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Rationality and Momentum in Real Estate Investment Forecasts[*]

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Abstract

This study examines the rationality and momentum in forecasts for rental, capital value and total returns for the real estate investment market in the United Kingdom. In order to investigate if forecasters are affected by the general economic conditions present at the time of forecast we incorporate into the analysis Gross Domestic Product (GDP) and the Default Spread (DS). The empirical findings show high levels of momentum in the forecasts, with highly persistent forecast errors. The results also indicate that forecasters are affected by adverse conditions. This is consistent with the finding that they tend to exhibit greater forecast error when the property market is underperforming and vice-versa.

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Rationality and Momentum in Real Estate Investment Forecasts

1: Introduction

Despite the increased use of econometric modelling and forecasting in both an academic and institutional context over the last two decades, very few studies have considered how accurate forecasts of the real estate market actually are. This paper expands upon this limited literature to specifically examine whether professional forecasts commercial real estate display bias and whether display momentum over the course of the forecast horizon. A key area of research in the forecasting literature has been the examination of those factors that may lead to variations in the accuracy of forecasts provided due to the provision of non-rational forecasts. Empirical tests based on the rational expectations hypothesis generally examine whether predictions are rational, i.e. unbiased and efficient. This form of test postulates that as forecasters are paid to be accurate, the forecasts they produce represent their best estimates. However, this assumption invites further examination. In particular, is the forecast that maximizes the pay of an individual forecaster always the "*best*" forecast in a statistical sense?

Real estate provides an interesting context in which to consider the accuracy and biases present in forecasts. As a combination of a real and investment asset it combines elements from both the macro-economy and the capital markets. This is especially evident in the data that we use in our consideration of rationality and momentum in forecasts. We consider the issue using three alternative forecast series'; all provided by the UK based Investment Property Forum (IPF). These series comprise forecasts of Rental Growth, Capital Value Growth and Total Returns. The rental series may possibly display different characteristics as it will be more highly associated with the economic dynamics and demand-supply factors in the underlying occupier market. In contrast, the capital value and total return series' bring into consideration investor behaviour. The difference in the series' was highlighted by Matysiak et al. (2012) with vastly reduced forecast accuracy in the case of the capital and total return series'.

The model specifications used in the paper are based upon the framework of Holden & Peel (1990). This allows us to consider rationality and momentum in the forecasts as the year progresses. In addition, we examine whether forecasters are affected not only by their previous estimates but also by each other. We also incorporate measures aimed at capturing economic and property market conditions at the time the forecasts were made. The empirical results show that all of the forecasts (rental growth, capital growth and total returns) exhibit significantly high levels of momentum (above 90%). This finding would suggest that the variation in the forecast errors can be largely explained by their past values. However, with the capital value and total return forecasts some instances were found of forecasters displaying momentum in excess of 100%, indicating highly persistent forecast errors. In other words, property forecasters tend to base their forecasts on their previous evaluations. In contrast, forecasters are more confident of predicting the trend in rents. We find that forecasters tend to bias the rental growth forecasts as the forecasting horizon comes closer to the target year. The inclusion of macroeconomic variables such as Gross Domestic Product (GDP) and the default spread show that property forecasters are affected by poor economic conditions at the time of forecast, with the forecast error negatively related to GDP and positively with the Default Spread. This indicates that forecast error increases when GDP declines and when the Default Spread widens. The results also illustrate that forecast accuracy reduces when the property market is underperforming.

The remainder of the paper is structured as follows. Section 2 briefly considers some of the pertinent forecast accuracy literature. Section 3 provides details concerning the data utilised, whilst Section 4 discusses the methodological framework adopted applied in the study. Section's 5 and 6 respectively report the empirical results and provide concluding remarks.

2: Literature Review

Stekler (2007) and Hendry & Clements (2003) note several possible reasons as to why models may fail to provide accurate forecasts. These include; model mis-specification, the use of inaccurate data, characteristics of the individual forecasters and the presence of structural breaks that may affect the deterministic trend. For example, both Stock and Watson (1993) and Fintzen & Stekler (1999) note that series that had previously managed to capture anticipated economic downturns failed to do so for the 1990 recession in the United States. In addition to the above issues, Oller & Barot (2000) show that problems with data can also lead to large forecast errors. Furthermore, the characteristics and the behaviour of the individual forecasters are additional features that may affect forecasting performance. Gjaltema (2001) argues that forecasters are distinctive social entities with individual characteristics that interact in different sociopolitical contexts. This can therefore influence the forecast outcomes. Furthermore, Fintzen & Stekler (1999) argue that the manner in which individuals prepare their forecasts can affect their accuracy. One key behavioral element is that forecasters may deliberately '*bias*' their forecasts. There are a number of studies that have argued that forecasters may not necessarily attempt to maximize forecast accuracy and may be motivated by factors such as their reputation when they release their forecasts. (Ehrbeck & Waldman, 1996; Laster et al., 1999; Pons-Novell, 2003).

Batchelor & Dua (1991) observe that forecasters not only display conservatism in order to be closer to the consensus but that, more generally, they revise their estimates by less than are warranted by new information. Instead, they prefer to wait until later revisions of data are available before adjusting their models. The findings of Isiklar et al. (2006) support this, reporting that it takes forecasters more than five months to incorporate 90% of new information. In line with this finding is Nordhaus (1987), who provides direct evidence of forecast inertia, in that forecasters prevail with forecasts for longer than is warranted. This inference is drawn from an analysis of fixed-event forecasts of GDP growth, which shows that forecast revisions tend to be highly serially correlated. Batchelor (2007) argues that there are three possible reasons why forecasters may publish persistently biased forecasts. One is the lack of appropriate skills and the inability to efficiently incorporate new information. Forecasters may also fail to learn from past forecast errors and as a result they produce biased forecasts on an ongoing basis. The second reason is that forecasters may fail to differentiate between the changes in the target variable that are *permanent* and those which are *transitory*. Effectively, they may assign an equal weight to each component, resulting in biased forecasts. The third possible reason, as has already been noted, is the financial or reputational incentives that may lead to overly optimistic or pessimistic forecasts.

The real estate specific literature on forecast accuracy is remarkably limited, with the majority of it considering the same IPF data as used in the current paper, for example McAllister et al. (2008) and Matysiak et al. (2012). The McAllister et al. (2008) paper is somewhat constrained by only being able to analyze data up until 2004. In contrast, by examining data through to 2011 Matysiak et al. (2012) is are able to consider the issues at hand during the extreme market movements observed during the last cycle. Not only was the market correction in 2008 of a very large magnitude but the positive performance observed in the three years running up to 2007 was also of historically high levels. The results illustrate that forecasters display a tendency to under-estimate growth rates during strong market conditions and over-estimate when the market is performing poorly. This conservatism not only results in smoothed estimates but also implies that forecasters display herding behaviour. There is also a marked difference in the relative accuracy of capital and total returns versus rental figures. Whilst rental growth forecasts are relatively accurate, considerable inaccuracy is observed with respect to capital value and total returns. Bond & Mitchell (2011) also consider the IPF data, although in a different context. Their analysis compares the forecasting accuracy of the IPF Consensus Forecast for total returns versus implied forecasts derived from total return swap contracts. The results, interestingly, show that for a one-year horizon, the derivatives based implied forecasts display greater accuracy than the consensus professional forecasts for total returns. Ling (2005) is one of the only papers to have considered non-UK data, analyzing forecasts provided by the Real Estate Research Corporation (RERC) for the U.S. commercial market. The results indicate that the consensus opinions analyzed are backward looking and reveal little information in terms of subsequent performance[1].

3: Data

Since the late 1990's the U.K. Investment Property Forum (IPF) has surveyed a variety of property advisory firms, fund managers and financial institutions, asking them to provide forecasts of the U.K. commercial market. The benchmark reference points specified by IPF are the relevant annual indices for rental income, capital values and total returns as constructed by Investment Property Databank (IPD). The forecasts contain information up to a three-year ahead period on a quarterly basis, and are produced in February, May, August and November. This therefore results in twelve-quarterly forecasting horizons. For the purpose of this study we utilize the quarterly forecasts over the period 1999-2011, thus the maximum possible number of forecasts for each of forecasters is 156. In total 69 firms contribute forecasts to IPF over the 13 year period. The forecasters are relatively evenly split between property advisors (22), fund managers (26) and other financial institutions (21). However, the sample for each period and the number of observations for individual forecasts varies quite considerably. Due to the methodological framework adopted in this paper we only consider those forecasters that had a coverage ratio in excess of 50%. Therefore, given a maximum number of 156 forecasts this means that a minimum of 78 forecasts were required. As can be seen from Figure 1, only 20 forecasters had sufficiently large coverage ratios. Whilst this is a substantial reduction in the sample of individual forecasts it is necessary in order to avoid large numbers of missing values. It also does effectively reduce the sample to those organizations that regularly and consistently produce forecasts of the UK market.

The use of the quarterly forecasts provides us with a rich vein of data that allows us to consider how the forecasts of the three property variables change as the year progresses. However, the forecasts do have to be adjusted in one important respect. In addition to the Annual Index, IPD also produce equivalent indices on a monthly and quarterly basis. Whilst not identical in terms of the properties they cover, they are broadly similar to each other, the primary difference revolving around the frequency of the periodic valuation of the properties. Table 1 reports the composition by sector across the three indices. As one would expect, the number of properties reduces as the frequency of the index increase. However, the monthly and quarterly indices are broadly similar in terms of composition. The primary differences that are observable are that the relative weights for offices and industrial are slightly up as the frequency increases whilst those for retail and other sectors are down. Within each sectors the most evident difference in the far higher weight for shopping centers in the annual index.

Our interest centers on the issue that some relevant information has already been published, through the monthly and quarterly indices, during the year. If is therefore important that we account for the observed component from the forecasts and isolate the *pure forecast* for the remaining forecasting horizons of each one of the 13 target years. These unobserved forecast series are then converted to an annual basis, as the quarterly IPF forecasts that are used in this study are annualized growth rates of the rents, capital values and total returns.

Given that our forecasts are on a quarterly basis the preferred sub-annual measure of performance is the IPD Quarterly Index. However, the IPD Quarterly Index is only available from 2001; therefore quarterly data for the three variables is not available for the period from March 1999 to December 2000. Therefore, for this period we have to rely on figures obtained from the Monthly Index. The monthly figures are converted to a quarterly basis and expressed in annual terms as follows:

$$\tilde{\varphi}_t = \left(\frac{\varphi_t}{\varphi_{t-4}} - 1\right) * 100 \tag{1}$$

where φ_t represents the current monthly IPD value for each variable and φ_{t-4} is the value one quarter before. We isolate the estimated unobserved (*pure*) forecasts for the last three forecasting horizons of each target year from 1999 to 2011. The forecasting horizons are denoted with h. For the last three forecasting horizons, i.e. when $1 \leq h < 4$, the unobserved component of the forecast is mixed with the observed component, from either the monthly or quarterly IPD, for each target year. We estimate the pure forecast for the last three forecasting horizons, denoted as $\tilde{y}_{ith}$, as follows:

$$\tilde{y}_{i,t,h} = \frac{1+y_{i,t,h}}{\prod_{j=1}^{4-h}(1+X_{t,j})} \tag{2}$$

where $y_{i,t,h}$ is the forecast value which includes the observed component from the sub-annual measures, h horizons before the end of each target year t and for i number of forecasters. $X_{t,j}$ represents the quarterly observed (actual) IPD growth for the corresponding last three quarters $j = 1,2,3$. However, since the forecast values are expressed on an annualized basis, the pure forecast values $\tilde{y}_{i,t,h}$ have to be converted to an annual basis as well, as displayed in Equation (3):

$$\hat{y}_{i,t,h} = (1 + \tilde{y}_{i,t,h})^{\frac{4}{4-h}} - 1 \quad ; \quad 1 \leq h \leq 3, \tag{3}$$

where $\hat{y}_{ith}$ is the annualized value of the pure forecast, i.e. the forecast without the observed component of the IPD index.

The primary focus of this study is the examination of the rationality (i.e. bias and efficiency) of the forecasts as the horizon shortens when the target year approaches. In line with Holden & Peel (1990) and Lahiri & Sheng (2010) we test for rationality by analyzing the corresponding forecast errors, defined as the difference between the actual value, $X_{t,j}$, and the corresponding forecast value, $y_{i,t,h}$.. Following the notation of Equations (2) and (3), the forecast errors $e_{i,t,h}$ can be defined as follows:

$$e_{i,t,h} = \begin{cases} X_{tj} - \hat{y}_{i,t,h} & ; \quad h \geq 4 \\ \left[\frac{1+\tilde{y}_{ith}}{\prod_{j=4-h+1}^{4}(1+X_{t,j})}\right]^{\frac{4}{4-h}} - 1 & ; \quad 1 \leq h \leq 3 \end{cases} \tag{4}$$

where $\hat{y}_{ith}$ is the annual pure forecast value for i number of forecasters, when the forecast horizon is greater than three (i.e. h≥4). Additionally, $\tilde{y}_{i,t,h}$ is the quarterly pure forecast value for $1 \leq h \leq 3$ expressed in annual terms, whilst $X_{t,j}$ is the corresponding actual value j quarters before the end of each target t .In order to examine the bias and accuracy of the forecasts three-dimensional panels (i.e. forecasting horizons, forecasters, and target years) were utilized for the rental growth, capital growth and total return variables. The variable of interest is the forecast error. As previously noted, in order to minimize the issue of missing values the sample was limited to those forecasters that had a coverage ratio in excess of 50% during the 1999-2011 period. However, there were some periods, especially in the case of the two-year ahead forecasts, with missing values. Therefore, the following linear interpolation method was used:

$$e_{i,t,h} = (1-\lambda)e_{i,t,h-1} + \lambda e_{i,t,h+1} \qquad (5)$$

where $e_{i,t,h-1}$ represents the previous missing forecast error value and $e_{i,t,h+1}$ is the next non-missing forecast error value. Additionally, λ denotes the relative position of the missing value divided by the total number of missing values in a row. For example, in cases where there was one missing value between other two the λ was the simple average (i.e. λ=1/2). The number of observations obtained was 2,168, 2,157 and 2,136 for the rental growth, capital growth and total return series' respectively.

4: Model Specification

The methodological framework adopted in this paper is based on that proposed by Holden & Peel (1990), although modifications are made due to the nature of the data. The base specification can be expressed as below:

$$e_{i,t,h} \equiv X_{tj} - \tilde{y}_{i,t,h} = \tau + \varepsilon_{i,t,h} \tag{6}$$

where $e_{i,t,h}$ denotes the forecast error for *i* forecasters, *h* forecasting horizons and *t* target years. X_{tj} represents the actual value of the property variables with *j* denoting the quarters of each target year *t*. Additionally, $\tilde{y}_{i,t,h}$ is the corresponding forecast value of *i*=20 forecasters and *h* forecasting horizons before each target year *t* comes to the end. According to Holden & Peel (1990) the significance of the constant, τ in the equation (6), indicates biased forecasts. However, when multi-step forecasts are considered, as in the current piece of research, autocorrelation needs to be taken into account (Lahiri & Sheng, 2010). This is obviously an issue given the vast evidence illustrating the degree of smoothing in appraisal based real estate index data. For this reason, we include the lagged forecast error into the specification as follows:

$$e_{i,t,h} = a + \beta e_{i,t,h-1} + v_{ith} \tag{7}$$

We denote as $e_{i,t,h}$ the pure forecast error for *i* number of forecasters (i.e. twenty in our case), *h* number of horizons (i.e. *h*=12) and *t* number of target years (i.e. 1999-2011). Since the dataset was divided into forecasting horizons the forecast errors will be lagged dependent on the forecasting horizons. For that reason $e_{i,t,h-1}$, which is the horizon dependent forecast error, was included as an explanatory variable. Additionally $v_{ith} \sim$ i.i.d.$(0,\sigma^2)$ with zero mean and constant variance.

A further issue with the Holden and Peel (1990) methodology, as specified in Equation (6), is that it is based upon a static framework and does not include any lagged dependent variables. We therefore cannot test for bias by simply examining the significance of the constant "α" in equation (7). Instead we need to convert the dynamic AR(1) specification in Equation (7) into a static model in order to obtain the long-run equilibrium, the significance of which will determine bias. We follow the approach proposed by Chiang & Wainwright (2005) in order to convert the dynamic AR(1) model into a static model, as follows:

$$e_{i,t,h} = a + \beta e_{i,t,h-1} \tag{8}$$

$$e_{i,t,h} - \beta e_{i,t,h-1} = a \tag{9}$$

Rearranging equation (9) we have:

$$e_{i,t,h-1} - \beta e_{i,t,h} = a \tag{10}$$

Let us assume that $y_{t-1} = e_{i,t,h-1}$ and $y_t = e_{i,t,h}$ and that $-\beta = c$, in order that the transformation are consistent with the Chiang & Wainwright (2005) notation. Equation (10) can therefore be re-expressed as:

$$y_{t-1} + cy_t = a \tag{11}$$

The general solution of Equation (11), i.e. the 1st order difference equation, will consist of the sum of two components, namely:

1) the particular integral y_p, which is any solution of the complete no-homogeneous Equation (11) and represents the intertemporal equilibrium level of y

2) y_c which is the complementary function and is the solution of the reduced (homogeneous) Equation (11).

In order to find the solution of Equation (11) it is assumed that α=0:

$$y_{t-1} + cy_t = 0 \tag{12}$$

According to Chiang & Wainwright (2005) the y_c component represents the deviations of the time-path from the intertemporal equilibrium. Therefore, the solution is in the form $y_t = Ab^t$, where $Ab^t \neq 0$, as otherwise y_t will tend to be a horizontal straight line lying on the t axis. Hence, $y_{t-1} = Ab^{t-1}$. If these two values hold then the Equation (12) becomes:

$$Ab^{t-1} + cAb^t = 0 \tag{13}$$

After cancelling the nonzero common factor the above can be expressed as:

$$b + c = 0 \quad or \quad b = -c \tag{14}$$

From Equation (14) the complementary function can then be derived as:

$$y_c (= Ab^t) = A(-c)^t \tag{15}$$

After obtaining the complementary function y_c the next step is to define the particular integral (y_p) in order to obtain the complete solution for equation (7). Since the purpose of the Chiang & Wainwright (2005) methodology is to find the long-run equilibrium of equation (11) let us assume that $y_t = k$ (a constant) and also $y_{t-1} = k$. The substitution of these values into the equation (11) leads to the following:

$$k + ck = a, \; k = \frac{a}{1+c} \tag{16}$$

The particular integral can therefore be written as:

$$y_p(= k) = \frac{a}{1+c} \quad , \; c \neq -1 \tag{17}$$

Hence the long run equilibrium of the equation (11) is the following:

$$y_p(= k) = \frac{a}{1-\beta}, \; \beta \neq 1 \tag{18}$$

The unconditional mean of equation (7) can be expressed as follows:

$$E(e_{i,t,h}) = a + \beta E(e_{i,t,h-1}) + E(v_{ith}) \tag{19}$$

By taking the common factor of equation (19) and assuming that the long term mean of $e_{i,t,h}$ exists, this implies that $\lim_{h\to\infty} E\left(e_{i,t,h}\right) \triangleq e^{*}_{i,t,h}$. Therefore, by assuming that $E(\nu_{ith}) \to 0$, from equation (19) we can derive the long term mean of the dynamic model (7) as follows:

$$e^{*}_{i,t,h}(1-\beta) = \alpha, \qquad e^{*}_{i,t,h} = \frac{\alpha}{1-\beta} \tag{20}$$

The analysis of the momentum and bias in the forecasts is therefore achieved by the implementation of equation (7). Based upon the transformation of the AR(1) dynamic model in equation (11) into a static process, the new constant term of the panel regressions will not be the 'α' coefficient but rather $\frac{\alpha}{1-\beta}$ as displayed in equation (21):

$$E(e_{i,t,h}) = \frac{a}{1-\beta} \tag{21}$$

where $E(e_{i,t,h})$ is the expected forecast error with β coefficient being the momentum and $\frac{a}{1-\beta}$ is the constant for the three static models. Therefore, the methodological framework focuses upon the testing of the significance of $\frac{\alpha}{1-\beta}$. If this is significant then this implies that that forecasters tend to make biased forecasts as the forecasting horizon reduces as the target year approaches. The necessary condition for the long term mean to exist is that the forecast errors of the property variables are stationary process (i.e. $\beta<1$). In the case where $\beta>1$ they can be referred to as explosive time-series, meaning that the long-term mean cannot be defined and therefore that bias cannot be examined.

5: Empirical Results

5.1: Analysis of Bias and Momentum in Property Forecasts

The first component of the empirical analysis is to consider the results from the estimation of Equation (7). Given that a panel specification is adopted a number of issues need to be initially considered. Firstly, whether the lagged forecast error is included in the specifications as a common or variable (i.e. cross-section specific) coefficient. To assess this we apply a test of restriction based on the common *F-statistic* as shown in equation (22):

$$F_{test} = \frac{(RSS_R - RSS_U)}{RSS_U} \times \frac{n-k}{J} \tag{22}$$

where J is the number of restrictions, n is the number of observations and k the number of regressors in the unrestricted regression including the constant. For the rental growth, capital growth and total returns the number of observations was 2,168, 2,157 and 2,136 respectively. Additionally, the number of restrictions will be J=19 and the number of regressors in the unrestricted model will be equal to the number of forecasters, i.e. twenty. The null hypothesis of this test is that the restricted model is appropriate. The estimated F-statistics are 0.30, 0.94 and 1.00 for the rental, capital value and total return series respectively, none of which are significant at conventional levels. Therefore, as these findings indicate that the restricted model is appropriate, the lagged forecast error is inserted as a common coefficient for the three variables.

The second specification issue revolves around the choice of fixed or random effects. We consider the issue by applying the redundant fixed effects test, which has as its null that the fixed effects specification is not appropriate. In each case the F-statistic (1.03, 0.26 and 0.47) is not statistically significant for the rental, capital value and total return series'. These findings therefore are supportive of estimating the models without the inclusion of fixed effects. The pooled models therefore used to test for bias in the rental growth (RG), capital growth (CG) and total returns (TR) forecasts are as follows:

$$FE_{RG} = e_{i,t,h} = a + \beta e_{i,t,h-1} + v_{ith} \quad , \quad E(e_{i,t,h}) = \frac{a}{1-\beta} \tag{23}$$

$$FE_{CG} = e_{i,t,h} = a + \beta e_{i,t,h-1} + v_{ith} \quad , \quad E(e_{i,t,h}) = \frac{a}{1-\beta} \tag{24}$$

$$FE_{TR} = e_{i,t,h} = a + \beta e_{i,t,h-1} + v_{ith} \quad , \quad E(e_{i,t,h}) = \frac{a}{1-\beta} \tag{25}$$

Where β denotes the momentum coefficient for *i=20* forecasters. However, prior to the estimation of the models it is necessary to test whether the three variables are stationary as it is a necessary condition for the long-term mean $E(e_{i,t.h})$ to exist. We utilise the Levin et al. (2002) unit root test, the null hypothesis of which is the existence of a common unit root. We also use three alternative Fisher-type panel unit root tests where the null hypothesis is the existence of individual unit roots. The three unit root tests are the Im et al. (2003), Fisher Augmented Dickey Fuller and Fisher Phillips-Peron tests. The results from these are reported in Table 2. In the case of the rental growth series we can reject the null hypothesis of a unit root and can conclude that the forecast errors are stationary. However, this is not the case for either the capital value or total return series, where the null hypothesis of a unit root is not rejected, indicating, therefore, non-stationary forecast errors. This would as such imply the absence of a long-term mean for these forecasts. This has the implication that equations (24) and (25) cannot be used to test for bias in the forecasts of capital value or total returns.

Whilst the Holden & Peel (1990) test of bias cannot be applied in the case of the capital value and total return forecasts due to non-stationarity, it is of interest to present some results in order to illustrate why the non-stationarity issue arises. As can be observed in Table 3, both capital growth and total returns forecasts have highly significant common momentum, 0.98 and 0.99 respectively. In addition, when the lagged forecast error is include as a variable coefficient, as displayed in Panel B of Table 3, in six instances when capital value returns are considered, and eight in the case of total returns, the momentum coefficient is equal to or greater than unity. (i.e. $\beta \geq 1$), indicating explosive time-series. These findings imply that forecasters do not update their forecasts as the time horizon progresses, leading to a cumulative effect on the forecast errors (Lahiri & Sheng, 2010). The results may also be interpreted as implying that forecasters display less confidence in the prediction of capital values and total returns in comparison to the case with rental growth. Effectively, this phenomenon, the accumulation of forecast errors, causes the absence of a long term mean in the forecast errors of the capital values and total returns' forecasts. This in turn leads to the stationarity problems in the forecast errors and therefore prevents the formal empirical examination of bias.

Although we are unable to undertake the analysis of bias for all series we can in the case of the rental growth forecasts, where equation (23) can be implemented. We apply the Wald test (Wald, 1943) to test for the significance of the long term mean $\left(E(e_{i,t,h}) = \frac{a}{1-\beta}\right)$ and therefore for bias in the forecasts (Holden & Peel, 1990). These results are reported in Table 4 and it can be observed that there is highly significant momentum (90%) in the rental growth forecast errors. Additionally, the R^2 can be interpreted as signaling that 85% of the variation in the forecast errors is explained by the common momentum coefficient, i.e. the lagged forecast error. Regarding bias, forecasters tend to make biased forecasts as the forecasting horizon progresses. In other words they feel more confident for short-term forecasting periods and they tend to differentiate their rental growth forecasts from the consensus.

5.2: Behavioral Analysis of Property Forecasts

The second major component of the empirical analysis considers whether the behaviour of forecasters is affected by market conditions at the time the forecasts were made. We empirically address this issue through include in the specifications Gross Domestic Product (GDP) and the Default Spread (DS). GDP has been extensively used as a proxy for general economic conditions not only in the general forecasting literature (e.g. Batchelor, 2007; Lahiri & Sheng, 2010; Dovern & Weisser, 2011) but also in the dedicated real estate literature. The default spread, defined as the difference between the corporate yield and the 10-year government bond, is often used as an indicator of expected economic growth (e.g. Harvey, 1991). The rationale in this case is that a widening spread implies negative expectations about future economic performance In addition to its broader use, papers such as Seck (1996) and Ling & Naranjo (1997) have made use of the default spread as an explanatory variable in real estate specific papers.

Consequently we augment equations (23-25) with the two macroeconomic variables (GDP, Default Spread) as well as a dummy variable to capture long-term property market performance. To construct the dummy we use the average return of the respective IPD indices from 1981 up to the date of the forecast, thereby avoiding any retrospective bias. When the forecasted value is greater than the long-run average performance of the IPD index then the dummy variable takes the value of unity, otherwise zero. The results from the dummy variable can therefore be used to indicate whether forecasters are systematically affected by the relative conditions prevalent at the time the forecast was made. As the dependent variable is the forecast error, the sign of the coefficient will reveal behavioural elements in the forecasts. For example a negative sign would imply that forecasts tend to systematically underestimate, as when the forecasts overestimate returns, smaller forecast errors are observed. In contrast, a positive sign would indicate that when forecasters overestimate returns, forecast errors are higher.

As noted previously, the forecast errors of the capital value and total returns forecasts were found to be non-stationary, hence the inability to formally test for bias. In order to conduct the augmented tests of behaviour we take the first difference of the two forecast error series. As the results in Table 5 illustrate, all of the alternative unit root tests show that the first differenced series are stationary. To test whether the default spread and GDP should be included as common or as cross-sectional specific variables in the three specifications we run tests of restrictions. In all cases the test statistic is insignificant, indicating that the restricted model (i.e. common coefficients) is more appropriate. With the addition of the aforementioned dummy variable the final specifications can be displayed as follows:

$$FE_{RG} = e_{i,t,h} = a + \beta_i e_{i,t,h-1} + \gamma \Delta GDP + \delta DS + \zeta MD + v_{ith} \tag{26}$$

$$\Delta FE_{CG} = \Delta e_{i,t,h} = a + \gamma \Delta GDP + \delta \Delta DS + \zeta MD + v_{ith} \tag{27}$$

$$\Delta FE_{TR} = \Delta e_{i,t,h} = a + \gamma \Delta GDP + \delta \Delta DS + \zeta MD + v_{ith} \tag{28}$$

where ΔGDP is the logarithmic difference of the *GDP*, *DS* is the default spread at the time of forecast. As the forecast errors for the capital values and total returns were not stationary, the first differences of them (i.e. $\Delta e_{i,t,h}$), are used instead[2]. As the first differences are used as the dependent variable and therefore the lagged forecast errors are contained in the dependent (i.e. $\Delta e_{i,t,h} = e_{i,t,h} - e_{i,t,h-1}$) we do not include the lagged errors as an explanatory variable. Finally, MD is the property market dummy previously described[3].

To consider the most appropriate econometric framework we check the statistical properties of the errors. In particular, the errors for different cross-sections may have differing variances (panel heteroskedasticity) or may be correlated across the sections. On the one hand, if the disturbances of the equations of different cross-sections are contemporaneously correlated and heteroscedastic then the most appropriate econometric technique is a GLS estimation of SUR (Seemingly Unrelated Regression), which gives more efficient estimates than separate OLS estimates of each cross-section. On the other hand, in the presence of panel heteroscedastic errors, then Weighted Least Squares is the most appropriate method to obtain consistent estimates of the variance-covariance matrix. In order to check the evidence of heteroscedastic panel errors the Breusch-Pagan (1979) test for heteroscedasticity was applied to each of specifications. We also use the likelihood ratio test for cross-sectional stochastic dependence (Mouzakis & Richards, 2007) to test for the presence of cross-sectional correlation[4]. The null hypothesis of this test is that the disturbance terms of the different cross-sections are correlated. The results from both tests are reported in Table 6. It can be seen that the variance of the residuals is not constant as the null hypothesis of homoscedastic errors is strongly rejected. However, this is not the case for the likelihood ratio test where the null hypothesis of no cross-section stochastic dependence is not rejected. In other words, the disturbance terms of different forecasters are not correlated, therefore, the most appropriate estimation method is weighted least squares. The final preliminary tests are concerned with whether fixed-effects are used are not. The redundant fixed effects test was used and in each case the F-statistic was not significant at conventional levels, with values of 1.24, 0.71 and 0.72 for the rental, capital growth and total return series respectively. These findings therefore indicate that there is no need for the inclusion of fixed effects in any of the three specifications.

The results for the models detailed in equations (26-28) are reported in Tables 7 and 8. Table 7 reports the findings without the inclusion of the default spread, whilst the specifications modelled and reported in Table 8 do include the spread. The reason behind this was to see how much of the variation in the forecast errors can be explained by the addition of the default spread as an explanatory variable. The results are broadly consistent when the default spread is included, indeed they do not substantially differ across the three series. All of the independent variables are significant at conventional levels and the sign of the coefficients is consistent. GDP is found to be negative and significant, implying that forecast errors increase during worsening economic conditions. It is important to recognise that given the specifications used this does not necessarily relate to forecasts for periods when the economy was in recession. Rather, as the GDP figure is taken as that of the time of the forecast it actually can be interpreted that poor economic conditions may contribute to future inaccuracy. This can be seen it that a consideration of the raw data and based on the analysis in Matysiak et al. (2012), the worst performing one-year rental growth forecasts were for 2009. These findings are supported by the findings when the default spread is included in the analysis. The default spread is defined as the yield spread between corporate and 10-year government bonds. A wider spread implies deteriorating economic conditions as the markets are pricing increased default risk into the corporate bond market and yields. As noted previously, the default spread has been used extensively as an indicator of economic expectations. The default spread results support those of GDP, with a significant positive sign reported for each three series. This indicates that there is a positive relationship between the default spread and the forecast errors, thus, when the default spread increases, implying worsening economic expectations, forecast inaccuracy increases.

The results with respect to the capital growth and total returns errors are broadly consistent with the rental growth case. As already noted the first difference of the forecast errors were used as the dependent variables in the capital growth and total returns specifications. However, as the explanatory variables are also in first differences, the interpretation of the results is exactly the same as in the rental growth case. As with the rental series, GDP is negative and statistically significant, confirming that forecasts tend to become more inaccurate, i.e. display greater forecast error, when the economy is underperforming. The sign of the property market dummy is negative and significant. The interpretation of this finding does need to be carefully considered as the dummy is defined as taking the value of unity when the forecast value is greater than the historical average of IPD at the time of forecast, otherwise zero. The negative sign of the coefficient therefore implies that forecast errors tend to be lower when the series are forecasted as being less than their long-run average. However, if one considers the underlying data it is clear that forecasters tend to under-predict all three series as the total number of "*zeros"* is higher than the corresponding number of "one's", showing that forecasts tended to be lower than the historical average. This is despite the strong market conditions prevalent during the 2002-7 period. This does provide a degree of support for the view that forecasters tend to be conservative in their forecasts.

6: Concluding Comments

This study has examined the bias and momentum in forecasts of the UK commercial property market for up to three years ahead. A distinctive feature of this research is the introduction of a quarterly forecasting horizon that allows for the examination of the rationality of property forecasts as the forecasting horizon progresses. The first key finding is that the forecasts for all three series (rental growth, capital growth and total returns) display very high levels of momentum, meaning that the variation of the forecast errors can be explained in a large part by their past values. This is particularly evident in the case of the capital and total return forecasts, where the momentum coefficient was significant and above

0.98. Additionally, individual cases were noted where the momentum coefficients was in excess of unity, indicating an explosive time series. This implies that forecasters do not update their capital growth and total returns forecasts, relying largely upon their previous estimates. This would therefore help to explain the presence of highly persistent forecast errors. In addition, the results also imply that property forecasters tend to more accurately predict trends in rents rather than those in capital and total returns, supporting the analysis contained in Matysiak et al. (2012). Regarding the examination of bias in the property forecasts it was found that property forecasters tend to bias their rental growth forecasts as the forecasting horizon progresses. However, the Holden & Peel (1990) approach could not be applied for the capital growth and the total returns forecasts due to non-stationarity in the forecast errors.

In order to examine behavioural elements in the forecasting process, we incorporate GDP and the Default Spread into the specifications. The results show that forecasters tend to be affected by both the general economic and property market conditions at the time the forecasts are made. Specifically, the results indicate property forecasters tend to exhibit greater forecast errors when the market is underperforming and vice-versa. This issue is also confirmed by the positive sign of the default spread coefficient.

References

Batchelor, R. (2007). Bias in Macroeconomic Forecasts, *International Journal of Forecasting*, **23**, 189-203.

Batchelor, R. & Dua, P. (1991). Blue Chip Rationality Tests, *Journal of Money Credit and Banking*, **23**, 692-705.

Bond, S. & Mitchell, P. (2011). The Information Content of Real Estate Derivative Prices, *Journal of Portfolio Management*, Special Real Estate Issue, 170-181.

Chiang A.C. & Wainwright, K. (2005). *Fundamental Methods of Mathematical Economics*, 4th Edition, McGraw-Hill, International Edition.

Dechow P.M., Hutton A.P. & Sloan, R.G., (2000). The Relation Between Analyst Forecasts of Long Term Earnings Growth and Stock Price Performance Following Equity Offerings, *Contemporary Accounting Research*, **17**, 1-32.

Dickey, D.A. & Fuller, W.A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root, *Econometrica*, **49**, 1057-72.

Dovern, J. & Weisser, J. (2011). Accuracy, Unbiasedness and Efficiency of Professional Macroeconomic Forecasts: An Empirical Comparison for the G7, *International Journal of Forecasting*, **27,** 452-465.

Ehrbeck, T. & Waldmann, R. (1996). Why are Professional Forecasts Biased? Agency Versus Behavioral Explanations, *Quarterly Journal of Economics*, **111**, 21.40.

Fintzen, D. & Stekler, H.O. (1999). Why Did Forecasters Fail to Predict the 1990 Recession?, *International Journal of Forecasting*, **15**, 309-323.

Gjaltema, A. (2001). Judgment in (Population) Forecasting, *Paper presented at European Population Conference*, Helsinki 2001.

Harvey, C. (1991). The World Price of Covariance Risk, *Journal of Finance,* **46**, 111–157.

Hendry D. and Clements M. (2003). Economic Forecasting: Some Lessons from Recent Research, *Economic Modeling*, **20**, 301-329.

Holden, K. & Peel, D.A. (1990). On Testing for Unbiasedness and Efficiency of Forecasts, *The Manchester School*, **58**, 120-127.

Hong, H. & Kubik, J.D. (2003*).* Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts, *Journal of Finance*, **58**, 313-351.

Im, K.S., Pesaran, M.H. & Shin, Y. (2003). Testing for Unit Roots in Heterogeneous Panels, *Journal of Econometrics*, **115**, 53-74.

Isiklar, G. Lahiri, K. & Loungani, P. (2006). How Quickly do Forecasters Incorporate News? Evidence from Cross-Country Surveys, *Journal of Applied Econometrics*, **21**, 703-725.

Lahiri, K. & Sheng, X. (2010). Measuring Forecast Uncertainty by Disagreement: The Missing Link, *Journal of Applied Econometrics*, **25**, 514-538.

Laster, D., Bennett, P. & Geoum, I. (1999). Rational Bias in Macroeconomic Forecasts, *The Quarterly Journal of Economics*, **114**, 293-318.

Ling, D. (2005). A Random Walk Down Main Street: Can Experts Predict Returns on Commercial Real Estate? *Journal of Real Estate Research*, **27**, 137-154.

Ling, D.C. & Naranjo, A. (1999). The Integration of Commercial Real Estate Markets and Stock Markets, *Real Estate Economics*, **27**, 483-516.

McAllister P., Newell, G. & Matysiak, G. (2008). Agreement and Accuracy in Consensus Forecasts of the UK Commercial Property Market, *Journal of Property Research*, **25**, 1-22.

Matysiak, G., Papastamos, D. & Stevenson, S. (2012). *Reassessing the Accuracy of UK Commercial Property Forecasts*, Report for the Investment Property Forum.

Mouzakis, F. & Richards, D. (2007). Panel Data Modeling of Prime Office Rents: A Study of 12 Major European Markets, *Journal of Property Research*, **24**, 31-53.

Nordhaus, W.D. (1987). Forecasting Efficiency: Concepts and Applications, *The Review of Economics and Statistics*, **69**, 667-674.

Oller, E. & Barot, B. (2000). The Accuracy of European Growth and Inflation Forecasts, *International Journal of Forecasting*, **16**, 293-315.

Pierdzioch, C., Rulke, J.C. & Stadtmann, G. (2012). Housing Starts in Canada, Japan and the United States: Do Forecasters Herd?, *Journal of Real Estate Finance and Economics*, **45**, 754-773.

Pierdzioch, C., Rulke, J.C. & Stadtmann, G. (2013). Forecasting US Housing Starts under Asymmetric Loss, *Applied Financial Economics*, **23**, 505-513.

Pons-Novell, J. (2003). Strategic Bias, Herding Behavior and Economic Forecasts, *Journal of Forecasting*, **22**, 67-77.

Seck, D. (1996). The Substitutability of Real Estate Assets, *Real Estate Economics*, **24**, 75-95.

Stekler, H.O. (2007). The Future of Macroeconomic Forecasting: Understanding the Forecasting Process, *International Journal of Forecasting*, **23**, 237-248.

Stock J. and Watson M. (1993). A procedure for predicting recessions with leading indicators: econometric issues and recent experience, in Stock J. and Watson M., Business Cycles, Indicators and Forecasting, *National Bureau of Economic Research Studies in Business Cycles*, **28**, University of Chicago Press, pp. 95-156.

Wald, A. (1943). Tests of Statistical Hypotheses Concerning Several Parameters when the Number of Observations is Large, *Transactions of the American Mathematical Society*, **54**, 426-482.

Zarnowitz, V. & Braun, P. (1993). Twenty Two Years of the NBER-ASA Quarterly Outlook Surveys: Aspects and Comparisons of Forecasting Performance, *University of Chicago Press*, 11-94.

Tables & Figures

Table 1: Composition of the Annual IPD All Property Index

	Annual Index		Quarterly Index		Monthly Index	
	Capital Value (£m)	**% Capital Value**	**Capital Value (£m)**	**% Capital Value**	**Capital Value (£m)**	**% Capital Value**
All Retail	**68,464**	**48.8%**	**53,733**	**46.4%**	**15,547**	**44.4%**
Standard Retail (South East of England)	12,993	9.3%	11,705	10.1%	2,628	7.5%
Standard Retail (Rest of UK)	9,669	6.9%	9,383	8.1%	2,939	8.4%
Shopping Centers	22,871	16.3%	11,965	10.3%	2,078	5.9%
Retail Warehouses	22,931	16.3%	20,681	17.9%	7,903	22.5%
All Offices	**37,190**	**26.5%**	**33,613**	**29.0%**	**11,037**	**31.5%**
City of London	5,027	3.6%	4,639	4.0%	1,256	3.6%
West End of London	17,279	12.3%	14,211	12.3%	4,086	11.7%
Rest of South East of England	9,404	6.7%	9,748	8.4%	3,632	10.4%
Rest of UK	5,481	3.9%	5,015	4.3%	2,063	5.9%
All Industrial	**21,459**	**15.3%**	**19,784**	**17.1%**	**6,490**	**18.5%**
South East of England	13,679	9.7%	11,960	10.3%	3,678	10.5%
Rest of UK	7,780	5.5%	7,824	6.8%	2,811	8.0%
Other Property	**13,216**	**9.4%**	**8,621**	**7.4%**	**1,981**	**5.7%**
All Property	**140,329**	**100%**	**115,752**	**100%**	**35,055**	**100%**

Notes: Table 1 provides details of the composition of the Annual IPD All Property Index for the UK as of the end of 2013. For comparative purposes the equivalent information is provided for the IPD quarterly and monthly indices.

Figure 1: Coverage Ratio of the 69 Property Forecasters during the period 1999-2011

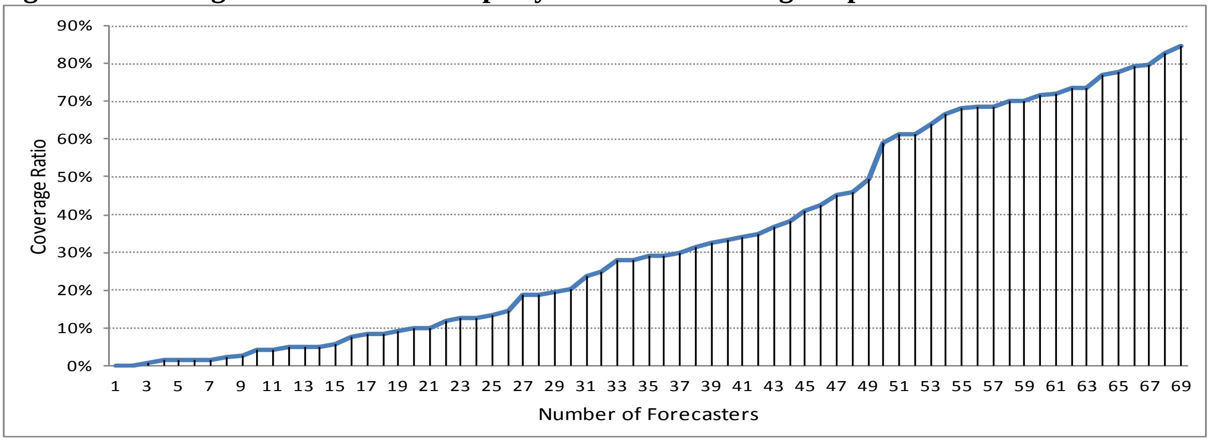

Table 2: Unit Root Tests for Forecast Errors

Variables	H_0 : (common unit root process)	Statistic	p-value
Rental Growth		-4.61	(0.00)
Capital Growth	Levin, Lin & Chu t*	2.18	(0.98)
Total Returns		2.57	(0.99)
Variables	**H_0 : (Individual unit root process)**	**Statistic**	**p-value**
	Im, Pesaran and Shin W-stat	-9.15	(0.00)
Rental Growth	ADF-Fisher chi-square	174.78	(0.00)
	PP-Fisher chi-square	127.92	(0.00)
	Im, Pesaran and Shin W-stat	0.38	(0.65)
Capital Growth	ADF-Fisher chi-square	34.87	(0.69)
	PP-Fisher chi-square	38.10	(0.55)
	Im, Pesaran and Shin W-stat	0.90	(0.81)
Total Returns	ADF-Fisher chi-square	32.65	(0.78)
	PP-Fisher chi-square	33.77	(0.74)

Note: Table 2 reports the panel unit root tests on the forecast error series.

Table 3: Momentum Tests for Capital Value Returns and Total Returns

Capital Growth		Total Returns	
Panel A: Common Momentum Coefficient			
Constant	0.002[a]	Constant	0.002[a]
Lagged Forecast Error	0.98[a]	Lagged Forecast Error	0.99[a]
Panel B: Variable Momentum Coefficient			
Constant	0.002[b]	Constant	0.002[a]
Forecaster 1	0.96[a]	Forecaster 1	0.95[a]
Forecaster 2	0.99[a]	Forecaster 2	1.00[a]
Forecaster 3	0.97[a]	Forecaster 3	0.98[a]
Forecaster 4	0.96[a]	Forecaster 4	0.96[a]
Forecaster 5	0.94[a]	Forecaster 5	0.95[a]
Forecaster 6	0.99[a]	Forecaster 6	0.99[a]
Forecaster 7	1.00[a]	Forecaster 7	1.00[a]
Forecaster 8	1.04[a]	Forecaster 8	1.04[a]
Forecaster 9	1.02[a]	Forecaster 9	1.03[a]
Forecaster 10	0.97[a]	Forecaster 10	0.98[a]
Forecaster 11	0.94[a]	Forecaster 11	0.95[a]
Forecaster 12	0.96[a]	Forecaster 12	0.92[a]
Forecaster 13	1.01[a]	Forecaster 13	1.02[a]
Forecaster 14	0.95[a]	Forecaster 14	0.96[a]
Forecaster 15	0.97[a]	Forecaster 15	0.98[a]
Forecaster 16	0.97[a]	Forecaster 16	0.98[a]
Forecaster 17	0.99[a]	Forecaster 17	1.00[a]
Forecaster 18	1.02[a]	Forecaster 18	1.01[a]
Forecaster 19	0.96[a]	Forecaster 19	0.98[a]
Forecaster 20	1.01[a]	Forecaster 20	1.00[a]

Note: “b” indicates a 5% level of significance and “a” 1% level of significance

Table 4: Tests for Bias and Momentum in the Rental Growth Forecasts

Momentum Analysis		Examination of Bias: $E(e_{i,t,h}) = \frac{a}{1-\beta}$		
Constant	0.002^a	X^2-stat.	DoF	*p-value*
Lagged Forecast Error	0.90^a	30.51	1	0.00
R^2=0.85, R^2-adj.=0.84				

Note: We denote with "a" 1% level of significance

Table 5: Unit Root Tests for First Differenced Capital and Total Return Forecast Errors

Variables	H_0 : (common unit root process)	Statistic	p-value
Capital Growth	Levin, Lin & Chu t*	-9.06	0.00
Total Returns		-10.24	0.00
Variables	**H_0 : (Individual unit root process)**	**Statistic**	**p-value**
Capital Growth	Im, Pesaran and Shin W-stat	-22.92	0.00
	ADF-Fisher chi-square	508.43	0.00
	PP-Fisher chi-square	504.85	0.00
Total Returns	Im, Pesaran and Shin W-stat	-24.38	0.00
	ADF-Fisher chi-square	538.07	0.00
	PP-Fisher chi-square	509.11	0.00

Note: Table 5 reports the panel unit root tests on the first differenced forecast error series'.

Table 6: Breusch & Pagan and LR Test Results

Panel A: Breusch & Pagan Test for Heteroskedatic Errors

	LM statistic	χ^2 p-value	Conclusion
Rental Growth	155.37	(0.0000)	Heteroscedasticity
Capital Growth	67.52	(0.0000)	Heteroscedasticity
Total Returns	72.81	(0.0000)	Heteroscedasticity

Panel B: LR tests for cross-section stochastic dependence

Variables	SUR (RSS)	OLS-WLS (RSS)	Log Likelihood	LL-ratio	Dof	χ^2 p-value	Conclusion
Rental Growth	5564.26	5594.64	30.38	60.75	105	0.99	Accept H_0
Capital Growth	4063.96	4065.28	1.31	2.64	105	1	Accept H_0
Total Returns	3994.53	4000.37	5.84	11.68	105	1	Accept H_0

Notes: The null hypothesis for the LR test is one of No Cross Section Stochastic Dependence

Table 7: Pooled Regression Results

	Rental Growth	Capital Value Returns	Total Returns
Constant	0.007[a]	0.012[a]	0.011[a]
	(0.0004)	(0.001)	(0.001)
GDP	-0.868[a]	-0.988[a]	-0.830[a]
	(0.053)	(0.125)	(0.134)
Lagged Forecast Error	0.903[a]	-	-
	(0.010)	-	-
Market Dummy	-0.010[a]	-0.024[a]	-0.023[a]
	(0.001)	(0.001)	(0.001)
Observations	2,168	2,156	2,136
R^2	0.87	0.16	0.13
R^2-adjusted	0.86	0.15	0.13

Note: “a” denote the 1% level of significance. The values in parenthesis (.) are the corresponding standard errors. All the models were estimated with the Weighted Least Squares method.

Table 8: Pooled Regression Results including the Default Spread

	Rental Growth	Capital Value Returns	Total Returns
Constant	0.006[a]	0.009[a]	0.009[a]
	(0.0007)	(0.001)	(0.001)
GDP	-0.868[a]	-0.662[a]	-0.547[a]
	(0.133)	(0.140)	(0.224)
Default Spread	0.069[c]	1.187[a]	1.057[a]
	(0.040)	(0.219)	(0.511)
Lagged Forecast Error	0.897[a]	-	-
	(0.009)	-	-
Market Dummy	-0.010[a]	-0.023[a]	-0.021[a]
	(0.001)	(0.001)	(0.001)
Observations	2,168	2,156	2,136
R^2	0.88	0.20	0.16
R^2-adjusted	0.87	0.19	0.15

Note: a ,b and c denote the 1%, 5% and 10% level of significance respectively. The values in parenthesis (.) are the corresponding standard errors. All the models were estimated with the Weighted Least Squares method.

Endnotes:

[1] Two recent papers by Pierdzioch et al. (2012, 2013) have considered forecast accuracy in the context of housing starts.

[2] In order to facilitate the interpretation we include in the capital value and total return specifications the first difference of the default spread.

[3] We also use the Lewis-Beck test for multicollinearity. The tolerance statistic for this test is $1-R^2$, with the rule of thumb being that only tolerance statistics lower than 20% are raise concerns about multicollinearity. In our case the tolerance statistic for each independent variable were 0.99 (lagged rental forecast error), 0.80(default spread) and 0.92 (GDP).

[4] It should be noted that this test was only applied to a sample comprising 15 out of the 20 forecasters. This is due the test requiring a balanced panel. The five excluded forecasters did not have sufficient observations.