlappi, Wang, and Uppal (2007). In this setting, the allocations to real estate are also lower than in standard portfolio optimization approaches. To summarize these findings, illiquidity should be a major factor for investors when investing in real estate.

However, the liquidity risk associated with OPFs is different from that of common direct real estate investments. Under normal circumstances, OPFs provide perfect liquidity, i.e., shares can be redeemed at net asset value. This is different from direct real estate, especially when “direct real estate” refers to office buildings or shopping malls. When fund liquidity falls below 5%, shares cannot be redeemed and thus must be sold on the secondary market. For these reasons, we modeled illiquidity implicitly by de-smoothing the OPF return series, which increases all risk measures (see Table 3 again). This increase in risk also affects optimal portfolio holdings negatively, as noted in the literature cited above, where illiquidity is considered explicitly. We strongly believe our approach satisfies the features of OPFs more fully. We follow Cumming, Haß, and Schweizer (2010) and Cavenaile, Coën, and Hübner (2011) by using the “corrected” return series in the asset allocation, and we analyze the special liquidity risk of OPFs arising from secondary market trading in the next section.

[30] This result remains valid when we use the August 1999–December 2008 period to construct the benchmark portfolios, and when we use the February 1991–July 1999 period to construct time series of future returns.

6. Liquidity risk analysis for open-ended property funds

In this section, we analyze OPF performance around the temporary suspension of share redemptions and the resulting (potential) liquidity risk that arises from trading in the secondary market at the regional exchange Börse Hamburg.

OPFs are required to redeem shares daily, so they normally hold some liquid assets because of the difficulty of disposing of property quickly. Investment laws in Germany (§ 80 InvG) mandate minimum holdings of 5% and maximum holdings of 49% of assets in cash, money market instruments, or bonds, which ensure theoretically that redemptions of outstanding shares can be met at all times. As Table 4 shows, the risk and return profiles of OPFs are positively correlated with money markets and bond markets, and do not correspond as much with property positions.[31]

However, there is an ever-present risk that investors may try to redeem too many shares at a time, and that the liquidity position could become too low to satisfy all the redemptions. If the liquidity position falls below 5%, OPFs may suspend share redemptions in order to raise funds by, e.g., selling property investments.[32] As detailed in § 80c para. 2 InvG and § 81 InvG, these periods of suspension can last up to two years.[33]

The primary reason for such share redemption suspensions is a real estate market downturn, which often results from a downturn in the capital markets. For example, during a downturn, landlords may find they can no longer obtain the same level of rental income. Furthermore, they may not be able to sell their properties at reasonable prices quickly enough. OPF management will desire to maintain their prior high appraisal values so they can adjust the NAV to market developments. Investors fearful of such developments may thus try to redeem more shares than have been issued and over a shorter time period than usual.

In the event of a temporary suspension of share redemptions, investors can sell their shares on the secondary market. However, the prices they obtain may not be comparable to the NAVs calculated by capital investment companies. Prices on the secondary market can be lower due to slower value adjustments, appraisals, earnings management, and liquidity reduction. Note also that the NAV may not be generally reflective of the market's assessment of share value, but the secondary market will be. In the next two subsections, we discuss how the secondary OPF market developed and we gauge the impact on investors, over both the short and long term.

6.1. Major development of the secondary OPF market

German OPFs have experienced temporary suspensions of share redemptions twice in their history, during 2005/2006, and during 2008/2010.[34] However, there were different circumstances surrounding each period, as we explain further next.

Prior to the 2005/2006 suspension, the market feared that some funds would need to revalue at least part of their property portfolios. This high appraisal uncertainty led to massive share redemption in a short period, and three funds (DB Grundbesitz Invest, KanAm Grundinvest and KanAm Grundinvest US) temporarily suspended redemptions (see Fecht & Wedow, 2010).

[31] See Maurer et al. (2004) and Gullett and Redman (2005) for more extensive discussions.

[32] See Sebastian and Tyrell (2006) for further details.

[33] By law, a fund may only suspend redemptions for a maximum of twelve months. By contractual agreement, this can be extended to twenty-four months. Alternatively, management may opt to only partially suspend redemptions, so that shares can only be redeemed monthly instead of daily.

[34] For a detailed description of events during the 2005/2006 period, see Bannier, Fecht, and Tyrell (2007).

It is obvious, when we compare the events of both periods, that the temporary suspension during the 2008–2010 global financial crisis was more significant for the OPF market. Investors' liquidity preferences increased considerably after the crisis, as they were much less willing to risk tying up funds for up to two years in the face of such severe market volatility. Thus, as compared to the 2005/2006 period, the second crisis was ultimately a global one.

A total of twelve OPFs suspended share redemptions from October 27 to 30, 2008. One of the OPFs had reopened by January 2009, and by December 2009, eight more had begun redeeming shares again. But the uncertainty continued. By November 2009, temporary share redemption suspensions were instituted again at two of the OPFs that had reopened.

6.2. Estimation of OPF market liquidity

To further study and assess how the suspensions affected valuations, we use data from the Börse Hamburg, which is a regional exchange that OPFs use for secondary market transactions. From January 2, 2004 to December 8, 2009, a period that covers both the crisis periods, we obtain data for all traded OPFs for all trading days, including prices and the number of shares traded.

To obtain a first impression about OPF market liquidity and the associated liquidity risks, we investigate several measures in the secondary market (trading volume, as well as the Amihud (2002) and Roll (1984) liquidity measures). We thus capture periods with and without suspensions of share redemptions. In the case of suspensions, the measured liquidity is composed of OPFs that suspended share redemptions and those accepting share redemptions.

However, OPF fund management fixes prices only once per day, meaning investors must commit to selling before they can know the prices. Thus, they may wish to sell on the secondary market even when share redemptions are not suspended. OPFs also have a further risk motivation (the temporary suspension risk). We analyze this risk and the associated valuation effects in the next two subsections.

As Fig. 4 shows, trading volume and the average number of funds traded on the secondary market increased dramatically during the two crisis periods (see also Table 7). We note further that the length of the suspensions was negatively correlated with trading volume. During the 2008–2010 global crisis, trading volume increased to an average of 10 million Euros per day (compared to about 4 million during the first crisis).

We next analyze liquidity, especially the price impact of orders, in the OPF market, in order to deepen our understanding of how resistant the market is during "normal" and more volatile times. However, we cannot observe liquidity directly, as it has several dimensions that cannot be captured by a single measure. To quantify liquidity risk, we use two common measures: the Amihud (2002) measure, and the Roll (1984) measure.

Table 7
Amihud's (2002) and Roll's (1984) liquidity measures. This table shows the mean and variance of Amihud's (2002) (scaled by the factor 10^6) and Roll's (1984) liquidity measures for all OPFs traded at Börse Hamburg during crisis and non-crisis periods. Crisis periods are December 2005–April 2006 and October 2008–December 2009. The complete observation period is January 2004–December 2009. Differences in means and variances between crisis and non-crisis periods are tested with t-tests and F-tests respectively.

	Amihud liquidity measure		Roll liquidity measure	
	Mean	Variance	Mean	Variance
Crisis periods	0.6719	0.1011***	0.2738	0.0026**
Non-crisis periods	0.6772	0.3741***	0.3027	0.0043**

*** Indicates that the assumption of equal means respectively variances are rejected at the 1% significance level.
** Indicates that the assumption of equal means respectively variances are rejected at the 5% significance level.

Roll's liquidity measure is order-based. In the absence of intraday data, we can approximate the spread, the difference between the bid and the ask, by using the serial covariance of price changes, which is calculated as follows:

$$S = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})},$$

where ΔP_t is the price change on day t.

Amihud's liquidity measure, in comparison, is trade-based. It measures the price impact, defined as the absolute price change per Euro of trading volume:

$$ALM = \frac{|r_t|}{Volume_t},$$

where r_t is the return on day t, and $Volume_t$ is the Euro trading volume on day t.

Fig. 5 shows Amihud's and Roll's liquidity measures for OPFs over time. Noticeable, the liquidity during crisis is as high as during 'normal' times and we do not observe obvious peaks. This finding is also supported by Table 7 as the differences in the average liquidity is insignificant. In contrast, the volatility of both liquidity measures is much higher during 'normal' times. In detail Roll's liquidity measure is almost twice volatile during 'normal' times than during crisis periods, and three times as volatile when considering Amihud's liquidity measure.

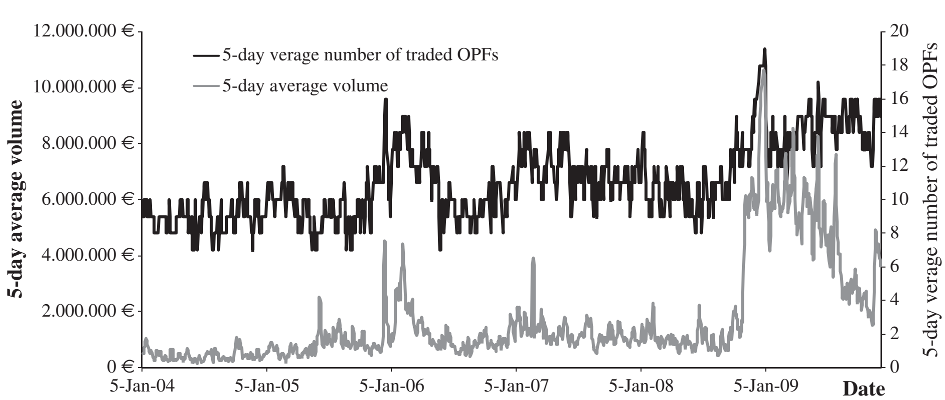

Fig. 4. Number and volume of traded OPFs in the secondary market.This figure shows the daily five-day average number of traded OPFs and the five-day average trading volume from January 2004 to December 2009.

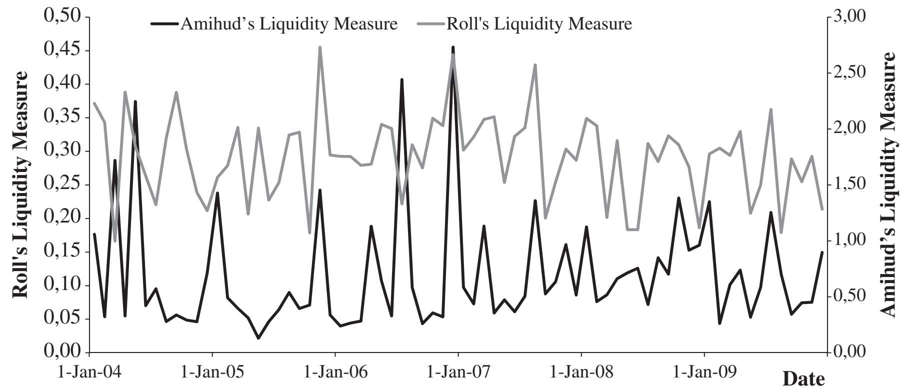

Fig. 5. Amihud's (2002) and Roll's (1984) liquidity measures.This figure shows Amihud's (2002) (scaled by the factor 10^6) and Roll's (1984) liquidity measures for all OPFs traded at Börse Hamburg. The observation period is January 2004–December 2009.

One explanation for this may be that investors with large shareholdings prefer to hold their OPF shares with the expectation of possibly redeeming them when share redemptions are reinstated. Thus, investors might expect that NAVs will not be written down to the same degree that share prices would decrease if sold through the stock exchange.

Even if the secondary market liquidity does not appear to be significantly influenced by crises, investors still tend to reevaluate risk and therefore redeem their shares which can lead to temporal suspension of share redemptions — a special form of liquidity risk not covered by the used liquidity measures. This Phenomenon is explicitly analyzed in the next two subsections.

6.3. Estimation of short-term valuation effects

We next measure market reactions to the temporary suspensions of share redemptions by calculating their discount from the secondary market compared to the net asset value (NAV) calculated by the OPFs themselves around the disclosure date (t_0). Following Brown and Warner (1985) we applied standard event study methodology to calculate the average discounts (*AD*). In detail we firstly divide the difference of every temporarily suspended OPFs NAV and its secondary market price by its NAV. Secondly, we sum up the discounts for all OPFs and divide it by the number of temporarily suspended OPFs.

We use a standard *t*-test statistic to draw statistical inferences about the different event windows for the average discounts (see Table 8). Note from Table 8 and Fig. 6 that the average discount increase significantly for OPFs that announce a suspension of share redemptions. These results hold for all event windows.[35]

The increase in investors' liquidity preferences was reflected in an increase in the average discount: Before the announcement of a suspension, it was about 0%; after the announcement, it increased to about 6%. During a share redemption suspension, there are many sources of uncertainty for investors. For example, how soon will suspended funds reinstate share redemptions? Is there a potential for "controlled liquidation" (will OPFs be forced to sell properties at "fire-sale" prices)? And, furthermore, the secondary market might only be used if investors believe the value of OPF properties will decrease further, since otherwise they could wait until a reopening and sell to NAV.

The discount thus reflects 1) a premium for reduced OPF liquidity (perfect liquidity versus secondary market liquidity) and uncertainty over the duration of the suspension period (up to two years), and 2) the write-off potential if funds are forced to sell or revaluate properties. Investors react to the uncertainty by incorporating into (secondary) market prices the new information that some OPFs have temporarily halted share redemptions.

Table 8
Secondary market comparison of market phases when all OPFs are redeemable and when some are temporarily suspended. This table shows the average discount (*AD*) for different event windows, both tested for statistical significance. In the columns Abnormal trading volume and Traded OPFs, we test the hypotheses that we will find higher trading volume and a higher number of OPFs traded during the specific event windows, compared to periods when no OPF is temporarily suspended.

Event window	AD	Abnormal trading volume	Traded OPFs	Nobs
[−10, +10]	3.28%***	$1.67 \cdot 10^6$***	2.99***	14
[−10, +90]	5.82%***	$3.62 \cdot 10^6$***	3.35***	9
[0, +5]	6.12%***	$3.70 \cdot 10^6$***	3.42***	14
[0, +30]	6.35%***	$4.36 \cdot 10^6$***	4.10***	12
[0, +60]	6.46%***	$4.38 \cdot 10^6$***	4.13***	9
[0, +90]	6.57%***	$4.10 \cdot 10^6$***	3.37***	9
[0, +120]	6.50%***	$3.81 \cdot 10^6$***	2.78***	9

*** Indicates statistical significance at the 1% level.

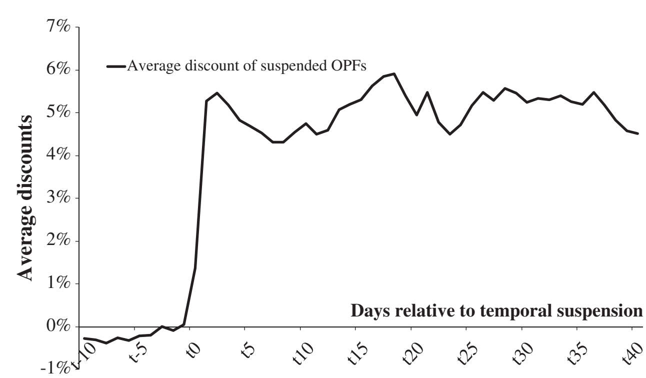

Fig. 6. Average discount of suspended OPFs relative to temporary share redemptions.This figure shows the average discount of suspended OPFs for both the 2005/2006 and 2008/2010 crisis periods relative to the suspension date t_0.

[35] We also calculate AD_t based on capital instead of equal weighting. The results remain stable. Tables are available upon request from the authors.

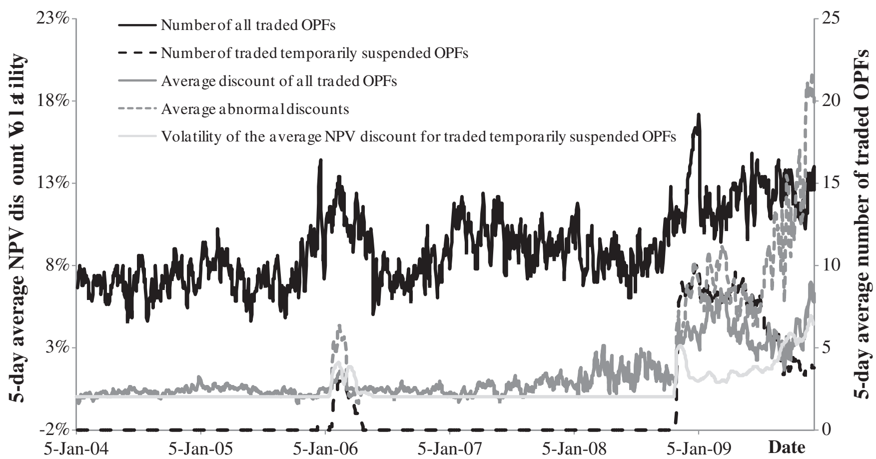

Fig. 7. Descriptive survey of the secondary market for OPFs.This figure shows the number of all traded OPFs (five-day average), the number of all temporarily suspended OPFs (five-day average), the average discount of all traded OPFs, the average abnormal discounts, and the volatility of the average NPV discount for traded temporarily suspended OPFs from January 2004 to December 2009.

Obviously, from Table 8 and from Figs. 6 and 7, we note that the secondary market dynamics change during redemption suspensions. As illustrated by the increases in trading volume and the number of traded OPFs during both periods, investors tend to flock to the secondary market when OPF liquidity decreases.

Note that the magnitude of the second crisis, when comparing the discounts, is again much higher than the first. We can see clearly from Fig. 7 how the average abnormal discounts increased, peaking at 20% by the end of the observation period. We interpret this as evidence that the market expects the three remaining OPFs not to begin accepting share redemptions again before the end of the two-year time limit, thus forcing a "fire-sale" of properties to ensure liquidity (controlled liquidation).

Therefore, we can interpret one part of the abnormal average discount as the market's expectation of seeing a discount off the OPF's NAV when management is forced to sell properties. Further evidence is the steep increase in volatility of the abnormal average discount at the end of the observation period. Because the two-year time limit is known, we believe the uncertainty must be driven by the uncertainty surrounding the expected property selling prices.

6.4. Estimation of long-term valuation effects

In this subsection, we compare the short-term valuation results with a buy-and-hold alternative. We again use OPFs that temporarily suspended share redemptions, and we determine how investors fared if they held their shares, instead of selling on the secondary market. To estimate the abnormal returns for the temporarily suspended OPFs versus the overall OPF market, we use three time frames: 1) the twelve-month period prior to the suspension, 2) the actual period of suspension, and 3) the twelve-month period after the suspension. To retain an investor perspective, we use buy-and-hold abnormal returns (BHARs) to gauge how the OPFs that suspended redemptions ultimately performed compared to the overall market.

Table 9 analyzes the first crisis period, 2005/2006. Note that average BHARs are positive for all three time periods, which implies that the sample of suspended OPFs performed better than the overall market before, during, and after the suspension. Examining the individual funds in Table 10, we see that only the DB Grundbesitz-Invest shows slightly negative returns before and during the suspension. However, its BHAR for the twelve months after reopening is quite high, at 10.7%.

These results indicate that investors did not redeem their shares before the suspension because of poor performance. Also, the overall positive performance during and after the suspension indicates that no asset fire-sales occurred.

Table 9
Buy-and-hold abnormal returns for temporarily suspended open-ended property funds (detailed analysis). This table shows buy-and-hold abnormal returns (BHARs) for DB Grundbesitz-Invest, KanAm Grundinvest, and KanAm Grundinvest US for the twelve months before suspension of share redemptions, the suspension period itself, and the twelve months afterwards. The benchmark for calculating BHARs is the value-weighted total market index without the suspended funds. The KanAm Grundinvest US is denominated in U.S. dollars, and was not converted to Euros for this analysis. The calculation of BHARs is based on continuous returns, and follows Barber and Lyon's (1997) approach. The data for the prices and distributions of the temporarily suspended funds come from Thomson Financial Datastream.

BHAR	DB Grundbesitz Invest	KanAm Grundinvest	KanAm Grundinvest US
12 months before suspension	−0.49%	3.13%	3.90%
During suspension	−1.52%	1.91%	2.36%
12 months after suspension	10.70%	1.38%	1.90%

Table 10
Buy-and-hold abnormal returns for temporarily suspended open-ended property funds. This table shows average buy-and-hold abnormal returns (BHARs) for temporarily suspended open-ended property funds for the twelve months before suspension of share redemptions, the suspension period itself, and the twelve months afterwards. The benchmark for calculating BHARs is the value-weighted total market index without the suspended funds. The KanAm Grundinvest US is denominated in U.S. dollars, and was not converted to Euros for this analysis. The calculation of BHARs is based on continuous returns, and follows Barber and Lyon's (1997) approach. The data for the prices and distributions of the temporarily suspended funds come from Thomson Financial Datastream.

Average of all suspended funds	BHAR
12 months before suspension	2.18%
During suspension	0.92%
12 months after suspension	4.66%

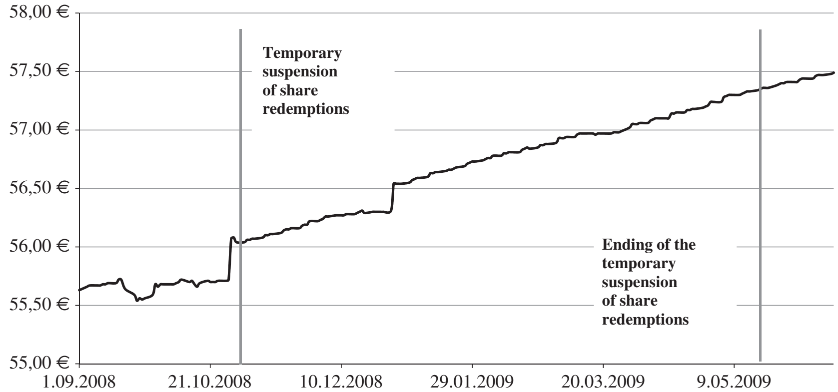

Fig. 8. SEB ImmoInvest performance chart.This figure charts the performance of SEB ImmoInvest from September 1, 2008 to June 15, 2009. Pricing data come from Thomson Financial Datastream.

In contrast to the first crisis period, the drivers of the 2008/2010 period were the financial crisis and the resulting high investor preference for liquidity. Interestingly, we again find no negative BHARs for investors for the twelve months prior to the suspension. The OPFs that suspended share redemptions had a 5.39% average return for the twelve months prior to the event.

The overall market without the suspended funds realized a slightly lower return of 5.21%, which yields a positive BHAR of 0.18%. Admittedly, we cannot conduct the same calculation for the period of share suspension and the subsequent twelve months. Thus, we make a case for one OPF that successfully reopened, although we know the results are likely to be the opposite for OPFs that were not able to provide liquidity again.

As an example, consider SEB ImmoInvest, which realized a 2.4% return during its October 29, 2008 through May 29, 2009 suspension. Fig. 8 graphs SEB ImmoInvest's performance, and shows that no decreases occurred during this period. Note that the share price continued to be calculated on a daily basis by regular appraisal surveys during the suspension. And investors were still able to trade shares on the secondary market.

In summary, the results from our short- and long-term analyses paint different pictures. The short-term analysis highlights that, during temporary share suspensions, investors who opt to sell their shares in the secondary market must accept substantial discounts off the NAV. These discounts have historically peaked at about 20%, and apply especially when investors believe the OPF may need to “fire-sell” properties to provide liquidity.

The results from our long-term analysis, however, show that, during the 2005/2006 crisis, investors were better off holding their shares than selling them in the secondary market. Admittedly, the recent crisis has proven that holding shares until the OPF reopens may only be beneficial if it does indeed reopen within the two-year time limit. Otherwise, investors may face high uncertainty about the selling price of portfolio properties, reflected in discounts as high as 20% in the secondary market.

7. Conclusion

In this study, we aimed to determine how OPFs, an alternative investment vehicle to direct and listed real estate investments, contribute to asset allocation. The specific regulatory framework of OPFs shifts the return distribution of the underlying real estate investment towards relatively steady and smooth returns with low variation. However, investors are subject to substantial liquidity risk when share redemptions are temporarily suspended. Our main results are as follows.

OPFs contribute significantly to investor portfolios by increasing expected portfolio returns, decreasing portfolio risks (as per several risk measures), and increasing diversification in private and institutional investor portfolios. These results hold for different optimization approaches and holding periods, and with an adjustment for autocorrelation in return time series (along with the resulting substantial increase in risk). We tested our results for robustness with several Monte Carlo simulations (in- and out-of-sample).

However, a potential liquidity risk for investors can result if share redemptions for OPFs are temporarily suspended. We studied the only two time periods this has occurred, in 2005/2006 and 2008/2010. We found that, during the first crisis period, the first three German funds that suspended share redemptions outperformed the overall OPF market before, during, and after the suspensions. During the 2008/2010 period (the current financial crisis), however, we found that twelve funds suspended share redemptions, and they exhibited higher average returns than the overall market before the suspension.

We note that some of those funds have already reopened, however, and may yet realize positive returns. And for those OPFs that are unlikely to reopen within the two-year time limit, there is a high uncertainty about the NAVs as reported by the OPFs themselves. Therefore, investors wishing to sell their shares during the redemption suspension must accept discounts as high as 20% in the secondary market (or even higher when controlled liquidation is expected as ultima ratio). Even when the OPFs are likely to reopen in a timely manner, investors normally face discounts of about 6% off the NAVs reported by the capital investment companies.

In conclusion, we show that OPFs offer a high diversification potential for investor portfolios, but there are significant risks if share redemptions are temporarily suspended. We believe OPFs are an attractive alternative to the well-established direct and listed real estate market investments.

Acknowledgments

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Appendix A

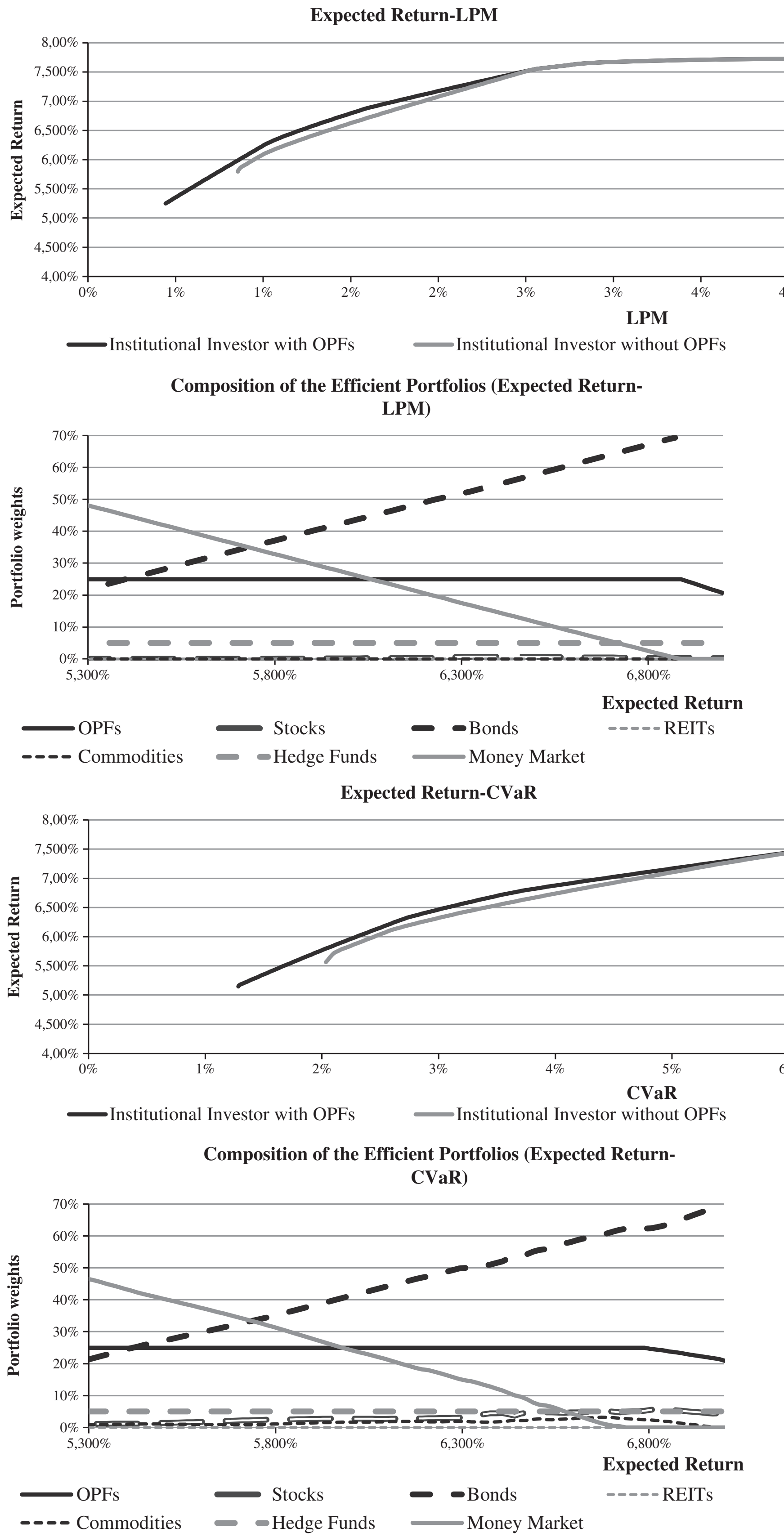

Fig. A1.

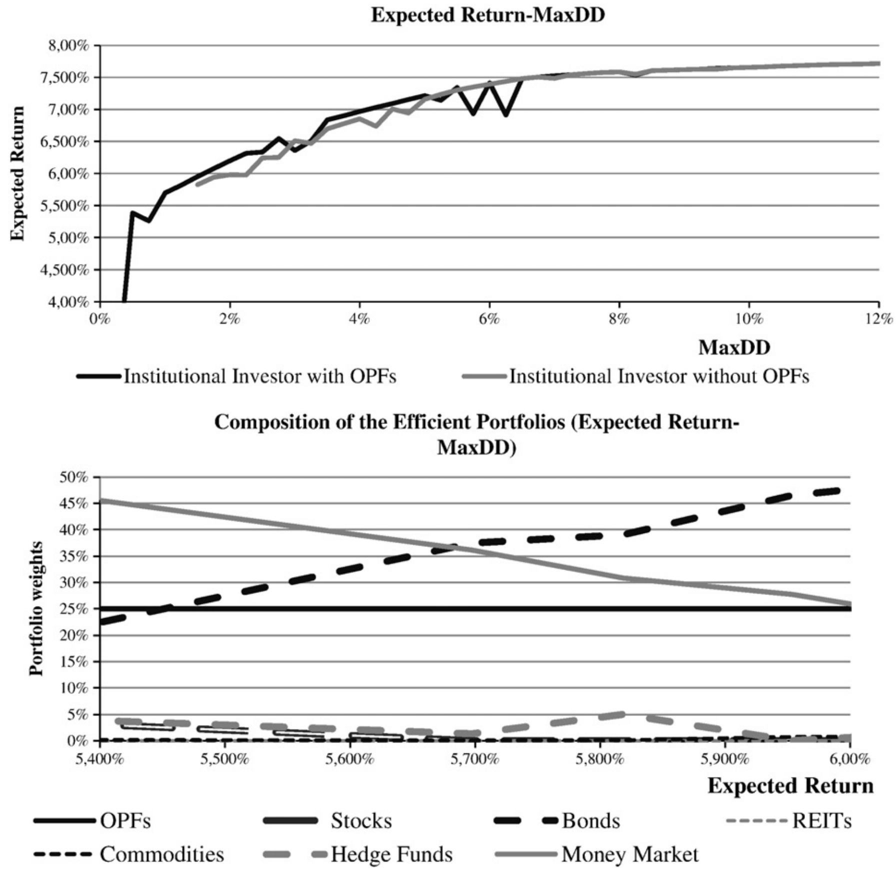

Fig. A1. Efficient portfolios and the respective portfolio holding for institutional investors with downside risk measures.These figures illustrate 1) the efficient frontiers with and without OPFs using LPM, CVaR, and MaxDD as the risk measures of choice, and 2) the portfolio weights for the asset classes in the portfolios on the efficient frontier with LPM, CVaR, and MaxDD as risk measures dependent on the expected return. All calculations are subject to the weight limits discussed in Section 4.1. The observation period is February 1991–December 2008.

Table A1

Optimal portfolio weights and risk reduction potential of all asset classes for U.S. investors (Markowitz approach). This table shows the optimal portfolio weights for the minimum standard deviation (Std) portfolio and the annual Std subject to the weight limits discussed in Section 4.1. All time series have been converted into U.S. dollars. We perform both analyses for the traditional and the modern retail investor. The period is February 1991–December 2008.

	OPFs	NIKKEI	S&P 500	DJ STOXX 600	JPM Europe	JPM US	JPM Japan	JPM UK	REITs	S&P GSCI	HFRI FoHF	MM	Std
Retail investor without OPFs (%)	0%	0%	15%	0%	54%	1%	0%	0%	0%	0%	0%	30%	4.69%
Retail investor with OPFs (%)	20%	0%	10%	0%	10%	32%	3%	0%	0%	0%	5%	20%	2.43%
Retail investor without OPFs (%)	0%	0%	25%	0%	44%	1%	0%	0%	0%	0%	15%	15%	4.51%
Retail investor with OPFs (%)	25%	0%	15%	0%	15%	17%	3%	0%	0%	0%	20%	5%	2.94%

Table A2

Portfolio return and risk for various holding periods. This table shows the expected return, standard deviation, square root of lower partial moment 2 with threshold 0 (LPM), CVaR with confidence level 95%, and maximum drawdown for one- to ten-year holding periods with increasing OPF weights in the benchmark portfolio. The first column gives the initial composition of the benchmark portfolio, which consists only of equities, bonds, and money market investments. Allocations to the three asset classes are determined by the Markowitz portfolio selection process, where the minimum-variance portfolio is selected. When OPFs are included, the equity, bond, and money market weights are reduced accordingly. Calculations are based on Efron and Tibshirani's (1994) standard block-bootstrap Monte Carlo simulation with five lags and 1000 runs. For the in-sample analysis, we use the February 1991–December 2008 period to construct the benchmark portfolio and a time series of future returns. For the out-of-sample analysis, we use the February 1991–December 1999 period to construct the benchmark portfolio, and January 2000–December 2008 to construct a time series of future returns. To evaluate risk-adjusted portfolio performance, we calculate a corresponding risk-adjusted performance measure for each risk measure. For the standard deviation, we calculate the Sharpe ratio (SR), for LPM, we calculate the Sortino ratio (SoR), for CVaR, we calculate the return on conditional value-at-risk (RoCVaR), and for MaxDD, we calculate the Sterling ratio (StR). All risk-adjusted performance measures are calculated using the same arithmetic equation: (portfolio return − risk-free return)/risk measure. For the in-sample analysis, the risk-free return is the average money market rate for February 1991–December 2008 (3.58% p.a.); for the out-of-sample analysis, it is February 1991–December 1999 (2.56%). Results remain stable when using 0% or 3% for the risk-free return.

Benchmark portfolio		OPFs	In-sample				Out-of-sample			
			Portfolio performance			Risk-adjusted performance	Portfolio performance			Risk-adjusted performance
			1 year	5 years	10 years		1 year	5 years	10 years	
Stock 0%–bonds 50%–money market 50%	Exp. return	0%	6.62%	33.34%	68.53%		2.12%	11.42%	25.42%	
		1%	6.60%	33.27%	68.38%		2.14%	11.52%	25.60%	

Table A2 (*continued*)

Benchmark portfolio		OPFs	In-sample						Out-of-sample					
			Portfolio performance			Risk-adjusted performance			Portfolio performance			Risk-adjusted performance		
			1 year	5 years	10 years				1 year	5 years	10 years			
Stock 0%–bonds 50%–money market 50%	Esp. return	10%	6.48%	32.63%	67.02%				2.34%	12.43%	27.20%			
		25%	6.26%	31.53%	64.66%				2.65%	13.90%	29.77%			
	Std	0%	5.35%	12.72%	18.77%	0.57	1.11	1.40	4.67%	10.01%	13.02%	−0.09	−0.21	−0.26
		1%	5.30%	12.60%	18.60%	0.57	1.11	1.41	4.63%	9.91%	12.88%	−0.09	−0.20	−0.25
		10%	4.84%	11.54%	17.12%	0.60	1.16	1.45	4.21%	8.98%	11.66%	−0.05	−0.12	−0.14
		25%	4.06%	9.75%	14.60%	0.66	1.26	1.54	3.51%	7.46%	9.66%	0.02	0.06	0.10
	LPM	0%	2.12%	5.08%	7.46%	1.43	2.77	3.53	1.80%	3.83%	4.92%	−0.24	−0.54	−0.69
		1%	2.10%	5.03%	7.40%	1.44	2.79	3.54	1.78%	3.79%	4.87%	−0.23	−0.52	−0.66
		10%	1.92%	4.61%	6.80%	1.51	2.91	3.65	1.62%	3.44%	4.40%	−0.14	−0.31	−0.36
		25%	1.61%	3.89%	5.79%	1.66	3.16	3.88	1.35%	2.85%	3.63%	0.06	0.14	0.27
	CVaR	0%	0.12%	−1.87%	−2.64%	24.64	−7.53	−9.99	−0.88%	−2.38%	−2.75%	0.50	0.87	1.23
		1%	0.13%	−1.85%	−2.61%	24.02	−7.58	−10.04	−0.87%	−2.35%	−2.72%	0.48	0.84	1.17
		10%	0.15%	−1.66%	−2.37%	19.40	−8.07	−10.50	−0.76%	−2.09%	−2.43%	0.30	0.51	0.66
		25%	0.19%	−1.34%	−1.95%	14.30	−9.19	−11.50	−0.59%	−1.67%	−1.95%	−0.14	−0.25	−0.50
	MaxDD	0%	3.26%	7.09%	9.39%	0.93	1.99	2.80	3.96%	7.99%	9.20%	−0.11	−0.26	−0.37
		1%	3.22%	7.00%	9.28%	0.94	2.01	2.82	3.91%	7.87%	9.05%	−0.11	−0.25	−0.35
		10%	2.83%	6.18%	8.29%	1.02	2.17	3.00	3.44%	6.80%	7.78%	−0.07	−0.16	−0.21
		25%	2.20%	4.85%	6.63%	1.22	2.53	3.39	2.67%	5.12%	5.81%	0.03	0.08	0.17
Stock 25%–bonds 25%–money market 50%	Exp. return	0%	7.58%	38.63%	77.71%				1.41%	8.27%	20.66%			
		1%	7.56%	38.52%	77.50%				1.44%	8.42%	20.90%			
		10%	7.36%	37.52%	75.57%				1.71%	9.69%	23.08%			
		25%	7.02%	35.76%	72.16%				2.15%	11.73%	26.53%			
	Std	0%	7.96%	18.55%	26.57%	0.50	1.05	1.34	7.07%	15.23%	19.89%	−0.16	−0.34	−0.41
		1%	7.88%	18.38%	26.34%	0.50	1.05	1.34	6.99%	15.07%	19.67%	−0.16	−0.34	−0.40
		10%	7.18%	16.84%	24.29%	0.53	1.09	1.37	6.35%	13.64%	17.75%	−0.13	−0.28	−0.32
		25%	6.02%	14.25%	20.79%	0.57	1.16	1.44	5.29%	11.29%	14.63%	−0.08	−0.16	−0.15
	LPM	0%	3.15%	7.42%	10.60%	1.27	2.61	3.35	2.72%	5.85%	7.56%	−0.42	−0.89	−1.08
		1%	3.12%	7.35%	10.51%	1.28	2.62	3.36	2.69%	5.79%	7.48%	−0.42	−0.88	−1.06
		10%	2.84%	6.73%	9.68%	1.33	2.71	3.45	2.44%	5.23%	6.73%	−0.35	−0.73	−0.85
		25%	2.38%	5.69%	8.27%	1.44	2.90	3.62	2.03%	4.32%	5.53%	−0.20	−0.41	−0.41
	CVaR	0%	0.01%	−2.90%	−3.89%	410.30	−6.68	−9.13	−1.47%	−3.77%	−4.33%	0.78	1.39	1.88
		1%	0.01%	−2.87%	−3.86%	291.27	−6.71	−9.16	−1.45%	−3.72%	−4.28%	0.77	1.36	1.85
		10%	0.05%	−2.60%	−3.52%	77.91	−7.04	−9.48	−1.29%	−3.33%	−3.83%	0.66	1.14	1.49
		25%	0.11%	−2.13%	−2.95%	32.65	−7.75	−10.16	−1.02%	−2.69%	−3.09%	0.41	0.65	0.73
	MaxDD	0%	5.27%	11.36%	14.44%	0.76	1.71	2.46	6.48%	13.84%	16.19%	−0.18	−0.38	−0.50
		1%	5.21%	11.23%	14.29%	0.76	1.72	2.47	6.40%	13.64%	15.95%	−0.18	−0.37	−0.49
		10%	4.64%	10.05%	12.91%	0.82	1.82	2.59	5.70%	11.92%	13.82%	−0.15	−0.32	−0.41
		25%	3.69%	8.08%	10.56%	0.93	2.05	2.84	4.54%	9.15%	10.48%	−0.09	−0.19	−0.22
Stock 25%–bonds 50%–money market 25%	Exp. return	0%	6.76%	34.44%	69.63%				2.83%	14.95%	32.18%			
		1%	6.74%	34.36%	69.47%				2.84%	15.02%	32.28%			
		10%	6.59%	33.60%	67.96%				2.96%	15.56%	33.17%			
		25%	6.34%	32.29%	65.35%				3.16%	16.46%	34.63%			
	Std	0%	4.36%	10.42%	15.37%	0.73	1.46	1.79	3.48%	7.50%	9.94%	0.08	0.20	0.34
		1%	4.32%	10.32%	15.24%	0.73	1.47	1.79	3.44%	7.42%	9.84%	0.08	0.21	0.35
		10%	3.94%	9.46%	14.04%	0.76	1.52	1.84	3.13%	6.73%	8.92%	0.13	0.31	0.49
		25%	3.32%	8.03%	12.02%	0.83	1.62	1.93	2.61%	5.61%	7.42%	0.23	0.53	0.79
	LPM	0%	1.74%	4.21%	6.18%	1.82	3.61	4.44	1.34%	2.89%	3.82%	0.20	0.51	0.88
		1%	1.72%	4.17%	6.13%	1.83	3.62	4.45	1.32%	2.86%	3.78%	0.21	0.53	0.92
		10%	1.57%	3.82%	5.64%	1.91	3.76	4.57	1.20%	2.59%	3.42%	0.33	0.80	1.28
		25%	1.32%	3.23%	4.81%	2.09	4.04	4.82	1.00%	2.15%	2.83%	0.60	1.38	2.06
	CVaR	0%	0.20%	−1.37%	−1.95%	15.98	−11.06	−14.07	−0.56%	−1.53%	−1.82%	−0.47	−0.96	−1.86
		1%	0.20%	−1.36%	−1.93%	15.76	−11.13	−14.13	−0.55%	−1.51%	−1.80%	−0.51	−1.01	−1.94
		10%	0.22%	−1.21%	−1.75%	13.92	−11.86	−14.73	−0.47%	−1.34%	−1.59%	−0.85	−1.55	−2.74
		25%	0.24%	−0.96%	−1.44%	11.41	−13.55	−16.05	−0.34%	−1.05%	−1.26%	−1.74	−2.84	−4.62
	MaxDD	0%	2.23%	4.75%	6.37%	1.42	3.20	4.31	2.49%	4.74%	5.36%	0.11	0.31	0.63
		1%	2.20%	4.69%	6.30%	1.43	3.23	4.33	2.46%	4.66%	5.27%	0.11	0.33	0.66
		10%	1.92%	4.11%	5.59%	1.57	3.49	4.61	2.13%	3.98%	4.49%	0.19	0.52	0.97
		25%	1.46%	3.17%	4.42%	1.90	4.12	5.24	1.60%	2.94%	3.30%	0.38	1.01	1.77
Stock 50%–bonds 50%–money market 0%	Exp. return	0%	6.04%	30.90%	62.83%				2.44%	12.83%	27.55%			
		1%	6.03%	30.85%	62.72%				2.46%	12.92%	27.70%			
		10%	5.95%	30.38%	61.75%				2.62%	13.67%	29.05%			
		25%	5.81%	29.58%	60.07%				2.88%	14.90%	31.25%			
	Std	0%	4.02%	9.79%	14.74%	0.61	1.19	1.40	3.48%	7.43%	9.65%	−0.03	−0.09	−0.13
		1%	3.98%	9.70%	14.61%	0.62	1.20	1.41	3.45%	7.36%	9.55%	−0.03	−0.08	−0.11
		10%	3.64%	8.88%	13.43%	0.65	1.26	1.46	3.14%	6.68%	8.66%	0.02	0.03	0.03
		25%	3.06%	7.52%	11.45%	0.73	1.38	1.56	2.62%	5.57%	7.20%	0.12	0.25	0.34
	LPM	0%	1.60%	3.91%	5.85%	1.54	2.98	3.53	1.34%	2.84%	3.64%	−0.09	−0.23	−0.34
		1%	1.58%	3.87%	5.80%	1.55	3.00	3.54	1.33%	2.81%	3.60%	−0.08	−0.20	−0.30
		10%	1.44%	3.54%	5.32%	1.64	3.14	3.68	1.21%	2.55%	3.26%	0.05	0.07	0.08
		25%	1.21%	3.00%	4.53%	1.83	3.45	3.95	1.01%	2.12%	2.70%	0.31	0.66	0.91
	CVaR	0%	0.17%	−1.35%	−2.00%	14.19	−8.62	−10.31	−0.60%	−1.69%	−1.97%	0.20	0.39	0.63
		1%	0.18%	−1.34%	−1.98%	13.98	−8.69	−10.37	−0.59%	−1.67%	−1.95%	0.17	0.34	0.56
		10%	0.19%	−1.19%	−1.79%	12.22	−9.39	−10.96	−0.51%	−1.48%	−1.73%	−0.11	−0.12	−0.15
		25%	0.22%	−0.94%	−1.46%	9.96	−10.99	−12.26	−0.37%	−1.16%	−1.37%	−0.84	−1.21	−1.79

(continued on next page)

Table A2 (*continued*)

Benchmark portfolio	OPFs		In-sample						Out-of-sample					
			Portfolio performance			Risk-adjusted performance			Portfolio performance			Risk-adjusted performance		
			1 year	5 years	10 years				1 year	5 years	10 years			
Stock 50%–bonds 50%–money market 0%	MaxDD	0%	2.19%	4.99%	6.90%	1.12	2.34	2.99	2.71%	5.28%	6.04%	−0.04	−0.12	−0.21
		1%	2.16%	4.92%	6.81%	1.14	2.36	3.01	2.68%	5.20%	5.94%	−0.04	−0.11	−0.18
		10%	1.88%	4.32%	6.04%	1.26	2.58	3.24	2.33%	4.46%	5.07%	0.02	0.04	0.05
		25%	1.43%	3.33%	4.77%	1.55	3.10	3.75	1.77%	3.30%	3.74%	0.18	0.43	0.66
Stock 33%–bonds 33%–money market 33%	Exp. return	0%	5.76%	29.25%	59.12%				3.98%	20.19%	40.85%			
		1%	5.75%	29.21%	59.04%				3.98%	20.19%	40.85%			
		10%	5.69%	28.85%	58.28%				3.99%	20.24%	40.91%			
		25%	5.58%	28.23%	56.99%				4.01%	20.32%	41.01%			
	Std	0%	1.97%	4.70%	6.89%	1.11	2.13	2.46	1.71%	3.92%	5.66%	0.83	1.71	2.13
		1%	1.95%	4.66%	6.83%	1.11	2.14	2.47	1.69%	3.89%	5.60%	0.84	1.73	2.15
		10%	1.80%	4.31%	6.33%	1.17	2.23	2.54	1.54%	3.54%	5.10%	0.93	1.91	2.38
		25%	1.56%	3.76%	5.52%	1.28	2.39	2.68	1.29%	2.98%	4.29%	1.12	2.30	2.85
	LPM	0%	0.76%	1.84%	2.70%	2.85	5.44	6.27	0.68%	1.59%	2.30%	2.09	4.21	5.24
		1%	0.76%	1.82%	2.68%	2.87	5.47	6.30	0.67%	1.58%	2.28%	2.12	4.25	5.30
		10%	0.70%	1.68%	2.47%	3.02	5.71	6.51	0.61%	1.43%	2.07%	2.35	4.71	5.85
		25%	0.60%	1.46%	2.15%	3.31	6.14	6.87	0.51%	1.20%	1.74%	2.84	5.68	7.03
	CVaR	0%	0.30%	−0.45%	−0.68%	7.24	−22.40	−24.99	−0.10%	−0.57%	−0.73%	−13.56	−11.65	−16.47
		1%	0.30%	−0.44%	−0.67%	7.20	−22.67	−25.19	−0.10%	−0.57%	−0.72%	−14.11	−11.84	−16.71
		10%	0.31%	−0.38%	−0.59%	6.86	−25.51	−27.17	−0.07%	−0.49%	−0.63%	−21.91	−13.91	−19.24
		25%	0.31%	−0.27%	−0.47%	6.34	−32.96	−31.49	−0.01%	−0.35%	−0.48%	−170.19	−19.29	−25.40
	MaxDD	0%	0.68%	1.37%	1.76%	3.18	7.29	9.62	0.69%	1.22%	1.48%	2.05	5.51	8.13
		1%	0.67%	1.35%	1.74%	3.23	7.37	9.71	0.68%	1.19%	1.45%	2.09	5.63	8.31
		10%	0.57%	1.18%	1.52%	3.68	8.15	10.58	0.56%	0.97%	1.18%	2.57	6.96	10.27
		25%	0.42%	0.93%	1.21%	4.76	9.71	12.22	0.37%	0.66%	0.79%	3.88	10.42	15.41

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