Reliability and Heterogeneity of Real Estate Indexes and their Impact on the Predictability of Returns.

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ABSTRACT

This paper addresses the issue of data quality in the real estate market. In many countries, the returns indices for direct markets are provided by several sources differing in terms of the methodology adopted and index weights. These differences produce a lack of informative standardization, which could negatively affect the ability of market participants to make predictions. By focusing on the Italian real estate market, the aim of the paper is therefore twofold: to investigate the reliability of property data sources, and to assess the impact for financial intermediaries involved in real estate investments. Our results show a significant level of divergence between the data, and considerable implications for those financial institutions dealing with them. These findings conflict with the requirements of an efficient (or at least sub-efficient) market.

Jel Classification: G11, G21, L85, L15
Keyword: real estate, data divergence, IRR, efficient frontier.

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GS conceived the study, designed and implemented the cointegration analysis, the IRR and Mean-Variance simulations and wrote the manuscript. FB assembled the input data, conducted the correlation/ratio analysis and helped GS to write paragraph 3.2.

Reliability and Heterogeneity of Real Estate Indexes and their Impact on the Predictability of Returns.

This paper will discuss issues concerning the quality of property data sources and its implication for market participants. The paper is divided into two sections. In the first section, we discuss the nature and the availability of property data for the Italian market. Our initial exploration of the quality and accessibility of some domestic data documents the presence of many property data sources, each of which uses different methods of data collection. The high number of data sources and their methodological heterogeneity produce an excessive data discrepancy hardly compatible with efficient research and professional investment processes. Using a set of longitudinal aggregated property values, we proceed to estimate the level of uniformity of data using correlation and cointegration analysis.

The second section will provide an examination of the potential effects of a data non-uniformity phenomenon on the decision-making process. To this end, we'll describe two simulations which deal with the implications that the lack of uniformity of data produce for real estate investments vehicles, and asset allocation plans.

Conceptual framework

In general, the nature of the real estate asset makes a convincing comparison with the other traditional asset classes difficult. Stephan (1999), examines the criteria behind collecting and evaluating real estate data, focusing on the difficulties encountered in compiling them as well as the various limitations to the data themselves. Some factors, such as the heterogeneity of property, the low frequency of transactions, and the high fragmentation (urbanization) of the markets, seriously impair ability to estimate real-estate relationships accurately (Sirmans et al., 1998). These features led the research team to prefer secondary data rather than primary data. While primary data are gathered by researchers (precisely for the problem at the hand), secondary data are collected from other sources: universities, government agencies, real estate appraisals, and market research firms. Secondary data are certainly less expensive and less time consuming than primary data, but they are seldom expressed appropriately for the intended purpose. Moreover, transaction records frequently contain empty data fields, and class definitions seldom fit analysts' needs exactly.

Because of the indisputable link between economic forecasting and the reliability of data, many governments have taken on the task of gathering data, and their involvement plays a vital role in providing reliable and valid information for property market performance. In many cases, however, data is often inaccurate or incomplete at the time of collection, making adjustment procedures necessary to ensure the validity and reliability of the dataset available (Ge and Harfield, 2007).

A large number of agencies, and low government involvement in data collection represent two factors able to severely reduce the efficiency of the real estate market. In those countries where these characteristics are found, there is also a noticeable lack of coordination and centralization between data-collectors, which negatively affects ability to calculate homogeneous estimates. As for the implications for the market, the inefficiency of data collection systems will undoubtedly affect the operation of financial institutions involved in the real estate sector, including performance measurement of real estate funds, and the identification of the real estate weight in a mixed-asset portfolio of pension or mutual funds.

In focusing on the real estate fund case, one of the more sensitive activities involved in its management is certainly the planning and monitoring of the expected financial results. From this point of view, the determination of an *interim* internal rate of return (IRR) represents an indisputable tool of measurement. The estimation of an expected internal rate of return must take multiple factors into account regarding the size and time of the in-coming and out-going cash flows. Concentrating on the incoming cash flows only, fund performance is typically attributable to the following three categories: a) ground rent; b) property sale values; c) returns from liquid management. Consistent with this consideration, the availability of reliable data for each of these sources of return (ground rent, property sale values, liquidity returns) constitutes an indispensable requisite from which to construct a financial plan endowed with objectivity and, in terms of its usability by third parties (investors, analysts, etc.), an adequate level of transparency. As a consequence, the unreliability of real estate data produces instability in IRR calculation (because it can change depending on the data source), which hinders making an appropriate investment choice.

Finally, we turn to the issue of the effect of data divergence on investment portfolio composition in a mean-variance framework. The role of real estate in diversifying mixed-asset portfolios has been well recognized in the literature (*inter alia*, Seiler et al, 1999). The majority of these studies focus on the effects of including real estate investment in a mixed-asset portfolio revealing results consistent with a diversification benefit. This benefit is typically explained by some attributes of real estate investments, such as low correlation with the other traditional asset classes, their aptitude for inflation-hedging, and their high level of risk-adjusted performance, etc. (Hudson-Wilson, Fabozzi, Gordon, 2003).

After including a sub-set of comparable property indices (provided by different data sources) in a set of *n* financial asset classes, we launched a series of portfolio optimizations in order to identify the sensitivity of efficient frontier curvature to the property data source employed. Also in this case, the results show how the non-uniformity of data constitutes a significant issue in ensuring correctness and validity in investment choices.

Study of domestic data harmonization

Data description

The set of data is composed of 21 time series, provided by 5 different data sources and containing the historical values of property indices for two geographical areas: Italy (10 out of 21) and Milan (11 out of 21). Each data-provider offers coverage of all or part of the traditional market segments: residential, commercial, office, and industrial[2]. The time interval of the data varies from a minimum of 5 to a maximum of 42 years as shown in Exhibit 1.

A preliminary analysis of the data revealed the presence of a different frequency of time observations, since in some cases the index values are monthly while in others they are half-yearly or yearly. To ensure the uniformity of the comparisons between data, we standardize the data frequency tracing it back to a common quarterly basis using linear interpolation.

The adoption of a linear interpolation raises legitimate questions about the significance of a comparison between manipulated time series rather than raw time series. However, an interpolation generates a smoothing out of values and, in general, this contributes to the blunting of outliers rather than to their amplification. In other words, while the use of data interpolation certainly affects the correctness of the results, its most likely effect would be an underestimation of data dissimilarity which, from a prudential point of view, represents a more acceptable effect than an overestimation.

Exhibit 1.
Data Description: time intervals and geographical markets

Real Estate market: Italy					
Real estate category	Source#1	Source #2	Source #3	Source #4	Source #5
Residential	1988-2007	1997-2007	2002-2007	n. a.	n. a.
Commercial	1988-2007	1997-2007	n. a.	n. a.	n. a.
Office	1988-2007	1997-2007	2002-2007	n. a.	n. a.
Industrial	n. a.	1997-2007	2002-2007	n. a.	n. a.
Real Estate market: Milan					
Real estate category	Serie#1	Serie#2	Serie#3	Serie#4	Serie#5
Residential	1965-2007	1993-2007	n. a.	2001-2007	1995-2007
Commercial	1965-2007	1993-2007	n. a.	2001-2007	2001-2007
Office	n. a.	1993-2007	n. a.	n. a.	1997-2007
Industrial	n. a.	1993-2007	n. a.	n. a.	n. a.

For each region, the data represents the historical average prices of housing, commercial, office and industrial properties. Because we get raw data for index values expressed in different units of measure, we proceed to standardize the time series families in order to allow a straight comparison between them. After converting the data into index numbers (with the base value equal to 100) we use a log transformation to stabilize the variance of series and then we estimate the first log difference. The choice of first log difference rather than log levels is explained in a series of graphs(omitted for brevity): while all the time series of log levels show an overall positive trend, as a reflection of the domestic market upturn of the last decade, the scatter plot of the first log difference shows various opposite movements between data related to the same property category but provided by different providers. This preliminary evidence reveals a substantial discrepancy in the change rate of the indices reflecting the lack of homogeneity in the data collection methods.

The data were gathered adopting both transaction-based and appraisal-based methods, but we are unable to recognize the prevalent approach for each data source due to the low transparency and the incompleteness of the methodology disclosure they make available. However, one of the five time series family, named Source#5, certainly follows a transaction-based approach to gathering data, while the data-collection methods of the other data sources appear indistinguishable.

Methodology

To investigate the discrepancies between data, we adopted a three-step analysis consisting of a 1) dissimilarity test, 2) correlation and 3) cointegration analysis.

To detect dissimilarities between the data, we implemented a simple test based on the ratio between property index values. For each pair of comparable time series, we calculate the value of a ratio R_{XY}. The ratio R_{XY} is the simple average of the quotients between the values of two comparable time series (X and Y) with a time interval length of *m*:

$$R_{XY} = \frac{1}{m}\sum_{i=1}^{m}\frac{X_i}{Y_i} \tag{1}$$

More precisely, two time series are comparable if they are related to a common time interval and to a homogeneous class of property. The interpretation of the ratio is straightforward: the closer the ratio gets to one, the closer the two series analyzed will be statistically equal; conversely, the further the ratio moves away from one, the less homogeneous the series will be. To assess the significance of the relationship between the two series, we test the null hypothesis H_0: ratio = 1 by using the F statistic.

The second step is the calculation of the correlation matrix of property indices both for log-levels and for first-differences. The aim of the correlation analysis is to validate the previous graph (omitted) according to which the log-levels time series appears characterized by a quasi-similar trend while the change rate (first log difference) is not. The lack of a single data gathering approach, and the consequent low level of standardization of information make a low positive correlation coefficient probable, while the presence of negative value would be considered unexpected and symptomatic of a more significant phenomenon of data divergence.

The cointegration analysis represents our third step towards reaching a definitive assessment on the issue of data uncertainty. The lack of homogeneity potentially observed in the two previous steps does not appear to be definitive since it does not take into consideration the possibility that, despite the divergence between the returns in the interval observed, two or more series can show a long-term equilibrium relationship. For this purpose, one can proceed to verify the existence of a common trend between the historical series, whose presence would moderate the opinion expressed about the dissimilarity between sources of property data, and the consequent inefficiency of market information processes.

Generally speaking, two variables are cointegrated if they have a common stochastic trend, that is, if they move together for a long period of time despite the trend not always being (visually) observable. More formally, two variables that are stationary in their first differences but non-stationary in their levels, are said to be cointegrated if there is a stationary linear combination between them. In order for the two historical series to be considered as cointegrated, it is necessary for both to be i) integrated by the same n level, and ii) their linear combination (i.e. *cointegration relationship)* to be integrated by a level less than n. The general relationship from which the identification of a cointegration phenomenon proceeds, is:

$$y_t = \beta_0 + \beta_1 x_t + \xi_t \tag{2}$$

The model illustrated by equation (5) represents the so-called cointegration regression, and can be interpreted as the stochastic representation of the relationship that connects the variables to each other (it is also worth mentioning that, $y_t = \beta_1 x_t$). The error term ξ_t is representative of the deviations from the equilibrium relationship. To test for cointegration it is therefore necessary to investigate the stationarity of the error term: in the case of stationarity of the residuals ξ_t there is cointegration between X and Y.

When there is cointegration between the variables, and therefore a long-term relationship between them, assuming certain conditions, it would be possible to establish an ECM (*Error Correction Mechanism*) able to estimate the velocity of convergence of the dependent variable (Y) with the equilibrium relationship corresponding to each variation of the independent variable (X).

The considerations expressed here until now thus make it necessary to consider the theme of cointegration by means of an investigation into the level of stationarity present in the residuals from the cointegration regression (1).

Empirical results

The main results of the three-step process are reported in Exhibit 2 (dissimilarity ratio, R_{XY}), Exhibit 3 (correlation analysis), and Exhibit 4-5 (ADF-t and cointegration analysis) respectively.

Exhibit 2
Dissimilarity ratio analysis

1st Panel – Dissimilarity ratio between national time series

	Ratio numerator									
Ratio denominator	***S.rce#1 retail***	***S.rce #1 comm.***	***S.rce #1 office***	***S.rce #2 retail***	***S.rce #2 comm.***	***S.rce #2 office***	***S.rce #2 ind.***	***S.rce #3 retail***	***S.rce #3 office***	***S.rce #3 ind.***
Sources#1_ret	1									
Source#1_com		1								
Source#1_off			1							
Source#2_ret	0.601**			1						
Source#2_com		1.1504			1					
Source#2_off			1.113			1				
Source#2_ind							1			
Source#3_ret	2.048**			1.887				1		
Source#3_off			0.036**			2.021**			1	
Source#3_ind							1.5131			1

2nd Panel – Dissimilarity ratio analysis among Milan time series

	Ratio numerator									
Ratio denominator	***S.rce#1 retail***	***S.rce #1 comm.***	***S.rce #2 retail***	***S.rce #2 comm.***	***S.rce #2 office***	***S.rce#4 retail***	***S.rce#4 comm.***	***S.rce #4 office***	***S.rce #5 retail***	***S.rce #5 comm.***
Source#1_ret	1									
Source#1_com		1								
Source#2_ret	1.162		1							
Source#2_com		0.739		1						
Source#2_off					1					
Source#4_ret	1.374		0.9598			1				
Source#4_com		0.9768		1.234			1			
Source#4_off					1.371			1		
Source#5_ret	1.108		0.879			0.848			1	
Source#5_com		2.074		1.145			0.875			1

*Note: ** statistically significant at 95% (H_0: ratio=1; H_A: ratio ≠ 1); grey cells indicate time series pairs not comparable for analysis purposes.*

With regard to the R_{XY} ratio analysis (step 1), we extended it to the 21 couples of comparable time series in terms of time interval and class of property, extracted from the original dataset. Achieving results with values close to 1 would be indicative of a convergence between data, while the results reported in Exhibit 2 are consistent with a preliminary signal of the lack of harmonization between data. The average value of R_{XY}, considering all the 21 cases, is 1.196, with a standard deviation equal to 0.509 (max = 2.049, min= 0.037). If we distinguish between the two geographical areas, we note a slight increase in divergence for the indices relating to Italy: in this case the R_{XY} average value is 1.297 (with a standard deviation of 0.718, ca. 55%) while for the indices related to Milan, the R_{XY} average value is 1.134 (with a standard deviation of 0.345, ca. 30%).

The results of correlation analysis seem to confirm the insight about the discrepancy in the data, especially for those relating to the national indices rather than the single urban area (Milan). The correlation matrix shown in Exhibit 3 points out a wide range of correlation coefficients, most of which were statistically significant.

With regard to the national indices, the range of correlations is $-0.698 \le \rho \le 0.721$ (with a standard deviation equal to 0.568), while for the city of Milan, we observe a smaller interval of $-0.2349 \le \rho \le 0.7484$ (st. dev.= 0.374). The presence in the correlation matrix of some negative signs is surprising since it represents an

Exhibit 3

Correlation matrix

1st Panel – Correlation coefficients among national time series

Market: Italy	***Source#1 retail***	***Source#1 Office***	***Source#1 comm.***	***Source#2 retail***	***Source#2 office***	***Source#2 comm.***	***Source#2 industrial***	***Source#3 Retail***	***Source#3 office***	***Source#3 industrial.***
Source#1_ret	1									
Source#1_off	0.9171**	1								
Source#1_com	0.8765**	0.8431**	1							
Source#2_Iret	**0.2700**	0.0401	0.041	1						
Source#2_off	0.6366**	**0.6233****	0.4855**	0.2661	1					
Source#2_com	0.246	0.0832	**-0.0867**	0.2164	0.484**	1				
Source#2_ind	0.1749	0.2056	0.0725	0.0217	0.4206**	0.1338	1			
Source#3_ret	**-0.6722****	-0.6622**	-0.695**	**-0.6982****	-0.4458**	-0.469**	0.5829**	1		
Source#3_off	0.3126	**0.5508****	0.2913	0.6186**	**0.7212****	-0.0119	-0.2218	-0.51	1	
Source#3_ind	-0.4242	-0.5042**	-0.4134	-0.6812**	-0.2679	-0.2123	**0.4401**	0.7571**	-0.5459**	1

2nd Panel – Correlation coefficients among time series of Milan city

Market: Milan	***Source#1 retail***	***Source#1 comm.***	***Source#2 retail***	***Source#2 comm.***	***Source#2 office***	***Source#2 ind.***	***Source#4 retail***	***Source#4 comm.***	***Source#4 Office***	***Source#5 retail***	***Source#5 comm.***
Source#1_ret	1										
Source#1_com	0.4659**	1									
Source#2_ret	**0.4528****	0.4393**	1								
Source#2_com	0.466**	**0.3524****	0.6909**	1							
Source#2_off	0.4739**	0.5137**	0.9337**	0.6828**	1						
Source#2_ind	0.4866**	0.4134**	0.7826**	0.8327**	0.8088**	1					
Source#4_ret	**0.5837****	0.5212**	**0.8937****	0.711**	0.8328**	0.7526**	1				
Source#4_com	0.418**	**0.6421****	0.7546**	**0.4125****	0.7694**	0.5299**	0.8317**	1			
Source#4_off	0.3932**	0.6909**	0.7137**	0.3271**	**0.7484****	0.3955**	0.74**	0.9788**	1		
Source#5_ret	**-0.2349**	0.2592	**0.2641**	0.6578**	0.1799	0.3489**	**0.4976****	0.3628**	0.3082	1	
Source#5_com	0.154	**-0.0188**	-0.1962	**-0.1623**	-0.0788	0.1561	-0.2921	**-0.2098**	-0.1752	-0.2066	1

Note: ** statistically significant at 95% (H_0: $\rho=0$; H_A: $\rho \neq 0$). Bold numbers indicate the correlation of two comparable time series. The time intervals for each correlation coefficient are shown in Exhibit 1.

outcome more compatible with a comparison between (different) asset classes rather than within a (similar) asset class. Although we cannot exclude some bias in the data, these findings clearly demonstrate the existence of a significant data divergence and raise some legitimate doubts about the informational efficiency of the domestic real estate market and the accuracy of information provided on it. In both cases (ratio and correlation analysis), the incongruity of data-base systems appears stronger for the national index case data (11 out 21 indices). This result could be explained by the adoption, in the urban area of Milan, of an advanced data collection procedure (provided by the local board of trade) not yet widespread in the rest of the market.

Our interest in looking more closely at this issue led us to continue with a further level of investigation with the aim of investigating the existence of a long-term relationship able to moderate, or refine, the assessment of dishomogeneity shown above. To this end, we proceeded to run a cointegration test for the time series of national indices by an investigation into the level of stationarity present in the residuals from the cointegration regression. We assess the stationarity of the residuals using three classical residual-based test: the Durbin Watson test (*DW test*), the ADF test (Augmented-Dickey-Fuller) the Phillips-Perron test (PP test). In order to enhance the statistical significance of the results, we selected the time-series pairs with an adequate time interval, excluding from the cointegration analysis any data with a time-interval of less than ten years. Imposing this selection criterion, we obtain three pairs of time series provided by two data property sources (Source #1-Italy and Source #2-Italy) which cover residential, commercial and office sectors respectively. Each time series pair was then submitted to an ADF test (Augmented Dickey Fuller) to estimate their order of integration (see Exhibit 4).

Exhibit 4
ADF Unit Root Test (time interval: 1997:6 to 2008:6)

Time Series	R.E. category	Levels	*p*-value	1st /2nd Difference	*p*-value	Order of integration
Source#1	*Residential*	-1.290 (4) [-3.536]	0.8904	-4.562 (4) [-3.544]	0.0012	I(2)
Source#2	*Residential*	-1.364 (4) [-3.536]	0.8712	-6.577 (2) [-3.536]	0.0000	I(2)
Source#1	*Commercial*	-2.178 (1) [-3.524]	0.5021	-4.081 (1) [-3.540]	0.0067	I(1)
Source#2	*Commercial*	-2.565 (1) [-3.524]	0.2963	-3.741 (1) [-3.528]	0.0198	I(1)
Source#1	*Office*	-2.734 (1) [-3.524]	0.2222	-4.863 (4) [-3.540]	0.0004	I(1)

Source#2	*Office*	-3.150 (1) [-3.524]	0.0948	-4.385 (4) [-3.536]	0.0023	I(1)

Note: Augmented Dickey Fuller (ADF) test to check the stationarity of a series under the null hypothesis that series is non stationary. We present a model with trend and constant. The ADF statistics are obtained from:

$$\Delta x_t = a_0 + b_0 u_{t-1} + \sum_{j=1}^{p} c_{0j} \Delta x_{t-j} + \varepsilon_t$$

where Δ is the difference operator, a_0, b_0 and c_0 are the coefficients to be estimated, x is the variable whose time series are examined and w is the white-noise error term. Values in parentheses show the lag length of the ADF test. Values in square brackets indicate 5% critical value adopted from MacKinnon (1991). Details of the ADF regression (trend and constant)are not included to save space but are available on request.

The resulting cointegration outcomes are reported in summarized form in Exhibit 5 while the detailed presentation of the residual test results of the cointegration regression are exhibited in Exhibit 6.

Exhibit 5.
Summary of cointegration analysis results

		Source #2-Italy		
		Residential	*Offices*	*Commercial*
Sourc #1 -Italy	*Residential*	not cointegrated*		
	Office		not cointegrated*	
	Commercial			not cointegrated*

*Note: *the absence of cointegration is observed both for the levels and first differences. The outcomes of the residual-based test are reported in Exhibit 6.*

Exhibit 5

Cointegration analysis between two real estate data sources

Real estate category		*Residential*		*Commercial*		*Office*	
dep variable		log (Source#2)	Δlog(Source#2)	log (Source#2)	Δlog(Source#2)	log (Source#2)	Δlog(Source#2)
ind. variable		log(Source#1)	Δlog(Source#1)	log(Source#1)	Δlog(Source#1)	log(Source#1)	Δlog(Source#1)
			Cointegration regression				
β (t value) [p –value]		1.59 (28.47) [0.000]	0.634 (1.83) [0.074]	0.818 (29.88) [0.000]	-0.116 (-0.57) [0.571]	0.916 (56.32) [0.000]	0.745 (5.23) [0.372]
R^2 (adjR^2)		0.948 (0.947)	0.0739 (0.0724)	0.953 (0.952)	0.075 (-0.0156)	0.986 (0.986)	0.388 (0.374)
Test statistic				***Residual- based test***			
CRDW[a]	DW	0.052 (*1.03*)	0.495 1.03	0.104 1.03	0.647 1.03	0.1261 1.03	0.878 1.03
ADF[b]	ADF-t	-0.744 . (lag 1) (*-3.5136*)	-2.545 (lag 1) (*-3.5136*)	-2.946 (lag 1) (*-3.5136*)	-2.908 (lag 4) (*-4.7690*)	-3.264 (lag 3) (*-4.3993*)	-3.195 (lag 1) (*-3.5136*)
PP [c]	Z_p	-2.33 (*-19.42*)	-18.2 (*-19.34*)	-5.03 (*-19.42*)	-16.1 (*-19.34*)	-5.91 (*-19.42*)	-18.1 (*-19.34*)
	Z_t	-1.56 (*-3.52*)	-3.47 (*-3.52*)	-1.53 (*-3.52*)	-3.13 (*-3.52*)	-1.72 (*-3.52*)	-3.306 (*-3.52*)

[a]The critical Values of the Cointegrating Regression Durbin-Watson test are reported in Engle and Yoo (1987).

[b]The critical Values for the ADF test are from MacKinnon (1991). The lag length was chosen according to the Schwartz criterion.

[c] The critical values of the Phillips-Perron test are taken from Philips and Ouliaris (1990).

The numbers in Italics in parentheses are critical values.

The results are consistent with the absence of cointegration for each of the cases analyzed, revealing non-negligible independence among data structures. Moreover, data show that the absence of cointegration is observed both for the historical series of absolute values (logarithmic levels) as well as for the returns series (first differences). Consequently, the lack of cointegration is an obstacle to achieving an ECM in order to approximate the convergence velocity to an equilibrium relationship between variables.

Basically, the lack of a long-term relationship between data gathered from distinct sources, as well as the aforementioned characteristic of nonconformity, leads to the opinion that the real-estate information systems are not at all adequate. However, some possible explanations of the empirical findings need to be explored. For example, the poor traceability of the valuation dates for the real estate portfolio to which the indices are linked impedes the correct synchronisation of time series which, incidentally, can render the results of a comparison between information sources inefficient or implausible. Further, in spite of the traditional asset class markets (i.e. stocks and bond), where the indices reflect the performance of a group of a similar type, real estate indices are based upon portfolios that differ among themselves in terms of urban location and other hedonic variables (green areas, proximity to transport infrastructures, parking, etc.).

Data quality and property management: implications for market participants.

The accuracy of real estate data is a topic of interest to many market participants. In this section we will develop three simulations to show how the level of homogeneity of data impacts on some operations of financial institutions involved in real estate investments management. The simulations refer respectively to: 1) the impact of disharmonized data on IRR calculation of real estate funds; 2) the relationship between the weights of optimal mixed-asset portfolio and the source of property data, in a mean-variance optimization framework.

The impact of time series heterogeneity on IRR funds: a simulation.

To assess the impact of data divergence upon the valuation of a real estate fund, we conducted a sequence of back-tests for the Internal rate of return (IRR) calculation, adopting a different real estate data source for each iteration.

As is well known, the IRR calculation of a real estate investment is a function of three parameters: 1) rental cash flow, 2) cash management, and 3) the end value of properties. Assuming a real estate fund with an extremely simplified structure of assets, we design a procedure of IRR backtesting consisting in an IRR sensitivity analysis, setting different values for the third of the previous parameters, the end value of the properties in portfolio, keeping the other two constant.

The back-testing procedure is iterated n times, where n represents the number of sub-periods selected and related to the different property end values.

The modulation of end values follows a mechanism defined as follows: given the i_{th} (i=1..n) subperiod of m years, and given the availability of property index data provided by the j_{th} source (j=1..h), the i_{th} property end value is set as equal to the (hypothetical) initial value of the property compounded at m annual yields intrinsic to the correspondent time series interval.

Following this mechanism, we selected six five-year long subperiods (n=6, and m=5) and three commercial property indexes related to the city of Milan, and provided by three different data-sources (h=3). The six subperiods started from 1998:1 and each one is separated from the previous one by a year; thus we obtain the following sequence of subperiods: 1st) 1998:1-2002:12; 2nd) 1999:1-2003:12; 3rd) 2000:1-2004:12; 4th) 2001:1-2005:12; 5th) 2002:1-2006:12; 6th) 2003:1-2007:12.

Therefore, we assumed a five-year investment in a real estate fund invested in only two properties (A and B) whose financial characteristics are illustrated in the upper part of Exhibit 7. With these established conditions, for each of the three data sources selected, we calculated six property portfolio end values and, consequently, six IRR values (keeping the other cash flow constant). The results are shown in Exhibit 7 where some sensitivity measures are used.

Exhibit 7
Simulating IRR calculation: main results.

Assumptions:

Portfolio composition	*Date of investment*	*Date of liquidation*	*Initial Price*	*Annual Rental*	*Costs*
Property A	t_0	t_5	100	1	0
Property B	t_0	t_5	200	2	0

End Values of the fund

Sub- period	Jan/1998-Dec/2002	Jan/1999-Dec/2003	Jan/2000-Dec/2004	Jan/2001-Dec/2005	Jan/2002-Dec/2006	Jan/2003-Dec/2007	SDWSP*
Data Source #1	413.3	409.1	409.3	414.2	399.2	388.9	2.41%
Data Source #2	433.3	691.7	565.2	453.1	433.3	339.8	25.47%
Data Source #3	416.6	444.4	413.3	389.9	364.5	345.8	9.19%
*SDDS***	2.5%	29.9%	19.2%	7.6%	8.6%	7.5%	

Internal Rate of Return (IRR) of the fund

Sub period	jan/1998-dic/2002	jan/1999-dic/2003	jan/2000-dic/2004	jan/2001-dic/2005	jan/2002-dic/2006	jan/2003-dic/2007	SDWSP
Data Source #1	18.1%	17.9%	17.9%	18.1%	17.5%	17.0%	2.49%
Data Source #2	19.0%	28.3%	24.1%	19.8%	19.0%	14.6%	22.87%
Data Source #3	18.2%	19.4%	18.1%	17.0%	15.8%	14.9%	9.67%
*SDBDS***	2.5%	25.6%	17.6%	7.6%	9.0%	8.3%	

**SDWSP: Standard Deviation within Sub-Periods*
***SDBDS: Standard Deviation between Data Sources*
SDWSP and SDBDS are expressed as percentages of the IRR average value

The last row and last column of Figure 2 show the standard deviation of the IRR "within" subperiods and "among" data-sources respectively. While analysis of the "within subperiod" indicator is not so important for our aim, an inspection of the results of the second indicator appears indispensable. By looking at the results of "between data-source" standard deviation, it becomes clear how the choice of data sources may affect the evaluation of the IRR in each subperiod; this influence is also significant in some cases, and varies between 2.5% and 25.6%.

These findings are consistent with the previous remarks about the existence of scarcely negligible data divergence for the Italian real estate market. In general, the results of this IRR simulation confirm how important access to comprehensive, reliable and timely evidence of property transactions is in order to make informed predictions, and how this represents an issue of great concern to both market participants and policymakers who rely on price signals for decision-making (Lum, 2004).

Data divergence, portfolio optimization and investment choices.

Finally, we turn to a discussion of the last issue of this paper: the relationship between data property divergence and the quality of investment choices. The basic idea is to select a set of asset class indices, including domestic real estate, and to create a sequence of portfolio optimizations, varying the property data at each iteration. By changing the property index at each optimization, we analyze the sensitivity of portfolio weights to the data source switch, measuring the consequent implications for the investment choices with an appropriate variable (DARaP, see below)..

The tenet of the portfolio theory is diversification within a mix of asset classes with an appropriate risk-return profile and a low correlation, to mitigate risk to the whole portfolio. In spite of its limitations (Chopra and Ziemba, 1999), the Markowitz Mean-Variance approach is widely used and represents the most suitable model for facing the optimal portfolio selection.

Dealing with the classical principles of efficient frontier construction, we selected 5 asset classes and estimated their expected returns as well as their covariance matrix. The set of asset classes is made up of equity, bond, and real estate indexes listed as follows: 1) S&P500 (Us stock market); 2) MIBTEL (Italian Stock market); 3) MTS BTP 10Y long-term domestic Government bonds; 4) domestic Risk free-rate (MTS BOT); 5) a property index selected from the available set (section 2.1 and Exhibit 1)

The estimation of efficient frontier input represents an issue widely discussed in literature. However, the merely descriptive purpose of this paragraph leads us to choose a simplified approach rather than more refined models (i.e. the Black and Litterman model, the Bayes-Stein approach, etc.). Thus, the expected returns are expressed as the annualized average of historical quarterly returns; the historical approach is then extended to the estimation of the covariance matrix.

From the available set of property indexes, we recognize three triplets of comparable time series belonging to three data sources and related to both geographical area and the three main real estate segments (residential, commercial, office). For each triplet (i.e., for each data source) we can potentially proceed to the construction of three efficient frontiers, by changing the property index at each optimization iterate. However, to improve the significance of optimization outcomes, we excluded from the subset of (nine) series those with less than ten years of data. By imposing this criterion, we finally identified two time series triplets (six series), provided by two different sources and related to the residential, commercial and office segment of the city of Milan respectively.

Then, we did six portfolio optimizations (one for each time series) obtaining three pairs of comparable efficient frontiers as shown by Exhibit 9.

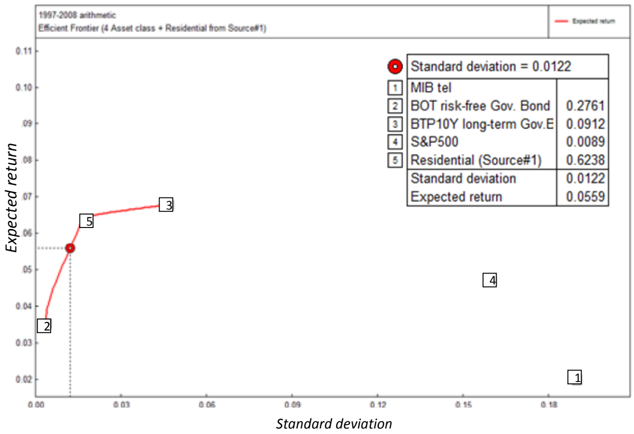
The expected returns and risks were estimated on an annual basis and are equal to the historical average and the standard deviation for the period 1997:6 to 2008:6 respectively[4].

To determine the sensitivity of portfolio composition to each data-change, we use a proxy of return/risk ratio for each frontier, which we call DARaP (Decile Average Risk adjusted Performance). In detail, the mean DARaP variable may be explained as follows: it represents, for each efficient frontier, the average value of the return to risk ratio of a ten "decile portfolio", where this term describes the portfolio with a risk equal to a decile of the volatility interval (max σ - min σ). Formally, we write:

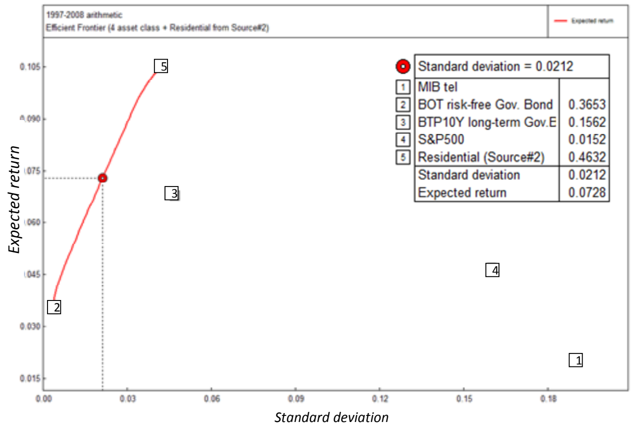
$$DARaP = \frac{1}{10}\sum_{i=1}^{10}\frac{R_i}{\sigma_i} \tag{4}$$

where with Ri and σi we denote the return and risk (σi) respectively of the optimal portfolio corresponding to the ith decile of the volatility interval of the frontier.

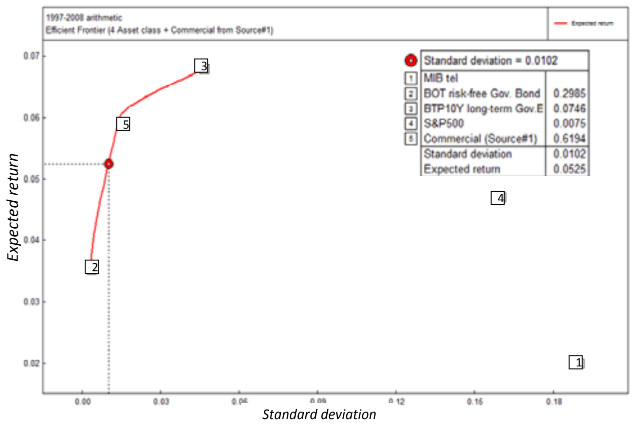
Exhibit 9
Set of comparable efficient frontiers
(input is historical values, 1997:6 – 2008:6)



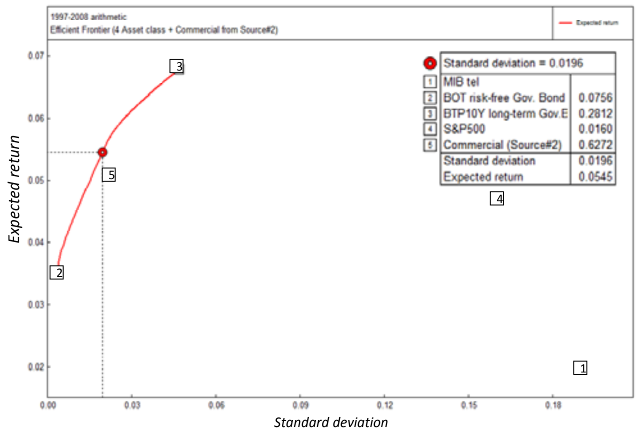
Real Estate Class: Residential Index (Source #1)



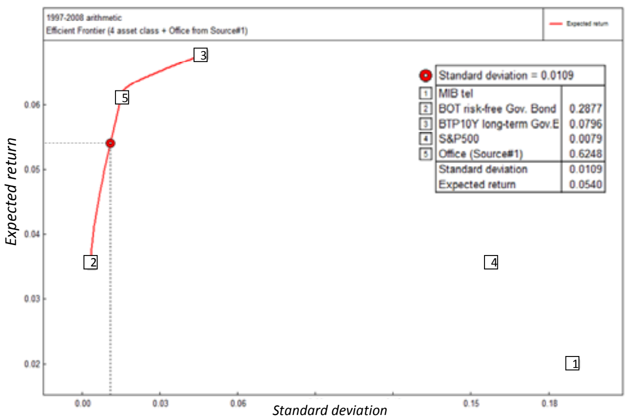
Real Estate Class: Residential Index (Source #2)



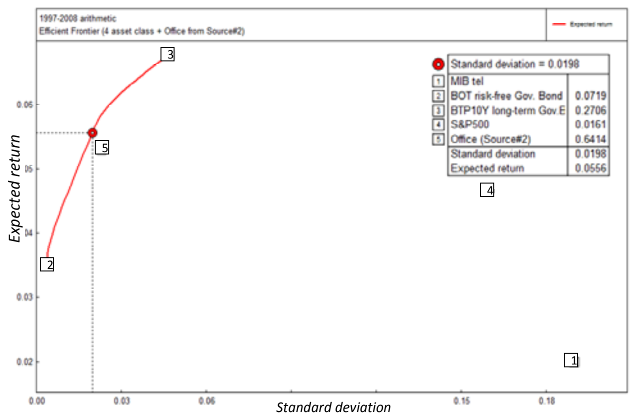
Real Estate Class: Commercial Index (Source #1)



Real Estate Class: Commercial Index (source #2)



Real Estate Class: Office Index (Source #1)



Real Estate Class: Office Index (Source #2)

In general, if we calculate the DARaP for two efficient frontiers (A and B) differing among themselves in terms of the source of data of one (or more) asset classes, a proxy of the sensitivity of portfolio composition to the data change would be shown by the value $\Delta DAR3_{A,B}$, where:

$$\Delta DARaP = \left| \frac{\max\{DARaP_A, DARaP_B\} - \min\{DARaP_A, DARaP_B\}}{\min\{DARaP_A, DARaP_B\}} \right| \tag{5}$$

The $\Delta DARaP_{A,B}$ variable captures the geometric translation of the efficient frontier when a data change occurs. Thus, a high (low) value of $\Delta DARaP_{A,B}$ is consistent with discrepancies (convergence) between sources of data.

The results of efficient frontier comparison are summarized in Exhibit 10, where rows indicate the data source of the property index inserted in the portfolio optimization and the $\Delta DARaP_{A,B}$ values, while the columns are indicative of the category of real estate indices.

Exhibit 10
Map of *Decile Average Risk adjusted Performance* (DARaP) values

	Real estate category		
Data	*Residential*	*Commercial*	*Office*
Source #1 (A)	3.668	4.727	5.349
Source #2 (B)	4.747	3.527	3.657
$\Delta DARaP_{A,B}$ (%)	29.22	34.02	46.27

DARaP denotes, for each efficient frontier, the average value of the return to risk ratio of a ten "*decile portfolio*", i.e. a portfolio with a risk equal to one decile of the frontier volatility interval (max σ - min σ).

The ΔDARaP value is between 29.22% and 46.27% revealing a significant change in portfolio weights due to the substitution of the property data source . These findings are consistent with those of the previous simulations, and suggest much caution in the selection of the property benchmark to include in portfolio optimization tests, especially for those which are mean-variance based. The most serious practical limitations of the mean-variance approach are, in fact, the ambiguity and instability of portfolios. Small changes in input assumption often lead to large changes in the composition of optimized portfolios

(Michaud 1998). Therefore, optimal weights will change significantly over time as a direct result of making estimation errors (Kallberg and Ziemba, 1984 and Adler, 1987). Thus, in the case of a high level of divergence between property indices (i.e., the office sector in Exhibit 10), and to impede the amplification of estimation errors, it would be at least appropriate to adopt a procedure able to mitigate the discrepancy of the data (i.e. the calculation of average index values).

Conclusions.

Data quality plays a vital role in providing reliable and valid information for property market performance. The relationship with the assessment of financial stability and monetary policy are much debated questions among academics and policymakers alike. The complexity of the market and varieties of market functioning impede the adoption of standardized data collection among countries. Thus, gathering reliable and comparable data on property markets has proved very difficult (Zhu, 2005). Even more, it is not uncommon to identify markets where very different multiple data collection methods coexist.

By focusing on the Italian real estate market, we have discussed the reliability of the domestic property data source, taking into account variables such as the frequency of collection, the data-gathering methodology, and the territorial area. Furthermore, we conducted two simulations in order to measure the impact of data divergence respectively for real estate investment vehicles, and the asset allocation of optimized portfolios. Our results show a poor level of homogeneity between data both for national time series and for urban data time series. These findings raise the issue of how important it is to have quick access to comprehensive and reliable evidence of property transactions in order to make informed predictions and how this represents a critical question for both policymakers and market participants who rely on price signals for decision-making. Looking forward, there is the need for action aimed at improving the quality of property data and enhancing the comparability of across-data sources.

Endnotes

[1]. The privacy disclaimers of some sources of data do not authorise the use of data for external research. For this reason, the historical series available are identified by code (data source 1, data source 2, etc.). As a guarantee of the truthfulness of the results, the authors are prepared to reveal their data sources upon private request (eieffe@uniparthenope.it).

[2]. For reasons of brevity, the covariance matrix and expected return are not shown here, but are available from the author on request.

References,

Chopra, Vijay K., William T. Ziemba, "The Effects of Errors in Means, Variances, and Covariances on Optimal Portfolio Choice." Journal of Portfolio Management, 20 (1993), pp. 6–11.

Engle, Robert F., Clive W. J. Granger. "Cointegration and Error Correction: Representation, Estimation and Testing." Econometrica, 55 (1987), pp. 251-76.

Engle, Robert, F. and Byung S. Yoo. "Forecasting and Testing in Co-integrated Systems." Journal of Econometrics, 35 (1987), pp. 143-159.

Fisher, J., D. Gatzlaff, D. Geltner, D. Haurin. "Controlling for the Impact of Variable Liquidity in Commercial Real Estate Price Indices." Real Estate Economics, 31 (2003), pp. 269-303.

Francis Jack. C., Roger G. Ibbotson. "Contrasting Real Estate with Comparable Investments, 1978 to 2008", The Journal of Portfolio Management, 36 (2009), pp. 141-155.

Garay, U., Horst E. "Real Estate and Private Equity: A Review of the Diversification Benefits and Some Recent Developments." The Journal of Alternative Investments, 11 (2009), pp. 90-101.

Ge, X., T. Harfield. "The Quality of Data and Data Availability for Property Research". Paper presented at the 13th Pacific Rim Real Estate Society Conference, Perth, Australia, January 2007

Hoesli, M., Lekander J. "Suggested Versus Actual Institutional Allocations to Real Estate in Europe." The Journal of Alternative Investments, 8 (2005), pp. 62-70.

Hudson-Wilson, S., Frank J. Fabozzi, Jacques N. Gordon. "Why Real Estate? - An Expanding Role for Institutional Investors.", Journal of Portfolio Management, 29 (2003), pp. 12–25.

Jorion, P. "Portfolio Optimization With Constraints on Tracking Error." Financial Analysts Journal, 59 (2003), pp. 70-82.

Kallberg, Jarl G., William T. Ziemba. Mis-Specification in Portfolio Selection Problems. In Bamberg, G. and A. Spremann, editor, Risk and Capital. Springer-Verlag: New York, 1984.

Koetter, M., T. Poghosyan. "Real Estate Markets and Bank Distress." Discussion Paper Series 2: Banking and Financial Studies, Deutsche Bundesbank, Research Centre, 18 (2008).

Goltz F., L. Martellini, M. Vaissié "Hedge fund indices: reconciling investability and representativity." European Financial Management Journal, 13 (2007), pp. 257-286.

Greer Gaylon E, Philip T. Kolbe, Investment analysis for real estate decisions, 6th ed. Deaborn Real estate Education: 2006.

Knight, John R., C. Sirmans, Alan E. Gelfand, Sujit K. Ghosh. "Analyzing Real Estate Data Problems Using the Gibbs Sampler." Real Estate Economics, 26 (2008), pp. 469-492.

Lum, Sau K. "Property price indices in the Commonwealth – Construction methodologies and problems." Journal of Property Investment & Finance, 22 (2004), pp. 25-54

Michaud, R. Efficient Asset Management. NY: Oxford University Press, 1998.

Phillips, Peter C.B., P. Perron. "Testing for a Unit Root in Time Series Regression." Biometrica, 75 (1988), pp. 335-346.

Phillips, Peter C.B., S. Ouliaris. "Asymptotic Properties of Residual Based Tests for Cointegration." Econometrica, 58 (1990), pp. 165-93.

Seiler, Michael J., James R. Webb, F.C. Neil Meyer. "Diversification Issues in Real Estate Investment." Journal of Real Estate Literature, 7 (1999), pp. 163-179.

Stephan, A. “Obtaining Real Estate Data: Criteria, Difficulties and Limitations.” In Bank for International Settlements, editor, Real estate indicators and financial stability. Bis Paper 21 (2005), pp. 63-69.

Zhu, H. “The Importance of Property Markets for Monetary Policy and Financial Stability.” In Bank for International Settlements, editor, Real estate indicators and financial stability. Bis Paper 21 (2005), pp. 9-29.