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Data uncertainty in real estate forecasting

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1. Introduction

Possibly uniquely, real estate forecasting organisations disagree about historic, current and future market levels and returns. Clearly, given the fundamental methodological linkage between past trends and future extrapolations[1], variations in recording historic time series are likely to result in forecast variation as well. This problem seems to be fairly distinctive to real estate forecasting. Although the preliminary nature of and subsequent revisions to estimates of real output provide a source of data uncertainty to macro-economic forecasters, many macro-economic data (e.g. exchange rates, interest rates and commodity prices) are easily available and not subject to measurement error. In contrast, real estate forecasters are faced with substantial hindsight uncertainty. Whilst Hendry and Clements (2003, 303) state that "all econometric models are mis-specified", this paper focuses on the potential contribution of data uncertainty to model mis-specification and consequent forecast uncertainty in real estate markets. Using data provided by three major real estate advisory firms, we investigate the level and pattern of variation in the measurement of historic real estate values and market indicators for the main European office centres.

The remainder of the paper is organized as follows. Section 2 reviews the literature on sources of disagreement in forecasting with reference to the role of data and discusses the nature of data production in European real estate markets. This is followed in Section 3 by a discussion of the data and the research objectives. Section 4 outlines the findings focussing on the extent of disagreement agreement among the data collection organisations on the performance of the markets. Finally, conclusions are drawn.

[1] An underlying assumption of econometric forecasting is that past patterns will continue into the future - or, to paraphrase Guilkey's (1999) more vivid image: better econometric modelling only forecasts the past with greater precision.

2. Literature Review

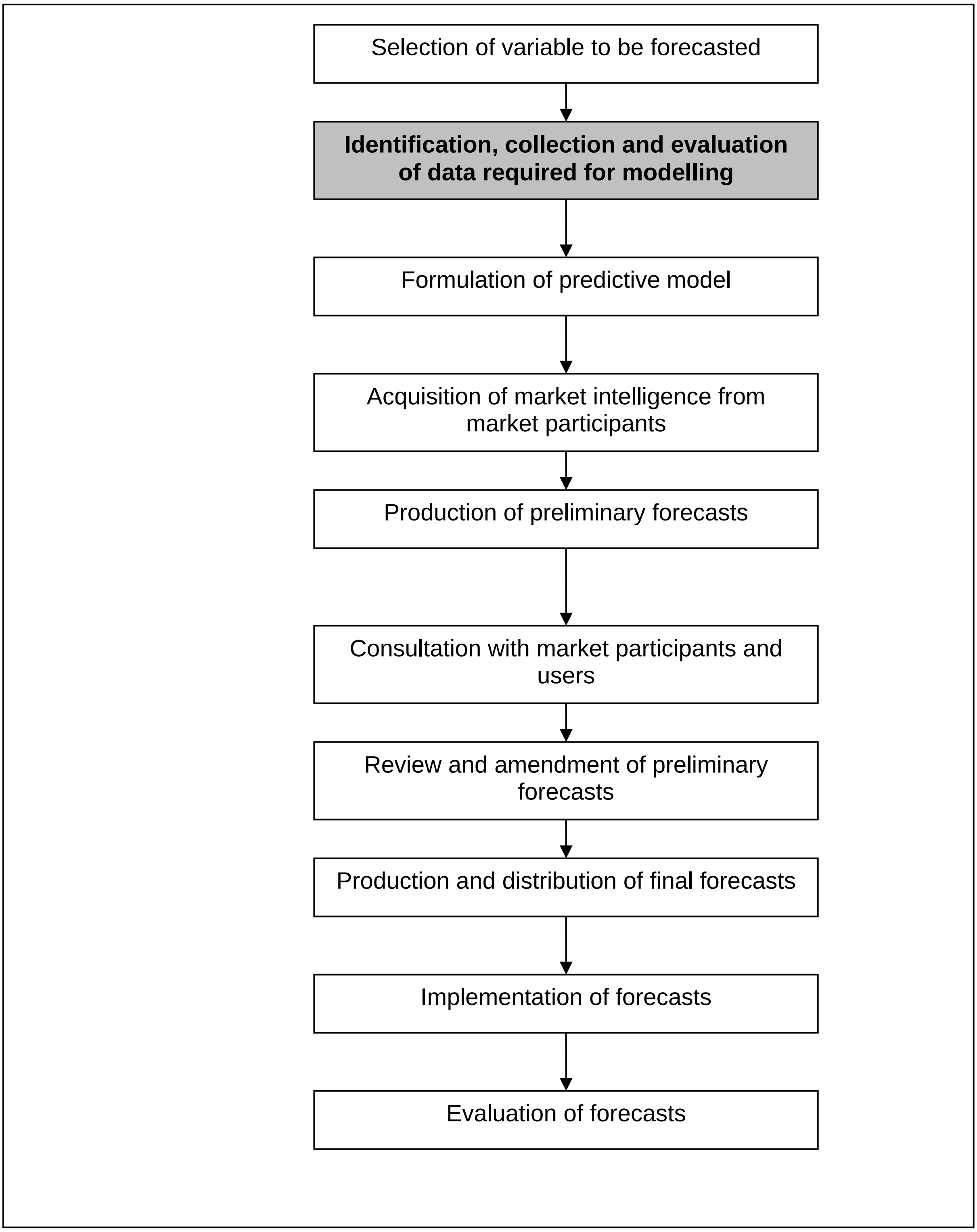
Research suggests that the dominant approach to real estate market forecasting in the UK and US is based upon a combination of econometric and financial modelling techniques (see Gallimore and McAllister, 2004 and Guilkey, 1999).[2] For econometric models, it is axiomatic that a purely objective forecast is unattainable. Previous research within and outside real estate indicates that subjectivity is intrinsic to economic and property forecast formation and is likely to generate disagreement among forecasters. It has been recognised that differences in property forecasts occur due to differences in the structure of the econometric models, statistical procedures and *data used* (Mitchell and McNamara, 1997). As highlighted by the following discussion, judgement also explains some variations between forecasts.

In terms of the specification, "mathematical models involve smoothing constants, coefficients and other parameters that must be decided by the forecaster" (Walonick, 2004, 2). The forecaster will also have to make decisions about forecast horizon, forecast interval, choice of computational model, as well as data selection and treatment.

[2] Although undocumented, the authors are confident that the vast majority of global property advisory firms and major investing organisations use econometric techniques to produce rental growth forecasts for most major real estate markets. However, approaches to forecasting shifts in capitalisation rates tend to be more diverse.

Exhibit 1

Schematic Representation of Forecasting Process



Quality of data also has implications for model development in the forecasting process. .There will be a trade-off between the benefits of improving the explanatory power of a model in the context uncertainty about the data inputs. In terms of model formation, Pascual, Stiber and Sunderland (2003) explore the interaction of uncertainty about whether the model incorporates complete knowledge of the factors that control the behaviour of the system (specification uncertainty) and uncertainty due to measurement errors and limited sample sizes (data uncertainty). Their central point is that there is an inherent trade-off between specification and data uncertainty and, therefore, optimal level of complexity for every model.

Exhibit 2

Data Uncertainty and Model Formation

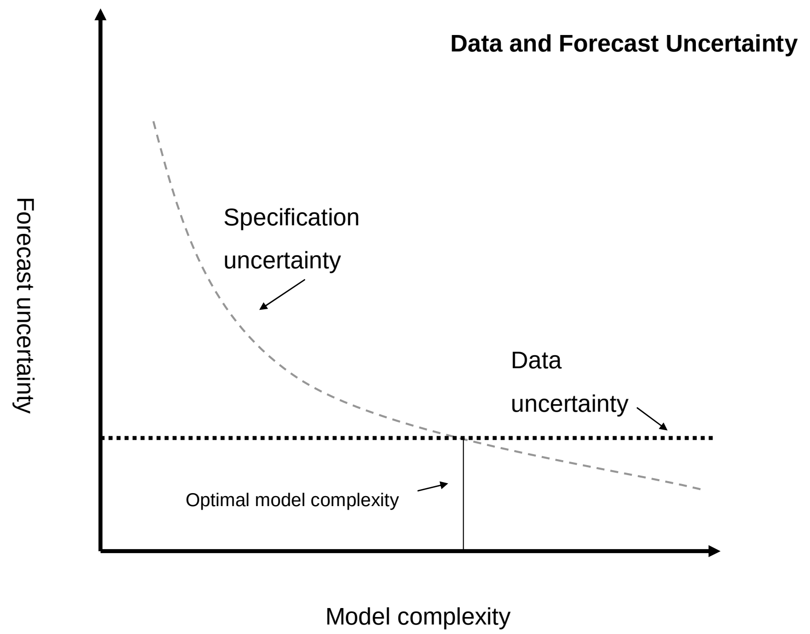


Exhibit 2 illustrates how the level of data uncertainty can place limits on the benefits of additional model complexity.

Guilkey (1999) investigated the practice of US property market forecasters in terms of their parameters, methodology and output, and identified significant differences in the variables used, model specifications and the exogenous variables obtained from macro-economic forecast providers. He found disagreement amongst forecasters, concluding that property forecasters "get to their conclusions using very different methodologies and obtain very different MSA rankings" (Guilkey, 1999, 40). Similarly, in the UK, Gallimore and McAllister (2005) found that judgement was pervasive in the real estate forecast formation process occurring in (econometric) model formation, due to variations in choice of causal variables, data selection and treatment, and constant and parameter specification. It is the effect of the data selection that is the focus of this paper.

It is clear that there are multiple sources of forecast disagreement. In explaining forecast disagreement, some commentators have focussed on differences in data in terms of availability and processing. Linden (2003, 5) emphasises the importance of data availability and physical and economic constraints on its collection arguing that “forecasters have both different types and different amounts of information to form their beliefs”. Williams (2003) draws upon theories of rational heterogeneity of beliefs which assume that agents have at their disposal a range of forecasting models, but are uncertain as to which model or models to use. Consequently, they adaptively update their model choice or priors over the various models based on forecasting performance. In essence, it is argued that idiosyncratic differences in agents’ characteristics (e.g. different initial conditions in model priors and costs to learning new models) implies that a range of models will be in use at any point in time. The result is forecast disagreement. Essentially variations in data are inherent and forecasters will have different types and amounts of information with which to form their beliefs. For example, research by Mankiw and Reis (2002) places ‘sticky information’ due to the costs of collecting and processing data as being an important explanatory variable of economic forecast disagreement. However, disagreement about historic and current real estate market data means that data issues often require critical forecaster attention.

The fundamental reasons that forecasting organisations disagree about the past relate to the nature of real estate markets. Estimates of market levels (of rents) are produced by professionals who must interpret ‘noisy’ market pricing signals. In essence, these estimates are real estate appraisals and there is a substantial body of research literature analysing the nature, causes and extent of appraisal uncertainty (see Quan and Quigley, 1991; Webb, 1994; Newell and Kishore, 1998; RICS, 2006 for examples of theoretical analysis and empirical investigation of appraisal uncertainty)[3]. In addition, rental appraisers are faced with the problem of interpreting pricing signals from actual buildings when applying them to hypothetical assets. As a result, most researchers would agree that some disagreement between the organisations recording market levels is, therefore, largely unavoidable. Given this inevitability of uncertainty and disagreement in real estate appraisals, the most interesting

[3] Although probably more relevant here, there has been much less empirical research on appraisal disagreement.

questions relate to the quantity and patterns of disagreement and uncertainty rather than their existence.

However, there are also institutional issues in the configuration of the real estate industry that tend to exacerbate the intrinsic data uncertainty associated with real estate market. Gallimore and McAllister (2005) found that for UK forecasters obtaining consistent and reliable time series for real estate rents was a recurring problem. In particular, forecasters emphasised the definitional problems with particular emphasis on disagreement about: What geographical area is being measured? How are centres/districts defined? What is the quality of building being measured? Do the data reflect prime or average quality stock? Are rents and capitalization rates reported net or gross? Are rental values effective or headline rents[4]? How have effective rents been calculated? Has the rental estimate been observed or is it a pure estimate? Sources of data uncertainty due to these inconsistencies are avoidable. It can be eliminated by a combination of firm cooperation and harmonisation of standards.

Data on the European real estate market are collected by the main agency companies. Typically, basic data are used for marketing purposes (e.g., market reports) while more detailed data are reserved for clients to support transactions. Most data providers started out as with a predominantly domestic (UK) client base. As a result, data were seldom used to compare investment opportunities across borders. One consequence of this was the development of local conventions for measurement and definitions associated with key time series. As a result, approaches used to define rents, yields and other key time series often varied by country and, sometimes, by market, sector and data provider (see Kennedy et al., 2004; Sanderson and Farrelly, 2005; Haddock, 2005; and Arend et al 2005). In addition to variations due to definition, variations in levels of market access and judgement often led to data inconsistencies.

Recently, some data providers have started to allow access to detailed market data via subscription. This process has been driven by the growth of pan-European real estate investment and the associated demand for pan-European research and investment strategies. Perhaps more importantly this trend has led advisers to move towards definitions that are consistent across borders (Kennedy, 2006). In addition, some advisers are starting to

[4] The distinction between headline and effective rents concerns whether leasing incentives e.g. rent free periods, taking on tenants' previous lease liabilities *inter alia* have been monetised to estimate an effective rent. There is no consensus on how leasing incentives should be monetised.

consider sharing market data. Taken together these two changes may lead to a reduction in both definitional and market access based data variations.

Data and Research Questions

Market rental data on 13 European cities (Vienna, Lisbon, Amsterdam, Athens, Berlin, Paris Centre West, Milan, Madrid, London West End, Stockholm, Dublin, Copenhagen and Brussels) has been provided by three leading pan-European real estate advisers. All data are either annual € headline rents from 1990. As noted above, the use of headline rents means that there is almost certainly a systematic upward bias in the estimates of rental values. In particular, downside variance is likely to under-estimated due to the fact that leasing incentives tend to be more prevalent in market downturns. As a result the relative performance of markets that have not experienced significant downturns is likely to be underestimated compared to markets that have had.

However, since the problem of different approaches to monetising to leasing incentives is avoided, a potential source of disagreement in the data is not present. It should also be noted that since the euro was introduced in 1999, two data collection organizations have used a synthetic euro series for the period 1990-1999. One organization did not convert non-Euro countries (UK, Denmark and Sweden) and we used a spliced euro exchange rate series.

There are a number of potential approaches to assessing the degree of disagreement. We focus on whether the recording organizations agree on market performance in terms of returns, risk and timing and also investigate whether there is any evidence to suggest that any organizations are systematically optimistic or pessimistic in their measurements. More specifically, this generates a number of questions:-

- Is there agreement on the level of rental growth?
- Is there agreement on the level of volatility?
- Has the degree of agreement changed over time?
- Is there agreement on market direction?
- Is any single organization biased?

Summary statistics are presented in Appendix 1. In order to preserve the confidentiality of the data collection organizations, we have labelled them - A, B and C.

Results

It is clear that there have been significant differences in performance among the cities analysed. As we can see, all organizations agree that during this period, Dublin has been the best performing city in terms of rental performance with nominal growth of over 7% per annum. There seem to be three broad groups. London, Amsterdam and Brussels (with Dublin) seem to have had relatively strong performance. Notably, weak performers have been, Lisbon, Berlin and Vienna. For instance, all organizations agree that Lisbon has on average experienced rental falls during the sample period. The third group consists of Milan, Madrid, Athens, Stockholm and Paris – all seem to have experienced positive nominal rental growth which has, however, typically below the rate of consumer price inflation in the Euro-zone. Copenhagen is one of the few markets where there is a major disagreement between the data collection organizations.

It is clear from Appendix 1 that there is substantial agreement about rental growth at the aggregate level. The un-weighted mean rental growth of the 13 European cities is used to estimate mean rental growth for Europe. All data collection organizations produce similar figures. However, at the city level, there are wide variations in terms of the level of agreement about historic rental performance. At one end of the scale are Dublin and London where there is little variation amongst the three organizations. Whilst at the other end are Berlin, Stockholm and Copenhagen. In a number of cases, the organizations disagree about whether the average rate of rental value growth has been negative or positive (Vienna, Milan and Vienna). *Prima facie*, this suggests that the effects of data uncertainty may vary between markets.

In order to assess the degree of dispersion among data collection organisations, we calculated the Mean Absolute Percentage Error (MAPE) for each organization. The 'true' observation was taken as the simple mean of the three rental observations. In Exhibit ?, the thick black line represents the trend in the average MAPE for Europe whilst each individual dotted line represents a city. At the aggregate level, from the data users' perspective the results seem to be positive in that the trend in rental dispersion is downwards. However, it is pretty clear that a large proportion of the high level of dispersion at the beginning of the period is due to three outliers (Milan, Madrid and Copenhagen). Within a few years of 1990, there was convergence in MAPE of the rental estimates to the average for all three. When the first 2-3 years are excluded, there is little evidence of change in the aggregate MAPE. When we examine the period 1996 to 2006 only, there seems to be a relatively stable 4% MAPE in the estimates of rental growth at the aggregate level.

However, when focussing on individual cities, no clear pattern emerges. Over the last 10 years, there are three cities, where the MAPE is consistently below average – Paris, Lisbon and Brussels. Five cities are close to the average – Amsterdam, Milan, Madrid, Dublin and London and five are well above the average – Vienna, Berlin, Copenhagen, Athens and Stockholm. It is difficult to find any rationalisation or identify a pattern here. It is unlikely that there is a systematic factor causing high levels of disagreement in some markets and low levels in others. There may be an element of randomness.

Appendix 1 also shows that there are similar patterns when data providers' estimates of market volatility are examined. At the aggregate level (Europe), the standard deviation of rental growth rates are similar for the three organizations. However, it is clear that there are marked differences among the individual cities. All firms record similar levels of volatility for London, Madrid and Stockholm but disagree substantially about Berlin, Paris and Copenhagen. It is not possible to explain differences in volatility by differences in rental growth levels. For instance, Stockholm had high levels of disagreement in rents but little disagreement on the level of market volatility. On the other hand, there were low levels of disagreement about rental levels in Paris but high levels of disagreement on market volatility.

In terms of agreement about market direction, the correlation coefficients between the three organizations provide a measure of disagreement. The coefficients are presented in Appendix 1. Once again a similar pattern emerges. Whilst cut-offs are inevitably arbitrary in describing correlations as strong or weak, at the aggregate level mean correlations are marginally weak. Once again at the individual city level, there are marked differences. Although we need to be careful about statistical significance given the sample size, there is strong correlation (>0.8) for only 16 of the 49 possible combinations. Generally for cities with low levels of disagreement about rental growth (in terms of MAPE) e.g. Paris, London and Dublin, there is strong correlation (Brussels is a notable exception here). Similarly for cities with high levels of disagreement, there tends to be weak correlation (again with Stockholm as a notable exception). In a small number of cases, correlation coefficients were not significantly different from zero. These findings suggest that there is a substantial amount of disagreement among data collection organizations about the direction of market movement.

In terms of modelling past relationships with explanatory variables, agreement on the *direction* of change seems fundamental. In order to investigate further, we simply examined whether there was consensus among the three data collection organizations on the direction of market movement in a given period. Three possible outcomes were stipulated – market rise, market fall and no change. Where at least one organisation differed from the other two, disagreement was recorded. One-year and three-year horizons were examined. The results are displayed in Exhibits ? and ?. Over the sample period, in 32% of total observations, there was disagreement. There are notable variations over time. In 1996 for over 60% of the cities, at least one data collection organization disagreed on the direction of market change in that year. In contrast, in 1998, 1999 and 2000 there was disagreement on the direction of change for only one city (Lisbon, Stockholm and Copenhagen respectively). Even over the three year horizon, there is still substantial disagreement. For instance, in the period 2004-2006, there was disagreement about the direction of market change for over half the cities. As ever, there are notable variations between cities. For Paris and London, there was disagreement about the direction of rental growth change over one year in 13% and 19% of years. In contrast, the figure for Milan and Copenhagen was 44%. For some periods and for some cities, the extent of disagreement about the direction of market rental change seems to be providing inconsistent and/or incorrect signals of market conditions and the effects of causal variables on rental levels

Finally, we investigate whether any single data collection is systematically biased in terms of its measurement of rental levels. It has already been noted that there were minor differences between the three organizations in terms of their aggregate mean level of rental growth for Europe (see Appendix 1). Although Company A records the highest rate of growth - this is attributable to one major outlier (Berlin 1990-1) at the beginning of the sample period. This level of agreement at the aggregate level would suggest that it is at the level of individual cities that differences may be significant. For instance, it was clear from Appendix 1 that in some cases the estimates were very similar, whilst for other cities there was notable divergence.

Appendix ? shows the results of a simple ranking of the rental estimates of each data collection company. However, the results are potentially misleading. For a number of cities, it seems that Company B is consistently optimistic. For Milan, Lisbon and Amsterdam they are ranked top in terms of rental estimates for 82%, 82% and 76% of the 17 years. However, perhaps surprisingly, this does not necessarily mean that they have the highest average level of rental growth. For instance, for Milan and Lisbon, their mean rental growth rate for the whole sample period is the lowest of the three companies. Given these issues, it is difficult to state that any organisation is consistently biased in their estimates.

Conclusion

Whilst the quality, range, depth and consistency of European real estate market data has improved dramatically over the last decade, real estate forecasters and analysts are faced with a large degree of hindsight uncertainty compared to many other categories of economic forecaster. Given the intrinsic linkage between analysing historic relationships and forecasting future market outcomes, uncertainty about the past will contribute to forecast uncertainty. The issue has practical consequences for forecast production. In an environment where there is a great deal of data uncertainty, there will be limited benefits in increasing model complexity. However, it is important to bear in mind that there are other sources of ex post uncertainty in real estate forecasts e.g. forecasts of explanatory variables.

For estimates of rental levels, there are both preventable and inescapable sources of data uncertainty. The former are caused by differences in market and corporate practices and can be reduced by a combination of co-operation and harmonisation. The latter are due to intrinsic attributes of real estate markets which tend to provide 'noisy' signals of market prices *inter alia*. In addition, there is unavoidable subjectivity in applying these 'noisy' signals from actual buildings to hypothetical buildings.

The data suggest that at the aggregate level and for many markets, there is substantial agreement on direction, quantity and timing of market change. However, there is substantial variability in the level of agreement among cities. Probably the most concerning finding is that the extent of disagreement on the direction of market change is high for many markets. This suggests that econometric models will produce much different specifications and forecast outcomes dependent upon choice of data.

Clearly there is scope for more in-depth analysis of data set. In addition, given the data set similar analyses can be performed for take-up/absorption, vacancy and capitalisation rates. Further work is needed to identify the effect of choice of data set on model specification and forecasts. To what extent do different data sets results in different explanatory variables, different coefficients (for common explanatory variables) and different forecast outcomes? It would also be interesting to explore the potential benefits to be gained from data pooling in the context of such disagreement.

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Summary Statistics: Disagreement in European Rental Trends 1990-2006

	Dispersion		Rental performance			Volatility			Market timing Correlation co-efficients		
	Mean MAPE		Mean Rental Growth p.a.			SD of Rental Growth					
	1990-2006	1996-2006	A	B	C	A	B	C	A-B	A-C	B-C
Vienna	6.3%	5.3%	-1.35%	0.60%	-0.50%	5.27%	7.21%	10.72%	0.60	**0.49***	0.59
Brussels	2.8%	2.6%	2.68%	2.39%	2.01%	7.58%	4.61%	6.99%	0.64	**0.44***	0.69
Milan	7.9%	4.0%	1.79%	1.81%	-0.01%	13.97%	11.30%	18.47%	0.75	0.84	0.87
Madrid	5.6%	3.8%	1.36%	0.29%	0.04%	20.06%	20.55%	22.76%	0.88	0.89	0.89
Berlin	5.1%	5.0%	0.66%	-1.22%	-0.50%	23.19%	15.44%	19.67%	0.86	0.75	0.72
Copenhagen	8.3%	5.1%	0.91%	0.54%	4.78%	3.74%	12.77%	11.97%	0.70	0.62	**0.37***
Athens	6.5%	6.1%	0.90%	1.72%	1.12%	7.19%	9.60%	16.32%	0.53	**0.46***	**0.42***
Dublin	4.3%	3.1%	7.19%	7.12%	7.06%	11.61%	14.51%	14.90%	0.80	0.86	0.79
Amsterdam	3.5%	3.4%	3.01%	3.60%	4.10%	6.93%	8.14%	9.02%	0.84	0.69	0.72
Lisbon	2.5%	1.9%	-2.13%	-2.80%	-3.13%	10.44%	9.80%	7.71%	0.80	0.91	0.84
Stockholm	6.8%	7.2%	2.13%	1.54%	0.74%	20.58%	19.92%	22.26%	0.96	0.85	0.88
London	4.6%	4.6%	4.19%	4.26%	4.05%	20.93%	20.31%	19.28%	0.95	0.95	0.91
Paris	2.4%	2.5%	0.80%	0.60%	1.14%	17.71%	12.80%	14.74%	0.97	0.92	0.94
Europe	5.1%	4.2%	1.70%	1.57%	1.61%	13.02%	12.84%	14.99%	0.79	0.74	0.74

* Not significantly different from zero at the 95% significance test

Vienna	1	2	3
A	53%	47%	0%
B	71%	18%	12%
C	0%	12%	88%

Brussels	1	2	3
A	53%	12%	35%
B	18%	53%	29%
C	53%	29%	18%

Milan	1	2	3
A	18%	41%	41%
B	12%	41%	47%
C	82%	12%	6%

Madrid	1	2	3
A	35%	47%	18%
B	6%	24%	71%
C	59%	29%	12%

Berlin	1	2	3
A	24%	53%	24%
B	65%	24%	12%
C	24%	18%	59%

Copenhagen	1	2	3
A	56%	44%	0%
B	6%	38%	56%
C	38%	19%	44%

Athens	1	2	3
A	15%	38%	38%
B	69%	8%	15%
C	8%	46%	38%

Dublin	1	2	3
A	47%	41%	12%
B	24%	35%	41%
C	29%	24%	47%

Amsterdam	1	2	3
A	24%	41%	35%
B	0%	47%	53%
C	76%	24%	0%

Lisbon	1	2	3
A	29%	29%	41%
B	18%	35%	47%
C	82%	18%	0%

Stockholm	1	2	3
A	6%	24%	71%
B	88%	12%	0%
C	12%	59%	29%

WE	1	2	3
A	71%	29%	0%
B	35%	24%	41%
C	12%	35%	53%

Paris (CW)	1	2	3
A	41%	41%	18%
B	24%	53%	24%
C	41%	6%	53%

Overall	1	2	3
A	36%	38%	26%
B	33%	32%	34%
C	40%	25%	34%