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Analysis of rental prices for the office market in Oslo

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1.0 Abstract

The main purpose of this paper is to examine the office rental prices in Oslo where there is little previous quantitative work. Norway is an open economy relying sincerely on import and export, where changes in global economic factors will have consequences for both the Norwegian economy and the local economy in Oslo. We find that the multivariate models outperform the univariate model and that the most important factors explaining the development of office rental prices are vacancy office space (-), GDP (+), construction costs (+) and the oil price (+). The findings of the first three factors are consistent with previous research on what determines fluctuations in office rental prices. No previous research links the connection between office rental prices and the oil price. The oil price has a significant impact in both our multivariate models indicating the importance of the oil price for the Norwegian economy and for the development in office rental prices.

2.0 Introduction

The use of single and multi-equation regression models dominate previous studies on what determines the fluctuations in office rental prices. Multivariate models are preferred as the regressions are built on specific variables being a proxy for the supply and demand for office space. These proxies should, therefore, determine how the office rental prices fluctuate. One popular approach in this determination is to use multi-equation regression models that create both supply and demand functions. Rosen (1984) and Heckman (1985) both use this approach in their research.

Tsolacos et al. (1998) expand this supply and demand foundation by the use of lagged changes for several variables to determine the rental adjustment model. An essential aspect of later research is to determine which variables that best reflect the supply and demand for office space. In the work by Orr and Jones (2003) they develop an urban office model where they point out the importance of the independent variables reflecting both local determinants and national influences.

The classical linear regression model is the dominant model in the determination of fluctuations in office rental prices, but research on the topic also considers other econometric models. For instance, Giussani and Tsolacos (1993) try to explain rental prices by incorporating cointegration for the UK office market, while McGough and Tsolacos (1995) construct ARIMA models and short-run forecasts for the commercial rental prices in the UK. Moreover, Tse (1997) also investigates whether it is possible to explain changes in rental prices by its previous values. Tse finds the ARIMA model challenging to explain real estate prices on its own.

In this study, we examine which factors are important in explaining the development of office rental prices for the Oslo area. For the Oslo market, there is little quantitative work on the determination of office rental prices, and we will try to fill this gap. The explanatory variables we are choosing for this empirical investigation are guided by theory and will work as a proxy for the supply (office vacancy, construction costs) and demand (GDP, oil price, employment, unemployment and CPI) for office space, and the capital market (interest rates). Moreover, the variables are local, national and commercial real estate specific. Our study builds on the developing of earlier multivariate models but contributes to the understanding of what drives office rental prices in a more expanded way by also including two other models.

We build one univariate model and two multivariate models to answer which factors are the most important in determining the development in office rental prices. Like most studies, we rely on the classical linear regression model (CLRM) where we build a single equation model. We use a VECM to capture both long and short-run dynamics between the variables in the system. An autoregressive integrated moving average (ARIMA) model is constructed to see if the poor results from previous univariate models differ for the Oslo rental market. By evaluating the forecast performance of the different models, we aim to find the model that best explains the development in office rental prices.

By evaluating the forecast performance, we find the multivariate models outperform the univariate model. Further, we find that the VECM outperforms the CLRM in two out of three performance measures. We do question our results from the VECM, as the model itself is a-theoretical. We, therefore, choose to emphasize the results from both of the multivariate models. The findings from the CLRM indicate that vacancy, oil, and GDP have a statistically significant impact on the development of rental prices. The findings from the VECM indicate that construction costs and oil have a statistically significant impact on the development of rental prices. Our two multivariate models imply that the most important variables explaining the development of rental prices are a mixture of both supply and demand variables. The signs of the variables from both models are similar to our a-priori expectations, and the results are consistent with previous research. The exception is the significance of the oil price. No previous research links the connection between office rental prices and the oil price. The oil price has a significant impact on both our multivariate models and this result show that the oil price stands out as the most critical factor determining fluctuations in office rental prices.

3.0 Literature Review

Over the years there have been done much research on the topic of commercial real estate rental prices, where researchers investigate which factors and variables that best explain changes in rental prices. The factors that the majority of the researchers seem to find most relevant from a macroeconomic perspective are the Gross domestic product (GDP), employment rate, and interest rates. The most relevant factors that are real estate specific are vacancy rate and new buildings. All of these factors come in addition to the building’s standard, size and of course location.

In a study, Rosen (1984) builds a multi-equation model that aims to predict vacancy rate, the amount of new construction added to the market and the rent for office space based on supply and demand equations. Rosen uses the office market in San Francisco in the period from 1961 to 1983 in his sample, where demand is proxy for the amount of occupied space. The main findings are that changes in vacancy rates are inversely related to the deviation of actual vacancies to optimal vacancy rates. He also finds a positive effect of employment on the demand of occupied space.

Heckman (1985) investigates both office rents and building supply. The study examines fourteen standard metropolitan statistical areas (SMSA) over the period 1979-1983. Heckman looks further into how rental prices respond to changes in both local and national economic conditions. Heckman finds that office rents respond vigorously to the current vacancy rate, GNP, and SMSA employment. He also finds that the growth in rents grows faster in larger cities. For the supply side, he finds that construction costs, employment growth, and rents are the variables that respond to the volume of office permits.

In two different studies done by Tsolacos and Giussani (1993) and Tsolacos et al. (1998), the authors look further into what determine real office rents.
Tsolacos and Giussani (1993) look into the relationship between economic growth and commercial property market performance in Europe. Their main finding is that demand-side variables like GDP and unemployment rate can explain rental values in the banking, finance and insurance sector (FIRE). Economic uncertainty as unpredictability changes in GDP does significantly explain variations in office rents. Tsolacos et al. (1998) study the British office market, and the authors find that changes in general economic conditions and employment in the FIRE sector are the primary determinants to changes in real office rents. New development affects the office rents with a lag of three to four years.

In a study, McGough and Tsolacos (1995), perform short-run forecasts of commercial rental values in the UK using ARIMA models. By transforming the data series, stationarity is induced and seasonality removed. Nevertheless, their main findings are that results are more satisfactory for retail and office rental rents than it is for industrial rental rates. For office rental rates past shocks affect the present and future changes in rental rates. However, as the forecasts are done on second differenced values, obstacles occur in the conversion back to level.

Moreover, Tse (1997) investigates whether it is possible to fit real estate prices in Hong Kong into an ARIMA model and use it to forecast. Tse uses the model to track the direction of changes in real estate prices. He finds the ARIMA model challenging to explain real estate prices on its own. Nonetheless, it can be useful as a supplement to an investor's investment strategy.

Orr and Jones (2003) focus on analysis and prediction of local office rents and the development of an econometric model for the two cities Edinburgh and Glasgow. In the paper, the authors review the sparsity of the existing urban office rent models. They claim that the existing models experience data problems, and they either make the mistake of ignoring supply constraints, or that supply is considered regarding the net change in floor space. The object of the paper is to address these deficiencies in the existing empirical work on the office rental market. This is attempted by using a local take-up variable to model the urban rents.

Additionally, the authors develop two models to capture the urban rents. The first model uses a single reduced-form price equation with the use of direct demand and supply measures, and the second model is a structural three-equation model. The analysis shows that Edinburgh responds more quickly than Glasgow to fundamental imbalance changes in the supply and demand. This study narrows their prediction down to the city level of two cities located close to each other, where many studies are examining rental prices at a regional or national level. Further, when developing an urban office model, the authors point out the importance of independent variables to measure both local determinants and national influences (2003).

In an empirical investigation of real office rents in 22 different European cities done by D'Arcy et al. (1997), they examine the influence of national economic conditions, market size and measures of economic growth for each of the cities. The authors find that national real GDP and real short-term interest rates are essential determinants of rental values across cities.

Further, when it comes to interest rates, the literature seems to be divided between short-term and long-term interest rates. In contradiction to D'Arcy et al.'s study, Karakozova (2004) uses long-term Government bonds in her study on the real estate market in Helsinki. She finds that the interest rate has a statistically significant impact on variations in office returns. Moreover, in two studies done by Dobson & Goddard (1992), and Matysiak & Tsolacos (2003), they both find that the relationship between rental prices and interest rates can be either positive or negative.

In the textbook "Commercial Real Estate, Analysis & Investments" written by Geltner et al. (2001) they compare residential rents with the consumer price index (CPI) in the US. Their finding is that the rents have risen at about the same rate as inflation or CPI, which means that rents have not been increasing.

In a more recent study done by Foo and Higgins in 2007 on the office market in Singapore, they investigate whether gross rent can be explained by a single equation model containing both supply variables and demand variables (Foo & Higgins, 2007). They find that 72 percent of the variation in current office rent in the central region of Singapore can be explained by changes in the vacancy rate from the previous year, changes in construction costs, changes in prime lending rate previous six months and changes in office sector employment (Foo & Higgins, 2007).

The Norwegian economy is highly exposed to the oil price and in a study done by Bjørnland & Thorsrud (2015), the authors state that a decrease in the oil price will lead to a decrease in GDP, employment, wages and investments in the mainland economy.

3.1 Three Markets Conceptual Framework

To find what drives the fluctuation in office rental prices we need a framework that defines the commercial real estate market. Archer and Ling (1997) illustrate the relationship between the space market, property market, and the capital market. This framework illustrates the space market using global, national or local economic factors that would lead to the demand for office space. The determination of construction feasibility occurs in the property market. Investors and developers would have an incentive to build new construction if property values exceed construction costs leading to a mechanism that controls the supply of office space. Lastly, investors who invest in commercial real estate have a required rate of return that consists of the risk-free rate and the risk premium. The risk premium is determined by the systematic risk to the specific property and the risk-free rate. Hendershott et al. (1998) suggest that the capital market with its risk-free rate and risk premium affects the space market by changing equilibrium rents.

We use Archer and Ling's three markets conceptual framework to capture the dynamics of the office rental price fluctuation. The selected variables are representative of the property (supply), space (demand) and capital market influences on office rental prices.

4.0 Research Questions and Hypotheses

By taking previous research into account, we are using different methodology to find the model that best describes the development in office rental prices in Oslo. This led us to the following research questions:

1) *Which econometric model is the best model to explain changes in rental prices for the office market in Oslo?*
2) *Which variables are the main determinants to explain changes in rental prices for the office market in Oslo?*

To address the second research question we need to find an answer to question one. We are developing five hypotheses based on the research questions, the three markets conceptual framework by Archer and Ling (1997), and how the variables proxies for this framework are categorized by most of the previous studies (Foo & Higgins, 2007). Hypotheses *1-2* relate to research question *1* and are tested in chapter 8. Hypotheses *3-5* relate to research question *2* and will be answered after completing the tests in chapter 8.

Hypotheses

1) *Multivariate models produce better forecasts than univariate models*
2) *CLRM produce better forecasts than VECM*
3) *Supply variables do not significantly influence the development of office rental prices in Oslo*
4) *Demand variables do not significantly influence the development of office rental prices in Oslo*
5) *The capital variable does not significantly influence the development of office rental prices in Oslo*

5.0 DATA

Our data series are quarterly ranging from 2004Q1 to 20015Q4. The explanatory variables for this empirical investigation are guided by theory and are originating from theoretical frameworks used in several studies of real estate market dynamics. We are including both local variables for the Oslo area, and variables reflecting the effect on Norway as a country and its economy. The included variables are consistent with the three markets conceptual frameworks by Archer and Ling (1997) where supply (vacancy, construction costs), demand (GDP, unemployment, employment, CPI, oil) and capital (interest rate) capture the fundamental concept that defines the commercial real estate rental market. This framework categorizes the property market as supply, and vacancy office space is therefore under the supply category.

Table 1 – Data

Variable	Retrieved from	Information	Expected sign
Rental Prices (Oslo)	Arealstatistikk AS	Nominal numbers	
Vacancy (Oslo)	Oslostudiet	Percentage	(-)
Construction Costs (Norway)	Statistics Norway	Indexed (2015=100)	(+)
GDP (Norway)	Statistics Norway	Absolute numbers (Market Value)	(+)
Oil Price	Bloomberg terminal	WTI Crude	(+)
Employment (Norway)	Statistics Norway	Absolute numbers (millions)	(+)
Unemployment (Oslo)	Statistics Norway	Percentage	(-)
CPI (Norway)	Statistics Norway	Indexed (2015=100)	(+)
Interest Rate	Bloomberg terminal	Norwegian 10 Year Government Bonds	(+) / (-)

Vacancy office space is only reported on a yearly basis. We are therefore using the quadratic match average function in EViews to convert it to quarterly numbers [1]. The impact on rental prices of an increase in interest rates is a little more complicated, and we expect the relationship between rental prices and interest rates to be either positive or negative, which coincides with previous research.

6.0 Methodology

We choose to transform our series to their logarithms, and the logged variables will be denoted (L). Many macro series grow exponentially and taking their logs would help to linearize them. When using the variables in their logarithms, this may also stabilize the variance of the series. In this thesis, we use Akaike Information criteria (AIC) as the chosen criteria for further analysis. In Appendix 1 a discussion of the information criteria can be seen. In our econometric models, the concept of stationarity is important [2]. We will apply the Augmented Dickey-Fuller (ADF) test to test for stationarity, where rejecting H0 indicates that the series are stationary. We are conducting the test allowing for an intercept, an intercept and deterministic trend, or none in the test regression. If we are witnessing non-stationarity in the levels of the series, a solution will be to difference the series.

[1] The Quadric match average function in EViews fits a local quadratic polynomial for each observation of the low frequency series then use this polynomial to fill in all observations of the high frequency series associated with the period. The quadratic polynomial is formed by taking sets of three adjacent points from the source series and fitting a quadratic so that either the average or the sum of the high frequency points matches the low frequency data actually observed. For most points, one point before and one point after the period currently being interpolated are used to provide the three points. For end points, the two periods are both taken from the one side where data are available (EViews, 2017).

[2] A time series is stationary if the probability distribution of the underlying process is stable over time. If the series have trending behavior, it can lead to spurious regressions, i.e. inefficient estimations of the parameters, invalid significance tests and suboptimal forecasts (Bönner, 2009). When we are dealing with time series, it is sufficient to make the series stationary at a weak form. For weak stationarity, the mean, variance, and the autocovariance need to be constant over time.

6.1 Classical Linear Regression Model (CLRM)

We can express the classical multivariate linear regression model as:

$$y = c + \sum_{i=1}^{n} \alpha_i x_i + \varepsilon_i$$

Where α_i is reflecting the coefficient of variable x_i, C denotes the constant, and ε_i is the error term. Changes in some of the explanatory variables may give a delayed response on the rental adjustment process, and quantitative techniques or intuition could be used to capture this effect [3]. If we expand the classical linear regression model with lags of the depended variable or the independent variables, the model can then be expressed as:

$$y_t = c + \sum_{i=1}^{n} \alpha_i x_{i,t-i} + \varepsilon_t$$

After going through the diagnostics, the linear regression model is constructed, and the relation between the endogenous variable and rental prices are estimated. We are using Ordinary Least Squares (OLS) as an estimation technique for determining the appropriate values of the coefficients α and β.

6.1.1 Diagnostics

There are five assumptions related to the CLRM. These are required to show that the estimation technique, Ordinary Least Squares, has some desirable properties that are consistent, unbiased and efficient. The estimators, $\hat{\alpha}$, and $\hat{\beta}$, determined from the OLS, will if these assumptions hold be known as best linear unbiased estimators (BLUE). We are checking if these five assumptions hold, and in addition checking for multicollinearity and structural breaks. Explanation of model assumptions and possible solutions if these are violated are given in Appendix 2.

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[3] We will use correlation analysis to find to what different degree lags in the explanatory variables convey influences on the rental prices. Variables that are not statistically significant on any of our tested lags will be removed from the further analysis (Bönner, 2009).

6.2 ARIMA Model

An important class of times series models is ARMA models. ARMA (p , q) is a combination of an autoregressive (AR) process and a moving average (MA) process. The model below can be looked at as a linear regression model where the lagged values of the variable are the exogenous variables (Bönner, 2009). The AR process in the model, which is the first part, determines the dependent variable y_t as the weighted sum of its own lagged values. Further, random events can affect the time part of the equation. These random events are implemented through the MA process, which is the second part of the equation. The letter δ is a constant term (Bönner, 2009).

$$y_t = \delta + \sum_{i=1}^{p} \alpha_i y_{t-i} + \mathcal{E}_t \sum_{i=0}^{q} \beta_i \mathcal{E}_{t-i}$$

We are having an ARIMA model if the data has been differenced *n* times to induce stationarity. The letter I stand for integrated and say how many times the data have been differenced.

The most common way of estimating an ARMA model is by following Box and Jenkins three steps (Box & Pierce, 1970):

(1) Identification
(2) Estimation
(3) Diagnostic checking

Identification involves determining the order of the model required to capture the dynamic features of the data and determine the most appropriate specification. Further, estimation involves estimating the parameters of the model specified using the least squares technique. Lastly, diagnostic checking involves determining whether the model is adequate.

6.3 Vector Autoregressive Model & Vector Error Correction Model

We can express a VAR(p) system as:

$$Y_t = \delta + \sum_{i=1}^{p} A_i Y_{t-i} + E_t$$

Where A_i is the k-dimensional quadratic matrices and *E* is the k-dimensional quadratic vector of the residuals at time *t*. δ is the vector of constant terms, and Y_t represents all the endogenous variables of the system (Bönner, 2009).

For the system to be stable, the VAR modeling requires that all the series is stationary. If the series is not stationary, they have to be differenced until stationarity is fulfilled. For a system where all the series are non-stationary in their levels but cointegrated, then one should apply a Vector Error Correction Model (VECM). A VECM is a type of VAR model, but with an additional error correction term. Another dynamic of the model is that it can capture both long and short-run dynamics between the variables in the system.

We can express a VECM(p) system as:

$$\Delta Y_t = \delta + \lambda Y_{t-1} + \sum_{i=1}^{p-1} A_i \Delta Y_{t-i} + E_t$$

In this equation, $\lambda = b \ x \ c,$ where *c* is the cointegrating vector. The relationship $c \cdot Y_t = d$ shows the underlying economic consistencies and *b* is representing the adjustment coefficient which returns the economic equilibrium (Bönner, 2009).

6.3.1 Cointegration

A set of variables is defined as cointegrated if the linear combination of them is stationary. A cointegrated relationship between different variables can be seen as an equilibrium or a long-term relationship. In the short-run, a set of cointegrated variables may deviate from their relationship, but this relationship would return in the long run.

Engle and Granger define cointegration as follow:

Let w_t be a k X 1 vector of variables, then the components of w_t are integrated of order (d, b) if:

1) All components of w_t are I(d)
2) There is at least one vector of coefficients α such that $\alpha' w_t \sim$ I(d-b)

We can test for cointegration by using the Johansen approach, where the setup allows testing of the hypothesis about the equilibrium relationship between the variables (Brooks, 2014).

6.4 Forecasting

To predict future values of rental prices we are generating forecasts for three periods, one in-sample forecast from 2004Q1 to 2015Q4, and two out-of-sample forecasts from 2016Q1 to 2016Q4 and from 2016Q1 to 2017Q4. We are using holdout sample to make the out-of-sample forecasts. The holdout sample contains the last eight quarters of the rental prices and is therefore not being included in the estimation window. Further, dynamic forecasts are being done for all of the three periods, as well as static forecasts for the in-sample forecasts. A dynamic forecast calculates multi-step forecasts starting from one period in the sample, and a static forecast calculates a sequence of one-step-ahead forecasts (Brooks, 2014). In other words, with a static forecast, it is only possible to forecast one period ahead. To make a comparison of the forecasts, we are generating forecasts for the ARIMA model, the CLRM and for the VECM. We are using Root Mean Squared Error (RMSE), Mean Absolute Percent Error (MAPE) and Theil's coefficient to measure and compare the forecast accuracy. Explanations of the different forecast measures are given in Appendix 3.

7.0 Analysis

For the analysis, we use a 5% rejection level. All of the analyzes have been done using EViews 7 and 10.

7.1 Stationarity

As discussed above, the concept of stationary series is essential, as we want to avoid spurious regressions. Moreover, the use of our three models requires that we know the order of integration for the different variables. By looking at the graphs for each series, we expect most of the logged series to be integrated of order one.

We conduct a formal stationarity test using the Augmented Dickey-Fuller test where the Akaike's information criteria (AIC) determine the optimal lag length. Since we are dealing with quarterly data, the maximum lag length is set to 4.

When testing for stationarity at levels, we could for all the variables except for the unemployment, not reject the H0 as the series contained a unit root. To induce stationarity, we are trying to first difference the variables and redo the ADF-test. The test now reveals that all the variables are stationary and therefore I(1). For consistency in our further analysis and when interpreting the results, we choose to also take the first difference of the unemployment series. The differences in the logged variables will be denoted (DL). The test results are given in Table 2.

Table 2 – Stationarity test

Variables	Levels					First difference					
	Trend & intercept		Intercept		None	Trend & intercept		Intercept		None	
L(rental price)	-3,4263		-1,1676		2,0645	-5,9710	***	-5,9807	***	-10,245	***
L(CPI)	-2,6772		0,0223		5,4308	-8,4502	***	-8,5409	***	-0,9864	
L(vacancy)	-2,7189		-2,7674		0,4654	-3,7342	**	-3,6411	***	-3,6241	***
L(construction)	-2,0106		-1,1051		1,2006	-2,6679		-2,7148		-2,413	**
L(interest)	-2,0357		-0,2480		-1,266	-6,5268	***	-6,5102	***	-6,3275	***
L(oil)	-1,0182		-2,5955		-0,204	-6,7556	***	-6,3080	***	-6,3959	***
L(GDP)	-3,0741		-2,3003		1,3487	-3,1468		-2,3712		-1,9606	**
L(employment)	-3,3444		-2,5981		0,9999	-2,5832		-1,9845		-2,5254	***
L(unemployment)	-3,8564	**	-3,9280	***	-0,853	-2,7822		-2,6951		-2,7006	***

*** Significant at the 0,01 level
** Significant at the 0,05 level

7.2 Classical Linear Regression Model (CLRM)

7.2.1 Correlation Analysis

We choose to lag some of the variables to capture the delayed response of the rental adjustment process. To determine the number of lags we are running a correlation analysis with the logged first difference of the rental price with the logged first difference of the independent variables. We incorporate a maximum of 12 lags for each independent variable, and we choose the number of lags that show the highest significance. Variables that are not significantly different from zero at the 5% rejection level are removed from further analysis. The results from the correlation analysis are given in Table 3.

Table 3 – Correlation analysis: Rent against potential explanatory variables

	Lags	dl(rental price)	
dl(CPI)		-	
dl(vacancy)	-2	-0,3055	**
dl(construction)	-4	0,4128	***
dl(interest)		-	
dl(oil)	-1	0,3014	**
dl(GDP)	-6	0,4062	***
dl(employment)	-4	0,5333	***
dl(unemployment)		-	

*** Significant at the 0,01 level
** Significant at the 0,05 level

From the correlation analysis, we find that CPI, interest rate and unemployment are not significantly different from zero at the 5% level. Since it looks like these variables do not have a high influence on rental prices, they are excluded from further analysis. The removal of unemployment is quite surprising. This series only concern the Oslo area, and we would expect it to have a more significant impact on office rental prices in Oslo than the national numbers for employment. We would also expect this correlation coefficient to be significant, referring to a lot of previous studies finding this demand-side variable to have a highly significant impact on rental prices.

There is a negative correlation between the vacancy with lag 2 and the rental prices, with the correlation coefficient being significantly different from zero at the 5% level. We would expect that changes in vacancy would lead to an instant change in rental prices. The interpolation of vacancy makes the series contain smoothing effects. Moreover, the interpolated data are only estimates and we are not obtaining the true quarterly values. The results from the correlation analysis for the interpolated data are therefore more uncertain than the results for the series not being interpolated. New rental contracts can also be a possible explanation for the number of lags as there is a mismatch between signing date and moving date, and this will have consequences for the vacancy in a short period of time.

The correlation between the oil price and the rental prices are a little more complicated, and many factors are determining this relationship. There is a positive relationship between the oil price with lag 1 and the rental prices, with the correlation coefficient being significantly different from zero at the 5% level. The highest significance is found at lag 1. This seems a little short, as the rental prices will adjust only a quarter later. We would not expect that the short-term volatility in the oil price would lead to an almost immediate effect on the rental prices. Rental prices are positively correlated with the variables GDP, employment, and construction costs with lags 6, 4 and 4 respectively. For all the variables, the correlation coefficient is significantly different from zero at the 1% level.

7.2.2 Diagnostics

Diagnostic tests are done on the residuals of the following regression:

$$\begin{aligned} DLrental\ prices \\ &= c + DLvacancy_{t-2} + DLconstruction_{t-4} + DLoil_{t-1} \\ &\quad + DLgdp_{t-6} + DLemployment_{t-4} + \varepsilon_t \end{aligned}$$

Appendix 4 shows a full review of the diagnostic tests and solutions if these are violated.

After going through the diagnostics, we see that violation of some assumptions may lead the estimators not to be BLUE. The solution of including a lagged depended variable to get rid of autocorrelation may lead to biased coefficient estimates (Keele & Kelly, 2005). Further, we see some evidence of multicollinearity between DLemployment(-4) and DLgdp(-6).

7.2.3 Final Model

From the estimated model in Appendix 5, we can see that DLconstruction and DLemployment are both insignificant. These variables are therefore removed from the model, and the model is re-estimated (Appendix 6). The final model is given by the equation:

$$\widehat{DLrental\,price} = 0{,}0060 - 0{,}2545DLrental\,price_{t-1} - 0{,}2726DLvacancy_{t-2} + 0{,}0662DLoil_{t-1} + 0{,}4956DLgdp_{t-6} + \varepsilon_t$$

All the variables in our final model show the correct a priori sign. The lagged variable of rental prices has a negative coefficient, indicating a reversion towards an equilibrium value, i.e. any price movement in one period will partially revert the following period.

A one percentage point increase in the vacancy growth gives a 0.2726% decrease in rental prices growth two quarters later. The negative impact of an increase in vacancy is supported by Heckman (1985). An increased vacancy will force the landlords to lower their rental prices to attract tenants. The increased vacancy will also give the tenants more bargaining power when negotiating leases.

For the GDP, a one percentage point increase in GDP growth gives a 0.4956% increase in rental price growth six quarters later. The findings of the positive impact an increase in GDP will have on the rental prices is supported by much previous research, where Tsolacos and Giussani (1993), among others, have found similar results. GDP is a measure of economic activity, and an increase in this variable would stimulate the demand services and goods. An increase in GDP will, therefore, increase the demand for office space, resulting in increased rental prices.

A one percentage point increase in the oil price growth gives a 0.0662% increase in rental prices growth one quarter later. We have no previous research on the relation between the oil price and office rental prices. However, the research of Bjørnland & Thorsrud (2015) confirms the importance of the oil price for the Norwegian economy. A higher oil price will, therefore, be reflected in higher rental prices following the same arguments used when explaining the relationship between GDP and rental prices.

Moreover, both DLvacancy and DLgdp are significant at the 1% level. DLoil is significant at the 5% level while the lagged value of DLrental price is significant at the 10% level. The constant term is insignificant. We are throughout the analysis using a 5% rejection level. However, we still choose to include the lagged value of DLrental price in our final model, as this variable is included to deal with autocorrelation problem amongst the residuals. The adjusted R-squared is equal to 0.3658, indicating that the model explains 36.58% of the variability in the rental prices. As DLemployment is removed from the final model, the presence of near multicollinearity is not a problem anymore.

By running a two-stage least squares (2SLS) model with instrument variables simultaneous in a system, it can strengthen the explaining power of the relationship between rental prices and vacancy or rental prices and construction costs[4]. We are expecting that vacancy and construction costs are correlated, and you should therefore use an instrument variable to avoid OLS biased and inconsistent estimates. However, a 2SLS analysis has not been done in this paper.

7.3 ARIMA Model

To build an ARIMA model one of the requirements is that the series must be stationary. From our stationary tests, we find that the rental prices are stationary in first-difference. The series is therefore differenced once before further analysis. The regression is run by using the least square method. By looking at correlogram of the differenced logged rental prices with 10 lags, we can see that the autocorrelation function (acf) and the partial correlation function (pacf) are only significant at the first lag, and they are both geometrically decaying (Appendix 7). It is therefore appropriate with a combination of an AR-process and an MA-process a (Brooks & Tsolacos, 2010).

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[4] An instrumental variable is another technique for parameter estimation. Instrument variables are variables that are not correlated with the errors. When the endogenous variables are correlated with the errors, OLS cannot be used directly on the structural equations.

2SLS: Stage 1. Obtain and estimate the reduced-form equations using OLS. Save the fitted values for the dependent variables. *Stage 2.* Estimate the structural equations using OLS, but replace any RHS endogenous variables with their stage 1 fitted values (Brooks & Tsolacos, 2010).

Further, we are using the criteria techniques to determine the correct model, and we are testing the model for different combinations of AR- and MA-orders. Table 4, 5 and 6 below show which combination of AR- and MA-order that minimizes the criteria from Akaike information criteria (AIC), Schwarz's Bayesian information criteria (SBIC) and the Hannan-Quinn information criteria (HQIC) respectively. AIC and HQIC suggest both a relatively high order of both AR and MA, but SBIC suggests a lower order. AIC suggest a model order of ARIMA(5,1,4), SBIC suggests ARIMA(2,1,3) and HQIC suggests a model order of ARIMA(4,1,5).

Table 4 – Akaike information criteria (AIC) - ARIMA

p/q		**0**	**1**	**2**	**3**	**4**	**5**
	0		-3,119	-3,099	-3,147	-3,09	-3,018
	1	-2,96	-3,116	-3,224	-3,173	-3,113	-3,111
	2	-2,928	-3,224	-3,179	-3,131	-3,157	-3,079
	3	-2,887	-3,183	-3,326	-3,263	-3,137	-3,076
	4	-2,857	-3,157	-3,084	-3,224	-3,437	-3,826
	5	-3,078	-3,284	-3,113	-3,24	-3,563	-3,163

Table 5 – Schwarz's Bayesian information criteria (SBIC) - ARIMA

p/q		**0**	**1**	**2**	**3**	**4**	**5**
	0		-3,04	-2,978	-2,985	-2,886	-2,769
	1	-2,882	-2,996	-3,063	-2,97	-2,867	-2,821
	2	-2,81	-3,065	-2,979	-2,888	-2,871	-2,748
	3	-2,73	-2,984	-3,085	-2,98	-2,809	-2,704
	4	-2,661	-2,919	-2,803	-2,889	-3,068	-2,968
	5	-2,841	-3,006	-2,792	-2,875	-3,154	-2,708

Table 6 - Hannan-Quinn information criteria (HQIC) - ARIMA

p/q		**0**	**1**	**2**	**3**	**4**	**5**
	0		-3,089	-3,054	-3,087	-3,015	-2,927
	1	-2,931	-3,071	-3,164	-3,098	-3,022	-3,004
	2	-2,884	-3,165	-3,105	-3,041	-3,052	-2,957
	3	-2,828	-3,108	-3,236	-3,158	-3,016	-2,94
	4	-2,783	-3,068	-2,98	-3,104	-3,301	-3,231
	5	-2,989	-3,18	-2,993	-3,105	-3,412	-2,996

However, according to Brooks & Tsolacos (2010), none of the information criteria is superior to others. Both AIC and HQIC suggest a high AR- MA-order.

We use AIC for both CLRM and VECM, and for consistency, we are continuing with the model order suggested by AIC, ARIMA(5,1,4). When running the model in EViews, the sample is adjusted from 48 observations to 42 observations, by removing the first four quarters. Further, Table 7 below shows the output from EViews. As we can see not all of the AR- nor the MA-lags are statistically significant. However, lag AR(4), and all the MA-lags are highly statistically significant at a 1% level. Further, the AR(2) lag is statistically significant at the 5% level. The R-squared is 0.489, which is higher than in the CLRM model. As ARMA models are not based on any economic or financial theory, it is often best not to interpret the individual parameters (Brooks, 2014).

Table 7 – ARIMA(5,1,4) output

Variable	Coefficient	Std. Error	Prob.
C	0.012196	0.007477	0.1127
AR(1)	-0.324559	0.180983	0.0824
AR(2)	0.417904	0.160809	0.0140
AR(3)	0.172357	0.169619	0.3172
AR(4)	-0.469808	0.157109	0.0053
AR(5)	-0.131425	0.155693	0.4049
MA(1)	0.290443	0.056860	0.0000
MA(2)	-0.892544	0.096084	0.0000
MA(3)	0.261285	0.053573	0.0000
MA(4)	0.940600	0.036994	0.0000

7.4 Vector Error Correction Model

When creating the Vector Autoregressive (VAR) model/ Vector Error Correction Model (VECM) we choose to include L(rental price), L(construction), L(interest), L(oil) and L(vacancy). We see from our empirical research that many studies find a significant positive relation between rental prices and the variables L(employment), L(GDP) and L(CPI). These variables are removed from our VECM analysis along with L(unemployment) which is stationary at levels.

There is not much empirical evidence on the impact of construction costs on rental prices, and this variable is included because we want to know the impact it has on rental prices in Oslo. The impact of interest rates is as mentioned a little more complex. The empirical research of the impact of interest rates is mixed, and we do not have a clear a priori opinion of whether the impact is positive or negative. This variable is therefore included to see what impact it has on the rental prices in Oslo. Vacancy and oil are included in the VECM to see if the results can confirm our findings from the CLRM.

Lag Structure

We use information criteria to determine the optimal lag length (p), and we let EViews determine the maximum lag, which is set to be three.

Table 8 – Lag structure - VECM

Lag	AIC	SBIC	HQIC
0	-7,1665	-6,9658	-7,0917
1	-13,9648	-12,7604 *	-13,5158
2	-14,8570	-12,6488	-14,0338 *
3	-14,9783 *	-11,7664	-13,7809

The determination of optimal lag length ranges from 1-3. If you include too many lags you may lose degrees of freedom, get statistically insignificant coefficients and multicollinearity. Including too few lags may, on the other hand, lead to specification errors. The range between the different information criteria is not too wide, and we are choosing the AIC for consistency throughout our paper. The AIC shows that the number of lags that minimizes the value of the information criteria is three.

Cointegration

We expect that some of the variables might be cointegrated. If we have some cointegrating relations, the appropriate model is a VECM. If it turns out that the variables do not have a cointegrating relation, we will estimate a VAR. The first step in any cointegration analysis is to ensure that the variables are non-stationary in their levels form, but stationary when we take the first difference. From our stationarity analysis, we saw that all the included variables are integrated of order one I(1). We could, therefore, perform the Johansen Cointegration test using three lags.

The Johansen Cointegration test gives conflicting results and a discussion of this is given in Appendix 8. We relate our analysis to the trace statistics and accept the null hypothesis of one cointegrating equation. Since we have cointegration, it is appropriate to estimate a VECM.

Results VECM

We estimate the VECM using (p-1) lags, and the model is given in Appendix 9.

Long run Causality

Since the coefficient of the cointegrating equation (C1 in Appendix 10) is negative and significant, we have a long run causality running from the independent variables to rental prices. When normalizing to rental prices (see Appendix 9) and reversing the signs, we get the following equation:

$$ect_{t-1} = 1{,}0000Lrental\,price_{t-1} + 2{,}9005Lconstruction_{t-1} + 0{,}2427Linterest_{t-1} + 0{,}2995Loil_{t-1} - 0{,}2932Lvacancy_{t-1} - 7{,}9593$$

We see that all the a priori of the signs are correct. In the long run, construction costs and oil have a positive and significant impact on rental prices, on average, ceteris paribus. Interest rates have a positive but insignificant impact, while vacancy has a negative but insignificant impact on rental prices. The positive impact on rental prices from an increase in the oil price follows the same arguments discussed under the subchapter 7.2.3.

The finding of a positive relationship between construction costs and rental prices is supported by the findings of Foo and Higgins (2007). An increase in the construction costs will lead to a lower supply of office buildings ceterus paribus. This will further put pressure on existing office space leading to an increase in rental prices. The supply will not decrease if both the expected market price of office buildings and constructions costs increases. Given that the market price is higher than the construction costs it will still be profitable for developers to build. However, as the purchase price of office buildings increase, this may put pressure on the rental prices, as the landlords must increase the rental prices to achieve a specified yield.

Short-run causality

We are also looking for any short-run causality between the independent variables and rental prices. We are running a Wald test if the lags of each independent jointly equal zero. The results are given in Appendix 11.

It is found that the test statistics for a Granger test should follow chi-square distribution instead of F-distribution. We see from the estimated p-values that we cannot reject the null hypothesis for any of the independent variables, and we conclude that there is no short-run causality.

Diagnostics

Diagnostics are done on the residuals of the estimated model (Appendix 12). The tests indicate that the residuals are normally distributed, and we cannot find any evidence of the presence of autocorrelation and heteroscedasticity.

8.0 Forecasting

This chapter shows the results from the forecasts generated by different econometric models. As explained in the methodology chapter, we are generating the forecasts by using EViews. We make forecasts for three periods, one in-sample forecast from 2004Q1 to 2015Q4, and two out-of-sample forecasts from 2016Q1 to 2016Q4, and 2016Q1 to 2017Q4. All of the forecasts use an estimation window from 2004Q1-2015Q4. For the in-sample forecast, we are making both dynamic and static forecasts, and for the out-of-sample forecasts, we are only doing dynamic forecasts. For the in-sample, it is expected that the static forecast will give more accurate forecasts, as the forecasts are being generated on the same data set as the model's parameters were estimated (Brooks, 2014).

8.1 Classical Linear Regression Model

For the CLRM forecast, EViews excludes some observations when generating the forecasts, and starts with 2005Q4.

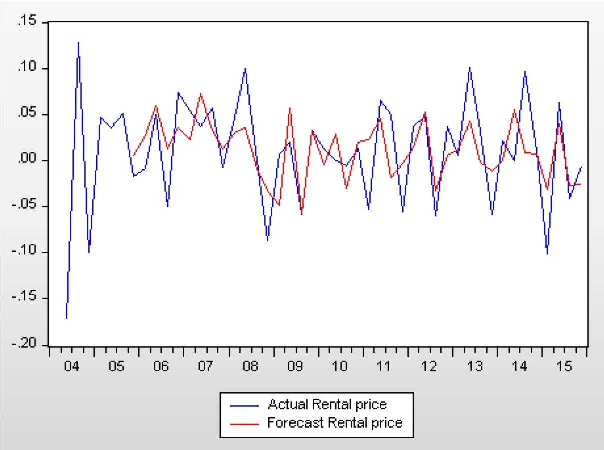

Figure1 – Dynamic – CLRM - Actual rental prices compared to forecasted rental prices 2004Q1–2015Q4

By looking at the graph above we can see that the CLRM predicts good in-sample dynamic forecasts. As we can see, the graph of the forecasted rental prices has almost always the same direction as the graph for the actual rental prices. For the year 2009 to 2010, we can see that the forecasting graph follows the graph of the actual rental prices very closely, and it captures both the bottoms and the tops. Nevertheless, for the rest of the period, the forecasting graph seems to miss most of the tops and bottoms.

Table 9 – Actual values compared to forecasted values 2016Q1–2017Q4 - CLRM

	Actual	**Dynamic**
2016Q1	-0,07654	-0,01442
2016Q2	0,049872	0,042721
2016Q3	0,031918	-0,00196
2016Q4	0,010417	0,007167
2017Q1	0,035627	0,00495
2017Q2	0,024693	0,022659
2017Q3	0	-0,02029
2017Q4	-0,01971	0,039747

In Table 9 above, we can see a comparison of the actual rental prices and the dynamic out-of-sample forecast. Moreover, for some quarters the forecasted values are very close to the actual ones, but for most quarters, the values differ. The quarters that predict the most accurate values are 2016Q2, 2016Q4, and 2017Q2.

As stated in the literature, RMSE and MAPE are the most common measures when interpreting the forecast results. Therefore, we will be focusing on these two measures in addition to Theil's U. Further, Table 10 below shows the statistical measures of how good the forecasts predict. By looking at the RMSE, it states that the 2-year dynamic forecast is the best, but according to the MAPE, the 1-year forecast is the best.

Table 10 – Comparison of Statistical Measures - CLRM

	Dynamic			Static		
	RMSE	**MAPE**	**Theil's U**	**RMSE**	**MAPE**	**Theil's U**
In-Sample						
2004Q1 - 2015Q4	0,03953	114,4752	0,4738	0,0373	101,2087	0,4395
Out-of-Sample						
2016Q1 - 2016Q4	0,0355	58,2120	0,4977			
2016Q1 - 2017Q4	0,0352	78,6125	0,5660			

8.2 ARIMA Model

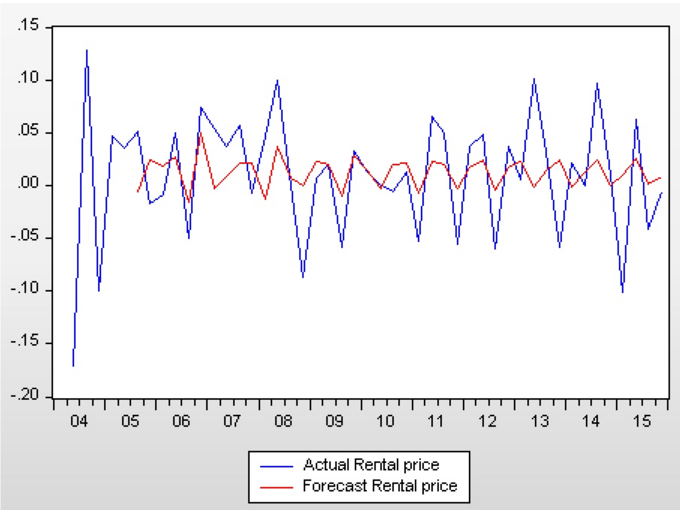

Figure 2 – Dynamic - ARIMA - Actual rental prices compared to forecasted rental prices 2004Q1-2015Q4

By looking at Figure 2 above we can see that the forecasting graph only shows the right direction of the development of the rental prices, but it is not even close to capture the tops nor the bottoms.

Table 11 below shows a comparison of the actual values for the rental prices to the forecasted values, for the period from 2016Q1 to 2017Q4. The dynamic forecasted values fluctuate a lot, and the forecasted values are only close to the actual values for some quarters. The quarters that predict best are 2016Q3, 2016Q4 and 2017Q3. Nonetheless, a comparison of the forecasts statistics gives a more accurate interpretation of the numbers.

Table 11 – Actual values compared to forecasted values 2016Q1-2017Q4 - ARIMA

	Actual	**Dynamic**
2016Q1	-0,07654	0,063015
2016Q2	0,049872	-0,04851
2016Q3	0,031918	0,033675
2016Q4	0,010417	0,007261
2017Q1	0,035627	-0,00927
2017Q2	0,024693	0,042647
2017Q3	0	-0,00962
2017Q4	-0,01971	0,027798

By comparing the measures from the dynamic forecasts in Table 12 below we can see that the measures differ over the forecast periods. The in-sample dynamic forecast from 2004Q1-2015Q4 gives as expected the lowest RMSE and MAPE. Further, for the out-of-sample forecast periods, the RMSE and Theil's U are lowest for 2016Q1-2017Q4, but the MAPE is lowest for the one-year forecast.

Table 12 – Comparison of Statistical Measures - ARIMA

	Dynamic			**Static**		
	RMSE	**MAPE**	**Theil's U**	**RMSE**	**MAPE**	**Theil's U**
In-Sample						
2004Q1 - 2015Q4	0,0471	88,3487	0,6287	0,0351	86,0961	0,3982
Out-of-Sample						
2016Q1 - 2016Q4	0,0853	103,8513	0,9282			
2016Q1 - 2017Q4	0,0650	106,9017	0,8772			

8.3 Vector Error Correction Model

As seen in Figure 3 below, the forecasting graph for the VECM shows a more conservative prediction, as the forecast graph is almost always below the graph for the actual rental prices. The forecasting graph seems to follow an upward average trend into infinity and misses, therefore, most of the tops. Table 13 below shows that only 2017Q1 is the only quarter where the forecasted value is close to the actual value.

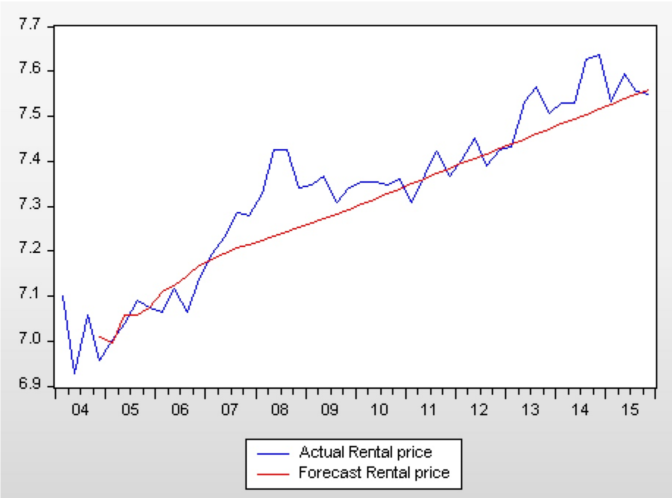

Figure 3 – Dynamic – VECM - Actual rental prices compared to forecasted rental prices 2004Q1–2015Q4

Table 13 – Actual values compared to forecasted values 2016Q1–2017Q4 - VECM

	Actual	**Dynamic**
2016Q1	7,473069	7,559797
2016Q2	7,522941	7,566193
2016Q3	7,554859	7,574001
2016Q4	7,565275	7,589646
2017Q1	7,600902	7,601183
2017Q2	7,625595	7,618813
2017Q3	7,625595	7,634502
2017Q4	7,605890	7,647679

By looking at the statistical measures in Table 14 below we can see that the dynamic out-of-sample gives the lowest RMSE, and it predicts best for the period 2016Q1-2017Q4. A Theil's U close to zero states that the forecasted values coincide with the actual values, which means that the VEC model forecasts accurate rental prices.

Table 14 – Comparison of Statistical Measures - VECM

	Dynamic			Static		
	RMSE	**MAPE**	**Theil's U**	**RMSE**	**MAPE**	**Theil's U**
In-Sample						
2004Q1 - 2015Q4	0,0668	0,6821	0,0045	0,0368	0,3926	0,0025
Out-of-Sample						
2016Q1 - 2016Q4	0,0508	0,5731	0,0033			
2016Q1 - 2017Q4	0,0390	0,3810	0,002577			

8.4 Comparison of the Forecasts

When comparing the statistical measures between the three different models, we can see that for the RMSE, the CLRM gives the lowest value for both the in-sample and out-of-sample forecasts. For the MAPE measure, the VECM has the lowest value for all of the forecasts. However, for the one-year forecast, the CLRM gives almost the same MAPE-value. When comparing Theil's U, the VECM model gives the lowest values for all of the forecasts. By looking at the in-sample static forecasts, we see that the models give almost the same answers as in the dynamic forecasts, where the only difference is that the ARIMA model gives the lowest RMSE.

Taking the comparison of the measures into account, we can see that multivariate models outperform the univariate model. This implicates that forecasts of rental prices in Oslo depend on more than just previous rental prices. Nevertheless, the VECM seems to outperform the CLRM model also, by comparing these three measures.

9.0 Conclusions

By evaluating the forecast performance, we find that the multivariate models outperform the univariate model. The fact that the ARIMA model is a poor model to explain fluctuations in rental prices coincides with the study by Tse (1997). The limitation of the ARIMA model does not differ for the Oslo market as we, along with Tse, finds it challenging to track the direction of rental prices with the use of this model. We further find that the VECM outperforms the CLRM in two out of three performance measures.

The signs of the variables in our two multivariate models are similar to our a-priori expectations, but the models give different significant variables. From the CLRM we found that the primary determinants to explain changes in rental prices for the office market in Oslo were vacancy, oil, and GDP. From the VECM we found that construction costs and oil were the only significant variables having an impact on rental prices. The reason that construction is significant in VECM, but insignificant in CLRM may be because of omitted variable bias. VECM is a-theoretical, and we may have left out one or more relevant variables. The effect of the missing variables may, therefore, be attributed to the estimated effects of the included variables. The vacancy variable is significant in CLRM but insignificant in the VECM. In the VECM all the variables have the same lag structure. Vacancy lagged two quarters in the CLRM may be better to capture the delayed response of the rental adjustment process, making it significant. Given that none of the multivariate models seems to superior outperform one another, we have chosen to emphasize the results from both of the models.

Our two multivariate models indicate that both supply and demand variables have a significant influence on the development of office rental prices in Oslo. Moreover, we do not reject the hypothesis that interest rates do not have a significant influence. Oil is on the other hand, included in both models, indicating the importance of this variable when explaining the changes in rental prices.

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11.0 Appendices

Appendix 1 – Information Criteria

Information criteria have two factors, one term that is a function of the residual sum of squares (RSS) and a penalty for the loss of degrees of freedom when adding extra parameters. The object is to choose the number of parameters that minimizes the value of the information criteria (Brooks, 2014).
The most common information criteria are the Akaike (1974) information criteria (AIC), Schwarz's (1978) Bayesian information criteria (SBIC) and the Hannan-Quinn information criteria (HQIC).

$$\text{AIC} = ln(\sigma^2) + \frac{2k}{T}$$

$$\text{SBIC} = ln(\sigma^2) + \frac{k}{T} \, ln\, T$$

$$\text{HQIC} = ln(\sigma^2) + \frac{2k}{T} \, ln(ln(T\,))\; T$$

(Brooks & Tsolacos, 2010)

To determine which information criteria to be used, all of the criteria above have different characteristics. SBIC has a stiffer penalty term than AIC, and the HQIC is somewhere in the middle (Brooks & Tsolacos, 2010). Further, according to Brooks (2014), SBIC is strongly consistent but inefficient, and AIC is not consistent but is generally more efficient. SBIC will asymptotically deliver the correct model order, while AIC will deliver on average too large a model. However, none of the information criteria is superior to others.

Appendix 2 – Diagnostics

BLUE

1) $E(\varepsilon_t) = 0$

The first assumption requires that the average value of the errors is zero. This assumption will never be violated if a constant term is included in the regression equation.

2) $var(\varepsilon_t) = \sigma^2 < \infty$

The second assumption is that the variance of the errors is constant, namely homoscedastic. Otherwise, the errors are said to be heteroscedastic. We will test this assumption using White's general test for heteroscedasticity, where rejecting the H0 indicates heteroscedasticity.
The consequence of ignoring the errors being heteroscedastic is that the estimated coefficients will no longer have the minimum variance among the class of unbiased estimators. If the errors are heteroscedastic the solution to fix this is to either transform the variables into logs or to use heteroscedasticity-consistent standard error estimates making hypothesis testing more conservative.

3) $cov(\varepsilon_i, \varepsilon_j) = 0$

The third assumption is that the errors are uncorrelated with each other. If the errors are correlated, they are said to be autocorrelated. We will test this assumption by using the Breusch-Godfrey test for autocorrelation, where rejecting H0 indicates autocorrelation. Another test that may be applied is the Durbin-Watson test for first-order autocorrelation, where H0 will not be rejected if DW is close to 2.

The consequence of ignoring the errors being autocorrelated is the same as ignoring heteroscedasticity, i.e. the estimated coefficients are inefficient. Several solutions can be applied to remove the autocorrelation problem. One solution is to make a distributed lag model. In our analysis this may already be done as our results from the correlation analysis may indicate that we should incorporate lags of the independent variables in our model. Another way in trying to eliminate autocorrelation is to switch to a model of first difference. However, as we expect the series to be stationary only at first difference, this would also have been incorporated in our model. Other solutions in the presence of autocorrelation may be to apply and autoregressive distributed lag model, or if the errors are heteroscedastic and autocorrelated, apply the Newey-West procedure for estimating the standard errors.

4) $cov(\varepsilon_t, \varepsilon_t) = 0$

The fourth assumption is that the x_t are non-stochastic. Nevertheless, if the regressors are not correlated with the errors, the OLS estimator will still be consistent and unbiased even in the presence of stochastic regressors.

5) $\varepsilon_t \sim N(0, \sigma^2)$

The fifth assumption is that the errors are normally distributed. We will test this assumption by using the Bera-Jarque test for normality, where rejecting H0 means that we reject that the errors are normally distributed.
If we are witnessing non-normality in the residuals, the interpretations we make of the estimated coefficients could be wrong. If we are having a large data sample, the violation of this assumption will not be that important as the central limit theorem states that the sample mean converges to a normal distribution. However, we are working with a relatively small data set, and if we are witnessing residual outliers causing the rejection of residual normality, we might have to create dummy variables for these outliers to engage normality.

Multicollinearity

When we are using the OLS estimation technique, an implicit assumption is that the variables included are not correlated with each other. We expect there to be some correlation, as there is almost always some degree of association between the independent variables. Some degree of correlation will not cause too much loss of precision, but the problem of multicollinearity occurs if the correlation is too high. We will use a correlation matrix between the independent variable to determine if multicollinearity is present.

The consequences of ignoring multicollinearity may be that the regression results look good shown by a high R^2, but the individual coefficients will not be significant. Another problem may be that the regression will become sensitive to small changes in the specification. Lastly, significance tests may give wrong conclusions, as the presence of multicollinearity will make the confidence intervals full. Solutions we have to consider if we are witnessing multicollinearity may be to ignore it, and drop the variables that are collinear or transform the same variables into a ratio. However, it is argued that the presence of multicollinearity is more of a problem coming from the data and not by the preferred model. A small data sample could initiate vast standard errors of the estimated coefficients. Increasing the data sample to solve the problem of multicollinearity will not be an option as we only have data on rental prices dating back to 2004.

Structural breaks

Our data sample may include structural breaks, i.e. an unexpected shift in the series. If the series includes structural breaks, this can lead to both forecasting errors and the model being unreliable. We will apply the Chow test to test for structural breaks, where rejecting H0 indicates breaks at specified breakpoints. We will check the assumption of constant parameters for several quarters where we suspect a structural break might have taken place.

Appendix 3 – Forecast measures

For the error measures the closer they are to zero; the more accurate is the forecast, unless the MAPE which is multiplied by 100. Further, Theil's inequality coefficient will be in the range between zero and one, where zero indicates that the predicted value and the actual value coincide. However, RMSE and MAPE are the most common measures. In a forecast on office returns in the Helsinki area done by Karakozova (2004), she finds the MAPE and RMSE closes to zero the most accurate forecasts. According to Brooks (2014), MAPE is a preferred measure over MAE when forecasting actual rents.

$$RMSE = \sqrt{\sum_{t=T+1}^{T+s} (\hat{y}_t - y_t)^2/s}$$

The equation shows the RMSE, where $\hat{y}_t$ is the forecasted value of y the endogenous variable and $\hat{y}_t - y_t$ as the forecasted error. The squared forecast error is divided by *s* to get an average value (Bönner, 2009). The RMSE is a better performance criterion than measures as MAE and MAPE when the variable of interest undergoes fluctuations and turning points (Brooks & Tsolacos, 2010). Further, the description of MAPE is quite similar to the RMSE, but it is different in the way that the forecasted error is divided by y, representing a relative measure, which does not depend on the scale of the endogenous variable (Bönner, 2009).

$$MAPE = 100 \sum_{t=T+1}^{T+s} \left|\frac{\hat{y}_t - y_t}{y_t}\right| /s$$

Theil's U can be expressed as follow:

$$U = \frac{\sqrt{\sum_{t=T_1}^{T} \left(\frac{y_{t+s} - f_{t,s}}{y_{t+s}}\right)^2}}{\sqrt{\sum_{t=T_1}^{T} \left(\frac{y_{t+s} - fb_{t,s}}{y_{t+s}}\right)^2}}$$

Where $fb_{t,s}$ is the forecast obtained from a benchmark model. A U-statistic of one implies that the model is equally correct or incorrect as the benchmark, and a U-statistic below 1 implies better than the benchmark. The benchmark is usually simple model such as naïve model or a random walk (Brooks, 2010).

Appendix 4 – Diagnostics - CLRM

Assumption 1

Since a constant is included in the regression equation, this assumption will never be violated.

Assumption 2

We tested for heteroscedasticity by using Whites test and test statistics. These tests and the p-values are given in the below.

White test – CLRM

F-statistic	0,4669	Prob. F(5,35)	0,7982
Obs*R-squared	2,5637	Prob. Chi-Squar	0,7669
Scaled explained SS	1,1713	Prob. Chi-Squar	0,9476

The F-version, χ^2-version and the Scaled explained SS concludes that there is no evidence of the presence of heteroscedasticity since the p-values exceed 0.05. The null hypothesis cannot be rejected, and the assumption of homoscedasticity is not violated.

Assumption 3

We tested for autocorrelation using the Breusch-Godfrey test, the test statistics, and p-values are shown in the table below. Since we are dealing with quarterly data, we chose four lagged residuals to be included in the test.

Breush-Godfrey Serial Correlation - CLRM

F-statistic	3,7208	Prob. F(4,31)	0,0138
Obs*R-squared	13,2992	Prob. Chi-Square(4)	0,0099

The F- and χ^2-versions of the test statistic both reject the H0 of no autocorrelation. The Durbin-Watson of 2.7 from the first regression also indicates some evidence of autocorrelation.

We have already applied a model of first differences and a distributed lag model. To cure the presence of autocorrelation we tried to apply an autoregressive distributed lag model. We included several lags of the depended variable on the right-hand side of the equation where only rental prices lagged one quarter was significant. We, therefore, include this variable in our equation and run the Breusch – Godfrey test once more:

Breush-Godfrey Serial Correlation LM Test - CLRM

F-statistic	2,1049	Prob. F(4,31)	0,1049
Obs*R-squared	8,9852	Prob. Chi-Squar	0,0615

From the test statistic, we see that we now cannot reject the H0 of no autocorrelation at a 5% level. After introducing an autoregressive distributed lag model, the assumption of no autocorrelation in the residuals is not violated.

Assumption 4

Since we have used lags of the depended variable on the right-hand side to remove autocorrelation, the fourth assumption is violated.

Assumption 5

The test statistic and the related p-value using the Jarque-Bera test are given in the table below.

Residual normality test - CLRM

Jarque-Bera	0,4772
Probability	0,7877

Even though we are dealing with a relatively small data sample where some outliers can cause the rejection of normality, the assumption of the residuals being normally distributed is not violated. The p-value clearly exceeds 0.05, and we cannot reject the H0 of normality among the residuals.

Multicollinearity

Multicollinearity - CLRM

Correlation matrix	DLrental price(-1)	DLvacancy(-2)	Dlconstruction(-4)	DLoil(-1)	DLgdp(-6)	Dlemployment(-4)
DLrental price(-1)	1,0000					
DLvacancy(-2)	-0,0441	1,0000				
DLconstruction(-4)	-0,1679	-0,0833	1,0000			
DLoil(-1)	0,2962	0,0394	-0,0934	1,0000		
DLgdp(-6)	-0,1096	0,0871	0,1087	0,0410	1,0000	
DLemployment(-4)	0,0489	0,0531	-0,1208	0,0817	0,5936	1,0000

The correlation matrix between the explanatory variables shows that we, for the most part, do not have a problem with near multicollinearity. Nonetheless, we are witnessing a relatively high correlation between DLemployment(-4) and DLgdp(-6) which is highlighted in red. The solution to this problem will be addressed later.

Structural Breaks

We checked the assumption of constant parameters on several dates that might have structural breaks. We focused mainly on the quarters surrounding the financial crisis (2008-2009), and the oil price crash that started in May 2014, which reached its bottom in January 2016. The Chow-test was conducted to detect if there was evidence of structural breaks and the results are given in the table below.

For the quarters surrounding the financial crisis, we found the lowest p-value to be in 2008Q4.

Chow test 2008Q4 - CLRM

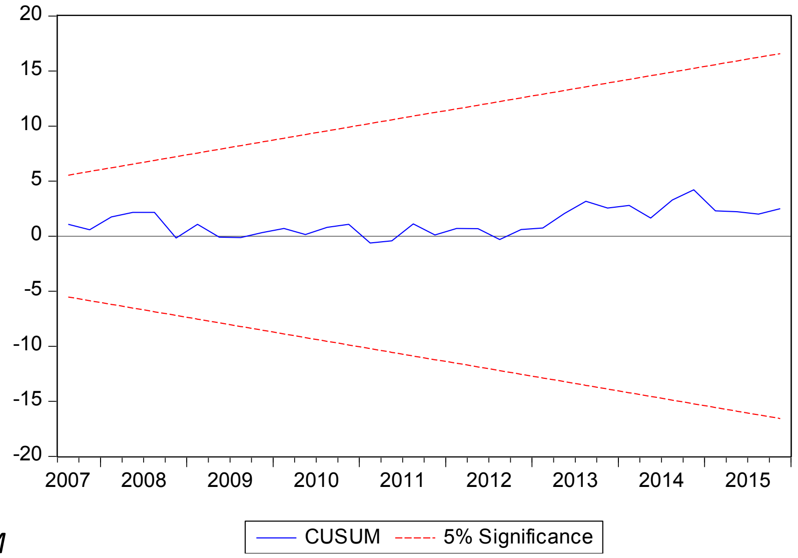
F-statistic	1,0880	Prob. F(7,27)	0,3982
Log likelihood ratio	10,1875	Prob. Chi-Squar	0,1782
Wald Statistic	7,6159	Prob. Chi-Squar	0,3677

For the quarters surrounding the oil price crack, we found the lowest p-value to be in Q2 2014.

Chow test 2014Q2 - CLRM

F-statistic	1,4023	Prob. F(7,27)	0,2450
Log likelihood ratio	12,7137	Prob. Chi-Squar	0,0794
Wald Statistic	9,8158	Prob. Chi-Squar	0,1993

We can see that for both quarters, all the three test statistics are smaller than their critical values. We do not reject H0 of constant parameters across the two subsamples, and we can conclude that there are no structural breaks concerning tested break dates. This is confirmed when we test if the model is stable for any break date throughout our sample, conducting the CUSUM test below. The blue line is well within the bands, and our conclusion remains that H0 of stability is not rejected.



CUSUM - CLRM

Appendix 5 – First model – CLRM

Dependent Variable: DLRENTAL_PRICE
Method: Least Squares
Date: 06/26/18 Time: 12:22
Sample (adjusted): 2005Q4 2015Q4
Included observations: 41 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005057	0.007399	0.683452	0.4990
DLRENTAL_PRICE(-1)	-0.281377	0.135448	-2.077375	0.0454
DLVACANCY(-2)	-0.280718	0.101303	-2.771069	0.0090
DLCONSTRUCTION(-4)	-0.065816	0.086675	-0.759349	0.4529
DLOIL(-1)	0.064315	0.031422	2.046778	0.0485
DLGDP(-6)	0.433120	0.176121	2.459219	0.0192
DLEMPLOYMENT(-4)	0.794938	1.140144	0.697226	0.4904

R-squared	0.450990	Mean dependent var	0.011208
Adjusted R-squared	0.354106	S.D. dependent var	0.049995
S.E. of regression	0.040180	Akaike info criterion	-3.436652
Sum squared resid	0.054890	Schwarz criterion	-3.144090
Log likelihood	77.45136	Hannan-Quinn criter.	-3.330117
F-statistic	4.654938	Durbin-Watson stat	2.301799
Prob(F-statistic)	0.001488		

Appendix 6 – Final CLRM model

Date: 06/08/18 Time: 19:05
Sample (adjusted): 2005Q4 2015Q4
Included observations: 41 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006046	0.006829	0.885308	0.3819
DLRENTAL_PRICE(-1)	-0.254489	0.132245	-1.924378	0.0622
DLVACANCY(-2)	-0.272610	0.099887	-2.729183	0.0098
DLOIL(-1)	0.066184	0.031093	2.128540	0.0402
DLGDP(-6)	0.495601	0.136494	3.630933	0.0009

R-squared	0.429192	Mean dependent var	0.011208
Adjusted R-squared	0.365769	S.D. dependent var	0.049995
S.E. of regression	0.039815	Akaike info criterion	-3.495277
Sum squared resid	0.057070	Schwarz criterion	-3.286305
Log likelihood	76.65317	Hannan-Quinn criter.	-3.419181
F-statistic	6.767124	Durbin-Watson stat	2.310027
Prob(F-statistic)	0.000361		

Appendix 7 – ARIMA correlogram

Date: 07/13/18 Time: 10:29
Sample: 2004Q1 2017Q4
Included observations: 55

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.333	-0.333	6.4230	0.011
		2	0.017	-0.105	6.4405	0.040
		3	0.033	0.005	6.5046	0.089
		4	-0.005	0.011	6.5064	0.164
		5	0.015	0.023	6.5205	0.259
		6	-0.104	-0.105	7.2123	0.302
		7	0.073	0.003	7.5650	0.373
		8	-0.099	-0.092	8.2251	0.412
		9	0.113	0.068	9.0896	0.429
		10	-0.097	-0.051	9.7515	0.463

Appendix 8 – Cointegration test - VECM

Date: 06/17/18 Time: 12:19
Sample (adjusted): 2005Q1 2015Q4
Included observations: 44 after adjustments
Trend assumption: Linear deterministic trend
Series: LRENTAL_PRICE LCONSTRUCTION LINTEREST LOIL LVACANCY
Lags interval (in first differences): 1 to 3

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.521965	72.14053	69.81889	0.0323
At most 1	0.401684	39.66538	47.85613	0.2347
At most 2	0.229506	17.06539	29.79707	0.6352
At most 3	0.094064	5.593541	15.49471	0.7429
At most 4	0.027941	1.246916	3.841466	0.2641

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.521965	32.47515	33.87687	0.0728
At most 1	0.401684	22.59998	27.58434	0.1912
At most 2	0.229506	11.47185	21.13162	0.6002
At most 3	0.094064	4.346625	14.26460	0.8211
At most 4	0.027941	1.246916	3.841466	0.2641

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The trace statistics and the maximum eigenvalue statistics give conflicting results. The Trace test indicates one cointegrating equation at the 0.05 level, while the maximum eigenvalue test indicates no cointegrating at the 0.05 level. Kasa (1992) argues that because the trace statistics considers all of the smallest eigenvalues, this test statistic will hold more power than the maximum eigenvalue statistic. Further, when these two statistics give conflicting results, Johnson and Juselius (1990) recommend that the trace statistic should be used. We will, therefore, relate our analysis to the trace statistics and accept the null hypothesis of one cointegrating equation.

Appendix 9 – VECM results

Vector Error Correction Estimates
Date: 06/17/18 Time: 12:53
Sample (adjusted): 2004Q4 2015Q4
Included observations: 45 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LRENTAL_PRICE(-1)	1.000000
LCONSTRUCTION(-1)	-2.900512 (0.77322) [-3.75121]
LINTEREST(-1)	-0.242693 (0.19574) [-1.23984]
LOIL(-1)	-0.299515 (0.14902) [-2.00984]
LVACANCY(-1)	0.293240 (0.31578) [0.92861]
C	7.959329

Error Correction:	D(LRENTAL_PRICE)	D(LCONSTRUCTION)	D(LINTEREST)	D(LOIL)	D(LVACANCY)
CointEq1	-0.092385 (0.03932) [-2.34962]	0.097755 (0.05531) [1.76746]	0.189863 (0.10274) [1.84806]	0.228727 (0.17911) [1.27702]	-0.086885 (0.03751) [-2.31626]
D(LRENTAL_PRICE(-1))	-0.452924 (0.15014) [-3.01671]	-0.085255 (0.21119) [-0.40369]	-0.303074 (0.39229) [-0.77257]	-0.998235 (0.68392) [-1.45959]	0.112201 (0.14323) [0.78335]
D(LRENTAL_PRICE(-2))	-0.248712 (0.14599) [-1.70367]	0.121367 (0.20535) [0.59102]	1.038605 (0.38144) [2.72282]	0.303204 (0.66500) [0.45594]	-0.042518 (0.13927) [-0.30529]
D(LCONSTRUCTION(-1))	-0.086478 (0.14592) [-0.59262]	-0.504040 (0.20526) [-2.45556]	0.620961 (0.38128) [1.62860]	1.200320 (0.66472) [1.80574]	-0.212420 (0.13921) [-1.52586]
D(LCONSTRUCTION(-2))	0.138968 (0.12501) [1.11168]	-0.004954 (0.17584) [-0.02817]	0.488729 (0.32663) [1.49628]	0.154561 (0.56944) [0.27143]	-0.026649 (0.11926) [-0.22346]
D(LINTEREST(-1))	0.010118 (0.07955) [0.12719]	-0.067397 (0.11190) [-0.60232]	0.206977 (0.20785) [0.99580]	-0.078686 (0.36236) [-0.21715]	-0.063294 (0.07589) [-0.83403]
D(LINTEREST(-2))	-0.132906 (0.07540) [-1.76257]	-0.006079 (0.10607) [-0.05731]	0.268229 (0.19702) [1.36141]	0.273632 (0.34349) [0.79663]	-0.169696 (0.07194) [-2.35898]
D(LOIL(-1))	0.033321 (0.04489) [0.74227]	0.032660 (0.06315) [0.51722]	0.056618 (0.11729) [0.48270]	0.319643 (0.20449) [1.56313]	-0.099194 (0.04283) [-2.31619]

Appendix 10 – Long run causality - VECM

Dependent Variable: D(LRENTAL_PRICE)
Method: Least Squares
Date: 06/17/18 Time: 12:57
Sample (adjusted): 2004Q4 2015Q4
Included observations: 45 after adjustments
D(LRENTAL_PRICE) = C(1)*(LRENTAL_PRICE(-1) - 2.90051165247
*LCONSTRUCTION(-1) - 0.242693023879*LINTEREST(-1) -
0.299515000918*LOIL(-1) + 0.29323965202*LVACANCY(-1) +
7.95932873817) + C(2)*D(LRENTAL_PRICE(-1)) + C(3)
*D(LRENTAL_PRICE(-2)) + C(4)*D(LCONSTRUCTION(-1)) + C(5)
*D(LCONSTRUCTION(-2)) + C(6)*D(LINTEREST(-1)) + C(7)
*D(LINTEREST(-2)) + C(8)*D(LOIL(-1)) + C(9)*D(LOIL(-2)) + C(10)
*D(LVACANCY(-1)) + C(11)*D(LVACANCY(-2)) + C(12)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.092385	0.039319	-2.349621	0.0249
C(2)	-0.452924	0.150138	-3.016713	0.0049
C(3)	-0.248712	0.145986	-1.703665	0.0978
C(4)	-0.086478	0.145925	-0.592620	0.5575
C(5)	0.138968	0.125008	1.111677	0.2743
C(6)	0.010118	0.079548	0.127188	0.8996
C(7)	-0.132906	0.075404	-1.762570	0.0872
C(8)	0.033321	0.044891	0.742269	0.4632
C(9)	0.076554	0.046651	1.641006	0.1103
C(10)	0.135298	0.170079	0.795503	0.4320
C(11)	-0.257562	0.159536	-1.614440	0.1160
C(12)	0.015267	0.007520	2.030058	0.0505

R-squared	0.472855	Mean dependent var	0.010965
Adjusted R-squared	0.297140	S.D. dependent var	0.051283
S.E. of regression	0.042994	Akaike info criterion	-3.232338
Sum squared resid	0.061000	Schwarz criterion	-2.750561
Log likelihood	84.72760	Hannan-Quinn criter.	-3.052736
F-statistic	2.691034	Durbin-Watson stat	1.874119
Prob(F-statistic)	0.013721		

Appendix 11 – Short-run causality - VECM

Construction

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	2.035144	(2, 33)	0.1467
Chi-square	4.070289	2	0.1307

Interest

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	1.554843	(2, 33)	0.2263
Chi-square	3.109686	2	0.2112

Oil

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	1.981745	(2, 33)	0.1539
Chi-square	3.963490	2	0.1378

Vacancy

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	1.383064	(2, 33)	0.2650
Chi-square	2.766127	2	0.2508

Appendix 12 – Diagnostics – VECM

First, we ran a test for autocorrelation. We used two lags, which is the same as we used when estimating the VECM and we could not reject the null hypothesis of no serial correlation.

VEC Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Date: 06/17/18 Time: 14:56
Sample: 2004Q1 2015Q4
Included observations: 45

Lags	LM-Stat	Prob
1	23.75248	0.5337
2	29.67573	0.2367

Probs from chi-square with 25 df.

We also tested if the residuals were jointly distributed using Cholesky of covariance as the orthogonalization method. From the joint test, we see that we could not reject the null hypothesis, as the residuals are multivariate normal.

VEC Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: residuals are multivariate normal
Date: 06/17/18 Time: 14:57
Sample: 2004Q1 2015Q4
Included observations: 45

Component	Skewness	Chi-sq	df	Prob.
1	-0.105946	0.084184	1	0.7717
2	-0.270637	0.549334	1	0.4586
3	-0.103959	0.081056	1	0.7759
4	0.074461	0.041583	1	0.8384
5	-0.530480	2.110571	1	0.1463
Joint		2.866728	5	0.7205

Component	Kurtosis	Chi-sq	df	Prob.
1	2.762170	0.106056	1	0.7447
2	1.952776	2.056272	1	0.1516
3	3.936805	1.645507	1	0.1996
4	3.194246	0.070746	1	0.7903
5	3.474833	0.422750	1	0.5156
Joint		4.301331	5	0.5069

Component	Jarque-Bera	df	Prob.
1	0.190240	2	0.9093
2	2.605606	2	0.2718
3	1.726563	2	0.4218
4	0.112329	2	0.9454
5	2.533321	2	0.2818
Joint	7.168059	10	0.7095

Lastly, we ran White's heteroscedasticity test with no cross term. We see that the null hypothesis cannot be rejected as the p-value indicates that there is no evidence of the presence of heteroscedasticity.

VEC Residual Heteroscedasticity Tests: No Cross Terms (only levels and squares)
Date: 06/17/18 Time: 14:58
Sample: 2004Q1 2015Q4
Included observations: 45

Joint test:

Chi-sq	df	Prob.
324.2522	330	0.5789

Individual components:

Dependent	R-squared	F(22,22)	Prob.	Chi-sq(22)	Prob.
res1*res1	0.301395	0.431423	0.9727	13.56276	0.9163
res2*res2	0.547941	1.212102	0.3279	24.65735	0.3137
res3*res3	0.549032	1.217452	0.3242	24.70644	0.3113
res4*res4	0.663199	1.969112	0.0598	29.84395	0.1223
res5*res5	0.555510	1.249768	0.3028	24.99794	0.2972
res2*res1	0.389833	0.638896	0.8496	17.54249	0.7327
res3*res1	0.294842	0.418121	0.9768	13.26788	0.9254
res3*res2	0.395528	0.654335	0.8364	17.79874	0.7179
res4*res1	0.613451	1.586994	0.1432	27.60529	0.1891
res4*res2	0.487094	0.949676	0.5476	21.91924	0.4647
res4*res3	0.475497	0.906565	0.5899	21.39735	0.4963
res5*res1	0.409726	0.694129	0.8007	18.43768	0.6797
res5*res2	0.658555	1.928733	0.0655	29.63500	0.1276
res5*res3	0.295643	0.419734	0.9763	13.30392	0.9243
res5*res4	0.527427	1.116076	0.3995	23.73422	0.3613