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A Comparative Analysis of the Accuracy and Uncertainty in Real Estate and Macroeconomic Forecasts[*]

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Abstract

We compare and contrast the accuracy and uncertainty in forecasts of rents with those for a variety of macroeconomic series. The results show that in general forecasters tend to be marginally more accurate in the case of macro-economic series than with rents. In common across all of the series, forecasts tend to be smoothed with forecasters under-estimating performance during economic booms, and vice-versa in recessions We find that property forecasts are affected by economic uncertainty, as measured by disagreement across the macro-forecasters. Increased uncertainty leads to increased dispersion in the rental forecasts and a reduction in forecast accuracy.

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1: Introduction

The importance of the macro-economy on real estate markets cannot be understated. Its nature as a real, as well as investment asset means that real estate is very directly influenced by overall economic conditions and performance. The direct link via the demand for the asset from an occupier perspective means that measures of economic performance are key drivers of real estate, in particular rents. This is clearly illustrated by the extensive use of macro-economic variables in both industry and academic econometric models of rental markets[i]. The use of macro-economic data is especially important in a forecasting context[ii]. These close linkages provide the motivation and the points of interest for this paper. Using professional forecast data for both rents and a variety of macro-economic variables for the U.K. we compare the accuracy of the series'. Whilst a large literature has considered the accuracy of macro-economic series (e.g. Batchelor & Dua, 1991; Zarnowitz & Braun 1993; Laster et al. 1999; Oller & Barrot, 2000; Loungani 2001; Batchelor 2007; Boero et al. 2008; Campbell & Sharpe 2009), a relatively small number of papers have considered the accuracy of real estate forecasters (e.g. Ling, 2005; McAllister et al., 2008; Matysiak et al., 2012). We expand upon this literature to explicit compare and contrast the accuracy and uncertainty in both rental and macro-economic forecasts, allowing us to consider whether real estate forecasters share common characteristics with their counterparts in economics.

The second element of the empirical analysis extends upon the preceding to consider more explicitly the interlinkages between the two sets of variables. Given the use of forecasts of macro-economic variables in econometric models of real estate, how do the economic forecasts impact upon those of rents ? We consider a number of aspects in this respect including the impact on the accuracy in property forecasts in a causal sense. However, we can also consider whether increased uncertainty, as measured by increased disagreement across the macro-economic forecasters, also affects the accuracy and uncertainty in property forecasts. The remainder of this paper is organised as follows. Section 2 briefly reviews the pertinent literature. Section 3 provides details concerning the data analysed in this study. The following two sections contain the main empirical results. Section 6 provides concluding remarks.

2: Literature

Amongst the large forecasting accuracy literature only a relatively small number of papers have explicitly and in depth considered however inaccuracy and/or uncertainty in one set of forecasts potentially impacts upon another. The majority of papers have focused on either empirical tests of forecast accuracy or considered those factors and circumstances that may help to explain and contribute to differences in forecast accuracy. Hendry & Clements (2003) and Stekler (2007) note several possible reasons that may contribute to reduced forecast accuracy, including: model mis-specification, the use of inaccurate data, the characteristics of the individual forecasters and the presence of structural breaks that may affect the deterministic trend. It is of particular interest in the context of the current paper that they highlight the importance of data, as indeed do Oller & Barot (2000). One of the key propositions underlying our empirical analysis is to consider whether heightened inaccuracy and uncertainty in the macro-economic forecasts has a corresponding impact upon the property forecasts.

In addition to the above elements it is also important to note how behavioural issues surrounding the individual forecasts may affect accuracy. Fintzen & Stekler (1999) note that the manner in which forecasts are prepared may affect their accuracy, whilst Gjaltema (2001) argues that forecast outcomes may be influenced by the distinct and individual characteristics of the forecasters. Furthermore, a number of studies have noted how factors such as forecaster reputation may lead to forecasters not solely concentrating on accuracy and thus deliberately biasing their forecasts (Ehrebeck & Waldman, 1996; Laster et al., 1999; Pons-Novell, 2003)[iii]. Batchelor (2007) argues that there are three key reasons as to why forecasters may persistently produce forecasts that are biased. The first relates to a lack of appropriate skills and a corresponding inability to efficiently incorporate new information. Forecasters may also fail to learn from past forecast errors, thus produce biased forecasts on an ongoing basis. The second reason is that forecasters may fail to differentiate between *permanent* and *transitory* changes in the target variable. Finally, financial or reputational incentives may lead to overly optimistic or pessimistic forecasts.

Generally the importance of judgemental overlays is a key issue in the resulting accuracy of forecasts. As we are dealing with a dynamic process, forecasters have to use their judgment during the entire process. A wide array of papers has highlighted the importance of judgmental adjustments on the predictive accuracy of econometric models (e.g. McNees, 1990; Donihue, 1993). There is empirical evidence (e.g. Lahiri & Sheng, 2010a) illustrating how individual judgment can contribute to forecast uncertainty and in turn accuracy. Batchelor (2007), over the sample period 1990 to 2005, documented the presence of systematic bias in real GDP, and to a lesser extent in inflation forecasts in some of the G7 economies. Specifically, he found that when GDP had been falling in Japan, Italy, Germany and France, forecasters tended to smooth their forecasts. The result being an upward bias, with overly optimistic predictions of economic performance. In contrast in the remaining countries (Canada, U.K. and U.S.) where GDP did not fall, the same bias was not observed. A similar result was also noted by Ager et al. (2009) specifically with respect to Germany and Italy. More generally Jonung & Larch (2006) find that over-optimism is a distinctive feature in macroeconomic forecasts for European countries such as Italy and France, though not in the UK. In addition, papers such as Zarnowitz & Braun (1993) also support the finding that there is a tendency to overestimate growth rates when the market underperforms and vice-versa.

Lahiri & Sheng (2010b), in their examination of the G7, report evidence that indicates that inflation forecasts are more accurate in comparison with those for GDP. They find that in comparison with GDP, inflation forecasters: i) produce more accurate forecasts with smaller forecast errors), ii) disagree to a lesser extent and iii) revise their forecasts much earlier in comparison with those for real GDP forecasts. Consistent with these findings is the study of Dovern & Weisser (2011) who examined rationality (i.e. the level of bias and efficiency) in a variety of macroeconomic forecasts for the G7 countries. They find that individual forecasters who accurately predict real GDP growth are also likely to perform well in forecasting other macroeconomic variables. Furthermore, consistent with previously cited work, they tend to smooth GDP forecasts. In contrast, the forecasts of inflation are unbiased.

In contrast to the large number of papers to have considered the performance of macro-economic forecasters, the number to have examined the issue in the context of real estate is limited. This is despite real estate sharing many of the same behavioural characteristics with macro-economic series, and certainly more in comparison to equities. In particular, real estate data has long been recognized to display smoothing, a characteristic which contributes to reduced volatility in comparison with exchange traded assets such as stocks. The nature of the forecasting process also differs with an increased emphasis on overall market conditions and trends in contrast to estimates of individual company performance. Therefore, in many respects a greater parallel exists with the forecasting literature to have considered the accuracy of macro-economic series rather than the literature concerning stocks.

The real estate forecasting literature can be broadly sub-divided into two. The first group of papers is those to have explicitly forecast the asset or to have compared the performance of different forecasting approaches. The second group is that which has specifically considered the performance of professional-published forecasts, a literature that is extremely limited. The majority of this literature has considered the same U.K. data as analysed in the current paper. The McAllister et al. (2008) paper reveals a number of interesting elements, specifically evidence that herding is a common characteristic. The paper is however constrained by only being able to consider data up until 2004. It therefore misses both the extreme positive market conditions through 2005-6 and the subsequent market correction in 2007-8.

By examining data through to 2011 Matysiak et al. (2012) are able to consider the issues at hand during the extreme market movements observed during the last cycle. Consistent with the previously discussed evidence from macro-economic series', the property 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. The authors present a number of possible reasons as to this heightened inaccuracy including; i) a failure to fully capture the impact of low yields and the non-linearity of the yield-capital value relationship; ii) increased difficulty in accounting for investor behaviour in capital values; iii) bias resulting from a confusion of modelling fundamental values rather than actual market conditions irrespective of any perceived irrationalities felt to be present. In addition, the authors also note that the findings may also indicate that forecasters in real estate may simply be better at predicting rents due to enhanced awareness and expertise in the behaviour of underlying occupational market fundamentals. The poor forecasting ability displayed when total returns are considered is also noted in the Bond & Mitchell (2011) paper. They compare the accuracy of the IPF (Investment Property Forum) 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 published consensus forecasts for total returns. Ling (2005) is one of the only papers to have considered non-U.K. data. The results based on forecasts provided by the Real Estate Research Corporation (RERC) for the U.S. commercial market, indicate that consensus forecasts are backward looking and reveal little information in terms of subsequent performance.

3: Data

The data used in this study is provided by the Investment Property Forum (IPF), a UK based industry body, whilst the macro-economic forecasts are obtained from Consensus Economics. We analyse one-year forecasts from 1999 (for 2000) through to 2010 (for 2011). The sample period is determined by the availability of the property forecasts. Since 1999 the IPF has collected professional forecasts of the U.K. commercial property market from a variety of fund managements, financial institutions and property service and research firms. The reference points specified by the IPF are the returns for the 'All Property' annual indices for rents, capital values and total returns produced by IPD (Investment Property Databank). For the purposes of this analysis we solely consider the rental growth forecasts. The reason for this is two-fold. Firstly, both McAllister et al. (2008) and Matysiak et al. (2012) provide a comparative analysis of the relative accuracy of the three series. As noted previously, it is evident, especially in the Matysiak et al. (2012) piece that forecast accuracy significantly differs when capital and total returns are considered. Secondly, the importance of macro-economic forecasts is more direct and relevant in the context of rents. The importance of economic conditions is heightened when the occupier market is considered. The total number of forecasters that have contributed to the IPF dataset is 69, comprising of 22 property advisors, 26 fund managers and 21 other financial institutions. The U.K. macro-economic data used is obtained from the Consensus Economics forecasting service and are the one-year-ahead forecasts for GDP, Consumer Spending, Inflation (RPI), and the Unemployment Rate. Consensus Economics obtain the data from a variety of organisations including banks, consultancy firms, research institutes, corporations, and universities. In total 70 organisations have contributed to the dataset over this period.

The descriptive analysis for both the property and macroeconomic forecasts is conducted on the entire sample. In order to assess the accuracy of the forecasts, we use the following measures: the Mean Absolute Error (MAE), the Mean Squared Error (MSE), and the Root Mean Squared Error (RMSE), all of which are commonly used in the forecast accuracy literature (e.g. McNees, 1986; Makridakis et. al., 1998; Clements et al., 2007; Lenten, 2012). In each case the smaller the value, the higher the degree of accuracy. The MAE can be defined as:

$$\mathrm{MAE} = \sum_{i=1}^{n} \frac{|e|}{n} \tag{1}$$

where, e is the forecast error that is the difference between the actual and the forecast value, $e_t = A_t - F_t$; and n is the number of the forecasting periods. The MAE measure therefore avoids offsetting effects from large positive and negative errors. The MSE overcomes the same issue by squaring the forecast error rather than taking the absolute error. In addition, by taking the square of the forecast error, this measure more heavily penalizes the forecasts with large errors.

$$\mathrm{MSE} = \sum_{i=1}^{n} \frac{e^2}{n} \tag{2}$$

The final measure is the RMSE that is the square root of the MSE, thereby returning it to the same unit of measurement. The RMSE can be displayed as follows:

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{e^2}{n}} \tag{3}$$

4: Measures of Forecast Accuracy

4.1: Preliminary Forecast Performance Measures

Table 1 displays the primary summary statistics for the five different one year forecasts. The table reports both the actual and simple average consensus forecast together with statistics concerning the range and dispersion of the individual forecasts. To complement this data Figure 1 graphically illustrates the overall performance of the series in question and the respective consensus forecast. A number of elements are clearly evident from this initial examination. Firstly, it is apparent that in each case, both property and macro-economic forecasters have a tendency to underestimate the series in question during outperforming periods. Secondly, the forecasts tend to be smoothed when the volatility of the series' are compared with the time-series behaviour of the actual outcome.

With respect to the first point it can be seen that rental growth was consistently underestimated during the 2004-7 period which saw sustained strong percentage increases in the IPD rental index. Indeed, across the entire sample only in 2001 do we observe overestimation of rental growth in strong market conditions when the consensus was 4.50% in contrast to the achieved percentage change of 3.60%. This tendency for under-estimation is also observed with three of the macro-economic series, namely GDP, Consumer Spending and inflation. For GDP and Inflation there is likewise only one year when positive percentage change in the actual series' was overestimated by the consensus, 2005 for GDP and 2002 for Inflation. In the case of Consumer Spending both 2005 and 2006 were exceptions. The unemployment rate series is slightly different, primarily due to the difference in its composition in that a high figure actual depicts worse rather than better economic conditions. However, the tendency to underestimate and be conservative on positive conditions, in this case lower unemployment, is also evident. Up until 2008, in only 2005 is the consensus forecast of the U.K's unemployment rate lower than that which was achieved.

This conservatism in forecasts, and the avoidance of *big* or *bold* forecasts, can be considered in the context of the behavioural considerations discussed earlier in the paper. Scotese (1994) argues that forecasters seek to avoid sudden and large adjustments in order to try and maintain their reputation and credibility. In the specific context of strong conditions an additional factor that may play a role in the provision of conservative forecasts is that the forecast error will be positive. Therefore, the 'better than expected' eventuality has a positive impact on sentiment about economic conditions and the forecast error associated is lost in the optimistic message. However, this conservatism is not only evidence during periods of strong economic performance. Studies such as Zarnowitz & Braun (1993) have noted how forecasters can have a tendency to make systematic errors, overestimating during downturns and underestimating during periods of economic growth. This over-estimation and positive bias of growth in poor conditions was also observed in 2008 and 2009 and the worsening economic conditions following and associated with the financial crisis. Across the different series the impact of the financial crisis and the economic contraction that followed was underestimated, the recovery observed in 2010 in many of the series, was not picked up.

This conservatism results in the forecasts being smoothed, an impact that be can be illustrated if one compares the time-series standard deviations of the consensus forecast with the actual results. As reported in Table 1, for all of the series, with the exception of the Unemployment Rate, the volatility of the actual series is greater, and in some cases substantially so, than that of the respective consensus forecast. For example, with respect to the rental data, the standard deviation of the consensus forecast is 3.40% in comparison 3.82% for the actual IPD index. For GDP the difference is more marked, 0.99% (consensus) in comparison to 2.33% (actual). It is interesting that the difference, and therefore the degree of smoothing, is smaller with the rental series than with GDP, Consumer Spending or Inflation[iv].

The avoidance of large numbers and the resulting forecast smoothing also implies that forecasters prefer being close to the consensus (Scotese, 1994; Batchelor & Dua, 1991). This literature implies that forecasters are not only conservative in order to be closer to the consensus but that, more generally, they revise their estimates by less than warranted by new information. Table 1 provides information concerning the range and dispersion of the individual forecasts. With the exception of the Unemployment Rate, when in only three years was the actual rate outside the range of any of the individual forecasts, for the remaining macro-economic forecasters this occurred in at last half of the years. In the case of inflation the actual rate of inflation observed was outside the range of individual forecasts in eight years. Consistent with some of the previous evidence, it would appear there is to some extent greater accuracy, certainly with respect to the dispersion observed in the rent forecasts. In only five of the twelve years was the percentage rate of rental growth outside the range of individual forecasts provided, less than in all of the macro series with the exception of the rate of unemployment.

Table 1 and Figure 1 do provide some preliminary evidence as to the relative accuracy of the different series over time. They do illustrate that in most cases, as would be expected, the greatest observed divergence, or inaccuracy, was in the aftermath of the financial crisis. However, from Figure 1 it is noticeable that in comparison to GDP, Consumer Spending and Inflation, the Rent forecasts were more accurate during the immediate worsening of conditions in 2008 and 2009. In contrast, property forecasters had their 'worse' performing year in 2010 when they failed to predict and forecast the bounce back in the market. To expand upon these initial findings Table 2 reports the four key measures of forecast accuracy; Mean Forecast Error (MFE), Mean Absolute Error (MAE), Mean Square Error (MSE) and the Root Mean Square Error (RMSE). Figure 2 graphically compares and contrasts the accuracy of the property and macroeconomic forecasts based on their corresponding RMSEs for the same target years. Both Table 2 and Figure 2 confirm the previous findings in that the rent forecasts displayed the least accuracy in 2010 when they failed to predict the recovery in the

U.K. market. This was also true with respect to the Unemployment Rate forecasts which predicted a continuation in the rise in unemployment, whereas in fact it marginally fell in 2010. However, for the remaining macro-economic series the year of heightened inaccuracy was either 2008 or 2009 when the extent of the economic downturn was under-estimated.

What is clear, especially when graphically depicted in Figure 2, is that the property rent forecasts are relatively less accurate than all of the macro-economic series in the majority of years. In 9 out of the 12 years the property forecasts exhibit greater RMSE's than all of the macro-economic ones. The only exceptions are 2007 (inflation), 2009 (GDP and inflation) and 2011 (GDP, consumer spending and inflation). In every other case the RMSE's for the rent forecasts are greater. This result does however have to be viewed in light of the caveat that the rental data itself is more volatile and sees a greater range of variables. The IPD index for rental growth sees actual annual returns across a range of -7.90% to +7.40% over the twelve year period. This is a far greater variation than observed with the macro-economic series.

4.2: Comparative Performance of Forecasts

To further consider the accuracy and performance of the forecasters we calculate both the correlation between the consensus forecasts and the eventual actual result obtained and also use Theil's U2 statistic to compare the performance against two alternative naive forecasts. Table 3 reports the simple correlation coefficients between the one year forecasts and the actual outcome. In each case the correlation is statistically significant. The property forecasts have a correlation of 0.7417 with the resulting rental growth reported by IPD. Whilst lower than the corresponding coefficients for GDP, Consumer Spending and Unemployment, all of which are in excess of 0.8, the correlation with respect to rents does indicate greater forecast accuracy in comparison to inflation forecasts. This highlights the point made earlier concerning first viewing of the forecast accuracy measures. Of the five series the inflation forecasts perform the weakest. The correlation with actual RPI is 0.5344 and this is only marginally significant at a 10% level.

For the analysis of the naive forecasts we use Theil's U2 statistic (Theil 1966;1971) which can be represented as follows:

$$\text{Theil's U2} = \sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{F_{t+1}-Y_{t+1}}{Y_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{Y_{t+1}-Y_{t+1}}{Y_t}\right)^2}} \tag{4}$$

where, *F* is the forecast, and *Y* is the observation. Therefore, the U2 statistic can be interpreted as dividing the RMSE of the given forecast by the RMSE of the no-change naive forecast. Hence, the statistic provides the basis for comparing alternative forecasts relative to a naive forecast. If the Theil's U2 has a value less than one, then the forecasts are better than those obtained by using a naive forecast. If the Theil's U2 has a value equal to one, then the forecasts add nothing. Therefore, the naive estimate is just as effective. If the value is greater than one, then the naive forecast can be interpreted as having outperformed the consensus forecasts.

Two alternative naive forecasts are assumed as a basis of comparison. The first naive forecast assumes that the following year's outcome is equal to the current year's outcome. This is effectively a forecast of "*same again*". The second naive forecast uses the long-term average up to the date of the forecast. For example, for rental growth forecasts made in 2002 for 2003, the second naive uses the long-term average growth rates of the IPD index up to 2002. This approach avoids the potential bias from the use of subsequent data that might be incorporated into the averages' figures. The same approach is used with each of the respective reference indices or series'. The results are displayed in Table 4 and do in the main provide positive evidence as to the ability and accuracy of forecasters in the real estate market. The first naive is more accurate than the consensus published forecast in five of the twelve years. In the case of the second naive the corresponding figure is six years. Therefore, the forecasters outperform the naive in at least half of the target years. Of particular interest is that with the exception of the second naive in 2010, all of the years when the naive forecasts outperformed and displayed greater accuracy were during the strong market pre-2007. This reaffirms our previous comments and findings regarding forecast conservatism often being heightened during strong economic conditions. At the time the forecasts actually matter, i.e., during the difficult post 2007 period, in the majority of cases the forecasters outperformed.

These findings also need to be viewed in light of the findings with respect to the macro-economic series'. The rent forecasts perform in a comparable manner against their naive's to those for GDP and Consumer Spending. Both of the naive forecasts outperform the

GDP forecasts in seven of the twelve years whilst for Consumer Spending the forecasts did worse in six and five years against the two naive's respectively. As with the property forecasts the majority of the under-performance versus the naive's came pre-2007. With regard to the Inflation and Unemployment Rate forecasts there is a marked difference in relative accuracy between the two alternatives. Naive 1, based on the previous year's actual figure performs very well, whilst the second naive, the long-run average, performs noticeably poorly. The first naive outperforms in seven and ten years against the forecasts for inflation and unemployment. This would indicate that certainly with respect to Unemployment a simple forecast based on the previous year's figures will outperform more elaborate estimates. In contrast, figures based on the long-run historical average rarely perform better than the professional forecasts, in only two and one years for inflation and unemployment respectively. However, given the major structural changes in the last twenty years in both inflation and unemployment levels this degree of inaccuracy based on long-term averages is hardly that surprising.

5: Interactions between Macroeconomic and Property Forecasts

The second key issue that this study address' is the examination of the relationship between the property and macroeconomic forecasts. The rationale in this respect is two-fold, although both issues are based on the importance of underlying economic conditions on the occupier market and therefore rents. In the first instance there will be potentially common factors driving both the economic and property variables. Secondly, the explicit use of macro-economic forecasts in the estimation of forecasts for the real estate sector may mean that variation in relative accuracy in the macro-economic forecasts feeds through into those for rents. We consider the issue in two ways. The first tests for casual relationships across the different forecasts whilst the second considers the impact of variation in the macro-economic forecasts on both uncertainty and accuracy in the rent forecasts.

5.1: Granger Causality Tests

In the case of the Granger Causality tests we adopt a Vector Autoregression Analysis (VAR) framework. We assesses the interactions among the rental growth forecasts with the corresponding forecasts for GDP, Consumer Spending, Inflation, and Unemployment. All of these forecasts are on a quarterly basis for the sample period of 1999 to 2011. This basis results in 47 one-year-ahead forecasts. The VAR specification that is used can be written as follows:

$$
\begin{aligned}
y_{j,t} &= \beta_j + \sum_{i=1}^{\rho} \gamma_{j,t-1} y_{j,t-1} + \sum_{k=1}^{4} \sum_{i=1}^{\rho} \alpha_{j,k,t-i} z_{k,t-i} + u_{j,t} \\
z_{k,t} &= \mu_k + \sum_{\substack{m=1 \\ m \neq k}}^{4} \sum_{i=1}^{\rho} \varphi_{m,,t-i} z_{m,t-i} + \sum_{i=1}^{\rho} \delta_{j,t-1} y_{j,t-1} + u_{k,t}
\end{aligned} \tag{5}
$$

where, $y_{j,t}$ denotes the forecasts for j=1,2,3 property variables. The $z_{k,t}$ are the forecasts for the four macroeconomic variables where $\{\mathrm{z_k}\}_{\mathrm{k=1}}^{4}$ represents respective macro-economic series for t-i quarters, and u_{1t} and u_{2t} are white-noise disturbances. The maximum lag length i, is determined by the minimisation of the multivariate versions of the information criteria such as Akaike (1974) and Schwarz (1978). These criteria can be defined as follows:

$$
MAIC = \log\left|\hat{\Sigma}\right| + {2k'}/{T} \tag{6}
$$

$$
MSBIC = \log\left|\hat{\Sigma}\right| + \frac{k'}{T}\log(T) \tag{7}
$$

where, $\hat{\Sigma}$ denotes the variance-covariance matrix of the residuals, T is the number of observations, and k' is the total number of independent variables in all equations. The rationale behind basing the analysis on Granger causality tests (Granger, 1969) is that there exists the possibility that when estimating a VAR that includes many lags of the variables, it might be difficult to distinguish which sets of variables have significant effects on each dependent variable and which do not. The use of Granger causality tests allow a clearer analysis of which the macroeconomic forecasts affect the property forecasts and vice versa.

This analysis uses the quarterly one-year-ahead property and macroeconomic forecasts for the period of 1999 to 2011. This sample results in 47 one-year-ahead forecasts. The analysis applies the VAR models as seen in Equation (5). The structure of the system incorporates feedback because $y_{j,t}$ (property forecasts) and $z_{k,t}$ (macroeconomic forecasts) are allowed to affect each other. For instance, $\alpha_{j,k,t-i}$ is the contemporaneous effect of a unit change in $z_{k,t-i}$ on $y_{j,t}$, and $\delta_{j,t-i}$ is the effect of a unit change in $y_{j,t-i}$ on $z_{k,t}$. The determination of the optimal lag length i is achieved by the minimisation of the multivariate versions of the Akaike (1974) and Schwarz (1978) criteria as seen in Equations (6) and (7). Before applying the VAR methodology, it is important to ensure the stationarity of the variables, we therefore use the Augmented Dickey-Fuller (ADF) test (1981). The results are reported in Table 4 and demonstrate that both the property and macroeconomic one-year-ahead forecasts are integrated by an order of one. For that reason, these forecasts are included in VAR system as first differences. The optimal lag length that minimises the Akaike and Schwarz criteria is four quarters before the time of the forecast.

Table 6 reports the findings from the Granger Causality tests. The findings shows that the one-year-ahead forecasts for Inflation and Unemployment significantly affect the rental growth forecasts. If one examines the underlying coefficients from the VAR system it can be seen that inflation and unemployment are negatively and positively related with the corresponding rent forecasts. Inflation is generally a key variable, significantly causing GDP and Consumer Spending as well as rental growth. It is also noticeable that there is a significant bilateral relationship between the Unemployment Rate and Consumer Spending. As would somewhat be expected there isn't however any evidence of the Rent forecasts significantly impacting upon those for the macro-economic series'.

5.3: The Impact of Economic Uncertanity

The last component of the empirical analysis investigates whether uncertainty in the macroeconomic forecasts affects uncertainty in the property forecasts and in turn if this uncertainty contributes to heightened inaccuracy in the rent forecasts. We follow recent studies in measuring uncertainty through the cross-sectional variance of the forecasts (e.g. Giordani & Soderlind 2003; Lahiri & Sheng, 2010a). Based on these annual measures of dispersion/disagreement as a proxy for uncertainty we then regress these on a similar measure of uncertainty in the rent forecasts. The regressions have the following form:

$$VAR(Y)_t = \alpha + \beta VAR(Z)_t + u_t \tag{8}$$

where, $Var(Y)_t$ denotes the current quarterly cross-sectional variance in property forecasts, $Var(Z)_t$ is the current quarterly cross-sectional variance in the relevant macroeconomic forecast and u_t is a white-noise process. These regressions enable us to consider whether uncertainty in macroeconomic forecasts at time t affects the dispersion in property forecasts at the same time. These regressions based on the quarterly cross-sectional variances. We estimate the models twice, once using the contemporaneous proxies of uncertainty and once with the independent variables lagged. The optimal lag length in the variance of macroeconomic forecasts is determined by the minimisation of the Schwartz Bayesian Criterion (SBC). The optimal lag is one quarter.

The results, reported in Table 7 clearly illustrate that the uncertainty in macroeconomic forecasts is positively related with the uncertainty in property forecasts. In other words, the greater the degree of disagreement across the forecasts of the macroeconomic forecasts, the greater the corresponding dispersion in the property forecasts. With the exception of Consumer Spending, significant positive coefficients are reported for the macro-economic series', both when contemporaneous and lagged measures are used. However, the R^2 clearly has greater explanatory power from contemporaneous uncertainty than from that lagged one-quarter. The results of the regression analysis disclose evidence that property forecasters are indeed affected by the current and the previous-quarter economic conditions at the time of their forecasts. In other words, increased uncertainty surrounding economic conditions, as proxied through the dispersion of the macroeconomic forecasts' does contribute to an increase in the disagreement shown and reported across the rent forecasts.

This analysis can then be extended to consider whether this increased dispersion in macro-economic forecasts also can be related to reduced accuracy in the forecasts of rental growth. We adapt Equation (8), and it's lagged equivalent, by replacing the dependent variable with the annual Mean Absolute Error of the rent forecasts. The model has the following form:

$$MAE(Y)_t = \alpha + \beta VAR(X)_t + u_t \tag{9}$$

where, $MAE(Y)_t$ denotes the quarterly Mean Absolute Error's (MAE) for the rent forecasts at time t and $Var(X)_t$ is the corresponding cross-sectional variances of both the macro-economic as well as the rental forecast. As with the preceding analysis this model is also run in a lagged variation. The results of this specification are shown in Table 8 and show that with the exceptional of Consumer Spending, significant beta coefficients are reported in each case. In addition, the beta coefficients are in each case positively signed, indicating that the uncertainty in both the property and macroeconomic forecasts leads to an increase in the Mean Absolute Error of the rent forecasts. In other words, the greater the uncertainty in these forecasts, the less accurate the forecasts of rental growth are. Thus, property forecasters are not only are affected by the current market conditions (uncertainty) at the time of forecasts but also in that increased uncertainty leads to reduced forecasting accuracy.

6: Conclusion

This paper has investigated the characteristics of property and macroeconomic forecasts for the one-year-ahead period. The first feature that is examined is the forecasting accuracy of these forecasts. The analysis suggests that both property and macroeconomic forecasters tend to be conservative in their predictions by exhibiting positive forecast errors during the sample period. However, both of the forecasters tend to overestimate when the market is underperforming and vice versa. The property forecasters feel more comfortable predicting the trend in rents than in capital growth and total returns, a finding that is in line with previous studies (Matysiak et. al. 2012).

Additionally, this research suggests that property forecasters are affected by macroeconomic forecasts. Uncertainty in the economy, as measured through dispersion in the macroeconomic forecasts, is positively related with uncertainty in the forecasts of rental growth. In other words, the greater the uncertainty in macroeconomic forecasts, the greater the uncertainty in property forecasts. Finally, the increased uncertainty both in property and macroeconomic forecasts lead to the production of more inaccurate property forecasts. Evidence is found that the greater the uncertainty (cross-sectional variance) of the forecasts, the greater the mean absolute errors of the property forecasts and in turn the smaller their accuracy.

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Tables and Figures

Table 1: Performance of the One-Year Forecasts

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	StDv
Panel A: Rental Growth Forecasts													
Actual	7.40	3.60	-1.20	-2.00	2.10	2.90	4.00	4.70	-1.20	-7.90	-0.50	0.60	3.8244
Consensus Forecast	4.00	4.50	1.30	0.20	-0.60	2.00	2.40	3.50	2.60	-6.30	-6.10	1.04	3.4036
Min	2.00	2.60	-2.00	-2.00	-2.10	0.60	0.60	2.60	1.10	-10.80	-12.80	-0.70	
Max	6.50	7.10	3.50	2.20	0.70	3.10	3.70	5.00	5.30	-2.10	-1.90	3.60	
Range	4.50	4.50	5.50	4.20	2.80	2.50	3.10	2.40	4.20	8.70	10.90	4.30	
StDev	1.20	1.30	1.60	1.20	0.90	0.60	0.60	0.50	1.00	2.30	2.30	0.87	
JB	2.30	1.50	4.30	1.10	1.90	0.30	6.30a	1.90	6.10a	0.60	6.20a	6.54a	
Obs	28	28	25	18	21	27	28	29	29	23	27	27	
Panel B: GDP Forecasts													
Actual	4.36	3.10	2.62	3.46	2.91	2.06	2.57	3.41	-1.11	-4.47	2.07	0.65	2.3333
Consensus Forecast	2.91	2.68	2.00	2.52	2.63	2.58	2.17	2.43	1.95	-0.95	1.24	1.96	0.9913
Min	2.10	2.30	1.40	1.60	0.30	0.80	0.20	0.50	-0.10	-2.10	-0.50	0.80	
Max	3.80	3.20	2.70	3.10	3.50	3.20	2.90	2.90	2.40	0.30	2.00	3.10	
Range	1.70	0.90	1.30	1.50	3.20	2.40	2.70	2.40	2.50	2.40	2.50	2.30	
StDev	0.41	0.19	0.35	0.33	0.59	0.44	0.50	0.46	0.50	0.69	0.54	0.50	
JB	0.44	2.15	0.27	5.84b	143.26a	152.25a	99.85a	211.01a	182a	0.95	19.46a	1.26	
Obs	22	23	24	20	25	27	30	27	24	28	24	26	
Panel C: Consumer Spending Forecasts													
Actual	5.21	3.90	4.16	3.06	2.94	2.11	1.77	2.62	-1.48	-3.60	1.23	-1.22	2.4927
Consensus Forecast	3.16	2.72	2.66	2.57	2.38	2.27	1.85	2.28	1.75	-1.23	0.23	1.25	1.1819
Min	2.20	2.20	1.80	1.50	1.60	1.00	0.60	1.30	0.60	-3.47	-1.10	-0.50	
Max	4.30	3.60	4.00	3.90	4.20	3.06	2.50	3.40	2.30	0.60	2.00	3.90	
Range	2.10	1.40	2.20	2.40	2.60	2.06	1.90	2.10	1.70	4.07	3.10	4.40	
StDev	0.54	0.36	0.52	0.55	0.59	0.47	0.46	0.47	0.48	1.06	0.82	0.94	
JB	0.18	3.61	0.72	0.92	16.04a	6.26b	2.93	0.32	3.29	0.20	1.18	3.97	
Obs	22	22	24	20	25	27	30	27	24	28	24	26	

Table 1: Performance of the One-Year Forecasts (continued)

Panel D: Inflation (RPI) Forecasts													
Actual	2.88	1.80	1.62	2.88	2.92	2.79	3.15	4.18	3.92	-0.53	4.52	5.07	1.4343
Consensus Forecast	2.26	2.30	2.33	2.32	2.48	2.33	2.27	2.71	2.66	2.51	2.54	3.46	0.3204
Min	1.60	1.80	1.90	2.00	1.80	1.90	1.40	2.00	2.10	1.01	1.30	3.00	
Max	2.70	2.80	3.30	2.90	2.90	2.90	2.90	3.20	3.40	4.00	4.00	4.14	
Range	1.10	1.00	1.40	0.90	1.10	1.00	1.50	1.20	1.30	2.99	2.70	1.14	
StDev	0.26	0.25	0.30	0.26	0.23	0.29	0.34	0.28	0.30	0.69	0.68	0.31	
JB	1.91	0.22	22.94a	2.83	7.04b	0.72	0.35	1.11	0.49	0.02	1.16	1.42	
Obs	22	23	23	20	25	27	26	26	22	25	20	22	
Panel E: Unemployment Rate Forecasts													
Actual	3.60	3.10	3.20	3.09	2.71	2.75	2.90	2.60	2.80	4.60	4.50	4.70	0.7500
Consensus Forecast	4.11	3.51	3.54	3.25	3.15	2.70	3.00	3.12	2.88	4.04	5.91	4.81	0.8876
Min	3.60	3.20	2.90	2.80	2.70	2.30	2.60	2.70	2.30	3.20	4.80	4.00	
Max	4.50	4.00	4.20	3.80	3.80	3.50	3.50	3.70	3.60	4.80	7.00	5.40	
Range	0.90	0.80	1.30	1.00	1.10	1.20	0.90	1.00	1.30	1.60	2.20	1.40	
StDev	0.24	0.23	0.33	0.22	0.23	0.28	0.22	0.20	0.29	0.42	0.55	0.33	
JB	0.67	1.95	0.43	2.70	4.72c	13.68a	1.33	8.93b	0.87	0.69	0.33	2.57	
Obs	22	21	23	20	22	24	26	25	22	24	21	18	

Note: Table 1 displays the actual figures for each of the five series together with descriptive statistics for the Consensus and individual forecasts. Each of the forecasts are one-year ahead.

Figure 1: Accuracy of Property and Macroeconomic Forecasts

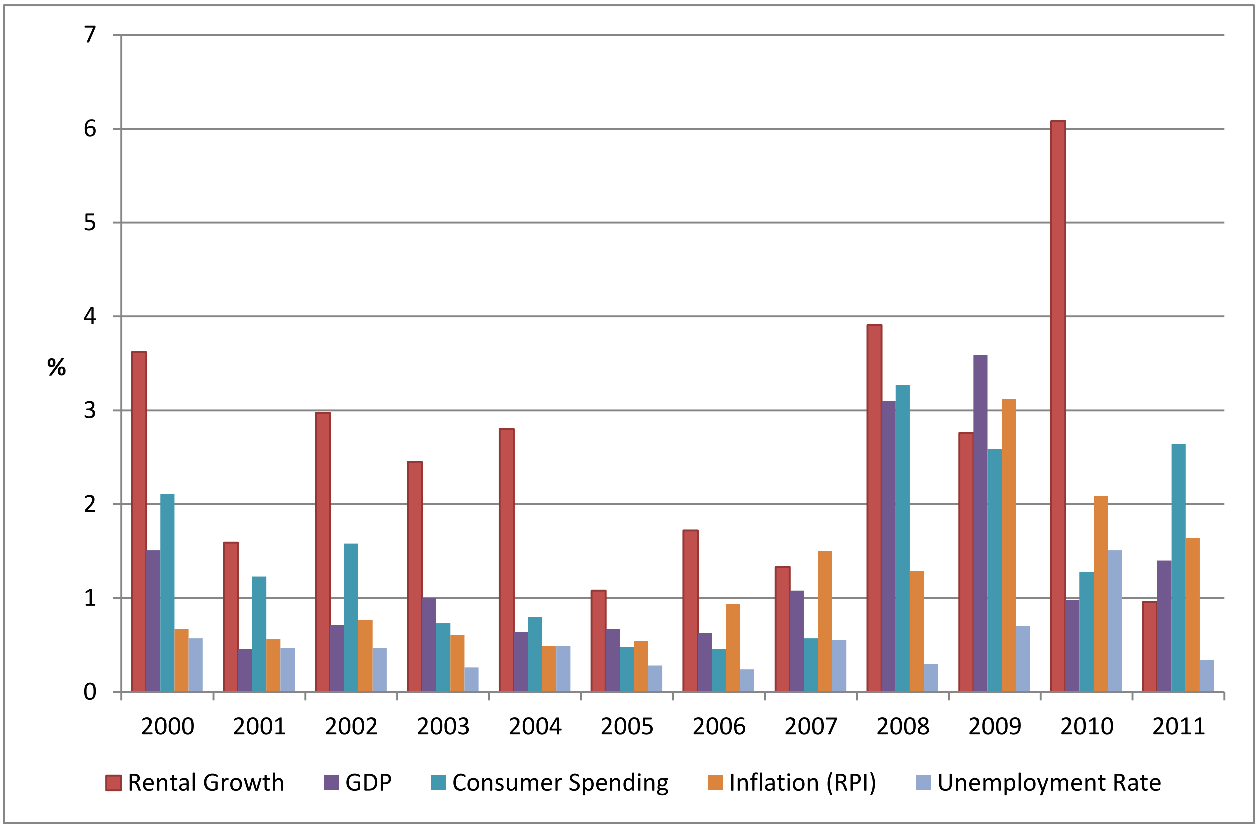
Note: Figure 1 displays the respective property and economic series' together with the corresponding consensus forecast.

Table 2: Forecasting Accuracy Metrics per year

		2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Rental Growth	**MFE**	3.43	-0.91	-2.55	-2.16	2.64	0.87	1.61	1.22	-3.78	-1.55	**5.63**	-0.44
	MAE	3.43	1.24	2.73	2.16	2.64	0.91	1.61	1.24	3.78	2.36	**5.63**	0.73
	MSE	13.13	2.54	8.8	5.99	7.82	1.16	2.96	1.77	15.25	7.6	**36.93**	0.93
	RMSE	3.62	1.59	2.97	2.45	2.8	1.08	1.72	1.33	3.91	2.76	**6.08**	0.96
GDP	**MFE**	1.45	0.42	0.62	0.95	0.28	-0.51	0.40	0.98	-3.06	**-3.53**	0.83	-1.31
	MAE	1.45	0.43	0.63	0.95	0.39	0.61	0.45	0.98	3.06	**3.53**	0.83	1.31
	MSE	2.27	0.21	0.50	1.01	0.41	0.45	0.40	1.16	9.58	**12.89**	0.97	1.96
	RMSE	1.51	0.46	0.71	1.00	0.64	0.67	0.63	1.08	3.10	**3.59**	0.98	1.40
Consumer Spending	**MFE**	2.05	1.18	1.49	0.49	0.56	-0.15	-0.08	0.34	**-3.24**	-2.37	1.00	-2.48
	MAE	2.05	1.18	1.49	0.61	0.71	0.39	0.38	0.44	**3.24**	2.37	1.09	2.48
	MSE	4.47	1.52	2.49	0.53	0.64	0.23	0.21	0.33	**10.69**	6.70	1.65	6.98
	RMSE	2.11	1.23	1.58	0.73	0.80	0.48	0.46	0.57	**3.27**	2.59	1.28	2.64
Inflation (RPI)	**MFE**	0.62	-0.50	-0.72	0.56	0.44	0.46	0.88	1.48	1.25	**-3.04**	1.98	1.61
	MAE	0.62	0.50	0.72	0.56	0.44	0.48	0.88	1.48	1.25	**3.04**	1.98	1.61
	MSE	0.45	0.31	0.60	0.38	0.24	0.29	0.89	2.25	1.66	**9.71**	4.36	2.69
	RMSE	0.67	0.56	0.77	0.61	0.49	0.54	0.94	1.50	1.29	**3.12**	2.09	1.64
Unemployment Rate	**MFE**	-0.51	-0.41	-0.34	-0.16	-0.44	0.05	-0.10	-0.52	-0.08	0.56	**-1.41**	-0.11
	MAE	0.51	0.41	0.39	0.21	0.44	0.21	0.18	0.52	0.22	0.58	**1.41**	0.26
	MSE	0.32	0.22	0.22	0.07	0.24	0.08	0.06	0.30	0.09	0.49	**2.27**	0.11
	RMSE	0.57	0.47	0.47	0.26	0.49	0.28	0.24	0.55	0.30	0.70	**1.51**	0.34

Note: MFE, MAE, MSE and RMSE are the Mean Forecast Error, Mean Absolute Error, Mean Squared Error and the Root Mean Squared Error respectively. Figures in bold indicate the year of highest forecast errors for rent and macro-economic forecasts.

Figure 2: Comparison of the Root Mean Square Error



Note: Figure 2 displays the Root Mean Squared Error for each target year, based on one-year ahead forecasts, for each of the series.

Table 3: Correlation between One Year Forecast and Actual

Series	Correlation
Rental Growth	0.7417*** {3.4972}
GDP	0.8731*** {5.6628}
Consumer Spending	0.8450*** {4.9962}
Inflation (RPI)	0.5344* {1.9993}
Unemployment Rate	0.8663*** {5.4849}

Note: Table 3 displays the correlation between the one year ahead forecast and the resulting actual figure obtained for each of the five series'. The figures in parentheses are the t-statistics. *** indicates 1% significance, ** 5% and * 1%.

Table 4: Theil's U2 Statistics for Naive Forecasts

Date of Forecast	Target Year	Rental Growth	GDP	Consumer Spending	Inflation (RPI)	Unemployment Rate
Panel A: Naive 1						
1999	2000	1.95	1.96	16.51	0.50	1.13
2000	2001	0.42	0.37	0.94	0.52	0.94
2001	2002	0.62	1.48	6.19	4.18	4.70
2002	2003	3.33	1.19	0.66	0.49	2.41
2003	2004	0.69	1.16	6.82	11.47	1.29
2004	2005	1.34	0.79	0.58	4.18	6.88
2005	2006	1.47	1.24	1.35	2.63	1.61
2006	2007	1.91	1.29	0.67	1.45	1.83
2007	2008	0.66	0.69	0.80	4.85	1.48
2008	2009	0.42	1.07	1.22	0.70	0.39
2009	2010	0.82	0.15	0.27	0.41	15.07
2010	2011	0.90	0.99	1.08	3.00	1.68
No. of Years Naive More Accurate than Consensus		5	7	6	7	10
Panel B: Naive 2						
1999	2000	1.35	0.74	0.86	0.17	0.16
2000	2001	1.33	0.64	1.18	0.12	0.12
2001	2002	0.48	4.41	1.30	0.16	0.13
2002	2003	0.36	1.03	9.05	0.18	0.07
2003	2004	1.12	1.52	9.92	0.16	0.12
2004	2005	0.77	1.45	0.53	0.17	0.07
2005	2006	12.41	18.52	0.37	0.35	0.07
2006	2007	2.19	1.22	1.52	0.96	0.15
2007	2008	0.73	0.85	0.74	0.73	0.09
2008	2009	0.23	0.51	0.40	0.51	0.47
2009	2010	1.38	2.65	0.81	1.99	1.02
2010	2011	0.33	0.88	0.69	5.05	0.27
No. of Years Naive More Accurate than Consensus		6	7	5	2	1

Note: Naive 1 approach indicates the previous year growth-rate for the respective series, or in the case of unemployment the previous year's percentage unemployment rate. Naive 2 is the long-term average of the actual values of the different series up to the date of forecasts. Figures less than unity indicate that the consensus forecast was more accurate than the respective naive. Figures greater than unity imply that the naive outperformed.

Table 5: Stationarity Tests

	Levels	Differences
Rental Growth	-2.55	-3.66***
GDP	-2.12	-7.88***
Consumer Spending	-1.53	-7.08***
Inflation (RPI)	-2.49	-4.40***
Unemployment Rate	-2.37	-4.52***

Note: Table 5 reports Augmented Dickey Fuller tests for stationarity. *** denote rejection of the null at the 1% level

Table 6: Granger Causality Tests

	Rental Growth	GDP	Consumer Spending	Inflation (RPI)	Unemployment Rate
Rental Growth		3.53	5.71	6.08	4.56
GDP	3.66		2.30	1.28	12.12[b]
Consumer Spending	1.59	0.68		4.92	11.96[b]
Inflation (RPI)	8.85[c]	20.43[a]	20.47[b]		6.25
Unemployment Rate	15.30[a]	5.36	9.50[b]	1.16	

Note: Table 6 presents χ^2 statistics for the pairwise Granger causality tests between the one-year-ahead rental growth (RG)and the corresponding one-year ahead macroeconomic forecasts for the gross domestic product (GDP), consumer spending (CS), retail price index (RPI), and unemployment rate (UR). The null hypothesis means that the column variables do not Granger-cause raw variables, and the a, b, and c, denote rejection of the null at the 1%, 5% and 10% significance levels respectively. The Granger causality tests are estimated with a lag of four quarters. The optimal lag length is chosen by the minimisation of the Akaike and Schwartz criterion.

Table 7: Impact of Macroeconomic Forecasts on Rental Forecast Uncertainty

	I	II	III	IV
Panel A: Contemporaneous Macroeconomic Forecasts				
Constant	-0.05	0.26	0.31	0.67***
	(0.78)	(0.65)	(0.24)	(0.21)
GDP	5.26*			
	(2.94)			
Consumer Spending		2.76		
		(1.89)		
Inflation (RPI)			7.50***	
			(1.65)	
Unemployment Rate				4.42***
				(0.22)
R^2	0.26	0.22	0.60	0.67
Panel B: Lagged Macroeconomic Forecasts				
Constant	-0.21	0.34	0.35	0.93***
	(0.76)	(0.54)	(0.28)	(0.31)
GDP	5.71**			
	(2.78)			
Consumer Spending		2.61		
		(1.68)		
Inflation (RPI)			7.15***	
			(2.34)	
Unemployment Rate				3.09***
				(0.69)
R^2	0.30	0.21	0.53	0.33

Note: Table 7 is based upon versions of Equation (8) where the dependent variable is the cross-sectional variance of the individual forecasts of rental growth. The explanatory variables are the cross-sectional variances of the respective macro-economic forecasts. The figures in parantheses are t-statistics. * indicates significance at a 10% level, ** at 5% and *** at 1%.

Table 8: Impact of Macroeconomic Forecasts on Rental Forecast Accuracy

	I	II	III	IV	V
Panel A: Contemporaneous Macroeconomic Forecasts					
Constant	0.94	2.27***	2.14***	2.34***	1.97***
	(0.85)	(0.75)	(0.47)	(0.44)	(0.44)
GDP	6.95***				
	(2.50)				
Consumer Spending		1.77			
		(1.79)			
Inflation (RPI)			5.76**		
			(2.39)		
Unemployment Rate				3.75***	
				(0.40)	
Rental Growth					0.72***
					(0.10)
R^2	0.29	0.06	0.22	0.31	0.33
Panel B: Lagged Macroeconomic Forecasts					
Constant	1.25	2.20***	2.28***	2.43***	2.07***
	(0.93)	(0.79)	(0.55)	(0.47)	(0.48)
GDP	5.82**				
	(2.73)				
Consumer Spending		1.85			
		(1.78)			
Inflation (RPI)			4.67		
			(3.24)		
Unemployment Rate				3.12***	
				(0.62)	
Rental Growth					0.63***
					(0.20)
R^2	0.20	0.06	0.14	0.21	0.26

Note: Table 8 is based upon versions of Equation (9) where the dependent variable is the Mean Absolute Error of the rent forecasts. The explanatory variables are the cross-sectional variances of the respective macro-economic forecasts and rental growth. The figures in parantheses are t-statistics. * indicates significance at a 10% level, ** at 5% and *** at 1%.

Endnotes:

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[i] A small selection of this literature includes; Brounen & Jennen (2009); D'Arcy et al. (1997); De Wit & van Dijk (2003); Englund et al. (2008); Ibanez & Pennington-Cross (2013); Hendershott (1996); Hendershott et al., (1999, 2002a, 2002b, 2010); Rosen (1984); Shilling et al., (1987); Wheaton (1987); Wheaton & Torto (1988, 1994); Wheaton et al. (1997).

[ii] See for example, papers such as Chaplin (1999); Brooks & Tsolacos (1999, 2000); Stevenson & McGrath (2003); Krystalogianni et al. (2004); Matysiak & Tsolacos (2003).

[iii] There is a related literature that has considered equity analysts, frequently observing similar behavioural effects. See for example, Barber et al. (2007); Clarke & Subramanian (2006); Clarke et al. (2006), Clement et al. (2011); Cooper et al. (2001); Cowen et al. (2006); Dechow et al. (2000); Hong & Kubik (2003); Jung et al. (2012); Kim et al. (2011); Welch (2000).

[iv] It does however, need to be noted that a further possible factor behind the reduced variability is an averaging effect. An element of smoothing may be introduced into the consensus forecast due to it being estimated as the simple average of the individual forecasts.