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- Forecasting rental rates for Norwegian commercial real estate -

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Abstract

This study seeks to identify key determinants of rents of commercial real estate in Oslo and formulate econometric models capable of describing and predicting their movements. Such a model will improve the precision of property valuations and be a useful aid in making real estate related investment decisions.

The study finds real rental rates to be a function of previous periods' rents, employment rates, real interest rates and vacancy rates. The forecast models examined are a classical linear regression model, an autoregressive moving average (ARIMA) model and a vector autoregressive (VAR) model. The performance of these are evaluated using root mean squared errors (RMSE), mean absolute errors (MAE), mean absolute percentage errors (MAPE) and Theil's u-stat as well as variance decomposition and the percentage of correct signs predicted by the model compared to the actual values.

The study concludes that given the available data, the classic linear regression model is able to produce the most precise forecasts, although the precision is not satisfactory. None of the forecasts are at present able to consistently beat a random walk, but a clear trend of improvement in forecast accuracy is detected when gradually increasing the estimation sample.

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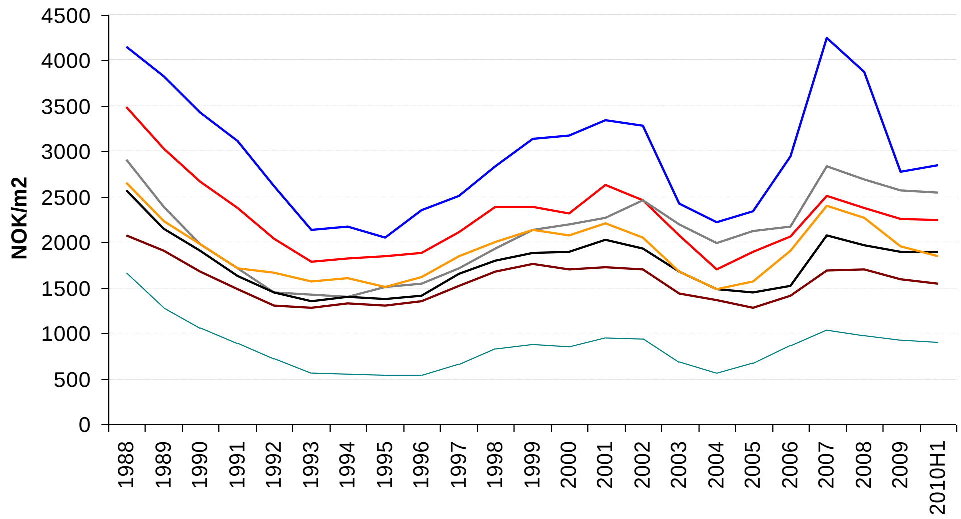
1. Introduction

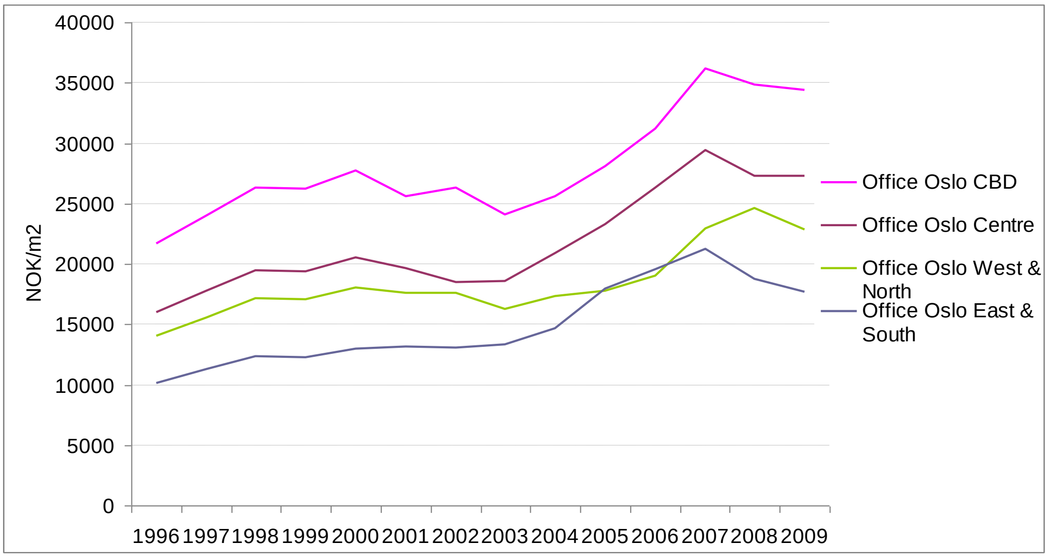
The value of commercial real estate is largely determined by the cash flow it is able to generate. More specifically, the net rent it commands given location, age and building characteristics. Thus, estimation of expected returns from real estate investments is largely an exercise in forecasting of said rents. Graph 1.1 below shows office rents in real terms per square metre in the Norwegian commercial property market by categories ranging from prime and down to the least attractive. The importance of timing is evident. In real prices the development from 1988 till date is flat to slightly negative on average. The volatility over the period does however mean that an investor who was able to buy property in 1993-95 or 2003-04 would generate a hefty profit if he sold at peaks in 2001-02 or 2007-08. Graph 1.2 shows the development in capital values for four Oslo office segments. An average of 66 % growth in real terms from 1996 to 2009 or 3,69 % annualized in real capital values, compared to 36% and 2,11% annualized for the real rents. However the turning points of the series coincide rather well, the rental rates being slightly lagged.

Graph 1.1



Graph 1.1: Real rents of office space in Oslo segments. Highest graph shows class A buildings, lowest shows out-dated buildings. NOK/m² per year, indexed to May 2010. Source: Dagens Næringsliv

Graph 1.2



Graph 1.2: Capital values of office space in Oslo segments in real prices, NOK/m^2 indexed to May 2010. Data from 2000 to 2009 from International Property Database. Prolonged with data from Statistisk sentralbyrå from 1996 to 1999.

Plazzi, Torous and Valkanov (2010, 3470) states that "Understanding what drives these fluctuations is an important research question as commercial real estate represents a substantial fraction of total U.S. wealth". Similarly, estimations done in 2007 show commercial real estate making up the second largest asset class in Norway with an approximate size of NOK 832,3 Billion, wedged between stocks estimated at NOK 2.000 Billion and bonds and certificates amounting to NOK 400 Billion (Frøyseth 2009).

Commercial real estate in Norway has traditionally been dominated by the state, companies who "build to live", and a small number of private investment companies. It is only over the past 20 years or so that we have seen commercial property become a widely available investment vehicle through the establishment of various real estate funds and syndicates (typically by banks and finance houses such as DnB NOR, Storebrand and Pareto). One also finds a small number of exchange traded real estate companies. As of 2011 there are 6 listed real estate companies on Oslo Stock Exchange, up from only 1 prior to 2006, and there are talks of several companies being listed through 2011.

The need for an improvement in the methodological framework for valuation of commercial property is highlighted in the Financial Supervisory Report of 20th December 2010, Valuation of Commercial Property – the Financial Supervisory's observations and assessments (Finanstilsynet 2010). By reviewing reports from listed real estate companies, interviewing key players in the market and comparing methods of valuation for a couple of real life properties, the Supervisory presents their observations and assessments of the current methodological framework, or rather lack thereof. The area of study most in lack of methodology is the prediction of future rental rates. The Supervisory points out that most often the models use rent levels as of today, with or without discretionary adjustments or projections based on historic rents. As such, the models do not take into account the highly cyclical movements of rents. Other points discussed in the report are the needs for a more robust methodological framework for the use of discount rates and more reliable data for vacancy, especially per segment and outside Oslo.

This study explores the characteristics of the Oslo real estate market. It seeks to identify the key determinants of real rental rates and subsequently applying these in a forecasting model.

2. Literature Review

This section goes through the main body of relevant research and literature relating to the research questions. It starts by mapping out the literature focusing on the determinants of real estate rental rates, property values and property returns. Then the three major forecasting methods applied in real estate research, that is time series regressions, ARIMA and VAR, are reviewed. Finally literature focusing on how to evaluate the performance of these models is presented.

2.1. Determinants of rental rates: Real estate and macroeconomic variables

A study on the relationship between commercial real estate and stock returns is done by Quan and Titman (1997). It concludes that, on average, the relation between real estate values and stock prices is strong and positive. In their follow-up paper, Quan and Titman (1999) used the same data as in the first study to try to determine the reason why stock prices and real estate values move together. Two hypotheses were tested; first whether the two series move together because of expectations about future growth and prices, and second, whether they move together because of changing macroeconomic and political fundamentals. The article concludes that the second hypothesis is most fitting. When controlling for changes in macroeconomic variables (GDP, interest rates and inflation) the relationship between stock prices and real estate values weakens considerably. It is also found that the primary determinant of real estate values, that is rental rates, is strongly correlated with GDP as well as stock prices. The researchers' results also imply that real estate provides a good inflation hedge over the long term, but performs poorly as a hedge in the short term. These studies by Quan and Titman show that a relation between rental rates and macroeconomic variables exists. This study will try to identify the key determinants of rental rates for the Norwegian market.

De Wit and Van Dijk (2003) found both real estate variables and macroeconomic indicators to be significant. Drawing on earlier research they looked at how rents respond to changes in economic growth and availability of space over 56 quarters (from 1986 to 1999) in 47 countries. Jones Lang LaSalle publications supplied real estate data from Europe while Torto Wheaton Research in combination with the National Real Estate Index was the source for US figures.

The study employs the Generalized Method of Moments to estimate a dynamic panel-data model allowing for both cross-sectional and time-series analysis of the data. The real estate variables are capital value, net rent, vacancy rate and stock of office space. Macroeconomic indicators used are GDP, inflation, employment levels and long-term interest rates. The study found evidence that the attractiveness of real estate investments is indeed determined by economic growth prospects and supply and demand of office space. A positive relationship to GDP and inflation and a negative relationship to changes in unemployment, vacancy rates and stock were found. Vacancy rate and unemployment are suggested as the most important indicators to include in a long-term return analysis. Moreover, returns in real estate markets are found to be very persistent with a significant and positive relation between current return and return in the previous period. This gives valuable insights as to what determinants to focus on, and how these are related to demand and supply functions.

Similar research presented by Plazzi, Torous and Valkanov (2010), concluded that 45% of the variability of realized rent growth rates can be explained by expected rent growth variability. It was shown that rent growth predictability is observed mostly in high population density areas, based on data from 53 US metropolitan areas. McGough and Tsolacos (1995) found that industrial property and office rents in the UK are linked to demand and supply shocks, whereas retail rents are more linked to previous values.

Other research applying panel data such as Giussani, Hsia and Tsolacos (1993) and D'Arcy, McGough and Tsolacos (1997) found change in GDP and levels of lagged short term interest rates to be significant to changes in rents. Dobson and Goddard (1992) found a positive and significant relationship between demand factors such as employment and real interest rates and rental prices of industrial properties and offices.

2.2. Classic linear regression models

Following the methodology of Brooks and Tsolacos (2010), this study employs a classic regression model to identify key determinants of rental rates using similar variables as discussed above. The regression results are then used to specify a forecasting model. The framework of above mentioned authors is again based on a number of studies: Dipasquale and Wheaton (1992), Clapp (1993), RICS (1994) and Ball, Lizieri and MacGregor (1998). Studies in real estate applying time series regressions include Hendershott (1996). He uses information from estimated equilibrium rents and vacancy rates to construct a rent model for the Sydney office market. He claims that effective rents may start adjusting even before the actual vacancy rate reaches its natural level. Karakozova (2004), models and forecasts capital values in the Helsinki office market. She evaluates the performance of regression, error correction and ARIMAX models and finds the latter model to have the better forecasting performance.

2.3. AutoRegressive Integrated Moving Average (ARIMA) models

According to Brooks and Tsolacos (2010), ARMA models are used mainly for short-term forecasting and to provide a benchmark for structural models. Tse (1997) makes use of ARIMA models to price indices for office and industrial real estate in Hong Kong. The dataset consisted of quarterly data from 1980 to 1995, a total of 62 observations. The sample is considered sufficient to fit such models based on research of Holden, Peel and Thompson (1990), that indicates a sample size of 50 is sufficient to enable ARIMA modelling. This study starts by creating an ARIMA forecast using data from 1996Q1 to 2006Q4, 44 observations, and then looking at how the model improves by adding more observations, up to 56. Similar to Tse, a price series deflated with the consumer price index is used. Tse finds an ARIMA of the order (2,1,1) to be the model that best fits the data, and Brooks and Tsolacos (2010, 258), in their review of Tse's paper, conclude that the "AR terms suggest that the cyclical effects generated in the past information are transmitted endogenously to current prices".

Wilson, John Okunew and Higgins (2000) investigate the ability of time series models to predict turning points in securitised real estate indices, and apply ARIMA models for the US, UK and the Australian markets, to compare how well they forecast out-of-sample. The US and UK forecasts are quite similar. They both fail to predict certain significant increases and decreases. However, by the end of the forecast period the models are fairly accurate in their predictions. The UK ARIMA yields the lowest absolute forecast errors.

2.4. Vector AutoRegressive (VAR) models

According to Brooks and Tsolacos (2010) one of the advantages of VAR modelling is that all the variables are endogenous. That means we are not only able to look at several variables' effect on average price, but also its effect on itself, univariately, and the average price effect on the other variables. As such we may be able to capture more features of the data and we can use OLS separately on each equation. Brooks and Tsolacos (2010) also refer to Sims (1972) and Mcnees (1986) that VAR models often perform better than traditional structural models. They also point out some disadvantages, one of which being that VAR models are a-theoretical by nature. Lag-length determination is an issue critical to finding the best VAR specification. As such, they advise using multivariate information criteria, e.g. Akaike's criterion (1974).

Literature focusing on VAR models in real estate studies include Brooks and Tsolacos (1999), who use the VAR methodology to find relationships between the UK real estate market and economic/financial factors. The model is specified as a VAR(14) using Akaike's information criterion. It is concluded that the macroeconomic factors have little explanatory power on UK real estate returns, but that unexpected inflation and interest rate term structure have contemporaneous effects on real estate returns.

2.5. Evaluating the performance of models

Research on real estate forecasts in Norway is a scarcity. Broker firms and forecasters in the Norwegian market do present their view on the future in market reports, but it is frequently coloured by their own conjectures and individual incentives. As such, they may not be reliable enough to base valuations on. We have selected one such forecast, produced by DnB NOR, to test our model against. In a review of the UK forecasts, Gallimore and McAllister (2004) interviewed 19 UK forecast producers. The study finds that the forecasts are primarily produced to find change in rental values, almost invariable nominal rents, and typically with a 5 year horizon. The method applied is most often multivariate time series. Gallimore and McAllister (2004, 337) point out that "When extreme forecasts are generated by a model, forecasters often engage in "self-censorship" or are "censored following in-house consultation"". The interviewed also suggested that when forecasting they often struggle with data problems and they are often unsure about the current level for both rents and yields.

In this study, statistical forecast evaluation tests commonly used in research and described by Brooks and Tsolacos (2010) are used to determine which model generates the best forecasts. However, as shown by Gerlow, Irwin and Liu (1993) the accuracy of forecasts according to traditional statistical criteria may give little guide to the potential profitability of employing those forecasts in a market trading strategy. Using a model that can predict the sign of future returns, that is if prices move up or down, has been proven more profitable (Leitch and Tanner 1991). Thus, the percentage of correct signs will also be considered one of the key performance indicators in concluding the best and most efficient model for forecasting.

A study by D'Arcy, McGough and Tsolacos (1997) compare predictions from a regression model of Dublin office rents to naïve forecasts. They find the regression model to outperform the naïve forecasts, as it yields the lowest residual mean squared errors. Matysiak and Tsolacos (2003) use mean errors and mean squared errors to examine whether the forecasts for rents obtained from regression models that contain leading economic indicators outperform those of simpler models. They find that not all leading indicators improve upon the forecast of naïve specifications and that forecasting with leading indicators is more successful for office and industrial rents than retail rents.

In their article, Stevenson and McGarth (2003) compare four alternative forecast models for the London office market. An ARIMA model and a single-equation model applying OLS using the following variables: Change in real-GDP, change in service sector real-GDP, new construction, real interest rates, employment in service sector, building costs, quantity of property transactions, inflation adjusted gross company trading profits and shorter and longer leading indicators. A Bayesian VAR (BVAR) and a simultaneous equations model are also specified. The authors use CB Hillier Parker London Office index with semi-annual data over the period 1977-1996, with out-of-sample testing undertaken on the following three years of data. The comparison reveals the BVAR model to give the best forecasts, followed by the single-equation model. The AR(1) yields the worst results. All models over-predict. Five statistical tests are applied to evaluate the models, including mean error and mean absolute error. Contrary to these findings, Brooks and Tsolacos (2000) find an AR(2) model to outperform a VAR model when trying to forecast UK retail rents. They conclude that the rent changes have substantial memory for two periods, and that most of the needed information to predict future rents is contained within its own lags. The study uses mean forecast error, mean squared forecast error and the percentage of correct sign predictions to select the best performing models.

3. Methodology

In order to identify key determinants of rental rates and produce forecasts, this study employs three different statistical methods to generate models, starting with the classic linear regression model. Then univariate time series modelling is used to build an autoregressive integrated moving average (ARIMA) model. Finally, a vector autoregressive (VAR) model is built. For all methods the model is initially estimated using the sample from 1996Q1 to 2006Q4, forecasting the 4 years out-of-sample period until 2010Q4. The study continues by adding more observations to the estimation and performing forecasts of various lengths, to see if the forecasts improve. The three methods are described in detail in sections 3.1.-3.3.

3.1. Linear regression model

This method assumes that changes in rents can be adequately explained by changes in a set of exogenous variables. Thus, accurate data on the exogenous variables should yield accurate forecasts for future rents if the model is correctly specified.

Changes in office rent levels are regressed on a selection of exogenous variables previous research suggests act as the foremost determinants of the supply and demand of office space. The regression equation appears as follows:

$$AP_t = \alpha_0 + \beta_1 EMP_{t-1} + \beta_2 GDP_{t-1} + \beta_3 INT_{t-1} + \beta_4 VAC_t + \beta_5 NEW_t$$

Where AP_t denotes aggregate real rents. The three first right hand side variables are macroeconomic variables that are likely to have a strong impact on rents. EMP denotes employment levels as number of people employed, GDP denotes real gross domestic product and INT is real interest rate levels. The two last variables are specific to the commercial property market. VAC is available vacant space in m^2 while NEW denotes expected future construction in m^2. Drawing on the experience of previous research we expect most of the data series to be non-stationary. The study tests for unit roots using the augmented Dickey-Fuller test (1979). In order to avoid a spurious regression, the series that contain unit roots are transformed by taking log-differences according to the level of non-stationarity in the variables. Given a de-trending of the variables and a correctly specified model, α_0 is expected to be not significantly different from 0.

A higher rate of employment (EMP) should lead to an increase in demand for office space. The coefficient is expected to be positive and significant. The level of economic activity (GDP) is likely of importance to the demand for office space. The coefficient is expected to be positive and significant. Increased economic activity should lead to increased demand and thus exert upwards pressure on rents. The third right hand variable is interest rates (INT), the intuition here is that high interest levels should make it relatively more attractive for firms to lease rather than build or buy a building by raising the cost of capital for investors. High interest rates should therefore increase demand for office space for lease and put upwards pressure on the price. Thus, also this coefficient is expected to be significant and positive.

The change in excess supply as measured by the vacancy rate (VAC) is expected to have a negative impact on prices, more available vacant space in the market will put downwards pressure on the rents. The intuition is similar for changes in expected future construction (NEW). When a lot of newly constructed office space is expected to become available it should exert downwards pressure on prices. Consequently, both of these coefficients are expected to be negative and significant.

Previous research suggests that the adjustment of rental rates in the real estate market to its macroeconomic determinants is not necessarily instant (Krystalogianni, Matysiak and Tsolacos 2004). To account for this EMP, GDP and INT are lagged with one period. EMP and GDP will not be observable at once, INT can be observed but the process of finding and writing a lease is time-consuming. The impact of VAC and NEW on AP is likely to be instant.

To estimate the coefficients the statistical method of ordinary least squares (OLS) is applied. OLS seeks to fit the line that minimises the sum of squared errors. According to the Gauss-Markov Theorem (Brooks 2008), the OLS estimators will be the best linear unbiased estimators (BLUE), given that a set of five assumptions holds.

The first assumption is that on average the value of the errors is zero. This assumption is never violated when a constant term is included, which is the case here. The second is the assumption that errors are homoscedastic, meaning that their variance remains constant over time. If the variance varies over time, they are said to be heteroscedastic. It is tested for heteroskedasticity using White's (1980) test. The third assumption states that errors should be uncorrelated with each other over time. If they are not, they are said to be autocorrelated. To check for autocorrelation Durbin and Watson (1951) and Breusch-Godfrey tests (Breusch 1978), (Godfrey 1978) are used. The fourth assumption is that the regressors are stochastic and uncorrelated with the error terms of the estimated equation. The final assumption is that the error terms are normally distributed. Tests of normality will be performed by assessing the descriptive statistics and applying the Bera-Jarque (1981) test. The study tests for multicollinearity by examining a correlation matrix of the variables. Testing for structural breaks is done using the Chow (1960) parameter stability test and a test for seasonality effects done by including dummy variables in the estimation.

Eviews is used to experiment with different lengths of estimation and test periods to produce dynamic and static forecasts. That way, the change in the parameters and their significance, as well as the accuracy of the forecasts with varying amounts of data behind, can easily be observed. Dynamic, or multi-step forecasts, produce predictions for several periods ahead (in this case up to 16 quarters) starting from the first period in the forecast sample. The static method however produce a sequence of one-step-ahead forecasts, that rolls the sample forwards and use actual values as lagged dependent variables (Brooks 2008). This study aims at finding the model that produce accurate forecasts for longer horizons, thus the model that yields the best dynamic forecasts is preferred. The static forecasts will be produced to see if the models are better suited to perform shorter forecasts.

3.2. ARIMA model

The ARIMA(p,d,q) model is a class of univariate time series models. It is a combination of the autoregressive (AR(p)) and moving average (MA(q)) models with the data differenced *d* times. As such, it tries to explain and predict values of a variable using only its own past values and current and past values of a white noise error term. An ARIMA model is not built on any underlying theory about the behaviour of the variable; it simply seeks to capture relevant aspects of the observed data that may have been the result of a number of different but unspecified processes (Brooks 2008).

In order to build the model, the Box and Jenkins (1976) 3-step approach is applied. Step 1 is identifying the order, and entails looking at plots of the sample autocorrelation (ACF) and partial autocorrelation (PACF) functions. A pure AR model will have a geometrically declining ACF and a number of non-zero PACF points determining the AR-order. Conversely, a pure MA process will have a number of non-zero ACF points determining order and a geometrically declining PACF. For an ARIMA process both the ACF and the PACF will be geometrically declining. Step 2 is estimating the parameters of the specified model using OLS. Step 3 is diagnostics checking, checking if the model is adequate. The goal is to obtain a parsimonious model. That is, a model that describes the data adequately using as few parameters as possible.

In practice, Eviews is used to estimate a number of ARIMA models of varying order and then the specification that minimizes a set of information criteria is selected. Information criteria contain the residual sum of squares and a penalty term for loss of degrees of freedom from adding additional terms. The value of the information criteria is reduced only if the reduction in residuals outweighs the increase in the penalty term.

The information criteria considered are the Akaike (1974) information criterion (AIC), Schwarz (1978) Bayesian information criterion (SBIC) and the Hannan-Quinn (1979) information criterion (HQIC). In general terms, SBIC has a much stricter penalty term than AIC, with the HQIC falling somewhere in between. Thus, AIC will tend to over-fit, suggesting a model that is too large, whereas SBIC is more likely to under-fit. None of the information criteria are definitely superior to the others, meaning that if they suggest different models, subjective reasoning must be applied to decide which model to choose.

As with the linear regression model, Eviews is used to experiment with different lengths of estimation and test periods to produce dynamic and static forecasts.

3.3. Vector Auto Regressive (VAR) model

A VAR model is a systems regression model with more than one dependent variable. The values of each of the g variables in the system depend on k lags of values of the other variables and error terms. As such, it can be viewed as a mix between simultaneous equation and univariate time series models. All variables are treated as endogenous (Brooks 2008).

In this study the same variables that were used in section 3.1 are also used to formulate a VAR model. The appropriate number of lags to include is decided using the Akaike (1974) multivariate information criterion (MAIC). Granger (1969) causality tests are applied to check for joint significance of all lags of the variables. Variance decompositions are run to look at the effect of ordering and impulse responses are examined to see how innovations in independent variables affect the dependent variable. Dynamic and static forecasts are then performed in a similar fashion to the two other models.

3.4 Performance evaluation

The precision of the various forecasts is evaluated looking at several measures of performance; square root of mean squared error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), Theil's (1989) inequality coefficient and the percentage of correct positive/negative signs of the forecasted values compared to the actual values.

It is desirable that RMSE and MAE are as close to zero as possible, whereas a MAPE below 1 (100%) means the model outperforms a simple random walk. Theil's inequality coefficient takes a value between 0 and 1, 0 indicating a perfect hit. A value below 0,2 is considered good. The MSE is divided into a bias, a variance and a covariance proportion. The bias portion shows how different the forecasted mean is from the actual mean, a high value indicating a high degree of systematic error. The variance portion shows how different the variance of the forecast is from that of the actual observations. The covariance portion captures the remaining unsystematic part of the errors. It is desirable that covariance accounts for as much of the forecast error as possible, meaning its error is a result of random events and not systematic traits of the data (Brooks 2008).

The comparison methodology of Brooks and Tsolacos (2000) using RMSE, MAE and percentage of correct signs is used to evaluate which of the three models that perform the best forecasts. The composition of the MSE is evaluated to see how the errors arise. Further on, MAPE and Theil stats are interpreted to see how the models forecasts perform compared to a random walk.

The study continues to asses if the best performing model improves by adding new observations. By continuously adding one quarterly observation to the estimation period, we will perform one, two and three-year forecasts and evaluate their performance measures. Finally the values of the best performing model are compared to those forecasts done by DnB NOR Næringsmegling.

4. Data

Given the proposed model and methodology, the necessary quantitative data series include rental rates, employment rates, GDP, interest rates, office vacancy rates and data on expected future construction. For the purposes of cancelling out the effect of inflation this study looks at real rather than nominal values. It is worth noting that virtually all lease contracts written in Norway are adjusted annually for inflation via the consumer price index (CPI).

4.1. Rental rates

Rental rate data as well as information on quality and location have been obtained from Eiendomsverdi Næring (EVN). EVN is a commercial company that collects data from the majority of real estate firms in Oslo/Norway. The data is published in a quarterly report and presented categorized in 8 geographical areas and 4 levels of attractiveness of the property. According to EVN, their coverage as of today is roughly 90% of all new contracts signed. The coverage-ratio is however much lower in the earliest entries and increases steadily through the years. As opposed to many other published series on rental rates, it is not open to individual conjecture or opinions of rent levels. The data is based on the actual signed contracts and consists of the actual rents and lease periods. It is important to note that the prices are recorded at the time when the tenant moves in, not at the time of signing the contract. Tenants generally move in 4-8 months after signing the contract, sometimes longer. As a consequence the other variables lag the price series by approximately two periods on average. This is further described in section 5.1.

The EVN series run from 1st quarter 1996 to 4th quarter 2010, meaning 60 observations. Objectively speaking this is not as long a series as hoped for, but it is the best available dataset for the Norwegian market at present. Unfortunately, the series with categorized data only go back to 2003. Therefore, the regressions use the average across all categories and look at Oslo as a whole. As the categorized series becomes longer it would be beneficial to organise the data in panels to examine similarities and differences over cross-sections based on location and quality. Also, the raw data consisting of 8551 contracts is unavailable due to confidentiality issues Thus, a series of aggregated values per quarter is used. Basic descriptive statistics are given in table 4.1.1.

Table 4.1.1

	AP (Aggregate data)	AP (Raw data)
Mean	1507.000	1644.636
Std. Dev.	168.0930	581.0811
Skewness	0.209363	0.780795
Kurtosis	2.204346	1.944107
Jarque-Bera (p-value)	2.020988 (0.364039)	1314.6366 (0.000000)

The first AP column contains the descriptives of the aggregated series whereas the second column contains the descriptive statistics of the raw data provided by Eiendomsverdi (no averaging of the data had yet happened). Each observation is weighted according to the number of square meters (sqm) in the contract (Sqm. contract A/total sqm). To ensure anonymity all contracts exceeding 10.000 sqm. are by default set to 10.000. The mean of all periods is 1645, whereas the mean of the aggregate data is 1507. Since these observations are simply the aggregate prices over aggregate contracts, done for 44 periods, it is obvious that the amount of small-sized contracts leads to a lower average. This shows the value of weighting the descriptive statistics.

The test by Bera and Jarque (1981) is used to check for normality. The raw data is not normally distributed. However the large amount of contracts (8851) should imply no consequence for the violation of normality (Brooks 2008). The aggregate data for 60 observations is however normally distributed. The difference observed in volatility between the raw and average data series for Oslo in total is somewhat expected, but the magnitude is admittedly quite large. The difference suggests that there is great variability in the contracts signed within each quarter, which is natural since the raw data consists of buildings from the very low end of the spectrum to the highest, both with regards to location and quality. This could imply that the forecasting model may turn out to be imprecise when looking at individual buildings.

One should be aware that the rents observed in the dataset will have a tendency to be slightly inflated. When leasing new offices, most tenants require modifications and improvements. Common practice is that the owners of the property deal with the initial outlay and then add the cost of modification to the rent as an annuity over the contract period, often with a premium. In some cases, new tenants are also offered discounts or no-pay periods at the start of their contract in exchange for higher prices later in the contract period. Unfortunately there is no way of quantifying this effect or correcting for it. As the study looks at changes from period to period, it can be assumed that the data will still be representative for the prevailing market conditions.

4.2. Macroeconomic variables

For interest rates, real 10 years NIBOR is used. It is available from the Norwegian central bank on a daily frequency. Data on real GDP and employment are readily available through Datastream from Statistisk Sentralbyrå (Statistics Norway) with quarterly frequency.

4.3. Market specific variables

Data on office vacancy rates as well as expected future construction are published by Eiendomsspar in an annual report called "Oslostudiet", with data available back to 1986. Eiendomsspar is a Norwegian professional real estate investment company. The series consist of estimates based on offices offered for rent in newspapers, advertisements and other relevant publications, visual inspection of Oslo city areas and conversations with about 100 active market participants. The series include both sub-lets and regular offers. The change from period to period is given by the sum of newly constructed or vacated space, less absorption of existing vacancy. The data is unfortunately only compiled annually so linear interpolation is used in order to get quarterly observations. Data on vacant space and expected future construction is only available in number formats from 1998. The previous periods are only available in the form of graphical presentations. The data for the years 1996 until 1999 was estimated by physically measuring bars in the published graph.

4.4. Forecasts by DnB NOR Næringsmegling

A series of forecasted rental rates has been made available from DnB NOR Næringsmegling. Going back to 2006, they have conducted forecasts every half-year until date. The forecasts consist of half-year predictions up to 2,5 years ahead in time, for various Oslo segments. In order to compare these values to the forecasts, the data is aggregated and linearly interpolated to get an aggregate quarterly data series for Oslo.

5. Analysis and results

5.1. Linear regression model

Eviews was used to estimate a linear regression model of rental rates with average price (AP) as the dependent variable and employment (EMP), gross domestic product (GDP), interest rates (INT), vacancy (VAC) and expected new construction in the following 2 years (NEW2) as independent variables.

All independent variables are lagged two periods to account for the fact that contracts on average start 4-8 months after signing, sometimes longer. The prices are recorded at the time when the tenant moves in, not at the time of signing the contract. GDP and EMP are lagged one additional period because the effect it has on price is not likely to be instant. INT are lagged once for the same reason and an additional lag is added because the interest rates are end of quarter numbers and therefore gives the return for the following quarter. In section 5.1.1 we check the assumptions of the Gauss-Markov theorem as well as test for structural breaks and seasonal effects. The final model is estimated in section 5.1.2 before forecasts are produced and their performance evaluated in section 5.1.3.

5.1.1. Diagnostics

First the variables were checked for unit roots, applying the augmented Dickey-Fuller (ADF) test. All variables except vacancy contain unit roots. The test statistic for interest rates is close to the critical value, but the null-hypothesis of a unit root cannot be rejected. To make the variables stationary the difference logs are taken of all the variables. Re-doing the ADF test reveals that all variables are now stationary. The new series are given a "D" prefix to distinguish them from the non-differenced series. The data series with the shortest sample horizon is AP and EMP, both starting from 1996Q1. Having the variables in log-difference removes the first observation, making it 1996Q2. Since DEMP is lagged 3 periods, or quarters, three more observations are omitted. The study proceeds by running the model for the in-sample observations, from 1997Q1-2006Q4, with the log-difference of average price (DAP) as the dependent variable. All variables follow the lag-structure mentioned above. The estimates are shown in table 5.1.1.1.

Table 5.1.1.1

Included observations: 40 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000197	0.016036	-0.012292	0.9903
DEMP(-3)	1.690529	1.550646	1.090209	0.2833
DGDP(-3)	-0.194501	0.368703	-0.527526	0.6013
DINT(-4)	0.101694	0.200874	0.506256	0.6159
DVAC(-2)	-0.146482	0.270884	-0.540754	0.5922
DNEW2(-2)	-0.056511	0.116087	-0.486794	0.6295

R-squared	0.052712	Mean dependent var	-0.003541
Adjusted R-squared	-0.086595	S.D. dependent var	0.089906
S.E. of regression	0.093718	Akaike info criterion	-1.759580
Sum squared resid	0.298622	Schwarz criterion	-1.506248
Log likelihood	41.19160	Hannan-Quinn criter.	-1.667983
F-statistic	0.378386	Durbin-Watson stat	3.098689
Prob(F-statistic)	0.860006		

None of the variables show significance, and the R^2 is very low. The next step is checking if OLS will provide the "Best Linear Unbiased Estimators" (BLUE). This is done by checking if the assumptions of the Gauss-Markov theorem hold.

The first of these assumptions is that on average, the errors are equal to 0. When an intercept is included, as it is here, this assumption is never violated.

The second assumption is that the variance of the errors remains constant over time, or in other words, that the errors are homoscedastic. White's general test for heteroscedasticity is applied to see if this assumption is violated. The results are shown in Table 5.1.1.2.

Table 5.1.1.2

Heteroskedasticity Test: White

F-statistic	1.125819	Prob. F(5,34)	0.3655
Obs*R-squared	5.681780	Prob. Chi-Square(5)	0.3384
Scaled explained SS	3.093269	Prob. Chi-Square(5)	0.6856

Included observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007509	0.003121	2.406175	0.0217
DEMP(-3)^2	21.41989	14.31598	1.496223	0.1438
DGDP(-3)^2	-0.085584	0.726635	-0.117781	0.9069
DINT(-4)^2	-0.190997	0.133807	-1.427411	0.1626
DVAC(-2)^2	-0.236653	0.194738	-1.215238	0.2326
DNEW2(-2)^2	0.005662	0.030325	0.186718	0.8530

R-squared	0.142045	Mean dependent var	0.007466
Adjusted R-squared	0.015875	S.D. dependent var	0.009282
S.E. of regression	0.009208	Akaike info criterion	-6.400091
Sum squared resid	0.002883	Schwarz criterion	-6.146759
Log likelihood	134.0018	Hannan-Quinn criter.	-6.308494
F-statistic	1.125819	Durbin-Watson stat	1.979730
Prob(F-statistic)	0.365460		

P-values close to or below the 5% threshold indicate heteroscedasticity. The results show no evidence of this. The assumption of homoscedasticity is not violated.

The third assumption is that the covariance between error terms is zero over time. If the covariance is not equal to zero they are said to be autocorrelated. The Durbin-Watson test is applied to check for autocorrelation. Three conditions must be met for this test to be valid; the regression must contain a constant term, the regressors must be non-stochastic and the regression cannot contain lags of the dependent variable. All these conditions are met here. A DW-stat of 3,10 is obtained. This value is outside the range given by the table of critical values and we must reject the null hypothesis of no autocorrelation. There is negative serial correlation in the residuals and the assumption of no autocorrelation is violated. The Breusch-Godfrey test performed with 10 lags confirms this (Table 5.1.1.3).

Table 5.1.1.3

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	3.229488	Prob. F(10,24)	0.0090
Obs*R-squared	22.94694	Prob. Chi-Square(10)	0.0109

Both the F and Chi-square probabilities are below the 5-percent threshold, indicating autocorrelation. The consequence of ignoring autocorrelation is that OLS is unbiased but inefficient, i.e. not BLUE even at large sample sizes (Brooks 2008). Thus, to correct for autocorrelation, lags of the dependent variable are included on the right hand side. The results of the new estimation of the model, including two lags of the dependent variable on the right hand side, are shown in table 5.1.1.4. Additional lags of DAP are insignificant.

Table 5.1.1.4

Included observations: 40 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005243	0.012257	0.427726	0.6717
DAP(-1)	-0.723387	0.140308	-5.155724	0.0000
DAP(-2)	-0.354016	0.134404	-2.633973	0.0129
DEMP(-3)	2.507255	1.191454	2.104366	0.0433
DGDP(-3)	-0.262745	0.281451	-0.933536	0.3575
DINT(-4)	0.318341	0.158789	2.004803	0.0535
DVAC(-2)	-0.365255	0.211146	-1.729869	0.0933
DNEW2(-2)	-0.039985	0.089916	-0.444694	0.6595

R-squared	0.483359	Mean dependent var	-0.003541
Adjusted R-squared	0.370344	S.D. dependent var	0.089906
S.E. of regression	0.071341	Akaike info criterion	-2.265836
Sum squared resid	0.162865	Schwarz criterion	-1.928060
Log likelihood	53.31672	Hannan-Quinn criter.	-2.143707
F-statistic	4.276946	Durbin-Watson stat	2.429966
Prob(F-statistic)	0.001955		

Now several variables are significant at the 5% level. DAP(-1), DAP(-2) and DEMP(-3) all have t-stats well above the critical value. DINT(-4) and DVAC(-2) are significant at the 10% level. The R^2 also shows significant improvement. Since the DW-test does not hold when using lagged dependent variables, the Breusch-Godfrey test is conducted. The results are shown in table 5.1.1.5. The test now shows no evidence of autocorrelation.

Table 5.1.1.5

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.445936	Prob. F(10,22)	0.2253
Obs*R-squared	15.86354	Prob. Chi-Square(10)	0.1036

The fourth assumption of non-stochastic explanatory variables is violated since lags of the dependent variable are used. This can lead to biased coefficient estimates in small samples, though they will still be consistent. Bias will disappear as sample size increases towards infinity (Brooks 2008).

The fifth assumption is that the disturbance terms are normally distributed. The test by Bera and Jarque is used to check for normality. When running tests of normality for the log-differenced series, the average price, employment and GDP are all normal. The vacant space, interest and new space series are non-normal. As the sample is relatively small, the non-normality of the errors could lead to drawing wrong inferences from the coefficient estimates. However, since the dependent variable is normally distributed and the other assumptions hold (except the fourth), this is of less importance and inferences can be drawn. Table 5.1.1.6 contains descriptive statistics for the all the variable series.

Table 5.1.1.6

	DAP	DEMP	DGDP	DINT	DVAC	DNEW2
Mean	-0.001311	0.000628	0.016922	-0.005744	-0.008466	0.007183
Median	-0.023167	0.001267	0.017276	-0.008779	-0.025383	0.015334
Maximum	0.256720	0.023380	0.095880	0.257500	0.192523	0.292335
Minimum	-0.187683	-0.021434	-0.055066	-0.151152	-0.116165	-0.529310
Std. Dev.	0.098313	0.010296	0.040744	0.083161	0.064266	0.148204
Skewness	0.192542	-0.231389	0.100582	0.906839	1.034811	-1.113959
Kurtosis	2.819060	2.496179	1.990906	4.199226	4.326665	5.198714
Jarque-Bera	0.324343	0.838497	2.249818	10.04609	12.84217	20.82067
Probability	0.850295	0.657541	0.324682	0.006584	0.001627	0.000030
Sum	-0.056353	0.026984	0.863003	-0.292939	-0.431790	0.366340
Sum Sq. Dev.	0.405947	0.004453	0.083003	0.345786	0.206505	1.098222

Finally, the implicit assumption of no multi-collinearity is checked, that the explanatory variables are not too highly correlated to each other. This is done using a correlations table (table 5.1.1.7). Variables with correlations in excess of 0,30 are highlighted in yellow.

Table 5.1.1.7

	DAP	DAP(-1)	DAP(-2)	DEMP(-3)	DGDP(-3)	DINT(-4)	DVAC(-2)	DNEW2(-2)
DAP	1.0000							
DAP(-1)	-0.0686	1.0000						
DAP(-2)	-0.0021	-0.1389	1.0000					
DEMP(-3)	-0.0407	0.2149	0.1446	1.0000				
DGDP(-3)	-0.0509	0.3846	-0.1931	0.5134	1.0000			
DINT(-4)	0.5283	0.0816	-0.0365	-0.2253	-0.2816	1.0000		
DVAC(-2)	-0.4457	-0.4603	-0.2667	-0.2092	-0.1988	-0.2839	1.0000	
DNEW2(-2)	0.2703	0.3440	0.2469	-0.0031	-0.0062	0.2347	-0.9015	1.000

A high correlation between GDP(-3) and DEMP(-3) of 0,51 is seen, as is to be expected. Between the demand side variables there is a very high correlation of 0,9 between DVAC(-2) and DNEW2(-2). However, due to their insignificance with regards to DAP, both DGDP(-3) and DNEW2(-2) will be excluded in the final model, meaning that this will not cause problems of near-multicollinearity. Given that all assumptions are fulfilled adequately, OLS can be assumed to provide the Best Linear Unbiased Estimates.

The study proceeds by performing a Chow test for structural breaks. The test was performed for several dates, but 2001Q1 gave the lowest p-values. The results indicate no structural breaks. Furthermore the Chow Forecast test suggests the model can adequately predict at least 4 periods ahead. The results are shown in table 5.1.1.8.

Table 5.1.1.8

Chow Breakpoint Test: 2001Q1
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 1997Q1 2006Q4

F-statistic	1.410216	Prob. F(8,24)	0.2426
Log likelihood ratio	15.41246	Prob. Chi-Square(8)	0.0516
Wald Statistic	11.28173	Prob. Chi-Square(8)	0.1862

Chow Forecast Test
Specification: DAP C DAP(-1) DAP(-2) DEMP(-3) DGDP(-3) DINT(-4) DVAC(-2) DNEW2(-4)
Test predictions for observations from 2006Q1 to 2006Q4

	Value	df	Probability
F-statistic	0.264365	(4, 28)	0.8983
Likelihood ratio	1.482828	4	0.8297

Testing for seasonality was conducted by including 4 dummy variables, one per quarter. The first quarter dummy variable would have a 1 in the first quarter, and 0 in the other 3. There is no significant seasonal effect. The results are shown in table 5.1.1.9.

Table 5.1.1.9

Dependent Variable: DAP
Method: Least Squares
Date: 07/20/11 Time: 11:10
Sample (adjusted): 1997Q1 2006Q4
Included observations: 40 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DAP(-1)	-0.731225	0.157825	-4.633135	0.0001
DAP(-2)	-0.330286	0.143346	-2.304116	0.0286
DGDP(-3)	-0.420549	0.556482	-0.755728	0.4559
DEMP(-3)	3.530261	2.417666	1.460194	0.1550
DINT(-4)	0.344966	0.167497	2.059536	0.0485
DVAC(-2)	-0.334541	0.220135	-1.519706	0.1394
DNEW2(-2)	-0.023510	0.094918	-0.247687	0.8061
Q1	-0.022095	0.033729	-0.655057	0.5176
Q2	0.018314	0.030289	0.604646	0.5501
Q3	0.021776	0.053666	0.405760	0.6879
Q4	0.014129	0.037491	0.376864	0.7090

R-squared	0.506873	Mean dependent var	-0.003541
Adjusted R-squared	0.336829	S.D. dependent var	0.089906
S.E. of regression	0.073215	Akaike info criterion	-2.162415
Sum squared resid	0.155453	Schwarz criterion	-1.697974
Log likelihood	54.24831	Hannan-Quinn criter.	-1.994488
Durbin-Watson stat	2.409165		

5.1.2. Model estimation

After going through the process of diagnostics checking and correcting for the issues found, the model is estimated. The estimation in table 5.1.1.4 had two insignificant variables, DGDP(-3) and DNEW2(-2). These were removed and the model re-estimated. Table 5.1.2.1 shows the results for the final model.

Table 5.1.2.1

Included observations: 40 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001638	0.011242	0.145737	0.8850
DAP(-1)	-0.719279	0.137830	-5.218589	0.0000
DAP(-2)	-0.350854	0.130998	-2.678309	0.0113
DEMP(-3)	2.317480	1.142170	2.029016	0.0503
DINT(-4)	0.303992	0.155668	1.952823	0.0591
DVAC(-2)	-0.299537	0.175792	-1.703931	0.0975

R-squared	0.467468	Mean dependent var	-0.003541
Adjusted R-squared	0.389154	S.D. dependent var	0.089906
S.E. of regression	0.070267	Akaike info criterion	-2.335539
Sum squared resid	0.167875	Schwarz criterion	-2.082207
Log likelihood	52.71079	Hannan-Quinn criter.	-2.243943
F-statistic	5.969176	Durbin-Watson stat	2.501648
Prob(F-statistic)	0.000458		

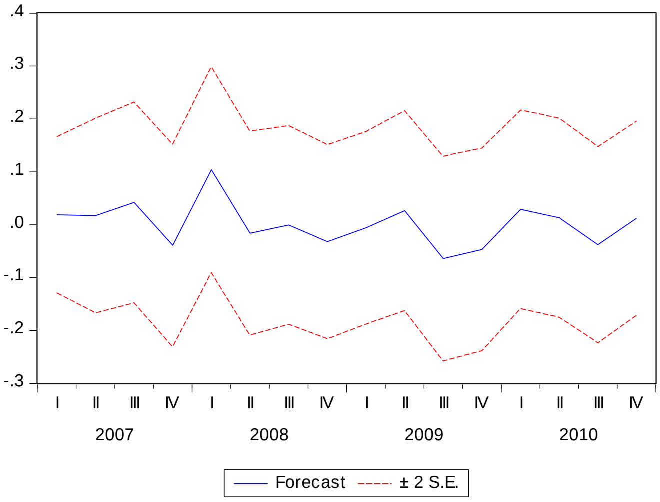
All variables are now significant at the 10% level, and all but DVAC(-2) are nearly significant at the 5% level. DAP(-1) is highly significant and DAP(-2) very close to significance at the 1% level. The adjusted R^2 is higher than before omitting the two variables, indicating a model that better fits the data. All coefficient signs are similar to the a-priori expectations. The lagged values of rental rates take a negative sign, indicating that the prices are mean reverting. That is, a positive return one period will on average be followed by a negative return next period. Increase in employment and interest rates both have a significant positive impact on rents, and an increase in vacancy induces a negative pressure on prices. The relatively high R^2 indicates a model with good fit where the above variables explain up to 46% of the variance in rental rate returns. The constant term is insignificant.

For the estimation periods ending 2007Q4, 2008Q4 and 2009Q4 the results show the same trend. The adj. R^2 sees a marginal improvement, and from 2007Q4 and onwards all variables are significant at the 5% level except DEMP(-3) in the 2009Q4 estimation, which is just above the threshold. The estimation outputs are available in the appendix A.1-A.3. In the next section forecasts with varying estimation and forecast periods are produced and the results evaluated.

5.1.3. Forecasting and performance evaluation

Eviews was used to generate both dynamic and static forecasts, starting with an estimation period from 1997Q1 to 2006Q4 and a forecast period from 2007Q1 to 2010Q4. Table 5.1.3.1 contains a graph of the forecasted values and the forecast error (±2 SE), along with a table of performance measures for the dynamic forecast.

Table 5.1.3.1

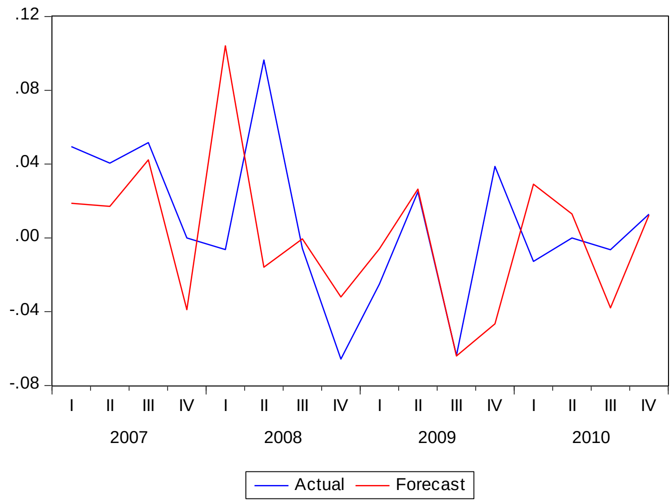


Forecast sample: 2007Q1 2010Q4	
Included observations: 16	
Root Mean Squared Error	0.049762
Mean Absolute Error	0.034812
Mean Abs. Percent Error	204.4370
Theil Inequality Coefficient	0.609700
Bias Proportion	0.018285
Variance Proportion	0.000211
Covariance Proportion	0.981504

Table 5.1.3.2 gives a table of the forecasted values and graphs them together with the actual values. It shows the forecasts mimicking the actual values. It captures the large increase and decrease at the end of 2007/start of 2008 in advance of the actual values. The signs and values for 2009Q2/Q3 and 2010Q4 are almost equal.

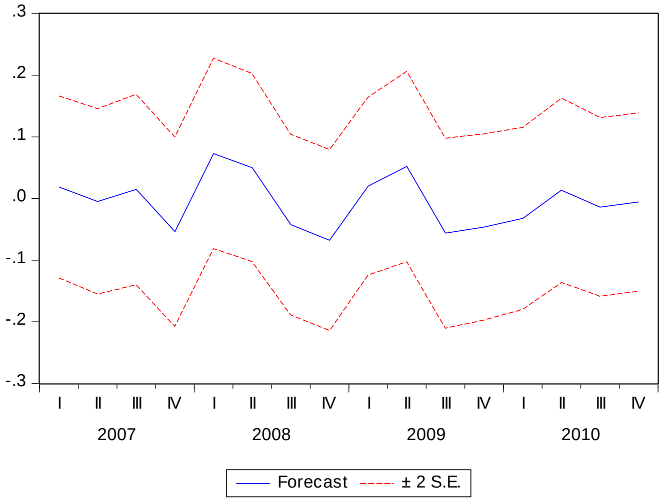
Table 5.1.3.2

Period	Actual	Forecast
2007Q1	0.049480	0.018776
2007Q2	0.040546	0.017093
2007Q3	0.051624	0.042283
2007Q4	0.000000	-0.038931
2008Q1	-0.006309	0.104104
2008Q2	0.096460	-0.015872
2008Q3	-0.005764	-0.000546
2008Q4	-0.065695	-0.032044
2009Q1	-0.025001	-0.005921
2009Q2	0.025001	0.026438
2009Q3	-0.063716	-0.064054
2009Q4	0.038715	-0.046575
2010Q1	-0.012739	0.029130
2010Q2	0.000000	0.012994
2010Q3	-0.006431	-0.037928
2010Q4	0.012821	0.012384



The same procedure was followed for a static forecast. The results are shown in Tables 5.1.3.3 and 5.1.3.4.

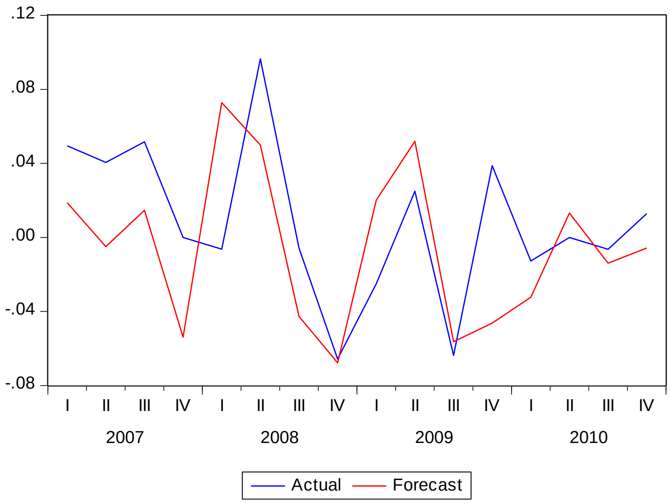
Table 5.1.3.3



Forecast sample: 2007Q1 2010Q4	
Included observations: 16	
Root Mean Squared Error	0.041896
Mean Absolute Error	0.034684
Mean Abs. Percent Error	195.2985
Theil Inequality Coefficient	0.504448
Bias Proportion	0.099415
Variance Proportion	0.000098
Covariance Proportion	0.900488

Table 5.1.3.4

Period	Actual	Forecast
2007Q1	0.049480	0.018776
2007Q2	0.040546	-0.004992
2007Q3	0.051624	0.014641
2007Q4	0.000000	-0.053878
2008Q1	-0.006309	0.072825
2008Q2	0.096460	0.049887
2008Q3	-0.005764	-0.042605
2008Q4	-0.065695	-0.067704
2009Q1	-0.025001	0.020114
2009Q2	0.025001	0.051969
2009Q3	-0.063716	-0.056326
2009Q4	0.038715	-0.046314
2010Q1	-0.012739	-0.032336
2010Q2	0.000000	0.013185
2010Q3	-0.006431	-0.013892
2010Q4	0.012821	-0.005713



Also here the forecasted values mimic the actuals. It leads the end of the 2007 increase and the 2008 decrease and lags the 2009/10 increase. New estimations were done including one more year of observations at a time and doing forecasts for the out-of-sample period to see if the model improves. The performance measures for all the forecasts are shown in tables 5.1.3.5 and 5.1.3.6. Estimation results for the three remaining periods are available in appendix A.

Table 5.1.3.5: Dynamic forecasts

Sample	Forecast	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1997-2006	1 yr	0,0278	0,0256	34,4977	0,3836	0,8473	0,1043	0,0484	75 %
1997-2007	1 yr	0,0669	0,0551	428,2724	0,6414	0,0097	0,0439	0,9463	25 %
1997-2008	1 yr	0,0454	0,0354	104,6902	0,5126	0,0607	0,0052	0,9340	50 %
1997-2009	1 yr	0,0185	0,0172	119,4681	0,5480	0,0706	0,5591	0,3703	100 %
1997-2006	2 yr	0,0603	0,0455	268,2795	0,6320	0,1844	0,0028	0,9787	63 %
1997-2007	2 yr	0,0570	0,0435	259,5084	0,5878	0,0073	0,0065	0,9862	50 %
1997-2008	2 yr	0,0363	0,0282	150,8446	0,5381	0,0046	0,0411	0,9544	63 %
1997-2006	3 yr	0,0553	0,0392	204,0946	0,6044	0,0387	0,0020	0,9593	67 %
1997-2007	3 yr	0,0491	0,0367	245,1255	0,5951	0,0003	0,0003	0,9994	58 %
1997-2006	4 yr	0,0498	0,0348	204,4370	0,6097	0,0183	0,0002	0,9815	69 %

Table 5.1.3.6: Static forecasts

Sample	Forecast	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1997-2006	1 yr	0,0427	0,0418	61,5009	0,6041	0,9580	0,0351	0,0069	50 %
1997-2007	1 yr	0,0495	0,0379	483,2347	0,4063	0,0152	0,0066	0,9782	75 %
1997-2008	1 yr	0,0517	0,0422	135,9991	0,5674	0,0007	0,0275	0,9719	50 %
1997-2009	1 yr	0,0132	0,0121	88,3292	0,4616	0,2792	0,3218	0,3990	100 %
1997-2006	2 yr	0,0462	0,0415	273,8514	0,4735	0,2200	0,0002	0,7798	63 %
1997-2007	2 yr	0,0512	0,0403	309,8082	0,4758	0,0011	0,0158	0,9831	63 %
1997-2008	2 yr	0,0380	0,0277	118,0859	0,5577	0,0150	0,0394	0,9457	75 %
1997-2006	3 yr	0,0475	0,0413	225,8630	0,5042	0,0984	0,0000	0,9016	58 %
1997-2007	3 yr	0,0428	0,0318	240,5517	0,4766	0,0009	0,0220	0,9771	75 %
1997-2006	4 yr	0,0419	0,0347	195,2985	0,5044	0,0994	0,0001	0,9005	63 %

For the dynamic forecasts, the 1-year forecasts have on average better (lower) RMSE, MAE, MAPE and Theil stats than the 2, 3 and 4-year forecasts. The percentage of signs correct is better (higher) for the 1-year than the 2-year, similar to the 3-year and outperformed by the 4-year. Excluding the 1997-2006 estimation 1-year forecast (which has a very high bias portion of 0,95), the measurements improve as the estimation sample grows. The same trend is seen with the 2-year forecasts. The limited amount of data allows only two 3-year forecasts and one 4-year forecast. All MAE measures have positive signs, indicating that the model over-predicts. The dynamic forecasts are incapable of producing forecasts with MAPE stats under 100 (except the first, which can be disregarded due to a high bias portion) or Theil stats close to 0,2. However, the 4-year forecast does manage to get 69% of the forecasted signs correct. From the improvement seen in the 1-year and 2-year forecasts with a larger sample, we expect to see better forecasts as the amount of data available grows.

The static forecasts produce on average marginally better RMSE and MAE measurements than the dynamic for the same periods. This is also underpinned by the lower Theil stats and higher percentage of signs correct. MAPE stats are on average worse. Similar to the dynamic measures, improvements can be seen in the 1-year and 2-year forecasts as the sample grows.

In summary, the dynamic and static forecasts do not perform very well, they are not consistently close to beating a random walk. Of the two, the static performs marginally better, indicating the model being better at shorter forecast periods. However the positive improvement in measures as the sample grows, gives expectations of more improvement as longer data series become available. In section 5.4 this is explored further and results underpinning these expectations are found.

5.2. ARIMA model

5.2.1. Model estimation

In this chapter forecasts are generated using a univariate ARIMA model. The same estimation and forecasting periods that were used for the linear regression model are used here as well to see how this performs in comparison to the forecast based on linear regression done above.

Table 5.2.1.1 shows a correlogram of DAP with 10 lags included. Both the autocorrelation and partial autocorrelation functions seem to be geometrically declining, suggesting that a combination of AR and MA terms is appropriate.

Table 5.2.1.1

Sample: 1996Q1 2010Q4
Included observations: 59

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.384	-0.384	9.1310	0.003
		2	-0.113	-0.305	9.9319	0.007
		3	0.133	-0.051	11.077	0.011
		4	0.020	0.042	11.104	0.025
		5	-0.026	0.051	11.149	0.049
		6	0.055	0.101	11.357	0.078
		7	0.028	0.112	11.410	0.122
		8	-0.178	-0.140	13.650	0.091
		9	0.276	0.174	19.120	0.024
		10	-0.284	-0.224	25.035	0.005

To be able to determine the correct order of the ARIMA model, DAP is ran with several combinations of AR and MA terms in Eviews. The goal is to find the model that minimizes the information criteria. A table of the information criteria values generated is shown in table 5.2.1.2.

Table 5.2.1.2

AIC	AR(0)	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
MA(0)		-2,21827	-2,30386	-2,39296	-2,56372	-2,52893
MA(1)	-2,2556	-2,24797	-2,27905	-2,46701	-2,52983	-2,50834
MA(2)	-2,25873	-2,38203	-2,49834	-2,51218	-2,51044	-2,47163
MA(3)	-2,34982	-2,35427	-2,47443	-2,49414	-2,47551	-2,44254
MA(4)	-2,2478	-2,35991	-2,47237	-2,61509	-2,56374	-2,65287
MA(5)	-2,28827	-2,32915	-2,49845	-2,5848	-2,60762	-2,61309

SBIC	AR(0)	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
MA(0)		-2,14722	-2,19633	-2,24829	-2,38124	-2,30794
MA(1)	-2,18517	-2,14139	-2,13568	-2,28617	-2,31085	-2,25051
MA(2)	-2,15309	-2,23993	-2,31913	-2,29518	-2,25496	-2,17697
MA(3)	-2,20897	-2,17665	-2,25937	-2,24098	-2,18354	-2,11104
MA(4)	-2,14046	-2,14676	-2,22146	-2,32575	-2,23526	-2,28454
MA(5)	-2,07699	-2,08048	-2,21171	-2,2593	-2,24265	-2,20793

HQ	AR(0)	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)
MA(0)		-2,19059	-2,26207	-2,33687	-2,49315	-2,4437
MA(1)	-2,22811	-2,20645	-2,22333	-2,3969	-2,44515	-2,40891
MA(2)	-2,21749	-2,32668	-2,42869	-2,42805	-2,41165	-2,35799
MA(3)	-2,29484	-2,28508	-2,39085	-2,39599	-2,3626	-2,31469
MA(4)	-2,31652	-2,27688	-2,37486	-2,50291	-2,43671	-2,51082
MA(5)	-2,20579	-2,23229	-2,38701	-2,4586	-2,46648	-2,45683

As can be seen from the table, both the Akaike and the Hannan-Quinn information criteria suggest that an ARIMA(5,1,4) will fit the data best. Schwartz's Bayesian criterion, which has a stronger penalty for additional terms, suggests a smaller ARIMA(4,1,0) model. Based on the examination of the ACF and PACF plots, the bigger model suggested by Akaike and Hannan-Quinn is favoured. After removing 5 lags, the regression is run on the sample 1997Q3 – 2006Q4, 38 observations. Full output of results is shown in table 5.2.1.3.

Table 5.2.1.3

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.004369	0.006996	-0.624487	0.5374
AR(1)	-0.467000	0.185537	-2.517024	0.0178
AR(2)	0.114243	0.201881	0.565891	0.5760
AR(3)	0.587114	0.157949	3.717109	0.0009
AR(4)	-0.059980	0.168287	-0.356416	0.7242
AR(5)	-0.177306	0.153768	-1.153075	0.2586
MA(1)	-0.459435	0.105151	-4.369276	0.0002
MA(2)	-0.244218	0.148502	-1.644543	0.1112
MA(3)	-0.413125	0.105191	-3.927391	0.0005
MA(4)	0.973291	0.042964	22.65361	0.0000

R-squared	0.681506	Mean dependent var	-0.001302
Adjusted R-squared	0.579133	S.D. dependent var	0.087484
S.E. of regression	0.056755	Akaike info criterion	-2.679217
Sum squared resid	0.090191	Schwarz criterion	-2.248273
Log likelihood	60.90512	Hannan-Quinn criter.	-2.525890
F-statistic	6.657078	Durbin-Watson stat	1.825894
Prob(F-statistic)	0.000048		

Inverted AR Roots	.59+.23i	.59-.23i	-.52	-.56-.72i
	-.56+.72i			
Inverted MA Roots	.87-.50i	.87+.50i	-.64+.75i	-.64-.75i

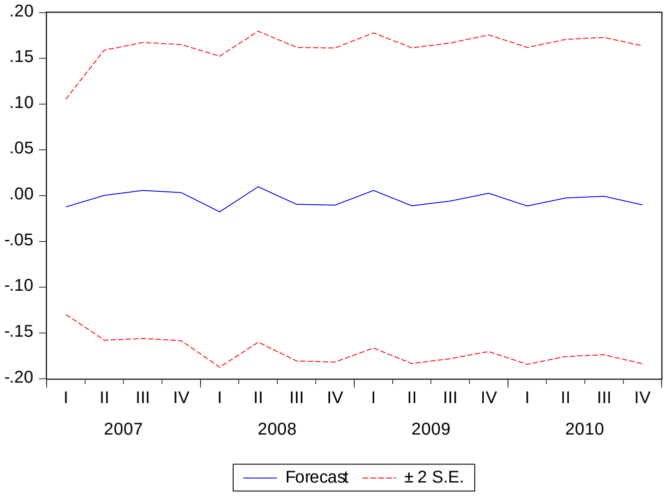
Not all AR or MA lags show significance. The AR(3), MA(1), MA(3) and MA(4) are all highly statistically significant at the 1% level and the AR(1) statistically significant at the 2,5% level. One should however exert caution in trying to interpret the coefficient estimates, seeing as the model is not based on any underlying theory. An R^2 of 0,68, which is greater than the one of the classical regression model (0,467), is obtained. The constant term is insignificant. It can also be noted that the inverted AR and MA roots all show values well below 1, indicating that the model is both stationary and invertible.

Estimation outputs for the later periods are available in appendix B.1 – B.3. For the 2007Q4 estimation period, the adjusted R^2 is lower (0,49) and the same variables are significant. The 2008Q4 estimation has an adjusted R^2 of 0,48, and now the AR(2) and MA(2) variables show significance. For the 2009Q4 estimation the adjusted R^2 keeps falling to 0,42, and now AR(2) - AR(5) and all MA terms show significance. The ARIMA model estimations does not seem to improve when adding more observations, and the forecasts are coloured by this.

5.2.2. Forecasting performance

Dynamic and static forecasts were generated in the same way as in section 5.1. Table 5.2.2.1 contains a graph of the forecasted values ±2 SE along with a table of performance measures for the dynamic forecast.

Table 5.2.2.1

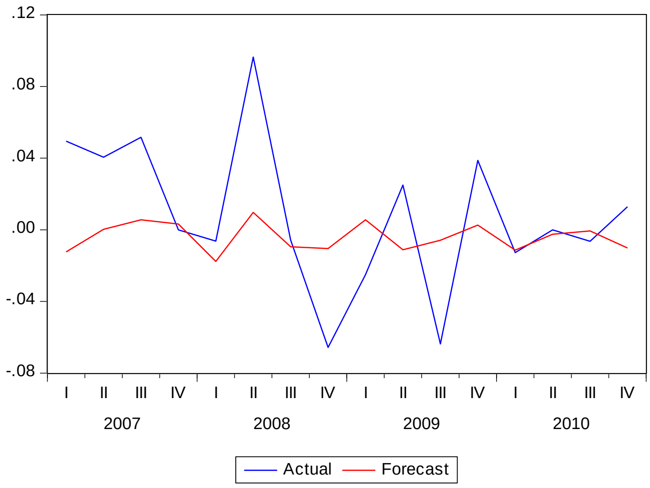


Forecast sample: 2007Q1 2010Q4	
Included observations: 16	
Root Mean Squared Error	0.040132
Mean Absolute Error	0.031365
Mean Abs. Percent Error	91.41765
Theil Inequality Coefficient	0.797435
Bias Proportion	0.090753
Variance Proportion	0.674967
Covariance Proportion	0.234280

Table 5.2.2.2 gives a table of the forecasted values and graphs them together with the actual values. Unlike in the linear regression graphs, the forecasted values show a flat curve, not getting the highs and lows of the actual values.

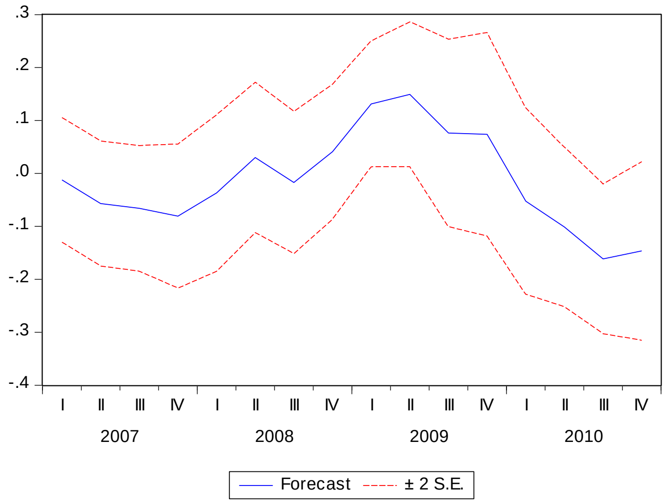
Table 5.2.2.2

Period	Actual	Forecast
2007Q1	0.049480	-0.012347
2007Q2	0.040546	0.000303
2007Q3	0.051624	0.005598
2007Q4	0.000000	0.003194
2008Q1	-0.006309	-0.017654
2008Q2	0.096460	0.009685
2008Q3	-0.005764	-0.009436
2008Q4	-0.065695	-0.010418
2009Q1	-0.025001	0.005584
2009Q2	0.025001	-0.011170
2009Q3	-0.063716	-0.005795
2009Q4	0.038715	0.002624
2010Q1	-0.012739	-0.011316
2010Q2	0.000000	-0.002520
2010Q3	-0.006431	-0.000629
2010Q4	0.012821	-0.010150



The same procedure was followed for a static forecast. The results are shown in Tables 5.2.2.3 and 5.2.2.4.

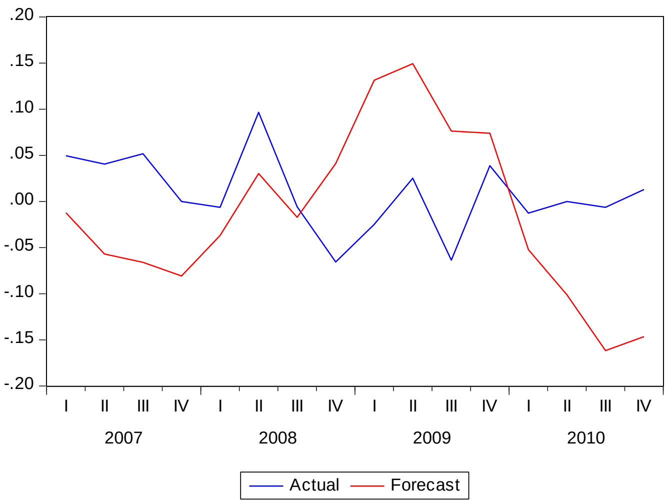
Table 5.2.2.3



Forecast sample: 2007Q1 2010Q4	
Included observations: 16	
Root Mean Squared Error	0.103870
Mean Absolute Error	0.092770
Mean Abs. Percent Error	431.8802
Theil Inequality Coefficient	0.788755
Bias Proportion	0.046637
Variance Proportion	0.215493
Covariance Proportion	0.737871

Table 5.2.2.4

Period	Actual	Forecast
2007Q1	0.049480	-0.012347
2007Q2	0.040546	-0.056976
2007Q3	0.051624	-0.066037
2007Q4	0.000000	-0.080820
2008Q1	-0.006309	-0.036964
2008Q2	0.096460	0.030156
2008Q3	-0.005764	-0.017255
2008Q4	-0.065695	0.040996
2009Q1	-0.025001	0.131307
2009Q2	0.025001	0.149393
2009Q3	-0.063716	0.076343
2009Q4	0.038715	0.073972
2010Q1	-0.012739	-0.052255
2010Q2	0.000000	-0.101237
2010Q3	-0.006431	-0.161633
2010Q4	0.012821	-0.146553



In contrast to the graph from the dynamic forecasts, the static is more volatile. However from 2008Q3 and onwards the forecast is very off the actual values.

New estimations, including one more year of observations at a time and doing forecasts for the out-of-sample period, were performed to see if the model improves. The performance measures for all the forecasts are shown in table 5.2.2.5 and 5.2.2.6. Estimation results for the three remaining periods are available in appendix B.1 – B.3.

Table 5.2.2.5: Dynamic forecasts

Sample	Forecast	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1997-2006	1 yr	0,0435	0,0378	78,3407	0,9051	0,6934	0,1028	0,2039	75 %
1997-2007	1 yr	0,0581	0,0495	251,1192	0,6564	0,1546	0,6419	0,2035	25 %
1997-2008	1 yr	0,0680	0,0570	168,9222	0,8220	0,2744	0,0289	0,6967	50 %
1997-2009	1 yr	0,0166	0,0154	130,0987	0,6412	0,5886	0,0104	0,4010	50 %
1997-2006	2 yr	0,0478	0,0385	91,3725	0,7900	0,2503	0,6058	0,1439	88 %
1997-2007	2 yr	0,0534	0,0465	184,1916	0,7222	0,1430	0,5018	0,3552	38 %
1997-2008	2 yr	0,0500	0,0367	160,1525	0,8258	0,2001	0,0112	0,7887	38 %
1997-2006	3 yr	0,0458	0,0391	98,5100	0,8073	0,1015	0,6817	0,2168	75 %
1997-2007	3 yr	0,0439	0,0336	144,3202	0,7225	0,0916	0,3801	0,5283	50 %
1997-2006	4 yr	0,0401	0,0314	91,4177	0,7974	0,0908	0,6750	0,2343	69 %

Table 5.2.2.5: Static forecasts

Sample	Forecast	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1997-2006	1 yr	0,0918	0,0895	148,3479	0,9100	0,9496	0,0026	0,0478	0 %
1997-2007	1 yr	0,0577	0,0414	118,8679	0,6221	0,1204	0,3573	0,5223	50 %
1997-2008	1 yr	0,0780	0,0725	219,9755	0,7050	0,8656	0,0690	0,0654	50 %
1997-2009	1 yr	0,0226	0,0196	182,4078	0,7357	0,5622	0,0008	0,4370	50 %
1997-2006	2 yr	0,0795	0,0716	188,7227	0,8054	0,3197	0,0043	0,6760	38 %
1997-2007	2 yr	0,0665	0,0544	165,3456	0,6734	0,3123	0,0826	0,6051	50 %
1997-2008	2 yr	0,0600	0,0495	237,1372	0,7205	0,1765	0,1029	0,7206	50 %
1997-2006	3 yr	0,0963	0,0857	245,2843	0,7786	0,0070	0,0800	0,9130	25 %
1997-2007	3 yr	0,0667	0,0580	295,5968	0,6811	0,0021	0,0469	0,9511	50 %
1997-2006	4 yr	0,1039	0,0928	431,8802	0,7888	0,0466	0,2155	0,7379	44 %

The dynamic forecasts produced by the ARIMA model yield on average worse measures than for the same estimation and forecasting periods in the linear regression model. For the 1-year forecasts they perform worse on average through all measures except MAPE. Although some forecasts have better RMSE measures, like the 2007 and 2009 estimations, this is offset by high Theil stats and high bias and variance portions. For the 2-year forecasts the RMSE and MAE measures are better than the linear regression for the 2006 estimation and the RMSE better for the 2007 estimation, however again both are troubled by higher Theil, bias and variance measures. Unlike the forecasts produced by the linear regression, there is no consistent improvement in the 1-year or 2-year forecasts as more observations are added to the estimation. The bias and variance portions are also much higher. MAE again all positive, implying overestimation of values by the model. None of the forecasts seem to perform well with regards to MAPE, Theil or variance decomposition.

For the static forecasts, all measures except MAPE, are worse than for the comparable linear regression static and dynamic forecasts. The measures are also mostly worse when comparing the static to the dynamic ARIMA forecasts. Only the Theil stat seem to come out better. Very high bias portions are also observed when reviewing the variance decomposition, and the percentage of signs correct are never above 50%. In conclusion, the ARIMA model performs best in producing dynamic forecasts, but is outperformed by the linear regression model. There is no sign of improvement when increasing the estimation periods, the ARIMA model seems ill-suited to forecast Oslo rents.

5.3. VAR model

5.3.1. Model estimation

In this section a VAR model is estimated using the same variables as in the structural equation as endogenous variables in the system. The same lag structure is also used. That is log-difference of price, employment, interest rates and vacancy. After log-differencing and establishing the lag structure, the sample for parameter estimation range from 1997Q1 to 2006Q4.

Eviews was used to generate a table of lag length criteria with 7 lags included. Based on the sample, that was the largest amount of lags possible to include. The final amount of lags to include was chosen based on Akaike's multivariate info-criterion. Similar to the univariate model, the number of lags that minimize this information criterion was chosen. As shown in table 5.3.1.1, Akaike and Hannan-Quinn suggests 7 to be the optimal number of lags.

Table 5.3.1.1

Lag	LogL	LR	FPE	AIC	SC	HQ
0	229.6797	NA	1.35e-11	-13.67756	-13.49616	-13.61652
1	270.8569	69.87648	2.96e-12	-15.20345	-14.29647*	-14.89828
2	293.4545	32.86930*	2.08e-12*	-15.60331	-13.97075	-15.05400
3	308.2432	17.92559	2.53e-12	-15.52989	-13.17175	-14.73645
4	322.2850	13.61631	3.69e-12	-15.41121	-12.32750	-14.37364
5	338.3710	11.69889	5.98e-12	-15.41642	-11.60713	-14.13471
6	360.2696	10.61754	1.07e-11	-15.77392	-11.23905	-14.24807
7	403.3833	10.45180	1.64e-11	-17.41717*	-12.15672	-15.64719*

Next the model was estimated in Eviews. The estimation output is given in table 5.3.1.2. After excluding 7 observations the regression is run on the sample 1998Q4 – 2006Q4.

Table 5.3.1.2

Included observations: 33 after adjustments

	DAP	DEMP	DINT	DVAC
R-squared	0.910838	0.861503	0.813397	0.961388
Adj. R-squared	0.286704	-0.107979	-0.492827	0.691103
Sum sq. resids	0.021438	0.000477	0.025894	0.004659
S.E. equation	0.073209	0.010920	0.080458	0.034128
F-statistic	1.459362	0.888622	0.622708	3.556940
Log likelihood	74.26999	137.0609	71.15427	99.45549
Akaike AIC	-2.743636	-6.549148	-2.554804	-4.270029
Schwarz SC	-1.428523	-5.234036	-1.239691	-2.954917
Mean dependent	-0.004482	-0.000610	-0.013900	0.018041
S.D. dependent	0.086682	0.010374	0.065851	0.061405
Determinant resid covariance (dof adj.)		1.31E-12		
Determinant resid covariance		2.84E-16		
Log likelihood		403.3833		
Akaike information criterion		-17.41717		
Schwarz criterion		-12.15672		

The output of coefficient estimates and t-stats are omitted in this table due to space concerns, but they are available in the appendix C.1. Running all variables with 7 lags on DAP yields poor estimates, with only DAP(-1) significant at the 5% level. The adjusted R^2 of 0,28 underpin these results. We do however note that regressing the variables on DVAC yields better results. DAP(-1), DAP(-3) and DVAC(-1) are all significant and the adjusted R^2 of 0,69 is high. It should be noted that the number of observations available for estimation is low (33) due to the lag structure.

As in the previous section, new estimations are done with 1-year of observations added. These estimations are fully available in the appendix in section C.2-C.4. The results show a large improvement in adjusted R^2 (0,48) for variables on DAP for the estimation period until 2007Q4. Now DAP(-1), DAP(-4), DAP(-5) and DINT(-3) are significant. Ran on DVAC the adjusted R^2 improves to 0,77, and now also DVAC(-2), DVAC(-4) and DVAC(-7) yield significant results. For the last estimation period until 2009Q4, the results keep improving. For DAP the adjusted R^2 is 0,53 and variables DAP(-1) – DAP(-5) are all significant, as well as DEMP(-2), DINT(-1), DINT(-3), DINT(-5) and DVAC(-6). As such the forecasts should improve for the latter periods, as the model itself improves in terms of explanatory power.

Granger causality tests are conducted for all estimation periods to check for the joint significance of all lags of the variables. Little causality is found in the system for the 2006Q4 estimation. The only relationship that shows significance is DAP on DVAC. Moreover, only DVAC seems to have lags that are jointly highly significant. Causality in this context does not mean that one variable directly causes movement in another, it simply suggest a chronological order of movements in the system. Full results are shown in table 5.3.1.3.

Table 5.3.1.3

Dependent variable: DAP

Excluded	Chi-sq	df	Prob.
DEMP	2.243622	7	0.9451
DINT	7.857801	7	0.3453
DVAC	7.120862	7	0.4164
All	20.16802	21	0.5106

Dependent variable: DEMP

Excluded	Chi-sq	df	Prob.
DAP	1.371352	7	0.9864
DINT	1.547049	7	0.9806
DVAC	0.447479	7	0.9996
All	3.969432	21	1.0000

Dependent variable: DINT

Excluded	Chi-sq	df	Prob.
DAP	2.972044	7	0.8876
DEMP	3.858107	7	0.7960
DVAC	5.715227	7	0.5734
All	15.73909	21	0.7841

Dependent variable: DVAC

Excluded	Chi-sq	df	Prob.
DAP	15.67981	7	0.0282
DEMP	6.378178	7	0.4963
DINT	8.656746	7	0.2782
All	38.80311	21	0.0104

Table 5.3.1.4 and 5.3.1.5 show the variance decomposition for the DAP equation for the following two orderings respectively: DAP, DEMP, DINT, DVAC and DVAC, DINT, DEMP, DAP, which are exact opposites.

Table 5.3.1.4

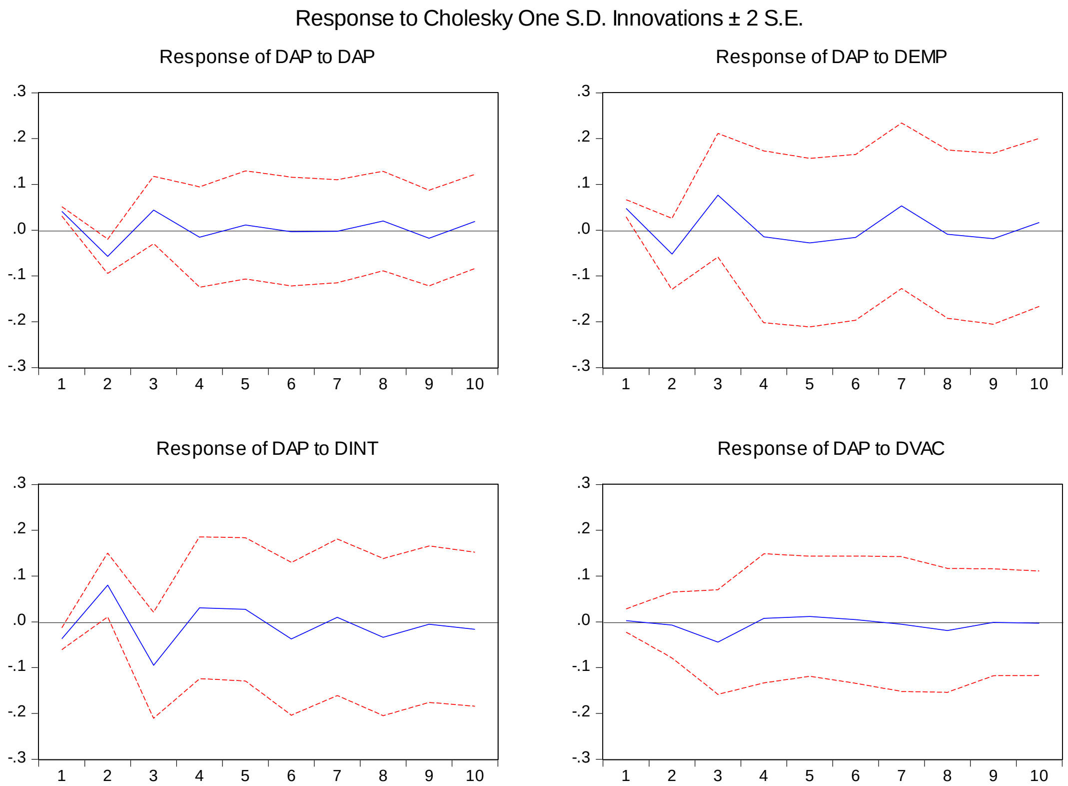
Variance Decomposition of DAP:					
Period	S.E.	DAP	DEMP	DINT	DVAC
1	0.073209	100.0000	0.000000	0.000000	0.000000
2	0.133678	94.26308	1.349733	4.289087	0.098102
3	0.191186	85.97333	2.615051	8.886756	2.524858
4	0.194924	85.62709	2.521293	9.325294	2.526318
5	0.199420	83.39260	4.067603	10.11186	2.427939
6	0.203625	80.09841	4.553569	12.89589	2.452129
7	0.210774	76.52843	8.019239	13.10212	2.350211
8	0.215377	74.30981	8.239755	14.15284	3.297590
9	0.216971	74.03202	8.131207	14.56783	3.268934
10	0.219116	74.47227	7.978555	14.29144	3.257736

Table 5.3.1.5

Variance Decomposition of DAP:					
Period	S.E.	DAP	DEMP	DINT	DVAC
1	0.073209	31.79902	42.51523	25.55473	0.131022
2	0.133678	27.93246	27.91601	43.81573	0.335803
3	0.191186	18.88237	29.58832	46.01609	5.513225
4	0.194924	18.77594	29.01944	46.74911	5.455507
5	0.199420	18.25135	29.64490	46.53605	5.567698
6	0.203625	17.53099	29.04716	48.02948	5.392374
7	0.210774	16.37730	33.48504	45.04556	5.092105
8	0.215377	16.53535	32.23876	45.57820	5.647695
9	0.216971	16.94499	32.51812	44.96974	5.567150
10	0.219116	17.38069	32.48467	44.65486	5.479783

The results are very sensitive to the ordering. This effect is still persistent at 10 quarters ahead. The first ordering shows 100% of the variance in the equation is accounted for by DAP in the first period, and gradually falling as DINT and DEMP account for a larger portion of the variance. Interestingly when reversing the ordering, DEMP and DINT accounts for a larger portion of the variance, around 70%. There is little change through the periods, except for DAP accounting for less of the variance. According to Brooks (2008) this shows evidence of a contemporaneous relationship between DAP and both DEMP and DINT. This is also to be expected, as these were identified as determinants of rents in section 5.1. Next, an impulse response test was performed. The graphs for DAP are shown in table 5.3.1.6.

Table 5.3.1.6



The blue line shows the unit shocks, the red the standard error bands to innovation. Unexpected changes in real interest rates and employment rates seem to have the largest effect on change in real rents. Innovations in interest rates appear to have a slightly negative impact on rents initially, before its followed by a large increase and an almost similar decrease before the effect gradually dies out. Surprisingly DEMP seems to have an opposite effect, the innovation yielding a rise and a fall and another rise before fading out. DVAC seems to have little impact. The effect from DAP on itself shows that innovations lead to a positive period followed by negative and positive periods of similar magnitude, before the effect gradually dies down. This underpins the argument of mean reverting rents.

The causality test for the 2009Q4 estimation is shown in appendix C.4. The results show large improvement compared to the results of the 2006Q4 estimation. Both DINT and DVAC are now significant on DAP. It is evident that the VAR estimation improves dramatically by including more observations and should yield better forecasts as the sample grows in size.

5.3.2. Forecasting performance

Dynamic and static forecasts are generated in the same way as in section 5.1 and 5.2. Table 5.3.2.1 presents the forecasted values and graphs them together with the actual values. The red line in the graph is the forecasted values. The graph shows very volatile forecasted values compared to the actual values. The forecast seem to lead the changes, but fail at predicting the strength of the movements. A table of performance measures for the dynamic forecast is given in table 5.3.2.2.

Table 5.3.2.1

Period	Actual	Forecast
2007Q1	0.049480	0.054924
2007Q2	0.040546	-0.019437
2007Q3	0.051624	0.050963
2007Q4	0.000000	-0.033776
2008Q1	-0.006309	0.021981
2008Q2	0.096460	0.051110
2008Q3	-0.005764	-0.013768
2008Q4	-0.065695	-0.042325
2009Q1	-0.025001	0.030959
2009Q2	0.025001	-0.059184
2009Q3	-0.063716	-0.014252
2009Q4	0.038715	0.054800
2010Q1	-0.012739	-0.101039
2010Q2	0.000000	-0.017772
2010Q3	-0.006431	-0.015688
2010Q4	0.012821	-0.063441

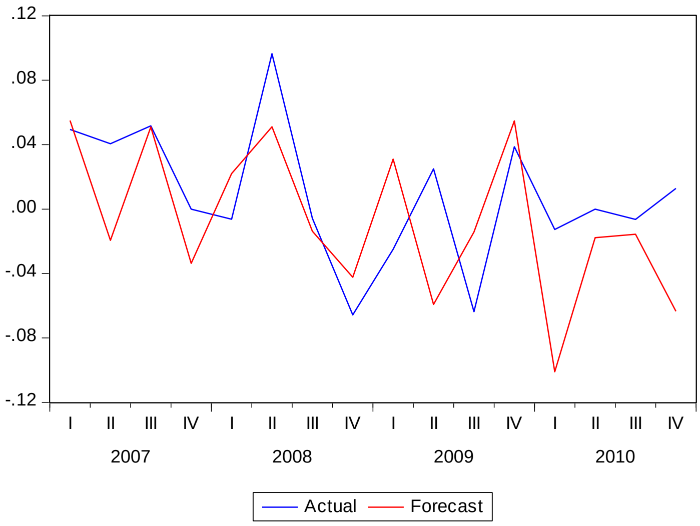


Table 5.3.2.2

Forecast sample:	2007Q1 2010Q4
Root Mean Squared Error:	0.046887
Mean Absolute Error:	0.037635
Mean Abs. Percent Error:	113.5392
Theil Inequality Coefficient:	0.532175

The same procedure was followed for a static forecast. The results are shown in Tables 5.3.2.3 and 5.3.2.4. The forecasted values seem to exhibit the same volatility as the dynamic, but at a greater negative strength. It predicts 4 drops in excess of 10%, whereas the actual values only twice show drops over 5%.

Table 5.3.2.3

Period	Actual	Forecast
2007Q1	0.049480	0.054924
2007Q2	0.040546	0.030227
2007Q3	0.051624	-0.015446
2007Q4	0.000000	-0.124792
2008Q1	-0.006309	0.042573
2008Q2	0.096460	0.033178
2008Q3	-0.005764	-0.141598
2008Q4	-0.065695	-0.151562
2009Q1	-0.025001	-0.022464
2009Q2	0.025001	0.017615
2009Q3	-0.063716	-0.070252
2009Q4	0.038715	-0.073445
2010Q1	-0.012739	-0.108556
2010Q2	0.000000	0.062531
2010Q3	-0.006431	0.063075
2010Q4	0.012821	-0.086923

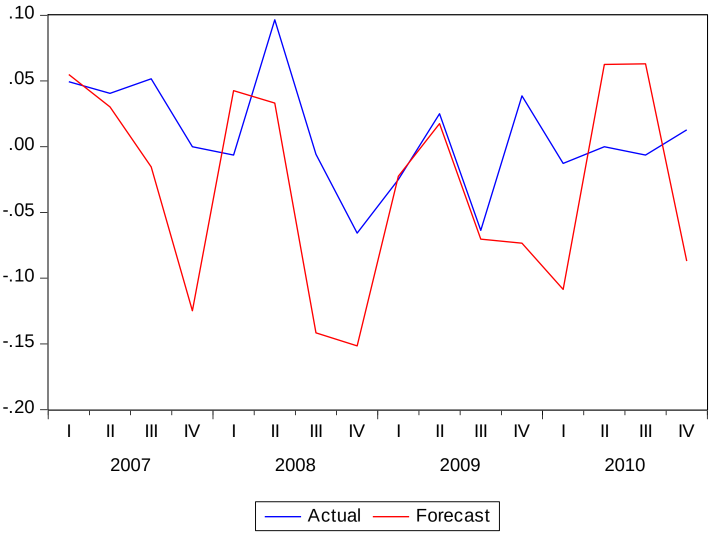


Table 5.3.2.4

Forecast sample:	2007Q1 2010Q4
Root Mean Squared Error:	0.076232
Mean Absolute Error:	0.062357
Mean Abs. Percent Error:	104.0537
Theil Inequality Coefficient:	0.623850

As with the linear regression model and the ARIMA model, more observations were added to the estimation sample one year at the time, to see if the results improved. The performance measures for all the forecasts are shown in table 5.3.2.5 and 5.3.2.6. Estimation and Granger causality test results are available in appendix C.

Table 5.3.2.5: Dynamic forecasts

Sample	**Forecast**	**RMSE**	**MAE**	**MAPE**	**Theil**	**Bias**	**Var.**	**Cov.**	**Pct**
1998-2006	1 yr	0,0345	0,0250	104,9532	0,4144	0,4150	0,3114	0,2738	50 %
1998-2007	1 yr	0,1024	0,0998	220,1729	0,8444	0,0001	0,0018	0,9982	25 %
1998-2008	1 yr	0,0670	0,0591	94,7213	0,5047	0,1205	0,4677	0,4118	75 %
1998-2009	1 yr	0,0963	0,0847	84,5455	0,8603	0,0142	0,9126	0,0721	100 %
1998-2006	2 yr	0,0321	0,0256	93,8247	0,3580	0,1248	0,0676	0,8077	63 %
1998-2007	2 yr	0,1018	0,0970	239,1949	0,8892	0,0118	0,0142	0,9741	13 %
1998-2008	2 yr	0,0987	0,0791	161,2822	0,7278	0,0228	0,5706	0,4114	63 %
1998-2006	3 yr	0,0420	0,0342	120,8349	0,4752	0,0112	0,0216	0,9671	67 %
1998-2007	3 yr	0,0894	0,0803	236,4934	0,8650	0,0558	0,0312	0,9122	25 %
1998-2006	4 yr	0,0469	0,0376	113,5392	0,5322	0,1066	0,0124	0,8810	56 %

Table 5.3.2.6: Static forecasts

Sample	Forecast	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1998-2006	1 yr	0,0711	0,0519	144,5665	0,6383	0,4789	0,4567	0,0646	50 %
1998-2007	1 yr	0,0814	0,0652	62,2358	0,4880	0,1148	0,3401	0,5451	88 %
1998-2008	1 yr	0,0679	0,0494	153,2072	0,7496	0,2240	0,0206	0,7555	50 %
1998-2009	1 yr	0,0728	0,0587	107,9631	0,8612	0,1949	0,6231	0,1820	25 %
1998-2006	2 yr	0,0810	0,0677	129,5502	0,5734	0,4467	0,2150	0,3382	63 %
1998-2007	2 yr	0,0824	0,0679	101,8033	0,5734	0,1898	0,1800	0,6302	50 %
1998-2008	2 yr	0,0763	0,0608	128,3814	0,7742	0,1744	0,1426	0,6827	50 %
1998-2006	3 yr	0,0737	0,0558	104,3040	0,5769	0,3962	0,1208	0,4830	67 %
1998-2007	3 yr	0,0849	0,0742	102,2202	0,6364	0,1332	0,2716	0,5955	50 %
1998-2006	4 yr	0,0762	0,0624	104,0537	0,6239	0,2583	0,1967	0,5449	56 %

The dynamic 1-year forecasts produce on average and individually worse measures for RMSE, MAE, Theil and percentage correct prediction of signs when comparing to the same dynamic forecasts produced by the linear regression model. All but the 2006 estimation period has lower MAPE stats, but reviewing the variance decomposition for the 2008 and 2009 estimation shows too high proportions attributed to variance. There is no clear trend that the measures improve as the sample size increases. The same results are to a large extent repeated in the 2-year forecasts. The first forecast gets lower RMSE and MAE stats than the in the linear regression, a MAPE of 93, Theil of 0,35, 63% of the predicted values correct and a decent variance decomposition. However the forecasts are not improving as the sample grows, the two latter forecasts being worse than the linear regression forecasts.

The static forecasts seem to produce rather similar results as the dynamic VAR, but less volatile measures. The 1-year forecast produced by the 2007 estimation is the only one managing a MAPE below 100, and getting 83% of the predictions correct. However Theil stats are again too high (0,48), RMSE and MAE measures outperformed by the static linear regression model. Comparing the rest of the forecasts to the linear regression model, all but the MAPE values are consistently worse. As for the dynamic VAR forecasts and contrary to the improvement in the estimation results, there is no trend of improvement as the sample grows.

In conclusion, both the dynamic and static VAR forecasts are outperformed by those generated by the linear regression model.

5.4. Improving the model by adding more observations

The linear regression model has been shown to outperform the ARIMA and VAR models, when comparing the RMSE, MAE and percentage correct stats. To further evaluate the linear regression model, this section checks if the forecast precision improves by adding more observations a quarter at the time, and constructing 1- 2- and 3-year forecasts.

Table 5.4.1 shows performance measures for the dynamic 1-year forecasts. The first estimation period ending 2006Q4 seem to produce some of the best performance measures, but the variance decomposition is way off with large portions attributed to bias and variance. The forecasts generated by the samples ending 2008Q1 and Q3 behave in a similar way. Disregarding those forecasts, RMSE, MAE and MAPE are clearly improving steadily as the dataset grows. There is no obvious trend in the Theil-stat.

Table 5.4.1

Sample	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct.
1997Q1-2006Q4	0,0278	0,0256	34,4977	0,3836	0,8473	0,1043	0,0484	75 %
1997Q1-2007Q1	0,0603	0,0471	454,8920	0,6609	0,0121	0,1865	0,8014	50 %
1997Q1-2007Q2	0,0825	0,0708	495,8714	0,7431	0,0288	0,1515	0,9560	25 %
1997Q1-2007Q3	0,0875	0,0732	551,8181	0,7731	0,0074	0,0512	0,9414	0 %
1997Q1-2007Q4	0,0669	0,0551	428,2724	0,6414	0,0097	0,0439	0,9463	25 %
1997Q1-2008Q1	0,0272	0,0237	69,7950	0,2787	0,0046	0,6632	0,3322	75 %
1997Q1-2008Q2	0,0271	0,0235	183,9066	0,3919	0,0839	0,0103	0,9058	75 %
1997Q1-2008Q3	0,0224	0,0160	53,6393	0,2193	0,1504	0,2332	0,6164	75 %
1997Q1-2008Q4	0,0454	0,0354	104,6902	0,5126	0,0607	0,0052	0,9340	50 %
1997Q1-2009Q1	0,0516	0,0461	179,0280	0,5195	0,0254	0,1308	0,8438	50 %
1997Q1-2009Q2	0,0496	0,0359	129,4029	0,6190	0,0402	0,0004	0,9594	50 %
1997Q1-2009Q3	0,0511	0,0424	249,9293	0,9291	0,1296	0,0513	0,8191	50 %
1997Q1-2009Q4	0,0185	0,0172	119,4681	0,5480	0,0706	0,5591	0,3703	100 %

Table 5.4.2 shows performance measures for the static 1-year forecasts. The same trends are visible here, but more of the forecasts have trouble with the variance decomposition as well as getting the direction of movement correct. Graphs for RMSE, MAE, MAPE and Theil is available for visual representation in appendix D.1 and D.2 for both the dynamic and the static forecasts.

Table 5.4.2

Sample	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct.
1997Q1-2006Q4	0,0278	0,0256	34,4977	0,3836	0,8473	0,1043	0,0484	75 %
1997Q1-2007Q1	0,0603	0,0471	454,8920	0,6609	0,0121	0,1865	0,8014	50 %
1997Q1-2007Q2	0,0825	0,0708	495,8714	0,7431	0,0288	0,1515	0,9560	25 %
1997Q1-2007Q3	0,0875	0,0732	551,8181	0,7731	0,0074	0,0512	0,9414	0 %
1997Q1-2007Q4	0,0669	0,0551	428,2724	0,6414	0,0097	0,0439	0,9463	25 %
1997Q1-2008Q1	0,0272	0,0237	69,7950	0,2787	0,0046	0,6632	0,3322	75 %
1997Q1-2008Q2	0,0271	0,0235	183,9066	0,3919	0,0839	0,0103	0,9058	75 %
1997Q1-2008Q3	0,0224	0,0160	53,6393	0,2193	0,1504	0,2332	0,6164	75 %
1997Q1-2008Q4	0,0454	0,0354	104,6902	0,5126	0,0607	0,0052	0,9340	50 %
1997Q1-2009Q1	0,0516	0,0461	179,0280	0,5195	0,0254	0,1308	0,8438	50 %
1997Q1-2009Q2	0,0496	0,0359	129,4029	0,6190	0,0402	0,0004	0,9594	50 %
1997Q1-2009Q3	0,0511	0,0424	249,9293	0,9291	0,1296	0,0513	0,8191	50 %
1997Q1-2009Q4	0,0185	0,0172	119,4681	0,5480	0,0706	0,5591	0,3703	100 %

Tables 5.4.3 and 5.4.4 show performance measures for the dynamic and static 2-year forecasts respectively. The positive trend seen in RMSE, MAE and MAPE for the 1-year forecasts is even more clear for the 2-year forecasts. The scores are also better on average. Moreover, the 2-year forecasts seem to have little problems with regards to the variance decomposition and they are able to consistently predict the correct direction of movement more than 50% of the time. On the whole the static 2-year forecast outperforms the dynamic by a slight margin. Again the Theil stat fails to show any clear trend. Graphs for visual representation are available in appendix D.3 And D.4.

Table 5.4.3

Sample	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1997Q1-2006Q4	0,0603	0,0455	268,2795	0,6320	0,0184	0,0028	0,9787	63 %
1997Q1-2007Q1	0,0591	0,0444	268,5556	0,6462	0,0029	0,0060	0,9911	50 %
1997Q1-2007Q2	0,0598	0,0436	284,2441	0,6637	0,0004	0,0045	0,9951	50 %
1997Q1-2007Q3	0,0633	0,0440	294,6157	0,6158	0,0018	0,0078	0,9904	50 %
1997Q1-2007Q4	0,0570	0,0435	259,5084	0,5878	0,0073	0,0065	0,9862	50 %
1997Q1-2008Q1	0,0366	0,0277	98,9077	0,3966	0,0206	0,0705	0,9089	63 %
1997Q1-2008Q2	0,0365	0,0292	154,5340	0,4777	0,0014	0,0005	0,9981	63 %
1997Q1-2008Q3	0,0361	0,0274	143,8755	0,4473	0,0076	0,0164	0,9760	75 %
1997Q1-2008Q4	0,0363	0,0282	150,8446	0,5381	0,0046	0,0411	0,9544	63 %

Table 5.4.4

Sample	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1997Q1-2006Q4	0,0462	0,0415	273,8514	0,4735	0,2200	0,0002	0,7798	63 %
1997Q1-2007Q1	0,0470	0,0423	288,8455	0,4893	0,0516	0,0002	0,9482	50 %
1997Q1-2007Q2	0,0451	0,0396	292,4128	0,4543	0,0002	0,0141	0,9858	63 %
1997Q1-2007Q3	0,0445	0,0364	287,6935	0,4246	0,0173	0,0302	0,9526	63 %
1997Q1-2007Q4	0,0512	0,0403	309,8082	0,4758	0,0011	0,0158	0,9831	63 %
1997Q1-2008Q1	0,0406	0,0326	162,5003	0,4073	0,0860	0,0088	0,9052	75 %
1997Q1-2008Q2	0,0393	0,0294	159,5612	0,4682	0,0233	0,0312	0,9455	75 %
1997Q1-2008Q3	0,0378	0,0268	109,1059	0,4620	0,0069	0,0240	0,9691	75 %
1997Q1-2008Q4	0,0380	0,0277	118,0859	0,5577	0,0150	0,0394	0,9457	75 %

Tables 5.4.5 and 5.4.6 show performance measures for the 3-year forecasts. None of the forecasts seem to have problems with the variance decomposition and they are consistently getting more than 50% of the signs correct. It is however tougher to detect a trend here, RMSE, MAE, MAPE and Theil scores are mostly flat across sample sizes. On the whole, the 3-year forecasts seem to perform similar to the 2-year forecasts on average. Graphs for the 3-year forecasts are available in appendix D.5 and D.6.

Table 5.4.5

Sample	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1997Q1-2006Q4	0,0553	0,0392	204,0946	0,6044	0,0387	0,0020	0,9593	67 %
1997Q1-2007Q1	0,0556	0,0409	227,2258	0,6201	0,0104	0,0004	0,9892	58 %
1997Q1-2007Q2	0,0564	0,0417	237,2553	0,6373	0,0017	0,0000	0,9982	67 %
1997Q1-2007Q3	0,0579	0,0434	273,9299	0,6481	0,0041	0,0106	0,9854	67 %
1997Q1-2007Q4	0,0491	0,0367	245,1255	0,5951	0,0003	0,0003	0,9994	58 %

Table 5.4.6

Sample	RMSE	MAE	MAPE	Theil	Bias	Var.	Cov.	Pct
1997Q1-2006Q4	0,0475	0,0413	225,8630	0,5042	0,0984	0,0000	0,9016	58 %
1997Q1-2007Q1	0,0470	0,0401	234,8315	0,5009	0,0775	0,0028	0,9197	67 %
1997Q1-2007Q2	0,0456	0,0372	228,6453	0,4867	0,0257	0,0140	0,9603	67 %
1997Q1-2007Q3	0,0446	0,0350	233,0325	0,4898	0,0132	0,0283	0,9585	75 %
1997Q1-2007Q4	0,0428	0,0318	240,5517	0,4766	0,0009	0,0220	0,9771	75 %

In summary, the model seems unable to consistently get MAPE scores below 100 or Theil stats close to 0 for any of the forecast horizons. There is however an improvement in measures as sample size is increased for the 1- and 2-year forecasts. This brings expectations that the model generated forecasts may improve and become consistently accurate as more observations are added to the data in coming years.

5.5. Comparing with forecasts from DnB NOR Næringsmegling

DnB NOR is one of the larger participants in the Norwegian real estate market and they release semi-annual reports with rent forecasts based mainly on qualitative conjecture. In this section RMSE, MAE and percentage of correct signs are calculated for these forecasts and compared to the performance of dynamic and static forecasts generated by the linear regression model for comparable horizons. The results are presented in table 5.5.1 below.

Table 5.5.1

	Dynamic			Static			DnB NOR		
Forecast horizon	**RMSE**	**MAE**	**Pct**	**RMSE**	**MAE**	**Pct**	**RMSE**	**MAE**	**Pct**
2007Q2-2009Q3	0,0529	0,0362	80 %	0,0431	0,0374	70 %	0,0458	-0,0073	40 %
2007Q4-2009Q3	0,0633	0,0440	63 %	0,0445	0,0364	75 %	0,0526	-0,017	38 %
2008Q2-2010Q1	0,0366	0,0277	75 %	0,0406	0,0327	75 %	0,0537	-0,0369	38 %
2008Q4-2010Q2	0,0370	0,0271	57 %	0,0403	0,0293	71 %	0,0315	0,0103	43 %
2009Q2-2010Q2	0,0464	0,0389	60 %	0,0447	0,0321	80 %	0,0201	0,0025	60 %
2009Q4-2010Q2	0,0561	0,0459	33 %	0,0441	0,0314	67 %	0,0188	0,0184	33 %

The DnB NOR forecasts seem to do better with regards both RMSE and MAE, MAE particularly. For the longer forecast horizons (>1,5 years) the dynamic forecasts from the linear regression model generates a similar RMSE as the DnB NOR forecasts, while the static are able to consistently outperform them. With regards to getting the direction of movement right, the forecasts produced in this study are clearly superior for both long and short horizons.

6. Conclusions

This study has identified key determinants of real rental rates of commercial real estate in Oslo and tried to create statistical models capable of predicting its movements using three econometric techniques; linear regression, ARIMA modelling and VAR modelling. The determinants identified are two periods of the rental rates' own lagged values along with employment rates, real interest rates and office vacancy. The evidence suggest that the classic linear regression model outperforms the VAR and ARIMA specifications, in that ranking order, in describing and predicting the evolution of real rents for office space in Oslo. That said, the performance of the linear regression model is still limited.

The graphs of predicted values for both the VAR and the Linear regression model, and the dynamic forecasts in particular, track the movements in actual values fairly well while the ARIMA graphs are quite off. The dynamic ARIMA forecasts seem to fail to capture the volatility. The performance measures confirm the results suggested by the graphs. Linear regression gets the best RMSE, MAE and Theil scores on average, with the static forecasts performing best with a slight margin. The static VAR forecast gets the best MAPE scores, but it is noted that none of the forecast methods, VAR included, is able to generate a MAPE of less than 100 on average. The Linear regression model also gets the best results in predicting the direction of movements, while the VAR and ARIMA models are unable to do so consistently. All three models overpredict, as shown by the positive MAE measures.

The study proceeded to construct 1-, 2- and 3-year forecasts using the linear regression model and adding one quarter at a time to the estimation sample to see if performance measures improved with more data behind. A trend of improvement in RMSE, MAE and MAPE scores is found for the 1- and 2-year forecasts. The 2-year forecasts in particular perform well, while the 1-year forecasts have some trouble with their variance decomposition. There is no obvious trend in the measures for the 3-year forecasts. Whereas the forecasts are at present not able to outperform a simple random walk, the trend of improvement gives expectations that the model may be able to produce more accurate forecasts consistently as more data becomes available. Consequently, future research is needed to continue the investigation of rental rate forecasts.

References

Akaike, H. 1974. New Look at Statistical-Model Identification. *Ieee Transactions on Automatic Control* Ac19 (6):716-723.

Ball, M., C. Lizieri and B. MacGregor. 1998. *The Economics of Commercial Property Markets*. London: Routledge.

Bera, A. K. and C. M. Jarque. 1981. Efficient Tests for Normality, Homoscedasticity and Serial Independence Regression Residuals - Monte-Carlo Evidence. *Economics Letters* 7 (4):313-318.

Box, G. E. P. and G. M. Jenkins. 1976. *Time Series Analysis: Forecasting and Control*. 2 ed. San Francisco: Holden-Day.

Breusch, T.S. 1978. Testing for Autocorrelation in Dynamic Linear Models. *Australian Economic Papers* 17 (31):334-355.

Brooks, C. and S Tsolacos. 1999. The impact of economic and financial factors on UK property performance. *Journal of Property Research* 16 (2):139-152.

Brooks, C. and S. Tsolacos. 2000. Forecasting models of retail rents. *Environment and Planning A* 32 (10):1825-1839.

Brooks, Chris. 2008. *Introductory econometrics for finance*. 2 ed: Cambridge: Cambridge University Press.

Brooks, Chris and Sotiris Tsolacos. 2010. *Real estate modelling and forecasting*. Cambridge: Cambridge University Press.

Chow, Gregory C. 1960. Tests of Equality Between Sets of Coefficients in Two Linear Regressions. *Econometrica* 28 (3):591-605.

Clapp, J. 1993. *Dynamic of Office Markets: Empircal Findings and Research Issues*. Washington, D.C.: Urban Institue Press.

D'Arcy, Eamonn, Tony McGough and Sotiris Tsolacos. 1997. National economic trends, market size and city growth effects on European office rents. *Journal of Property Research* 14 (4):297-308.

De Wit, Ivo and Ronald Van Dijk. 2003. The Global Determinants of Direct Office Real Estate Returns. *Journal of Real Estate Finance & Economics* 26 (1):27.

Dickey, D.A. and W.A. Fuller. 1979. Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association* 76 (366):427-431.

Dipasquale, D. and W. C. Wheaton. 1992. The Markets for Real-Estate Assets and Space - a Conceptual-Framework. *Journal of the American Real Estate and Urban Economics Association* 20 (2):181-197.

Dobson, S. M. and J. A. Goddard. 1992. The Determinants of Commercial Property Prices and Rents. *Bulletin of Economic Research* 44 (4):301-321.

Durbin, J. and G. S. Watson. 1951. Testing for Serial Correlation in Least Squares Regression .2. *Biometrika* 38 (1-2):159-178.

Finanstilsynet. 2010. Verdsettelse av investeringseiendom. edited by Finanstilsynet: Finanstilsynet.

Frøyseth, Alexander. 2009. Eiendomsinvesteringer i Norge - Ett porteføljeperspektiv.87.

Gallimore, Paul and Patrick McAllister. 2004. Expert judgement in the processes of commercial property market forecasting. *Journal of Property Research* 21 (4):337-360.

Gerlow, M. E., S. H. Irwin and T. R. Liu. 1993. Economic-Evaluation of Commodity Price Forecasting Models. *International Journal of Forecasting* 9 (3):387-397.

Giussani, Bruno, Marshall Hsia and Sotiris Tsolacos. 1993. A comparative analysis of the major determinants of Office rental values in Europe. *Journal of Property Valuation and Investment* 11 (2):17.

Godfrey, L.G. 1978. Testing against General Autoregressive and Moving Average Error Models when the Regressors Include Lagged Dependent Variables. *Econometrica* 46 (6):1293-1301.

Granger, C. W. J. 1969. Investigating Causal Relations by Econometric Models and Cross-Spectral Methods. *Econometrica* 37 (3):414-&.

Hannan, E.J and B.G. Quinn. 1979. Determination of the Order of an Autoregression. *Journal of the Royal Statistical Society Series B-Methodological* 41 (2):190-195.

Hendershott, P. H. 1996. Rental adjustment and valuation in overbuilt markets: Evidence from the Sydney office market. *Journal of Urban Economics* 39 (1):51-67.

Holden, K., D. A. Peel and John L. Thompson. 1990. *Economic forecasting: an introduction*. Cambridge: Cambridge University Press.

Karakozova, Olga. 2004. Modelling and forecasting office returns in the Helsinki area *Journal of Property Research* 21 (1):51-73.

Krystalogianni, A, G Matysiak and S Tsolacos. 2004. Forecasting UK commercial real estate cycle phases with leading indicators: a probit approach. *Applied Economics*:2347-2356.

Leitch, G. and J. E. Tanner. 1991. Economic-Forecast Evaluation - Profits Versus the Conventional Error Measures. *American Economic Review* 81 (3):580-590.

Matysiak, George and Sotiris Tsolacos. 2003. Identifying short-term leading indicators for real estate rental performance. *Journal of Property Investment & Finance* 21 (3):212-232.

McGough, Tony and Sotiris Tsolacos. 1995. Forecasting commercial rental values using ARIMA models. *Journal of Property Valuation and Investment* 13 (5):18.

Mcnees, S. K. 1986. Forecasting Accuracy of Alternative Techniques - a Comparison of United-States Macroeconomic Forecasts. *Journal of Business & Economic Statistics* 4 (1):5-15.

Mills, Edwin S. 1992. Office Rent Determinants In the Chicago Area. *Journal of the American Real Estate & Urban Economics Association* 20 (2):273-287.

Plazzi, Alberto, Walter Torous and Rossen Valkanov. 2010. Expected Returns and Expected Growth in Rents of Commercial Real Estate. *Review of Financial Studies* 23 (9):3469-3519.

Quan, Daniel C. and Sheridan Titman. 1997. Commercial Real Estate Prices and Stock Market Returns: An International Analysis. *Financial Analysts Journal* 53 (3):21-35.

Quan, Daniel C. and Sheridan Titman. 1999. Do Real Estate Prices and Stock Prices Move Together? An International Analysis. *Real Estate Economics* 27 (2):183-207.

RICS. 1994. *Understanding the Property Cycle*. London: Royal Institution of Chartered Surveyors.

Schwarz, G. 1978. Estimating Dimension of a Model. *Annals of Statistics* 6 (2):461-464.

Sims, C. A. 1972. Money, Income, and Causality. *American Economic Review* 62 (4):540-552.

Slade, Barrett A. 2000. Office Rent Determinants During Market Decline and Recovery. *Journal of Real Estate Research* 20 (3):357.

Stevenson, S. and O. McGarth. 2003. A comparison of alternative rental forecasting models: empirical tests on the London office market. *Journal of Property Research* 20 (3):235-260.

Theil, H. 1989. Citation Classic - Principles of Econometrics. *Current Contents/Social & Behavioral Sciences* (1):18-18.

Tse, Raymond Y.C. 1997. An application of the ARIMA model to real-estate prices in Hong Kong. *Journal of Property Finance* 8 (2):155-163.

White, H. 1980. A Heteroskedasticity-Consistent Covariance-Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica* 48 (4):817-838.

Wilson, Patrick J, Craig Ellis John Okunew and David M. Higgins. 2000. Comparing Univariate Forecasting Techniques in Property Markets. *Journal of Real Estate Portfolio Management* 6 (3):283-306.

Appendix

A. Linear regression model

A.1. Est. period: 1997Q1 – 2007Q4

Included observations: 44 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005212	0.010276	0.507260	0.6149
DAP(-1)	-0.707030	0.131883	-5.361062	0.0000
DAP(-2)	-0.332821	0.123537	-2.694106	0.0104
DEMP(-3)	2.262858	0.995315	2.273509	0.0287
DINT(-4)	0.334726	0.142565	2.347879	0.0242
DVAC(-2)	-0.355999	0.160585	-2.216888	0.0327

R-squared	0.462328	Mean dependent var	-3.12E-19
Adjusted R-squared	0.391582	S.D. dependent var	0.086602
S.E. of regression	0.067551	Akaike info criterion	-2.425752
Sum squared resid	0.173398	Schwarz criterion	-2.182454
Log likelihood	59.36655	Hannan-Quinn criter.	-2.335525
F-statistic	6.535020	Durbin-Watson stat	2.501443
Prob(F-statistic)	0.000178		

A.2. Est. period: 1997Q1 – 2008Q4

Included observations: 48 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004791	0.009652	0.496345	0.6222
DAP(-1)	-0.695694	0.125257	-5.554147	0.0000
DAP(-2)	-0.336545	0.118106	-2.849506	0.0068
DEMP(-3)	1.862359	0.917770	2.029222	0.0488
DINT(-4)	0.321476	0.131175	2.450740	0.0185
DVAC(-2)	-0.357966	0.150829	-2.373330	0.0223

R-squared	0.457814	Mean dependent var	0.000389
Adjusted R-squared	0.393268	S.D. dependent var	0.084574
S.E. of regression	0.065878	Akaike info criterion	-2.485567
Sum squared resid	0.182274	Schwarz criterion	-2.251667
Log likelihood	65.65360	Hannan-Quinn criter.	-2.397176
F-statistic	7.092827	Durbin-Watson stat	2.522977
Prob(F-statistic)	0.000069		

A.3. Est. period: 1997Q1 – 2009Q4

Included observations: 52 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004654	0.009049	0.514259	0.6095
DAP(-1)	-0.678420	0.120709	-5.620311	0.0000
DAP(-2)	-0.317222	0.114434	-2.772099	0.0080
DEMP(-3)	1.772887	0.889379	1.993399	0.0522
DINT(-4)	0.289607	0.114796	2.522798	0.0152
DVAC(-2)	-0.325341	0.144288	-2.254800	0.0289

R-squared	0.439291	Mean dependent var	-0.000121
Adjusted R-squared	0.378344	S.D. dependent var	0.082009
S.E. of regression	0.064660	Akaike info criterion	-2.531178
Sum squared resid	0.192323	Schwarz criterion	-2.306035
Log likelihood	71.81063	Hannan-Quinn criter.	-2.444863
F-statistic	7.207790	Durbin-Watson stat	2.439696
Prob(F-statistic)	0.000047		

B. ARIMA model

B.1. Est. period: 1997Q3 – 2007Q4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001110	0.010437	0.106317	0.9160
AR(1)	-0.288692	0.180853	-1.596278	0.1203
AR(2)	0.275097	0.185443	1.483458	0.1477
AR(3)	0.623329	0.150525	4.141044	0.0002
AR(4)	-0.178495	0.196956	-0.906269	0.3716
AR(5)	-0.242986	0.164525	-1.476892	0.1495
MA(1)	-0.368492	0.101710	-3.622953	0.0010
MA(2)	-0.256679	0.153870	-1.668153	0.1050
MA(3)	-0.417712	0.093807	-4.452892	0.0001
MA(4)	0.945346	0.033300	28.38851	0.0000

R-squared	0.606856	Mean dependent var	0.002195
Adjusted R-squared	0.496285	S.D. dependent var	0.084073
S.E. of regression	0.059669	Akaike info criterion	-2.595748
Sum squared resid	0.113933	Schwarz criterion	-2.182017
Log likelihood	64.51071	Hannan-Quinn criter.	-2.444099
F-statistic	5.488354	Durbin-Watson stat	1.884150
Prob(F-statistic)	0.000144		

B.2. Est. period: 1997Q3 – 2008Q4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002454	0.014027	0.174917	0.8621
AR(1)	-0.090205	0.186203	-0.484442	0.6310
AR(2)	0.476663	0.191501	2.489091	0.0176
AR(3)	0.784206	0.096625	8.115975	0.0000
AR(4)	-0.185083	0.180037	-1.028030	0.3108
AR(5)	-0.273743	0.173064	-1.581745	0.1225
MA(1)	-0.571443	0.067486	-8.467599	0.0000
MA(2)	-0.326913	0.065630	-4.981118	0.0000
MA(3)	-0.567568	0.047459	-11.95905	0.0000
MA(4)	0.909414	0.041744	21.78542	0.0000

R-squared	0.576583	Mean dependent var	0.002410
Adjusted R-squared	0.470728	S.D. dependent var	0.082115
S.E. of regression	0.059739	Akaike info criterion	-2.607989
Sum squared resid	0.128477	Schwarz criterion	-2.210459
Log likelihood	69.98376	Hannan-Quinn criter.	-2.459072
F-statistic	5.446945	Durbin-Watson stat	1.953167
Prob(F-statistic)	0.000102		

B.3. Est. period: 1997Q3 – 2009Q4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002594	0.010049	-0.258150	0.7976
AR(1)	-0.091481	0.154265	-0.593009	0.5565
AR(2)	0.662189	0.148785	4.450653	0.0001
AR(3)	0.723372	0.107759	6.712880	0.0000
AR(4)	-0.322672	0.150004	-2.151091	0.0376
AR(5)	-0.392066	0.142743	-2.746650	0.0090
MA(1)	-0.440320	0.043837	-10.04443	0.0000
MA(2)	-0.552531	0.053689	-10.29136	0.0000
MA(3)	-0.460277	0.034110	-13.49375	0.0000
MA(4)	0.936491	0.028397	32.97826	0.0000

R-squared	0.531666	Mean dependent var	0.001717
Adjusted R-squared	0.426290	S.D. dependent var	0.079585
S.E. of regression	0.060281	Akaike info criterion	-2.602752
Sum squared resid	0.145351	Schwarz criterion	-2.220348
Log likelihood	75.06881	Hannan-Quinn criter.	-2.457130
F-statistic	5.045450	Durbin-Watson stat	2.018636
Prob(F-statistic)	0.000146		

C. VAR model

C.1. Est. period: 1998Q4 – 2006Q4

	DAP	DEMP	DINT	DVAC
DAP(-1)	-1.388801	0.037994	-0.272546	-0.510745
	(0.41799)	(0.06235)	(0.45938)	(0.19486)
	[-3.32259]	[0.60940]	[-0.59330]	[-2.62115]
DAP(-2)	-0.880227	0.061346	-0.946722	-0.349104
	(0.66882)	(0.09976)	(0.73505)	(0.31179)
	[-1.31609]	[0.61494]	[-1.28798]	[-1.11969]
DAP(-3)	-0.627955	0.044345	-0.277207	-0.545115
	(0.54893)	(0.08188)	(0.60328)	(0.25589)
	[-1.14397]	[0.54161]	[-0.45950]	[-2.13023]
DAP(-4)	-1.126823	0.013033	-0.262068	-0.363937
	(0.63355)	(0.09450)	(0.69628)	(0.29534)
	[-1.77859]	[0.13791]	[-0.37638]	[-1.23225]
DAP(-5)	-1.243849	0.008946	-0.075532	-0.593895
	(0.72270)	(0.10780)	(0.79426)	(0.33690)
	[-1.72111]	[0.08299]	[-0.09510]	[-1.76280]
DAP(-6)	-0.620202	0.013796	-0.210333	-0.095560
	(0.59839)	(0.08925)	(0.65764)	(0.27895)
	[-1.03645]	[0.15457]	[-0.31983]	[-0.34256]
DAP(-7)	-0.124239	-0.011720	0.317908	-0.215949
	(0.37679)	(0.05620)	(0.41410)	(0.17565)
	[-0.32973]	[-0.20854]	[0.76772]	[-1.22944]
DEMP(-1)	1.394215	-0.422830	-0.505570	-0.452213
	(3.80164)	(0.56704)	(4.17807)	(1.77223)
	[0.36674]	[-0.74568]	[-0.12101]	[-0.25517]
DEMP(-2)	5.198864	-0.149052	6.085842	-1.122563
	(4.09577)	(0.61091)	(4.50132)	(1.90934)
	[1.26933]	[-0.24398]	[1.35201]	[-0.58793]
DEMP(-3)	3.893509	-0.585262	3.398055	0.937749
	(4.16899)	(0.62183)	(4.58180)	(1.94348)
	[0.93392]	[-0.94119]	[0.74164]	[0.48251]
DEMP(-4)	-0.720636	-0.003368	-3.955604	0.536612
	(4.87983)	(0.72786)	(5.36302)	(2.27485)
	[-0.14768]	[-0.00463]	[-0.73757]	[0.23589]
DEMP(-5)	-1.239704	0.210109	-1.310977	0.974555
	(4.66272)	(0.69548)	(5.12441)	(2.17364)
	[-0.26588]	[0.30211]	[-0.25583]	[0.44835]
DEMP(-6)	-0.886117	-0.002806	0.709262	-0.374386
	(3.85699)	(0.57530)	(4.23890)	(1.79803)
	[-0.22974]	[-0.00488]	[0.16732]	[-0.20822]
DEMP(-7)	-1.130425	0.052604	-2.273131	0.950446
	(4.11163)	(0.61328)	(4.51875)	(1.91673)
	[-0.27493]	[0.08577]	[-0.50304]	[0.49587]

DINT(-1)	0.414347	0.048347	0.023286	-0.091536
	(0.37494)	(0.05592)	(0.41206)	(0.17479)
	[1.10511]	[0.86451]	[0.05651]	[-0.52371]
DINT(-2)	-0.120866	-0.037707	0.464215	0.181861
	(0.40795)	(0.06085)	(0.44834)	(0.19017)
	[-0.29628]	[-0.61969]	[1.03541]	[0.95629]
DINT(-3)	-0.694746	-0.019670	0.280334	-0.293169
	(0.43548)	(0.06495)	(0.47860)	(0.20301)
	[-1.59537]	[-0.30282]	[0.58574]	[-1.44413]
DINT(-4)	0.065669	-0.018435	-0.894947	0.036917
	(0.41879)	(0.06247)	(0.46025)	(0.19523)
	[0.15681]	[-0.29513]	[-1.94446]	[0.18910]
DINT(-5)	0.498938	0.030587	0.232177	0.249572
	(0.41358)	(0.06169)	(0.45453)	(0.19280)
	[1.20640]	[0.49583]	[0.51081]	[1.29447]
DINT(-6)	-0.030142	-0.047284	0.499508	0.095253
	(0.49890)	(0.07442)	(0.54830)	(0.23258)
	[-0.06042]	[-0.63541]	[0.91101]	[0.40956]
DINT(-7)	-0.552736	0.030919	-0.412769	0.035354
	(0.37324)	(0.05567)	(0.41019)	(0.17399)
	[-1.48092]	[0.55538]	[-1.00628]	[0.20319]
DVAC(-1)	-0.137402	0.034757	-0.371597	1.066464
	(0.85421)	(0.12741)	(0.93879)	(0.39821)
	[-0.16085]	[0.27279]	[-0.39583]	[2.67815]
DVAC(-2)	-0.926206	-0.055348	1.296926	-0.909939
	(1.07813)	(0.16081)	(1.18488)	(0.50259)
	[-0.85909]	[-0.34418]	[1.09456]	[-1.81048]
DVAC(-3)	-0.786635	0.035237	-2.490271	0.611393
	(1.07818)	(0.16082)	(1.18494)	(0.50262)
	[-0.72960]	[0.21911]	[-2.10161]	[1.21642]
DVAC(-4)	0.714382	0.012630	1.000927	-0.828627
	(0.98966)	(0.14762)	(1.08766)	(0.46136)
	[0.72184]	[0.08556]	[0.92026]	[-1.79607]
DVAC(-5)	0.460892	0.023507	-0.153526	0.788010
	(1.12102)	(0.16721)	(1.23202)	(0.52259)
	[0.41114]	[0.14059]	[-0.12461]	[1.50789]
DVAC(-6)	-0.796221	-0.066082	1.076019	-0.731398
	(0.90781)	(0.13541)	(0.99770)	(0.42320)
	[-0.87708]	[-0.48803]	[1.07850]	[-1.72827]
DVAC(-7)	-0.223983	0.032567	-1.171384	0.055429
	(0.63770)	(0.09512)	(0.70084)	(0.29728)
	[-0.35123]	[0.34238]	[-1.67139]	[0.18646]
C	-0.013217	-0.000443	-0.005226	0.000695
	(0.01822)	(0.00272)	(0.02002)	(0.00849)
	[-0.72549]	[-0.16299]	[-0.26103]	[0.08188]

R-squared	0.910838	0.861503	0.813397	0.961388
Adj. R-squared	0.286704	-0.107979	-0.492827	0.691103
Sum sq. resids	0.021438	0.000477	0.025894	0.004659
S.E. equation	0.073209	0.010920	0.080458	0.034128
F-statistic	1.459362	0.888622	0.622708	3.556940
Log likelihood	74.26999	137.0609	71.15427	99.45549
Akaike AIC	-2.743636	-6.549148	-2.554804	-4.270029
Schwarz SC	-1.428523	-5.234036	-1.239691	-2.954917
Mean dependent	-0.004482	-0.000610	-0.013900	0.018041
S.D. dependent	0.086682	0.010374	0.065851	0.061405

Determinant resid covariance (dof adj.)	1.31E-12
Determinant resid covariance	2.84E-16
Log likelihood	403.3833
Akaike information criterion	-17.41717
Schwarz criterion	-12.15672

C.2. Est. period: 1998Q4 – 2007Q4

	DAP	DEMP	DINT	DVAC
DAP(-1)	-1.289426	0.063434	-0.380515	-0.413074
	(0.32146)	(0.05270)	(0.39050)	(0.16909)
	[-4.01121]	[1.20379]	[-0.97443]	[-2.44294]
DAP(-2)	-0.584999	0.077071	-0.865642	-0.202565
	(0.47414)	(0.07773)	(0.57598)	(0.24940)
	[-1.23381]	[0.99159]	[-1.50289]	[-0.81220]
DAP(-3)	-0.424177	0.040306	-0.159769	-0.482308
	(0.41093)	(0.06736)	(0.49919)	(0.21615)
	[-1.03224]	[0.59834]	[-0.32005]	[-2.23134]
DAP(-4)	-0.923468	0.022651	-0.371630	-0.251442
	(0.45546)	(0.07466)	(0.55328)	(0.23957)
	[-2.02757]	[0.30338]	[-0.67168]	[-1.04954]
DAP(-5)	-1.038993	0.030315	-0.054768	-0.462128
	(0.53464)	(0.08764)	(0.64948)	(0.28123)
	[-1.94335]	[0.34590]	[-0.08433]	[-1.64326]
DAP(-6)	-0.438619	-0.006308	0.110310	-0.078103
	(0.40698)	(0.06672)	(0.49439)	(0.21407)
	[-1.07775]	[-0.09455]	[0.22312]	[-0.36484]
DAP(-7)	-0.143408	-0.017035	0.431069	-0.243736
	(0.29290)	(0.04802)	(0.35582)	(0.15407)
	[-0.48961]	[-0.35479]	[1.21149]	[-1.58199]
DEMP(-1)	2.424976	-0.752368	2.929217	-1.025467
	(2.51324)	(0.41199)	(3.05306)	(1.32198)
	[0.96488]	[-1.82618]	[0.95944]	[-0.77570]
DEMP(-2)	5.743679	-0.209003	6.640499	-1.162087
	(3.15198)	(0.51670)	(3.82901)	(1.65797)
	[1.82224]	[-0.40450]	[1.73426]	[-0.70091]
DEMP(-3)	4.323589	-0.563399	3.257634	1.190806
	(3.32029)	(0.54429)	(4.03346)	(1.74650)
	[1.30217]	[-1.03511]	[0.80765]	[0.68182]
DEMP(-4)	-0.988359	-0.310279	-3.061700	-0.192435
	(3.62380)	(0.59404)	(4.40217)	(1.90615)
	[-0.27274]	[-0.52232]	[-0.69550]	[-0.10095]
DEMP(-5)	-1.413361	0.336553	-3.263599	1.319134
	(3.61748)	(0.59301)	(4.39449)	(1.90283)
	[-0.39070]	[0.56754]	[-0.74266]	[0.69325]
DEMP(-6)	-0.662233	0.156933	-0.030575	0.179839
	(2.86639)	(0.46988)	(3.48207)	(1.50775)
	[-0.23103]	[0.33398]	[-0.00878]	[0.11928]
DEMP(-7)	-0.918753	-0.293678	-0.905350	0.335343
	(2.60102)	(0.42638)	(3.15971)	(1.36816)
	[-0.35323]	[-0.68877]	[-0.28653]	[0.24510]

DINT(-1)	0.474436	0.046617	0.087423	-0.090141
	(0.26219)	(0.04298)	(0.31851)	(0.13792)
	[1.80949]	[1.08460]	[0.27447]	[-0.65359]
DINT(-2)	-0.055991	-0.012107	0.310789	0.265605
	(0.31391)	(0.05146)	(0.38134)	(0.16512)
	[-0.17836]	[-0.23528]	[0.81499]	[1.60855]
DINT(-3)	-0.631347	-0.017425	0.190632	-0.254109
	(0.33096)	(0.05425)	(0.40205)	(0.17409)
	[-1.90761]	[-0.32117]	[0.47415]	[-1.45965]
DINT(-4)	0.198249	-0.017307	-0.760001	0.091881
	(0.27185)	(0.04456)	(0.33024)	(0.14300)
	[0.72926]	[-0.38835]	[-2.30134]	[0.64254]
DINT(-5)	0.477238	-0.010957	0.534870	0.128053
	(0.28580)	(0.04685)	(0.34718)	(0.15033)
	[1.66985]	[-0.23388]	[1.54060]	[0.85180]
DINT(-6)	-0.199339	-0.009514	0.083880	0.134681
	(0.32866)	(0.05388)	(0.39925)	(0.17288)
	[-0.60652]	[-0.17659]	[0.21009]	[0.77905]
DINT(-7)	-0.519932	0.030861	-0.286118	0.042811
	(0.27870)	(0.04569)	(0.33856)	(0.14660)
	[-1.86555]	[0.67549]	[-0.84509]	[0.29203]
DVAC(-1)	0.134547	-0.008981	-0.151013	1.078529
	(0.56184)	(0.09210)	(0.68252)	(0.29553)
	[0.23948]	[-0.09751]	[-0.22126]	[3.64945]
DVAC(-2)	-1.211893	0.005967	0.856332	-0.865249
	(0.78834)	(0.12923)	(0.95767)	(0.41467)
	[-1.53727]	[0.04617]	[0.89418]	[-2.08657]
DVAC(-3)	-0.590191	-0.003650	-2.209843	0.607100
	(0.79310)	(0.13001)	(0.96345)	(0.41718)
	[-0.74416]	[-0.02807]	[-2.29367]	[1.45525]
DVAC(-4)	0.661643	0.035184	1.111600	-0.832505
	(0.70384)	(0.11538)	(0.85501)	(0.37022)
	[0.94005]	[0.30494]	[1.30010]	[-2.24865]
DVAC(-5)	0.638040	-0.013209	-0.070917	0.780814
	(0.84653)	(0.13877)	(1.02836)	(0.44528)
	[0.75371]	[-0.09519]	[-0.06896]	[1.75353]
DVAC(-6)	-0.934038	-0.020222	0.711568	-0.670809
	(0.69339)	(0.11367)	(0.84233)	(0.36473)
	[-1.34706]	[-0.17791]	[0.84476]	[-1.83919]
DVAC(-7)	-0.036562	0.003563	-0.902757	0.065715
	(0.41328)	(0.06775)	(0.50205)	(0.21739)
	[-0.08847]	[0.05259]	[-1.79813]	[0.30229]
C	-0.005943	0.000236	-0.001779	0.004157
	(0.01261)	(0.00207)	(0.01532)	(0.00663)
	[-0.47131]	[0.11403]	[-0.11617]	[0.62678]

R-squared	0.886636	0.826928	0.751869	0.949012
Adj. R-squared	0.489861	0.221178	-0.116587	0.770555
Sum sq. resids	0.028098	0.000755	0.041466	0.007774
S.E. equation	0.059265	0.009715	0.071994	0.031174
F-statistic	2.234606	1.365131	0.865753	5.317867
Log likelihood	80.38399	147.2921	73.18476	104.1542
Akaike AIC	-2.777513	-6.394167	-2.388365	-4.062387
Schwarz SC	-1.514901	-5.131556	-1.125754	-2.799776
Mean dependent	-0.000169	-0.000313	-0.007755	0.007862
S.D. dependent	0.082976	0.011009	0.068132	0.065080

Determinant resid covariance (dof adj.)	7.88E-13
Determinant resid covariance	1.72E-15
Log likelihood	418.9139
Akaike information criterion	-16.37372
Schwarz criterion	-11.32328

Granger causality test:

Dependent variable: DAP

Excluded	Chi-sq	df	Prob.
DEMP	5.226714	7	0.6323
DINT	14.35116	7	0.0453
DVAC	13.14651	7	0.0686
All	35.80953	21	0.0230

Dependent variable: DEMP

Excluded	Chi-sq	df	Prob.
DAP	2.762565	7	0.9061
DINT	2.856754	7	0.8979
DVAC	0.387714	7	0.9998
All	8.371832	21	0.9934

Dependent variable: DINT

Excluded	Chi-sq	df	Prob.
DAP	5.086923	7	0.6494
DEMP	5.934997	7	0.5474
DVAC	6.814538	7	0.4484
All	21.68381	21	0.4179

Dependent variable: DVAC

Excluded	Chi-sq	df	Prob.
DAP	17.21598	7	0.0161
DEMP	9.182611	7	0.2398
DINT	11.00140	7	0.1386
All	47.05385	21	0.0009

C.3. Est. period: 1998Q4 – 2008Q4

	DAP	DEMP	DINT	DVAC
DAP(-1)	-1.248918	0.047197	-0.549951	-0.287202
	(0.26074)	(0.04042)	(0.30764)	(0.14658)
	[-4.78996]	[1.16775]	[-1.78765]	[-1.95933]
DAP(-2)	-0.778508	0.095762	-0.626847	-0.219579
	(0.37786)	(0.05857)	(0.44583)	(0.21243)
	[-2.06032]	[1.63495]	[-1.40603]	[-1.03367]
DAP(-3)	-0.602077	0.074196	0.021294	-0.494524
	(0.36953)	(0.05728)	(0.43600)	(0.20774)
	[-1.62932]	[1.29530]	[0.04884]	[-2.38047]
DAP(-4)	-0.983162	0.035058	-0.337096	-0.201990
	(0.41061)	(0.06365)	(0.48447)	(0.23084)
	[-2.39442]	[0.55081]	[-0.69581]	[-0.87504]
DAP(-5)	-1.028874	0.032637	-0.073335	-0.406874
	(0.47981)	(0.07438)	(0.56612)	(0.26974)
	[-2.14432]	[0.43881]	[-0.12954]	[-1.50837]
DAP(-6)	-0.457574	-0.001072	0.163274	-0.073999
	(0.37080)	(0.05748)	(0.43750)	(0.20846)
	[-1.23403]	[-0.01865]	[0.37320]	[-0.35499]
DAP(-7)	-0.158692	-0.015011	0.338410	-0.158015
	(0.26918)	(0.04173)	(0.31760)	(0.15133)
	[-0.58955]	[-0.35976]	[1.06554]	[-1.04420]
DEMP(-1)	3.407823	-0.739838	3.012328	-1.840903
	(1.92176)	(0.29789)	(2.26745)	(1.08038)
	[1.77328]	[-2.48356]	[1.32851]	[-1.70393]
DEMP(-2)	6.106268	-0.229287	5.567592	-0.450044
	(2.91343)	(0.45161)	(3.43750)	(1.63788)
	[2.09590]	[-0.50771]	[1.61966]	[-0.27477]
DEMP(-3)	2.967690	-0.316246	5.515166	0.587829
	(2.87584)	(0.44579)	(3.39315)	(1.61675)
	[1.03194]	[-0.70941]	[1.62538]	[0.36359]
DEMP(-4)	-0.217343	-0.207926	-3.392912	-0.519441
	(2.86256)	(0.44373)	(3.37748)	(1.60929)
	[-0.07593]	[-0.46859]	[-1.00457]	[-0.32278]
DEMP(-5)	0.918513	0.093229	-5.020057	1.461226
	(3.13594)	(0.48610)	(3.70003)	(1.76298)
	[0.29290]	[0.19179]	[-1.35676]	[0.82884]
DEMP(-6)	0.024225	0.091062	0.908923	-0.731621
	(2.33807)	(0.36243)	(2.75865)	(1.31443)
	[0.01036]	[0.25126]	[0.32948]	[-0.55661]
DEMP(-7)	-1.258948	-0.248923	-0.623431	0.241062
	(2.47765)	(0.38406)	(2.92334)	(1.39290)
	[-0.50812]	[-0.64813]	[-0.21326]	[0.17306]

DINT(-1)	0.541550	0.049335	0.093668	-0.141913
	(0.23236)	(0.03602)	(0.27415)	(0.13063)
	[2.33068]	[1.36973]	[0.34166]	[-1.08640]
DINT(-2)	-0.049487	-0.014397	0.363890	0.232002
	(0.29347)	(0.04549)	(0.34626)	(0.16499)
	[-0.16862]	[-0.31648]	[1.05090]	[1.40619]
DINT(-3)	-0.625818	-0.026940	-0.012511	-0.106145
	(0.29418)	(0.04560)	(0.34710)	(0.16539)
	[-2.12730]	[-0.59076]	[-0.03604]	[-0.64181]
DINT(-4)	0.149401	-0.008833	-0.645640	0.059283
	(0.23796)	(0.03689)	(0.28077)	(0.13378)
	[0.62783]	[-0.23947]	[-2.29956]	[0.44314]
DINT(-5)	0.495168	0.005873	0.611203	0.052865
	(0.21997)	(0.03410)	(0.25954)	(0.12367)
	[2.25103]	[0.17223]	[2.35491]	[0.42748]
DINT(-6)	-0.084243	-0.021151	-0.079407	0.198557
	(0.30127)	(0.04670)	(0.35546)	(0.16937)
	[-0.27963]	[-0.45290]	[-0.22339]	[1.17233]
DINT(-7)	-0.410610	0.015728	-0.330140	0.021428
	(0.25025)	(0.03879)	(0.29526)	(0.14069)
	[-1.64080]	[0.40545]	[-1.11812]	[0.15231]
DVAC(-1)	-0.165938	0.031278	0.323960	0.927774
	(0.47592)	(0.07377)	(0.56153)	(0.26756)
	[-0.34866]	[0.42398]	[0.57692]	[3.46758]
DVAC(-2)	-1.025959	-0.012604	0.362926	-0.627914
	(0.68062)	(0.10550)	(0.80305)	(0.38263)
	[-1.50739]	[-0.11946]	[0.45193]	[-1.64103]
DVAC(-3)	-0.502477	-0.032423	-2.173493	0.576018
	(0.66634)	(0.10329)	(0.78620)	(0.37460)
	[-0.75409]	[-0.31390]	[-2.76456]	[1.53767]
DVAC(-4)	0.683760	0.053565	1.187086	-0.928134
	(0.63662)	(0.09868)	(0.75114)	(0.35790)
	[1.07404]	[0.54279]	[1.58038]	[-2.59328]
DVAC(-5)	0.557829	-0.006544	0.125474	0.682554
	(0.80817)	(0.12528)	(0.95355)	(0.45434)
	[0.69023]	[-0.05223]	[0.13159]	[1.50229]
DVAC(-6)	-1.037779	-0.019269	0.452914	-0.408052
	(0.63042)	(0.09772)	(0.74382)	(0.35441)
	[-1.64616]	[-0.19719]	[0.60890]	[-1.15134]
DVAC(-7)	0.025410	0.009640	-0.742237	-0.070999
	(0.37579)	(0.05825)	(0.44339)	(0.21126)
	[0.06762]	[0.16549]	[-1.67400]	[-0.33607]
C	-0.001845	0.000313	-0.004746	0.005388
	(0.01028)	(0.00159)	(0.01213)	(0.00578)
	[-0.17937]	[0.19605]	[-0.39114]	[0.93186]

R-squared	0.848963	0.808761	0.710952	0.927826
Adj. R-squared	0.496545	0.362538	0.036508	0.759422
Sum sq. resids	0.039504	0.000949	0.054994	0.012485
S.E. equation	0.057376	0.008894	0.067697	0.032256
F-statistic	2.408963	1.812459	1.054131	5.509499
Log likelihood	84.19463	160.6293	77.41264	107.8075
Akaike AIC	-2.692421	-6.420940	-2.361592	-3.844271
Schwarz SC	-1.480382	-5.208902	-1.149554	-2.632232
Mean dependent	0.000303	6.65E-05	-0.005067	0.002282
S.D. dependent	0.080863	0.011139	0.068967	0.065763

Determinant resid covariance (dof adj.)	8.86E-13
Determinant resid covariance	6.50E-15
Log likelihood	436.9530
Akaike information criterion	-15.65625
Schwarz criterion	-10.80809

Granger causality test:

Dependent variable: DAP

Excluded	Chi-sq	df	Prob.
DEMP	5.260307	7	0.6282
DINT	19.45097	7	0.0069
DVAC	16.20683	7	0.0233
All	38.38116	21	0.0116

Dependent variable: DEMP

Excluded	Chi-sq	df	Prob.
DAP	4.417363	7	0.7306
DINT	2.524959	7	0.9252
DVAC	1.016883	7	0.9946
All	10.04901	21	0.9783

Dependent variable: DINT

Excluded	Chi-sq	df	Prob.
DAP	8.460041	7	0.2938
DEMP	10.86127	7	0.1448
DVAC	12.22765	7	0.0933
All	27.24825	21	0.1628

Dependent variable: DVAC

Excluded	Chi-sq	df	Prob.
DAP	14.41261	7	0.0443
DEMP	9.975085	7	0.1900
DINT	10.86295	7	0.1447
All	48.76608	21	0.0005

C.4. Est. period: 1998Q4 – 2009Q4

	DAP	DEMP	DINT	DVAC
DAP(-1)	-1.343495	0.032410	-0.714364	-0.241639
	(0.20912)	(0.03159)	(0.26662)	(0.12044)
	[-6.42463]	[1.02607]	[-2.67931]	[-2.00636]
DAP(-2)	-0.921069	0.079085	-0.867853	-0.127379
	(0.30693)	(0.04636)	(0.39133)	(0.17677)
	[-3.00092]	[1.70589]	[-2.21769]	[-0.72060]
DAP(-3)	-0.673819	0.065630	-0.133439	-0.447776
	(0.31797)	(0.04803)	(0.40542)	(0.18313)
	[-2.11910]	[1.36647]	[-0.32914]	[-2.44511]
DAP(-4)	-1.038437	0.029053	-0.228423	-0.230864
	(0.37635)	(0.05685)	(0.47984)	(0.21675)
	[-2.75924]	[0.51108]	[-0.47604]	[-1.06511]
DAP(-5)	-1.124881	0.010755	-0.470392	-0.329354
	(0.39218)	(0.05924)	(0.50002)	(0.22587)
	[-2.86830]	[0.18155]	[-0.94074]	[-1.45818]
DAP(-6)	-0.450462	-0.003100	-0.132436	-0.002483
	(0.31462)	(0.04752)	(0.40114)	(0.18120)
	[-1.43177]	[-0.06524]	[-0.33015]	[-0.01370]
DAP(-7)	-0.123660	-0.014153	0.088569	-0.106519
	(0.21932)	(0.03313)	(0.27963)	(0.12631)
	[-0.56384]	[-0.42725]	[0.31674]	[-0.84330]
DEMP(-1)	3.060852	-0.738019	3.483693	-1.659044
	(1.67634)	(0.25320)	(2.13732)	(0.96545)
	[1.82591]	[-2.91472]	[1.62993]	[-1.71841]
DEMP(-2)	6.128992	-0.083395	8.266810	-0.464482
	(2.25929)	(0.34126)	(2.88058)	(1.30119)
	[2.71279]	[-0.24438]	[2.86984]	[-0.35697]
DEMP(-3)	2.948402	-0.204151	6.047285	0.979975
	(2.42597)	(0.36643)	(3.09309)	(1.39719)
	[1.21535]	[-0.55713]	[1.95510]	[0.70139]
DEMP(-4)	-0.416343	-0.191910	-2.410642	-0.725182
	(2.39622)	(0.36194)	(3.05516)	(1.38005)
	[-0.17375]	[-0.53023]	[-0.78904]	[-0.52547]
DEMP(-5)	-0.052354	-0.051121	-2.501783	0.662006
	(2.47355)	(0.37362)	(3.15376)	(1.42459)
	[-0.02117]	[-0.13683]	[-0.79327]	[0.46470]
DEMP(-6)	0.431708	0.061641	-1.434175	-0.472718
	(1.93631)	(0.29247)	(2.46878)	(1.11518)
	[0.22295]	[0.21076]	[-0.58092]	[-0.42389]
DEMP(-7)	-0.306046	-0.130040	-1.946990	0.467577
	(1.73493)	(0.26205)	(2.21203)	(0.99920)
	[-0.17640]	[-0.49623]	[-0.88018]	[0.46795]

DINT(-1)	0.413488	0.034274	0.102764	-0.121136
	(0.16744)	(0.02529)	(0.21349)	(0.09644)
	[2.46943]	[1.35518]	[0.48136]	[-1.25614]
DINT(-2)	0.092293	0.011985	0.543363	0.214068
	(0.20921)	(0.03160)	(0.26674)	(0.12049)
	[0.44115]	[0.37927]	[2.03704]	[1.77664]
DINT(-3)	-0.687850	-0.037121	-0.268733	-0.042144
	(0.22720)	(0.03432)	(0.28968)	(0.13085)
	[-3.02750]	[-1.08170]	[-0.92769]	[-0.32208]
DINT(-4)	0.092220	-0.015939	-0.573546	0.040079
	(0.21470)	(0.03243)	(0.27375)	(0.12365)
	[0.42952]	[-0.49150]	[-2.09518]	[0.32412]
DINT(-5)	0.450318	-0.003367	0.594665	0.042739
	(0.19544)	(0.02952)	(0.24919)	(0.11256)
	[2.30412]	[-0.11405]	[2.38644]	[0.37970]
DINT(-6)	0.079621	-0.000360	0.203303	0.099679
	(0.19839)	(0.02997)	(0.25295)	(0.11426)
	[0.40133]	[-0.01202]	[0.80373]	[0.87238]
DINT(-7)	-0.511216	-0.004746	-0.600076	0.073162
	(0.16054)	(0.02425)	(0.20469)	(0.09246)
	[-3.18431]	[-0.19573]	[-2.93163]	[0.79128]
DVAC(-1)	-0.275842	0.035712	0.489932	0.978558
	(0.42118)	(0.06362)	(0.53700)	(0.24257)
	[-0.65492]	[0.56136]	[0.91234]	[4.03412]
DVAC(-2)	-0.909888	-0.012090	0.181322	-0.668001
	(0.61108)	(0.09230)	(0.77912)	(0.35194)
	[-1.48898]	[-0.13099]	[0.23273]	[-1.89806]
DVAC(-3)	-0.682694	-0.059715	-2.123195	0.558024
	(0.58284)	(0.08804)	(0.74312)	(0.33568)
	[-1.17132]	[-0.67830]	[-2.85714]	[1.66239]
DVAC(-4)	0.637167	0.035155	0.537350	-0.778659
	(0.51395)	(0.07763)	(0.65528)	(0.29600)
	[1.23975]	[0.45286]	[0.82004]	[-2.63063]
DVAC(-5)	0.749609	0.047958	0.956321	0.567856
	(0.58801)	(0.08882)	(0.74970)	(0.33865)
	[1.27483]	[0.53997]	[1.27560]	[1.67682]
DVAC(-6)	-1.113744	-0.037251	-0.018220	-0.309351
	(0.53178)	(0.08032)	(0.67801)	(0.30627)
	[-2.09438]	[-0.46376]	[-0.02687]	[-1.01007]
DVAC(-7)	-0.073434	-0.000459	-0.673062	-0.070942
	(0.33892)	(0.05119)	(0.43212)	(0.19519)
	[-0.21667]	[-0.00896]	[-1.55758]	[-0.36344]
C	-0.000166	7.92E-05	-0.009168	0.004125
	(0.00897)	(0.00135)	(0.01144)	(0.00517)
	[-0.01847]	[0.05847]	[-0.80165]	[0.79846]

R-squared	0.831396	0.802843	0.716380	0.919296
Adj. R-squared	0.536339	0.457818	0.220046	0.778064
Sum sq. resids	0.045247	0.001032	0.073553	0.015008
S.E. equation	0.053178	0.008032	0.067802	0.030627
F-statistic	2.817749	2.326913	1.443341	6.509107
Log likelihood	91.44935	176.5071	80.51702	116.2790
Akaike AIC	-2.775526	-6.555873	-2.289645	-3.879067
Schwarz SC	-1.611233	-5.391580	-1.125352	-2.714773
Mean dependent	-0.000280	-0.000266	-0.009193	0.006430
S.D. dependent	0.078097	0.010909	0.076772	0.065011

Determinant resid covariance (dof adj.)	5.37E-13
Determinant resid covariance	8.59E-15
Log likelihood	473.3332
Akaike information criterion	-15.88147
Schwarz criterion	-11.22430

Granger causality test:

Dependent variable: DAP

Excluded	Chi-sq	df	Prob.
DEMP	7.998381	7	0.3327
DINT	25.01342	7	0.0008
DVAC	23.96760	7	0.0012
All	47.83244	21	0.0007

Dependent variable: DEMP

Excluded	Chi-sq	df	Prob.
DAP	4.875553	7	0.6751
DINT	3.216513	7	0.8643
DVAC	1.908855	7	0.9647
All	13.45379	21	0.8919

Dependent variable: DINT

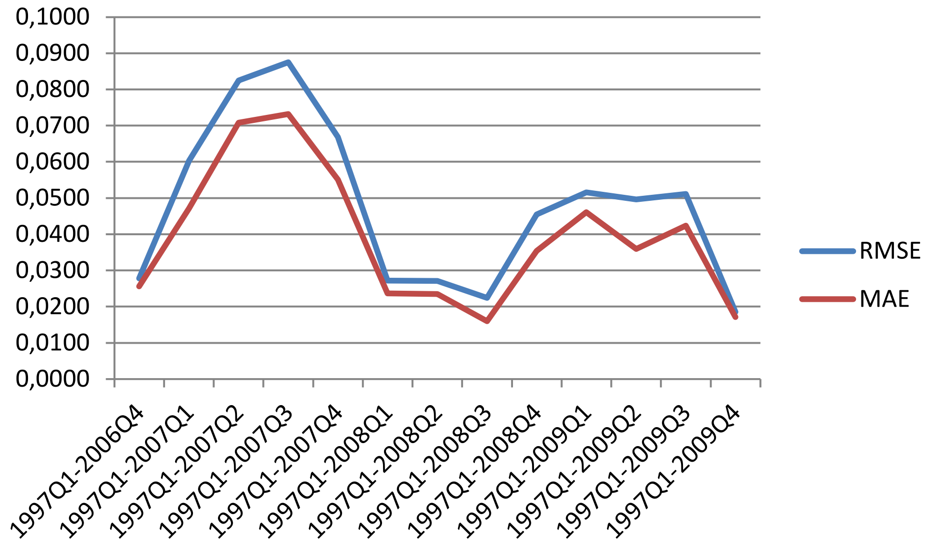
Excluded	Chi-sq	df	Prob.
DAP	11.50571	7	0.1180
DEMP	13.24219	7	0.0664
DVAC	16.73003	7	0.0192
All	35.69182	21	0.0237

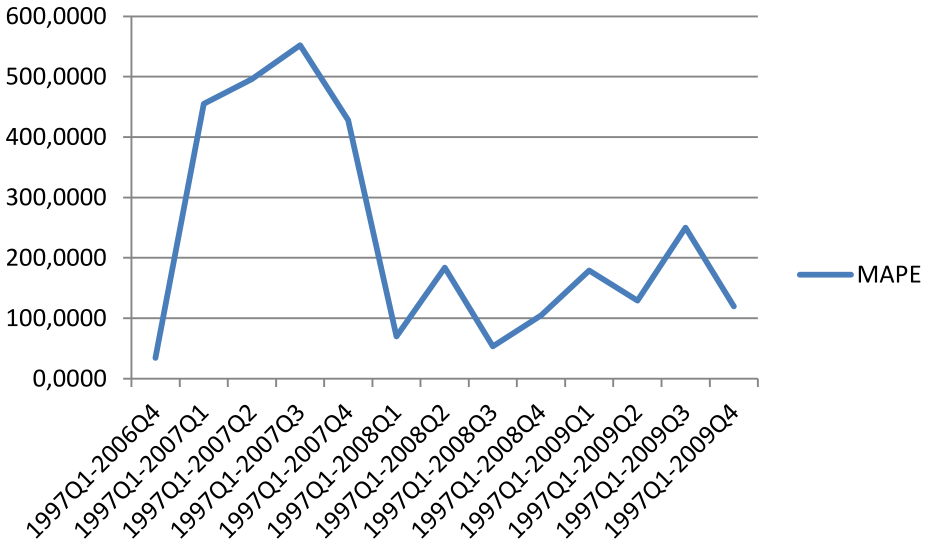
Dependent variable: DVAC

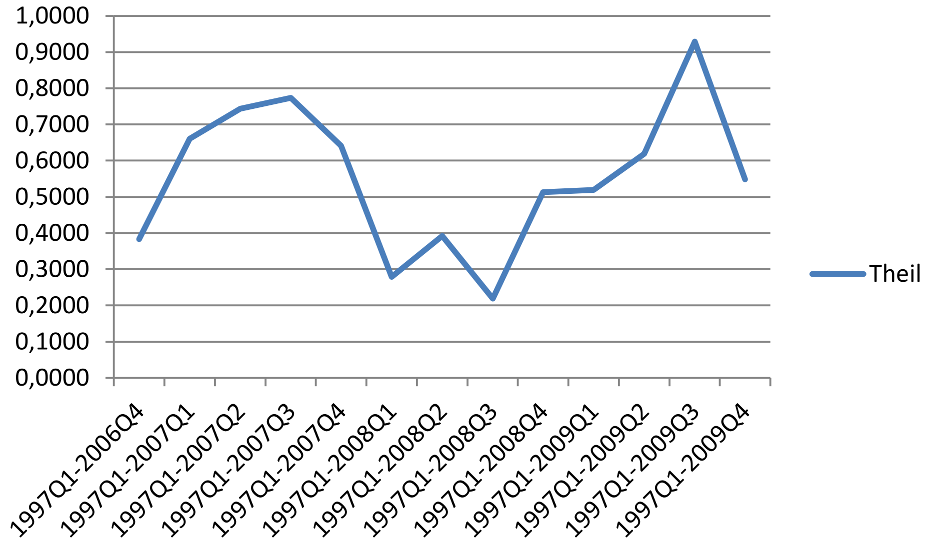
Excluded	Chi-sq	df	Prob.
DAP	17.35557	7	0.0152
DEMP	11.26297	7	0.1276
DINT	12.60441	7	0.0824
All	57.25773	21	0.0000

D. Performance measures for section 5.4

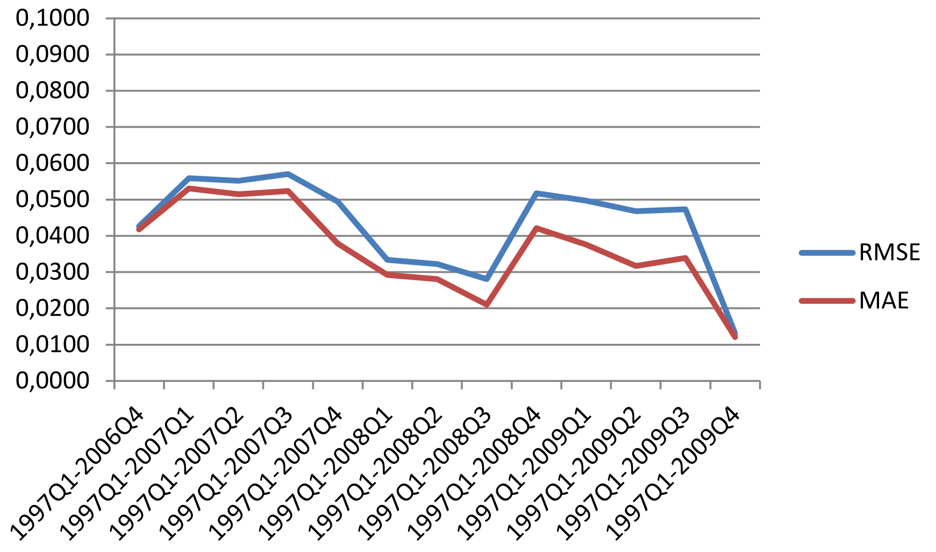
D.1. Dynamic 1-year forecasts

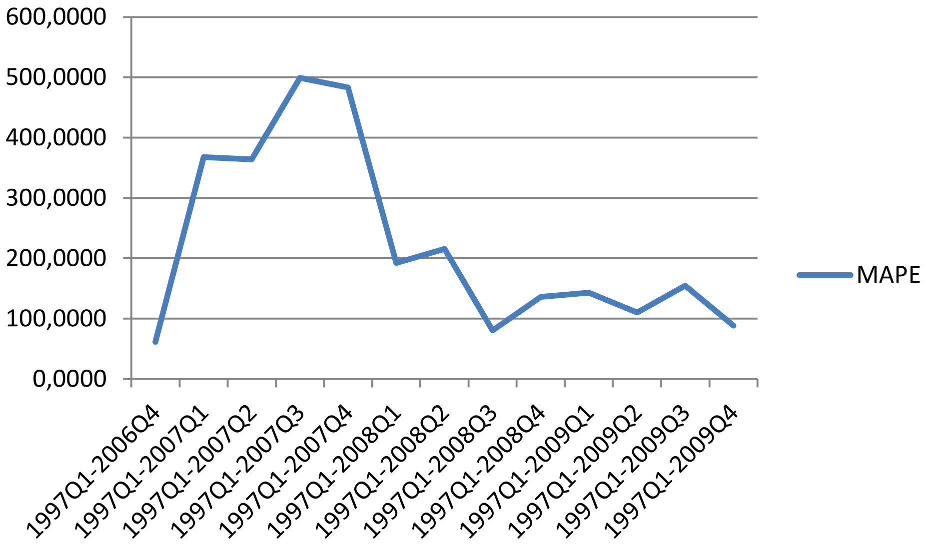


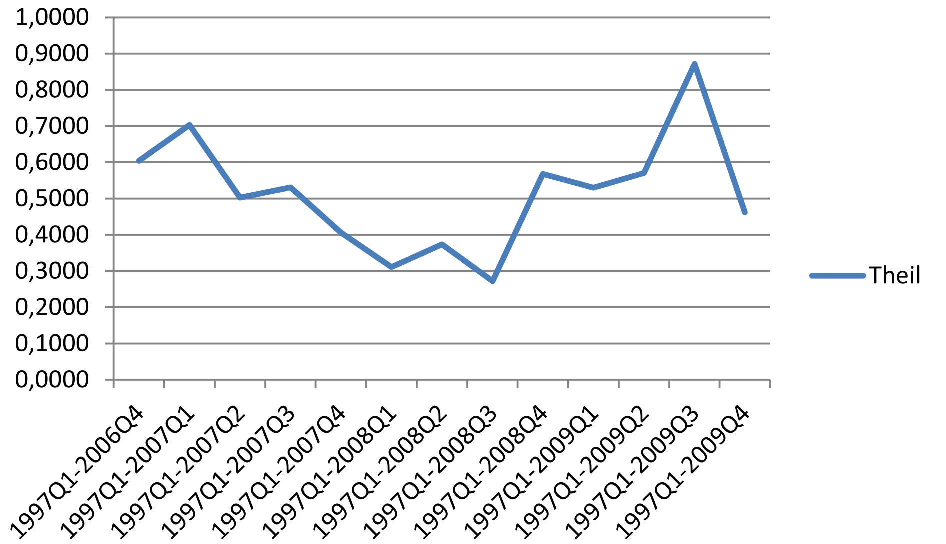




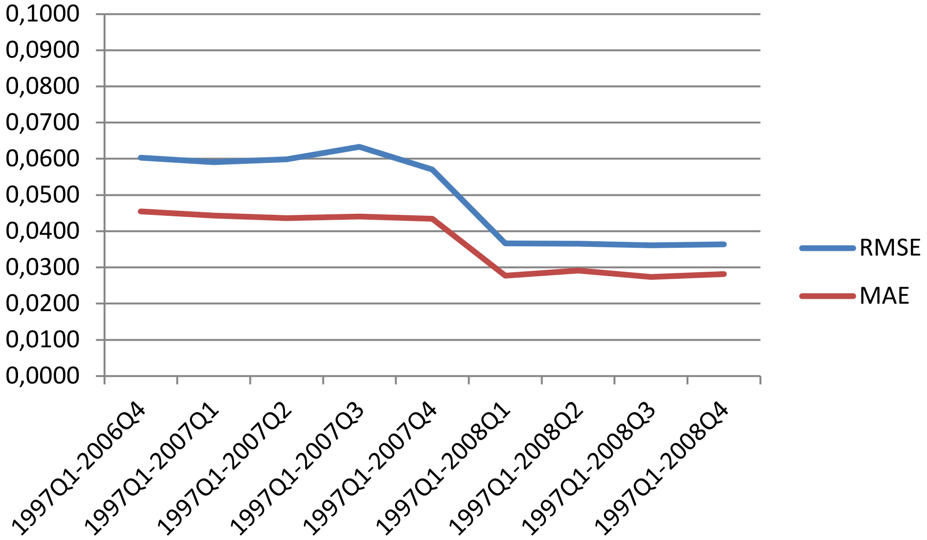
D.2. Static 1-year forecasts

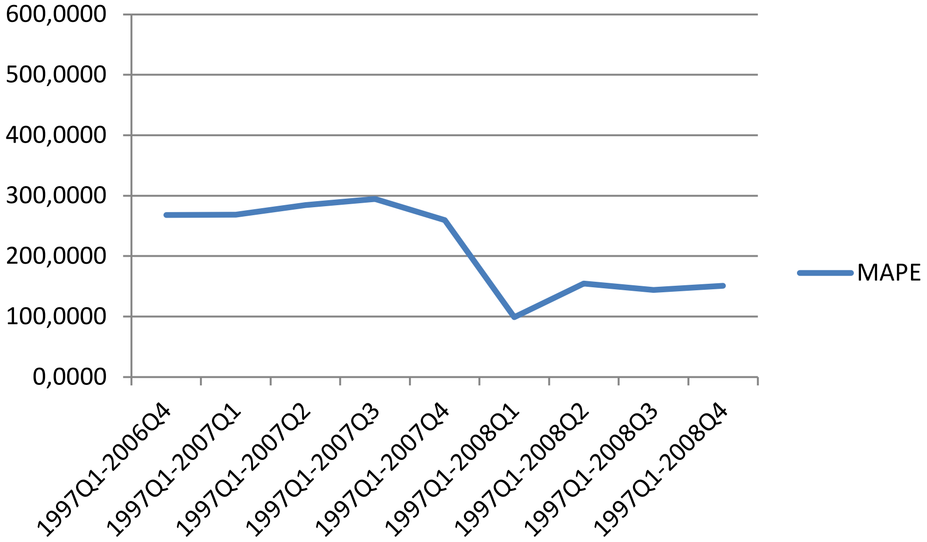


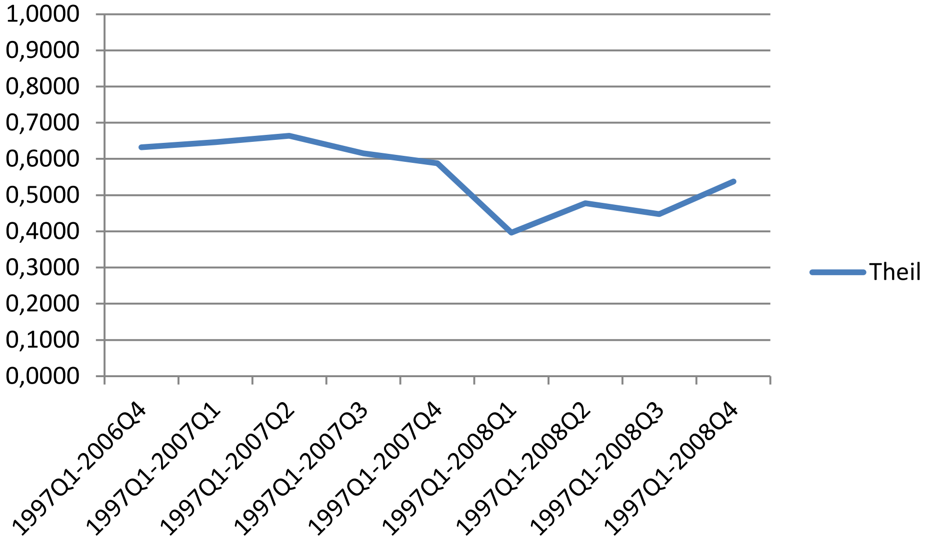




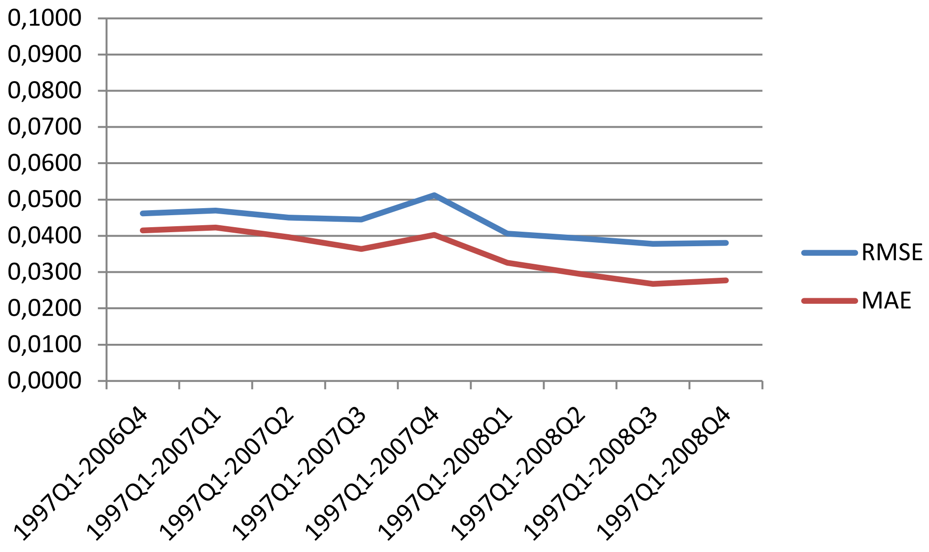
D.3. Dynamic 2-year forecasts

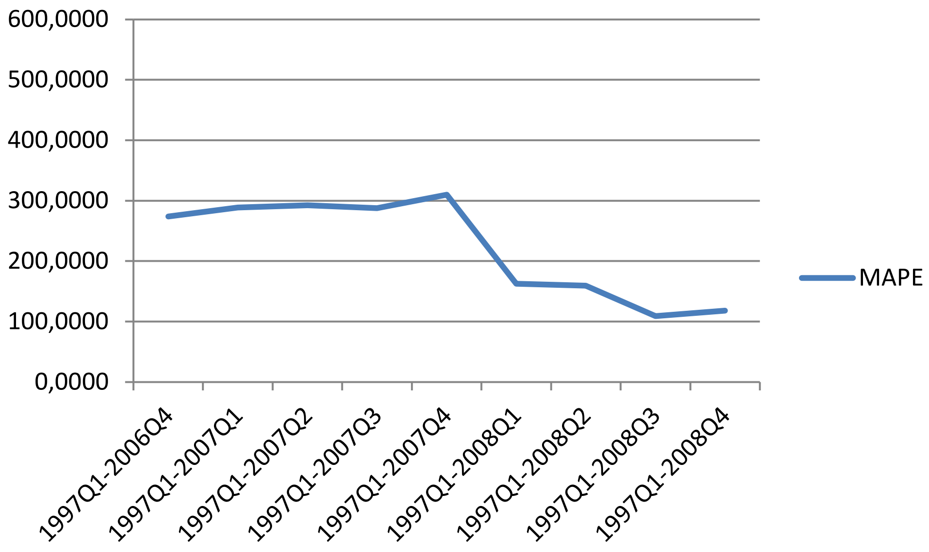


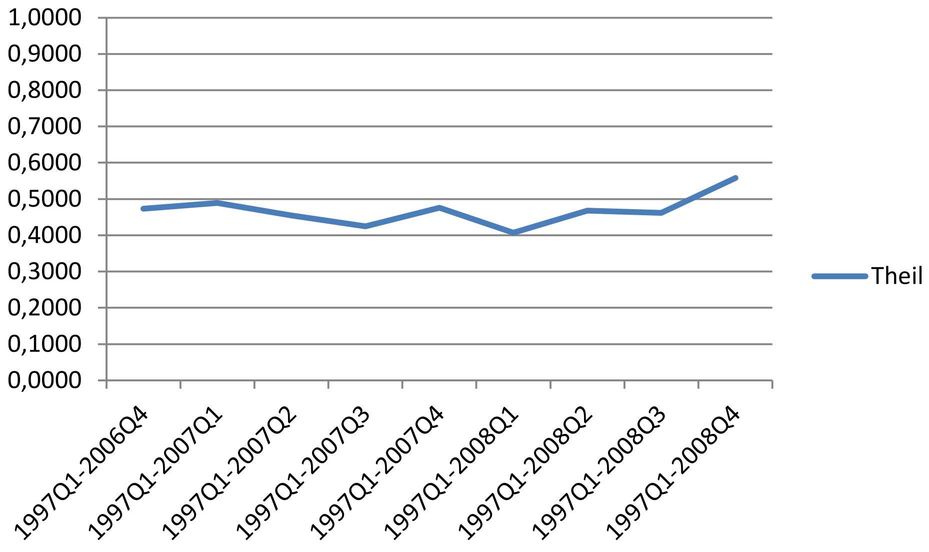




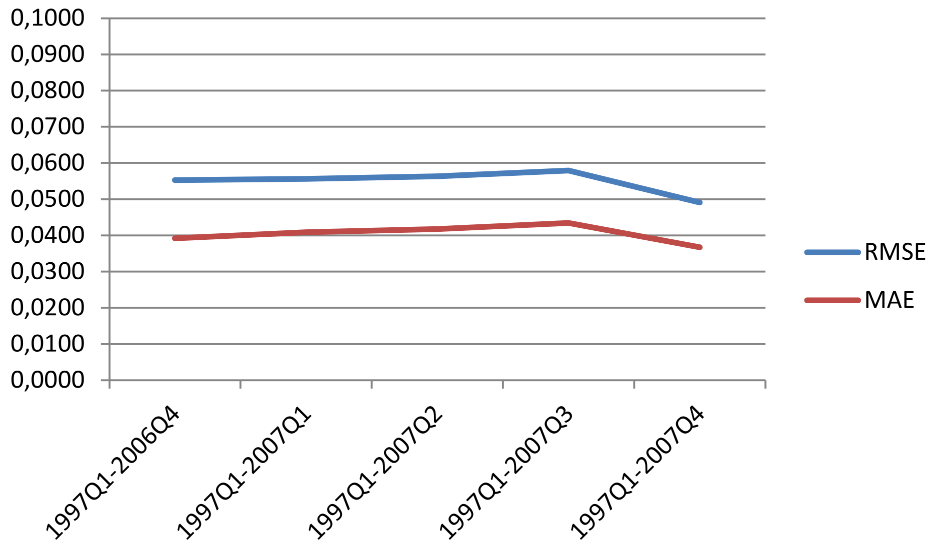
D.4. Static 2-year forecasts

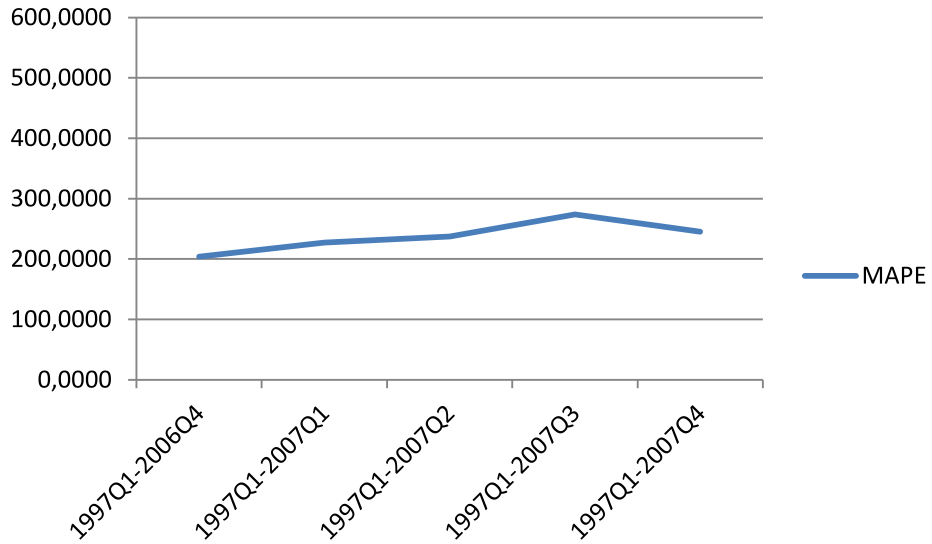


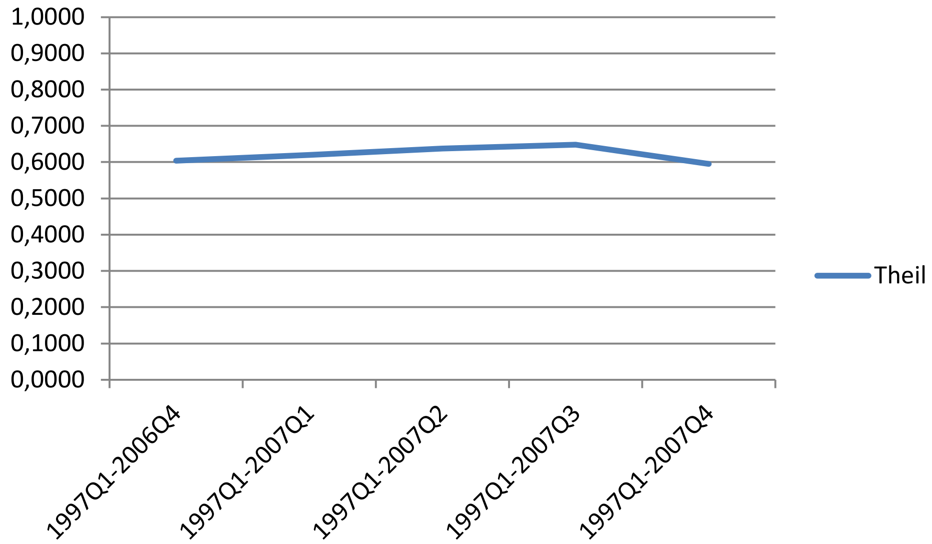




D.5. Dynamic 3-year forecasts







D.6. Static 3-year forecasts