Risk Factors of U.S. Real Estate Investments

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Spring 2017

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Draft for American Real Estate and Urban Economics Association international conference submission.

Abstract

This research focuses on macroeconomic risk factors pertaining to the various types of real estate exposure, i.e. direct, listed and non-listed investments. We apply panel model techniques which make it possible to take advantage of both the cross-sectional and time series dimensions of our data. Much emphasis is placed on comparing sensitivities to risk factors across the types of real estate exposure. This is important in order to assess whether indirect (listed and non-listed) exposures react in the same way as direct investments to the macroeconomy and how well such investments replicate direct real estate behavior. The empirical analyses are conducted using U.S. data from 1984Q1 to 2016Q2. Allocations both by sector and geography are considered. For indirect exposures, we also control among other things for size and leverage. The various types of real estate exposure generally respond similarly to risk factors with GDP, money supply, construction costs, expected inflation, and expected economic activity positively impact returns, while the term and credit spreads, unemployment, and unexpected inflation negatively affect returns.

Keywords: Risk factors; Direct real estate; Non-listed real estate; Listed real estate; Macroeconomy.

1. Introduction

Non-listed real estate funds have developed considerably over the last decades and according to the Association of Real Estate Funds (AREF)[1], which rely upon Property Fund Research (PFR) data, the Gross Asset Value (GAV) of such funds worldwide amounted to $ 2,128 billion as of 2014Q4 with $ 602 billion for North American funds. Non-listed funds are appealing alternatives to direct real estate investments because, on the one hand, investors can achieve a real exposure with a limited amount of money and, on the other hand, funds benefit from the expertise of fund managers. Whereas funds share those advantages with listed investments such as Real Estate Investment Trusts (REITs), they will not be exposed to stock market noise given that they do not trade on an exchange. Against this background, several important questions must be answered to help investors and other stakeholders make relevant decisions. Indeed, it would be useful to know to what extent non-listed real estate funds behave like the underlying real estate markets, whether their returns respond similarly to changes in the economic context, and what the linkages with other exposures to real estate and the macroeconomy are. The present paper aims to expand the rather scarce literature pertaining to non-listed real estate funds by addressing some of those questions.

In this study, we consider U.S. real estate markets over the period 1984Q1 to 2016Q2. We first aim at identifying how real estate fund performance is determined by specific fund characteristics and how it is influenced by the macroeconomy. We conduct a corresponding analysis for direct and listed real estate. We test for the effects of the GDP, expected inflation, the inflation surprise, the money supply, construction costs, the expected economic activity, interest rates, unemployment, the term and credit spreads, and stock returns and volatility. Return differences across sectors and regions are also investigated. For non-listed funds and listed companies, we also control for the effect of leverage and size on returns. In addition, the price-earnings ratio (PER) is included in the analysis for REITs as a proxy for the value/growth factor. These analyses are conducted using panel data models allowing for random effects. The dynamics between real estate exposures, macroeconomic risk factors, as well as other asset classes are also investigated in the framework of Structural Vector Auto Regressive (SVAR) and Structural Vector Error Correction (SVEC) models.

We consider the smoothing bias inherent to using appraisal-based direct and non-listed data. We consider the standard desmoothing method proposed by Geltner (1991) and Fisher,

[1] Global Real Estate Funds Review H1 2016. The reported figures have been converted to U.S. dollars.

Geltner & Webb (1994), its regime-switching extension developed by Lizieri, Satchell & Wongwachara (2012), as well as a combination of those methods and robust filtering techniques that we introduce. We select the preferred desmoothing method as the one which best replicates the return distribution characteristics of those of transaction-based direct indexes.

The paper contributes to the extant literature in several ways. First, we propose an improvement in the desmoothing techniques for appraisal-based direct real estate series which proves particularly useful in dealing with unusually large returns. Second, we transpose the desmoothing techniques to non-listed real estate fund data. Third, we consider the effects of a wide array of macroeconomic factors on non-listed fund returns using data for a long time period which includes the Global Financial Crisis (GFC). Finally, we compare the results for non-listed funds with those for direct and listed real estate, thus providing for a much better understanding of the nature of the three types of real estate exposure which should prove particularly useful in optimizing the real estate component of a portfolio.

The remainder of the paper is structured as follows. After the literature review in Section 2, we present the details of our method for desmoothing and for the risk factor analysis in Section 3. Our data are presented in Section 4 while descriptive analyses are discussed in Section 5. Section 6 contains our results while a final section contains some concluding remarks.

2. Literature Review

Of the three main ways of gaining exposure to real estate (directly, by acquiring REIT shares, and through non-listed funds), the latter route has been the least extensively investigated in the literature, mainly due to data limitations. A body of the literature focuses on measuring the performance of funds across various characteristics such as investment structures and/or styles, also looking at how fund performance compares with the performance of other asset classes such as stocks and whether there is evidence of managerial performance persistence. Bond & Mitchell (2010) show that only a few managers of U.K. funds are able to deliver positive alpha. Geltner, Gerardo-Lietz & Hahn (2005) report evidence of managerial performance persistence for a sample of U.S. opportunity funds. Controlling value-added and opportunity fund returns for geographic allocation and vintage, Aarts & Baum (2016) also conclude that there is a short term persistence of fund performance across global funds with the same manager, but a reversal of performance in the long term. Comparing core, value-

added and opportunistic U.S. non-listed funds, Shilling & Wurtzebach (2012) conclude that the latter two categories outperform core investments mainly due to favorable market conditions and the possibility to access cheap debt. In contrast, from an international perspective, Fisher & Hartzell (2016) conclude that fund investment style (value-added vs. opportunistic) does not help explain returns. Fisher & Hartzell (2013) conclude that U.S. value-added and opportunity funds outperformed the stock market for vintages prior to 2004 but not for more recent years. In, addition, funds are found to underperform direct real estate as well as REITs.

A number of studies further analyze the impacts of fund characteristics on performance, as well as that of various risk factors. Tomperi (2010) finds that U.S. value-added and opportunistic fund performance is positively linked to size and that emerging funds are more likely to produce high returns. Farrelly & Stevenson (2016) identify a negative influence of size and a positive effect of sector specialization, as opposed to sector diversification on U.S. value-added and opportunistic fund returns. In addition, total vintage year capital flows are negatively linked to performance and there is limited evidence that geographic focus can be detrimental. The authors find no significant impact for managerial track record.

Anson & Hudson-Wilson (2003) illustrate that leverage should be used with moderation in order to optimize performance relatively to risk. Case (2015) controls for investment style of U.S. funds and reports that leverage has such large negative effects during the few down market periods compared to the small positive effect during the up market periods that the impact is eventually negative (see also Alcock, Baum, Colley & Steiner, 2013, who additionally control for the corresponding real estate market with an international perspective). Investigating the impact of leverage over the long run, Baum, Fear & Colley (2011, 2012) also conclude that leverage has generally a negative impact on European fund returns.

Our study is most closely related to a limited number of papers whose focus has been to examine the risk factors of non-listed real estate funds. Using European data, Fuerst & Matysiak (2013) and Fuerst, Lim & Matysiak (2013) conclude that the most important determinants of fund returns are the geographical and sectoral focus of investments, while leverage also plays a role with an asymmetric effect depending on whether the fund is making gains or losses. They also find a positive link with size as well as GDP, bond and stock

markets, but a negative one with fund's age. Delfim & Hoesli (2016) analyze risk factors of core and value-added European funds and report that both fund characteristics and country specific macroeconomic variables help explaining returns. Rather complex relationships with size and leverage are found, suggesting an optimal fund size and an optimal leverage level. Vehicle structure is also been found to be of importance, especially during down markets. They further document positive impacts of the GDP, inflation, money supply, and stock market excess returns, as well as negative impacts of interest rates. Similar responses to macroeconomics for the three exposure types (direct, listed, and non-listed) are found, although responses are of greater magnitude for REITs than non-listed and direct real estate. Pedersen, Tiwari & Hoffman (2012) find that core, value-added, and opportunity fund returns as well as REIT returns in the U.S. are all positively linked to the stock market, the credit spread, liquidity, and a common real estate factor. Core, value-added and opportunity funds are less, equally and more responsive, respectively, than REITs to these factors.

In contrast, much more research exists on listed and direct real estate investment performance and risk factors. For international REIT returns, Edelstein, Qian & Tsang (2011) and Pavlov, Steiner & Wachter (2015) identify importance of governance, legal and accounting principles, as well as the local credit market conditions, in addition to positive links with GDP and inflation and a negative one with term spread. find linkages between REIT returns and the GDP, interest rates, the term spread, stock returns, as well as country, size, and leverage. Ro & Ziobrowski (2011) conclude for the U.S. that specialized REITs do not outperform diversified REITs but have higher volatility. This contrasts with the aforementioned result of Farrelly & Stevenson (2016) for real estate funds. Chung, Fung, Shilling & Simmons-Mosley (2016) find that the implied volatility is negatively linked to current and future returns, but positively linked to future implied volatility, in the U.S. . Controlling for Fama-French and momentum factors, as well as liquidity, inflation, and crisis periods, Giacomini, Ling & Naranjo (2015) report that leverage usually has a positive impact on international REIT returns but a negative one during downturns.

Regarding direct real estate, Ling & Naranjo (1997) find positive impacts on U.S. real estate returns of per capita consumption and negative sensitivities to short-term interest rates, the term structure, and unexpected inflation. A comparison with REITs shows same signs for those variables. Using data for the U.S. and the U.K., Hoesli, Lizieri & MacGregor (2008) also document positive linkages with GDP and emphasize the role of direct real estate as an inflation hedge contrasting with the so-called perverse inflation hedge of listed real estate.

Location and sector are found to be important in Lee (2001), with U.K. data. Finally, Clayton, Ling & Naranjo (2009) report a negative impact of investor sentiment on U.S. real estate cap rates. The effects of the macroeconomy on housing returns have also been well documented. For instance, Adams & Füss (2010) show positive impacts of economic activity and construction costs on international house prices, while long-term interest rates have a negative impact.

The dynamics between real estate markets and the macroeconomy are further investigated in several studies. For example, using data for Germany and the U.K., Schätz & Sebastian (2009) report long-run relationships between the real estate market and inflation, government bond returns, and unemployment. For international REITs, Yunus (2012) reports a cointegration relationship with stock markets and key macroeconomic factors. In particular, REITs are usually positively linked to the GDP, money supply, and inflation, while long-run interest rates have a negative impact on REIT returns.

Concerning the linkages between real estate exposures, Ang, Nabar & Wald (2013) find a common factor in public and private U.S. real estate markets. Ling & Naranjo (1999) report that U.S. listed real estate and the stock market are integrated, while this is not the case for direct real estate and the stock market. Hoesli, Oikarinen & Serrano (2011, 2015), Boudry, Coulson, Kallberg & Liu (2012), and Ling & Naranjo (2015) focus on the linkages between U.S. direct and listed real estate and conclude that a cointegrating relationship between both exposures exists with short run dynamics indicating that listed real estate leads direct real estate. Authors usually consider sector level indices and control for several exogenous variables such as the GDP, stock returns, inflation, short-term interest rates, the term and credit spreads and consumer confidence. In an attempt to determine if real estate private equity is more real estate or private equity, Anderson, Krautz & Rottke (2016) conclude that U.S. real estate value-added and opportunistic fund returns are more closely related to direct real estate than to private equity in the long run, while in the short run opportunity funds are cointegrated with both and value-added funds only with private equity market investments. A positive relationship between non-listed and direct real estate is also reported by Delfim & Hoesli (2016) who additionally highlight such a relation between non-listed and listed investments.

The above discussion is important in guiding the choice of risk factors in the current study. Size, leverage, investment style, vehicle structure, and vintage have been identified as

potential drivers of non-listed real estate returns. Geography often appears to matter more than sector. Previous studies, focusing mostly on direct real and listed estate investments but in some cases also on non-listed investments, highlight that returns are positively related to the GDP, industrial production, consumption, employment, and also to leading and sentiment indicators. Monetary policy also appears to be important. Interest rates, and the term and credit spreads are usually negatively linked to real estate returns. The impacts of inflation components on real estate returns are less clear-cut and can vary depending on the type of real estate exposure. The stock market often displays positive linkages with listed and non-listed returns but not as clearly with direct returns. Finally, short- and long-term relationships across real estate exposures are reported and are particularly well documented across listed and direct investments.

3. Method

3.1 Desmoothing and the Robust Filter

Most direct real estate indices are appraisal-based. Also, non-listed fund return series are largely based on NAVs which also rely on the periodic appraisal of properties. Hence, direct and non-listed real estate returns are likely to suffer from the well-known smoothing and lagging bias. This lowers artificially the observed volatility and could lead one to believe those investments are less risky than they actually are. This phenomenon has been explored quite extensively in the real estate but also in the private equity literature (Geltner, 1991; Cumming, Hass & Schweizer, 2013). In order to overcome this issue several methodologies have been proposed. The most common one is exposed, for example, in Geltner (1991), Fisher, Geltner & Webb (1994) as well as in Marcato & Key (2007). This methodology considers that the current observed appraised value depends partly on the past appraised values and on the current public information available. This feature comes from the fact appraisers tend to significantly rely on the values they produced during the previous periods, adjusting them with respect to the current market environment. Then, the current appraised value can be written as follows:

$$V_t^a = \alpha V_{t-1}^a + (1-\alpha)P_t \tag{1}$$

with V_t^a the current appraised value, V_{t-1}^a the appraised value of the previous period, P_t the unobserved current market price that should prevail due to the market conditions, α the proportion of the current appraised value that relies on the previous appraised value (the (de)smoothing parameter). Following the same reasoning and using logarithmic

approximation, one obtains the smoothing equation by rewriting equation (1) in terms of returns as:

$$r_t^a = \alpha r_{t-1}^a + (1-\alpha) r_t \tag{2}$$

with r_t^a the appraised return observed at time t measured on the appraised values of t and t-1, r_{t-1}^a the appraised return for the previous period and, r_t, the return that should prevail with respect to the variation of the unobserved market price. This equation can be rewritten in order to express the actual market return as a function of appraised returns:

$$r_t = \frac{(r_t^a - \alpha r_{t-1}^a)}{(1-\alpha)} \tag{3}$$

According to this equation, as r_t^a and r_{t-1}^a are known the only unknown that must be estimated is α. Estimating α requires to make some assumptions. These assumptions particularly pertain to the way the actual unobserved market return r_t is generated. As reported in Lizieri, Satchell & Wongwachara (2012), these returns are commonly assumed to follow an AR(1) process, such as:

$$r_t = \gamma + \varphi r_{t-1} + \varepsilon_t \tag{4}$$

with φ the autoregressive coefficient of the model, γ the constant term and $\varepsilon_t$the error term at period t. Of course, a more sophisticated return generating process could be chosen among the ARMA(p, q) family. By substituting equation (3) in equation (4) one obtains another representation of the appraised return process:

$$r_t^a = \gamma(1-\alpha) + (\alpha+\varphi) r_{t-1}^a + \alpha\varphi r_{t-2}^a + \omega_t \tag{5}$$

with given values of γ and φ one can estimate $\hat{\alpha}$ as:

$$\hat{\alpha} = argmin \sum_{t=1}^{T} \omega_t^2(\alpha; \gamma, \varphi) \tag{6}$$

Once the estimate is obtained, one computes r_t, with t=1:T, using $\hat{\alpha}$ in equation (3). Then, with this series and relying on equation (4) we estimate new values $\hat{\gamma}$ and $\hat{\varphi}$ as:

$$(\hat{\gamma}, \hat{\varphi}) = argmin \sum_{t=1}^{T} \varepsilon_t^2(\gamma, \varphi; \alpha) \tag{7}$$

These last two estimates feed into equation (5) and the procedure is repeated until convergence. As this classical desmoothing model relies on AR processes in both the smoothing equation (2) and return process (4) we can refer to it as the AR-AR model.

As proposed by Lizieri, Satchell & Wongwachara (2012) more sophistication can be brought into this model by allowing for regime switching features in the smoothing equation (TAR-AR model) or in the return process (AR-TAR) or in both equations (TAR-TAR). Indeed, regime switching in the smoothing equation reflects the fact appraisers work differently according to the economic context, while the regime switching in the return process reflects how it is altered across market situations.

In the case of the regime switching smoothing equation, (2) becomes:

$$r_t^a = (\alpha_H 1_{z_{s;t-1}>c_s} + \alpha_L 1_{z_{s;t-1}\leq c_s}) r_{t-1}^a + (1 - (\alpha_H 1_{z_{s;t-1}>c_s} + \alpha_L 1_{z_{s;t-1}\leq c_s})) r_t \qquad (8)$$

where α_H and $\alpha_L$are the desmoothing parameters prevailing in high and low regimes, respectively, and $1_{z_{s;t-1}>c_s}$ and $1_{z_{s;t-1}\leq c_s}$, indicate if the previous period was in a high or low regime according to $z_{s;\,t-1}$, the exogenous variable used for determining smoothing regimes, and c_s is the threshold separating smoothing regimes.

In the same way, the return process (4) becomes:

$$r_t = \left(\gamma_H 1_{z_{r;t-1}>c_r} + \gamma_L 1_{z_{r;t-1}\leq c_r}\right) + \left(\varphi_H 1_{z_{r;t-1}>c_r} + \varphi_L 1_{z_{r;t-1}\leq c_r}\right) r_{t-1} + \varepsilon_t \qquad (9)$$

where (γ_H, φ_H) and (γ_L, φ_L) are the return equation parameters prevailing in high and low regimes, respectively, and $1_{z_{r;t-1}>c_r}$ and $1_{z_{r;t-1}\leq c_r}$, indicate if the previous period was in a high or low regime according to $z_{r;\,t-1}$, the exogenous variable used for determining return process regimes, and c_r, is the threshold separating return process regimes. The exogenous variable used for determining regime thresholds can be the same for the smoothing equation and the return process. As suggested by Lizieri, Satchell & Wongwachara (2012) we choose the stock market returns as the exogenous variable for both processes[2].

Despite the additional flexibility brought to the desmoothing method by the TAR-TAR specification, it appears that the desmoothing procedure still produces extreme values while underlying series display relatively large changes. Treatment of extreme, outlying, observations can be addressed by means of robust statistical techniques. Hence, we propose to apply a robust time series filter to desmoothed series in order to overcome this outlier issue. Several robust methods exist for filtering time series, as least median of square regression (Rousseeuw, 1984), or deep regression (Rousseeuw & Hubert, 1999). We choose to rely on

[2] We also tested with economic activity and interest rates as thresholds and results indicated that stock market returns were the best choice as the exogenous variable, according to the proximity reached with the corresponding transaction-based series.

the Tukey biweight (or bisquare) function with dynamic distribution parameters. The Tukey biweight function aims at underweighting observations whose distance from the center of the observed distribution is unlikely. The more unlikely is the observation, the more shrunk toward the central parameter of the distribution the observation will be. For very unlikely observations that trespass a given threshold, the value is reduced to equal the center of the distribution. Hence, in order to gauge if an observation is likely with respect to the whole observed distribution, under the assumption of normality, the function requires information on the central value of the distribution, μ, and on its dispersion, σ. In the usual static framework, the former can for example be taken as the distribution average or the median, and the latter as its standard deviation of even median absolute deviation. In addition, as mentioned above, a threshold, the so-called tuning constant, c_w, must be defined[3]. Nevertheless, as we work in a dynamic framework, several adjustments must be made. In particular, because we assume the return series average and dispersion parameters change with time, we model the two parameters using an ARMA(1, 1)-GARCH(1, 1) model[4] applied on *x*, the series of returns[5]. We iteratively fit this model on the interval $[1{:}\,t-1]$ with $\epsilon\,[t_{init}{:}\,T]$ [6]. Then, we can extrapolate for the following period the estimates the average parameter, $\hat{\mu}_t$, and the volatility parameter, $\hat{\sigma}_t$. The observation robust weight at time *t*, w_t, is therefore computed through the following two steps:

$$\rho_t = \begin{cases} \dfrac{x_t - \hat{\mu}_t}{\hat{\sigma}_t} * \left(1 - \left(\dfrac{\frac{x_t - \hat{\mu}_t}{\hat{\sigma}_t}}{c_w}\right)^2\right)^2 & ;\ if\ abs(x_t) < \hat{\mu}_t + c_w * \hat{\sigma}_t \\ 0 & ;\ if\ abs(x_t) > \hat{\mu}_t + c_w * \hat{\sigma}_t \end{cases} \tag{10}$$

[3] The function is usually recognized to be the most efficient with a threshold value of 4.6851. It is also possible to introduce asymmetry by defining a tuning parameter with a different absolute value depending on the sign of the observation. We retained a threshold value of twice the commonly used 4.6851 value. This implies we completely cut only the most extreme outliers. Others being however more or less downsized depending on how exaggerated they are.

[4] Filtered time series must be stationary. Stationarity is tested by augmented Dickey-Fuller, Elliot-Rothenberg-Stock, Phillips-Perron, and Zivot-Andrews unit root tests. If stationarity is rejected by a majority of tests, series differences are taken for computing robust weights. Then, those weights are applied to the original series.

[5] For the desmoothing procedure, we work on price returns instead of total returns as smoothing does not impact the income component of returns.

[6] As a minimum number of observations is needed to fit the ARMA(1,1)-GARCH(1, 1) model, for the initial periods of observations $t = 1{:}t_{init}$ (we choose $t_{init} = 12$ quarters), parameters $\hat{\mu}_t$ and $\hat{\sigma}_t$ are taken as the median and the median absolute deviation computed on the initial periods.

$$w_t = \frac{\rho_t}{\left(\frac{x_t - \hat{\mu}_t}{\hat{\sigma}_t}\right)}$$

Now, the original $x_t$value is replaced by its robust estimation computed as:

$$x_t^{rob} = w_t x_t + (1 - w_t)\hat{\mu}_t \tag{11}$$

Then, the parameter estimation process is repeated successively for each following period in order to compute x_t^{rob} for all t[7]. Finally, we obtain a whole filtered series x^{rob}.

3.2 Panel Regression Models

We regress excess total returns of each real estate exposure we investigate on macroeconomic risk factors and specific characteristics mentioned above. In order to identify a relatively large number of risk factors, while at the same time controlling for specific investment characteristics, a sufficient number of observations is required. Due to the quite low frequency of observations, implying relatively short time series for each asset (direct real estate, funds, and REITs), and the relatively large number of control variables that are included in the analysis, it is not possible to fit one model for each series. In order to offset the weakness of the time series dimension of the dataset, we take advantage of its cross-sectional dimension as we have access sector/region indexes for direct real estate, fund-level data for funds, and company-level data for REITs. To model the available data properly we rely on panel regression techniques. Indeed, this class of statistical models takes advantage of the depth of the data while fulfilling the requirements implied by the time series data limitations mentioned above.

Our model specification also allows for random effects if needed (Laird & Ware, 1982), which makes it possible to control for non-observed characteristics of identified clusters of data, leading to improved precision in the estimation. In a longitudinal setting such as ours, clusters are formed with repeated measures over time for a specific subject, i.e. for a specific asset (a sector/region index for direct real estate, a fund or a REIT). Each asset is considered as a specific subject and a random effect is placed on the variable pertaining to the real estate investments' ID. Including random effects is also helpful while the number of corresponding fixed effects to estimate is large and would consume lots of degrees of freedom. Indeed, if we wanted to model the residual return for each fund with fixed effects this would require the estimation of one coefficient for each index (each fund and each REIT,

[7] Note that in the case that w_t= 0, x_t is taken as a missing value in the parameters estimation process and extrapolated values for $\hat{\mu}_{t+1}$ and $\hat{\sigma}_{t+1}$are set as the values computed at the previous period, $\hat{\mu}_{t+1}$ and $\hat{\sigma}_t$.

respectively), corresponding to intercept adjustments for each asset. Using random effects instead requires fitting only one coefficient, i.e. the variance of the distribution of residual asset returns[8]. The general equation of the mixed models we use is the following:

$$r_{i,t} = X_{i,t}\beta + Z_{i,t}u_i + \varepsilon_{i,t} \tag{11}$$

$$with \quad u_i \sim N_q(0, \Psi) \quad and \quad \varepsilon_i \sim N_{n_i}(0, \Sigma_i)$$

where $r_{i,t}$ is the $n_i \times 1$ response vector of excess returns for the n_i assets of cluster i, at time t, $X_{i,t}$ the $n_i \times p$ matrix of observations for fixed effect variables corresponding to assets of cluster i at time t, β the $p \times 1$ vector of fixed effect coefficients common to all n assets of the full sample. Following the same logic, $Z_{i,t}$ is the $n_i \times q$ matrix of random effect variables at time t, $u_i$the $q \times 1$ vector of random effect coefficients for cluster i, and ε_i the $n_i \times 1$ vector of errors of cluster i. Ψ is the $q \times q$ covariance matrix of random effects and Σ_i the $n_i \times n_i$covariance matrix of errors of cluster i. Obviously, if the model has no random effects, cluster indices i and $Z_{i,t}u_i$ vanish.

4. Data

In this research, we use U.S. data for the period 1979Q1-2016Q2. We consider five main sectors for real estate (apartments, hotels, industrial, offices, and retail) and four U.S. regions (East, Midwest, South, and West) which can be decomposed into eight subregions (Mideast, Northeast, East North Central, West North Central, Southeast, Southwest, Mountain, and Pacific). Data for direct real estate are for the national NCREIF appraisal-based Property Index (NPI) with regional and sectoral components, as well as subregional components by sector. This represents 39 appraisal-based sector/subregion series[9] used for the risk factor analysis. In addition, we use data for the national NCREIF Transaction-Based Index (NTBI) with regional and sectoral components. The latter group of indices is particularly useful for testing the ability of desmoothing methods to produce return series with characteristics close to transaction-based indices. Transaction-based indices are not used in the risk factor analysis because despite the fact that the national index starts as early as 1984Q1, components start in 1994Q1 only.

[8] In addition, as our sample has a time series dimension, possible residual autocorrelation is modelled through ARMA (p, q) processes.
[9] There is no series for Hotel in the West North Central subregion.

Data for non-listed funds are related to the NCREIF Open-end Diversified Core Equity (ODCE) Index and its constituents. There are 35 funds observed between 1979Q1 and 2015Q3, although not all funds have data for the entire period. These funds are by construction diversified by sector and subregion. Hence, if we take a 60%[10] threshold of market value in order to determine if a fund belongs to a certain category, we observe that 96% of observations are related to funds diversified by sector and 99% diversified by subregion. Therefore, we consider that all funds are diversified by both sector and subregion and hence that those categories are not relevant to discriminate between non-listed funds in the risk factor analysis. As fund returns are computed from appraisal-based series, we also apply the aforementioned desmoothing method[11]. Some funds also include a marginal share of investments in land, self-storage, and other property types. Among fund characteristics, we focus on fund size, taken as the gross value of real estate assets[12], leverage, taken as the ratio of debt over total asset value, fund age, and fund vintage year.

For REITs, we consider the NAREIT All-Equity Index and its components. REIT level data are sourced from Thomson Reuters Datastream as well as Compustat. In addition to the five main sectors we consider, some NAREIT constituents are classified as mainly investing in health care and specialized (storage or other sectors) properties. These are presented in the following descriptive analysis but are not considered in the risk factor analysis. Observations are included in the sample only when the corresponding REIT is actually part of the NAREIT All-Equity Index. Among REITs characteristics we focus on size, taken as total assets, leverage, taken as the ratio of debt over total asset value, and the price-earnings ratio (PER), used as a proxy for the value/growth factor.

Finally, macroeconomic and financial series we consider as potential risk factors are mainly sourced from Thomson Reuters Datastream. Corporate bond yields and expected inflation series are from St. Louis Fed. Construction cost series are from RSMeans[13]. Note also that series are tested for seasonality and adjusted if necessary by applying the X-12-ARIMA method of the U.S. Census Bureau.

[10] 60% is the threshold used in the Global Industrial Classification Structure (GICS) of MSCI we rely on for REITs. Hence, we apply the same criterion for non-listed funds.

[11] For non-listed funds, desmoothing parameters are estimated on the ODCE Index and applied on each fund series. We do so as for some funds series are relatively short compared to the whole period of observation.

[12] In models for risk factors analysis, the size variable is in real terms in order to neutralize the price effect. We do the same for REITs.

[13] As the RSMeans series are available at the yearly frequency only, we rely on the CPI Shelter series and interpolation techniques for filling the intermediate quarters.

We investigate the impact on real estate excess returns of the following macroeconomic risk factors: Growth of GDP, money supply (M2), construction costs, the Conference Board leading Economic Indicator[14], as well as expected inflation and the inflation surprise, the change in the 10-year interest rate, the unemployment rate, the VIX index, the term spread (the spread between the 10-year and the 3-month rates), the credit spread (Baa bond rates minus Aaa bond rates), and the stock market excess total returns (MSCI). Dummy variables for crisis periods are also added if necessary. Growth rates and interest rates are expressed in real terms.

5. Descriptive Analysis

We first present descriptive statistics about real estate investments. Figure 1 displays the breakdown of direct real estate, non-listed real estate and REIT samples by sector as of 2015Q3. It appears that both are very close: Offices is the largest category with 38% of market value, followed by apartments at 24%, retail slightly over 20%, industrial at almost 15% and hotels below 3%. In addition, non-listed funds invested 2% in storage, about 1% in other sectors and almost nothing in land. With respect to the main sectors for REITs, retail is the largest at 37%, apartments is still the second one with 24% which is very close to the figure for private markets, while offices is now third at 21%. With 8%, industrial has a smaller share than for private markets. The reverse holds for hotels which represent 9%.

Figure 1. Market Value Breakdown by Sector for Direct, Non-listed and REITs

[14] The Markit Purchasing Manager Index (PMI) and Consumer Confidence Index are alternatively tested in models. Note that these three indicators are orthogonalized with respect to other macro variables.

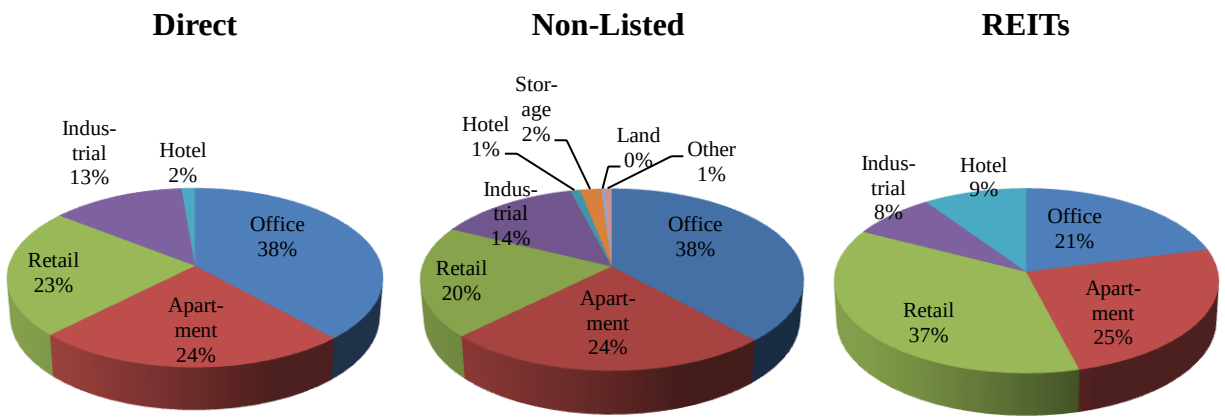


Figure 2 show the evolution of the average size of non-listed funds and REITs. One observes a strong increase of the size for both exposures since the mid 1990's, with a particularly large peak for non-listed funds before the 2008 GFC. Interestingly, nowadays the average size is about the same for REITs and funds.

Figure 2. Average Size of Non-Listed Funds and REITs ($Bn)

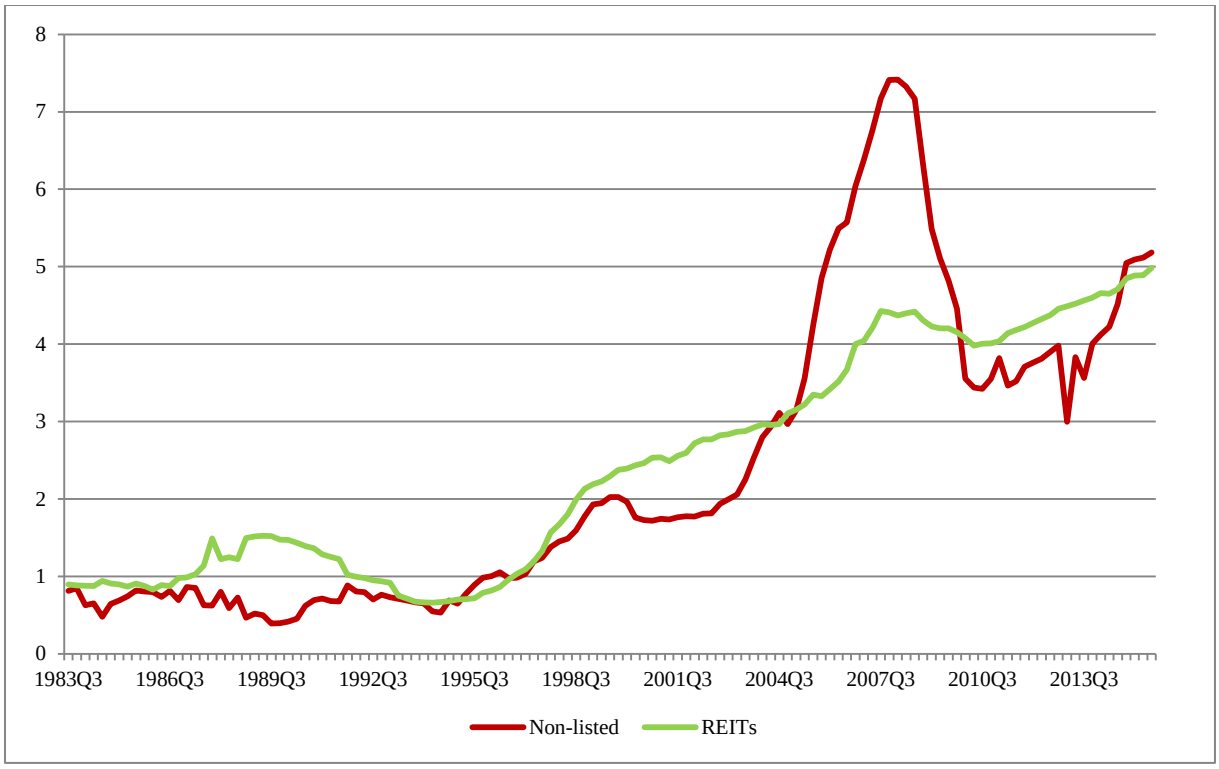
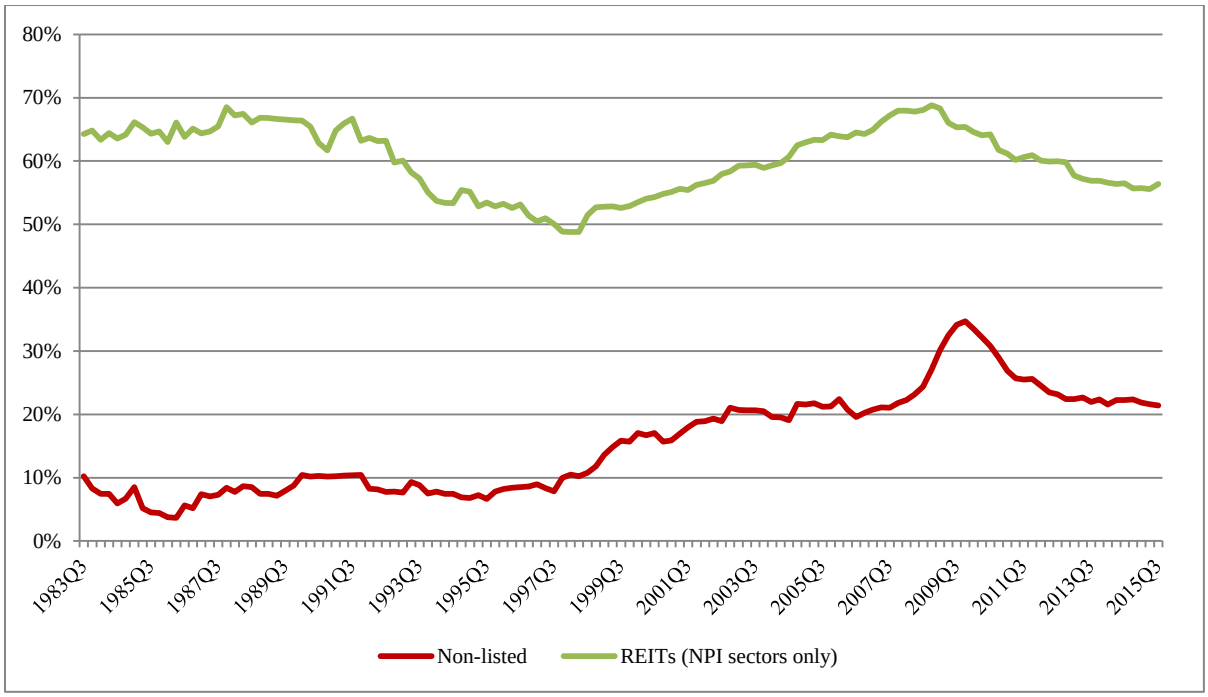


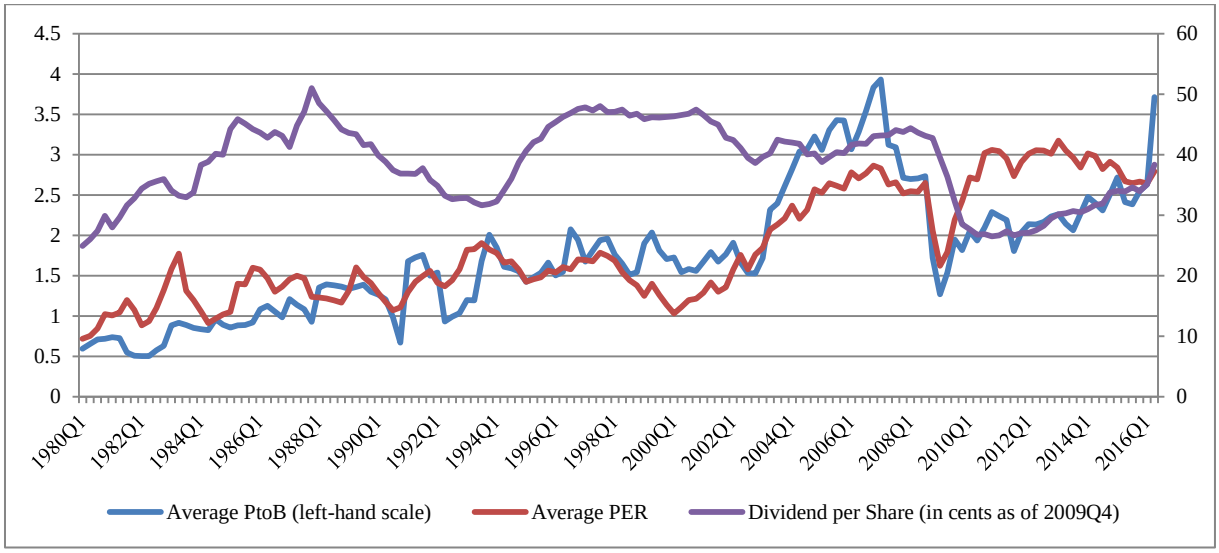
Figure 3 compares the leverage of non-listed funds and REITs. The leverage level is clearly lower for funds than for REITs. For the latter, it evolves between 50% and 70%, while for the former it goes from being about 10% until the late 1990's to being approximately 20% since the early 2000's. The peak observed during the GFC is mainly due to a mechanical effect as asset values fall more than debt values.

Figure 3. Leverage of Non-Listed Funds and REITs



Finally, we present in Figure 4 the evolution of three REIT metrics that can be used as proxies for the value/growth factor. We observe a positive trend for both price-to-book and price-earnings ratios from about 0.5 and 10 at 1980Q1 to about 3 and almost 40 at 2016Q2, respectively. The quarterly average dividend per share fluctuates between 30 and 50 cents, with a large increase during the second half of the 1990's and a sharp decline during the GFC.

Figure 4. Average Price-to-Book and Price-Earnings Ratios and Dividends per Share



We now turn to asset returns with Figure 5 comparing total return indices for appraisal-based (NPI) and transaction-based (NTBI) national direct indices, the non-listed ODCE index, a REIT index including only the five main sectors we consider and a U.S. stock index (MSCI). First, it is clear all indices follow a similar strong positive trend with private (direct and non-listed) indices being very close to one another. REITs appear to grow faster than other asset classes during years preceding the GFC and in the current bull market. The stock market displayed a bubble (the technology bubble) in the late 1990's contrary to the REIT index.

Figure 5. Total Return Indices: Real Estate and Stocks (100 at 2002Q4)

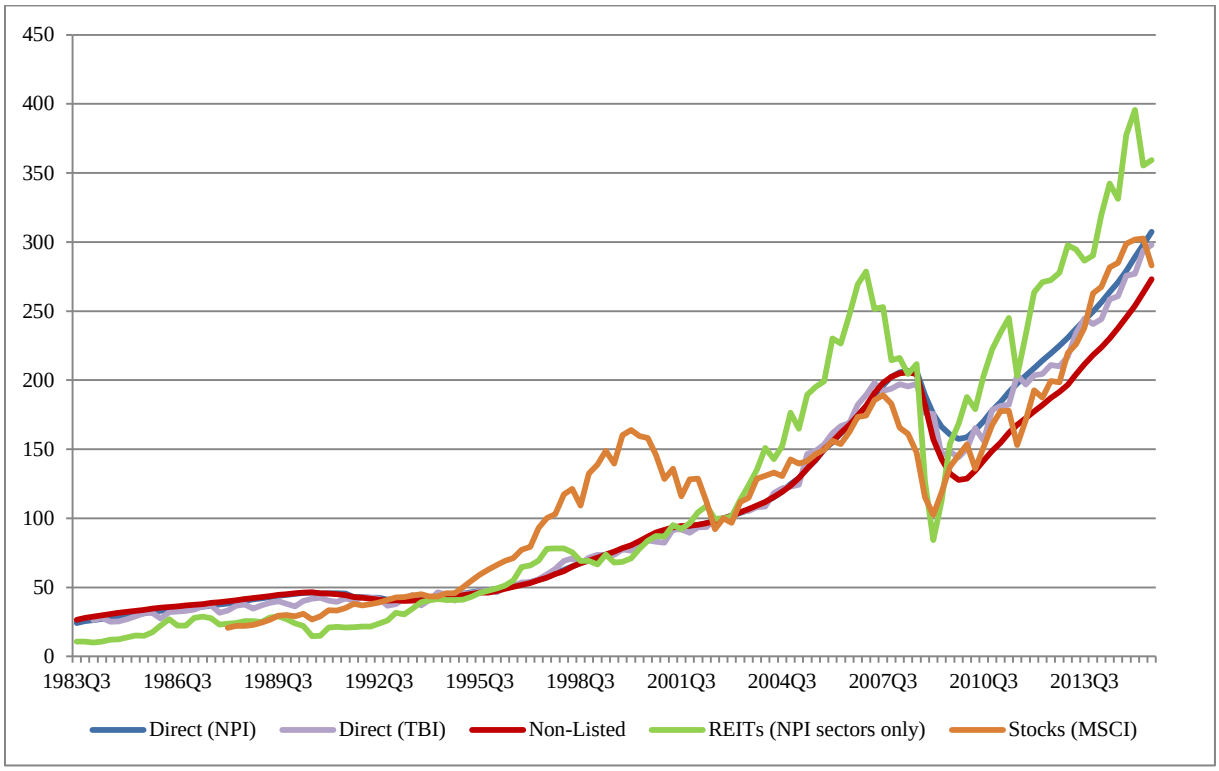


Figure 6 and Table 1 present information on quarterly total return distributions by real estate exposure and other asset classes (stocks, 10-year government bonds, AAA/AA corporate bonds and BBB corporate bonds). The first striking observation is the difference between the total return distributions of the NPI and the NTBI. Indeed, despite the fact that their medians are quite similar, the NTBI volatility is almost three times larger than the NPI one. The NTBI skewness is negative but closer to zero than that of the NPI. The latter has a large kurtosis of 7.55 almost five times larger than that of the NTBI. Another important

observation is the difference between autocorrelations, which is slightly negative for the NTBI and 0.8 for the NPI. This large value illustrates well the smoothing issue coming from the appraiser behavior. The aforementioned elements explain the much higher Sharpe ratio for the NPI. When the NPI figures are desmoothed with the robust TAR-TAR method, the distribution characteristics are close to those of the NTBI. In particular, the volatility, Sharpe ratio, skewness, kurtosis and autocorrelations are very close to the NTBI figures. REITs display average total returns of 3.17% and a volatility of 9.09%. The skewness is more negative and the kurtosis higher than for the NTBI, while the autocorrelation of both series is low. The Sharpe ratio of REITs is higher than for direct real estate. For the non-listed ODCE fund index, original and desmoothed return series teach us a similar story than direct indices. Indeed, once desmoothed, returns display volatility, autocorrelation and a Sharpe ratio that are more in line with a transaction-based index. In particular, average returns are also around 2% while the volatility is 6.33%, slightly larger than for the NTBI. However, the Sharpe ratio is lower than for the NTBI. Statistics for stocks are as expected close to those of REITs. In particular, the Sharpe ratio of 0.54 is only 0.02 higher than that of REITs. With a volatility between 3% and 3.5%, the three bond indices have the lowest risk among all asset classes. However, their average returns are around 2% like those of private real estate. Therefore, they show relatively high Sharpe ratios compared to most of real estate series, between 0.47 for 10-year government bonds and 0.68 for BBB corporate bonds.

Figure 6. Total Returns Boxplots - 1984Q2-2016Q2

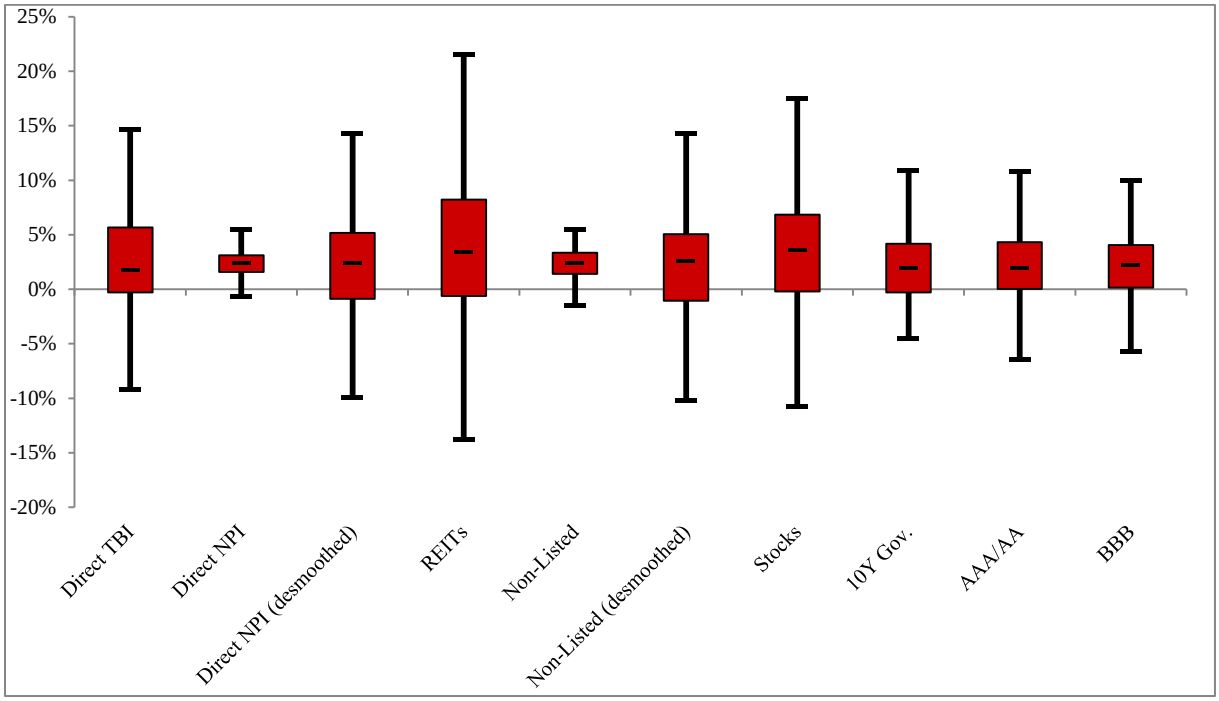


Table 1. Total Returns Summary Statistics - 1984Q2-2016Q2

	Direct (NTBI)	Direct (NPI)	Direct (NPI) *(Desmoothed)*	REITs	Non-Listed	Non-Listed *(Desmoothed)*	Stocks	10 Y Gov. Bonds	AAA/AA Bonds	BBB Bonds
Max	17.84%	5.43%	24.36%	33.28%	5.45%	19.26%	21.90%	11.01%	13.79%	13.10%
Pct99	16.09%	5.16%	17.77%	27.14%	5.18%	16.05%	19.76%	10.90%	10.00%	9.75%
Pct95	11.37%	4.48%	12.20%	15.03%	4.84%	10.80%	15.59%	8.37%	7.65%	6.86%
Pct90	9.06%	3.88%	9.64%	12.18%	4.00%	9.29%	11.84%	6.55%	6.06%	5.71%
Quart3	5.68%	3.13%	5.18%	8.23%	3.34%	5.06%	6.86%	4.18%	4.34%	4.07%
Median	1.77%	2.40%	2.43%	3.40%	2.33%	2.54%	3.55%	1.90%	1.93%	2.18%
Average	2.11%	2.00%	2.24%	3.17%	1.86%	1.95%	2.98%	2.17%	2.07%	2.15%
Quart1	-0.30%	1.60%	-0.88%	-0.60%	1.40%	-1.06%	-0.21%	-0.29%	0.02%	0.15%
Pct10	-4.37%	-0.19%	-4.84%	-6.06%	-0.78%	-4.67%	-8.75%	-1.68%	-2.09%	-1.45%
Pct05	-10.16%	-1.84%	-7.72%	-9.56%	-1.74%	-7.02%	-12.73%	-2.99%	-3.30%	-2.41%
Pct01	-16.16%	-6.77%	-12.82%	-27.17%	-10.41%	-20.09%	-20.84%	-3.97%	-6.17%	-4.69%
Min	-17.17%	-8.29%	-19.11%	-38.80%	-13.69%	-22.76%	-22.80%	-4.60%	-9.37%	-5.71%
St. Dev.	6.03%	2.14%	6.24%	9.09%	2.79%	6.33%	8.09%	3.36%	3.49%	3.09%
Skewness	-0.58	-2.32	0.10	-0.77	-2.94	-0.93	-0.63	0.51	0.03	0.29
Kurtosis	1.64	7.55	1.82	5.12	11.87	3.18	1.03	0.16	1.00	0.77
Autocorrelation	-0.168	0.798	-0.356	0.113	0.873	-0.016	0.048	0.010	-0.081	0.217
Sharpe Ratio	0.44	1.30	0.45	0.52	0.95	0.54	0.71	0.47	0.51	0.68

Now, we turn to summary statistics for macroeconomic and financial risk factors we consider in the panel models presented in Section 6. From Table 2, we learn that for most of variables expressed as growth rates, the volatility is low (below 1%), but their autocorrelation is rather large (around 0.8).

Correlations presented in Table 3 are also interesting. It appears that most of coefficients are low in absolute value, below 0.5. However, one observes that expected inflation and the inflation surprise are positively linked and both are quite negatively linked with money supply and construction costs. The leading indicator and the stock market are positively linked. Stock market volatility is negatively linked with most of the other risk factors.

Table 2. Risk Factors Summary Statistics - 1984Q2-2016Q2

	Real GDP growth	Expected Inflation	Inflation Surprise	Real Money Supply growth	Real Construction Costs growth	Leading Indicator growth	Unemployment Rate change	Term Spread	Real 10Y Int. Rate change	Credit Spread	Excess Stock Total Returns	VIX change
Max	1.63%	1.16%	0.45%	2.28%	1.44%	1.70%	1.15%	3.75%	0.80%	2.65%	17.77%	4.44%
Pct99	1.39%	1.07%	0.39%	2.10%	1.32%	1.54%	0.82%	3.60%	0.64%	2.11%	16.12%	3.73%
Pct 95	1.29%	0.96%	0.29%	1.62%	0.77%	0.96%	0.38%	3.41%	0.44%	1.36%	13.95%	2.54%
Pct 90	1.18%	0.92%	0.21%	1.47%	0.62%	0.66%	0.26%	3.19%	0.31%	1.28%	11.31%	1.66%
Quart3	0.97%	0.80%	0.10%	1.20%	0.27%	0.31%	0.08%	2.83%	0.13%	1.09%	6.32%	0.77%
Median	0.72%	0.75%	0.00%	0.69%	0.00%	0.00%	-0.08%	2.07%	-0.08%	0.87%	2.73%	-0.08%
Average	0.68%	0.76%	-0.06%	0.68%	0.04%	-0.08%	-0.02%	1.94%	-0.08%	0.91%	2.25%	0.02%
Quart1	0.44%	0.69%	-0.21%	0.21%	-0.21%	-0.44%	-0.17%	1.08%	-0.28%	0.68%	-1.26%	-0.79%
Pct10	0.16%	0.64%	-0.44%	-0.27%	-0.54%	-1.02%	-0.25%	0.42%	-0.48%	0.58%	-8.83%	-1.61%
Pct05	-0.09%	0.63%	-0.53%	-0.46%	-0.66%	-1.42%	-0.27%	0.22%	-0.61%	0.51%	-11.15%	-2.23%
Pct01	-0.37%	0.59%	-0.81%	-0.62%	-0.79%	-1.76%	-0.45%	-0.24%	-0.90%	0.29%	-15.14%	-3.58%
Min	-0.53%	0.59%	-0.86%	-0.67%	-0.82%	-1.90%	-0.47%	-0.35%	-1.02%	0.28%	-17.29%	-3.85%
St.dev.	0.41%	0.10%	0.26%	0.67%	0.44%	0.69%	0.24%	1.06%	0.32%	0.33%	7.09%	1.42%
Skewness	-0.55	1.11	-0.81	-0.10	0.60	-0.29	1.79	-0.30	-0.17	1.68	-0.40	0.19
Kurtosis	0.26	1.71	0.53	-0.73	0.78	0.33	5.23	-0.99	0.41	6.60	0.13	0.85
Autocor.	0.80	0.89	0.70	0.88	0.88	0.69	0.79	0.93	0.62	0.76	0.05	0.69

Table 3. Risk Factors Correlations - 1984Q2_2016Q2

	Real GDP growth	Expected Inflation	Inflation Surprise	Real Money Supply growth	Real Construction Costs growth	Leading Indicator growth	Unemploy-ment Rate change	Term Spread	Real 10Y Int. Rate change	Credit Spread	Excess Stock Total Returns	VIX change
Real GDP growth	1.00	-0.14	0.02	-0.12	-0.07	0.04	-0.24	0.03	0.10	-0.27	0.07	-0.02
Expected Inflation	-0.29	1.00	0.31	-0.24	-0.21	-0.05	-0.07	-0.12	0.02	0.10	-0.06	0.11
Inflation Surprise	-0.02	0.45	1.00	-0.33	-0.34	-0.18	0.21	-0.06	0.08	0.05	-0.10	0.04
Real Money Supply growth	-0.17	-0.36	-0.52	1.00	0.20	-0.12	0.00	-0.08	-0.14	0.25	0.00	0.06
Real Construction Costs growth	0.01	-0.40	-0.39	0.24	1.00	0.15	-0.04	-0.09	0.06	-0.01	-0.03	-0.03
Leading Indicator growth	0.22	-0.20	-0.25	-0.22	0.26	1.00	-0.14	0.21	0.14	-0.04	0.13	-0.26
Unemployment Rate change	-0.55	0.06	0.25	0.11	-0.11	-0.22	1.00	-0.07	-0.12	0.14	-0.10	0.02
Term Spread	0.02	-0.18	-0.10	-0.10	-0.07	0.33	0.06	1.00	0.05	0.12	0.02	-0.25
Real 10Y Int. Rate change	0.15	0.02	0.10	-0.23	0.13	0.15	-0.10	0.06	1.00	-0.01	0.04	-0.15
Credit Spread	-0.46	0.18	0.02	0.43	-0.05	-0.24	0.42	0.20	-0.12	1.00	-0.09	-0.05
Excess Stock Total Returns	0.19	-0.12	-0.13	-0.06	0.03	0.31	-0.15	0.02	0.13	-0.26	1.00	-0.23
VIX change	-0.06	0.30	0.07	0.07	-0.14	-0.43	-0.04	-0.34	-0.23	0.04	-0.46	1.00

Correlation coefficients below the diagonal are computed according to the Pearson method (used in other tables) and those being over the diagonal are computed according to the Kendall method. The latter produces a more robust metric as it neutralizes the influence of extremes and outlying values.

6. Results

6.1 Desmoothing Model Analysis

For our analysis, several desmoothing models are applied on national NCREIF appraisal-based index (NPI) price returns and compared with the corresponding transaction-based index (NTBI) series. As explained in the method section, for desmoothing purposes we work on price returns instead of total returns as smoothing does not affect income returns. The NPI is first desmoothed with the classic AR model. Then, the TAR-TAR method is applied. Finally, each desmoothed series is passed into the robust filter. The estimated parameters for the AR and the TAR-TAR models are presented below[15]:

AR Model:

- The returns generating process equation:

$$R_t = \underset{(0.0076)}{0.0025} - \underset{(0.0859)}{0.1742^{**}} R_{t-1} + \varepsilon_t \tag{12}$$

$$with\ \varepsilon_t \sim N(0, 0.0865)$$

- For the smoothing equation, the alpha parameter is 0.8536^{***} (0.0402).

TAR-TAR Model:

- The returns generating process equation:

$$R_t = \begin{cases} \underset{(0.0007)}{-0.0143^{***}} + \underset{(0.0131)}{0.1892^{***}} R_{t-1} + \varepsilon_{L;\,t} \ ;\ if\ R_{stocks;\,t-1} < \underset{(0.0004)}{-0.0273^{***}} \\ \underset{(0.0014)}{0.0271^{***}} - \underset{(0.0072)}{0.5914^{***}} R_{t-1} + \varepsilon_{H;\,t} \ ;\ if\ R_{stocks;\,t-1} \geq \underset{(0.0004)}{-0.0273^{***}} \end{cases} \tag{13}$$

$$with\ \varepsilon_{L;\,t} \sim N(0, 0.3441) \quad and \quad \varepsilon_{H;\,t} \sim N(0, 0.0808)$$

- For the smoothing equation, the alpha parameters are:

$$\begin{aligned} alpha_L &= \underset{(0.0062)}{0.8446^{***}} \ ;\ when\ R_{stocks;\,t-1} < \underset{(0.0078)}{-0.0027} \\ alpha_H &= \underset{(0.0032)}{0.8731^{***}} \ ;\ when\ R_{stocks;\,t-1} \geq \underset{(0.0078)}{-0.0027} \end{aligned} \tag{14}$$

[15] The significance level of parameter estimates is indicated by the stars, with "*", "**", and "***" corresponding to a p-value of 10%, 5% and 1% respectively. The standard error is indicated in brackets.

We observe that parameter estimates of the returns generating process of the TAR-TAR models are more significant than those of the AR model. For the former process, the threshold between the High and Low regimes of -2.73% corresponds to the first fifth of stock market total returns distribution. Comparing estimates for the smoothing equation, the alpha parameter is 0.8536 in the AR model, which is in between the High and the Low regime alpha parameters in the TAR-TAR model, being 0.8731 and 0.8446, respectively. In the latter equation, the threshold between regimes is not significantly different from zero, which corresponds to the first third of stock mark total returns distribution. Values of $alpha_L$ and $alpha_H$ seems relatively close. However, further tests[16] indicate that they are significantly different at 1% confidence level.

Now we graphically represent and compare on Figure 7 various desmoothed series together and with the transaction-based target series. Classic AR and TAR-TAR desmoothed series are represented with dashed lines and their robust versions are in solid lines. We first observe that both desmoothing models produce very close series. Nevertheless, the AR one seems to generate slightly larger values, especially while changes are important. Most of time, all desmoothed series appear rather close to the NTBI series, except during the most volatile events. This is precisely when the robust series prove to be the most useful by importantly shrinking extreme values. The rest of time, the difference is small.

We also compare results obtained for regional and sectoral subindices and further test differences between all desmoothed series and their transaction-based counterpart, on the period 1994Q1-2016Q1. We first test if series of each pair can come from the same distribution with the Kruskal-Wallis test, which is a non-parametric alternative to the classic ANOVA. Then, the Brown-Forsythe test of equality of variance is applied. In addition, difference in quantiles is further examined with the Anderson-Darling test[17]. Finally, we assess the significance of tracking error between transaction-based and desmoothed series[18]. Results are summarized in Table 3, where is reported the proportion of series that fail to match the benchmark, for each type of desmoothed series and for each test.

Comparison tests show first, that according to the Kruskal-Wallis test distribution of no desmoothed series significantly differ to the one of its transaction-based counterpart at

[16] Difference between the two alpha parameter estimates is tested by Welch t-test and Kruskal-Wallis test. Both tests reach the same conclusion of significant difference between parameters.
[17] The Anderson-Darling test is more sensitive to tail observations and the well-known Kolmogorov-Smirnov test, which is more concerned by central observations.
[18] Critical values of the test are obtained by bootstrap.

95% confidence level[19]. However, according to the Brown-Forsyth test, one third of desmoothed series, whatever the type, is found having significantly different variance than the benchmark distribution. Regarding the Anderson-Darling test only from 0% to 22% of series are found to differ from the benchmark. Moreover, it seems that this proportion is systematically lower for robust series. The latter conclusion is the same, and even more pronounced, for the tracking error test.

Table 3. Proportion of mismatch

	Kruskal-Wallis	**Brown-Forsythe**	**Anderson-Darling**	**Tracking Error**
TAR-TAR	0.0%	33.3%	22.2%	55.6%
TAR-TAR robust	0.0%	33.3%	11.1%	11.1%
AR	0.0%	33.3%	11.1%	44.4%
AR robust	0.0%	33.3%	0.0%	0.0%

Table 3 indicates for each test, the proportion of desmoothed series that is found to significantly differ from the corresponding transaction-based one, at a 95% confidence level.

[19] Note that the same result is obtained with the Welsh t-test.

Figure 7. Appraisal based, transaction based and desmoothed price returns - 1984Q1:2016Q1

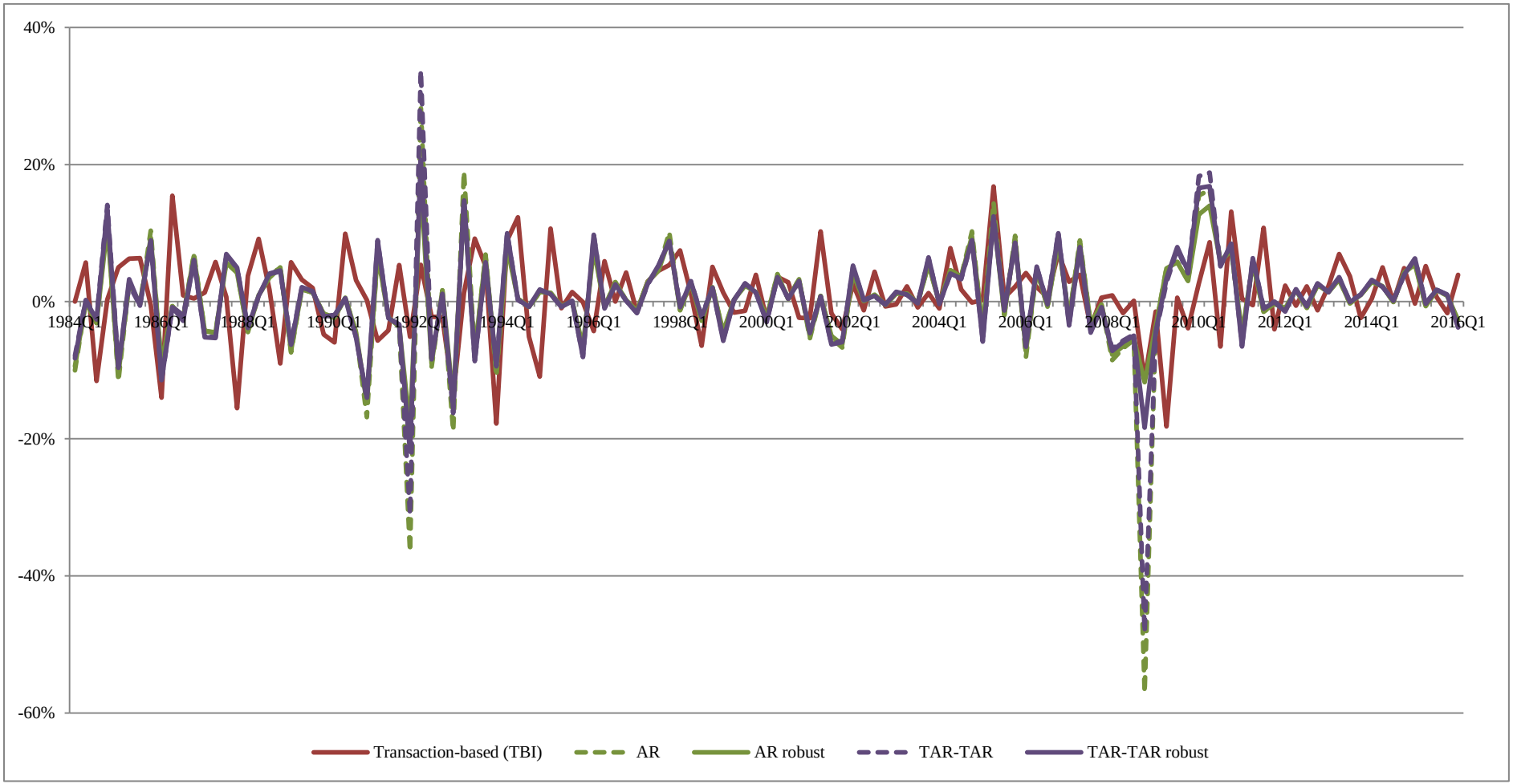


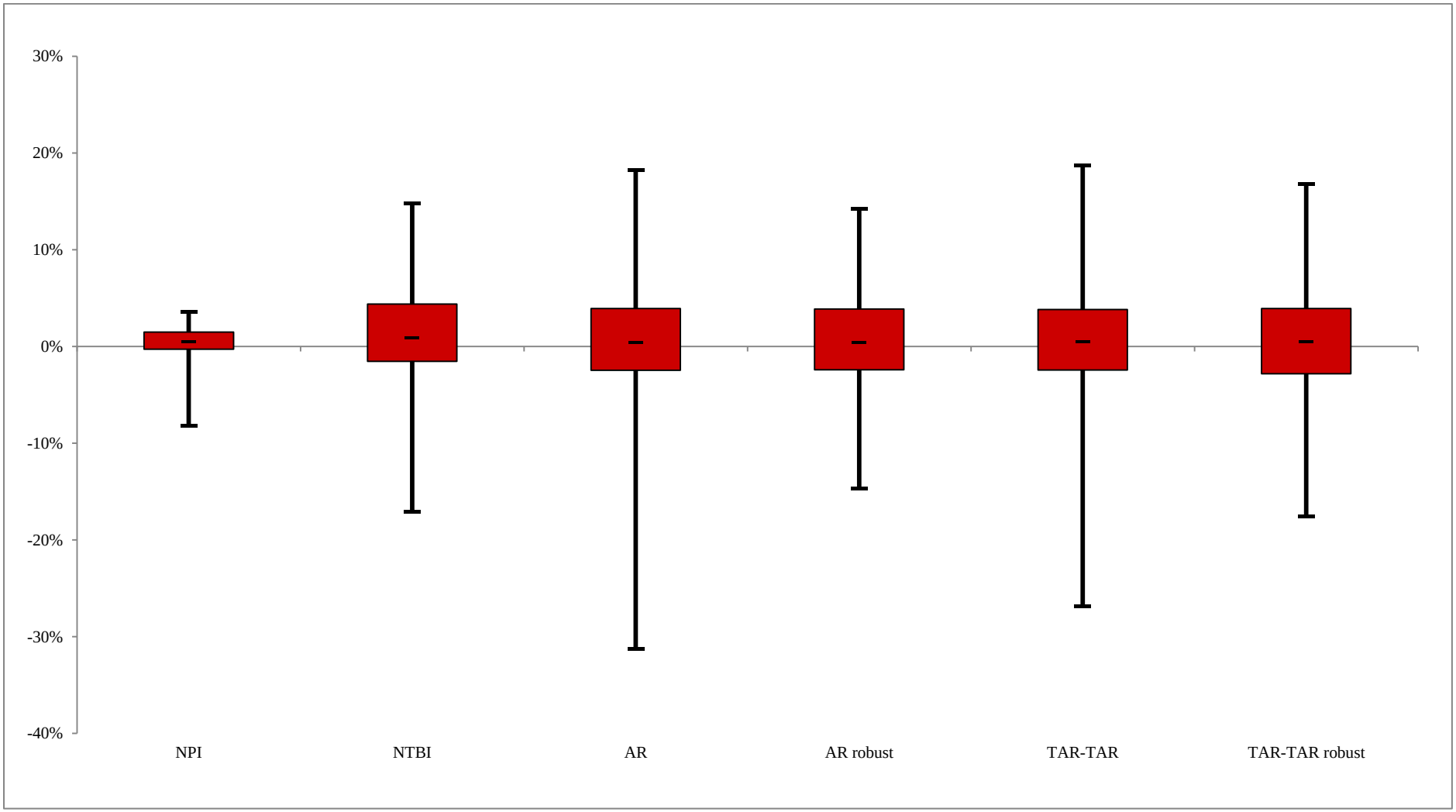
Table 4 and Figure 8 present statistics and boxplots of returns distribution for all series. Central parameters of desmoothed return distributions are close to the NPI ones (this is especially the case of the median). The autocorrelation levels of desmoothed return series are more in line with the NTBI autocorrelation level and significantly lower than that of the raw NPI. As expected, volatility increases significantly after desmoothing, from 2.14% for the NPI, to 8.80% for the AR model and 8.27% for the TAR-TAR model. Skewness of non-robust series relatively more negative than the one of NTBI and their kurtosis is much larger. Once the robust filter is applied, volatility, skewness, and kurtosis values move toward the NTBI counterparts. They are actually very close to the NTBI for the two robust alternatives.

Similarity with the NTBI is also measured by correlation and tracking error. The desmoothed series exhibit correlations between 0.28 and 0.32 with the NTBI returns, while most of the tracking errors are between 7.14% and 8.99%. The correlations of robust series with the NTBI are close to the aforementioned ones and their tracking errors are slightly lower. Hence, according to tracking errors and moments of distribution it appears that robust desmoothed series do better than their non robust counterparts in producing returns corresponding to those of the transaction-based index. This is true for both the AR and the TAR-TAR desmoothing models. However, on these bases it is rather difficult to conclude if the robust TAR-TAR is preferable to the robust AR or not. A comparison of various distribution quantiles, especially in the tails, tends to corroborate the idea that the robust TAR-TAR model generally works the best. Indeed, quantiles values for the robust TAR-TAR, both upside and downside tend to be closer to the corresponding NTBI values than the robust AR ones are.

Table 4. Price Return Distribution Characteristics - 1984Q1-2016Q1

	NPI	NTBI	AR	AR robust	TAR-TAR	TAR-TAR robust
Max	3.83%	16.79%	28.55%	17.52%	33.74%	20.68%
Pct99	3.53%	14.79%	18.18%	14.25%	18.68%	16.76%
Pct95	2.70%	10.10%	10.30%	9.44%	10.05%	9.99%
Pct90	2.23%	7.53%	8.38%	7.77%	8.59%	8.64%
Quart3	1.50%	4.38%	3.93%	3.87%	3.83%	3.93%
Median	0.53%	0.91%	0.40%	0.40%	0.46%	0.44%
Mean	0.26%	0.95%	0.14%	0.51%	0.40%	0.56%
Quart1	-0.29%	-1.53%	-2.46%	-2.40%	-2.43%	-2.81%
Pct10	-1.83%	-5.24%	-7.04%	-6.63%	-6.23%	-6.55%
Pct05	-3.47%	-11.19%	-9.93%	-9.26%	-9.05%	-9.12%
Pct01	-8.22%	-17.14%	-31.32%	-14.73%	-26.86%	-17.54%
Min	-9.54%	-18.21%	-56.95%	-18.42%	-48.21%	-21.85%
Std Dev	2.14%	5.96%	8.80%	5.88%	8.27%	6.53%
Skewness	-2.05	-0.59	-2.37	-0.15	-1.37	-0.13
Kurtosis	6.23	1.68	15.61	1.01	11.59	1.59
Autocorrelation	0.80	-0.17	-0.18	-0.27	-0.18	-0.24
Correlation with NTBI	0.37	1.00	0.32	0.28	0.31	0.29
Tracking Error with NTBI	5.59%	0.00%	8.99%	7.14%	8.57%	7.46%

Figure 8. Boxplots of appraisal based, transaction based and desmoothed price returns - 1984Q1-2016Q1



We further investigate the difference between the target transaction-based index distribution and those of the different desmoothed indices through estimation of their densities. This is shown on Figure 9 and Figure 10. Figure 9 compares the NTBI with the TAR-TAR desmoothed index and its robust alternative. The three distributions appear to be rather close. However, the TAR-TAR one displays extreme observations on the negative side, what does not appear for the NTBI and the robust TAR-TAR. It illustrates the ability of the robust filter do deal with outliers on a relevant way and, doing so, help achieving a result closer to the target series.

Figure 10 now compares NTBI with robust versions of TAR-TAR model and the AR model. As expected, both robust desmoothed series distributions present no outlier. Again, both robust desmoothed returns series have distributions being very close to the NTBI one. Maybe the robust AR better match the NTBI in the center and the right and side of the distributions, while the robust TAR-TAR gives slightly larger weights to observations on the left hand side of the distribution.

Figure 9. Densities of distributions of returns - classic vs. robust

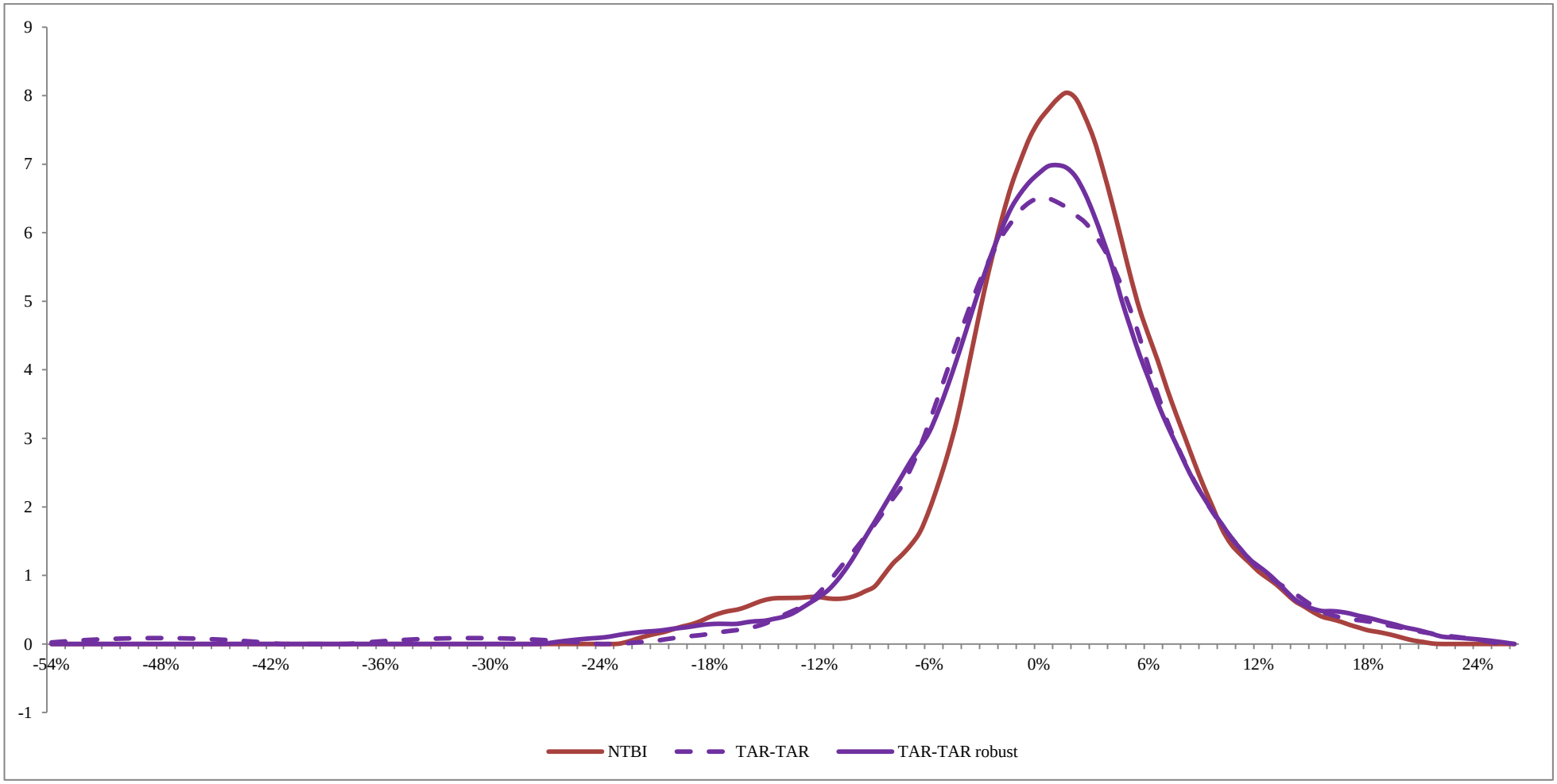
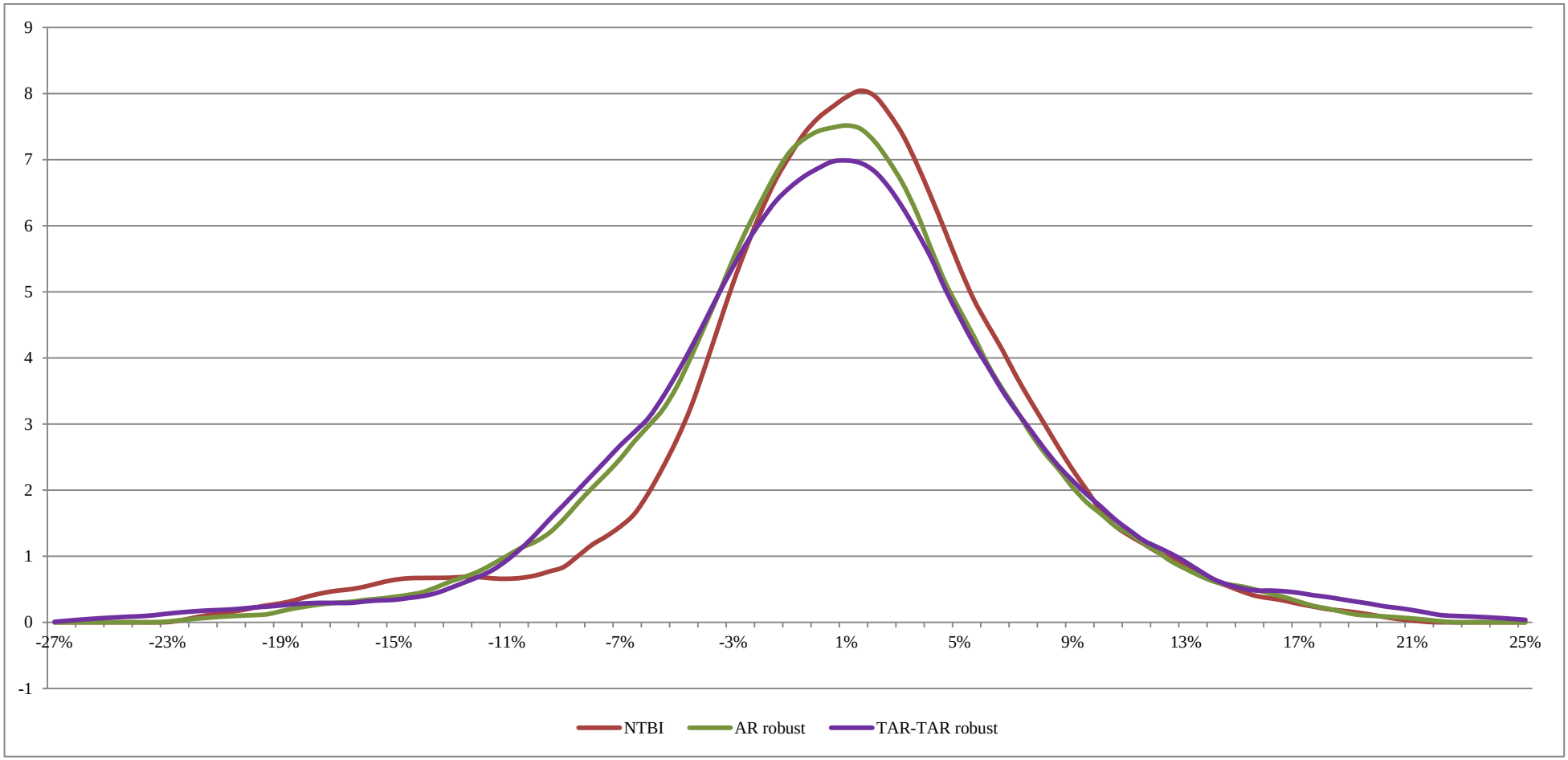


Figure 10. Densities of distributions of returns - AR vs. TAR-TAR



6.2 Risk Factor Analysis

As detailed in the method section, panel models presented in the following tables regress excess total returns of direct subindices, non-listed funds and REITs on a set of macroeconomic factors, specific investment characteristics, and control variables. First, we run models for direct appraisal-based, transaction-based, and desmoothed indices to check if the three kinds of indices display the same responses to risk factors. Due to the availability of transaction-based indices, we consider sector (except Hotel) and region subindices but not indices which consider both sector and region simultaneously, from 1994Q1. For identification reasons, we cannot include both sector and region dummies in the same model. Results are contained in Table 5.

The adjusted R^2 (64.06) of the model with uncorrected appraisal-based returns is much higher than that of models with transaction-based and desmoothed indices (15.85 and 16.62, respectively). The lower explanatory power in the latter two models is likely due to the effects of the much higher volatility of the transaction-based and desmoothed returns. For the model using uncorrected appraisal-based returns, most of the risk factors have significant coefficients. Except for real GDP growth, which is not significant anymore, and the term spread, which has a surprisingly positive coefficient now, the results for the model with transaction-based returns are similar. In addition, a crisis dummy variable for 2008Q4 is found to have a significant negative impact. The model with indices desmoothed by the robust TAR-TAR model show fewer significant coefficients than the former models. The inflation surprise and the crisis dummy are significant with coefficients of about the same magnitude as in the model with transaction-based returns. The leading indicator lagged by two periods is significant and much larger than in the other two models. Surprisingly, expected inflation has a large negative significant coefficient and unemployment has a positive coefficient. The term spread is positive as for transaction-based indices.

From this models comparison between, appraisal-based, transaction-based and desmoothed indices, it particularly appears appraisal-based help achieve a better explanatory power. The explanation could be that these indices represent a trend of the market better than they reflect shorter term variation. As such behavior is similar to the one of most of macroeconomics values we consider having also low volatility and rather large autocorrelation. In this first model, signs and magnitudes of coefficients are by and large relevant with respect to the theory and the bulk of literature. The two other models have lower explanatory power, fewer significant coefficients with one or two of them having

counterintuitive signs. Therefore, in the further risk factor analysis of Section 8, we consider models with both appraisal-based and desmoothed series for direct and non-listed.

Table 5. Panel Regression Model - Direct Investments (1994Q1 - 2016Q2)

		Excess Total Return							
		Appraisal-based		**Transaction-based**		**Desmoothed**		**Desmoothed**	
Variable Category	**Main Effects**					*(AR; robust)*		*(TAR-TAR; robust)*	
	Constant	*1.1139*	*(0.6219) **	*1.5005*	*(1.395)*	*4.3265*	*(1.6956) ***	*6.9592*	*(2.2733) ****
Region	Midwest	-0.3596	(0.19)	-0.3958	(0.2915)	-0.3567	(0.5382)	-0.1227	(0.7215)
	Multiregion	0.0569	(0.1502)	0.0333	(0.2305)	-0.0149	(0.4255)	0.0407	(0.5704)
	South	-0.1283	(0.19)	-0.1336	(0.2915)	-0.2905	(0.5382)	-0.1222	(0.7215)
	West	0.2239	(0.19)	0.1784	(0.2915)	0.2731	(0.5382)	0.5973	(0.7215)
Macro & Market factors:	Real GDP growth t	0.4442	(0.1744) **	-0.2692	(0.4481)	1.0118	(0.5057) **	1.0977	(0.6779)
	Expected Inflation t	0.8059	(0.6788)	1.2064	(1.4526)	-3.2761	(1.7929) *	-6.617	(2.4037) ***
	Inflation Surprise t	-1.6968	(0.2546) ***	-1.8342	(0.7013) ***	-2.7367	(0.7186) ***	-2.1557	(0.9634) **
	Real Money Supply growth t	1.0085	(0.1332) ***	0.6948	(0.2847) **	-0.1805	(0.3764)	-0.4944	(0.5046)
	Real Construction Costs growth t	1.1563	(0.1267) ***	1.3697	(0.2609) ***	0.9205	(0.3415) ***	0.6545	(0.4579)
	Leading Indicator growth t-2	0.8855	(0.0964) ***	0.7075	(0.2653) ***	1.842	(0.2724) ***	2.0619	(0.3653) ***
	Unemployment Rate change t	-2.3142	(0.3133) ***	-3.5635	(0.847) ***	2.5462	(0.8746) ***	3.5649	(1.1726) ***
	Term Spread t	-0.1036	(0.0543) *	0.2177	(0.107) **	0.2589	(0.1526) *	0.4227	(0.2046) **
	10Y Real Interest Rate change t	0.0765	(0.135)	-0.2478	(0.3906)	0.3134	(0.3871)	0.6448	(0.519)
	Credit Spread t	-1.61	(0.2088) ***	-2.0949	(0.5679) ***	-1.0642	(0.6081) *	-1.215	(0.8153)
	Crisis 2008Q4			-6.0512	(1.8109) ***	-1.2746	(1.4427)	-6.5492	(1.9342) ***
Adjusted R^2		*64.06*		*15.85*		*19.34*		*16.62*	

For each model, coefficients estimates are presented with significance level. The significance level is symbolized by the stars, with "*", "**", and "***" corresponding to a p-value of 10%, 5% and 1% respectively. Note also that, for models regressing appraisal-based series, every risk factor is lagged one quarter more than what is indicated in the table. This is true except for expected inflation.

Table 6 summarizes results for the risk factor analysis of the three types of exposure for the period 1985Q1-2015Q3[20]. For the model based on appraisal-based returns, we observe differences across sectors and subregions. The hotel, industrial and office sectors perform worse (in a range from 0.26% to 0.73%) each quarter than apartments, while the Retail sector does not differ from apartments. Compared with the Northeast region, the two Southern and the two Central subregions underperform (in a range from 0.28% to 0.43%). Regarding macroeconomic risk factors, we observe a significant response of 0.56% on excess returns to a 1% increase in real GDP growth, which supports the hypothesis that economic growth is beneficial for real estate performance. Real estate returns appear to be positively related with expected inflation but negatively associated with the inflation surprise. The positive link of 1% with money supply reflects how an accommodating monetary policy stimulates demand on the real estate market. Construction costs impact positively direct real estate by 1.3%, which could be seen as acting through the supply side of the market. Facing higher construction costs, the supply curve would be shifted upward, increasing equilibrium prices and at the same time, real estate space being relatively scarcer, rents would increase too, resulting in higher performance for real state owners.

The leading economic indicator is also positively linked with a coefficient of 0.5%, suggesting expectations with respect to general economic perspectives made two quarters ago are incorporated in real estate prices. Unemployment has a negative impact of -3.4%, likely because a current increase in unemployment is a sign of lower future economic growth and of increased uncertainty. The term and credit spreads have negative coefficients, which illustrates the detrimental effect of expectations of higher interest rates and of increased default risk. Compared to models whose results are reported in Table 5, we also consider the change in the stock market implicit volatility (VIX) variable to capture the evolution of the risk environment. The change in that variable displays a negative link with direct real estate returns.

The discussion above highlights that most of the responses to economic shocks are consistent with economic theory. The model R^2 (47.04%) is good. For desmoothed returns, the R^2 is much lower again most likely due to the increased volatility of returns. Most of the variables have similar impacts on desmoothed returns, with economic growth, money supply

[20] Note that for all models we estimate, we previously check for multicollinearity issues among explanatory variables with a Variance Inflation Factor (VIF) test.

growth, construction costs, the leading economic indicator positively affecting returns and the inflation surprise, the credit spread and the change in VIX negatively impacting upon returns.

For non-listed funds, as explained in the data section, we cannot distinguish between subregions and sectors as funds are largely diversified. However, we include controls for leverage and size. Funds with leverage lower than 5%[21] tend to underperform by 0.33% per quarter on average relative to funds using more leverage. Size appears to matter too as funds with less than $ 300 million[22] of assets perform worse than larger funds by -0.59% per quarter on average. Interestingly, regarding macroeconomic risk factors, we observe that the same coefficients than in the model with the original direct series are significant with the same sign. In addition, most of these coefficients are not significantly different across models and are often very close. This suggests that non-listed funds react in the same way as direct real estate to risk factors. The response to changes in several macroeconomic risk factors is similar when desmoothed fund returns are considered. However, money supply, the credit spread and the VIX change are no longer significant, while unemployment and long-term interest rates become significant but with an unintuitive sign.

Finally, for REITs, hotels underperform apartments as is the case for direct real estate. Other sectors do not exhibit differences in performance relative to apartments. Low leverage does not seem to be associated with lower returns as was found for funds[23]. However, size matters as REITs having less than $ 500 million of assets tend to underperform by 0.72% per quarter on average. In addition, REITs with price-earnings ratios greater than 13 have on average a lower quarterly performance by 0.62%. A surprisingly low number of risk factors display significant links with REITs returns. Only the inflation surprise, the credit spread, and the VIX change are identified. The sign of these coefficients corresponds to what has been found for other exposures while their magnitude is substantially greater.

[21] This leverage threshold represents around one fifth of observations.
[22] This size threshold represents around one fourth of observations.
[23] For REITs, we consider a leverage threshold of 20% that corresponds to the fifth of observations like for non-listed funds.

Table 6. Panel Regression Model - Direct, Non-Listed and REITs (1985Q1 - 2015Q3)

		Excess Total Return									
Variable Category	**Main Effects**	**Direct Appraisal-based**		**Direct Desmoothed** *(TAR-TAR; robust)*		**Non-Listed**		**Non-Listed** *(TAR-TAR; robust)*		**REITs**	
	Constant	*0.2779*	*(0.3804)*	3.8466	(2.16) *	-1.1049	(0.6925)	2.022	(1.8251)	2.1396	(6.4699)
Sector	Hotel	-0.5755	(0.1165) ***	-0.0832	(0.6121)					-1.0978	(0.4327) **
	Industrial	-0.2616	(0.0906) ***	-0.064	(0.4708)					0.7112	(0.4463)
	Office	-0.7293	(0.0906) ***	-0.0834	(0.4708)					0.2832	(0.3428)
	Retail	0.0276	(0.0906)	0.1039	(0.4708)					0.4737	(0.3086)
Subregion	East North Central	-0.279	(0.1196) **	0.1556	(0.6212)						
	Mideast	0.1509	(0.1172)	0.1735	(0.6087)						
	Mountain	-0.1814	(0.1203)	0.8516	(0.6251)						
	Pacific	0.165	(0.1184)	-0.0896	(0.615)						
	Southeast	-0.3617	(0.1207) ***	-0.1381	(0.6271)						
	Southwest	-0.426	(0.1193) ***	0.0083	(0.6195)						
	West North Central	-0.3957	(0.1247) ***	-0.5474	(0.6471)						
Specific Characteristics:	Leverage < 5%					-0.3336	(0.1763) *	-1.4021	(0.3914) ***		
	Leverage < 20%									-0.296	(0.3076)
	Real Assets < $ 300 M					-0.5915	(0.2353) **	-0.439	(0.4965)		
	Real Assets < $ 500 M									-0.7205	(0.2462) ***
	PER > 13									-0.6183	(0.2562) **
Macro & Market factors:	Real GDP growth t	0.5565	(0.1035) ***	1.4338	(0.6059) **	1.0555	(0.1853) ***	2.5711	(0.5204) ***	-1.0528	(1.8327)
	Expected Inflation t	1.3619	(0.439) ***	-3.1059	(2.3922)	2.1773	(0.7893) ***	-2.1036	(2.0289)	6.9449	(7.1824)
	Inflation Surprise t	-1.4327	(0.17) ***	-2.8217	(0.9497) ***	-2.2567	(0.2978) ***	-4.0049	(0.7797) ***	-5.9579	(2.6264) **
	Real Money Supply growth t	1.004	(0.0778) ***	1.1638	(0.4297) ***	0.7478	(0.1444) ***	-0.183	(0.3831)	1.0442	(1.3003)
	Real Construction Costs growth t	1.3019	(0.0724) ***	1.718	(0.4015) ***	1.6591	(0.1433) ***	0.9704	(0.3735) ***	0.9408	(1.1869)
	Leading Indicator growth t-2	0.5031	(0.0568) ***	1.6045	(0.3273) ***	0.6854	(0.1012) ***	2.4882	(0.2776) ***	-0.2601	(0.9755)
	Unemployment Rate change t	-3.3997	(0.2141) ***	1.0084	(1.2039)	-5.352	(0.3764) ***	2.8759	(1.0091) ***	2.7004	(3.2618)
	Term Spread t	-0.0885	(0.0348) **	0.2358	(0.1954)	-0.1757	(0.0633) ***	-0.0722	(0.1702)	0.7918	(0.5947)
	10Y Real Interest Rate change t	0.1403	(0.0963)	0.7624	(0.5694)	0.0021	(0.1697)	2.6921	(0.4731) ***	1.4522	(1.4143)
	Credit Spread t	-0.9001	(0.1784) ***	-2.7063	(0.9205) ***	-1.0202	(0.3114) ***	0.0705	(0.7836)	-7.0297	(2.39) ***
	VIX change t	-0.1107	(0.0273) ***	-0.5069	(0.1461) ***	-0.1129	(0.0485) **	-0.0462	(0.1268)	-1.7013	(0.4221) ***
	Crisis 2008Q4	-6.4759	(0.3412) ***	-24.6741	(2.3681) ***	*-7.1084*	*(0.6204)* ***	*-10.4753*	*(1.786)* ***	-14.0247	(6.4739) **
Adjusted R^2		*47.04*		*5.32*		*61.86*		*19.25*		*20.26*	

For each model, coefficients estimates are presented with significance level. The significance level is symbolized by the stars, with "*", "**", and "***" corresponding to a p-value of 10%, 5% and 1% respectively. Note also that, for models regressing direct or non-listed appraisal-based series, every risk factor is lagged one quarter more than what is indicated in the table. This is true except for expected inflation.

7. Conclusion

In this research, we have first shown how the application of a robust filtering method can improve features of desmoothed series by neutralizing outlying values that can be generated through the usual desmoothing process. This process is applied alternatively on the usual classic AR desmoothing model and the so-called TAR-TAR regime switching model. Results have shown that, once filtered, both desmoothing models are quite effective in replicating transaction-based return series. However, in addition to being conceptually more relevant, various analyses indicate that the TAR-TAR model is slightly preferable than the AR model.

The risk factor analysis has shown that the results with appraisal-based returns are largely in line with what would be expected according to theory and also that such models have a high explanatory power. In comparison, models fitted for corresponding transaction-based series produce lower explanatory power despite the fact that most of the estimated coefficients are in line with those of models with appraisal-based series. Regarding models based on desmoothed series, the explanatory power is usually quite low and fewer coefficients are found to be significant. The relatively good explanatory power obtained with the appraisal-based series can be linked to the fact that these series have low volatility, as most of the risk factors included in the models as explanatory variables, and mainly reflect a trend rather than contemporaneous variations. Conversely, by construction desmoothed series display higher volatility, as transaction-based series do, that can explain the lower explanatory power. The fewer significant coefficients found for models with desmoothed series likely results from the desmoothing process which introduces a large amount of noise that makes it more difficult to identify true signals in the data.

Our results further show that responses to risk factors for direct and non-listed real estate are close with respect to sign and magnitude. We generally identify positive links with GDP growth, expected inflation, money supply, construction costs, and the leading indicator. In contrary, negative linkages are observed for the inflation surprise, the term and credit spreads, as well as the stock market volatility. Surprisingly, unemployment has a negative coefficient in models with appraisal-based indices and a counterintuitive positive coefficient in the model with desmoothed non-listed returns. For REITs, only the coefficients for the inflation surprise, the credit spread, and the stock market volatility are significant. These responses are substantially larger for REITs than for private investments. Specific characteristics matter too. For non-listed funds, we find that funds with very low leverage tend to underperform those with higher leverage. Smaller funds and REITs also tend to

perform worse than larger entities. In addition, overpriced REITs with respect to price-earnings ratios tend to underperform.

The results contained in this paper stress the importance of considering both specific characteristics and macroeconomic risk factors while analyzing real estate investments whatever the selected type of exposure. In addition, our results show that non-listed open-ended funds are very similar to direct real estate investments as they respond in the same way to risk factors. Due to the gain in flexibility they allow, they constitute an interesting alternative to direct investments without their being impacted by financial risks like the stock market volatility as is the case for REITs.

References

Aarts, S., Baum, A., 2016. Performance Persistence in Real Estate Private Equity, *Journal of Property Research*, 33(3), 236-251.

Adams, Z., Füss, R., 2010. Macroeconomic Determinants of International Housing Markets, *Journal of Housing Economics*, 19(1), 38-50.

Alcock, J., Baum, A., Colley, N., Steiner, E., 2013. The Role of Financial Leverage in the Performance of Private Equity Real Estate Funds, *Journal of Portfolio Management, Special Real Estate Issue*, 99-110.

Anderson, R. I., Krautz, S., Rottke, N. B., 2016. Is Real Estate Private Equity Real Estate? – Dynamic Interactions Between Real Estate Private Equity Funds, Non-Real Estate Funds, and Direct Real Estate Investments, *Journal of Property Research*, 33(3), 252-268.

Ang, A., Nabar, N., Wald, S. J., 2013. Searching for a Common Factor in Public and Private Real Estate Returns, Journal of Portfolio *Management*, 39(5), 120-133.

Anson, M. J. P., Hudson-Wilson, S., 2003. Should One Use Leverage in a Private Equity Real Estate Portfolio? *Journal of Portfolio Management*, 29(5), 54-61.

Baum, A., Fear, J., Colley, N., 2011. Have Property Funds Performed? *Urban Land Institute Europe Policy and Practice Committee report*.

Baum, A., Fear, J., Colley, N., 2012. Have Property Funds Performed? *Urban Land Institute Europe Policy and Practice Committee report*.

Bond, S. A., Mitchell, P., 2010. Alpha and Persistence in Real Estate Fund Performance. *Journal of Real Estate Finance and Economics*, 41 (1), 53-79.

Boudry, W. I., Coulson, N. E., Kallberg, J. G., Liu, C. H, 2012. On the Hybrid Nature of REITs, *Journal of Real Estate Finance and Economics*, 44(1-2), 230-249.

Case, B., 2015. What Have 25 Years of Performance Data Taught Us About Private Equity Real Estate? *Journal of Real Estate Portfolio Management.* 21(1), 1-20.

Chung, R., Fung, S., Shilling, J. D., Simmons-Mosley, T. X., 2016. REIT Stock Market Volatility and Expected Returns, *Real Estate Economics*, 44(4), 968-995.

Clayton, J., Ling, D. C., Naranjo, A., 2009. Commercial Real Estate Valuation: Fundamentals Versus Investor Sentiment, *Journal of Real Estate Finance and Economics*, 38(1), 5-37.

Cumming, D., Hass L. H., Schweizer, D., 2013. Private Equity Benchmarks and Portfolio Optimization, *Journal of Banking & Finance*, 37(9), 3515-3528.

Delfim, J.-C., Hoesli, M., 2016. Risk Factors of European Non-Listed Real Estate Fund Returns, *Journal of Property Research*, 33(3), 190-213.

Edelstein, R., Qian, W., Tsang, D., 2011. How Do Institutional Factors Affect International Real Estate Returns? *Journal of Real Estate Finance and Economics*, 43 (1-2), 130-151.

Farrelly, K., Stevenson, S., 2016. Performance Drivers of Private Real Estate Funds, *Journal of Property Research*, 33(3), 214-235.

Fisher, J., Geltner, D., Webb, R, 1994. Value Indices of Commercial Real Estate: A Comparison of Index Construction Methods, *Journal of Real Estate Finance and Economics*, 9(2), 137-164.

Fisher, L. M., and Hartzell, D. J., 2013. Real Estate Private Equity Performance: A New Look. *Working paper*, http://areas.kenan-flagler.unc.edu/finance/PERC/REPE%20Performance%20May%202013%20v2.pdf.

Fisher, L. M., and Hartzell, D. J., 2016. Class Differences in Real Estate Private Equity Fund Performance, *Journal of Real Estate Finance and Economics*, 52(4), 327-346.

Fuerst, F., Lim, W., Matysiak, G., 2013. Drivers of Funds Performance, *INREV Research Paper*.

Fuerst, F., Matysiak, G., 2013. Analysing the Performance of Nonlisted Real Estate Funds: A Panel Data Analysis. *Applied Economics*, 45(14), 1777-1788.

Geltner, D., 1991. Smoothing and Appraisal-Based Returns, *Journal of Real Estate Finance and Economics*, 4(3), 327-345.

Geltner, D., Gerardo-Liez, N., Hahn, T. C., 2005. Real Estate Opportunity Funds, *Journal of Portfolio Management*, 31(5), 143-153.

Giacomini, E., Ling, D. C., Naranjo, A., 2015. Leverage and Returns: A Cross-Country Analysis of Public Real Estate Markets, *Journal of Real Estate Finance and Economics*, 51(2), 125-159.

Global Real Estate Funds Review H1 2016. The Association of Real Estate Funds & Property Funds Research, 23 Camomile Street, London, 2016. http://www.aref.org.uk/sites/default/files/newsletters/PFR-AREF_Global%20Real%20Estate%20Review_H1%202016.docx_.pdf

Hoesli, M., Lizieri, C., MacGregor, B. D., 2008. The Inflation Hedging Characteristics of US and UK Investments: A Multi-Factor Error Correction Approach. *Journal of Real Estate Finance and Economics*, 36(2), 183-206.

Hoesli, M., Oikarinen, E., Serrano, C., 2011. The Long-Run Dynamics between Direct and Securitized Real Estate, *Journal of Real Estate Research*, 33(1), 73-103.

Hoesli, M., Oikarinen, E., Serrano, C., 2015. Do Public Real Estate Returns really lead Private Returns? *The Journal of Portfolio Management*., 41(6), 105-117.

Laird, N. M., Ware, J. H., 1982. Random-Effects Models for Longitudinal Data, *Biometrics*, 38(4), 963-974.

Lee, S. L., 2001. The Relative Importance of Property Type and regional Factors in Real Estate Returns. *Journal of Real Estate Portfolio Management*, 7 (2), 159-167.

Ling, D. C., Naranjo, A., 1997. Economic Risk Factors and Commercial Real Estate Returns, *Journal of Real Estate Finance and Economics*, 15 (3), 283-307.

Ling, D. C., Naranjo, A., 1999. The Integration of Commercial Real Estate Markets and Stock Markets, *Real Estate Economics*, 27(3), 483-515.

Ling, D. C., Naranjo, A., 2015. Returns and Information Transmission Dynamics in Public and Private Real Estate Markets. *Real Estate Economics*, 43(1), 163-208.

Lizieri, C., Satchell, S., Wongwachara, W., 2012. Unsmoothing Real Estate Returns: A Regime-Switching Approach, *Real Estate Economics*, 40(4), 775-807.

Marcato, G., Key, T., 2007. Smoothing and Implication for Asset Allocation Choices, *Journal of Portfolio Management*, 33(5), 85.99.

Pavlov, A., Steiner, E., Wachter, S., 2015. Macroeconomic Risk Factors and the Role of Mispriced Credit in the Returns from International Real Estate Securities. *Real Estate Economics*, 43(1), 241-270.

Pedersen, N., Tiwari, A., Hoffmann, A., 2012. Modeling the Risk Characteristics of Real Estate Investments, *PIMCO Analytics*.

Ro, S., Ziobrowski, A. J., 2011. Does Focus Really Matter? Specialized vs. Diversified REITs, *Journal of Real Estate Finance and Economics*, 42(1), 68-83.

Rousseeuw, P. J., 1984. Least Median of Squares Regression, *Journal of the American Statistical Association*, 79(388), 871-880.

Rousseeuw, P. J., Hubert, M., 1999. Regression Depth, *Journal of the American Statistical Association*, 94(446), 388-402.

Schätz, A., Sebastian, S., 2009. The Links between Property and the Economy - Evidence from the British and German Markets, *Journal of Property Research*, 26(2), 171-191.

Shilling. J. D., Wurtzebach, C. H., 2012. Is Value-Added and Opportunistic Real Estate Investing Beneficial? If So, Why? *Journal of Real Estate Research*, 34(4), 429-461.

Tomperi, I., 2010. Performance of Private Equity Real Estate Funds, *Journal of European Real Estate Research*, 3 (2), 96-116.

Yunus, N., 2012. Modeling Relationships among Securitized Property Markets, Stock Market, and Macroeconomic Variables, *Journal of Real Estate Research*, 34(2), 127-156.