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Essays on Takeover Auctions and Real Estate Markets

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Chapter 1

Introduction

The market for corporate control, as the mergers and acquisitions (M&A) market is often referred to, is one of the largest markets economists face. As an example, the aggregate M&A transaction volume in 2018 was about $1.7 trillion in the US and $4.2 trillion worldwide.[1] Those figures let us imagine, how important a thorough understanding of the interactions and the market mechanisms in this market are. Also in the real estate industry, a substantial amount of assets regularly change hands through corporate transactions.

This thesis aims to enhance our understanding of mergers and acquisitions in the real estate sector by 1) analysing mergers and acquisitions of Real Estate Investment Trusts (REITs) for the deal structure with the highest prevalence nowadays, takeover auctions, by 2) analysing mergers and acquisitions around an important type of event, the legal form change of a Real Estate Operating Company (REOC) into a REIT and by 3) analysing an important real estate

1 Numbers from Brownstein et al. (2019) via https://corpgov.law.harvard.edu/2019/01/15/mergers-and-acquisitions-2019 (Accessed: 20.01.2021).

performance index and corresponding unsmoothing procedures to provide a better understanding of their reliability for portfolio management purposes, e.g. for benchmarks of M&A investment performance or for judging the riskiness of appraised portfolios. Those three main topics are represented by the three independent empirical studies constituting chapters two, three and four of this thesis.

The research project presented in chapter two is entitled "The Auction Perspective on Takeovers of REITs". It investigates the interaction of target homogeneity, bidder homogeneity and firm characteristics on the outcomes of takeover auctions. It employs an empirical auction framework recently established in the corporate finance literature to the real estate M&A market, in order to shed light on the interaction between firm homogeneity, synergies and deal premiums in auction-like acquisitions. The focus on REITs is particularly enlightening and entails implications for the entire M&A literature, since REITs are, by legislation and due to their business models, more transparent and homogenous than entities of other industries.[2] One key finding with both scientific and practical implications is, that bidder homogeneity and target homogeneity are positively linked to the effectiveness of auctions as a sales mechanism, thus to the realizable returns to targets. Accordingly, premiums for REITs are low due to limited synergistic gains from business combinations but, due to the extreme effectiveness of auction procedures in this constellation, they largely absorb the maximum willingness to pay from bidders.

From previous research in financial economics by Harford (2005) and Mar-

[2] See e.g. Anderson et al. (2012) for a discussion thereunto.

tynova and Renneboog (2008), it is evident that regulatory changes or shocks are a key driver of merger waves. In turn, market concentration adversely impacts REIT market participants (Zhang and Hansz, 2019). Introducing a REIT regime to an economy means allowing for a new legal form. This legal form, among others, requires REIT candidates to hold a certain fraction of qualifying real estate assets. Hence a relationship with real estate M&A markets is likely to exist but not yet described or examined. The article in chapter three, "Strategic Transactions Around REIT Conversions?", analyses and characterizes M&A activity around REOC to REIT conversions, situations in which existing listed real estate operating companies approach a legal form change towards a REIT. It shows, that there are an extraordinarily high number of M&A deals and high transaction volumes associated with the transition processes and their aftermaths. Building on this observation, the study intends to discover a common rationale behind the conducted deals and unveils important determinants and performance implications of restructuring activities.

When it comes to the assessment of portfolio performance or the evaluation of investment decisions, e.g. in an M&A context, this includes assessing the risk-return profile of the underlying assets. Indices provide valuable benchmarks. But, as opposed to indices for equities, index construction in real estate is more difficult, due to low transaction frequencies and heterogeneity. An extensive strand of literature addresses issues of real estate index design. Thereby, appraisal-based indices, which aggregate appraisers' opinions on the values of properties, appear uncommonly smooth in terms of volatility and entail significant positive autocorrelation. In practice, this means that risk assessment within traditional asset pricing models is not straightforward, and for research, this means that results derived with appraisal-based numbers need careful treatment. Starting from Blundell and Ward (1987), unsmoothing techniques are designed to derive a more realistic volatility pattern for those series. However, as the dynamic analyses of various unsmoothing methods in the study “Unstable Unsmoothing – An Evaluation of Appraisal-Based Real Estate Indices” (chapter four) show, the majority of models produce infeasible results once being confronted with simple alternation of sample periods. Based on these results, the use of such procedures in research and practice must be questioned and alternatives are considered.

The remainder of this thesis comprises the three outlined chapters and finishes with a brief subsumption including perspectives for future research in those fields.

Chapter 2

The Auction Perspective on Takeovers of REITs

– joint project with Steffen Sebastian –

2.1 Introduction

There is a high prevalence of non-public multiple-bidder contests preceding acquisitions of corporates, as Boone and Mulherin (2007) depict. However, empirical studies of takeover efficiency and shareholder gains in mergers and acquisitions of Real Estate Investment Trusts (REITs) still mainly rely on event-study analyses, whereby takeover events are implicitly perceived as the outcomes of bilateral initiation. Ignoring the underlying competition might be most serious for M&A analyses of REITs since Mulherin and Womack (2015) show that the relative amount of auction-type deals is particularly large among them. This calls for an empirical analysis of takeovers in REIT markets which adequately incorporates the prevalent deal structure and which provides a new perspective on acquisitions of REITs.

A modification of the Gorbenko and Malenko (2014) empirical auction model enables assessing bidder valuations and their determinants for a unique hand-collected sample of takeover contests for U.S. equity REITs over the 1999-2018 period. The employed approach exploits all available information on bidder interaction in advance of deal announcements. The collected data comprise bids placed along the entire bidding processes, from the initiation to the conclusion of the deals. Correspondingly, estimation results are based on individual bids and permit inferences on underlying valuations, besides prices, final deal premiums or abnormal returns. Stipulated by Glascock et al. (2018), the analysis furthermore addresses bidder-type heterogeneity and provides a distinct view of type-specific valuation determinants for the considered public and private bidders engaged.

We report evidence for an agile and efficient competitive environment in REIT takeover contests, for which an additional formal bid increases the deal premiums realized by targets. We also find that winning bidders in auctions for REITs approach their maximum willingness to pay more closely than bidders for entities of other industries. Bidders in auctions for REITs exhibit less dispersed private valuations than bidders for non-REIT entities indicating larger bidder homogeneity and fewer realizable idiosyncratic synergies. Correspondingly, our analyses show that the valuation patterns associated with bidders in takeover contests for REITs most closely resemble those of private (equity) bidders within deals of other industries. The dispersion of individual valuations among bidders for REITs is relatively small. It also differs between types, but this difference is far less pronounced. Regarding valuation determinants, we observe a significant impact of frequently examined corporate-level- and macroeconomic variables on individual bidder valuations and the impact of considered valuation determinants is found to vary with respect to bidder types. Our results characterize unique features of auctions for REITs, which entail a large number of bidders, but also larger bidder homogeneity and lower excess utility to acquirers. The findings can be attributed to fewer realizable synergies and help explain the reduced returns through takeovers in the REIT industry. Even more, it explains the simultaneous existence of high bidder competition and low takeover premiums.

The conducted analysis extends the literature on mergers and acquisitions of REITs along multiple dimensions. Mulherin and Womack (2015) are the first to emphasize the relevance of non-public bidder interaction accompanying takeovers of REITs while we are – to the best of our knowledge – the first to exploit information on submitted bids in order to analyze valuation determinants for REITs in an empirical auction framework, to characterize the unique valuation patterns of REIT takeover auctions through an inter-industry comparison, and to provide a distinct view on valuations of the involved private and public bidders.

Our study is based on the auction-theoretic view on corporate takeovers developed by Hansen (2001), Haile and Tamer (2003), Eckbo (2009), Aktas et al. (2010), Gorbenko and Malenko (2014) and Gorbenko (2019) and uses micro-level deal data from SEC disclosures along the lines of Boone and Mulherin (2007), Betton et al. (2008), Gorbenko and Malenko (2014) and Mulherin and Womack (2015). While Mulherin and Womack (2015) use the deal-level information in a CAR analysis, we use it in the auction context to deduce information on the nature and determinants of bidder valuations (willingness to pay) in such deals, which is our first contribution. Investigations on real estate auctions, like Chow et al. (2015) and Kallberg et al. (2019), consider individual properties or property portfolios. In this respect, we also build a bridge between property transactions and acquisitions of firms.

Second, the impact of firm-level financial characteristics, government variables and macroeconomic factors on merger outcomes has been examined in the real estate and general finance literature. The case of REIT takeover performance has been studied by Allen and Sirmans (1987), Sahin (2005), Eichholtz and Kok (2008), Campbell et al. (2001, 2005, 2009, 2011) and Womack (2012), among others. Since the results are not unambiguous and since none of them accounts for the actual deal structure, we perform our respective analysis based on the more suitable empirical approach.

Thirdly, a distinct view on public and private bidders is motivated by Glascock et al. (2018) and prior investigations on heterogeneous bidders of Bargeron et al. (2008), Dittmar et al. (2012), Gorbenko and Malenko (2014) and Hege et al. (2018) in the general finance context and of Eichholtz and Kok (2008), Ling and Petrova (2011), Mulherin and Womack (2015) for REITs. The employed approach allows capturing the peculiarities and the effects of bidder heterogeneity which yields further insights on this important aspect of deals. For practical purposes, the results of the analysis support the design of an optimal deal-structure and the identification of a beneficial set of bidders from the target perspective. Enhanced knowledge on the efficiency of the sales mechanisms, on bidder interaction and bidder preferences can be exploited, so as to enhance profitability in takeovers.

The paper evolves as follows: section two provides a literature review and develops the investigated research hypotheses. Section three contains the conducted empirical analysis. The fourth section concludes.

2.2 Related Literature and Hypotheses

2.2.1 Takeover Auctions

Modeling takeovers with more than one bidder in an auction framework relates to the actual course of deals, as reported by acquired firms within the deal background paragraphs of obligatorily published SEC filings.[1] From the target perspective, deals in which more than one potential buyer is involved are characterized by a sales mechanism that consecutively entails the search for bidders, the signing of non-disclosure agreements with those third parties, several rounds of due diligence and informal bidding, formal bidding and, finally, the settlement of a merger agreement.[2]

From the theory perspective, auctions represent a suitable method for selling a firm that allows the maximization of merger-related returns to target shareholders. Under mild assumptions Bulow and Klemperer (1996) and Kirkegaard (2006) establish that an English (ascending-bid) auction with $N+1$ bidders generally dominates any optimal mechanism with N parties, and Bulow and Klemperer (2009), in consideration of the outlined peculiarities of corporate auctions, conclude that sellers of firms should prefer them over other sales mechanisms.

An early transition from auction theory to corporate finance is made by Hansen (2001) who outlines the commonalities of corporate takeover contests with ascending-bid auctions, but also highlights their distinct features, like informal

[1] The terms takeover, merger and acquisition are used synonymously throughout this paper.

[2] This refers to target-initiated deals. Boone and Mulherin (2007), Gorbenko and Malenko (2014) and Mulherin and Womack (2015) provide a detailed perspective on this deal process.

bidding, preemptive bidding, jump-bidding, lock-up periods and the reduction of bids.[3] Haile and Tamer (2003) and Gorbenko and Malenko (2014) define three mild assumptions enabling us to relate reported bids to bidder valuations (max. willingness to pay) in the observed auctions of firms: First, maximum willingness to pay constitutes an upper bound for each bidder's offer. Second, a bidder is assumed to beat the highest prevailing bid if its maximum willingness to pay exceeds it, and third, a bidder would not participate in a takeover contest at all if her valuation would not exceed the target's market price, due to the associated opportunity costs of participation.

Empirically, the picture for superior shareholder revenue from auctions is not unambiguous which confirms the observation that in sectors other than real estate, about one half of deals is settled bilaterally (Boone and Mulherin, 2007). The main reasons are that conducting an auction is costly in terms of the non-public information revealed to many third parties (Hansen, 2001, Boone and Mulherin, 2009) and that latent competition enhances premiums in bilaterally negotiated deals (Aktas et al., 2010 and Calcagno and Falconieri, 2014).[4] Through their standardized reporting, tax-transparency and homogenous business models, we, like Mulherin and Womack (2015), assume the associated costs of conducting an auction and the costs of participation to be lower in takeover contests for REITs – one reason for their high prevalence in about two thirds of deals. But how effective are they?

[3] A comprehensive survey on bidding strategies in corporate takeovers is provided by Eckbo (2009).

[4] For bidders, entering an auction entails the costs of information gathering (Dimopoulos and Sacchetto, 2014).

2.2.2 Acquisitions of REITs

M&A research by Campbell et al. (2001, 2005, 2011) and Sahin (2005) has confirmed a positive abnormal effect on target market prices around the merger announcement date and a negative or neutral effect on those of acquirers in REIT takeover situations.[5] Average deal premiums and abnormal returns are substantially lower than for non-real estate corporates as surveyed by Mulherin and Womack (2015) and Glascock et al. (2018).

Inter-industry comparisons which investigate takeover profitability report relatively low premiums and abnormal returns to targets, accompanying REIT mergers (Glascock et al., 2018). Because acquiring a REIT resembles buying a portfolio of real estate assets, prior investigations by Eichholtz and Kok (2008), Womack (2012), and Mulherin and Womack (2015) attribute low merger profitability to the nature of real estate: Womack (2012) suspects reduced takeover benefits to be related to predictable cash flows and limited synergies, while Eichholtz and Kok (2008) relate the reduced premiums to the high transparency and comparability.

These suspected low synergies are further investigated in the present study. According to auction-based evidence by Gorbenko and Malenko (2014), more homogenous private valuations of bidders are related to reduced synergistic benefits. Gorbenko (2019) shows that low bidder heterogeneity, in turn, results in inferior auction outcomes, i.e., low premiums achieved by targets. This could ultimately help to explain the substantially lower average deal premiums

[5] Reported evidence on REITs is in line with findings for non-real estate firms, e.g. Fuller et al. (2002) and Moeller et al. (2004).

and abnormal returns aligned with the acquisitions of REITs.

Following the results on auctions of firms by Gorbenko and Malenko (2014) and Gorbenko (2019), bidder valuations for REITs should then be less dispersed. We expect to find relatively low volatility in the private valuation components across both groups of bidders. From the outlined findings on takeover auctions and the evidence on takeover-profitability in the REIT industry, we suspect that we will observe the following pattern:

Hypothesis 1: *Private valuations of bidders in auctions for REITs are more homogeneous than such bidder valuations in auctions for other corporates.*

Hypothesis 2: *Winning bidders in auctions for REITs more closely approach their maximum willingness to pay.*

2.2.3 Heterogeneous Bidders

Since the meta-analysis of Glascock et al. (2018) motivates a distinct view on takeovers with private vs. public acquirers for REITs, we distinguish between public (listed) and private (non-listed) bidders in a second step and report valuation patterns for those two groups separately.

From prior evidence on public and private acquirers, we assume that the impact of firm-level and macro-level variables differs between the two groups: in the general finance literature, studies on the differences between public and private acquirers in takeovers by Bargeron et al. (2008), Dittmar et al. (2012) and Gorbenko and Malenko (2014) find diverging takeover premiums and abnormal returns between those two types of acquirers.[6]

Bargeron et al. (2008) suggest that shareholder profitability in acquisitions is related to the types of bidders involved. Public bidders typically tend to pay larger premiums than private bidders, where a link to lower realizable synergies by private acquirers serves as the prevailing explanation. Gorbenko and Malenko (2014) refine the Bargeron et al. (2008) findings. They confirm a more dispersed private component in valuations of strategic parties and report strategic bidders as appreciating growth opportunities like greater research and development expenditures, cash flows or intangible assets, whereas private equity bidders possess a valuation surplus for larger and under-performing firms. Private equity valuations also increase in phases of worsening macroeconomic conditions and in times of low cost of debt.[7]

In order to complement the perspective, the relationship with auction size has to be highlighted. Private bidders are more likely to be found among auctions with a larger total number bidders (Officer et al., 2010, Boone and Mulherin, 2011). Differences in CARs among REIT takeover deals with private and public bidders (also private and public targets) are reported by Ling and Petrova (2011) who also outline differences in the impact of target characteristics on those two types of buyers. Eichholtz and Kok (2008) and Campbell et al. (2011) find differences among private and public buyers in the context of

6 Public bidders are associated with larger takeover premiums. Public bidders are most commonly firms from similar industries attempting to integrate the targets' assets.

7 Kaplan and Stromberg (2009) and Axelson et al. (2013) report increased takeover activity of private buyers when the access to credit is relatively cheap.

REIT takeovers where private acquirers are associated with larger shareholder gains among REITs. Mulherin and Womack (2015) find no differences in premiums related to bidder type.

In accordance with the findings of Gorbenko and Malenko (2014) we expect private bidders to possess a smaller private valuation component. However, we hypothesize the difference between the two groups to be less pronounced with respect to the outlined homogeneity and transparency of REITs, which is likely to result in lower idiosyncratic benefits to acquirers. For our analysis on differences in valuations, we expect:

Hypothesis 3a: *The dispersion of private valuations among private bidders is lower than among public bidders in auctions for REITs.*

Hypothesis 3b: *The difference in the dispersion of private valuations between public and private bidders in auctions for REITs is lower than between public and private bidders in auctions for other corporates.*

Focusing on target characteristics and their impact on merger profitability, Campbell et al. (2001) report a negative impact of target size and target leverage throughout mergers for publicly traded targets.[8] Ling and Petrova (2011) find higher target leverage and growth opportunities to be valued by public

[8] Since we know only the identity of the winning bidder, the effects of geographical diversification on bidder valuation cannot be accounted for in our analysis. However, such effects do not yield consistent and significant impact on premiums in a large number of previous REIT merger studies.

acquirers. From the findings on the differences between the target features preferred by different bidder types, we also expect to detect type-dependent differences in the impact of valuation determinants:

Hypothesis 4: *The impact of firm-level and macroeconomic variables on valuations of public and private bidders in auctions for REITs differs across bidder types.*

2.3 Empirical Analysis

2.3.1 Data and Methods

The hand-collected dataset comprises 780 bidders in 54 takeover contests for publicly traded U.S. equity REITs, and 3875 bidders in 344 takeover contests for publicly traded non-financial corporates across all remaining industries. The information on non-public bidder competition is extracted from the SEC DEFM14A filings' deal backgrounds within the 1999-2018 period, in accordance with Boone and Mulherin (2007).[9] We focus on cash-settled deals in order to obtain a cleaner assessment of offers and thus clean evidence on valuations where we obey the following peculiarities of cash-settled deals:[10]
The focus on cash-settled deals is likely to result in a larger average number of bidders per auction and a larger share of private bidders involved (Mulherin and Womack, 2015). According to prior investigations by Ling and Petrova (2011), cash deals in REIT acquisitions are furthermore associated with larger abnormal returns which may imply larger average premiums for the entities under study. The fraction of REIT acquirers and public acquirers among the observed deals may likewise be lower, since REITs prefer stock deals or those that involve fractions of cash and stock, due to the statutorily limited cash holdings.[11]

We collect information on each bidder's bid $b_{i,j}$ (formal or informal), on the dollar amounts of formal bids and on the types of bidders $t_{i,j}$ (public or pri-

[9] Documents are obtained from the Federal Reserve's EDGAR database.
[10] According to Mulherin and Womack (2015), the fraction of cash-settled deals increases and accounts for 68% of REIT takeovers in the 2000-2010 period.
[11] A comprehensive survey on this issue can be found in Glascock et al. (2018).

vate) over the entire course of the auction.[12]

We follow the assumption of Gorbenko and Malenko (2014) that bidders would not participate in a takeover contest if they would not value a REIT at least at its current market price (USD/share). According to this rationale, a third party is perceived as bidder if it signs a non-disclosure agreement with the target firm. Bidders who place non-binding indications of interest are treated as informal bidders. Bidders who submitted binding final round offers for the target REIT are treated as formal bidders.

A losing bidder type may be public, private or unknown. Type-specific information is always available for the winner of the auction. Valuations are modeled as:[13]

$$\log\left(\frac{V_{i,j}}{M_i}\right) = X_i'\beta_{t_{i,j}} + \sigma_{t_{i,j}}\epsilon_{i,j} \tag{2.1}$$

where $\sigma_{t_{i,j}}\epsilon_{i,j}$ is the private valuation component and M_i depicts the target's market price one month before the date of the takeover announcement.[14] The matrix of explanatory variables X contains balance-sheet information on the target i.e. on firm size, leverage, q-ratio and cash.

Firm size is defined as the log book value of assets. Leverage is the book value of debt, divided by the sum of the book value of debt and the market value of

12 The subscript p (np) indicates public (private) bidders throughout the remainder of the article.

13 The subsequently described estimation strategy for REIT takeover contests is a modified application of the empirical auction approach developed by Gorbenko and Malenko (2014). For further technical details, such as derivations and proofs, please consult the original publication.

14 This should prohibit the incorporation of deal-related bias in stock prices through information leakage in advance of the official disclosure. If there are is a press release concerning the deal which is made public prior than one month before the official public announcement, the stock price is taken from the day prior to such a release. Corresponding information is obtained from the Nexis newspaper database.

equity. Tobin's Q is computed in accordance with Chung and Pruitt (1994) as the sum of market value of equity and book value of debt, divided by the book value of assets. Cash comprises cash, short-term investments and marketable securities and is normalized by size.

X also captures the prevailing market and credit conditions (return on S&$P500$ and corporate bond spread) of the day when the market premium has been calculated. Firm-level variables are calculated from the last annual and quarterly financial statements prior to disclosure of the deal. Market prices and firm-level data are obtained from Refinitiv, respectively.[15] Bond yields are deduced from the Federal Reserve's FRED database. Moreover, following Gorbenko and Malenko (2014), entities with negative cash, negative leverage or with a q-ratio larger than four are omitted. The parameter vector is estimated using the maximum-likelihood approach under the assumption of standard normally-distributed bidder valuations. Submitted bids serve as a lower bound for valuations of participating bidders. From the submitted losing bids one can infer a maximum valuation in the range between the winning- (or the next higher) bid and the actual bid submitted for each participant.

In the first place, we estimate the impact of the valuation determinants and the predicted winning bids over the entire sample of bidders. In a second step, we discriminate between auction participants with respect to their types in order to obtain a distinct perspective on the public and private bidders involved. For the unknown-type bidders, the probability of an undefined bidder in the contest for target i being of a certain type is recovered from a logistic

[15] In a control setting we use the NAREIT All Equity Index as the market index for REITs which does not substantially change the results.

regression, such that the corresponding (expected) likelihood expression for the auction of target i is:

$$L_i(v_i|N_{p,i}, N_{np,i}, N_{u,i}, X_i, b_i, t_i; \theta) = \prod_{j=1}^{N_i} E(l_{i,j}(v_{i,j}|X_i, b_{i,j}, t_{i,j}; \theta)|t_i, j) \tag{2.2}$$

where $v_{i,j}$ is $V_{i,j}/M_i$, $N_{p,i}$ is the number of public bidders, $N_{np,i}$ is the number of private bidders and $N_{u,i}$ is the number of unknown bidders in the respective auction. Individual likelihoods $l_{i,j}$ are related to the type of submitted bids. The likelihood of submitting a winning bid corresponds to the probability that the valuation of the winning bidder $v_{i,1}$ is larger than or equal to the highest submitted bid $b_{i,1}$, which translates to:

$$l_{i,1}(v_{i,1}|X_i, b_{i,1}, t_{i,1}; \theta) = P(b_{i,1} \leq v_{i,1}|X_i, t_{i,1}; \theta) = 1 - \Phi\left(\frac{\log(\frac{b_{i,1}}{M_i}) - X_i\beta_{t_{i,1}}}{\sigma_{t_{i,1}}}\right) \tag{2.3}$$

Similarly, the likelihood that a formally bidding party j does not win the auction equals $P(b_{i,j} \leq v_{i,j} \leq b_{i,1}|X_i, t_{i,j}; \theta)$, the likelihood that an informal bidder loses is $P(M_i \leq v_{i,j} \leq b_{i,1}|X_i, t_{i,j}; \theta)$ and the likelihood expression for an auction participant that does not submit any bid or withdraws is obtained from $P(0 \leq v_{i,j} \leq b_{i,1}|X_i, t_{i,j}; \theta)$.[16]

The estimated parameter vectors $\hat{\theta}$, $\hat{\theta}_p$ and $\hat{\theta}_{np}$ (all bidders, public and non-public) are obtained through numerical optimization of the aggregate likelihood function. We use the Nelder and Mead (1965) simplex algorithm which exhibits robust convergence properties throughout our applications, i.e. consistently approaches the global optimum.

An additionally provided least squares specification regresses final deal premiums on deal and target characteristics. In order to incorporate information on the competitive structure, the number of bidders and their respective types are included consecutively as explanatory variables.

2.3.2 Descriptive Statistics

The deal-level descriptive statistics with information on the participating bidders i.e. on their numbers and types are provided in Table 2.1. The average auction for REITs attracts fourteen bidders, and the average amount of $private$ bidders is slightly larger than the number of $public$ bidders. The total number of bidders is larger among REITs than among targets of other industries (median of 7.5 bidders vs. median of 6 bidders), with an almost equivalent

16 Following Gorbenko and Malenko (2014) pp. 2544-45. $\Phi(\cdot)$ represents the cumulative density function of the standard normal distribution. If a withdrawing bidder states that his valuation is below the target's market value, M_i is the upper bound to valuations.

variation in auction-size between the two samples.[17] At the same time, the number of bidders without information on types is greater.[18]

[17] Collected data for non-REIT corporates is partly based on Baur (2017).
[18] Therefore, in a later specification we restrict the sample to formal and informal bidders.

Table 2.1: Deal-Level Descriptive Statistics

	Bidder Composition			
	Total	# Public	# Private	# Undefined
REITs				
Mean	14.444	1.148	1.611	11.685
SD.	14.753	1.379	1.731	15.138
Median	7.500	1.000	1.000	3.500
Other Industries				
Mean	11.265	2.311	2.744	6.209
SD.	15.119	2.862	7.238	12.896
Median	6.000	2.000	0.000	1.000
t-Statistic	1.514	-5.744	-3.778	8.246

	Bid submission			
	# Informal	# Formal	Formal Bids	Winning Bids
REITs				
Mean	2.500	1.685	1.205	1.223
SD.	3.045	1.043	0.215	0.233
Median	1.000	1.000	1.151	1.180
Other Industries				
Mean	1.922	1.416	1.410	1.434
SD.	2.637	0.724	0.309	0.321
Median	1.000	1.000	1.342	1.350
t-Statistic	2.055	2.361	-7.724	-5.838

Note: The table reports descriptive statistics on the bidding processes and bidder composition in an sample auctions for REITs and non-REIT entities (Other Industries). Statistics on numbers of participating bidders are decomposed according to bidder types (public, private and undefined). Information on bid submission contains the number of informal and formal bids, the implied premiums by final round offers and the winning bid premiums (Formal Bids, Winning Bids). The t-Statistic of differences between numbers for REITs and non-REIT entities is provided.

The volatility in the number of private bidders per target is reduced among REITs. Overall, the presence of private bidders is more volatile than that of public bidders in the observed deals. The observation on the size of auctions in the REIT sector may be explained by the regulatory requirements on the transparency of REITs, which implies lower entry costs for bidders.

As depicted throughout the lower part of Table 2.1, the number of submitted informal and formal bids is slightly larger among auctions for REIT targets. Winners of REIT takeover auctions are reported as paying substantially lower average deal premiums of 24% as compared to 43% for the set of non-REIT entities. The difference between private and public acquirers is remarkable across the other industries (47.64% for public acquirers and 32.59% for private acquirers), but virtually absent across acquirers of REITs (22.02% for public acquirers and 22.68% for private acquirers).[19]

44% of winning bidders are private while the remainder are public. This fraction is only slightly larger than the 38% of private buyers in the closely related study of Mulherin and Womack (2015) and confirms the tendency towards an increasing fraction of private acquirers implied by Mulherin and Womack (2015).[20]

[19] Since the focus of this study is on cash-settled deals, the reported premiums for REITs are higher than in other studies. Ling and Petrova (2011) e.g. they report average premiums for REIT takeover targets of about 10%. If this translates into valuations, our evidence on private valuation can be considered conservative.

[20] The fraction of private acquirers increased between their sample periods from 11% in the period 1989-1999 to 38% in the period 2000-2010.

Table 2.2: Target Characteristics

	Size	Tobin's Q	Leverage	Cash
REITs				
Mean	1660.554	1.121	0.502	0.024
SD.	1507.022	0.249	0.148	0.034
Median	1254.343	1.069	0.489	0.010
Other Industries				
Mean	759.029	1.598	0.129	0.266
SD.	1728.312	1.220	0.189	0.245
Median	252.470	1.320	0.035	0.181
t-Statistic	4.002	-6.443	16.535	-17.281
REITs				
Hotels/Lodging	1134.653	1.111	0.494	0.039
n=10	(1043.591)	(0.274)	(0.111)	(0.049)
Residential	1448.996	1.157	0.556	0.027
n=12	(1264.931)	(0.239)	(0.141)	(0.034)
Retail	2041.267	1.165	0.472	0.010
n=12	(1627.034)	(0.269)	(0.113)	(0.007)
Healthcare	1909.697	0.831	0.641	0.039
n=3	(2499.201)	(0.092)	(0.140)	(0.019)
Office	1848.097	1.127	0.501	0.022
n=11	(1449.489)	(0.278)	(0.169)	(0.043)
Others	1730.346	1.113	0.402	0.015
n=6	(2222.635)	(0.154)	(0.200)	(0.019)
Other Industries				
Consumer Durables, etc.	799.801	1.492	0.160	0.113
n=67	(1437.333)	(1.179)	(0.207)	(0.124)
Manufacturing, etc.	947.071	1.178	0.222	0.100
n=34	(1814.932)	(0.456)	(0.187)	(0.145)
Business Equipment	659.224	1.432	0.077	0.372
n=150	(2006.064)	(0.873)	(0.150)	(0.227)
Healthcare	789.139	2.462	0.156	0.295
n=58	(1443.915)	(1.956)	(0.213)	(0.283)
Others	876.152	1.486	0.161	0.216
n=35	(1302.833)	(0.867)	(0.206)	(0.262)

Note: The table reports descriptive statistics for 54 REIT takeover targets (REITs) and 344 non-REIT takeover targets (Other Industries) from the period 1999-2018. The upper part contains means, standard deviations and medians for the entire sample. The t-Statistic of differences between numbers for REITs and non-REIT entities is provided. The lower part decomposes the sample, according to the REITs' business focus and according to the Fama and French (1997) five industry classification for non-REIT entities. Standard deviations for the lower part are provided in parentheses, below the corresponding mean.

The overall sizes of formal bids and winning bid premiums and the pronounced inter-industry difference are consistent with prior evidence in the real estate- and general finance literature.[21] Similar to the observations of Womack (2012) for excess returns in REIT mergers, the reduced premiums and final round bids may be explained by the characteristics of real estate as an asset class and, what will be further elicited within this study, by a reduced possibility to generate synergistic benefits. The analysis of the winning slack (underbidding), together with information on the average number of bidders, indicate that reduced premiums are unlikely a result of impaired competition.

The target REIT balance-sheet information (Table 2.3) does, in short, not reflect any atypical features of REITs. REIT entities exhibit a large book value of assets with an average size of about 1.5 billion dollars (representing their real estate portfolios). Correspondingly, the q-ratio which relates the target market value of equity to the book value of equity, is relatively low across REITs, but highest for those with a focus on Retail and Residential properties.

Cash holdings are likewise of small magnitude, which is related to the statutory demands on the distribution of profits to shareholders. High levels of leverage are commonly observed among REITs, where the group of Healthcare REITs entails the highest leverage among our sample firms.[22] A total of 41 REITs, representing three quarters of the entire REIT-sample, make use of an operating partnership.

21 See e.g. Boone and Mulherin (2007), Boone and Mulherin (2011) for evidence on premiums in the corporate finance context and Womack (2012) and Mulherin and Womack (2015) for a comparison between premiums of REITs and other industries.

22 The reported numbers for cash holdings and leverage were normalized by target size.

2.3.3 Results

Initial evidence can be obtained from the regressions on winning bid premiums tabulated in Table 2.3. A significantly positive contributor to premiums from the set of firm-level variables is the target's relative leverage indicating that auction winners may realize strategic gains from debt restructuring if they have access to superior lending conditions.

The size of the target only contributes significantly to the final bid premiums for targets of other industries, which implies a relatively low excess winning bid for larger firms, i.e. firms with more balance-sheet assets, by the winning bidders for those entities. This observation appears to be primarily a size-level effect and not a distinct feature of REITs, since re-estimation of the regression on the upper quartile of non-REIT firms makes the pattern disappear.

The negative coefficient for the q-ratio refers to a larger premium for corporates which are undervalued by the market. The observation on bond spreads, and thus the costs of debt financing are contradictory to prior evidence of leveraged buyouts by Axelson et al. (2013).[23] This is attributed to the period of the financial crisis, where a small amount of high premium deals were settled in an environment with extraordinary high debt-financing costs. After exclusion of deals taking place during the period 2008-2010, the coefficient finally becomes insignificant.

[23] The authors report increased leverage buyout activity and overpayment by private equity firms in phases of low cost debt.

Table 2.3: OLS Regression Results

	REITs			
	I	II	III	IV
Constant	0.630*	0.669*	0.446	0.760*
	(0.376)	(0.397)	(0.407)	(0.423)
Size	0.015	0.012	0.018	0.013
	(0.033)	(0.034)	(0.034)	(0.038)
Tobin's Q	0.002	-0.007	0.015	-0.024
	(0.145)	(0.150)	(0.145)	(0.153)
Leverage	0.460*	0.455*	0.395	0.446*
	(0.250)	(0.253)	(0.247)	(0.264)
Cash	-1.025	-0.998	-1.250	-1.066
	(0.886)	(0.898)	(0.878)	(0.943)
Market Return	-0.005	-0.010	-0.018	-0.011
	(0.329)	(0.332)	(0.328)	(0.345)
Credit Spread	0.125**	0.125**	0.167***	0.109*
	(0.059)	(0.060)	(0.061)	(0.064)
Private Winner		-0.021	-0.039	
		(0.062)	(0.061)	
Informal			-0.002	
			(0.010)	
Formal			0.069**	
			(0.031)	
Public				-0.012
				(0.024)
Private				-0.010
				(0.018)
Undefined				-0.002
				(0.002)
Adj. R^2	0.203	0.187	0.237	0.164

Note: The table displays the output of the least squares specification for REIT targets (N=54). Winning bid premium is the dependent variable. Model I includes firm-level characteristics, Model II adds information on the winning bidder's type (private or public), Model III includes the number of bidders per auction, Model IV includes the number of bidders according to types. * (**) (***) indicates statistical significance at the 10% (5%) (1%) level. Standard errors are reported in parentheses.

Interestingly, the contests won by private bidders are associated with reduced premia for the sample of non-REIT entities, but not for REITs, an observation which will be investigated further within the auction-model analysis, and which is likely to coincide with the higher commonalities in private valuations among bidder-types in auctions for REITs.[24]
Correspondingly, the amount of private bidders has no significant impact on deal premiums among REITs, but reduces premiums among other corporates. The variables capturing participating bidder types, by contrast, do not significantly impact the premiums for acquired REITs.
The need to incorporate the competitive deal structure in the analysis of REIT takeovers is once more emphasized by the significant increase in premiums through the participation of an additional formal bidder in the deal.
The auction model (Table 2.4) yields inferences on inherent valuations. It is based all the documented bidders and bids and provides a perspective of the private valuation component which serves as a proxy for the existence and the extent of synergistic benefits. The variance of this component is consistently higher in takeovers of other industries, compared to takeovers of REITs. Making a distinction between bidder types, it is mainly attributable to the relatively low variance in private valuations of public bidders in REIT auctions which becomes evident through the inter-industry comparison in 2.5. Public bidders for REITs still possess more dispersed private valuations but the difference between types is far less pronounced due to the more homogenous public bidder valuations.

[24] Indicative comparative evidence for REITs vs. takeover targets of other industries can be drawn from the regression results in Table 2.8.

Table 2.4: Estimation Output: Empirical Auction Model

	REITs				Other Industries			
	All	Public	Private	Difference	All	Public	Private	Difference
SD. Priv. Val.	0.138***	0.159***	0.122***	0.037**	0.230***	0.299***	0.147***	0.152***
	(0.007)	(0.017)	(0.008)	(0.019)	(0.016)	(0.012)	(0.005)	(0.013)
Constant	-0.480***	-0.809***	-0.379***	-0.430	-0.010	-0.042	0.090**	-0.132*
	(0.072)	(0.278)	(0.080)	(0.289)	(0.096)	(0.063)	(0.038)	(0.074)
Size	0.028***	0.032	0.026**	0.006	-0.006	-0.015*	0.000	-0.015
	(0.009)	(0.021)	(0.011)	(0.024)	(0.012)	(0.008)	(0.005)	(0.009)
Tobin's Q	0.115***	0.248**	0.061	0.187*	0.012	0.021**	-0.016*	0.036***
	(0.028)	(0.098)	(0.041)	(0.106)	(0.017)	(0.010)	(0.008)	(0.013)
Leverage	0.345***	0.577***	0.263***	0.314	0.010	0.110	-0.031	0.141*
	(0.073)	(0.197)	(0.051)	(0.204)	(0.084)	(0.069)	(0.028)	(0.074)
Cash	-0.354***	2.509*	-0.370***	2.879**	0.040	-0.017	0.018	-0.036
	(0.086)	(1.329)	(0.103)	(1.333)	(0.080)	(0.050)	(0.032)	(0.060)
Market Return	-0.067	-0.280	-0.041	-0.239	-0.096	0.066	-0.148***	0.214*
	(0.050)	(0.184)	(0.081)	(0.201)	(0.143)	(0.094)	(0.056)	(0.110)
Credit Spread	0.011	0.021	0.015	0.006	0.040	0.077***	0.004	0.073***
	(0.013)	(0.037)	(0.017)	(0.041)	(0.026)	(0.018)	(0.010)	(0.021)

Note: This table reports estimation results from the Gorbenko and Malenko (2014) auction-based estimation strategy for 720 (public and private) bidders in 54 takeover contests for REITs and 3875 bidders in 344 corporate takeovers of other industries where bidder valuation is the dependent variable. * (**) (***) indicates statistical significance at the 10% (5%) (1%) level. Standard errors are reported in parentheses.

Following Gorbenko and Malenko (2014), the observation of more homogenous bidder valuations implies fewer idiosyncratic benefits to be realized by the potential acquirers, hence lower levels of synergistic benefits are realized in takeovers for REITs, irrespective of the invited or attracted bidder type. According to Gorbenko (2019) the (lack of) dispersion in private valuations is the key driver of reduced premiums through auctions.

A closer look at the determinants of overall and type-specific bidder valuations reveals a number of differences. Without making a distinction between bidder types, valuations for REITs are found to increase in size, q-ratio and leverage and are found to decrease in target liquidity. A desired target can thus be characterized as a sizable, but under-performing, entity with sufficient growth opportunities. Higher liquidity, by contrast, makes targets more resistant towards takeovers, as found by Harford (1999). The findings here imply that liquidity also adversely translates into valuations of structured bidding processes for which the target is already for sale.

The observed coefficients for leverage refers to a comparative advantage in debt restructuring by acquirers of REITs implying higher relative benefits from acquisitions through benefits debt-restructuring that is associated with higher target leverage.

The distinct estimation for public and private bidder types enables a closer view of differences in the impact of the considered explanatory variables. Public bidders predominately value growth opportunities, whereby the negative aggregate impact of cash holdings is driven only by the preferences of private bidders.

Among the group of other corporates from other industries, a negative effect of size is found for public bidders. Growth opportunities, as measured by the q-ratio, induce a positive differential in the comparison of bidder types, corresponding to our findings for REITs.

For the analysis of valuation determinants, mainly the importance of macroeconomic quantities distinguishes REITs from non-REIT entities. Private bidders for other entities exhibit relatively higher valuations in downturns which is consistent with the findings in Gorbenko and Malenko (2014) while the prevailing economic environment neither promotes nor impairs valuations in contests for REITs.

Having restricted the considered bidders to the submitters of informal and formal bids, the picture changes slightly. Here, private bidders' valuations reduce with an increasing size of the target, while the q-ratio is not a significant contributor to valuation. Higher liquidity is associated with reduced valuations. The prevailing market conditions increase valuations of public bidders in upturns, but increase valuations of private bidders in downturns.

Using the estimated coefficients to predict winning bidders' target valuations, and relating them to the actually submitted final round bids, thus reveals the extent of underbidding relative to the maximum willingness to pay, i.e. takeover gains to acquirers[25].

From the Figures 2.1 - 2.3, it is obvious that the winning bidders' valuations, i.e. their maximum willingness to pay, is on average approached more closely

25 Gorbenko and Malenko (2014) refer to this discrepancy as the winning slack of the auction. An overview of prior findings on distributions of takeover gains for REITs is provided by Glascock et al. (2018)

for REIT takeovers than for those of other corporates. The corresponding distributional parameters for the ratio of valuations to submitted winning bids in table 2.6 show that the average preserved willingness to pay and its volatility, is smaller than in any other considered industry (following the Fama and French (1997) classification).

2.3.4 Further Testing

Analyses of different model specifications are conducted. First, the model is equipped with industry-fixed effects along the observed REIT specializations and with time-fixed effects according to the presence or absence of a merger wave in the US economy for the respective year. Second, a possible impact of uncertainty with respect to unknown bidder types is moderated. Therefore, only the informally and formally bidding parties are incorporated in one setting and only the bidder types which are known with certainty are included in another setting. Lastly, deals taking place during the financial crisis were removed from the sample. The key results on REIT takeover synergies are not impaired, as shown in table 2.7.

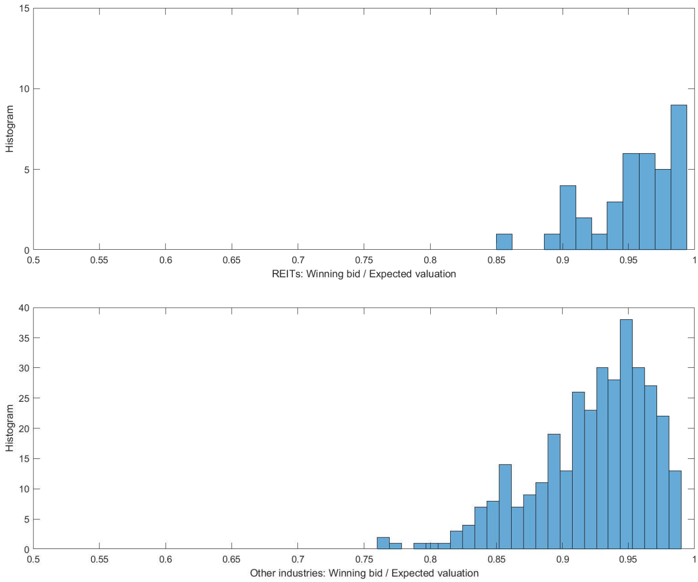


Figure 2.1: Submitted Winning Bids to Predicted Valuations: REITs vs. Other Industries

Note: This graph displays the distribution of one minus predicted winning bidder valuations divided by submitted winning bids as a measure of preserved utility by acquirers for bidders in auction for REITs (upper diagram) and bidders in auctions for other corporates (lower diagram).

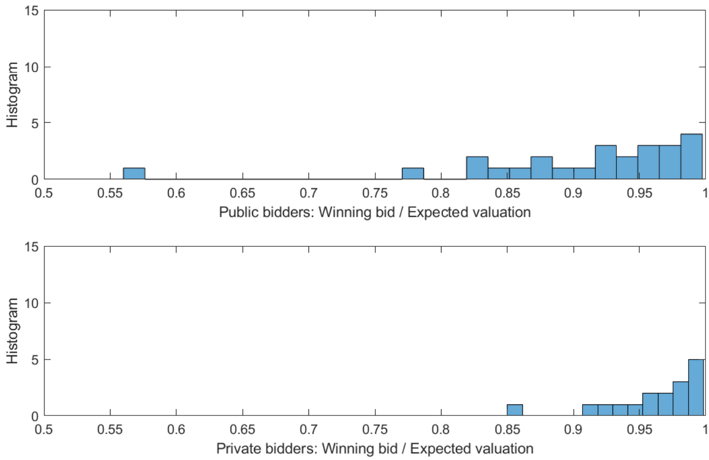


Figure 2.2: Submitted Winning Bids to Predicted Valuations for Public and Private Bidders: REITs

Note: This graph displays the distribution of one minus predicted winning bidder valuations divided by submitted winning bids as a measure of preserved utility by public (upper diagram) and private (lower diagram) acquirers for bidders in takeover auctions for REITs.

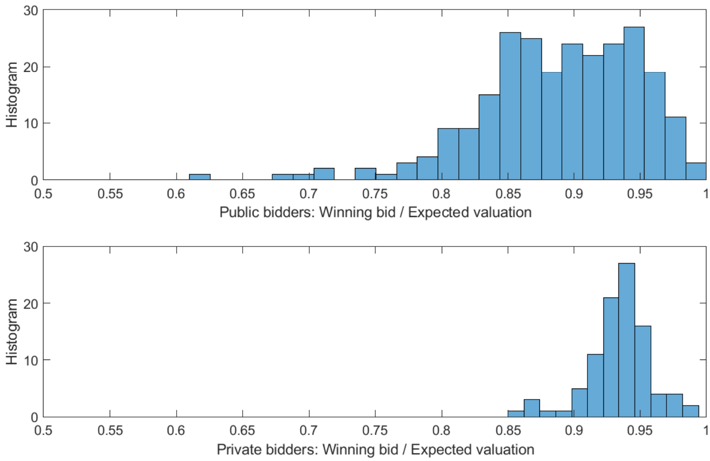


Figure 2.3: Submitted Winning Bids to Predicted Valuations for Public and Private Bidders: Other Industries

Note: This graph displays the distribution of one minus predicted winning bidder valuations divided by submitted winning bids as a measure of preserved utility by public (upper diagram) and private (lower diagram) acquirers for bidders in takeover auctions for targets of other industries.

Table 2.5: Private Valuations Across Industries

	σ_p	σ_{np}
REITs	0.159	0.122
Consumer Durables etc.	0.221	0.130
Manufacturing etc.	0.263	0.128
Business Equipment	0.268	0.167
Healthcare	0.323	0.097
Others	0.348	0.107

Note: This table reports estimated standard deviations of the private valuation components $\hat{\sigma}_i$ for public and private bidders in takeover auctions for REITs and for takeover targets of other industries (Fama and French, 1997 five-industry classification).

Table 2.6: Distributional Parameters of Predicted Excess Valuations

	μ_p	σ_p	μ_{np}	σ_{np}
REITs	0.906	0.092	0.962	0.036
Consumer Durables etc.	0.834	0.096	0.927	0.029
Manufacturing etc.	0.774	0.120	0.870	0.056
Business Equipment	0.859	0.037	0.938	0.041
Healthcare	0.750	0.125	0.808	0.174
Others	0.813	0.149	0.873	0.005

Note: This table reports means and standard deviations of predicted excess valuations i.e. ratio of predicted valuation to submitted winning bids for winners of takeover auctions for REITs and for targets of other industries (according to the Fama and French, 1997 five-industry classification).

Table 2.7: Private Valuations: Further Specifications

	Public	Private	Difference
Informal Bids	0.149***	0.106***	0.043***
	(0.009)	(0.004)	(0.010)
Ex Unknown	0.173***	0.127***	0.046***
	(0.015)	(0.008)	(0.017)
Ex Fin Crisis	0.168***	0.107***	0.061***
	(0.019)	(0.008)	(0.020)
Fixed Effects	0.159***	0.123***	0.036*
	(0.018)	(0.009)	(0.020)

Note: This table reports estimated volatilities of the private valuation components $\hat{\sigma}_i$ for public and private bidders in takeover auctions for REITs with respect estimated for informal bidders, without unknown bidders, without the years of financial crisis and with fixed effects, respectively. Standard deviations are reported in parentheses. * (**) (***) indicates statistical significance at the 10% (5%) (1%) level.

Table 2.8: Regression Output REITs and Other Targets

	I	II	III	IV
Constant	1.369*** (0.081)	1.374*** (0.088)	1.392*** (0.080)	1.394*** (0.087)
Size	−0.028*** (0.010)	−0.033*** (0.011)	−0.025** (0.010)	−0.028** (0.011)
Tobin's Q	−0.017* (0.010)	−0.017* (0.010)	−0.021** (0.010)	−0.022** (0.011)
Leverage	0.269** (0.116)	0.305** (0.138)	0.284** (0.114)	0.318** (0.142)
Cash	0.068 (0.061)	0.064 (0.063)	0.058 (0.059)	0.053 (0.061)
Market Return	0.092 (0.120)	0.100 (0.132)	0.093 (0.113)	0.096 (0.125)
Credit Spread	0.056** (0.024)	0.066** (0.027)	0.053** (0.022)	0.062** (0.026)
Private Winner			−0.078*** (0.022)	−0.090*** (0.026)
REIT	−0.235*** (0.048)	−0.482** (0.213)	−0.241*** (0.048)	−0.505** (0.243)
REIT x Size		0.049** (0.021)		0.044* (0.023)
REIT x Tobin's Q		0.015 (0.061)		0.021 (0.063)
REIT x Leverage		0.045 (0.212)		0.032 (0.216)
REIT x Cash		−0.727** (0.298)		−0.719** (0.310)
REIT x Market Return		−0.006 (0.241)		−0.001 (0.237)
REIT x Credit Spread		−0.058 (0.042)		−0.053 (0.042)
REIT x Private Winner				0.092** (0.043)
Adjusted R^2	0.178	0.183	0.203	0.208

Note: This table displays the output of the least squares specifications for 54 REIT targets and 344 takeover targets of other Industries where winning bid premium is the dependent variable. Models of columns I und II include firm-level and macro characteristics, the model of columns III and IV adds winning bidder's type (private or public) * (**) (***) indicates statistical significance at the 10% (5%) (1%) level. Standard errors are reported in parentheses.

2.4 Conclusion

Recent contributions by Mulherin and Womack (2015) and Glascock et al. (2018) motivate further investigations on the deal-structure and on heterogeneous buyers in mergers and acquisitions of REITs.

This study perceives REIT takeover contests as ascending-bid auctions and presents the mechanism behind seemingly low premiums. This reveals that bidders in auctions for REITs display remarkably low variation in their private target valuations representing large bidder homogeneity and few realizable synergies.

Low synergistic benefits and low bidder heterogeneity cap achievable premiums, but for target shareholders, conducting an auction proves particularly efficient in this constellation, since it is shown to effectively absorb the buyer's willingness to pay.

The observation regarding auction winners that exhaust their willingness to pay, together with the findings on a positive relationship between premiums and the number of formal bidders, help to understand the high prevalence of multi-bidder deals in takeovers of REITs.

Apparently, the combination of low entry costs for bidders and pronounced peculiar benefits to target shareholders result in a high, and perpetually increasing, fraction of conducted auctions in that industry.

Future investigations could build on these findings and shed further light on related aspects of REIT takeovers, specifically on pivotal aspects of the deal micro-structure. Future inquiries on acquisitions of REITs should ideally incorporate variables that are eligible to characterize their unique competitive environment.

Chapter 3

Strategic Transactions Around REIT Conversions?

– joint project with Dominik Wagner, René-Ojas Woltering, David H. Downs and Steffen Sebastian –

3.1 Introduction

Real Estate Operating Companies (REOCs) and Real Estate Investment Trusts (REITs) regularly engage in strategic transactions in the form of mergers and acquisitions.[1] However, existing M&A research in the REIT sector only focuses established REITs, and, so far, lacks an explicit in-depth analysis of the deal environment that accompanies the (REOC-to-) REIT conversion process. Moreover, despite the increasing number of REIT regimes around the world and increasing research interest in REIT conversions (Ling et al., 2020) and the

[1] See Glascock et al. (2018) for a comprehensive review. Following Mulherin and Womack (2015), we use the terms “mergers,” “acquisitions,” and “takeovers,” as well as “target” and “seller,” interchangeably throughout this article.

market entry of REITs (Chan et al., 2019), the related restructuring process has not yet been explored from a scientific perspective.

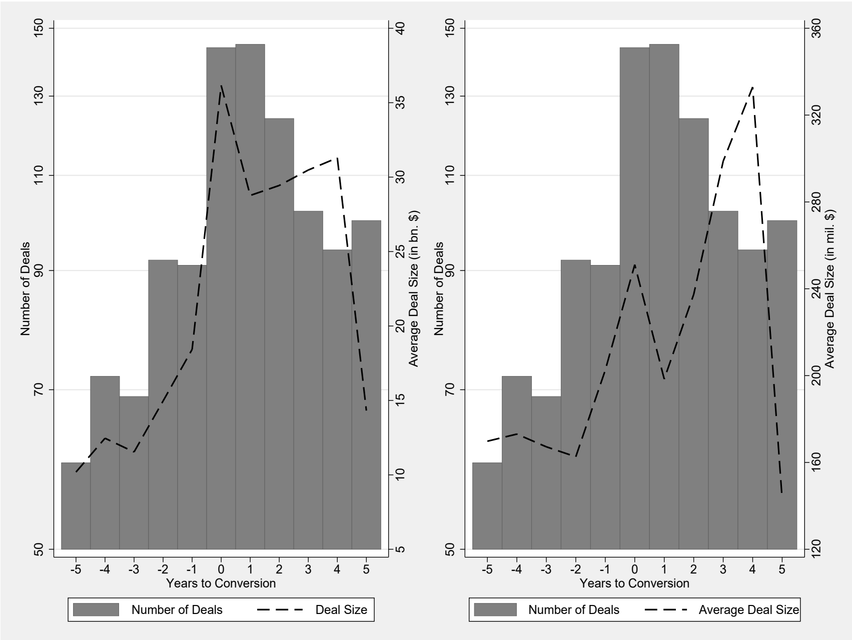
This study aims to fill this gap by investigating conversion-related M&A activities. First, we categorize deal types, as well as the role of each respective REIT in the observed deals, and provide a distinct view of the internal and external reorganization activities. Second, we identify the determinants that drive the pursued transactions. Third, we examine whether REITs are willing to pay a substantial premium to achieve the desired portfolio allocation, and we assess the M&A-related long-term performance of companies that adopted REIT status.

This work aims to provide a better understanding of the strategic decision making surrounding one common goal: preparing for the REIT market. By focusing on established REOCs that opted to convert, we are able to characterize the realignments of those companies more precisely. We can also track their evolution in terms of both assets and capital structures, as caused by the increased attractiveness to equity investors.

We gather a unique, partially hand-collected dataset to examine the M&A environment of REIT conversions at a global level. The global setting allows us to observe and explore differences and commonalities in post-conversion performance across countries. Our dataset comprises conversions of listed real estate companies across nine large markets for the 1999-2018 period. All firms are index constituents of the FTSE EPRA/NAREIT Global Real Estate Index.

We note that a remarkably high amount of strategic transactions occur among converting entities around their respective election date (Figure 3.1).

Figure 3.1: Number of Sample Deals and (Average) Deal Size around Conversion Dates



Note: This figure shows the aggregate number of deals (bars) and corresponding deal values (lines) within the window of $-5\ to\ 5$ years around the conversion date. The left-hand (right-hand) graph shows total (average) deal value.

In particular, we observe an increase in the number of M&A transactions conducted during the conversion period that appears dissociated from the general M&A environment in the economy and industry. We also observe a sharp increase in average post-conversion deal size. Similarly to the number of post-conversion deals, this is attributable to the inflows that result from the adoption of the REIT structure. The corporate finance literature shows that regulatory shocks, usually in the form of changes in prevailing antitrust regimes, tend to cause waves of acquisitions (e.g., Harford, 2005; Martynova and Renneboog, 2008). Since many REIT conversions take place in close proximity to the introduction of a REIT regime, we discover and examine an M&A-inducing regulatory shock that is both unique to the real estate sector and new to the literature.

We find that restructuring activity interacts with long-term performance. Converted REITs in the largest REIT markets are associated with positive post-conversion returns, and firms with the lowest levels of restructuring outperform entities with higher pre-conversion activity. Higher levels of transaction activity, in turn, lead to beneficial risk-adjusted returns. These novel insights into the M&A environment of REIT conversions should be of enduring interest to market protagonists. It is valuable for investors and REIT executives to fully understand how restructuring relates to conversions, and how restructuring around conversions impacts post-conversion performance. Enhanced knowledge about the firm-level process of adopting the REIT form, and about the market consolidation effects of REIT regimes, is also advantageous for governments and tax authorities, because they create and enforce the respective legal frameworks.

The remainder of this article is organized as follows: Section 2 provides a brief review of the related literature and develops our research hypotheses. Section 3 introduces the data, while Section 4 focuses on conversion-related M&A activity. Post-conversion performance is discussed in Section 5. Section 6 concludes.

3.2 Related Literature and Hypotheses

The testable implications of M&A activity along REIT conversions build on the general finance and real estate literature. Research on strategic transactions in the property sector predominantly focuses on established REITs, but lacks an analysis of the deal environment accompanying the conversion processes. In particular, the entire restructuring process and how it interacts with post-conversion performance has not yet been the subject of any scientific inquiries. We note that M&A deals in the property sector are more homogeneous than those in other branches. The underlying rationale for the decision making may not be evident for every transaction. However, in the context of REIT conversions, REOCs pursue an organizational form change into REITs that implies a defined goal. Given the companies' geographic domiciles, the respective legislation demands the fulfillment of certain criteria regarding the attainment of REIT status. For our analysis, the most relevant criterion is that REITs must hold a specific level of qualifying real estate assets.[2] If a firm is closer to this legal requirement, its related restructuring expenses should be *ceteris paribus* lower. Therefore, REOCs are subject to potential restructuring on a company level that may affect asset allocation.

Moreover, Freybote and Qian (2015) document that REIT mergers tend to be strongly incentivized by acquiring strategically relevant properties for managers. Similarly to evidence for IPOs in Malmendier and Tate (2008), REOCs

[2] This refers to the criterion Asset Test, which is defined as the proportion of qualifying real estate to overall assets. The ratio must exceed a nationally defined threshold, for example, 75% in the U.K. EPRA (2018) lists the most recent regime requirements for REITs. Note that those criteria may change over time.

may use the opportunity of a REIT conversion to signal their ability to form higher-quality portfolios. In general, the M&A deals of REITs involve deal premiums (cumulative abnormal returns) of lower than 10%. For example, Sahin (2005) and Womack (2012) report premiums of about 5%, Ling and Petrova (2011) find about 7%, and Campbell et al. (2001) find between 1% and 3%. In the case of regulatory incentivized transactions or strategic restructuring, converting REOCs are likely willing to purchase a certain portfolio to gain a higher amount above market value. Taking those aspects together, we formulate our first pair of hypotheses as follows:

Hypothesis 1a: *Deals are conducted to meet the Asset Test REIT criterion.*

Hypothesis 1b: *Converting REOCs are willing to pay a premium to acquire the desired portfolio allocation.*

Gyourko and Sinai (1999) describe the net benefits (tax savings over capital raising costs) of the U.S. REIT structure. To date, over 30 countries have introduced REIT regimes in order to facilitate capital flows to the real estate sector (Eichholtz and Kok, 2007). In addition, REITs are increasingly used by investors who seek real estate exposure (Downs et al., 2019). Adopting the status is regularly rewarded by a positive market valuation. For example, Damodaran et al. (2005), Piao et al. (2017), and Ling et al. (2020) find positive announcement effects result from signaling a REIT conversion.

The prevailing literary evidence suggests that REIT frameworks are also associated with higher inflows, which may in turn lead to higher levels of M&A activity and larger relative deal size, i.e., relative to the companies average deal size.[3] Putting those aspects together, we formulate our second hypothesis as follows:

Hypothesis 2: *Conversion-induced increases in inflows lead to higher numbers of deals and an increase in excess deal size.*

[3] $Average\,Deal\,Size_{i,t} = Aggregate\,Deal\,Size_{i,t}\,/\,Number\,of\,Deals_{i,t}$. See Appendix 3.6 for detailed variable definitions.

Numerous studies have analyzed mergers and acquisitions of real estate firms. However, they tend to focus on returns around takeover events and the pre- and post-merger performance of targets and acquirers in the (U.S.) REIT sector. As Sahin (2005) and Ratcliffe et al. (2018) note, studies on the long-run post-acquisition performance of REIT acquirers find no persistent evidence of positive effects on REIT performance or even negative impact of acquisitions on acquirers' returns in the years following an acquisition, as described in Campbell et al. (2009). Thus, if the conversion process is accompanied by an increased number of acquisitions, and if long-lasting adverse performance of acquirers accompanies REIT takeovers, we presume, regarding performance, that on average:

Hypothesis 3a: *Converted REITs will exhibit relatively high performance in the post-conversion period.*

Hypothesis 3b: *Higher M&A activity implies lower long-term performance for converting REITs.*

3.3 Data and Descriptive Statistics

Our empirical analysis is based on the constituents of the FTSE EPRA/NAREIT Global Real Estate Index, which is comprised of listed firms with relevant real estate activities.[4] The observation period ranges from the index's introduction

[4] The index provider defines relevant real estate activities as the ownership, trading, and development of income-producing real estate (Russell, 2019).

in 1999 through 2018. The constituent list is updated on a monthly basis, and is not subject to survivorship bias. Moreover, by focusing on index firms, we ensure a high degree of data quality and comparability at the multinational level.[5]

For REOCs, we identify conversion events by tracking the year of listing and the year of REIT election. Those dates are collected partially via the S&P Global Intelligence database, using CRSP share code changes for U.S. firms, and hand-collected from company reports. We include firms with at least 24 months of listings in order to exclude entities that pursued conversion from inception.[6] For the purpose of our analysis, we exclude countries that had no conversions during our sample period, which leaves us with 90 conversion events.

5 The data collection process and related definitions follow Wagner et al. (2019).

6 Our sample companies remain stable from 12 months onward. In line with Ooi et al. (2007), we require 24 months of listings in order to analyze the conversion process of sample REITs from an initial equilibrium position.

Table 3.1: Number of (Converted) REITs Across Countries

Country	All REITs	Converted REITs	Sample
Belgium	9	3	3
Canada	37	10	10
France	16	12	11
Germany	3	1	0
Italy	3	3	3
Netherlands	8	3	2
S. Africa	20	14	13
Spain	4	2	2
U.K.	39	24	21
U.S.	222	18	15
Total	361	90	80

Note: This table illustrates the multinational REIT conversion sample. The second column shows the overall number of historical and actual REIT constituents of the FTSE EPRA/NAREIT Global Real Estate Index. Of those, the third column reports the identified converted REITs. The last column gives the number of converted REITs that have available M&A data.

We obtain data on the existence and the nature of the deals, for a total of 80 converted REITs from nine countries from the Securities Data Company (SDC) Mergers and Acquisitions database. Table 3.1 provides an overview. Using the entire observation period, ± 5 years around the event, we are able to track M&A activities in common business cycles during restructuring times (two years prior to conversion date), and during the post-conversion era.[7] We

7 The average time span from REIT election announcement to actual conversion is two years,

observe asset deals, for which parts of the assets, the majority of assets or the entire assets of the respective party change hands and share deals i.e. the acquisitions of partial and remaining interest, of 100% of stocks and mergers. This yields a total amount of $1,093$ transactions in which a sample REIT is involved on the acquirer or target side.

Within the eleven years time span, we observe a substantial increase in deal activity for the years in which the REIT conversion takes place. The average number of deals settled by the observed entities in the years of the conversions is about two times as large as during the preceding years. This is accompanied by an increase in total deal volume. The average deal volume reaches its high point four years after a conversion has taken place (Figure 3.1), which is disassociated from the evolution of the overall M&A market in the respective economies.

as documented in Carlock and Wilkin (2018).

Table 3.2: Number of Internal Sample Deals

Deal Description	Number of Firms
REIT buys from subsidiary	34
REIT buys from parent	2
REIT sells to parent	1
REIT buys from subsidiary of subsidiary	3
Total	40

Note: This table shows deals within concerns. The first column refers to the role of the sample REIT in the deal; the second lists the aggregate number of deals.

Table 3.3 reports the number of deals in each period by deal type and role of the sample REIT in the respective deal. The acquisition of shares is predominant (56% of deals). In 55% of the observed transactions, a sample REIT directly acquires the assets or shares of another entity. Only a small fraction of deals (3.7%), conducted by 25 sample firms, can be characterized as internal restructuring activities, i.e., when the sample REIT is simultaneously engaged on the acquirer and target side of a deal. This can happen reciprocally, or as the parent of the respective deal party. Highest prevalence among internal deals exhibit acquisitions from immediate subsidiaries (Table 3.2).

Table 3.3: Number of Sample Deals per Deal Type

	Deal Type		Role of the REIT			
Years to Conversion	Asset Deals	Share Deals	Acquirer	Acquirer Parent	Target	Target Parent
-5	27	33	40	2	4	10
-4	32	40	50	2	2	13
-3	29	40	44	5	2	11
-2	35	57	41	15	5	24
-1	39	52	42	16	3	22
0	57	87	78	16	3	35
1	62	83	75	16	6	40
2	56	68	69	13	7	28
3	44	58	58	4	4	22
4	47	47	53	11	1	23
5	55	45	49	11	2	27
Total	483	610	599	111	39	255

Note: This table reports the number of deals within the window of $-5\ to\ 5$ years around the conversion date. Deals are classified as asset deals, for which parts of the assets, the majority of assets or the entire assets of the respective party change hands and share deals i.e., the acquisitions of partial and remaining interest, of 100% of stocks and mergers (second and third columns). The fourth through seventh columns show the role of the sample REIT (acquirer, acquirer parent, target, or target parent).

3.4 Conversion-Related M&A Activity

3.4.1 Strategic Restructuring

In order to control for potential structural differences between more (less) active sample firms, we build portfolios and characterize them along the quartile-levels of restructuring activity, i.e. number of conducted deals (Table 3.4). As shown in Table 3.5, a comparison of typical M&A-related firm-level variables for high and low restructuring entities two years prior to conversion does not show substantial ex ante divergence. From a regulatory perspective, 49 firms already hold adequate qualified real estate portfolios. The remainder of the sample firms are sufficiently close to the necessary benchmark ratio (on average, 0.2% below).

To definitely rule out a related regulatory requirement as key driver, we empirically analyze how the Asset Test impacts the decision to reallocate the property portfolio. Detailed variable definitions are provided in Appendix 3.6. Our analysis is geared in two directions. For this reason, we use a Poisson estimation on number of deals, and a linear panel regression on relative deal size. The results are in Table 3.6. Controlling for firm-level characteristics, we find no significant impact of the Asset Test requirements on either variable in any considered model specification.[8] Thus, in contrast to Hypothesis 1a, we conclude that M&A deals are not subject to the Asset Test.[9] Consequently, the desire to

8 Model ii uses country fixed effects, respectively, to account for heterogeneity between systems. We use robust standard errors clustered on company-level throughout the paper.

9 The proximity to the fulfillment of the asset test criterion might impact the decision to convert at all. For our further analyses only converters are relevant, hence such potential endogeneity does not impair the results.

form high-quality property portfolios in advance of conversion may drive M&A activity and deal volume, and these transactions may be perceived as strategic.

Table 3.4: Distribution of Sample Deals and Firms across Quartiles

	Full Sample		Acquirer Subsample	
Quantile	# Deals	# Firms	# Deals	# Firms
0.25	5	26	2	25
0.5	29	36	10	36
1	78	18	31	19

Note: This table shows the overall number of deals and the number of deals in which the sample REIT appears as an acquirer. Sample REITs are grouped into pre-conversion (two-year) M&A activity quartiles. The number of deals reflect the thresholds of each quartile, e.g., the first line (25% quartile) displays 26 firms conducting 5 or fewer deals in the full sample. The middle quartiles are given in aggregate.

But what is the instantaneous return on those deals? To answer this question, we follow the common event study approach to obtain information on the deal premium. A fraction of 37 deals qualifies for this part of our analysis. Those deals are acquisitions of public targets with sufficiently high market liquidity. For this subsample of M&A deals, following the typical approach, we derive cumulative abnormal returns (CARs) using an estimation period of 120 days to 20 days prior to deal announcement, and a symmetric event window of ± 5 days. We estimate predicted returns by using the market model. Compared to prior results in the REIT literature, we find a high average premium of approximately 9.1% (surveyed by Glascock et al., 2018).[10]

Table 3.5: Two-Sample t-Test for High- and Low Restructuring Quartiles

	Low	High	High-Low
Leverage	0.497	0.395	-0.102
M/B Ratio	1.683	1.938	0.255
Asset Test	11.905	-0.195	-12.100
Age	13.738	20.629	6.891
Market Cap	601.092	1695.208	1094.117
Total Debt	608.785	1615.682	1006.897
Total Assets	1189.059	3650.925	2461.866

Note: This table displays the arithmetic means of typical M&A-related firm characteristics according to the upper and lower trading activity quartiles for the U.K. and the U.S. for the two years pre-conversion. The last column reports the difference between the quartiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

This indicates a relatively high willingness to pay for the REITs from the excerpt of our converted REITs M&A sample. Internal differentiation between pre- and post-REIT-conversion deals reveals that the premiums tend to be larger on average for pre-conversion deals (10.3% versus 8.1%).

10 If we vary the event window, we find 8.3% for ± 2 days.

Based on these findings, one can conclude that the restructuring process involves transactions that are primarily conducted to build attractive portfolios and that are relatively expensive. Consistent with Hypothesis 1b, we find that REITs pay higher prices to achieve this goal, which means that converting RE-OCs accept short-term return compression. Section 3.5 shows how this pays off in the long run.

Table 3.6: Regression Results for the Impact of the Asset Test Criterion

	Deal Number		Relative Deal Size	
	i	ii	i	ii
Key Variable				
Asset Test Criterion	-0.006	-0.010	-0.002	-0.002
	(0.008)	(0.007)	(0.002)	(0.002)
Control Variables				
Cash	4.616***	5.264***	1.017**	0.715**
	(1.227)	(1.394)	(0.406)	(0.284)
Leverage	0.075**	0.075**	0.017**	0.010*
	(0.035)	(0.037)	(0.008)	(0.006)
Leverage Squared	-0.001**	-0.001**	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Return on Assets	-6.263*	-3.055	2.597	2.018
	(3.772)	(4.710)	(2.166)	(1.815)
M/B Ratio	0.009***	0.013***	0.000	0.000
	(0.003)	(0.005)	(0.000)	(0.000)
Dividend Yield	0.015	0.037	0.010	0.019
	(0.044)	(0.053)	(0.014)	(0.016)
Size	-0.061	0.174	-0.044**	0.020
	(0.116)	(0.145)	(0.020)	(0.036)
Age	0.031***	0.019	0.002	-0.003
	(0.012)	(0.015)	(0.002)	(0.004)
Constant	-1.668	-4.548*	0.233	-0.527
	(2.332)	(2.655)	(0.436)	(0.642)
Country FE	No	Yes	No	Yes
Observations	235	235	120	120
Adj. / Pseudo R^2	0.1136	0.1514	0.1161	0.1589

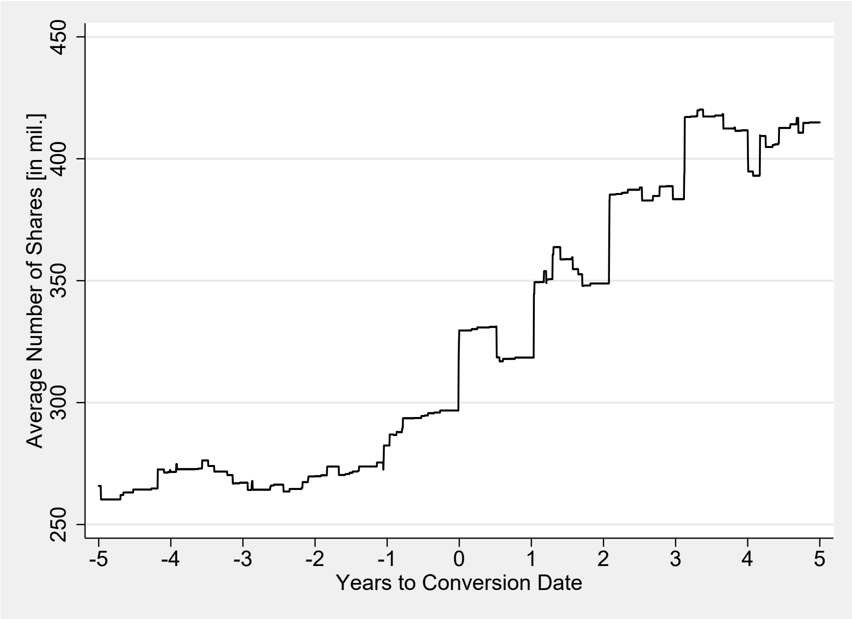
Note: This table shows the Poisson and linear panel regression results on the Number of Deals and Relative Deal Sizes within the window of $-5\ to\ 1$ year around the conversion date. The unit of observation is Deal Number (first and second columns) and Relative Deal Size (third and fourth columns). Models i lag all explanatory variables by one period; Models ii also use country fixed effects. We use robust standard errors clustered on company-level, which are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

3.4.2 Conversion-Induced Deals

The observation of a remarkable increase in absolute and average deal size over the four subsequent years post-conversions motivates an in-depth analysis of those deals. Figure 3.2 shows the average number of outstanding shares in the five-year horizon around REIT conversion dates. It illustrates how the level of equity rises simultaneously during this period. The persistently increasing number of outstanding shares reflects the possibility issue and place shares as REIT more easily. Because we observe deals in relative time around the conversion dates in nine countries, we conclude that equity issuance is not driven by market dynamics.

The subsequent part of our inferential analysis tests the effect of increasing inflows on M&A activity and deal size for the set of acquirers (acquirer subsample in Table 3.4). We proxy for inflows by changes in equity. We use the number of shares (corrected for stock splits) to capture the full picture of all equity-affecting issues such as SEOs, ATMs, and stock repurchases (following Harrison et al. (2011). We perform a Poisson regression to test the influence of inflows on the higher number of transactions, and then employ two-step estimation techniques to disentangle the possible effect of REIT status on inflows. We therefore use REIT status and firm-specific characteristics to estimate inflows in a first stage. We define an indicator variable that equals 1 if the company operates as a REIT in period t, and 0 otherwise. The change in these linearly predicted inflows serves as a key explanatory variable for the number of transactions. Equation 3.1 represents the second stage of our model.

Figure 3.2: Inflows Around REIT Conversions



Note: This figure shows the average number of outstanding shares for all sample companies within the window of $-5\ to\ 5$ years around the conversion date.

$$
\begin{aligned}
Number\,of\,Deals_{i,t} = \alpha & \\
& + \beta_1 Inflows_{i,t} + \beta_2 Inflows_{i,t-1} \\
& + \sum_{k=1}^{K} \gamma_k Firm\text{-}level\ control_{k,i,t} \\
& + \sum_{c=1}^{C-1} \delta_c D_{c,i} + \epsilon_{i,t}
\end{aligned}
\tag{3.1}
$$

Table 3.7: Regression Results for Inflows, Number of Deals, and Excess Deal Size

	Inflow	Deal Number	Excess Deal Size
Key Variables			
REIT status	0.130*** (0.032)		
Inflows		0.662** (0.299)	0.648** (0.314)
L1 Inflows		0.858* (0.447)	-0.056 (0.222)
Control Variables			
Cash	-0.180 (0.172)	2.053* (1.169)	-0.299 (0.760)
Return on Assets	0.899 (0.561)	-7.378** (2.980)	-5.958 (6.137)
M/B Ratio	-0.001 (0.001)	0.001 (0.003)	-0.009 (0.025)
Dividend Yield	0.010** (0.005)	0.012 (0.022)	-0.058 (0.035)
Size	0.447*** (0.028)	0.390*** (0.085)	(0.087) (0.222)
Age	-0.010 (0.009)	-0.019 (0.013)	- -
Leverage	-0.000 (0.001)	0.030 (0.019)	0.038 (0.027)
Leverage^2		-0.000** (0.000)	-0.000 (0.000)
Constant	4.988*** (0.466)	-8.519*** (1.367)	-1.645 (3.076)
Country FE	Yes	Yes	Yes
Firm FE	No	No	Yes
Observations	659	495	225
Adj. / Pseudo R^2	0.4783	0.1524	0.1054

Note: This table gives the results of the two-stage Poisson and linear panel regressions within the window of -5 *to* 5 years around the conversion date. Model i represents the first stage, which explains inflows (by REIT status). Model ii represents the second stage, which explains number of deals. Model iii reports the linear panel (FE) regression results, which explain excess deal size. We use robust standard errors clustered on company-level, which are given in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

$Number\, of\, Deals_{i,t}$ is the number of completed transactions of company i in period t. $Inflows_{i,t}$ reflects the difference in each company's logarithmized number of shares between period t and $t-1$. Firm-level controls are explanatory variables that are homogeneously and frequently documented in the general and REIT M&A literature. We control for country-specific effects (country-dummy $D_{c,i}$) to account for time-invariant heterogeneity in different REIT markets (e.g., Dogan et al., 2019). In addition, we estimate the effect of inflows on excess deal size, which is defined as the percentage deviation from the average deal size of each company by linear panel regression.

Table 3.8: Combined Effect of Inflows

Coef.	Std. Err.	z	p-value	[95% Conf.	Interval]
1.520	.596	2.55	0.011	0.351	2.689

Note: This table shows the combined effect of the contemporaneous and one-year lagged inflows on the number of M&A deals around REIT conversions estimated in Model ii.

Next, we describe how the number of M&A deals relates to the inflows triggered by REIT conversions. Table 3.7 shows the results of our corresponding set of estimations. The first column refers to the first-stage estimation, which identifies REIT status as highly statistically significant contributor to inflows, besides certain firm characteristics. On average, REIT status induces c.p. approximately 13% higher annual inflows. The second-stage estimation reveals a significantly positive influence of predicted inflows on deal activity, at a 5% level for contemporaneous inflows and a 10% level for one-period lagged inflows. Because our observations are on an annual basis, we note that the contemporaneous inflows are as reasonable as those in the preceding year. Lagged inflows also strengthen the causal inference on the direction of the effects. The results in Table 3.8, with a statistically significant combined effect of inflows, corroborate our findings. Increased inflows also explain the observed increase in excess (above average) deal size which is characteristic for the post-conversion period. As shown in the last column of Table 3.7, the increase in REITs' equity leads them to conduct larger deals. On average, excess deal size increases by 0.6 percentage points for each percentage point increase in net inflows. Overall, the results are consistent with Hypothesis 2.

3.5 Post-Conversion Performance

Lastly, we investigate long-term post-conversion performance for REITs with different levels of conversion-related restructuring activities via a buy-and-hold abnormal return (BHAR) approach. We form portfolios from the lowest to the highest M&A activity quartile according to the number of deals conducted during the two years prior to the conversion date (Table 3.4). We track the performance of converted REITs over three, four, and five years post-conversion. In addition, we compute the Sharpe (1966) ratios for those periods in order to capture risk-adjusted performance with respect to individual trading activity.
We calculate BHARs in accordance with Barber and Lyon (1997) and Lyon et al. (1999). The BHAR of REIT i is:

$$BHAR_i = \prod_{t=1}^{T}(1 + r_{i,t}) - \prod_{t=1}^{T}(1 + r_{PF,t}) \tag{3.2}$$

$r_{i,t}$ is the individual daily total return of company i at day t, and $r_{PF,t}$ represents the total return of each country's EPRA real estate index. Similarly to previous BHAR analyses of REITs by Sahin (2005), Campbell et al. (2009), and Ratcliffe et al. (2018), the benchmark portfolio reflects an eligible peer group of the respective REIT market.

Table 3.9: Post-Conversion Performance across Countries

	U.K.	U.S.	SA	FR	CA
3y	0.073	0.351*	0.564***	-0.111	-0.158
	(0.347)	(0.669)	(0.405)	(0.861)	(0.507)
4y	0.177*	0.644**	0.927***	-0.587	-0.145
	(0.427)	(0.797)	(0.808)	(1.261)	(0.570)
5y	0.263**	0.764***	0.872***	-0.533	-0.120
	(0.446)	(0.786)	(0.784)	(1.889)	(0.652)

Note: This table shows abnormal buy-and-hold returns (BHAR) for the five countries with the largest number of conversions. Beginning from the conversion date, we observe post-conversion windows of 3, 4 and 5 years. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

The results of the BHAR analysis in Table 3.9 show significantly positive abnormal returns for converting REOCs in the three countries with the largest numbers of conversions – the U.K., the U.S., and South Africa. This indicates they have realized the advantage of changing the legal organizational form. The results are supportive of Hypothesis 3a. The findings on positive BHARs are in line with evidence in Damodaran et al. (2005) and Piao et al. (2017), but in contrast to Sahin (2005), Campbell et al. (2009), and Ratcliffe et al. (2018), who do not find positive excess returns in M&As of established REITs.

Building on the positive BHARs, we form three converted REIT portfolios for the two largest developed – thus sufficiently homogeneous – REIT markets in our sample according to trading activity – the U.K. and the U.S. Table 3.4 reports that 26 firms from the lower quartile conduct up to five deals during the observation window; the 18 most active conduct up to 78 deals over that time span. The high (low) group comprises the firms in the upper (lower) quartile of trading activity, while the medium group captures the 50% of firms with moderate pre-conversion M&A activity.[11]

As shown in Table 3.10, despite their overall positive post-conversion performance, the entities with the highest levels of restructuring tend to underperform relative to converted REITs with low M&A engagement in terms of BHARs. The underperformance is persistent over the three time horizons. This may imply that the benefit from a conversion is offset in part by the costs of conducting the strategic transactions i.e. the high premiums paid. This can be explained by the neutral or negative post-acquisition performance to acquirers documented in the REIT and general finance literature (e.g., Glascock et al. (2018); Bargeron et al. (2008)), and it corroborates Hypothesis 3b.

Computing excess portfolio returns entails comparing the returns of single assets with those of a set of assets. Holding the latter is generally less risky for investors. Thus, some of the excess return may simply be due to the related risk premium. A key benefit of M&A activity is the composition of an adequately diversified property portfolio in advance of a REIT conversion.[12] Therefore, in the next step, we derive long-run excess returns using the Sharpe (1966) ratio, which accounts for the return volatility of the asset and the benchmark portfolios. Table 3.10 shows the results for risk-adjusted returns. We con-

11 Cross-country differences can be explained by differences in the design of the respective REIT regime, as reported by Ghosh and Petrova (2020).

12 For established U.S. REITs, Huerta-Sanchez et al. (2020) find no significant difference in market returns for the type of acquisition (asset vs. share deals).

clude that, as opposed to the simple buy-and-hold strategy, the considerable difference between high and low restructuring entities is no longer apparent. This implies that investors who benefit from the advantageous performance of low restructuring firms must accept higher risk. Simultaneously, the results show that only high restructuring REITs generate positive risk-adjusted abnormal post-conversion performance. Due to lower raw BHARs, this indicates there is reduced risk associated with investments in those firms. Together, it reveals a strategic advantage of high restructuring REITs, which explains the decision to conduct numerous M&A transactions preceding the adoption of REIT status.

Table 3.10: Post-Conversion (Risk-Adjusted) Performance by M&A Activity Quartile

	Simple BHAR				Risk-Adjusted BHAR			
	Low	Medium	High	High-Low	Low	Medium	High	High-Low
3y	0.487***	0.120	0.138	-0.349**	0.187	0.162	0.102**	-0.084
	(0.231)	(0.663)	(0.506)	(0.141)	(0.267)	(0.220)	(0.216)	(0.111)
4y	0.848***	0.525*	0.201	-0.647***	0.224	0.164	0.092**	-0.132
	(0.457)	(0.523)	(0.633)	(0.234)	(0.302)	(0.176)	(0.182)	(0.130)
5y	0.926**	0.611*	0.281*	-0.645**	0.230	0.145	0.103**	-0.127
	(0.591)	(0.494)	(0.612)	(0.279)	(0.315)	(0.164)	(0.182)	(0.135)

Note: This table shows simple and risk-adjusted abnormal buy-and-hold returns (BHARs over three relative time horizons for the U.K. and the U.S.). We calculate the risk-adjusted returns from the Sharpe (1966) ratio. The first through third columns for both return types show the results according to M&A activity quantiles. The respective fourth column for each states the difference between the upper and lower quartiles. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses.

3.6 Conclusion

This article examines M&A activity related to REOC-to-REIT conversions on a multinational level. Drawing on a unique dataset of internationally listed FTSE EPRA/ NAREIT property companies over the 1999-2018 period, we analyze 80 companies that elect REIT status. We find several interesting key insights:
First, REIT conversions generate an increased amount of M&A activity. This, in turn, leads to a high amount of restructuring deals that are tied closely to the conversion date, and to a high share of large-volume deals in the four years post-conversion. We find that REOCs are willing to pay a premium of approximately 9.2% above market valuation in order to acquire desired portfolios for strategic – but not regulatory – realignment. Second, adopting REIT status enhances equity inflows, which drives post-conversion M&A transaction activities and volume. Third, REIT converters in established REIT markets outperform their peers over the long run. Converters with lower restructuring activity exhibit even higher performance, and REOCs that undergo high restructuring show beneficial risk-adjusted returns.
Taken together, our results indicate that converting REITs tend to conduct substantial restructuring efforts during the pre-conversion period. Subsequently, they can follow a rapid path of growth through large-scale reinvestment of the inflows attracted by their REIT status, and exhibit demonstrably better performance than their peers.

Appendix – Variable Definitions

- Dependent Variables
  - $Number\,of\,Deals_{i,t} = \,Number\,of\,Deals\,of\,firm\,i\,in\,period\,t$
  - $Average\,Deal\,Size_{i,t} \,=\, Aggregate\,Deal\,Size_{i,t}\,/\,Number\,of\,Deals_{i,t}$
  - $Relative\,Deal\,Size_{i,t} = Aggregate\,Deal\,Size_{i,t}\,/\,Total\,Assets_{i,t}$
  - $Excess\,Deal\,Size_{i,t} = log(Aggregate\,Deal\,Size_{i,t}\,/\,Average\,Deal\,Size_{i,t})$
- Explanatory Variables
  - $Cash_{i,t} = Cash_{i,t}\;/\;Total\;Assets_{i,t}$
  - $Return\,on\,Assets_{i,t} = EBITDA_{i,t}\;/\;Total\;Assets_{i,t-1}$
  - $M/B\text{-}Ratio_{i,t} = Market\,Value\,of\,Equity_{i,t}\;/\;Book\,Value\,of\,Equity_{i,t}$
  - $Dividend\,Yield_{i,t} = Dividends\,per\,Share_{i,t}\;/\;Earnings\,per\,Share_{i,t}$
  - $Size_{i,t} = log(Total\;Assets_{i,t})$
  - $Age_{i,t} = Years\;since\;IPO_{i,t}$
  - $Leverage_{i,t} = Total\;Debt_{i,t}\;/\;Total\;Assets_{i,t}$
  - $Leverage\;Squared_{i,t} = Leverage^2_{i,t}$
  - $Asset\,Test_{i,t} = \frac{Qualifying\;Assets\;Ratio_{i,t} - National\;Regulation\;Ratio_{j,t}}{National\;Regulation\;Ratio_{j,t}}$; $country\,index\,j$

Chapter 4

Unstable Unsmoothing – An Evaluation of Correction Procedures for Appraisal-Based Real Estate Indices

– joint project with Andreas Gohs and Steffen Sebastian –

4.1 Introduction

Since the late 1980s, real estate research has addressed the "smoothness" of appraisal-based real estate index series, i.e., the dampened volatility and substantial positive autocorrelation. Edelstein and Quan (2006), for example, report that realistic market return variances within the NCREIF Property Index (NPI) are underrepresented on average by 75%.

Measuring the risk and return of real estate investments is tied to the challenging valuation of heterogeneous assets with only a limited amount of market transactions, as well as to the need to adequately aggregate individual valuations into informative benchmark indices. By their very nature, appraisal-based indices do not display contemporary market outcomes. And, appraisal behavior at the individual property level and the effects of cross-sectional aggregation induce the smoothing phenomenon (Geltner, 1989). However, as Young et al. (2017) note, appraisal-based indices are frequently used to develop and justify investment decisions ex ante, as well as to track investment performance. Booth and Matysiak (2001), Brooks and Kat (2002), and Getmansky et al. (2004) show that reliance on appraisal-based numbers may adversely affect investment decisions, and thus hinder efficient capital allocation.

In order to adequately quantify risk, real estate scholars have developed a number of time series correction techniques, known as unsmoothing or de-smoothing procedures. This paper challenges forty years of research on the development and application of unsmoothing procedures to appraisal-based indices. Our contributions are twofold.

First, we offer a condensed and focused survey of research on appraisal-based indices, systematically outlining the most important insights into correction procedures. An extensive survey of related studies was last provided by Geltner et al. (2003), so it does not cover more recent contributions. Our survey of prior research is concisely designed, in order to enable familiarity with the topic with relatively low effort. This should provide researchers and finance practitioners with a critical judgment of the informational content of appraisal-based index series, and of the distributional features induced by prevailing unsmoothing techniques.

Second, and more important, we provide a thorough empirical investigation of the stability of the results and the distributional features of selected correction procedures. Our empirical exercise benefits from the series of index returns that is now available, and incorporates forty years of data from the appreciation component of appraisal-based NPI. Despite their wide use in research and praxis, to date, there is remarkably little evidence on the distributional features of unsmoothed time series in general, and no evidence on the dynamics of their statistical properties over time. To the best of our knowledge, no comparative study has yet examined an equivalent time length of data with a similar focus or methodology. We analyse single-parameter and regime-switching unsmoothing techniques. For each technique, we dynamically estimate unsmoothing weights along rolling and increasing time-windows. We then apply them to the index series, and evaluate each resulting unsmoothed series statistically.[1]

We observe that a simple sample variation induces substantial changes in the results for both single-parameter and regime-switching models. We apply and test variants proposed in the literature, as well as our own modifications of the original approaches. The implicit criticism of the methods investigated, and their use for scientific and practical purposes, is based on the statistical instability of the results from our unsmoothing exercises.

The remainder of this paper is structured as follows: Section two provides a survey of the literature on appraisal-smoothing and correction procedures. Section three presents our empirical insights into the robustness of the outcomes from the approaches considered. Section four concludes.

1 At a technical level, inference with rolling and expanding time-windows is inspired by McKenzie et al. (2014), among others.

4.2 Literature

Early investigations by Cole et al. (1986) found substantial divergence between sample properties' transaction prices and their corresponding appraisals. A closely related finding concerns the divergence of aggregate measures for securitized investments versus appraisal-based indices for direct investments in real estate (Gyourko and Keim, 1992), and transaction-based versus appraisal-based indices (Fisher et al., 1994).

One reason for these differences is embedded in the individual appraisal process: Surveyors tend to be reluctant to update prior assessments.

Such "anchoring"-related patterns have been theoretically derived, empirically documented, and experimentally tested by Quan and Quigley (1989, 1991), Diaz and Wolverton (1998), Young and Graff (1999), and Campbell et al. (2001), among others. Surveyors have been found to weigh historical information on properties more heavily than contemporary information if few recent property transactions are available. This phenomenon appears to be most prevalent when prices of comparable properties are fluctuating strongly, and when past values have been disproportionately stable (Quan and Quigley, 1989).

During the valuation aggregation process for index construction, we note that non-synchronicity and "stale" appraisals may further dilute information about underlying market values. Non-synchronous appraisals may arise because appraisal dates and reporting dates usually differ for individual properties and across comparables (see, e.g., Geltner, 1989 and Bond and Hwang, 2007). Similarly, stale appraisals may occur because only a fraction of appraisals for index properties is updated each reporting period. The remaining data are adapted from prior periods (Bond and Hwang, 2007).

Such lags in information processing translate into index returns that exhibit dampened volatility and substantial positive autocorrelation. The corresponding "smooth" index patterns have been documented consistently by, e.g., Ross and Zisler (1991), Geltner (1993b), Barkham and Geltner (1994, 1995), Shilling (1993), Fisher et al. (1994), and Edelstein and Quan (2006).[2]

The observed time series patterns of real estate returns lead to an academic debate: How can we correct for appraisal-induced "smoothness" as a prerequisite for investigating optimal asset allocation using real estate assets? A precise specification of price volatility patterns would be indispensable for assessing portfolio riskiness and diversification effects. Actual risk may otherwise be understated if, for example, asset allocation to real estate, such as by pension funds, were conducted with an appraisal-based benchmark.

The correction procedures introduced by Blundell and Ward (1987) and Firstenberg et al. (1988) are designed to depict market volatility more realistically based on the weak-form market efficiency considerations of Fama (1970). Through eliminating positive autocorrelation, they attempt to impose immediate volatility on appraisal-based time series. Correspondingly, the unsmoothing parameters are estimated from autoregressive models that are typically

2 Giliberto (1988) and Edelstein and Quan (2006) also report reduced mean returns of appraisal-based indices. Lai and Wang (1998) theoretically derive that, under the assumption of random appraisals and errors, the aggregation of appraisals into an index should yield increased volatility patterns. This stands in contrast to common perceptions, however. As shown by Young and Graff (1999), random appraisal error is not an adequate assumption, and sticky appraisals can better explain dampened volatility through aggregation (Brown and Matysiak, 2000).

of the first order for annual data, and up to the fourth order for quarterly data. This group of zero-autocorrelation techniques addresses the time series effects of smoothing without explicitly considering its sources. However, the underlying assumption of weak-form efficiency is highly questionable for unsecuritized real estate markets.

Geltner (1991, 1993a) and Barkham and Geltner (1994) were the first to specifically consider property-level appraisal behavior in their derivations of feasible unsmoothing weights for U.S. and U.K. appraisal-based indices. Their approach is based on Bayesian updating, and on the Quan and Quigley (1989) appraiser behavior-related findings of Quan and Quigley (1989). The resulting unsmoothing models are known as "reverse-engineering" procedures.[3]

Corgel and deRoos (1999) conduct a comparative investigation of the performance of unsmoothing procedures in an asset allocation context. They criticize the accompanying change in mean returns because it renders the corrected index return series intractable for asset allocation models.

Cho et al. (2003) further test and enhance several unsmoothing procedures. During the more recent years of their sample period, they attest specifically to the instability of the Fisher et al. (1994) zero-autocorrelation procedure. They update the procedure through model refinements to obtain a better fit.

Bond et al. (2006), Bond and Hwang (2007), and Bond et al. (2012) propose a more refined procedure, characterized by the separate treatment of the effects of smoothing and non-synchronous appraisals on indices using an ARFIMA model. The study provides a thorough (theoretical) investigation of the im-

3 For a comprehensive survey of such models, see Geltner (1993b).

plications of cross-sectional aggregation of appraisals at the index level. The results indicate significant market inefficiency for the U.K. real estate market, but not for the U.S. market, which is contrary to the findings of Geltner (1993a) and Barkham and Geltner (1994).[4].

Note also that constant parameter models may exhibit limitations in incorporating actual market environments characterized by dynamics and structural patterns. Matysiak and Wang (1995) and Cho et al. (2014) investigate contextual state dependency, and find that market conditions significantly impact appraisal behavior, and thus the extent of smoothing. Cho et al. (2014) further confirm that smoothing is positively correlated with the level of property prices and overall insecurity in the market. Smoothing is therefore likely to be misspecified by static unsmoothing parameters (or single regimes). Chaplin (1997) propose unsmoothing techniques that can alter market environments. This would allow for state-dependent alterations in the relationship between market- and property-level valuation distortion. The threshold autoregressive (TAR) models of Lizieri et al. (1998), Lizieri et al. (2012), and Delfim and Hoesli (2020), and the Markov-switching procedure of Maitland-Smith and Brooks (1999), also enable the incorporation of different states, and demonstrate the unsmoothing properties of models with regime-switching designs. As outlined by Cheng et al. (2011), the heterogeneity of appraisers, in addition to non-static market conditions, plays a significant role.

A related strand of the literature attempts to explain peculiarities by means of

[4] As Bond and Hwang (2007) point out, *"the conventional assumption that the smoothing level estimated from an appraisal-based index represents the average smoothing level of individual properties is appropriate only when all individual properties have the same smoothing level"* (p. 361)

common factors. Although beyond the scope of our analysis, we note that unobservable inherent values are inferred via the estimation of latent variable models, which combine information from securitized and unsecuritized real estate markets. Giliberto (1990), Wang (1998), Ling et al. (2000), and Booth and Marcato (2004) provide studies on this issue.

4.3 Time-Variant Performance of Correction Procedures

4.3.1 Data and Methods

First, NCREIF appreciation index is unsmoothed for the entire sample period at hand, 1977/IV-2017/IV, and the obtained results are presented.[5] Second, the robustness of results from constant-parameter unsmoothing techniques shall be tested while their parameters are estimated for moving sections of the time series (i.e. rolling and increasing time windows). Examined are the models of Blundell and Ward (1987), Firstenberg et al. (1988), Geltner (1993a), Barkham and Geltner (1994), Fisher et al. (1994), Chaplin (1997), Cho et al. (2003), Bond and Hwang (2007) and Lizieri et al. (2012). At the technical level, inference with rolling and expanding time windows follows McKenzie et al. (2014), among others.

The considered unsmoothing methods are applied on quarterly or annual basis, depending on the underlying approach. For correction methods which are designed for application on quarterly series, statistical properties are additionally computed and reported for annual periodicity.[6]

First and seconds moments of the corrected NPI returns and their ratios with the corresponding moments of the original NPI returns are calculated for each sample window. To evaluate the robustness of these ratios, statistical characteristics of their distributions are computed across windows. The obtained

5 In this article we use the abbreviation NPI while focusing solely on the appreciation component of this index.

6 Parts of the methodology are proposed by Gohs (2014)

statistics of the applied correction-procedures are compared across each other and with a number of US (real estate) market indices. For a correction procedure to be feasible, ratios of standard deviations should be stable across the moving windows i.e. if varying ratios are obtained for different windows, there should be narrow dispersion. The levels of reported standard deviations are indicated by the graphical representation in Figure 4.1 for selected indices of different asset classes. In what follows, the considered correction-procedures are briefly introduced.

4.3.2 Considered Models

Blundell and Ward (1987) propose to estimate the unsmoothing weight ϕ_1 from the following $AR(1)$ model, where ϵ_t is a white noise term of innovations:[7]

$$r_t = \phi_0 + \phi_1 r_{t-1} + \epsilon_t \quad (4.1)$$

The corresponding unsmoothed annual returns are given by:

$$r_t^{BW} = \frac{r_t - \widehat{\phi_1} r_{t-1}}{1 - \widehat{\phi_1}} \quad (4.2)$$

Firstenberg et al. (1988) propose to unsmooth appraisal-based real estate returns in quarterly periodicity, based on an $AR(4)$ process. The corresponding

7 Error terms are assumed to be white noise throughout the paper, if not stated differently.

unsmoothed return in period t is thus:

$$r_t^{FRZ} = \frac{\widehat{\phi_0} + \widehat{\epsilon_t}}{1 - \sum_{\rho=1}^{4} \widehat{\phi_\rho}} \tag{4.3}$$

Since the mean which is linked to the constant of an unsmoothed return series is inflated if the denominator in equations 4.2 and 4.3 approaches zero, we propose to apply this correction rule on a demeaned series. In doing so, the mean must be added again after the elimination of autocorrelation. We also provide results for an AR(1,4) version of the Firstenberg et al. (1988) procedure - correcting only lag one and lag four.

Based on inflation-adjusted returns Fisher et al. (1994) propose to estimate unsmoothing weights from an AR(1,4) model and to apply the following correction rule:

$$r_t^{FGW} = \pi_t + \omega_0[(r_t - \pi_t) - \widehat{\phi_1^*}(r_{t-1} - \pi_{t-1}) - \widehat{\phi_4^*}(r_{t-4} - \pi_{t-4})] \tag{4.4}$$

where π_t denotes the periods' inflation rate according to the national consumer price index.[8][9]

Cho et al. (2003) point at two conceptual shortcomings of the Fisher et al. (1994) correction procedure, which have the potential to induce biased es-

8 $\omega_0 = \frac{\sigma_{SP}}{2\sigma_\epsilon^*}$ enables the adjustment of the standard deviation of corrected returns, as proposed by Fisher et al. (1994). The weight is related to a corresponding stock market index, e.g. S&P500 for the US.

9 A star indicates elements which are derived from real returns: $r_t^* = r_t - \pi_t$. Accordingly, AR-parameters ϕ_i^* are estimated for real time series.

timates of the corrected series. First, the expectation of the models' error is found to be non-zero. Second, the error term is most likely time-variant. They conclude that accounting for real returns does not prevent substantial inconsistencies in time-series correction. Also, the possibility of an artificially introduced negative autocorrelation in corrected returns must be considered, in their opinion. To overcome related issues, a "generalized differences" model is proposed by Cho et al. (2003).

In line with Fisher et al. (1994), the estimation procedure is based on inflation-deducted returns, while parameters are now derived from differences of real returns. Thus, the AR(1,4) model is applied:

$$r_t^* - r_{t-2}^* = \phi_0^* + \phi_1^*(r_{t-1}^* - r_{t-3}^*) + \phi_4^*(r_{t-4}^* - r_{t-6}^*) + \epsilon_t \qquad (4.5)$$

Estimated parameters from this differences-model are directly inserted into the correction formula:[10]

$$r_t^{CKS} = \pi_t + \frac{1}{\omega_2}(r_t^* - \widehat{\phi_1^*} r_{t-1}^* - \widehat{\phi_4^*} r_{t-4}^*) \qquad (4.6)$$

From the similarity of the approaches, it is obvious that the proposed modifications of the Fisher et al. (1994) procedure may also be applied to the latter specification. The Cho et al. (2003) unsmoothed time series closely follows the trend of the original NPI series, but incorporate higher volatility. A graphical representation is provided by Figure 4.2.

10 $\omega_2 = \frac{2\sigma_\epsilon^*}{\sigma_{SP}}(r_t^* - \widehat{\phi_1^*} r_{t-1}^* - \widehat{\phi_4^*} r_{t-4}^*)$

The application of a zero-autocorrelation correction procedure on time series of appraisal-based returns implies the assumption of a weakly informational efficient market.[11] Thus, autocorrelation in appraisal-based returns series should originate completely from the smoothing-phenomena and cannot be inherent in market returns. This is a strong assumption, so that the results of previous studies indicate that information processing is not efficient in some real estate markets, as discussed in the literature section. Serially correlated market returns may exist. Furthermore, users of correction-procedures may select the targeted volatility of the corrected series, for example via the adjustment factor ω or via the lag structure of the AR process or by choosing between nominal or real returns.

As outlined in the literature section, the family of reverse-engineering methods overcomes the implicit ex-ante assumption of weakly informational efficient real estate markets. Geltner (1993a) proposes a reverse-engineering approach to appraisal-based index returns reported for the US commercial real estate market. Reappraisal is assumed to take place with annual periodicity. The correction coefficient a is derived for this appraisal-frequency and via the following relationship:

$$a^* = \mathit{arg\ min}_{a} \left| a - \frac{\alpha(2-3f)}{2} + \sum_{t=1}^{T-1} a(1-a)^t - \frac{\alpha}{2}(2-2\alpha+3\alpha f)(1-\alpha)^{t-1} \right| \tag{4.7}$$

The reverse-engineering expression can then be written as:

[11] See e.g. Fama et al., 1969, Fama, 1970 and Fama, 1991 for a discussion of information processing in efficient markets.

$$r_t^{Geltner} = \frac{r_t - (1 - a^*)r_{t-1}}{a^*} \tag{4.8}$$

Geltner (1993a) finds the optimal correction parameter a^* of 0.4. for a plausible appraiser-alpha α of 0.5 and a parameter representing the reappraisal frequency f of 0.15.[12] Here, the NPI is unsmoothed using the Geltner (1993a) approach, where α is likewise assumed to be 0.5 and the parameter value for f is calculated, adopting the Geltner approach as described in footnote 12 to identify f for our series at hand. We obtained values different from Geltner (1993a) and different values for nominal and real returns. Gohs (2014), reports parameter values of 0.2712 and 0.2183, respectively.

The parameter a^* is derived from a scatter-search procedure for the present study. We receive an optimal $a^* = 0.4155$ for inflation-deducted returns (Geltner) and 0.3929 for nominal return series (Geltner-n).[13]

Barkham and Geltner (1994) suggest a reverse-engineering formula for the Jones Lang Wootton Index (British commercial properties) which is, when adapted, easily applicable to the NPI series. The authors correct continuously compounded annual returns and account for appraisal-smoothing and non-synchronous appraisal. The determination of parameters differs with respect

12 To obtain the value of the parameter f, Geltner (1993b) proceeds as follows: "The fact that the fourth-quarter mean is nearly 3.5 times greater than the quarterly mean for the other quarters during this period suggests that some 3.5 times more properties are typically appraised during the fourth quarter than in each of the other quarters. This suggests that we apply a value of $f = 0.15$" (p. 331). Remark: By taking weights of 1 for each of the first three quarters and 3.5 for the fourth, one obtains $1 + 1 + 1 + 3.5 = 6.5$ and $f = 1/6.5 = 0.1538$. This implies that 55% of all properties are reappraised during the fourth calendar quarter.

13 Geltner (1993a) suggests deducting the inflation rates (obtained from a consumer price index) from real estate index returns before applying the correction procedure. The inflation component is added again after correction.

to the previously discussed Geltner procedure. We find it optimal to use an α of 0.75 and 0.625, respectively, for the purposes of this study (BG34 and BG58).

Prior models implicitly assume the index smoothing level to be a linear aggregate of property-level smoothing. As pointed out by Bond et al. (2006) smoothing varies across individual properties. Accordingly, the estimated smoothing levels from previous approaches can be upward-biased. The authors show that the features of both appraisal smoothing and cross-sectional aggregation, can be more adequately represented by ARFIMA-models. The average smoothing level for returns of individual properties is then obtained from the parameter of fractional integration d. Bond and Hwang (2007) propose the following relationship for an ARFIMA(p,d,1) process:

$$(1-\phi(L))\underbrace{(1-L)^d\underbrace{(r_{mt}-\mu_m)}_{:=r_t}}_{:=\Delta^d r_t} = \theta_1\epsilon_{t-1}+\epsilon_t \tag{4.9}$$

for which L is the lag-operator and r_{mt} the index return reported for the real estate market in period t. Since Bond and Hwang (2007) correct demeaned series r_t are excess returns. μ_m represents the mean return on the market in the period under review and d is a long-run memory parameter or parameter of fractional integration, which captures the average smoothing level in the return series of individual properties caused by appraisal-smoothing.

If an informationally efficient real estate market is assumed ex-ante, the term $(1-\phi(L))$ is omitted and an ARFIMA(0,d,1) process is adopted. Otherwise, the AR-term with one or four lags is included, depending on the frequency of the series at hand (annual or quarterly data). Accordingly, the fractionally differentiated de-meaned returns $\Delta^d r_t$ follow an ARMA(1,1), respectively, MA(1) process.

The smoothing effects of non-synchronous appraisals are captured by the moving average component θ. The AR-parameters ϕ_i reflect the persistence of the market component which is common to all properties in the respective market. Thus, the AR-component would reflect the inertia of information processing (i.e. market (in)efficiency) and has to be omitted when an informationally efficient market is assumed ex-ante. Thus, if an analyst assumes an efficient market, she estimates the ARFIMA(0,d,1), if not, she estimates the ARFIMA(1,d,1)-model. Further autoregressive terms can be added, resulting in an ARFIMA(p,d,1) specification. The following relationship for time-series correction can be derived from the Bond and Hwang (2007) considerations:

$$\hat{\varepsilon}_t = \Delta^d r_t - \hat{\theta}_1 \hat{\varepsilon}_{t-1},\ \forall t = \omega + 2, ..., T \tag{4.10}$$

which is iteratively solved starting with $\varepsilon_{\omega+1} = \frac{\Delta^d r_{\omega+1}}{1+\hat{\phi}_1}$ and the corrected series

$$r_t^{BoHw} = \frac{\sigma_i}{\sigma_{ci}} \hat{\varepsilon}_t + \hat{\mu} \tag{4.11}$$

is obtained. Thereby, $\hat{\theta}_1$ is the MA(1) parameter as estimated from the ARFIMA (p,d,1) model, r_t^{BoHw} are corrected returns for period t. This applies irrespective of prevalence of informational efficiency, since only the MA(1) term is eliminated. The obtained return series is now subject to volatility adjustment. The proportion of volatilities of individual property returns σ_{ci} to those of the market returns σ_i is assumed to be:[14]

$$\frac{\sigma_{ci}}{\sigma_i} = (1 - \phi_{si})\sqrt{\frac{1}{2}(1 + 2v_i^2\lambda_i^2 + \sqrt{1 + 4v_i^2\lambda_i^2})} \tag{4.12}$$

In application, the estimated quantity for expected appraisal smoothing at the individual level $E(\phi_{si})$ is replaced by the estimated parameter $\widehat{d}$. From this equation, one finally obtains the corrected returns. The value for the term $\delta := 2v_i^2\lambda_i^2$ is obtained from the estimated MA coefficient, since the following equation is fulfilled and can be inserted into equation 4.12.

$$\widehat{\theta}_1 = -\frac{\delta}{1 + \delta + \sqrt{1 + 2\delta}} \tag{4.13}$$

The outlined variants of the baseline model of Bond and Hwang (2007) are the estimation of an ARFIMA(4,d,1) model for quarterly return series and the estimation of an ARFIMA(1,d,1) model for annual return series if inertia in information processing is not ruled out. Similarly, ARFIMA(0,d,1)-models are estimated for both frequencies if informational efficient real estate markets are assumed ex-ante. These variants are indicated by BoHw4, BoHw, BoHw-a1 and BoHw-a throughout the following subsections. [15] Their relationship to the original NPI series is depicted in Figure 4.3.

Beyond the presented constant-parameter unsmoothing procedures, the regime-switching approaches of Lizieri et al. (2012) and Chaplin (1997) are evaluated. In contrast to the single parameter models, these approaches allow the α to

14 Notation refers to Bond and Hwang (2007). λ_i^2 is the variance of a "non-synchronous variable" representing the stochastic time-interval between two appraisals, which is assumed to be exponentially distributed, v_i is the Sharpe-Ratio.

15 A list of abbreviations and corresponding data definitions is provided in the Appendix A1.

vary over time, e.g. according to macroeconomic conditions. For the Chaplin (1997) procedure, exogenous regime-dependant parameters for three regimes are 0.25, 0.1 and 0.25, respectively, with an inner interval of 0.5 standard deviations for quarterly returns. For the Lizieri et al. (2012) procedure, regime-changes are derived from the evolution of the real estate market (NPI) and the stock market (Dow).

4.3.3 Static Comparison

Descriptive statistics of the original and unsmoothed time series are reported in Table 4.1. The first seven rows capture the raw return series of the NCREIF Appreciation Index, U.S. consumer prices (CPI), large-cap stocks (Dow Jones), REITs, long-term government bonds, the equally weighted NCREIF Transaction-Based Index (NTBI-EW), and the value-weighted NCREIF Transaction-Based Index (NTBI-VW). The latter two indices display transaction prices complemented by appraisal values. The reported numbers start from the last quarter of 1977, except for those of the transaction-based indices, which begin in the first quarter of 1984.[16]

For the entire time-horizon, one can observe an average quarterly (annual) return of 0.24% (0.79%) for the NPI, compared to 1.08% (4.04%) for REITs and 2.12% (8.60%) among large-cap stocks. As expected, the NPI entails the lowest standard deviations on annual and quarterly bases, relative to the other indices under consideration.

[16] For comparison, we index the time series to the end of the fourth quarter of 1984 throughout the paper.

A crucial feature of appraisal-based index returns is revealed by the difference of standard deviations of returns over the forty-year timespan. This holds for quarterly and annual figures. From Table 4.1 it can be seen that the volatility of the NAREIT returns (representing securitized real estate) is more than four times larger than the volatility of NPI returns. The fluctuations of the NTBI-returns are almost three times as large on the quarterly basis. The difference is less pronounced, but still apparent, for annual data.[17] The difference in volatilities compared to large-cap stocks and to government debt is likewise of substantial magnitude.

17 Data for NTBI-EW and NTBI-VW are provided by NCREIF since 1984. The indices are in fact constructed via estimation of linkages between transaction prices and appraisal values.

Table 4.1: Descriptive Statistics of (Corrected) Index Returns

Quarterly	Mean	Std.Dev.	Min.	25%-Q.	50%-Q.	75%-Q.	Max.
NPI	0.24	2.18	-10.15	-0.29	0.54	1.49	3.82
CPI	0.66	0.50	-2.32	0.50	0.71	0.91	1.71
Dow	2.12	7.77	-29.20	-0.88	2.57	6.76	19.52
REITs	1.08	9.45	-51.07	-2.60	1.85	6.37	27.66
LTGvtBds	1.40	9.05	-27.84	-6.74	1.99	3.06	31.14
NTBI-EW	0.70	6.00	-19.09	-1.30	0.99	4.37	15.57
NTBI-VW	0.77	6.03	-20.10	-1.52	0.91	4.25	15.52
FRZ	0.20	6.26	-44.46	-1.66	0.66	2.60	16.52
FRZ14	0.21	5.50	-38.19	-1.09	0.57	2.31	13.22
FGW	0.51	3.79	-20.57	-1.90	0.13	1.38	7.45
CKS	0.44	3.73	-18.40	-2.06	0.04	1.58	7.92
BoHw	0.40	2.29	-13.71	-0.13	0.77	1.29	5.74
BoHw4	0.25	1.90	7.07	-0.32	0.62	1.42	3.26
Annual	**Mean**	**Std.Dev.**	**Min.**	**25%-Q.**	**50%-Q.**	**75%-Q.**	**Max.**
NPI	0.79	7.82	-24.96	-1.55	2.43	6.07	12.01
CPI	2.63	1.23	0.41	1.72	2.59	3.36	6.09
Dow	8.60	14.72	-41.31	2.18	10.46	20.39	28.86
REITs	4.04	18.12	-52.96	-2.08	6.35	17.28	25.86
LTGvtBds	5.80	20.08	-52.83	-20.50	4.87	6.41	34.74
NTBI-EW	3.04	9.84	-22.29	0.84	3.96	8.65	20.38
NTBI-VW	3.26	9.56	-24.93	1.42	4.72	9.09	18.50
FRZ	0.73	15.25	-59.16	1.49	3.15	6.75	33.67
FRZ14	0.75	14.27	-52.09	2.89	3.87	6.23	34.50
FGW	2.17	10.26	-32.85	3.99	0.05	2.27	21.18
CKS	2.07	9.08	-24.62	5.02	0.07	3.88	11.32
BoHw	1.61	7.43	-20.41	0.21	2.98	5.04	19.29
BoHw4	0.78	7.35	-25.09	1.69	1.81	5.07	10.68
BW	0.86	14.07	-38.68	-1.63	2.39	7.50	38.49
Geltner	1.55	17.62	-47.00	-7.02	0.06	6.16	54.29
Geltner-n	0.89	16.89	-43.83	-2.44	4.12	8.32	50.69
BG34	0.81	9.46	-29.31	-1.48	2.27	7.05	16.29
BG58	0.83	11.05	-32.80	-1.43	2.71	7.51	24.54
BoHw-a	0.88	3.49	-5.69	-1.45	1.49	3.01	7.05
BoHw-a1	0.77	4.42	-9.25	-1.18	1.83	3.14	8.32

Note: Descriptive statistics are reported for the original and the corrected return series of constant-parameter unsmoothing procedures analyzed in quarterly- (top) and annual (bottom) periodicity for the entire sample period. Time series definitions are provided in Appendix A1.

Another observation from the numbers in Table 4.1 refers to the effects of constant-parameter correction procedures on the NPI series. Standard deviations are shown to rise through the application of all types of techniques, as intended by most authors, except for variants of the Bond and Hwang (2007) model. Among the group of techniques correcting quarterly data, the Firstenberg et al. (1988) model induces the largest increase in volatility which almost approaches volatilities of transaction-based measures, but remains substantially lower than the volatility of the REIT index. For the techniques based on annual index returns, the Geltner (1993a) reverse-engineering procedure and its modified version induce large volatility, followed by the Blundell and Ward (1987) method. The level of volatility after correction thereby closely approaches the level reported for REITs. From the modified approaches, the FRZ14 imposes minor assimilation of the mean return at the cost of a reduction in volatility, compared to the NPI and to the original FRZ model. The proposed modifications of the Geltner (1993a) model - i.e. direct reverse-engineering of nominal- instead real returns - is capable of replicating the actual long-run mean of the NPI more accurately. It thereby slightly reduces the increase in volatility in comparison to the original version of the Geltner procedure. Lastly, the two versions of the Barkham and Geltner (1994) procedure leave the mean nearly unchanged and show a moderate increase in volatility.[18]

[18] Barkham and Geltner (1994) impose unsmoothing weights without estimating them. We provide evidence to support two plausible parameter values.

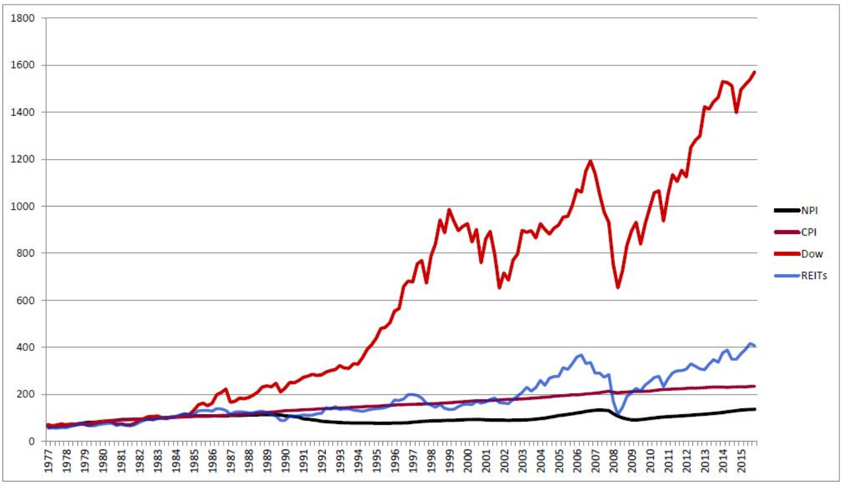


Figure 4.1: U.S. (Real Estate) Market Indices

Note: The figure depicts the evolution of US market indices for large-cap stocks (Dow Jones), REITs (NAREIT All Equity Price Index) and direct real estate (NCREIF Appreciation Index) for the sample period. CPI is the US consumer price index.

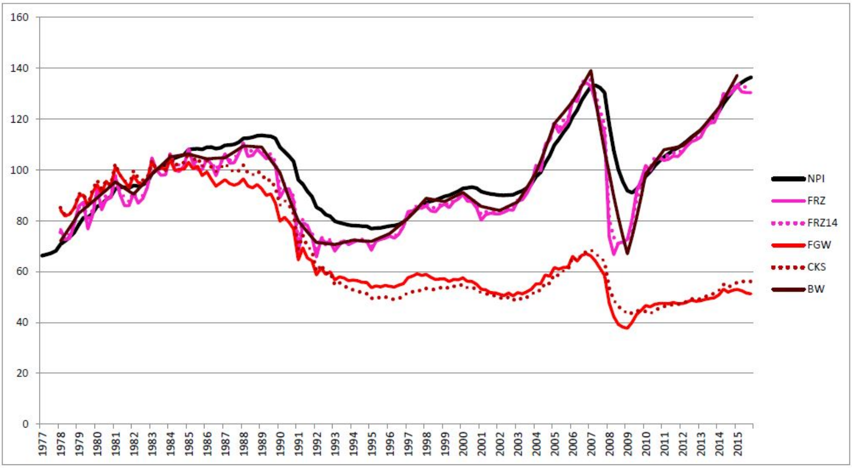


Figure 4.2: Graphical Comparison of Series from Zero-Autocorrelation Procedures and the original NPI

Note: The figure visualizes the original NCREIF Appreciation Index series and corresponding corrected series using the approaches of Firstenberg, Ross and Zisler (1988), Fisher, Geltner and Webb (1994), Cho, Kawaguchi and Shilling (2003), and Blundell and Ward (1987) for the sample period. Series are indexed in 1984/IV.

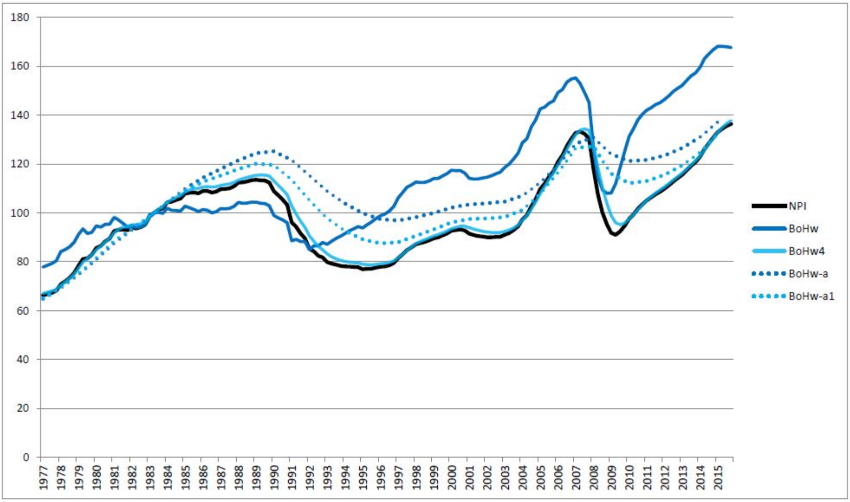


Figure 4.3: Graphical Comparison of Series from Variants of the Bond and Hwang (2007) Procedure and the Original NPI

Note: The figure visualizes the original NCREIF Appreciation Index and corresponding corrected series from variants of the Bond and Hwang (2007) procedure (BoHw) for the sample period. Series are indexed in 1984/IV.

Table 4.2: Autocorrelations of (Corrected) Index Returns

Lag (Qr.)	NPI	CPI	Dow	REITs	LTGvtBds	NTBI-EW	NTBI-VW	FRZ	FRZ14	FGW	CKS	BoHw	BoHw4
1	0.79	0.33	-0.01	0.16	0.16	-0.15	-0.17	0.08	0.07	0.17	0.00	0.62	0.93
2	0.69	0.09	-0.03	-0.14	-0.15	-0.15	-0.17	0.00	0.32	0.40	0.40	0.49	0.81
3	0.50	0.13	-0.05	-0.10	-0.02	0.06	0.04	0.07	-0.01	0.05	0.00	0.26	0.64
4	0.39	0.05	0.04	0.01	-0.05	0.21	0.21	0.29	0.27	0.30	0.52	0.20	0.47
5	0.15	0.16	0.05	0.09	-0.18	0.05	0.04	-0.21	-0.24	-0.22	-0.12	-0.12	0.28
6	0.03	0.20	0.04	0.00	-0.05	-0.14	-0.16	-0.20	-0.11	-0.07	0.12	-0.19	0.13
7	-0.05	0.11	-0.22	-0.12	-0.08	0.08	0.06	-0.05	-0.14	-0.13	-0.02	-0.22	0.02
8	-0.08	0.09	0.08	-0.09	-0.09	0.04	0.06	0.01	-0.03	-0.01	0.15	-0.17	-0.06
9	-0.12	0.02	-0.05	-0.18	-0.07	-0.08	-0.09	-0.11	-0.12	-0.17	-0.13	-0.19	-0.11
10	-0.13	0.03	0.08	0.06	-0.03	-0.09	-0.10	-0.06	-0.06	-0.04	-0.01	-0.14	-0.14
11	-0.12	0.11	0.04	0.02	0.09	-0.02	-0.02	0.08	0.03	-0.01	-0.03	-0.08	-0.17
12	-0.15	0.10	0.02	-0.11	-0.10	0.04	0.06	-0.03	-0.05	-0.07	-0.07	-0.11	-0.19
13	-0.17	0.03	-0.13	-0.04	-0.02	0.01	0.01	-0.08	-0.05	-0.07	-0.10	-0.12	-0.21
14	-0.18	0.12	0.03	-0.04	0.10	-0.12	-0.12	-0.04	-0.07	-0.04	-0.05	-0.13	-0.22
15	-0.17	0.01	0.05	0.04	0.11	0.00	-0.01	0.03	-0.01	-0.07	-0.07	-0.11	-0.22
16	-0.19	-0.03	0.11	-0.01	-0.01	0.09	0.10	-0.09	-0.09	-0.09	-0.11	-0.13	-0.22

Lag (An.)	NPI	CPI	Dow	REITs	LTGvtBds	NTBI-EW	NTBI-VW	FRZ	FRZ14	FGW	CKS	BoHw	BoHw4
1	0.47	0.34	-0.02	0.00	-0.26	0.36	0.28	0.15	0.20	0.31	0.57	0.29	0.51
2	-0.07	0.29	-0.04	-0.33	-0.39	-0.17	-0.22	-0.30	-0.30	-0.25	0.01	-0.27	-0.03
3	-0.19	0.16	0.10	0.00	0.13	-0.26	-0.26	-0.12	-0.14	-0.19	-0.20	-0.21	-0.21
4	-0.23	0.05	0.11	-0.14	0.07	-0.17	-0.20	-0.09	-0.10	-0.11	-0.21	-0.17	-0.25

	BW	Geltner	Geltner-n	BG34	BG58	BoHw-a	BoHw-a1
1	0.16	0.10	0.12	0.33	0.25	0.75	0.71
2	-0.29	-0.26	-0.32	-0.17	-0.23	0.36	0.27
3	-0.12	-0.08	-0.11	-0.16	-0.14	0.06	-0.04
4	-0.14	-0.09	-0.13	-0.19	-0.16	-0.14	-0.21

Note: The table reports serial correlations of the analyzed original and corrected time series along 16 lags (quarterly frequency) and 4 lags (annual frequency). The NPI is analyzed in quarterly- (top) and annual (bottom) periodicity for the sample period. Time series definitions are provided in Appendix A1.

Positive autocorrelation is reported for the appraisal-based NPI series in Table 4.2. The original return series of the NPI exhibits an autocorrelation of 0.79 for the first lag. The serial correlation decreases in the number of lags, but remains positive and significant for the first four lags of quarterly data and to the second lag of annual data (10% level)[19]. Unsmoothing leads to a substantial reduction of first-order autocorrelation by virtually all techniques, except for the Bond and Hwang (2007) and Cho et al. (2003) models which even increase autocorrelation. Significant serial correlation is likewise apparent for a number of quarterly correction procedures, e.g. for the Firstenberg et al. (1988) model through the transmission from previous periods. The corrected series derived from annual numbers are free from significant serial correlation for, except the Bond and Hwang (2007) procedure and the Cho et al. (2003) model.

4.3.4 Rolling and Increasing Time Windows

The availability of forty years of index data allows us to compute corrected time series for different sample periods, to update them, to compute descriptive statistics from the manipulated series and to assess the obtained distributional features. In doing so, the series are evaluated for moving and expanding time windows on quarterly and annual levels, respectively.

The investigation of moving (or rolling) time windows is based on sub-samples of 125 quarters each. The first rolling correction window encompasses NCREIF appreciation index returns from the first quarter 1978 (1978/I) to the second

[19] Partial auctocorrelations and the results of the conducted Ljung-Box test are provided in the Appendix.

quarter of 2009 (2009/II). They are shown in Figure 4.4. The analysis on expanding or increasing windows comprises 100 quarters at the beginning and then increases consecutively by one quarter, such that the last window comprises the entire period 1978/I to 2017/IV.

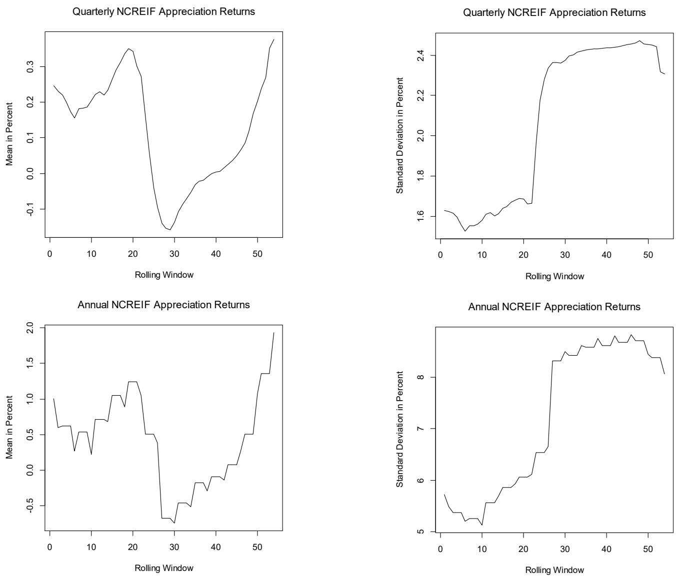


Figure 4.4: Rolling Time Windows of the NPI in Annual and Quarterly Periodicity

Note: The figure reports means and standard deviations of the NPI index returns estimated from rolling time windows.

We assume that a correction procedure produces stable results if the relative figures between the unsmoothed and original series remain stable across the periods studied. In this case, the ratios of standard deviations of the corrected series to those of the original time series should not vary substantially along the different time-windows. We test these features for each considered correction procedure.[20]

Note that we can deduce the distributional information for the fraction of correction-based means to the mean of the original NPI series, and for the fraction of the standard deviation of the corrected time series to the original NPI standard deviation. The median, maximum, and minimum ratios are computed across varying windows. Furthermore, we report the range $(max - min)$, mean absolute difference, and whisker range in absolute terms and in relation to the corresponding median in order to adequately describe the resulting distributions of corrected returns. See the figures in Table 4.3 for rolling time-windows, and in Tables 4.4 for increasing time-windows, respectively.

For the investigation applying rolling time-windows, all of the correction procedures, except the model variants of Bond and Hwang (2007), are mean-inflating. This is inconsistent with the majority of empirical findings, and with the theoretical demand on the mean return for appraisal-based series and their corresponding (but unobservable) true market series. The pattern is stronger for the Firstenberg et al. (1988) models applied to quarterly returns, and for

[20] Smoothing phenomena have a particularly strong impact on the volatilities of reported returns. Analogously, the ratio of means of returns should remain stable. Statistics on the ratios of means are in the Appendix.

the Blundell and Ward (1987) models applied to annual returns. The proposed FRZ(1,4) specification thereby improves on the outcome for the Firstenberg et al. (1988) model. In our statistical evaluation, this decreases the range of calculated volatility ratios for different windows.

An inflation of standard deviations is likewise apparent, and desired. Here, the fluctuations in the ratios of standard deviations are central, and should be low. The median, mean, minimum, and maximum of calculated ratios should coincide for an optimal correction procedure, which should lead to an optimal range close to zero. The ratio of zero implies that the ratio of the volatility of the unsmoothed (corrected) or true returns to the volatility of the appraisal-based index returns remains constant across all moving windows. The span is particularly large for the Firstenberg et al. (1988) model, as Table 4.3 shows. Among the original annual-level unsmoothing rules, the Blundell and Ward (1987) procedure exhibits the largest divergence in the observed relation to standard deviations of the original NPI series. The highest stability is implied by the results for the Barkham and Geltner (1994) procedure on an annual basis and for a Bond and Hwang (2007) variant at the quarterly level. However, parameters of the Barkham and Geltner (1994) model are imposed according to plausibility considerations, and are thus fixed across the variant windows.

Table 4.3: Ratio of Standard Deviations of Corrected NPI Returns to Original Standard Deviations of NPI Returns: Statistical Figures from Rolling Time Windows.

	Mean	Med	Min	Max	Range	Range/Med	WR	WR/Med	MAD	MAD/Med
FRZ	3.16	2.74	2.69	7.21	4.52	1.65	0.28	0.10	0.16	5.67
FRZ14	2.82	2.69	2.37	4.25	1.88	0.70	0.60	0.22	0.14	5.37
FGW	1.72	1.73	1.63	1.88	0.24	0.14	0.16	0.09	0.01	0.64
CKS	1.70	1.71	1.61	1.87	0.26	0.15	0.18	0.10	0.01	0.69
BoHw	1.03	1.02	0.95	1.09	0.15	0.15	0.15	0.15	0.02	2.22
BoHw4	56.23	0.85	0.79	1994.15	1993.36	2349.92	0.05	0.06	56.97	6716.29
Chaplin	1.09	1.09	1.08	1.12	0.04	0.04	0.01	0.01	0.00	0.15
LSW (AR)	4.46	4.03	3.80	13.23	9.43	2.34	0.21	0.05	0.32	7.85
LSW (NPI)	1.02	1.02	1.00	1.12	0.12	0.11	0.03	0.03	0.01	0.55
LSW (Dow)	1.13	1.13	1.10	1.16	0.05	0.05	0.05	0.05	0.00	0.31
FRZ	2.12	1.78	1.73	5.46	3.73	2.09	0.20	0.11	0.13	7.55
FRZ14	2.01	1.87	1.67	3.60	1.93	1.03	0.45	0.24	0.13	7.11
FGW	1.26	1.26	1.17	1.49	0.33	0.26	0.16	0.12	0.02	1.79
CKS	1.05	1.00	0.94	1.47	0.53	0.53	0.26	0.27	0.02	2.42
BoHw	0.93	0.94	0.83	0.98	0.15	0.16	0.08	0.08	0.02	1.85
Chaplin	1.01	1.01	1.00	1.05	0.05	0.05	0.00	0.00	0.00	0.20
LSW (AR)	2.81	2.57	2.18	8.08	5.90	2.30	0.18	0.07	0.20	7.77
LSW (NPI)	1.01	1.00	1.00	1.07	0.07	0.07	0.00	0.00	0.00	0.24
LSW (Dow)	1.03	1.03	1.01	1.07	0.05	0.05	0.03	0.03	0.00	0.29
BW	1.96	1.64	1.59	4.21	2.61	1.60	0.06	0.04	0.13	8.08
Geltner	2.31	2.41	1.78	2.46	0.68	0.28	0.09	0.04	0.03	1.21
Geltner-n	2.24	2.33	1.79	2.43	0.64	0.28	0.30	0.13	0.04	1.75
BG34	1.20	1.21	1.16	1.22	0.07	0.05	0.01	0.01	0.00	0.21
BG58	1.40	1.42	1.30	1.44	0.14	0.10	0.03	0.02	0.01	0.39
BoHw-a	1.87	0.48	0.44	23.48	23.04	48.08	0.36	0.76	1.32	274.65
BoHw-a1	0.56	0.47	0.44	0.89	0.45	0.94	0.45	0.94	0.02	4.52
Chaplin-a	1.62	1.67	1.42	1.70	0.28	0.17	0.04	0.02	0.01	0.59
LSW-a (AR)	1.37	1.28	1.25	1.99	0.75	0.58	0.02	0.02	0.04	3.08
LSW-a (NPI)	1.01	1.01	1.00	1.05	0.04	0.04	0.04	0.04	0.01	0.50
LSW-a (Dow)	1.01	1.01	1.00	1.03	0.03	0.03	0.01	0.01	0.00	0.21

Note: The NPI is corrected on quarterly- (upper third) and on annual basis (bottom) depending on the correction procedure. For procedures applicable in quarterly periodicity, ratios are additionally derived and reported in annual periodicity. Statistical figures are computed from rolling time windows, 125 quarters each. The first window covers the period 1978/I-2009/II. Windows are consecutively updated by adding and dropping one quarter. Med is median, range is $max - min$, WR is the whisker range, MAD the mean absolute distance. Time series definitions are provided in Appendix A1.

Table 4.4: Ratio of Standard Deviations of Corrected NPI Returns to Original Standard Deviations of NPI Returns: Statistical Figures from Increasing Time Windows

	Mean	Med	Min	Max	Range	Range/Med	WR	WR/Med	MAD	MAD/Med
FRZ	4.38	3.03	2.91	7.21	4.30	1.42	4.30	1.42	0.18	5.97
FRZ14	2.68	2.58	2.51	4.22	1.71	0.66	0.13	0.05	0.07	2.83
FGW	1.94	1.75	1.71	2.39	0.67	0.38	0.67	0.38	0.01	0.77
CKS	1.93	1.73	1.70	2.38	0.68	0.39	0.68	0.39	0.01	0.78
BoHw	0.96	1.01	0.82	1.04	0.22	0.22	0.22	0.22	0.01	0.56
BoHw	0.88	0.87	0.85	1.14	0.29	0.33	0.02	0.02	0.01	1.48
Chaplin	1.10	1.09	1.09	1.15	0.07	0.06	0.07	0.06	0.00	0.21
LSW (AR)	5.21	4.16	4.05	13.23	9.18	2.21	4.93	1.19	0.33	7.91
LSW (NPI)	1.02	1.01	1.00	1.12	0.12	0.12	0.03	0.03	0.00	0.43
LSW (Dow)	1.08	1.11	1.00	1.13	0.12	0.11	0.12	0.11	0.00	0.25
FRZ	3.12	1.93	1.78	5.46	3.68	1.91	3.68	1.91	0.16	8.25
FRZ14	1.97	1.82	1.72	3.59	1.86	1.02	0.36	0.20	0.07	3.90
FGW	1.48	1.32	1.16	1.82	0.67	0.50	0.67	0.50	0.03	1.99
CKS	1.43	1.11	1.08	1.96	0.88	0.79	0.88	0.79	0.02	1.99
BoHw	0.86	0.92	0.75	0.94	0.19	0.21	0.19	0.21	0.01	0.85
Chaplin	1.01	1.01	1.00	1.05	0.05	0.05	0.00	0.00	0.00	0.20
LSW (AR)	2.66	2.44	2.23	8.08	5.85	2.40	0.50	0.20	0.22	8.92
LSW (NPI)	1.00	1.00	1.00	1.06	0.06	0.06	0.00	0.00	0.00	0.22
LSW (Dow)	1.02	1.02	1.00	1.07	0.07	0.06	0.03	0.03	0.00	0.23
BW	2.44	2.35	1.69	3.98	2.29	0.97	2.29	0.97	0.09	4.01
Geltner	1.89	1.85	1.46	2.32	0.86	0.47	0.86	0.47	0.02	1.10
Geltner-n	1.84	1.89	1.48	2.13	0.64	0.34	0.64	0.34	0.02	1.09
BG34	1.15	1.16	1.08	1.20	0.13	0.11	0.13	0.11	0.00	0.25
BG58	1.30	1.32	1.16	1.40	0.24	0.18	0.24	0.18	0.01	0.44
BoHw-a	0.66	0.65	0.52	0.79	0.27	0.42	0.27	0.42	0.01	0.99
BoHw-a1	0.75	0.76	0.54	0.94	0.41	0.53	0.41	0.53	0.01	1.22
Chaplin-a	1.47	1.42	1.26	1.65	0.39	0.27	0.39	0.27	0.01	0.59
LSW-a (AR)	1.37	1.31	1.26	1.95	0.69	0.53	0.23	0.18	0.03	1.96
LSW-a (NPI)	1.01	1.01	1.00	1.04	0.04	0.04	0.02	0.02	0.00	0.17
LSW-a (Dow)	1.02	1.01	1.00	1.07	0.07	0.07	0.07	0.07	0.00	0.23

Note: The NPI is corrected on quarterly- (upper third) and on annual basis (bottom) depending on the correction procedure. For procedures applicable in quarterly periodicity, ratios are additionally derived and reported in annual periodicity (middle). Statistical figures are computed from expanding time windows, starting in 1978/I. The first window covers 100 quarters from 1978/I-2002/IV. The last window comprises the entire period 1978/I to 2017/IV. Consecutive windows are updated by one period. Med is median, range is $max - min$, WR is the whisker range, MAD the mean absolute distance. Time series definitions are provided in Appendix A1.

A similar picture emerges from the analysis of the expanding sample period. From the perspective of ratios of standard deviations (Table 4.4), a couple of procedures yield remarkably large fluctuations in their relation to those from the original index. This is most evident for the Fisher et al. (1994), Cho et al. (2003) and Geltner (1993a) models.[21] According to the specifications with moving and growing time windows, the corrected series derived from Bond and Hwang (2007) exhibits the greatest stability. Likewise, it induces the lowest standard deviation. However, if volatility-ratios change over time due to changing market conditions, this should result at least in a steady transition in consecutive moving windows, and not display erratic volatility-ratios for moving time windows. A rather steady transition should produce a lower mean absolute deviation of ratios across consecutive moving windows compared to the erratic case.

The proposed modifications improve on this outcome across several dimensions. The nominal return modification of Geltner (1993a) , for example, adjusts for the bias in means of corrected series and increases the ratio of standard deviations while decreasing their spread. Similar features can be observed for the Firstenberg et al. (1988) AR(1,4) modification from the expanding window analysis.

The extraordinary increases in variances and reduction in means towards original returns around the financial crisis, induces a change in implied unsmoothing levels for several procedures, while other unsmoothing weights recover to their pre-crisis level. For the procedures applied on a quarterly level, the im-

21 Similar results can be derived for the ratio of means (see Appendix). Mean returns are changed by virtually all procedures.

plied range of volatilities for the Firstenberg et al. (1988), Fisher et al. (1994), Cho et al. (2003) and Bond and Hwang (2007) procedures tend to change persistently. Suggested underlying volatilities decline in the post-crisis period for all approaches, except for the Bond and Hwang (2007) procedure. The latter implies slightly reduced volatility in market returns during the post-crisis windows, while it implies increased volatility in the pre-crisis period. The post-crisis findings likewise contradict the evidence in the original contribution.

The proposed variants of the Firstenberg et al. (1988) FRZ14 and of the Bond and Hwang (2007) procedure BoHw4 add stability, according to our growing time window analysis. For those specifications, the ratios of variances of corrected- to those of original returns remain relatively constant along the bulk of estimation windows and quickly recover after inclusion of a low number of post-crisis periods.

On an annual basis (Figure 4.6), the Blundell and Ward (1987) approach entails the largest fluctuations in implied smoothing levels, whereas those of the reverse-engineering methods of Geltner (1993a) and Barkham and Geltner (1994) remain relatively constant. The decision to unsmooth real or nominal returns does not substantially impact outcomes according to our analysis. The Bond and Hwang (2007) variant (BoHw-a1) based on annual periodicity implies a gradually reducing smoothing level along the expanding estimation windows.

Overall, the distribution of calculated ratios for volatilities or means of corrected to original return series - from zero-autocorrelation and reverse-engineering methods - are characterized by a large degree of instability in phases of low overall market volatility. The dynamic perspective (Figures 4.5 - 4.8), moreover, reveals the extraordinary sensitivity of correction-procedures towards periods with high fluctuations in original returns or market phases of high uncertainty.

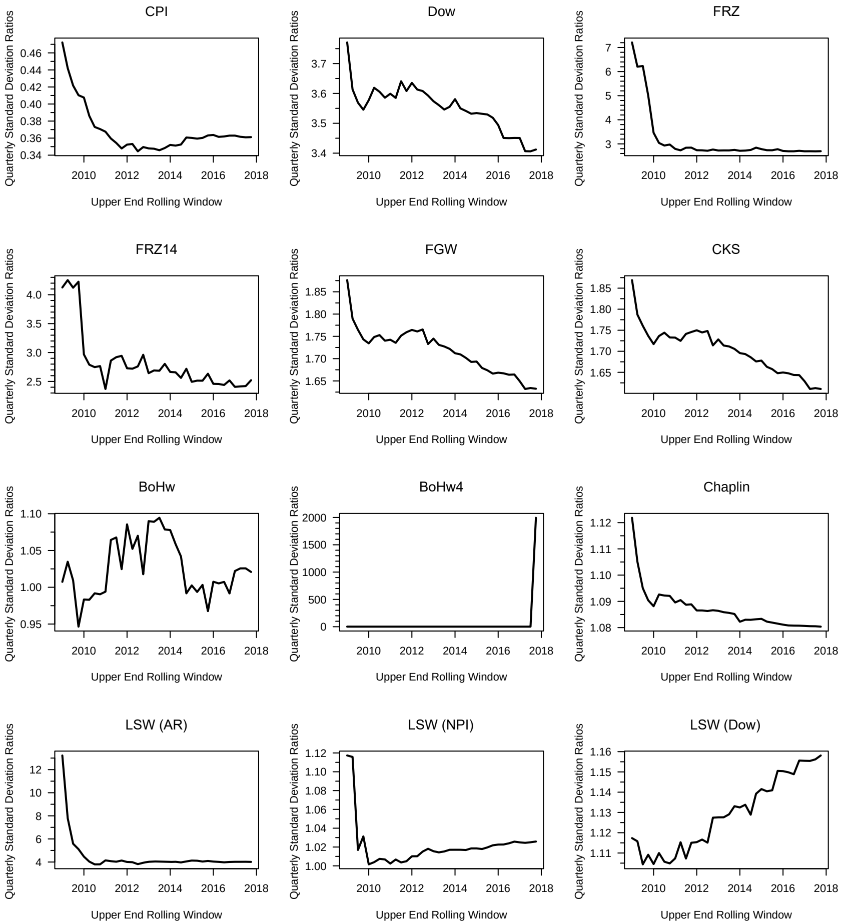
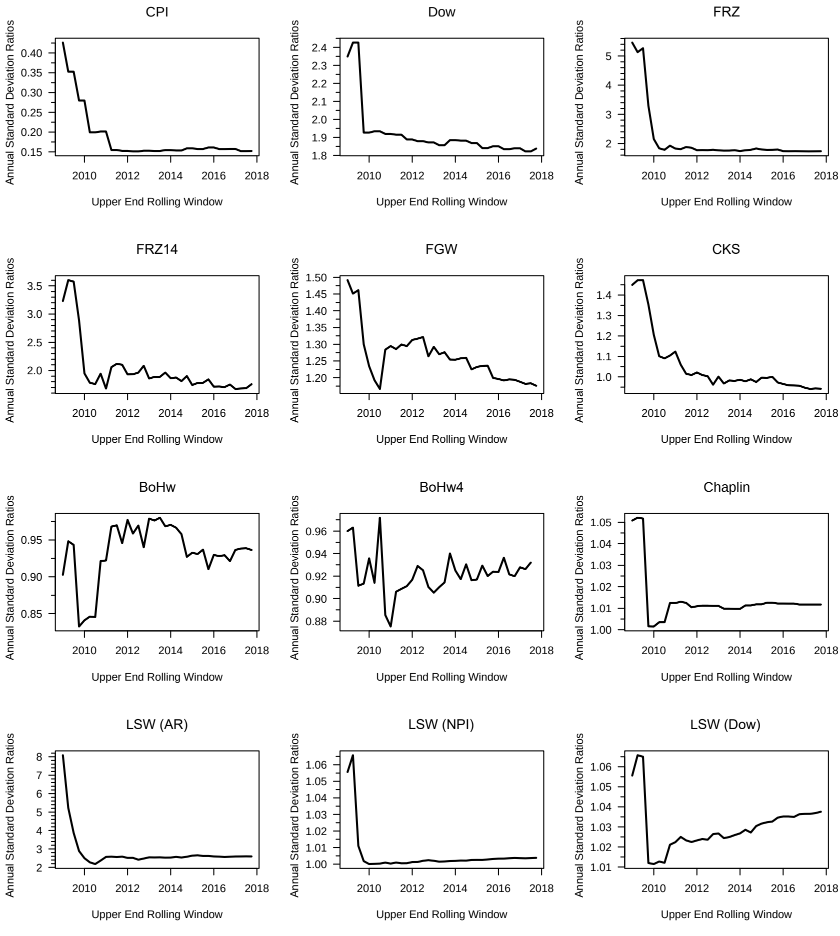


Figure 4.5: Rolling Time Windows of the Corrected NPI in Quarterly Periodicity: Ratio of Standard Deviations

Note: The figure reports the ratio of standard deviations of the annually corrected NPI returns to the standard deviations of the original NPI returns, repeatedly estimated from rolling time windows. Each window comprises 125 consecutive periods from the years 1977-2017.



CPI
Dow
FRZ
FRZ14
FGW
CKS
BoHw
BoHw4
Chaplin
LSW (AR)
LSW (NPI)
LSW (Dow)
Annual Standard Deviation Ratios
Upper End Rolling Window
2010
2012
2014
2016
2018

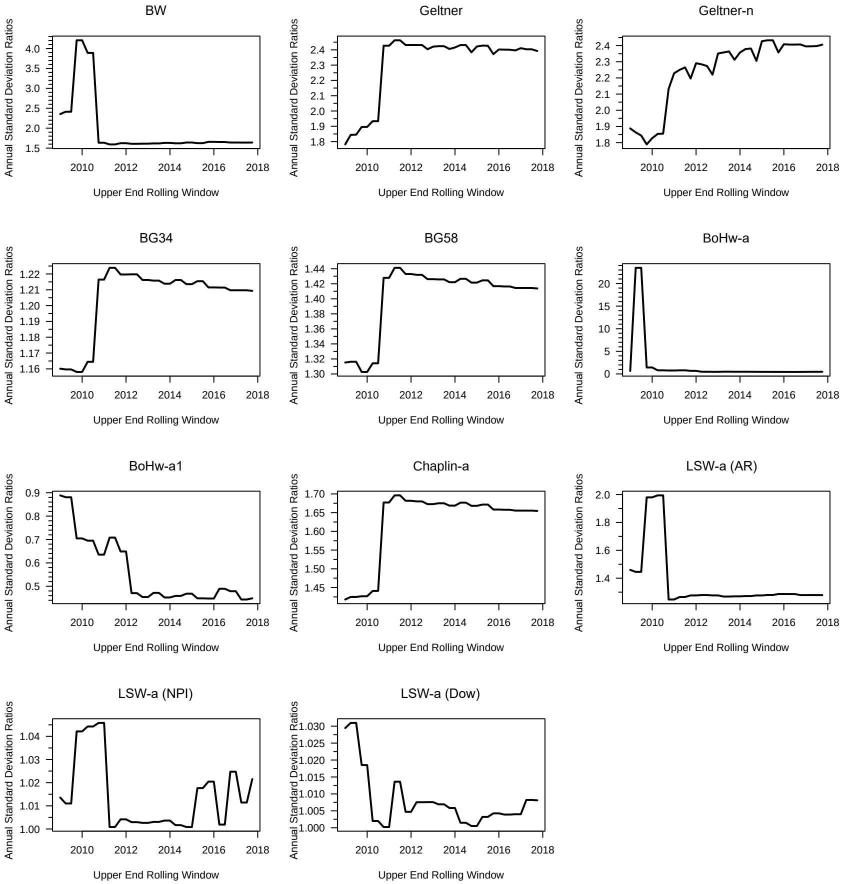


Figure 4.6: Rolling Time Windows of the Corrected NPI in Annual Periodicity: Ratio of Standard Deviations

Note: The figure reports the ratio of standard deviations of the annually corrected NPI returns to the standard deviations of the original NPI returns, repeatedly estimated from rolling time windows. Each window comprises 125 consecutive periods from the years 1977-2017.

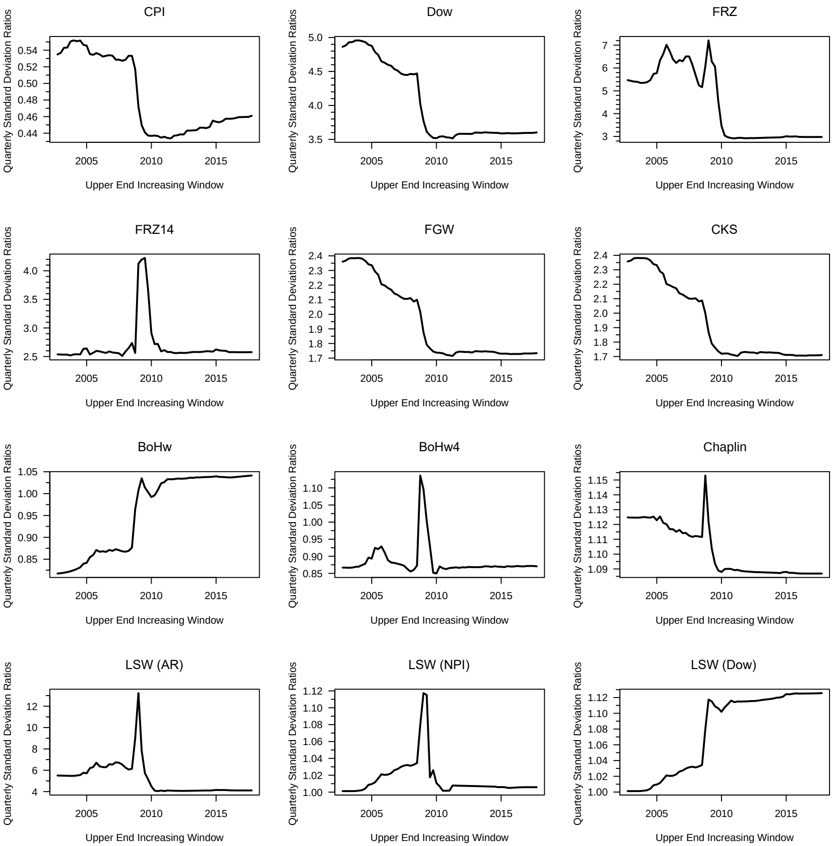
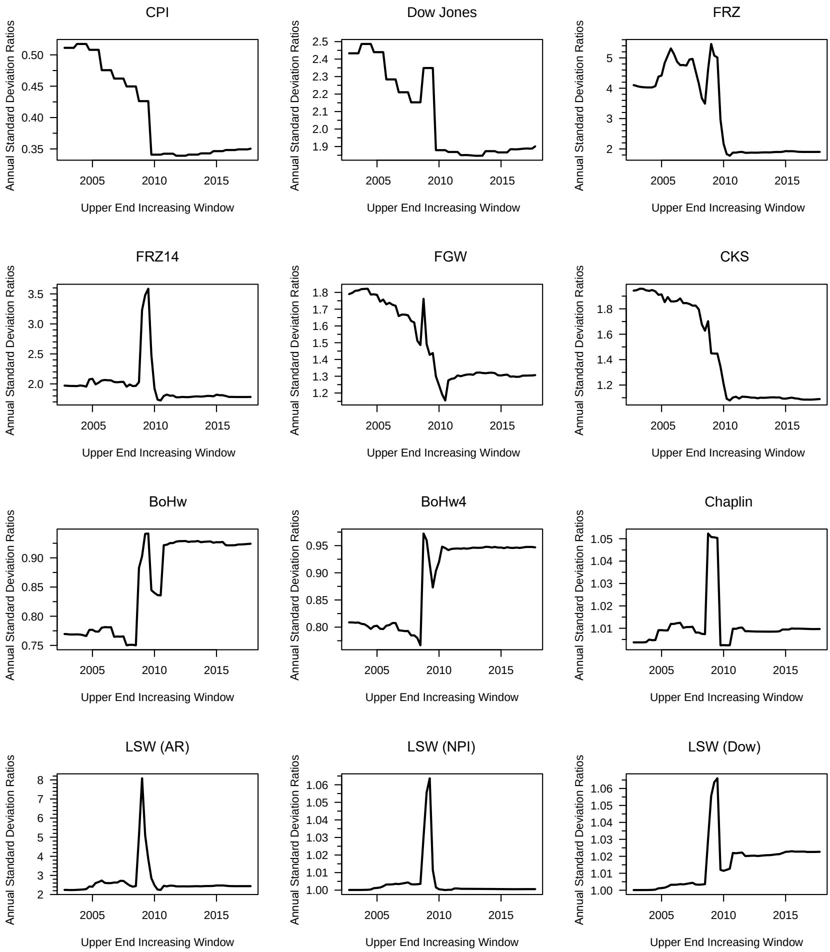


Figure 4.7: Increasing Time Windows of the Corrected NPI in Quarterly Periodicity: Ratio of Standard Deviations

Note: The figure reports the ratio of standard deviations of the annually corrected NPI returns to the standard deviations of the original NPI returns, repeatedly estimated from increasing time windows. The first window comprises 100 consecutive quarters from the years 1977-2001.



CPI
Annual Standard Deviation Ratios
0.50
0.45
0.40
0.35
2005
2010
2015
Upper End Increasing Window
Dow Jones
Annual Standard Deviation Ratios
2.5
2.4
2.3
2.2
2.1
2.0
1.9
2005
2010
2015
Upper End Increasing Window
FRZ
Annual Standard Deviation Ratios
5
4
3
2
2005
2010
2015
Upper End Increasing Window
FRZ14
Annual Standard Deviation Ratios
3.5
3.0
2.5
2.0
2005
2010
2015
Upper End Increasing Window
FGW
Annual Standard Deviation Ratios
1.8
1.7
1.6
1.5
1.4
1.3
1.2
2005
2010
2015
Upper End Increasing Window
CKS
Annual Standard Deviation Ratios
1.8
1.6
1.4
1.2
2005
2010
2015
Upper End Increasing Window
BoHw
Annual Standard Deviation Ratios
0.90
0.85
0.80
0.75
2005
2010
2015
Upper End Increasing Window
BoHw4
Annual Standard Deviation Ratios
0.95
0.90
0.85
0.80
2005
2010
2015
Upper End Increasing Window
Chaplin
Annual Standard Deviation Ratios
1.05
1.04
1.03
1.02
1.01
2005
2010
2015
Upper End Increasing Window
LSW (AR)
Annual Standard Deviation Ratios
8
7
6
5
4
3
2
2005
2010
2015
Upper End Increasing Window
LSW (NPI)
Annual Standard Deviation Ratios
1.06
1.05
1.04
1.03
1.02
1.01
1.00
2005
2010
2015
Upper End Increasing Window
LSW (Dow)
Annual Standard Deviation Ratios
1.06
1.05
1.04
1.03
1.03
1.02
1.01
1.00
2005
2010
2015
Upper End Increasing Window

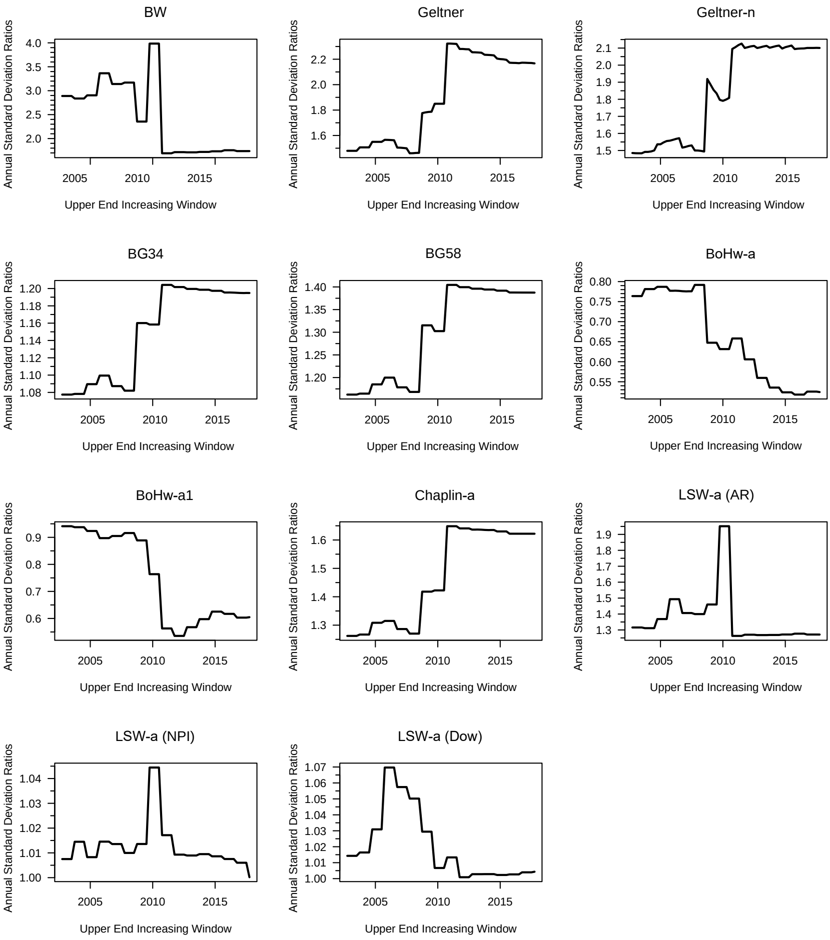


Figure 4.8: Increasing Time Windows of the Corrected NPI in Quarterly Periodicity: Ratio of Standard Deviations.
Note: The figure reports the ratio of standard deviations of the annually corrected NPI returns to the standard deviations of the original NPI returns, repeatedly estimated from increasing time windows. The first window comprises 100 consecutive quarters from the years 1977-2001.

4.4 Conclusion

The features of appraisal-based indices have been investigated comprehensively across decades. The issue of inherent appraisal-smoothing, as well as other biases, matters both for practitioners and for scientific inquiries. It is perhaps most relevant in terms of asset allocation and the assessment of portfolio performance regarding risk. Thus, accurate treatment is crucial – but how robust are the most common related correction procedures? Efficiency is not a typical feature of direct real estate markets. Thus, the work of Blundell and Ward (1987), and other early developers and adopters of similar techniques, suffers from the infeasibility of this underlying assumption. Nevertheless, we find that the estimation of appraiser weights and equivalent corrections, in the spirit of Geltner (1993a), exhibit distributional instability. The corresponding models tend to aggregate average appraiser behavior. Our paper shows that the distributional patterns of the analyzed constant parameter correction procedures turn out to be unstable and highly sensitive to extreme values and specific return patterns of the underlying sample period. The estimation of systems of equations of cointegrated variables, or the modeling of heterogeneous appraiser behavior via multiple-regime models, has only limited ability to overcome those weaknesses. Our results suggest that transaction-based indices and hybrid indices are superior for actual portfolio management decision-making. Regarding the unsmoothing of appraisal-based data, even simple heuristics (such as assuming one-half of stock market volatility, as proposed by Fisher et al. (1994)) are not unreasonable in light of our results.

Appendix

A1-Data definitions of evaluated time series

Raw data:

1. NPI - NCREIF Appreciation Index (appraisal-based) starting in 1977/IV.
2. CPI - US consumer price index starting in 1977/IV.
3. Dow - Dow Jones Index starting in 1977/I.
4. REITs - All Equity REITs Price Index starting in 1977/IV.
5. LTGvtBds - Yield of the 10-year US government bond starting in 1977/IV.
6. NTBI-EW - NCREIF equally-weighted transaction-based-index starting in 1984/I.
7. NTBI-VW - NCREIF value-weighted transaction-based-index starting in 1984/I.

NPI corrected in quarterly periodicity:

1. FRZ - Firstenberg-Ross-Zisler procedure.
2. FRZ14 - Modificated Firstenberg-Ross-Zisler procedure.
3. FGW - Fisher-Geltner-Webb procedure.
4. CKS - Cho-Kawaguchi-Shilling procedure.
5. BoHw - Bond and Hwang procedure assuming an efficient market.
6. BoHw4 - Bond and Hwang procedure allowing for inertia in information processes.

7. Chaplin - Chaplin procedure with regime-dependant correction parameters.
8. LSW (AR) - Lizieri-Satchell-Wongwachara procedure, single parameter.
9. LSW (NPI) - Lizieri-Satchell-Wongwachara procedure, regime switch according to NPI Index.
10. LSW (Dow) - Lizieri-Satchell-Wongwachara procedure, regime switch according to Dow Jones Index.

NPI corrected in annual periodicity:

1. BW - Blundell and Ward procedure.
2. Geltner - Geltner-procedure.
3. Geltner-n - Modified Geltner procedure with correction of nominal returns.
4. BG34 - Barkham and Geltner procedure with correction factor 3/4.
5. BG58 - Barkham and Geltner procedure with correction factor 5/8.
6. BoHw-a - Modified (applied on annual returns series) Bond and Hwang-procedure assuming an efficient market.
7. BoHw-a1 - Modified (applied on annual returns series) Bond and Hwang-procedure allowing inertia in information processes.
8. Chaplin-a - Modified (applied on annual return series) Chaplin procedure with regime-dependant correction parameters.
9. LSW-a (AR) - Modified (applied on annual return series) Lizieri-Satchell-Wongwachara procedure, single parameter.
10. LSW-a (NPI) - Modified (applied on annual return series) Lizieri-Satchell-Wongwachara procedure, regime switch according to NPI Index.
11. LSW-a (Dow) - Modified (applied on annual return series) Lizieri-Satchell-Wongwachara procedure, regime switch according to Dow Jones Index.

A2 - Partial Autocorrelations

Qr.	NPI	CPI	Dow	REITs	LTGvt Bds	NTBI-EW	NTBI-VW	FRZ	FRZ14	FGW	CKS	BoHw	BoHw4
lag 1	0.79	0.33	-0.01	0.16	0.16	-0.15	-0.17	0.08	0.07	0.17	0.00	0.62	0.83
lag 2	0.15	-0.02	-0.03	-0.17	-0.18	-0.17	-0.20	0.00	0.32	0.38	0.40	0.16	-0.40
lag 3	-0.24	0.12	-0.05	-0.05	0.04	0.00	-0.03	0.07	-0.06	-0.07	0.00	-0.17	-0.31
lag 4	0.04	-0.03	0.04	0.01	-0.08	0.20	0.19	0.28	0.19	0.18	0.43	0.08	0.03
lag 5	-0.38	0.17	0.05	0.06	-0.16	0.14	0.13	-0.28	-0.29	-0.34	-0.18	-0.41	-0.25
lag 6	0.04	0.10	0.04	-0.03	-0.01	-0.05	-0.07	-0.19	-0.24	-0.21	-0.23	-0.04	0.26
lag 7	0.19	0.02	-0.22	-0.10	-0.14	0.05	0.03	-0.05	0.05	0.13	0.08	0.14	0.08
lag 8	-0.03	0.03	0.09	-0.04	-0.07	-0.02	-0.01	-0.03	0.01	0.04	-0.08	-0.03	-0.12
lag 9	0.02	-0.04	-0.06	-0.20	-0.11	-0.10	-0.10	0.06	0.06	0.00	-0.02	0.04	-0.04
lag 10	-0.09	0.02	0.07	0.10	-0.08	-0.11	-0.11	0.01	-0.02	-0.03	0.00	-0.06	-0.11
lag 11	-0.07	0.06	0.05	-0.08	0.06	-0.10	-0.10	0.03	-0.01	-0.03	-0.03	-0.07	-0.05
lag 12	-0.11	0.03	0.04	-0.10	-0.22	-0.02	-0.01	-0.10	-0.11	-0.13	-0.10	-0.13	-0.06
lag 13	-0.01	-0.04	-0.12	0.00	0.02	0.07	0.06	-0.09	-0.10	0.00	0.00	-0.05	0.07
lag 14	0.04	0.11	-0.02	-0.07	-0.01	-0.04	-0.05	-0.05	-0.03	0.02	0.03	0.01	0.01
lag 15	-0.01	-0.08	0.08	0.02	0.04	0.00	-0.02	-0.01	-0.01	-0.10	-0.09	-0.02	-0.04
lag 16	-0.01	-0.03	0.06	-0.09	-0.02	0.08	0.06	-0.04	-0.02	0.01	-0.02	-0.03	-0.01

An.	NPI	CPI	Dow	REITs	LTGvtBds	NTBI-EW	NTBI-VW	FRZ	FRZ14	FGW	CKS	BoHw	BoHw4
lag 1	0.47	0.34	-0.02	0.00	-0.26	0.36	0.28	0.15	0.20	0.31	0.57	0.29	0.61
lag 2	-0.37	0.19	-0.04	-0.33	-0.49	-0.34	-0.32	-0.33	-0.35	-0.39	-0.47	-0.39	-0.40
lag 3	0.04	0.02	0.10	0.00	-0.21	-0.07	-0.11	-0.02	0.00	0.05	0.11	0.02	0.02
lag 4	-0.22	-0.07	0.11	-0.27	-0.20	-0.11	-0.18	-0.18	-0.20	-0.20	-0.17	-0.26	-0.20

	BW	Geltner	Geltner-n	BG34	BG58	BoHw-a	BoHw-a1
lag 1	0.16	0.10	0.12	0.33	0.25	0.75	0.71
lag 2	-0.32	-0.27	-0.34	-0.31	-0.31	-0.47	-0.49
lag 3	0.00	-0.02	-0.02	0.02	0.01	0.03	0.05
lag 4	-0.23	-0.16	-0.25	-0.22	-0.22	-0.13	-0.15

Note: The table reports partial autocorrelations for returns of considered indices and the corrected NPI on annual- (bottom) and on quarterly basis (top).

A3 - Results of the Ljung-Box test

Qr.	NPI	CPI	Dow	REITs	LTGvt Bds	NTBI-EW	NTBI-VW	FRZ	FRZ14	FGW	CKS	BoHw	BoHw4
lag 1	200.70	18.40	0.70	7.30	6.70	12.20	13.60	12.60	24.70	38.00	57.80	98.10	287.70
	0.00	0.00	0.96	0.12	0.15	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00
lag 2	204.90	30.20	9.20	11.40	13.50	16.30	18.10	24.80	37.50	47.80	65.00	115.80	301.[illegible]
	0.00	0.00	0.33	0.18	0.10	0.04	0.02	0.00	0.00	0.00	0.00	0.00	0.0[illegible]
lag 3	214.80	33.80	10.70	18.10	16.80	18.80	21.20	28.20	40.40	53.20	68.20	126.30	315.[illegible]
	0.00	0.00	0.56	0.11	0.16	0.09	0.05	0.01	0.00	0.00	0.00	0.00	0.0[illegible]
lag 4	233.10	36.30	15.30	18.90	20.10	22.20	25.00	30.80	42.70	55.90	72.70	135.30	342.[illegible]
	0.00	0.00	0.50	0.27	0.21	0.14	0.07	0.01	0.00	0.00	0.00	0.00	0.00

An.	NPI	CPI	Dow	REITs	LTGvt Bds	NTBI-EW	NTBI-VW	FRZ	FRZ14	FGW	CKS	BoHw	BoHw4
lag 1	11.00	7.90	0.80	4.50	8.60	8.90	8.20	4.70	5.60	7.30	14.30	8.20	[illegible]
	0.03	0.10	0.93	0.35	0.07	0.06	0.08	0.32	0.23	0.12	0.01	0.08	[illegible]
lag 2	13.30	10.20	10.60	6.10	9.10	10.40	9.30	5.10	5.90	8.00	16.90	8.70	[illegible]
	0.10	0.25	0.23	0.63	0.34	0.24	0.32	0.75	0.65	0.43	0.03	0.37	[illegible]
lag 3	15.00	11.60	15.00	11.70	9.90	12.40	11.10	5.80	6.60	9.00	18.70	9.40	17.80
	0.24	0.48	0.24	0.47	0.63	0.41	0.52	0.92	0.88	0.70	0.10	0.67	0.12
lag 4	17.80	13.00	19.20	14.40	11.40	19.50	18.80	7.30	8.10	10.90	21.40	11.20	[illegible]
	0.34	0.67	0.26	0.57	0.78	0.24	0.28	0.97	0.95	0.82	0.16	0.80	[illegible]

	BW	Geltner	Geltner-n	BG34	BG58	BoHw-a	BoHw-a1
lag 1	5.00	3.20	5.10	6.90	5.60	24.70	21.60
	0.28	0.52	0.28	0.14	0.23	0.00	0.00
lag 2	5.50	3.60	5.40	8.10	6.30	29.50	25.40
	0.71	0.89	0.71	0.42	0.61	0.00	0.00
lag 3	6.10	4.50	6.00	9.20	7.20	39.10	31.30
	0.91	0.97	0.92	0.69	0.85	0.00	0.00
lag 4	7.10	5.50	6.90	11.10	8.60	42.70	35.10
	0.97	0.99	0.98	0.81	0.93	0.00	0.00

Note: The table reports test statistics (χ^2) and p-values (below) of the Ljung-Box test for returns of considered indices and the corrected NPI.

A4 - Means of the Corrected NPI Returns Compared to the Original Mean Returns: Ratios from Rolling Time Windows.

Quarterly Returns	Mean	Median	Min	Max	Range	Range/Med	WR	WR/Med	MAD	MAD/Med
FRZ	4.43	3.43	2.25	8.11	5.86	1.71	5.86	1.71	0.31	0.09
FRZ14	2.66	2.53	1.95	3.92	1.97	0.78	1.07	0.42	0.19	0.08
FGW	1.95	1.77	1.52	2.51	0.99	0.56	0.99	0.56	0.03	0.02
CKS	1.96	1.77	1.51	2.53	1.01	0.57	1.01	0.57	0.03	0.02
BoHw	0.94	0.95	0.81	1.05	0.24	0.25	0.24	0.25	0.02	0.02
BoHw4	6,394	0.87	0.82	345,218	345,218	398,401	0.18	0.21	13,027	15,034

Annual Returns	Mean	Median	Min	Max	Range	Range/Med	WR	WR/Med	MAD	MAD/Med
FRZ	3.26	2.24	1.51	6.51	5.00	2.23	5.00	2.23	0.26	0.12
FRZ14	1.99	1.88	1.33	3.48	2.15	1.14	1.15	0.61	0.17	0.09
FGW	1.48	1.26	1.00	2.05	1.05	0.84	1.05	0.84	0.04	0.03
CKS	1.42	1.24	0.80	2.15	1.35	1.09	1.35	1.09	0.05	0.04
BoHw	0.87	0.87	0.75	0.98	0.22	0.26	0.22	0.26	0.02	0.02
BoHw4	0.93	0.91	0.76	1.90	1.14	1.24	0.20	0.22	NA	NA
BW	2.41	2.14	1.54	3.44	1.90	0.89	1.90	0.89	0.13	0.06
Geltner	1.86	1.85	1.43	2.21	0.78	0.42	0.78	0.42	0.03	0.02
Geltner-n	1.88	1.85	1.47	2.51	1.04	0.56	1.04	0.56	0.06	0.03
BG34	1.16	1.17	1.07	1.23	0.16	0.14	0.16	0.14	0.01	0.01
BG58	1.32	1.34	1.15	1.46	0.31	0.23	0.31	0.23	0.01	0.01
BoHw-a	0.65	0.67	0.44	1.45	1.01	1.52	0.65	0.98	0.04	0.07
BoHw-a1	18,740	0.80	0.43	337,310	337,310	420,882	0.52	0.64	12,729	15,882

Note: The NPI is corrected in quarterly- (top) or in annual periodicity (bottom) depending on the correction procedure. For procedures applicable in quarterly periodicity, descriptive statistics are additionally reported in annual periodicity. Statistical figures are derived from rolling time windows. WR is the whisker range, MAD the mean absolute distance. Time series definitions are provided in Appendix A1.

A5 - Means of the Corrected NPI Returns Compared to the Original Mean Returns: Ratios From Increasing Time Windows.

Quarterly Returns	Mean	Median	Min	Max	Range	Range/Med	WR	WR/Med	MAD	MAD/Med
FRZ	0.45	0.81	-3.46	1.65	5.11	6.30	1.25	1.54	0.24	0.30
FRZ14	0.66	0.86	-2.23	1.22	3.45	3.99	0.69	0.80	0.15	0.18
FGW	-2.88	-2.23	-7.61	-0.76	6.85	-3.08	6.85	-3.08	0.35	-0.16
CKS	-2.45	-1.94	-6.06	-0.48	5.58	-2.88	5.58	-2.88	0.29	-0.15
BoHw	0.95	1.03	0.16	1.15	0.99	0.96	0.31	0.30	0.04	0.04
BoHw4	0.99	1.02	0.41	1.13	0.72	0.70	0.22	0.21	0.04	0.04

Annual Returns	Mean	Median	Min	Max	Range	Range/Med	WR	WR/Med	MAD	MAD/Med
FRZ	0.47	0.85	-1.95	1.65	3.60	4.21	2.73	3.20	0.19	0.22
FRZ14	0.67	0.89	-1.50	1.22	2.72	3.04	1.05	1.17	0.12	0.14
FGW	-2.93	-2.22	-7.56	-0.73	6.82	-3.07	6.82	-3.07	0.35	-0.16
CKS	-2.50	-2.05	-5.98	-0.48	5.50	-2.68	5.50	-2.68	0.28	-0.14
BoHw	0.96	1.04	0.15	1.22	1.07	1.03	0.52	0.50	0.05	0.05
BoHw4	1.02	1.02	0.58	1.32	0.73	0.72	0.31	0.30	0.04	0.04
BW	0.49	0.99	-4.63	1.56	6.19	6.24	1.90	1.91	0.26	0.26
Geltner	-1.82	-1.62	-4.96	-0.61	4.34	-2.68	2.62	-1.62	0.21	-0.13
Geltner-n	0.81	0.99	-0.74	1.17	1.91	1.94	0.71	0.72	0.09	0.09
BG34	0.96	1.00	0.60	1.04	0.45	0.45	0.16	0.16	0.02	0.02
BG58	0.92	1.00	0.27	1.07	0.80	0.81	0.29	0.29	0.04	0.04
BoHw-a	1.48	1.26	1.08	2.54	1.46	1.16	0.66	0.53	0.06	0.05
BoHw-a1	1.19	1.09	0.97	1.93	0.96	0.88	0.50	0.45	0.04	0.04

Note: The NPI is corrected on quarterly- (top) and on annual basis (bottom) depending on the correction procedure. For procedures applicable in quarterly periodicity, descriptive statistics are additionally reported in annual periodicity. Statistical figures are derived from expanding time windows. WR is the whisker range, MAD the mean absolute distance. Time series definitions are provided in Appendix A1.

Chapter 5

Summary and Outlook

The aim of this thesis was to enhance our understanding of takeover auctions, of M&A activity in real estate markets and of the time series properties of corrected real estate indices. The results have implications for economic policy, for corporate governance, for investors and for future research in those fields. With respect to takeover auctions as an important sales mechanism in corporate transactions, it becomes evident that homogenous businesses like REITs generate disproportionally large benefits to target shareholders when being sold by a multiple-bidder contest. This explains the high, and increasing, use of auctions by REITs, which has been described (e.g. by Mulherin and Womack, 2015). For future analyses of takeover auctions among REITs, and also among other corporates, this demands a more intense consideration not only of bidder types, which are increasingly regarded in this context, but also of target types – with a focus on the heterogeneity, respectively homogeneity, of business models. For a further development of the theory on auctions of firms, the special case of REITs emphasizes the importance of a careful modeling of private and common value auctions.

With respect to mergers and acquisitions of real estate firms around their conversions towards REITs, the implications are of economic importance because the establishment of a REIT framework turns out to be accompanied by market consolidation. At the individual REIT-level this can be measured by extraordinary M&A activity from the beginning of the conversion plans, and during the conversion and post-conversion periods. Those deals are relatively expensive, but they are much more strategic than regulation-driven and beneficial for REIT investors and executives, since they increase risk-adjusted post-conversion performance. This interaction between REIT conversions and the M&A market, which is first described here, deserves high attention by future research. Many aspects have to be considered on the micro- and macro level. One could, for example, go down to the property-level of deals and investigate the characteristics of properties and property portfolios involved in a more granular manner. And, one should certainly further quantify the economic costs and benefits of REIT regimes in the light of our results on the effects of restructuring.

With respect to the results on unsmoothed indices, the informational content of results from such procedures needs careful reflection. This does potentially concern every investment decision where appraisal-based indices play a role, or where simply consecutively appraised properties are involved (e.g. the case of portfolios bought by an M&A transaction), but it does also concern a large number of empirical studies in real estate research, in which unsmoothing, at a least as robustness check, still plays a role.

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