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Is Volatility the Appropriate Risk Measure for Direct Real Estate?

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IS VOLATILITY THE APPROPRIATE RISK MEASURE FOR DIRECT REAL ESTATE?

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Abstract: The volatility (annualised standard deviation) of returns is probably the most widely used risk measure for real estate. This is somewhat surprising since a number of studies have cast doubts on the view that standard deviation of returns can capture the manifold and complex risks attached to properties. Based on an extensive literature review and an analysis of indi-vidual and market data we provide evidence that volatility alone is inappropriate for measur-ing the risk of direct real estate. Instead we suggest that a combination of quantitative and qualitative risk measures probably more adequately captures real estate risks and conforms better to investor attitudes to risk.

Keywords: risk management, real estate, volatility, portfolio management

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Is Volatility the Appropriate Risk Measure for Direct Real Estate?

Introduction

Since the development of Modern Portfolio Theory (MPT) volatility has become the standard measure of risk for any kind of investment. For a long time this concept was widely accepted by both academics and practitioners in securities markets. However, almost from the beginning doubts were raised as to the appropriateness of volatility (or annualised standard deviation) as the measure for risk in the direct real estate market[1]. In particular, Webb and Pagliari (1995) identified various reasons why volatility as a risk measure for real estate should be seen with some scepticism: (1) the poor quality of the direct real estate data, (2) the cyclicality of real estate returns, (3) high transaction costs, and (4) appraisal based returns which lead to unrealistic volatility values for direct real estate compared with stocks and bonds. In addition, recent studies have provided evidence that real estate returns are not normally distributed which invalidates the standard deviation as an appropriate measure of risk (see, King and Young, 1994; Young and Graff, 1995; Graff et al., 1997; Brown and Matysiak, 2000; Maurer et al., 2004; Young et al., 2006; Morawski and Rehkugler, 2006, Young, 2008, and Richter et al., 2011, among others).

Nonetheless, whilst academics are aware that standard deviation is not an appropriate for direct real estate many still use the volatility as their measure of risk anyway (see, Staley et al., 2008; Cheng and Roulac, 2007; Heydenreich, 2010; Cheng et al., 2010; and Kaiser and Clayton, 2008), Lee, 2003; Lee and Stevenson, 2006; Hoesli et al., 2004; and Pagliari and Scherer, 2005, among others). This is not the case for real estate practitioners. For instance, in a survey of 180 major German real estate companies (housing companies, commercial real estate investors, corporates, and others), Schwenzer (2008), found that only 35% of all respondents use the standard deviation as a risk measure, with the vast majority of real estate managers employing qualitative measures instead. In the UK, Booth et al. (2002) and Frodsham (2007) found that most real estate fund and investment managers use qualitative risk measures. In a similar vein, Dhar and Goetzmann (2005) found that US investors were more concerned about the uncertainty of input data in an investment decision model rather than with the properties' volatility.

Given the importance of the debate as to whether volatility is an appropriate risk measure for direct real estate this paper examines the issue from a theoretical and empirical perspective and contributes to the literature in a number of ways. First, we examine whether volatility is an acceptable, or a coherent, measure of risk by examining whether it satisfies the axioms of Artzner et al. (1999). Second we use the categorisation of Webb and Pagliari (1995) to see if the assumptions on which volatility is based, to be an acceptable measure of risk, apply in a direct real estate market. Next, we test empirically whether individual and market data in the German direct real estate is normally distributed. Lastly we identify the distribution shape of the individual and market data.

The remainder of our paper is structured as follows. The next section will examine whether volatility can theoretically be seen as an appropriate risk measure. Section 3 reviews the conditions needed for standard deviation to be acceptable as a measure of risk in the direct real estate context. The next section presents the results of normality tests on a large sample of individual and index data in the German direct real estate market. The last section concludes

[1] See for example, Cook (1971) and Findlay et al. (1979).

the study and questions whether qualitative risk measures might be more appropriate to estimate future real estate risk and suggest some requirements regarding more appropriate risk measures.

The Appropriateness of Volatility from a Theoretical Viewpoint

To assess the appropriateness of risk measures, several authors have developed a set of axioms that a well-behaved risk measure should satisfy[2]. One that is widely used in the literature was defined by Artzner et al. (1999). The authors consider a risk measure acceptable, or coherent, if it satisfies four specific axioms: subadditivity, homogeneity, translation invariance, and monotonicity. Subadditivity in this context means that the risk of a portfolio should not exceed the sum of the individual risks. A risk measure satisfies the axiom of homogeneity if the risk increases proportionally with the invested capital in a risky investment. Translation invariance means that investing capital in a risk free investment reduces the risk of the portfolio by the additionally invested risk-free amount; therefore less capital is needed to cover the risk. Monotonicity finally means that if a random variable X, under all scenarios, has better values than a random variable Y, the risk of X should be less than the risk of Y.

Volatility satisfies the basic properties of subadditivity and positive homogeneity. However, it does not satisfy the axiom of monotonicity (Tihiletti, 2006). Bradley and Taqqu (2003) also suggest that volatility fails to satisfy translation invariance because the volatility measure does not decrease when an additional amount is prudently invested. Therefore, according to Artzner et al. (1999), volatility cannot be considered an appropriate risk measure. Nonetheless, if an investor defines risk as the deviation of returns from an expected return, volatility is indeed appropriate, according to Pedersen and Satchell (1998).

The Appropriateness of Volatility from an Empirical Viewpoint

This section deals with the question whether the assumptions on which the use of volatility is based, do apply in a real estate context—using the categorisation of Webb and Pagliari (1995): the existence of a significant data base, the efficiency of the real estate market, investors' understanding of risk as the variation of returns, and the normally distributed returns.

Significant data base

An important preposition regarding the appropriateness of volatility as a risk measure for real estate is that the data is sufficient in terms of quality as well as quantity. However, this is often doubted, both for the individual property level and for the portfolio and index level. In this context it is frequently argued that historical return series are not long enough to serve as a basis for risk estimations.[3]

Another problem with the real estate return data that does exist is its accuracy. A problem that occurs when appraisal-based data is used as a proxy for the property's value is the so-called appraisal smoothing effect. According to Geltner (1993), this smoothing effect is "due to the combined effects of appraisers' partial adjustments at the disaggregate level plus temporal aggregation in the construction of the index at the aggregate level", which results in appraisers

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[2] See, for example, Kijima and Ohnishi (1993), Bell (1995), Pedersen and Satchell (1998), and Rockafellar *et al.* (2002).
[3] See, for example, Wheaton *et al.* (2002), Coleman and Mansour (2005), Ducoulombier (2007).

failing to fully capture the actual movement of the property value.[4] Therefore, the fluctuation in the property's value is likely to understate the volatility of real estate.

To solve the problem of the smoothing effect, two alternatives are discussed in the literature, either de-smooth the appraisal based data or use a transaction-based real estate index, both of which are not without their problems. De-smoothing techniques typically use smoothing-factors which express the ratio of volatility of de-smoothed return data compared to the volatility of original appraisal-based data.[5] However, no model to de-smooth the appraisal-based data is perfect, and the calculated smoothing factors depend on both the chosen model and its calibration.[6] And transaction based indexes are problematic as well due to a limited and time-varying number of data points.[7]

Market efficiency

The next assumption for using the volatility as a proxy for real estate risk is that real estate markets are efficient and that returns follow a random-walk. This further implies that it is not possible to forecast risk and return. If however real estate returns do not follow a random-walk but are predictable, it would be inappropriate to use historical volatility as a risk measure. In fact, risk and return characteristics should be forecasted and the use of historical data should be avoided.

However, there is ample evidence that direct real estate markets are, at best, weak form efficient.[8] The reason is in the nature of real estate markets that "are typically characterized by high transaction costs, low turnover volumes, carrying costs, specific tax issues, asymmetric information, and unstandardised heterogeneous commodities, compared in particular to assets on financial markets" (Schindler, 2010). As a consequence real estate markets show significant autocorrelation as such property returns are somewhat predictable and the random-walk hypothesis does not hold.[9]

Investor's definition of risk as the variation of returns

The third assumption as to whether volatility is an appropriate measure of risk depends on the investor's definition of risk. In other words, despite the intuitive appeal and computational convenience of standard risk measures, the definition of risk as a positive or negative deviation from an expected return is increasingly questioned. In particular, Prospect Theory asserts that for many investors loss aversion is more suitable to characterise their attitude to risk than risk aversion *per se*. Because of the high value that is typical for direct real estate investments and various emotional factors, this phenomenon may even be more prevalent for real estate investors.[10] Therefore, employing volatility as a risk measure that captures upside as well as

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[4] See, for example, Webb and Pagliari (1995), Corgel and deRoos (1999).
[5] For an overview of various smoothing-factors that are used in practice see, for example, Hoesli *et al.* (2002), Geltner et al. (2003), Wang (2006).
[6] See, for example, Lee and Stevenson (2006), Marcato and Key (2007), Wang (2006).
[7] See, for example, Feldman (2003), Fourt et al. (2006), Gardner and Matysiak (2006), Fisher *et al.* (2007).
[8] See, for example, Sanders et al. (1995), Maier and Herath (2009), Schindler (2010).
[9] See, for example, Wheaton et al. (1999), Coleman and Mansour (2005). For studies that found autocorrelation in real estate return series see, for example, Newell and Webb (1996), Cheng et al. (2010).
[10] See, for example, Har *et al.* (2005) and Bokhari and Geltner (2010) for studies that found significant loss aversion among real estate investors.

downside potential will lead to results that are not in line with most investors' actual understanding of risk.

Normality of Real estate returns

Finally, from a theoretical perspective volatility can only be an appropriate measure of risk if the direct real estate returns data is normally distributed. However, since the mid-1980s authors such as Miles and McCue (1984b) and Hartzell et al. (1986) first suggested that real estate returns are not normally distributed. Hartzell et al. (1986), for example, stated that "the measures of skewness and kurtosis for the quarterly returns indicate that the distribution of the returns is not normal." However, these studies did not delve deeper into this issue, and it was not until the early 1990s that the normal distribution of direct real estate returns was fundamentally questioned by authors such as Myer and Webb (1992) and Liu et al. (1992). In the following years various studies were published that dealt with the distribution of real estate returns[11]. Following Young et al. (2006), these studies can be classified as either time-series analyses or cross-sectional analyses.

Using data on 2,000 properties in the Russell-NCREIF Property Index between 1978 and 1992, King and Young (1994) concluded that real estate returns are not normally distributed. For the same data set Young and Graff (1995) used the McCulloch's (1986) distributional quantile-based estimation technique and found that annual property returns are not normally distributed for any calendar year during the period 1980-1992 on the cross-section of real estate returns. Given these results, the authors argue that without modification standard risk measures are inapplicable for direct real estate investments. Using the same methodology studies in other countries support this conclusion (Young (2008) in the US, Graff et al. (1997) in Australia, Young et al., 2006; in the UK, and Richter et al. (2011) in Germany).

Brown and Matysiak (2000) were the first to analyse return distributions of individual properties. Based on IPD data, the authors demonstrated that monthly returns are also skewed and leptokurtic, i.e. the monthly data is non-normal. However, the authors found that the return distributions of individual properties are much closer to being normal when using quarterly or annual return data or when aggregated on a portfolio or index level. They concluded that "combining properties into portfolios also increases the probability that the distribution of returns will approach normality".

At least two studies have analysed the distribution of German real estate returns Maurer et al. (2004) and Richter et al., (2011). Maurer et al. (2004) argued that the IPD index history is relatively short and so only allows for analyses of annual returns the authors used publicly available information from German open-ended real estate funds to construct a synthetic real estate index. Then using the quarterly and annual returns data for the period from 01/1987 to 12/2002 the authors analysed the distributional characteristics of German real estate market returns using the Jarque-Bera, the Anderson-Darling and the Shapiro-Wilk normality tests. The authors found that there was no evidence of non-normality in annual returns but that the quarterly return series differed significantly from normality. When further accounting for smoothing of real estate returns as well as for inflation, they found that normality of quarterly and yearly returns could not be rejected in both cases.

[11] See, for example, Byrne and Lee (1997) and Young *et al.* (2006) for reviews.

Richter et al. (2011) used data from the Investment Property Databank (IPD) on 8,938 individual German properties from 2000 to 2009 and tested the normality of total returns, capital returns and income returns for three property-types; retail, office and residential, using McCulloch's (1986) quantile-based methodology. The authors find that the assumption of normality in each return distribution can be rejected for virtually all sub-samples of all property-types and for all years. Nonetheless, Richter et al., (2011) note that the kurtosis values of the income returns were less pronounced than those for the capital returns, which the authors attribute to the stable nature of property income compared with capital values.

In the following section we analyse individual German data similar to Richter et al. (2011), however, there are important differences from their study and ours. First we use data on individual and index data over a longer period with data from 1996 to 2009. Second we use a battery of normality tests rather than one methodology: the Jarque-Bera test (J-B), the Kolmogorov-Smirnov test (K-S), the Lilliefors test (L), the Shapiro-Wilk test (S-W), the Anderson-Darling test (A-D), the Cramer-von-Mises test (C-vM) and the Watson test (W) to see if the results are robust to the different methods employed. Lastly, Richter et al., (2011) argue that "investors can benefit from the knowledge about distribution shapes" since "[i]nvestors pursuing buy-and-hold strategies might need to incorporate different asset-specific risk parameters compared to opportunistic investors", yet provide no evidence as to the distributional shape of German real estate returns. Instead we use the same approach as Lizieri and Ward (2001) to identify the distributional shape of German real estate data.

The Non-Normality of German Real Estate Returns

In this section we analyse the time-series and cross-sectional distributional characteristics of total returns[12] of 939 properties that have at least 10 years over the period from 1996 to 2009 from IPD Investment Property Databank GmbH. This sample consists of 523 office properties, 189 retail properties, 152 residential properties and 75 classified as "others". Due to data confidentiality we did not receive any information on smaller sectors such as industrial properties. Therefore the breakdown of properties in our sample does not equal the breakdown of properties in the whole IPD databank when measured by number of properties; however, the composition is fairly similar when measured by the value.

Subsequently, the time-series and cross-sectional distributional characteristics of two German real estate market indices were analysed in order to provide some information regarding the distribution of market returns. For that purpose, BulwienGesa AG provided us with the German Property Index (GPI) data for the period 1995-2010 and IPD with the German IPD index (also known as Deutscher Immobilienindex, DIX) for the period 1996-2010. The IPD index is a performance index which is constructed from data delivered to IPD by institutional investors. According to the IPD homepage the IPD index comprised of 4,281 properties with an appraisal value of more than €46bn at the end of 2010. The GPI is also a performance index, but based on collected market data instead of individual properties. This makes it more representative for the whole market than the IPD index.

[12] We also examined capital growth and income returns with similar results but due to space limitations we do not report the results. Full results are available upon request.

Time-series analysis of individual properties returns

To analyse the distributional characteristics of the properties' time-series returns, we estimated the average return, standard deviation (SD), skewness and kurtosis statistics of the 939 properties. Then we performed a battery of normality tests: the Jarque-Bera test (J-B), the Kolmogorov-Smirnov test (K-S), the Lilliefors test (L), the Shapiro-Wilk test (S-W), the Anderson-Darling test (A-D), the Cramer-von-Mises test (C-vM) and the Watson test (W). Tables 1 and 2 provide a summary of the results.

Table 1: Distributional characteristics and test statistics of total returns in the sample, 1996-2009

Sector (No. of properties)		Avg. return p.a.	Avg. SD p.a.	Skew-ness	Kurto-sis	Tests						
						J-B	K-S	L	S-W	A-D	C-vM	W
All Property (939)	Mean	2.25%	8.58%	-0.51	3.98	5.42	0.24	0.24	0.84	0.87	0.15	0.14
	Min	-18.78%	0.62%	-3.31	1.11	0.00	0.10	0.10	0.33	0.13	0.01	0.01
	Max	16.94%	64.75%	3.16	12.00	72.72	0.53	0.53	0.99	4.80	0.96	0.91
Office (523)	Mean	1.73%	8.47%	-0.68	3.90	5.21	0.23	0.23	0.84	0.84	0.14	0.13
	Min	-12.00%	0.70%	-3.07	1.36	0.00	0.10	0.10	0.43	0.13	0.01	0.01
	Max	13.52%	45.14%	2.85	10.76	56.02	0.46	0.46	0.99	3.47	0.66	0.61
Retail (189)	Mean	1.69%	9.33%	-0.53	4.10	5.69	0.25	0.25	0.83	0.90	0.15	0.14
	Min	-18.78%	1.59%	-3.24	1.49	0.00	0.11	0.11	0.41	0.15	0.02	0.02
	Max	11.06%	64.75%	2.18	11.73	68.93	0.46	0.46	0.98	3.87	0.75	0.69
Others (75)	Mean	2.71%	8.01%	-0.28	4.22	7.68	0.26	0.26	0.81	1.09	0.19	0.18
	Min	-7.81%	0.62%	-3.31	1.11	0.12	0.11	0.11	0.33	0.17	0.02	0.02
	Max	10.07%	21.91%	3.16	12.00	72.72	0.53	0.53	0.98	4.80	0.96	0.91
Residential (152)	Mean	4.55%	8.31%	-0.02	4.00	4.71	0.24	0.24	0.85	0.81	0.14	0.13
	Min	-10.89%	1.23%	-2.55	1.42	0.00	0.10	0.10	0.50	0.16	0.02	0.02
	Max	16.94%	26.56%	2.46	8.92	34.51	0.46	0.46	0.98	2.89	0.57	0.53

As can be seen from Table 1, the values of the average skewness and kurtosis measures are relatively close to zero and three respectively. Furthermore, the average statistics for most normality tests and most property types indicate measures below the respective critical values[13] hence, for the majority of return distributions, normality cannot be rejected. This result is underscored by the following table that indicates the number of properties for which normality cannot be rejected at the 5% significance level.

[13] For an overview of critical values see, for example, D'Agostino and Stephens (1986).

Table 2: Number of properties in the sample with normally distributed total returns, 1996-2009[14]

Sector (No. of properties)	Tests													
	J-B		K-S		L		S-W		A-D		C-vM		W	
All Property (939)	713	(76%)	900	(96%)	557	(59%)	528	(56%)	510	(54%)	519	(55%)	522	(56%)
Office (523)	405	(77%)	505	(97%)	314	(60%)	304	(58%)	288	(55%)	294	(56%)	296	(57%)
Retail (189)	140	(74%)	182	(96%)	108	(57%)	98	(52%)	101	(53%)	101	(53%)	100	(53%)
Others (75)	53	(71%)	67	(89%)	39	(52%)	36	(48%)	36	(48%)	35	(47%)	36	(48%)
Residential (152)	115	(76%)	146	(96%)	96	(63%)	90	(59%)	85	(56%)	89	(59%)	90	(59%)

Table 2 shows that although the number of properties with normally distributed returns varies depending on the chosen test, the table indicates that for all normality tests and sectors, normality cannot be rejected in more than 50% of the cases. Even though these results are in line with results of other studies that investigated annualized or annual return distributions at the property level, the significance of these results is questionable, due to the relatively short time period which does not cover a full market cycle.

Cross-sectional analysis of returns

In order to arrive at more meaningful results, we conducted a cross-sectional analysis to determine the distributional of the total returns for each year. A major advantage of the cross-sectional analysis over the time-series analysis is that many more data points - up to 939 return observations in some years - are available for each distribution. In order to employ a cross-sectional analysis, we followed Young et al. (2006) and assumed “that expected variations in annual property returns due to differences in property type account for all of the differences in returns on individual properties”. The results are presented in Table 3.

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[14] Normality has been assessed by referring to the estimated p-value for each normality test and each return distribution. A p-value greater 5% hereby indicates that the null hypothesis of a normal distribution is unlikely to be rejected at the 5% significance level.

Table 3: Distributional characteristics and test statistics of total returns in the sample, all properties

Year	Observations	Return p.a.			Avg.	Skew-	Kurto-	Tests						
		Min.	Mean	Max.	SD p.a.	ness	sis	J-B	K-S	L	S-W	A-D	C-vM	W
1996	312	-91.62%	2.64%	57.45%	12.37%	-2.23	18.93	3,558 (0.00)	0.22 (p < .01)	0.22 (p < .01)	0.77 (0.00)	18.46 (0.00)	3.56 (0.00)	3.46 (0.00)
1997	473	-69.31%	2.10%	35.21%	9.55%	-3.15	23.55	9,110 (0.00)	0.20 (p < .01)	0.20 (p < .01)	0.73 (0.00)	26.63 (0.00)	4.89 (0.00)	4.67 (0.00)
1998	556	-46.17%	2.96%	56.28%	9.38%	-0.82	11.48	1,729 (0.00)	0.16 (p < .01)	0.16 (p < .01)	0.81 (0.00)	31.46 (0.00)	5.85 (0.00)	5.70 (0.00)
1999	707	-126.98%	3.14%	48.00%	8.87%	-5.45	73.03	147,953 (0.00)	0.17 (p < .01)	0.17 (p < .01)	0.66 (0.00)	48.20 (0.00)	9.20 (0.00)	8.79 (0.00)
2000	939	-49.73%	5.27%	64.50%	8.65%	0.49	15.47	6,120 (0.00)	0.19 (p < .01)	0.19 (p < .01)	0.78 (0.00)	57.80 (0.00)	11.09 (0.00)	11.05 (0.00)
2001	939	-91.98%	4.38%	59.42%	8.55%	-2.21	27.59	24,417 (0.00)	0.18 (p < .01)	0.18 (p < .01)	0.74 (0.00)	66.47 (0.00)	12.86 (0.00)	12.63 (0.00)
2002	939	-87.79%	4.03%	67.04%	8.18%	-2.07	29.26	27,659 (0.00)	0.17 (p < .01)	0.17 (p < .01)	0.73 (0.00)	64.76 (0.00)	12.51 (0.00)	12.23 (0.00)
2003	939	-102.00%	2.34%	39.19%	8.78%	-3.05	32.40	35,263 (0.00)	0.17 (p < .01)	0.17 (p < .01)	0.75 (0.00)	55.87 (0.00)	10.61 (0.00)	10.14 (0.00)
2004	939	-134.92%	0.18%	40.80%	11.40%	-3.94	33.98	39,982 (0.00)	0.18 (p < .01)	0.18 (p < .01)	0.70 (0.00)	64.42 (0.00)	12.02 (0.00)	10.99 (0.00)
2005	939	-92.79%	-1.42%	40.01%	11.50%	-2.66	17.48	9,307 (0.00)	0.14 (p < .01)	0.14 (p < .01)	0.79 (0.00)	43.48 (0.00)	7.81 (0.00)	6.95 (0.00)
2006	905	-155.23%	-1.52%	54.76%	16.02%	-3.47	25.10	20,236 (0.00)	0.20 (p < .01)	0.20 (p < .01)	0.70 (0.00)	70.24 (0.00)	13.16 (0.00)	12.10 (0.00)
2007	754	-219.61%	3.04%	58.42%	13.12%	-6.49	113.61	389,665 (0.00)	0.17 (p < .01)	0.17 (p < .01)	0.65 (0.00)	48.01 (0.00)	9.30 (0.00)	9.27 (0.00)
2008	608	-79.94%	2.57%	54.59%	10.93%	-1.99	17.32	5,594 (0.00)	0.12 (p < .01)	0.12 (p < .01)	0.81 (0.00)	22.65 (0.00)	3.97 (0.00)	3.81 (0.00)
2009	510	-77.80%	1.62%	62.98%	12.44%	-1.84	13.21	2,504 (0.00)	0.19 (p < .01)	0.19 (p < .01)	0.76 (0.00)	37.65 (0.00)	7.05 (0.00)	6.70 (0.00)

With few exceptions Table 3 shows that normality can be rejected for each of the fourteen years. All normality tests indicate that German total returns are not normally distributed when all properties are considered. Furthermore, for each year the statistical measures indicate that the distributions are negatively skewed, are more peaked near the mean and have weaker shoulders as well as fatter tails than a corresponding normal distribution[15].

This is illustrated by the following figures which show the distribution of continuously compounded returns and the QQ plot of all properties for the period 1996-2009.

[15] Similar distributional characteristics are apparent for the various property types but due to space limitations we do not report the results. Full results are available upon request. .

Figure 1: Density function of total returns of all properties in the sample, 1996-2009

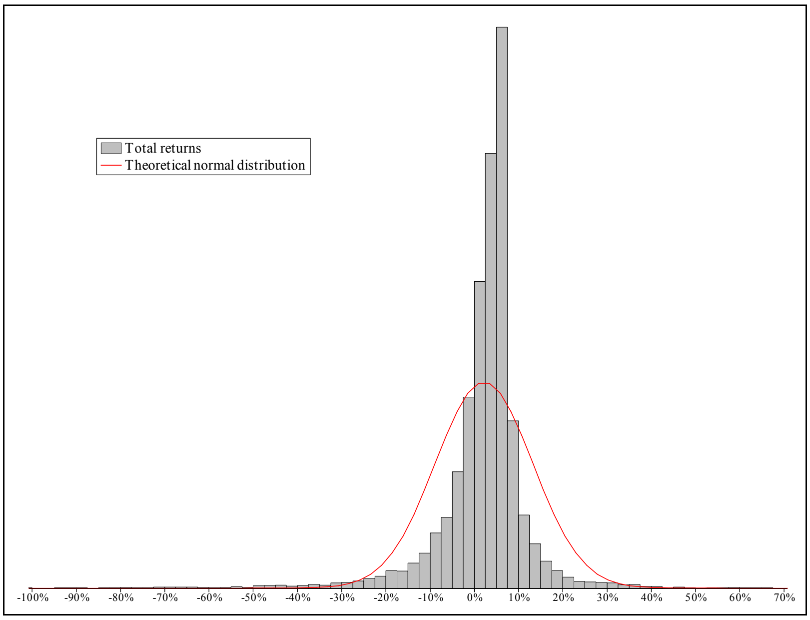
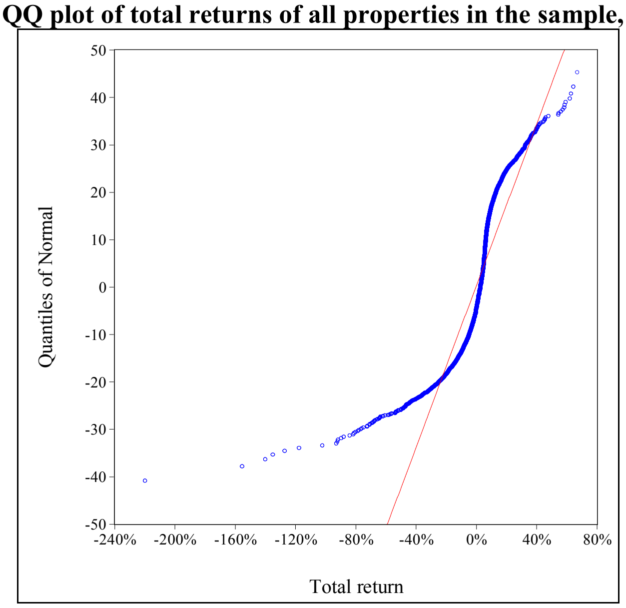


Figure 2: QQ plot of total returns of all properties in the sample, 1996-2009



German real estate market return distributions

Following the same approach we also analysed the distributional characteristics of the two major German real estate market indices: the German IPD index and the GPI by BulwienGesa using continuously compounded annual total returns.[16] Table 4 shows that, when employing five different normality tests, normality could not be rejected for the IPD all property index as

[16] We did not correct the annual data for possible smoothing by following Coleman and Mansour (2005) who concluded that "the application of a statistical model to *unsmooth* returns - has the effect of increasing the size of the second moment (variance). In effect, this will *widen* the distribution of returns, increasing the volatility. But it will not, in general, transform a non-normal return distribution into a normal one."

well as for the GPI index. Also when the IPD sub-indices were analysed, normality cannot be rejected for all property types except for the industrial segment.

Table 4: Distributional characteristics of the German IPD index (1996-2010) and the GPI index (1995-2010)

Sector	Observations	Return p.a.			Avg. SD p.a.	Skewness	Kurtosis	Tests				
		Min.	Mean	Max.				J-B	L	A-D	C-vM	W
IPD All Prop.	15	0.61%	3.43%	5.41%	1.50%	-0.56	2.23	1.15* (0.56)	0.14* (> 0.1)	0.37* (0.43)	0.05* (0.48)	0.05* (0.52)
Office	15	-0.75%	2.98%	5.64%	2.03%	-0.49	2.26	0.93* (0.63)	0.12* (> 0.1)	0.34* (0.50)	0.04* (0.62)	0.04* (0.64)
Retail	15	2.54%	4.54%	6.79%	1.18%	0.06	2.26	0.35* (0.84)	0.14* (> 0.1)	0.26* (0.71)	0.05* (0.58)	0.05* (0.53)
Residential	14	1.30%	4.48%	6.24%	1.43%	-0.90	2.92	1.88* (0.39)	0.20* (> 0.1)	0.56* (0.15)	0.10* (0.13)	0.08* (0.15)
Industrial	14	-2.94%	4.98%	7.40%	2.88%	-1.74	5.26	10.07 (0.01)	0.25 (0.02)	1.28 (0.00)	0.21 (0.00)	0.18 (0.01)
Others	15	0.05%	3.43%	4.93%	1.33%	-1.19	3.87	3.99* (0.14)	0.17* (> 0.1)	0.64* (0.10)	0.10* (0.11)	0.09* (0.15)
GPI Index	16	0.00%	5.94%	10.62%	3.26%	-0.29	1.78	1.21* (0.55)	0.16* (> 0.1)	0.46* (0.26)	0.08* (0.23)	0.07* (0.21)

* indicates that normality cannot be rejected at a 5% significance level

In summary, the results of the analysis indicate that although normality cannot be rejected for annual German market returns, strong evidence was found that normality is likely to be rejected at the individual property level. These results are in line with those reported by Maurer et al. (2004), Morawski and Rehkugler (2006), and Richter et al. (2011).

The Distributional Shape of German Real Estate Returns

If real estate returns are not normal, what are they? Very little work has been undertaken in order to fit more appropriate theoretical distributions to observed frequency distributions. A notable exception is work of Lizieri and Ward (2001) who found out that a logistic distribution fitted best the UK real estate returns. Following the same approach we fitted theoretical distributions to the observed frequency distributions of German real estate returns using @Risk, a Microsoft Excel add-in.

a) Time-series returns of individual properties returns

Using the @Risk software for the individual data showed that the logistic distribution appears to be the most likely theoretical distribution for direct German properties, whereas the normal distribution is ranked as the most likely distribution in less than 10% of the cases, see Table 5.[17] However, due to the small sample size, the significance of these results is questionable, and it is therefore necessary to conduct similar tests on a cross-sectional data set.

[17] The goodness of fit test and of the various property sectors produces similar results but due to space limitations we do not report the results. Full results are available upon request.

Table 5: Frequency of theoretical distributions to be ranked as the most likely distribution, all properties, 1996-2009

Chi-Square test			Anderson-Darling test			Kolmogorov-Smirnov test		
Distributions	Frequency		Distributions	Frequency		Distributions	Frequency	
	Absolut	In percent		Absolut	In percent		Absolut	In percent
Logistic	394	41.96%	Logistic	535	56.98%	Logistic	519	55.27%
Extvalue	223	23.75%	Loglogistic	134	14.27%	Loglogistic	115	12.25%
BetaGeneral	106	11.29%	***Normal***	***87***	***9.27%***	Triang	66	7.03%
Triang	68	7.24%	Weibull	80	8.52%	***Normal***	***60***	***6.39%***
Expon	60	6.39%	Uniform	38	4.05%	Weibull	55	5.86%
Normal	***29***	***3.09%***	Pearson5	17	1.81%	BetaGeneral	55	5.86%
InvGauss	21	2.24%	InvGauss	16	1.70%	Uniform	22	2.34%
Gamma	11	1.17%	Lognorm	15	1.60%	Extvalue	19	2.02%
Loglogistic	9	0.96%	Extvalue	11	1.17%	InvGauss	11	1.17%
Weibull	8	0.85%	Triang	4	0.43%	Lognorm	8	0.85%
Uniform	7	0.75%	Expon	2	0.21%	Pearson5	5	0.53%
Pareto	2	0.21%	Gamma	0	0.00%	Expon	2	0.21%
Pearson5	1	0.11%	BetaGeneral	0	0.00%	Gamma	1	0.11%
Lognorm	0	0.00%	Pareto	0	0.00%	Pareto	1	0.11%
	939	100.00%		939	100.00%		939	100.00%

b) *Cross-sectional returns of individual properties returns*

When fitting theoretical distributions to the cross-sectional return data for all properties, the logistic distribution was again ranked as the most likely theoretical distribution for most years and goodness of fit tests. Only for 2000 did all tests suggested that the data is most likely to follow a log-logistic distribution, and for 2005 the Chi-Square test ranked the Weibull distribution as the most likely distribution. However, as the high test statistics as well as the p-values below 5% for all years and all tests indicate, no theoretical distribution is likely to perfectly fit the empirical data for any of the years under consideration[18].

Table 6: The most likely theoretical distributions to fit the cross-sectional data, all properties, 1996-2009

Year	Chi-Square test			Anderson-Darling test			Kolmogorov-Smirnov test		
	Rank 1 Distribution	Statistic	p-value	Rank 1 Distribution	Statistic	p-value	Rank 1 Distribution	Statistic	p-value
1996	Logistic	185.19	0.00	Logistic	7.11	< 0.005	Logistic	0.14	< 0.01
1997	Logistic	172.53	0.00	Logistic	7.58	< 0.005	Logistic	0.12	< 0.01
1998	Logistic	193.98	0.00	Logistic	13.64	< 0.005	Logistic	0.12	< 0.01
1999	Logistic	215.74	0.00	Logistic	16.18	< 0.005	Logistic	0.11	< 0.01
2000	LogLogistic	311.77	0.00	LogLogistic	23.26	N/A	LogLogistic	0.12	N/A
2001	Logistic	345.93	0.00	Logistic	26.80	< 0.005	Logistic	0.12	< 0.01
2002	Logistic	350.50	0.00	Logistic	26.47	< 0.005	Logistic	0.12	< 0.01
2003	Logistic	349.51	0.00	Logistic	24.14	< 0.005	Logistic	0.13	< 0.01
2004	Logistic	303.37	0.00	Logistic	25.25	< 0.005	Logistic	0.11	< 0.01
2005	Weibull	218.37	0.00	Logistic	17.40	< 0.005	Logistic	0.10	< 0.01
2006	Logistic	285.76	0.00	Logistic	27.23	< 0.005	Logistic	0.12	< 0.01
2007	Logistic	179.72	0.00	Logistic	13.83	< 0.005	Logistic	0.11	< 0.01
2008	Logistic	56.58	0.00	Logistic	5.29	< 0.005	Logistic	0.07	< 0.01
2009	Logistic	184.60	0.00	Logistic	15.94	< 0.005	Logistic	0.14	< 0.01

[18] Similar results were obtained when individual sub-sectors are analysed but due to space limitations we do not report the results. Full results are available upon request.

c) *German real estate market return distributions*

Finally we examined the theoretical distribution of the real estate market return data. The results are presented in Table 7.

Table 7: The most likely theoretical distributions to fit the German market return data

Sector	Chi-Square test			Anderson-Darling test			Kolmogorov-Smirnov test		
	Rank 1 Distribution	Statistic	p-value	Rank 1 Distribution	Statistic	p-value	Rank 1 Distribution	Statistic	p-value
IPD All prop.	Logistic	0.00	1.00	Logistic	0.32	> 0.25	Triang	0.11	N/A
Office	Weibull	0.00	1.00	Weibull	0.24	N/A	Logistic	0.11	> 0.1
Retail	InvGauss	0.40	0.82	Normal	0.25	> 0.25	Normal	0.14	> 0.15
Residential	Logistic	0.57	0.75	Logistic	0.45	> 0.1	Triang	0.17	N/A
Industrial	Logistic	1.00	0.61	Logistic	0.83	< 0.05	Logistic	0.20	> 0.05
Others	Logistic	0.40	0.82	Logistic	0.43	> 0.1	Logistic	0.13	> 0.1
GPI Index	Triang	0.88	0.65	Weibull	0.43	N/A	Weibull	0.15	N/A

In line with the results by Lizieri and Ward (2001), the Chi-Square statistic as well as the Anderson-Darling test suggest that the logistic distribution is most likely to be the best fit for the all property index and most appropriately fits the sub-indices for residential, industrial and other properties. According to Lizieri and Ward (2001) this might be due to the high proportion of returns that are close to zero which "is a result of the thinly traded market and slow arrival of information, resulting in static individual valuations." Slightly different results can be obtained using the Kolmogorov-Smirnov test which ranks the triangular distribution as the best fit for the all property index. In contrast, the Weibull distribution best fits the GPI Index according to the Anderson-Darling and the Kolmogorov-Smirnov test while the Chi-Square test suggests that a triangular distribution is the best fit for this index.

In summary, the findings are somewhat inconclusive as to the 'true' distributional shape of the German real estate index data. Nonetheless, it appears that German real estate returns are closer to a logistic distribution than to a normal distribution.

Conclusions and Implications

This paper has examined whether volatility is an appropriate measure of risk in the direct real estate market from a theoretical and empirical perspective. On theoretical grounds we argue that volatility cannot be considered an appropriate, or coherent, measure of risk. Of course it is not completely without use, but it may yield erroneous results when used for risk control, constructing portfolios or other purposes. Secondly, several fundamental assumptions for the use of volatility as a risk measure do not apply in the direct real estate context. In particular our study of German individual and market data, as well as other studies, find that the assumption of normality does not hold for direct real estate returns. In fact a logistic function can better describe the distribution of real estate returns. Furthermore, there is growing evidence that the definition of risk as the variation of returns does not comply with the common understanding of risk of most investors. Accordingly, many real estate professionals and academics regard downside risk measures as more appropriate.[19] Nonetheless, a review of the real estate literature review reveals that volatility is still widely used for measuring the risk of real estate market data. Furthermore, the downside risk measures are not without their problems. For instance, although downside risk measures better fit with investor's view of risk as

[19] See, for example, Sitivanides (1998), Sing and Ong (2000), Byrne and Lee (2004), Hamelink and Hoesli (2004), Morawski and Rehkugler (2006).

an aversion to losses almost all fail one or more of the axioms that risk measures should satisfy to be a coherent measure of risk, are typically difficult to interpret and/or are difficult to implement in practice.

For instance, value at risk (VaR), which is a standard risk measure in banking, relies on normally distributed returns and does not satisfy the axiom of subadditivity defined by Artzner et al. (1999) hence; it is not a coherent risk measure. Furthermore, while the modified value at risk (MVaR), suggested by Signer and Favre (2002), overcomes the problem of non-normal returns in calculating the VaR by penalizing assets with negative skewness and excess kurtosis; it is incoherent as well. In addition, as Lee (2007) points out, the MVaR is difficult to use on prospective future returns because various scenarios have to be simulated for a non-normal return-generating process. In contrast, the conditional value-at-risk (CVaR), which is defined for a confidence level α as the negative expected value in the worst α * 100% cases, is a coherent risk measure, but it is difficult to interpret (Booth et al., 2002).

Since no singular quantitative figure seems to satisfy all requirements it could be useful to shift the focus to a set of risk measures which - in combination - yields a more comprehensive picture of the riskiness of an investment and better reflects the subjective risk preferences of the investor (Booth et al., 2002). Useful as this may be, to our knowledge none of them is widely used in the field of real estate or object of further research.

A different approach is the use of qualitative risk measures such as scores, ratings, or scenarios. Although the academic literature on this topic is limited,[20] great progress was made in the industry in the last decade, mainly due to the huge effort that financial institutions had to put into their rating systems in order to comply with the rules of Basel II.

For instance, in the UK, the Investment Property Forum and the Investment Property Databank issued a report in 2000 in which they emphasized the need for more powerful risk assessment measures that match the complexity of properties (IPD, 2000). Following this report, Hutchison et al. (2005) put forward an alternative approach for the reporting of real estate quality risk. In the first phase of their research, the authors applied a scoring technique to estimate the risk of failure over the next three to twelve months. Subsequently, an Analytic Hierarchy Process (AHP) was used in order to calibrate the scoring method to various property-specific factors. The last phase included discussions with focus groups and clearly indicated that bankers, valuers and investors welcome attempts to enhance reporting of investment quality risk.

A similar approach was suggested by Blundell et al. (2011) who updated the earlier work of Blundell et al. (2005). The authors argued that portfolio risk should be depicted in terms of scores for various factors that were believed to influence overall risk, e.g., asset concentration, vacancy rate, lease length, etc. The so-called Risk Web included thirteen factors that "did appear to exercise a statistical influence over portfolio risk, with levels of correlation that were far superior to that of prior portfolio volatility". But according to the authors, this Risk Web is more suitable to the properties' intrinsic characteristics than applications used by conventional capital market theory. Nonetheless, this and similar approaches seem to be a promising alternative because they combine the advantages and softens the disadvantages of both meth-

[20] For literature on qualitative approaches in real estate risk measurement see, for example, Goodman and Scott (1997), Gordon (2003), Hutchison *et al.* (2005), Adair and Hutchison (2005), Lausberg and Wiegner (2009), and Chen and Khumpaisal (2009).

ods, for instance, the Global Real Estate Risk Index by Chen and Hobbs (2003) and the Extended Risk Rating (ERR) by Bürkler and Hunziker (2008). This latter approach measures the ex ante risk of various asset classes using various risk indicators such as maximum drawdown, deviation from normality, and recovery potential. The risk for each category is then assessed, and the overall risk can be expressed when combining the individual measures.

A more recent approach is that of Lausberg and Wiegner (2009) which combines a number of quantitative and qualitative elements and has been successfully employed by a group of European banks for their commercial real estate loans. Here, for example, a quantitative cash flow model measures the downside risk of a property while a scoring measures the location quality based on the analyst's opinion; then both are combined to determine the borrower's probability of default. We believe that this type of rating constitutes the state of the art for qualitative risk management in the real estate industry because it had to be developed on a sound empirical basis with accepted statistical methods due to the strict requirements of Basel II (Lausberg and Wiegner, 2009). The aforementioned rating system has not only survived the world financial crisis, but it has achieved an extremely high reliability because it is trained with hundreds of new data sets each year.

In our view such approaches will need to be expanded in the future with the tightening in regulation, the increase in the professionalization of the industry, and improvements in data quality. Furthermore, we expect that volatility will not be followed by another "one-size-fits-all" super measure, but instead by several systems which integrate various risk measures in various ways depending on such factors as investor's understanding for and attitude towards risk, the purpose of measuring risk, and the availability of property data.

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