Bidders’ reactions on valuation signals
-An empirical study of commercial property auctions in the UK

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**Master of Science thesis**

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**Abstract**

Auctions have always been an important transaction tool for objects that requires an individual pricing, such as properties, antiquities, art, cars, jewellery and so on. However, few commercial property markets are employing this market making function with the consequence of more illiquid market segments. Previous research has focused on whether or not providing information signals about the object is beneficial to the seller or not from a theoretical point of view. Therefore, this report aims at empirically assess how provided valuation information affects the sale-outcome of commercial real estates.

This study examines the quality of the sellers’ and auctioneer’s announced valuation signal to the bidders by utilizing conventional econometric hedonic models, where the dependent variables are factors determining the success of the auction and based on a dataset including guide-prices and an investment grade for each object. The result is that the sale probability increases and price settles closer to the ex-ante valuation for objects with a low signalled risk (low guide price yield) and a high grade (A). There is a strong correlation between guide price yields and initial transaction yields, i.e. bidders’ risk/reward assessment follows that of which is signalled from the sell side. Furthermore, the transaction yields are more inelastic than the guide price yields, i.e. this happens at less than a 1:1 proportional rate increase. This indicates that guide prices not optimally reflect the bidders’ valuation. Furthermore, the bidders do take external factors into account when assessing whether or not to make a bid. In general bidders tend to prefer low yielding buildings with a high investment grade.
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I sincerely hope that this paper will provide a clearer picture of what is happening in an auction setting, not only in the commercial property market but also in a wider perspective, in order to provide a deeper understanding of auction outcomes.

Stockholm, October 6th, 2013
Jakob Folkesson
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1. Introduction

1.1 Introduction
Transacting goods through auctions has a long history and lies deep in our culture and tradition of trading. One of the first known auctions is described in a report estimated to be from the fifth century B.C, authored by the Greek historian Herodotus reciting the transaction of women to become wives in Babylonia. Reports of auctions from other empires, such as the Chinese dynasties and the Roman Empire suggests that treasure from raids were frequently sold through auctions, which indicate the interest of the auction as a mechanism of transacting goods early in the history of civilization due to its intuitive form (Milgrom & Weber, 1982).

Auctions are not only a very old tool through which actors could exchange goods; it is also used in a wide variety of sectors such as commodities, perishables (e.g. Fish), art, durables and financial assets (such as US treasury bills sold through first-price sealed bid auctions). One common denominator for objects usually sold at auction is the need to establish individual prices for each object, as opposed to e.g. consumer goods, which usually are collectively priced (Milgrom, 1985). However, commercial real estate – a sector consisting of relatively individual and heterogeneous objects – quite rarely transact through auctions in many markets, unless there is a distressed asset or a firm under foreclosure. Instead, properties put on auction tend to be vacant industry-, retail- or other purpose building and thus transacted at a high yield due to perceived high risk in the asset. This marginalized usage of auctions can easily result in a negative view of property auctions as a transaction tool, due to the association with the risky assets.

Generally, an auction could be characterized as an asymmetric “thin market”-situation where a monopolistic seller can sell a good to a buyer from a population of several bidders (Riley & Samuelson, 1981). The price of the good, as well as the formation of bids may vary with different forms of auctions, e.g. the English ascending-bid auction, or the “Dutch” auction where bids descend throughout the auction. There is also a distinction between auctions known as “first-price” (where the price equals to the highest bid) and “second-price” auction (a.k.a. the “Vickery” auction, where the price equals to the second highest bid).

There are many ways through which the commercial real estate market transacts today. Often, the transaction of a property for sale on the market occur through agents, or consultants, who
not only finds the buyer and/or the seller, the agent(s) also conduct a valuation in order to establish a price for the principal (either the buyer or seller) whom he is consulting. Furthermore, the agent provides a solution of financing to the buyer, either through a bank loan, emitting bonds, utilizing mezzanine-loans or tailored debt/equity intruments etc. Sometimes, more frequent lately, the transaction of one or more commercial properties occur through a company-package solution, where the seller creates a company that owns the particular property/ies, and where the company is transacted instead of the real estate. The processes can differ quite a lot depending on the property agents and incentive, but one common denominator is that the process is non-transparent, as no actors have incentives to reveal any important information. Auctions, however, is inherently transparent, requires little time and gives a strong exposure to the market in a standardized and efficient manner. This makes auctions an efficient market making mechanism for an otherwise illiquid market. Hence, it might be adequate to include it more extensively for the transactions of commercial real estates than it presently is.

Yet, there are some markets where auctions have become frequently utilized; example are the residential real estate markets of United Kingdom, Australia, Scotland, Singapore and Scandinavia ((Lusht, 1996); (Chow, Hafalir, & Yavas, 2011)). In most occasions the English ascending-bid price auction is utilized. However, some local differences exists: in Sweden, for example, the auctions does not necessarily occur during a one-time event and are rather a process stretching over several days during which the broker receives bids from the buyers on the phone. Another important exception in the Swedish residential real estate market from a conventional auction is that the bids on the objects are not legally binding before any agreements are signed and the seller doesn’t have to sell to the highest bidder. Due to the longevity of the process (as opposed to an one-time auction-event) and the ability to back out from a bid, the bidders’ received signals and responses may differentiate from a one-time auction event with legally binding bids, and may therefore be more difficult to interpret (Hungria-Gunnelin, 2012).

Another real estate market in which auctions are frequently utilized is the UK commercial property market, which has a fairly large part of the market share: on average the last 5 years £4.8 Bn of properties annually transacted of a total commercial transaction market of average £35 Bn, equivalently having an average market share of 14% of the total UK commercial property market ((Davis, McGough, & Vrensen, 2011); (Savills Commercial Research,
2010)). Usually, the properties on auction are smaller units, averaging in the range of £500,000-200,000 during last five years (depending on market situation), and prices almost never cross the £5 Millions (Savills Commercial Research, 2010). This frequent use of auctions in a commercial property environment makes it a reliable statistical source and an interesting phenomenon to study.

The auction as a market mechanism increases the liquidity and transparency of the commercial property market and gives clearer signals to both buyers and sellers of the market price-situation (Tse, Pretorious, & Chau, 2011). Auctions are in the UK regarded as an optimum method for sale by many retail sellers as well as pension funds, property companies, banks, local authorities and other institutional actors (Allsop Commercial Auctions, 2013). It is also an alternative investment for entrepreneurs and defensive investors who are looking for high yield value-investments (Savills Commercial Research, 2010). The examples above of the residential markets and the UK commercial property market suggests that auctions are a successful mechanism for mid-market segments, where a larger portion of the investor-community can afford to bid, and Milgrom (1987) reasons that auctions allocates the outcomes more efficiently than negotiations, since it enhances a weak sellers’ bargaining-position.

1.2 Background

There have been a number of earlier studies that has laid the foundation of theory and discovered connections empirically in the field of real estate auctions pricing. Thus far, a majority of the papers publicized has focused on an auction framework in the residential real estate sector and much important work has proven that the result of an auction depends on bidder-populations’ features; e.g. Bulow and Klemperer (1996), Ong et. Al. (2005) as well as Hungria-Gunnelin (2012), who shows that the number of bidders on an object is positively correlated with both auction sale probability and a marginal average price increase for each increased bidder. Some earlier work have also assessed the sellers situation, primarily arguing whether it would be beneficial for the seller to increase or decrease the amount of information signalled about the object ((Milgrom & Weber, 1982); (McAfee & McMillan, 1987)). Though, that argumentation is usually almost solely based on theoretical articles in which the optimal behaviour is mathematically derived, and very little actual experimental work has been focused on that niche. Accordingly, this paper will through observations
statistically examine the signal sent from the seller via the auctioneer in the commercial real estate auction-market.

The ex-ante investment quality-grade and the guide-price in this study is a subjective opinion given by the auctioneer, which is supposed to signal what type of investment the particular lot is, e.g. whether it is a low- or high-risk investment. The interpretation of the grade when one assesses the property lies certainly in the eye of the spectator. One investor may see possibilities where others may see a bundle of problems. This results in different valuations, and an investment grade can help the investor assess the risk of the property investment. This research attempts to empirically evaluate if the investor agree with this signal, and in that case how it affects the outcome of the auction.

Intuitively, the method of evaluating the quality of that signal is to analyze whether the bidders agree with the investment-quality grade after they have assessed the property information (e.g. receiving tenant information, visiting and examining the property, etc.). Tentatively three alternative outcomes can be yielded from this:

- The bidders will agree with the signaled guide price, and the price at auction will establish not too far from the guide price
- The last alternative is that the investors completely ignore the guide price, leaving it with zero correlation with the price at auction
- The bidders disagrees with sell side valuation signals, making the dataset negatively correlated

Similarly, the same hypothetical alternatives can be set up regarding investment grade’s and the guide-price’s impact on the probability of sale and the price premium.

The existence of price premiums in the business is not only considered general knowledge, it is a matter of pricing strategy in the signalled guide price. Consequently, as seen in Picture 1 (below) the average price premium during 2009/2010 was 15.7% and over the last 7 years it was 16.6%. Furthermore, the data suggest that when the auction guide-prices are low, the premiums above the guide prices are significantly higher than when the guide-prices are higher (lots with guide-prices ranging around £50,000 - £100,000 usually achieve an average
30% resulting price above that guide price, while lots with guide prices of £2,000,000 and above only receive an 5% premium).

Picture 1. Price premiums and guide prices from Savills report (2010, top) and from the data utilized in this research (bottom).

This inverse relationship could be caused by many things (e.g. increased risk-behavior on smaller amounts, or a larger demand for lower value-properties) and implies that the bidders believe less in the auctioneer’s and sellers signal when the guide prices are lower. One could assume that the causality in this relationship should be that the price at auction is dependent of the guide price due the chronological order of which the two prices are determined. Hence, one hypothesis that could be tested is if the guide price affects the resulting price premium.
with any statistical significance (that is, that its regression coefficient ≠ 0). This will be done in the results section, however, as discussed and presented in the Method- section below, the measure that is defined, utilized and analysed in this research is the rent to guide price yield (instead of the total figure), which has a different interpretation (historical risk adjusted performance) and due to that, the pattern of the data is notably different in picture 1 than as depicted in picture 4.

the relationship presented in picture 1 will not be the same for that measure (which can be seen in picture 4 in the Data- section).

1.3 Research Questions
Assuming the auctioneer being knowledgeable of the market and fairly truthful in determining an attractive guide price, naturally, the hypothesis to be tested should be whether or not his “valuation” makes sense, and therefore this study aims to empirically investigate the ex-ante sell-side determined guide price\(^1\) and investment-quality\(^2\) effects’ on:

I. The probability of sale
II. The price at auction
III. The premium of the sale price\(^3\)

How these questions will be assessed is presented in the Methods Section.

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\(^1\) A subjective guiding price established by the auctioneer and the seller, assessed in more detail in the Data section (Allsop Commercial Auctions, 2013).

\(^2\) A qualitative investment grade established by the auctioneer described in more detail in the Data-section (Allsop Commercial Auctions, 2013).

\(^3\) The difference between the price at auction and guide-price.
2. Earlier studies

There are a number of studies focused on auction theory and empirical work. One of the earliest was Vickrey (1961) who analysed the auction setting and its dynamics in imperfectly competitive markets, and concludes that the progressive auction type, or ascending bid-type, will have higher chances to find the optimal allocations for the participants than the "Dutch" auction bid-type (descending bid-auctions). Vickrey also proposes the set of auction rules known as the 'Vickrey-auction', in which the second sealed-bid becomes the price of the object, but the highest bidder will be the winner of the auction. Vickrey reasons that this type will optimize the outcome for the participants.

Riley and Samuelson (1981) shows that the reservation value of the bidder (above which the buyer will remain out of the auction) is very important for the auction results, and concludes the following propositions: (1) If buyers are risk neutral, for any of the given auction rule-settings (Dutch or English) the results will be the same, independent of the choice of auction rules; (2) The bidders bidding strategy will not alter depending on whether the seller announces a reservation price or not, since the bidders’ reservation price being below or above that announced price is independent of that announcement; (3) The sellers’ outcome-maximizing auction-type is the one for which the seller’s minimum reservation price will be below the bidders reservation value; (4) The seller will enjoy a larger expected profit in the high-bid auction than in the auction-type that Vickrey proposed. Furthermore, Myerson, (1981) proves that the highest expected revenue for a seller of an object whom would like to optimize his outcome utilizing any of the known auction forms, cannot find any other auction-mechanism, which can yield a higher expected utility.

Milgrom and Webers (1982) proposes a number of theorems explaining the connections between the resulting auction price and strategies of the participants and it is proposed that (1) it is optimal for the seller to reveal all available information about the object and the auction, as this should increase the expected auction-price; (2) The highest valuation will equal the expected price, which also equates the expected revenue for seller; (3) Aligned with Riley and Samuelson (1981) it is concluded that the sellers expected price received from the English auction is equal or larger than the expected price in the second price auction. In a follow-up study Milgrom (1985) continues his reasoning regarding information signaling, and he determines that the seller should prefer to reveal all information that he has available about the object and link the price to any available exogenous value (due to Milgrom’s theorem that
the bidders’ expected profit from the auction is maximized when he has private info that the auctioneered object is valuable) because it will result in higher valuations and thus higher bids. Furthermore he concludes that a rational seller should prefer an ascending-bid auction, rather than a sealed-bid auction. McAfee and McMillan (1987), however show that the full information-transparency strategy will not be beneficial for the seller in a setting where bidders are risk-averse, with independent private values (IPVs). The analysis is based on a setting where the probability of a price increase is assessed after information-signals are released, and the results provide indications that the seller’s payoff is optimized from concealing information.

Independent private values of the object transacted in the auction were frequently a focus in early empirical reports ((McAfee & McMillan, 1987); (Myerson, 1981); (Riley & Samuelson, 1981)). In essence, the proposed idea of the IPV is that bidders receive information signals about the good, and then observe only their own resulting valuation, ignoring others valuations and bids, and are therefore considered independent from each other. This is relevant as the assumption clears for identically independent distributions (IDD), which are easier to handle in statistics, as opposed to populations where outcomes are dependent. Recently, however, studies have been more concentrated on common value auctions (CVA), where the value of the auctioneered article is considered equal to all bidders. Furthermore, Dholakia & Soltysinski (2001) examine herd behavior-bias as another bidder behavior, which is determined to be increased when it is difficult to evaluate the quality of the object, and decreased when the bid-price rises. This implies that the assumption of IDD may not be valid in an auction setting.

Since the bidder in a common value auction do not know the market value of the auctioneered object for certain, he can only estimate its market value and Wilson (1977) has showed that when the amount of bidders goes to infinity, the sealed-bid auctions have asymptotic optimality properties; when the number of bidders go to infinity it is “essentially certain” that the object will auction at it’s ‘true value’. In contrast to this, there is the “Winners Curse”-theory which assumes that the price-estimate from the bidders are on average correct in regard to the market value, and since they are, it will follow that the bidder with the highest estimate of the market value will not only be the highest bidder, but he/she will also be likely to “overpay”, meaning that his expected value from the auction will be negative (expected market value of item – paid price) (Lind & Plott, 1991).
In regard to the asymptotically optimal properties of increasing number of bidders examined by Wilson (1977), there is a consensus in the academic community that more bidders in an auction will lead a preferable outcome for the seller. Ong et al. (2005) analyzes the sales probability of residential real estate in Singapore sold by auction and shows empirically that the variables ‘bidder turnout’ (amount of bidders in the auction) and ‘distress’ (whether the asset is under foreclosure or not) are important factors of an increase in sale-probability. Likewise, Hungria-Gunnelin (2012) empirically shows that there is a positive correlation between increase in number of actors bidding and the price of a given apartment in the residential real estate market in the Stockholm area in Sweden. Furthermore Amidu and Agboola (2009) empirically show from a sample of first-price sealed bids of 120 residential property auctions owned by the federal government in Ikoyi, Lagos in Nigeria, that the number of bidders are positively correlated with the auction winning premium and bids.

Tse et al. (2011) examine how the stock market assess the outcome of open-bid English auctions of rights to develop residential real estate ventures in Hong Kong and conclude that (1) with higher uncertainty, bidders will lower their bids, ratifying the predictions of the winner’s curse thesis, (2) joint bidding will not increase bids, even though the bidders’ information now is pooled, (3) the market interprets that the auction outcome are signals for developers’ expectations, except when the winning bid is “too” high, (4) joint bidding winners are interpreted as victims of the ‘winner’s curse’ by the stock-market, despite a pooled information source, (5) market interprets increased auction-competition as a marker of higher future prices. Conversely, Chow et al. (2011) find that objects on auction finds a higher relative price than other negotiation transaction mechanisms when the demand for the asset is high, which indicate that the profit for the seller on the auction is dependent on the market situation. When the market is down, there is no such effect and they also find that auctions are more efficient than negotiations when the underlying asset is homogeneous and the bidders have high IPVs. In addition to that study, Bulow and Klemperer (1996) found that adding one bidder from the \( n \) amount of actors in a negotiation in an auction will result in higher profits for the seller than in a negotiation with \( n + 1 \) actors. Furthermore Bulow and Klemperer (2009) show that auction with a limited amount of bidders will still generate higher revenues for the monopolistic seller given that the bids have a larger price dispersion than in a negotiation. These results suggest that Milgrom’s (1987) argumentation of more efficient and stable outcomes in auctions are accurate.
3. Method

This section will present the method with which the research question was assessed in order to provide tailored models that describes the causal effects in the data.

3.1 Hedonic models

The hedonic regression is a model which utilizes the explanatory power of a certain quantifiable factor or variable (X) to explain movements in another variable (Y), where one assumes that X is independent from Y while Y is dependent on X. Usually a regression method, such as the Ordinary Least Square (OLS) estimator, is used in order to estimate the factor by which a one-unit change in X on average will impact Y, while minimizing the error-vector in order for the explanatory power of the model to be optimized. This hedonic model can generally be represented by:

\[ Y = f(X_1, ..., X_n) + \varepsilon \]

There has been a lot of work employing regression models in order to deduct estimated real estate prices from other attributes inherent in the property. Malpezzi et al. (1980) argue that a property is a collection of characteristics from which it derives its value and utilizes an equivalent model which first was applied by Rosen (1974) who determined values of real estates through regressions.

The utilized hedonic regression coefficient estimators in this paper were the probit model and the OLS. The purpose of the regressions in this paper is not to determine the value from direct characteristics; rather they are employed in order to make the assessment of the quality of the signaled valuations inherent in the guide price and the investment grades more intuitive.
3.1.1 The OLS General Linear Regression Model (OLS GLRM)

For the OLS GLRM estimator, the regression model is

\[ E(Y_i|X_{i,1}, \ldots, X_{i,n}) = \beta_0 + \beta_1 X_{i,1} + \cdots + \beta_n X_{i,n} + \varepsilon \]

Where the estimated coefficient $\beta_k$ is interpreted as the expected change in $Y$ for a one-unit change in $X_k$, while all other variables are held constant i.e. it is a ceteris paribus comparison for a marginal change in one variable. The GLRM OLS estimation of the $\beta$s, that is, the estimation of the vector $\hat{\beta}$ is

\[ \hat{\beta} = (X'X)^{-1}X'y \]

(Greene, 2003)

3.1.2 The Probit Binary Regression Model (Probit)

The Probit model is adequate when the dependent variable $Y$ is binary, since it applies the Gaussian Normal distribution in order to estimate a cumulative distribution function $\Phi(z)$ which can create a well fitted expected value of the probability impact of a variable that goes from 0 to 1. Picture 2 deposits an example of a probit model, with probability on the x-axis. Note that the non-linear feature of the model makes it a more intuitive and usually a better estimator of probability than a linear model.

Picture 2. A plot of the Probit function $\sqrt{2}erf^{-1}(2p - 1)$ (Wikipedia, 2007)
The Probit estimator models the probability that \( Y = 1 \) for a given setting of variable preferences \( z = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n \), i.e.

\[
4) \quad \Pr(Y = 1|X_{i,1}, \ldots, X_{i,n}) = \Phi(z) = \Phi(\beta_0 + \beta_1 X_{i,1} + \ldots + \beta_n X_{i,n} + \varepsilon)
\]

Where the predicted probabilities \( \mathcal{F} \) is generally estimated by

\[
5) \quad \mathcal{F}(X'\hat{\beta}) = \mathcal{F}
\]

I.e. the expected probability is estimated by the vector cross product of the estimated betas \( \hat{\beta} \) and the function (Greene, 2003).

Due to the non-linear features of the Cumulative Normal Distribution Function, the marginal change is not constant independent from the values of \( X \). One commonly used convention is to calculate the Average Marginal Effects (AMEs) of the independent variable \( X \) on the dependent variable \( Y \). The marginal effect is computed for each of the variable ceteris paribus, and then the effects are averaged. This provides a relatively intuitive way of interpreting the variable features of the model. However, the probability marginal effect depends on the value of all the \( X \)'s, thus limiting the power of this model, even though it is intuitive. (Freese & Long, 2006). Generally, the marginal probability effect at point \( \mathbf{x} \) that \( \Pr(Y = 1|X) \) is

\[
6) \quad \frac{\partial E(Y|X)}{\partial x} \bigg|_{x=\mathbf{x}} = \frac{\partial \mathcal{F}(X'\hat{\beta})}{\partial x} \bigg|_{x=\mathbf{x}} = f(X'\hat{\beta}) \times \hat{\beta} = \mathcal{F}
\]

(Greene, 2003)

3.1.3 Interacting Variables

Interacting variables are variables that describe the simultaneous influence of two or more independent variables on the dependent variable. Generally, an interacting variable is constructed when one can suspect that the marginal change in \( Y \) from a marginal change in the independent variable \( X_k \) is different depending on the value of one or more of the other independent variables. Thus, from the following example of an OLS regression with two independent variables and an interacting variable:

\[
7) \quad Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 (X_1 \times X_2)
\]

the marginal effect of \( X_1 \) is
$$\frac{\partial y}{\partial x_i} = \beta_1 + \beta_3 x_2$$

In other words, the marginal effect on Y of $x_i$ depends on the current value of $x_2$.

### 3.1.4 Notable Regression Metrics

A fundamental challenge in statistics and econometrical studies is random error. In order to determine whether a result is statistically reliable despite random errors or based mostly on random errors, convention is to find the statistical significance. Statistical significance (also referred to the *type I error rate*, $\alpha$) is the probability of incorrectly rejecting a given null hypothesis in favor of a second alternative hypothesis. This probability limit (known as the $\alpha$-level) is in economic studies usually set to 5% by convention (Fischer, 1935). The null hypothesis tested in this research is if the coefficient of the $i$:th variable ($\beta_i$) is equal to zero, and the alternative hypothesis is that the coefficient of the $i$:th variable ($\beta_i$) is not equal to zero. If the null hypothesis can be rejected, the result can be deemed as statistically significant at the 5%-level, meaning that one can reject the “extreme” result that coefficient is equal to zero with a 95% probability (Fischer, 1935). In order to do this the t-statistic is derived from the ratio

$$t = \frac{\beta_i - 0}{\sigma_i}$$

That is, determining how many standard deviations the coefficient of the $i$:th variable ($\beta_i$) are from being zero. If the variable have properties such that its distribution can be approximated with the Gaussian Normal Distribution, the alpha limits of the t-value is approximately 1.96, meaning that when the t-value exceeds this value, the hypothesis that the coefficient of the $i$:th variable is zero can be rejected at the 5-percent level. This means that one can reject that the coefficient is insignificant, and thus implicitly, conclude that the coefficient is significant. The implication of non-significant coefficient is that the variable has no statistically effect on Y that can be proved. Note that the equivalent metric for a Probit model is known as the $z$-statistic. (Greene, 2003)

The R-squared ($R^2$) determines model’s fit to the data and is estimated as

$$R^2 = 1 - \frac{\sum(y_i - f(x_{i1}, \ldots, x_{in}))^2}{\sum(y_i - \bar{y})^2}$$

Which results in a number ranging between 0 and 1, often interpreted as the percentage
amount of movements in the dependent variable (y) that can be explained by the independent variables (the X’s), i.e. the explanatory power of the model. (Greene, 2003)

The F-test is, like the t-test, a significance test for the null hypothesis that all/selected coefficients are equal to zero. The F-test is given by

\[ F[k - 1, n - k] = \frac{R^2/(k-1)}{(1-R^2)/(n-k)} \]

Where \( n \) observations and \( k \) number of variables. The null can be rejected at the 5%-level if the F-ratio is larger than 2.37. Note that the equivalent test for a Probit model is known as a Wald-test (Greene, 2003).

### 3.1.4 Bias

Bias in regressions is an inherent part of any regression model, and can very rarely be completely avoided. A Bias occurs when the error term (\( \varepsilon \)) is correlated with any of the independent variables, that is, when:

\[ E(\varepsilon_i | X_i) \neq 0 \]

It can be caused by a number of reasons, such as sample selection errors, errors in the variables / collection errors, simultaneous causality or endogeneity. Sample selection bias occurs when the sample does not represent the population, thus creating a bias in the coefficient. An example of error in variable bias can be data written unknowingly by the respondent, or respondents hiding information. Causality or endogeneity bias occurs when X is not independent of Y, and the independent variables are correlating with the error term. (Greene, 2003)

### 3.2 The Research

The Probit model was applied in order to estimate sale probability function (i.e. regression 1). When assessing the regression for the price premium and yield, the linear OLS estimator was utilized. The hedonic regression models were conducted including a number of dummy-control-variables in order to increase the explanatory power of the model and to control for exogenous effects. Besides the investigated investment grades and the guide price, variables controlling for time effects, auction-location effects, and macro property transaction effects were included. Furthermore, a variable telling at which point during the auction-event the property was included.
The investment grades were constructed as dummy-variables in order to not distort any of the data by parameterization. Furthermore, both the guide price and resulting prices was normalized by creating the ratio of “rent to guide price”\(^4\) and initial transaction yield respectively. These are deemed preferable over the total figures, since relative values will provide the regressing model a measure of risk adjusted performance, rather than just a number, without an inherent meaning. In order to answer the questions presented in the Research Questions-section, the coefficients for each independent variable will be assessed and analyzed, and a discussion regarding the model’s validity and applicability (assessing the R-squared) will be conducted in the Results and Discussion- sections.

### 3.2.1 Regression Equations

The following three (3) regression-equations estimated was:

1. \[
\text{sale\_probability} = \Phi(\beta_0 + \beta_1\text{rent\_to\_guide\_price} + \beta_2\text{grade\_B} + \beta_3\text{grade\_C} + \\
\beta_4\text{multilet} + \beta_5\text{vacant} + \beta_6\text{rent\_to\_guide\_price\_grade\_interaction}_{6\rightarrow9} + \\
\beta_{10\rightarrow41}\text{control\_variable}_{10\rightarrow41})
\]

2. \[
\text{initial\_yield\_net} = \beta_0 + \beta_1\text{rent\_to\_guide\_price} + \beta_2\text{grade\_B} + \beta_3\text{grade\_C} + \\
\beta_4\text{multilet} + \beta_5\text{vacant} + \beta_6\text{rent\_to\_guide\_price\_grade\_interaction}_{6\rightarrow9} + \\
\beta_{10\rightarrow41}\text{control\_variable}_{10\rightarrow41}
\]

3. \[
\text{sale\_premium} = \beta_0 + \beta_1\text{rent\_to\_guide\_price} + \beta_2\text{grade\_B} + \beta_3\text{grade\_C} + \\
\beta_4\text{multilet} + \beta_5\text{vacant} + \beta_6\text{rent\_to\_guide\_price\_grade\_interaction}_{6\rightarrow9} + \\
\beta_{10\rightarrow41}\text{control\_variable}_{10\rightarrow41}
\]

Where the respective variable has the following interpretations:

- **sale\_probability** = binary variable, 1 for sold lot and 0 for unsold lot
- **sale\_premium** = \(\frac{[\text{price\_at\_auction}] - [\text{guide\_price}]}{[\text{guide\_price}]}\)
- **initial\_yield\_net** = yield\(^6\) from property sale, net of auction fees

---

\(^4\) Note that throughout this report, this ratio is either referred to as the “rent to guide price ratio” or “guide price yield”

\(^5\) If the guide price was a range, the guide price was defined as the average of the two range values
grade_B = binary variable, 1 if the lot is graded B and 0 otherwise
grade_C = binary variable, 1 if the lot is graded C and 0 otherwise
multilet = binary variable, 1 if the property is multilet, 0 otherwise
vacant = binary variable, 1 if the property is vacant, 0 otherwise

rent_to_guide_price = \frac{\text{rental\_income}}{\text{guide\_price}}

rent_to_guide_price\_grade\_interaction = [\text{rent_to_guide_price}] [\text{grade\_B}]
rent_to_guide_price\_grade\_interaction = [\text{rent_to_guide_price}] [\text{grade\_C}]
rent_to_guide_price\_grade\_interaction = [\text{rent_to_guide_price}] [\text{multilet}]
rent_to_guide_price\_grade\_interaction = [\text{rent_to_guide_price}] [\text{vacant}]

When all the independent variables are zero the only regression-value left is the coefficient \(\beta_0\). This coefficient consists of all the information that is not captured by the dependent variables, which is; the lots auctioned that was graded A, sold during the auction event December 4th 2012 and auctioned at the Park Lane venue.

---

6 Yield is defined as the rental income over the auction property price
3.3. Data

Table 1. Brief description of the data provided

<table>
<thead>
<tr>
<th>Variable</th>
<th>Average</th>
<th>Std.Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Initial Yield</td>
<td>6.23%</td>
<td>3.24%</td>
</tr>
<tr>
<td>Price Premium</td>
<td>16.59%</td>
<td>45.48%</td>
</tr>
<tr>
<td>Sale Successful</td>
<td>72.15%</td>
<td>44.83%</td>
</tr>
<tr>
<td>Rent to Guide Price</td>
<td>7.26%</td>
<td>3.83%</td>
</tr>
<tr>
<td>A</td>
<td>42.87%</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>32.30%</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>5.96%</td>
<td></td>
</tr>
<tr>
<td>Multilet</td>
<td>14.45%</td>
<td></td>
</tr>
<tr>
<td>Vacant</td>
<td>4.43%</td>
<td></td>
</tr>
</tbody>
</table>

Allsop LLP, a market leading auction-agent for commercial properties in the UK, provided the Data (Allsop Commercial Auctions, 2013). The observations in the data sample are tracing back 7 years, with almost 5000 observations, only including sales during the auction event (i.e. observations from sales prior or after the auction event was omitted). A number of variables were provided in the original dataset, including (but not limited to) address and region of property, price, net yield and guide price. The average property had a probability of sale of 72% to be sold at a yield of 6%, received a price premium of almost 17% and was graded A (not necessarily at the same time).

3.3.1 The Investment Grade

Table 2. Brief descriptions of the grades

<table>
<thead>
<tr>
<th>Grade Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
</tr>
<tr>
<td>B</td>
</tr>
<tr>
<td>C</td>
</tr>
<tr>
<td>Multilet</td>
</tr>
<tr>
<td>Vacant</td>
</tr>
</tbody>
</table>

The investment grade is a qualitative assessment of how well invested your money will be when buying a particular property (Moir, 2013). From a theoretical perspective, the wording “good quality” can be replaced with “low risk”, since referring to quality in an investment might be misleading. An investor may find “quality” in a high-risk investment; as such transactions usually are of lower volume, resulting in the possibility of a higher return. It is rather a matter of the investors’ risk averseness, strategy and finding the appropriate
opportunity for the investor. The investment grade and their descriptions can be seen in table 2 with the quality in descending order from top to bottom.

**Picture 3. The average sale metrics distributed over investment grade**

The overview of the average sale results (Initial yield, price premium and successful sale) as distributed over the investment grades is presented in picture 3. Picture 3 presents a trend for decreasing sale-probabilities as well as increasing yield for each increase in grade, except for vacant lots (“V”), which in all aspects seems to be a trend breaker. At first reflection, the reason to this could be the lack of rent in vacant buildings and/or a guide price strategy. However, this picture provides a too simplistic overview and the impact of the investment grade on the sale results will be deeper assessed from the results of regression 1-3.

When conducting the regression, some variables – such as property type, tenant type and region (in which the property is located) – were provided in the dataset but omitted in the final regression. When these variables were included in the first regressions (during the execution of the research), almost all variables (including themselves) became insignificant. The reason to this is that the inclusion of the above stated variables was “stealing” significance from the variables of focus in this research. One proposed explanation could be that they are more or less substitutable, i.e. describing similar phenomena (inducing multicolinearity), since the professional should already take such things as location, region,
type of property etcetera, into account when assessing the guide price and investment grade. And as seen in table 2 of the investment-grade descriptions, the description of the investment grades do mention the above stated property-features (location, rental income, vacancy, tenant building quality and lease length) suggesting that this certainly could be the reason to why multicollinearity occurs when including these variables in the regression.

3.3.2 The Guide Price

Picture 4. The average sale metrics distributed over some guide price yield intervals

In picture 4 the sale results can be seen distributed over intervals of the rent to guide price ratio. As one could guess; the initial yield follows the guide price-yield quite strictly. Harder to guess is the sale probability, which is fairly high in the high and low end of the spectrum, but has its dips of 70% for properties in the 9-15% as well as 18-21% guide price yield. Even more spectacular is the price premium, which has two major tops of 56% and 98% (at 0-3% and 18-21% guide price yield respectively), and is otherwise quite consistently around 10-20%. Furthermore, the average of price premium distribution does not follow the same pattern as in picture 1 (as discussed in the Background-section), allegedly due to the different inherent meaning between absolute price figures and relative rent/guide price ratio.

Understanding the guide price is vital in interpreting the results from the regression models. The guide price is not a market valuation comparable to the methods provided in the RICS red book or an equivalent market valuation (Moir, 2013). Allsop (2013) states that the “Guide Prices are not necessarily figures at which a property will sell…” as it is both Allsop and the
seller who determine the guide price, tailored to “...present a realistic but also attractive price for the bidders...” while it fulfils the sellers minimum expectation. Thus, it is explicitly stated to generate competitive bidding in the auction room in order to achieve a good price and not a market value, and thus fills a strategic purpose, while providing the bidder some information about sell-side reservation price.

However – for the purpose of this research – whether the guide price is a quality assessment of a realistic value should be, or a matter of pricing strategy from the sell-side, the main focus is how the buy-side responds to that released object information. A well-merited and knowing auctioneer with reference experience will have some clue where the price will end up (with the exceptions of large outliers explained by something else than the general investor demand) and could from this experience tailor a price he/she believes will be attractive. But when looking at Picture 4 above, the distribution of initial yield over rent to guide price seem to provide evidence that the sell-side signalled value seems efficient in estimating the net initial yield (as an increase in the rent to guide price yield seems to consistently increase the initial yield). This could either have its explanation in that the sell-side consistently values the object close to their honest value opinion, or hypothetically, that their price strategy seems to be believed by the bidders to be a “fair” value. Whatever the case, the indicated ex-ante rent to guide price ratio seems to be a good estimator of the net initial yield.
4. Results

Provided in this section is a presentation of the results from regression 1 - 3. Under each subsection, the concluding results will first be explained. This will be followed by a deep-dive of the results, where:

i. The independent variables’ significance will be shown (wald/F-tests)
ii. The rent to guide price intra-grade marginal effect on the dependent variable will be presented
iii. The inter-grade marginal impact on the dependent variable for given rent to guide prices (mean +/- one standard deviation)

The reason to this setup is due to the fact that the marginal effect of a change in grade or rent to guide price is dependent on value of the rent to guide price or grade (since they are interacted with each other, a explained by equation 8 in section 3).

The results will be presented with the regression-equation coefficients and t-values or z-values based on heteroscedastic robust coefficient standard deviation. Interaction variables were used in all three regressions, named: $RTGPxB$, $RTGPxC$, $RTGPxM$ and $RTGPxV$, which are interaction variables for the independent variables’ simultaneous effects as indicated in the name. As described in the Method-section (section 3), when interaction variables are constructed and used, the interpretation of marginal effect is not equal to the coefficient for the respective variable, as the marginal effect depends on the value of the interacted variables. Therefore, in each result section there will be tables providing the marginal effect for some different values of the interacted variables to present a picture how they affect sale probability, initial yield and price premium. The dummy variables that are missing a coefficient in the result-tables was automatically omitted by the statistical package due to collienarity. The utilized significance tabulation is:

*** -Significant at 1%-level  
** -Significant at 5%-level  
* -Significant at 10%-level

4.1 Sale Probability, Regression 1

The coefficients in the presented equation of regression 1, (the Probit model) is the Average Marginal coefficient Effect (AME) on sale probability at the independent variable means. The regression resulted in low pseudo explanatory power, but very significant coefficients, suggesting that the grades and guide prices are affecting the sale probability. As shown in
Table 3 below, grades do have a strong effect, and given a certain rent to guide price, two otherwise similar objects can differ around 10-20% in sale probability when comparing a grade-A object and a lot with lower grade. Furthermore, the probability of sale does not consistently follow the rent/guide price ratio; the marginal effect of an increase in the rent to guide price is highly dependent on the grade-label of the lot.

Table 3. (4.1.i) Regression Results & Wald-tests, Regression 1

<table>
<thead>
<tr>
<th>Regression Results</th>
<th>dy/dx</th>
<th>z</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rent to Guide Price</td>
<td>-2.049684</td>
<td>-2.12</td>
<td>**</td>
</tr>
<tr>
<td>Grade B</td>
<td>-0.1863578</td>
<td>-2.69</td>
<td>***</td>
</tr>
<tr>
<td>Grade C</td>
<td>-0.2765769</td>
<td>-3.56</td>
<td>***</td>
</tr>
<tr>
<td>Multilet</td>
<td>-0.3341822</td>
<td>-4.82</td>
<td>***</td>
</tr>
<tr>
<td>Vacant</td>
<td>-0.1773762</td>
<td>-2.47</td>
<td>**</td>
</tr>
<tr>
<td>RTGPxB</td>
<td>1.356975</td>
<td>1.37</td>
<td></td>
</tr>
<tr>
<td>RTGPxC</td>
<td>2.85E+00</td>
<td>2.78</td>
<td>***</td>
</tr>
<tr>
<td>RTGPxM</td>
<td>2.607015</td>
<td>2.66</td>
<td>***</td>
</tr>
<tr>
<td>RTGPxV</td>
<td>-0.5367738</td>
<td>-0.22</td>
<td></td>
</tr>
</tbody>
</table>

Wald tests

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>Chi2</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rent to Guide Price &amp; Grade B &amp; RTGPxB = 0</td>
<td>62.36</td>
<td>***</td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Grade C &amp; RTGPxC = 0</td>
<td>14.87</td>
<td>***</td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Multilet &amp; RTGPxM = 0</td>
<td>78.46</td>
<td>***</td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Vacant &amp; RTGPxV = 0</td>
<td>8.55</td>
<td>***</td>
</tr>
</tbody>
</table>

As seen in table 3 above, all but three of the studied independent variables (which all are interaction variables) were significant on the 1% or 5% level. However, when testing the simultaneous significance (Wald-tests) of the grades’ effect, rent to guide price effect and interaction variables’ effect, the results was clearly significant. This clearly suggests that one can reject that the marginal effect on the sale probability of both ex-ante grades and rent to guide-prices are zero.
As seen in table 4, the results of regression 1 presents that a lot with a 1% higher rent to guide price when the property investment is graded A will on average receive almost a 2% decrease in probability of getting sold under the hammer. Furthermore, both grade B and a vacant building is also less likely to get sold when the initial rent to guide price increases with one percent (0.7% and 3% of decreased sale probability respectively), whereas a C-graded and Multilet property increases in sale probability more than half a percent per increase of rent/guide-price. This means that when a property has grade A or is vacant, an increase in the implicit guide price yield will result in a quite big decrease in probability of getting sold, on average.

As seen in table 5, it is notable that the average marginal effects of sale probabilities are consistently negative when comparing an A-graded lot and a lot with a lower grade (B-, C-, Multilet or vacant), regardless of the rent-guide-price ratio. That is, a lower grade is strictly affiliated with an average decrease of sale probability, and the effect is much bigger at low rent to guide price ratios. The effects on sale probability at low guide price-yield lots (around 3%) can be up to a 20% decrease when comparing an A-grade lot to a B-, C-, multilet or vacant labeled lot. This could be a result of sending mixed signals; indicating a low lot-grade whilst presenting a high valuation relative to the rent might make the bidder think twice. When the rent to guide price indication from the auctioneer/seller is high – around 10% - the difference in probability of selling two similar lots with Grade A compared to lower grades decreases to less than 10%, except for vacant buildings where the probability actually
increases a little over 20%. That is, a vacant lot with a 10% indicated rent to guide price is almost 30% less likely to get sold than a lot with grade A and 10% implied rent to guide price. The analysis of this will be discussed in section 5.

### 4.2 Net Initial Yield, Regression 2

Regression 2 is a OLS estimation of the yield dependent on the signalled ex-ante yield, (or: rent to guide price) as well as the grades, interaction variables and other control variables. The regression has a very high explanatory power, where little over 88% of the movements in the yield could be explained by the signalled implied rent/guide price. The rent to guide price is solely the most important and significant factor that can explain the movements of the yields, and it has an almost 1:1 effect on the resulting yield. The grades had little impact (less than 1% - often only a fraction of a percent) and their coefficients proved to be much less significant than the rent to guide prices.

#### Table 6. (4.2.i) Regression results and F-Test, Regression 2

<table>
<thead>
<tr>
<th>Regression Results</th>
<th>Coef.</th>
<th>t</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Initial Yield</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rent to Guide Price</td>
<td>0.8618052</td>
<td>23.28</td>
<td>***</td>
</tr>
<tr>
<td>Grade B</td>
<td>0.0074001</td>
<td>2.11</td>
<td>**</td>
</tr>
<tr>
<td>Grade C</td>
<td>0.0152188</td>
<td>2.38</td>
<td>**</td>
</tr>
<tr>
<td>Multilet</td>
<td>0.0099787</td>
<td>1.53</td>
<td></td>
</tr>
<tr>
<td>Vacant</td>
<td>0.0000597</td>
<td>0.02</td>
<td></td>
</tr>
<tr>
<td>RTGPxB</td>
<td>-0.0751243</td>
<td>-1.5</td>
<td></td>
</tr>
<tr>
<td>RTGPxC</td>
<td>-0.1644428</td>
<td>-2.12</td>
<td>**</td>
</tr>
<tr>
<td>RTGPxM</td>
<td>-0.114839</td>
<td>-1.43</td>
<td></td>
</tr>
<tr>
<td>RTGPxV</td>
<td>0.0035521</td>
<td>0.03</td>
<td></td>
</tr>
</tbody>
</table>

#### F-tests

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>F</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rent to Guide Price &amp; Grade B &amp; RTGPxB = 0</td>
<td>757.75</td>
<td>***</td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Grade C &amp; RTGPxC = 0</td>
<td>338.45</td>
<td>***</td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Multilet &amp; RTGPxM = 0</td>
<td>524.51</td>
<td>***</td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Vacant &amp; RTGPxV = 0</td>
<td>8427.31</td>
<td>***</td>
</tr>
</tbody>
</table>

The resulting coefficients provided in regression 2 (table 6) shows not only that the guide price proves significant in explaining price movements in the auction setting, but also that its explanatory power to initial yield movements is very strong, and it is the absolutely most
important factor determining the ending bidder’s valuation. There is very high correlation between the initial yield and the rent to guide price, and a regression only including the rent to guide price ratio as dependent variable would provide a $R^2$ of 87.3%. In other words, when including variables in the regression, which are controlling for external effects, only an additional 0.9% of explanatory power is added in the model. It is also quite notable that the F-tests of the coefficients for the rent to guide price, the respective grade and their interaction variable seemed to be highly significant, spite the low significance of the latter two. This is, of course, due to the high significance of the rent to guide price coefficient.

**Table 7. (4.2.ii) Marginal Effect of Rent to Guide Price, Regression 2**

<table>
<thead>
<tr>
<th>Marginal Effect of Rent to Guide Price for the Different Grades</th>
<th>Grade A</th>
<th>Grade B</th>
<th>Grade C</th>
<th>Multilet</th>
<th>Vacant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rent to Guide Price</td>
<td>0.8618</td>
<td>0.7866</td>
<td>0.6974</td>
<td>0.7469</td>
<td>0.8654</td>
</tr>
</tbody>
</table>

The regression marginal effect on the Net Initial Yield of the rent to guide price is quite consistent throughout the different grades, i.e. a lot with 1% lower rent/guide price-ratio than another otherwise comparable lot would on average sell at around 0.8% lower yield. This Marginal effect is biggest for A-graded lots, with a marginal increase of 0.86% in yield from a 1% increase in rent to guide price, whereas a lot with grade C will increase 0.7% in yield from a 1% increase in rent/guide price. In general it is quite notable that the effect from a 1%-change in the rent to guide price is not affiliated with an equivalent 1%-change in the initial yield.

**Table 8. (4.2.iii) Marginal Effects of Grades, Regression 2**

<table>
<thead>
<tr>
<th>Marginal Effect of the Grades for Different Values of Rent To Guide Price</th>
<th>-1 standard deviation</th>
<th>Mean</th>
<th>+1 standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rent to Guide Price</td>
<td>0.0299</td>
<td>0.0623</td>
<td>0.0947</td>
</tr>
<tr>
<td>Grade B</td>
<td>0.00515383</td>
<td>0.00271986</td>
<td>0.00028583</td>
</tr>
<tr>
<td>Grade C</td>
<td>0.01030196</td>
<td>0.00497401</td>
<td>-0.0003539</td>
</tr>
<tr>
<td>Multilet</td>
<td>0.006545014</td>
<td>0.00282423</td>
<td>-0.0008966</td>
</tr>
<tr>
<td>Vacant</td>
<td>0.000165908</td>
<td>0.000281</td>
<td>0.00039608</td>
</tr>
</tbody>
</table>

When looking at inter-grade changes (table 8), a grade-A lot is in general affiliated with a slightly lower initial yield than a lot with a lower grade. Now, as seen in table 6, this effect is quite small (0.5% or less for a down-grade) for lots selling with the average rent to guide
price (6.23%). The biggest marginal effect that can be seen from the presented results is when a lot graded A is compared to a lot graded C, and when both receives a low rent/guide price-ratio (around 3%), the effect is an average 1% on the net initial yield under the hammer. However, for high-yield lots (around 9-10%) this effect is actually slightly negative when comparing a C-graded lot (around -1‰) and a Multilet-labeled lot (-0.35‰) to a lot with grade A. Effectively this means that grading a lot “C” or labelling it “Multilet” will on average actually result in a very slightly lowered yield when the rent to guide price-ratio is at high levels.

4.3 Price Premium, Regression 3

Regression 3 is a OLS GLRM estimation of the price premium of the resulting price under the hammer minus the given guide price, as regressed to wards the rent to guide price, the grades, their interaction variable and control dummy variables. The model turned out to be quite inefficient in explaining price premium movements, and the coefficients of the independent variables are less significant than in the other two regressions; only the marginal effect from adjusting the rent to guide price, grade B and vacant-label was significant in explaining the price premium (as seen in the F-test, table 6). Increasing the rent to guide price of 1% within grade B and vacant lots presented a very strong negative effect on price premiums of -4.2% and -5.9%. At the same time, a B-graded lot will on average receive a higher premium, while vacant lots will receive a higher premium than an A-graded lot at low-yielding properties (where a majority of them are distributed due to the lack of rental income)

Table 9. (4.3.i) Regression Results and F-tests, regression 3

<table>
<thead>
<tr>
<th>Regression Results</th>
<th>Coef.</th>
<th>t</th>
<th>R2 = 0.0597</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>rent_to_guide_price</td>
<td>-1.38934</td>
<td>-1.83</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>grade_B</td>
<td>0.2650554</td>
<td>1.89</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>grade_C</td>
<td>-0.1285622</td>
<td>-2.21</td>
<td>**</td>
<td></td>
</tr>
<tr>
<td>multilet</td>
<td>-0.187345</td>
<td>-2.47</td>
<td>**</td>
<td></td>
</tr>
<tr>
<td>vacant</td>
<td>0.1631599</td>
<td>2.01</td>
<td>**</td>
<td></td>
</tr>
<tr>
<td>RTGPxB</td>
<td>-2.844113</td>
<td>-1.69</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>RTGPxC</td>
<td>1.719739</td>
<td>2.16</td>
<td>**</td>
<td></td>
</tr>
<tr>
<td>RTGPxM</td>
<td>2.388168</td>
<td>2.3</td>
<td>**</td>
<td></td>
</tr>
<tr>
<td>RTGPxV</td>
<td>-4.488168</td>
<td>-0.89</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
As seen in table 9 above, a relatively low R-squared suggest that the model cannot explain price premiums very well. Furthermore, as seen in the F-test, the marginal effects of comparing a grade-B lot to a grade-A lot, as well as comparing a vacant to a grade-A lot are significant at the 1% level. However, the coefficient for lots with grade B (compared to A) are on its own not significant (seen in the regression results), and the F-test show that the marginal effect on price premiums of grade C and Multilet are also not significant. Thus, one cannot reject that their effect is zero on the price premiums at the 5%-level.

Table 10. (4.3.ii) Marginal Effect of Rent to Guide Price, regression

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>F</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rent to Guide Price &amp; Grade B &amp; RTGPxB = 0</td>
<td>3.06</td>
<td>***</td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Grade C &amp; RTGPxC = 0</td>
<td>1.65</td>
<td></td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Multilet &amp; RTGPxM = 0</td>
<td>2.39</td>
<td>*</td>
</tr>
<tr>
<td>Rent to Guide Price &amp; Vacant &amp; RTGPxV = 0</td>
<td>7.39</td>
<td>***</td>
</tr>
</tbody>
</table>

The marginal effect of rent to guide price on price premiums are very strong for comparison between lots within grade B and the vacant-label. A lot with grade B on auction with indicated rent to guide price of 1% above that of a similar lot (also with grade B), will on average receive a 4.23% lower price premium. When making a similar comparison for vacant properties, a 1% increase in rent to guide price is affiliated with almost 5.9% lower price premiums. This effect may certainly be due to the strategy of setting the guide prices on the sell-side, as well as investors on the buy-side seeing opportunities in objects with these grades making them willing to pay a premium. It is notable that this strong effect is only observed on grade B and vacant, and as the effect of the other grades are not significant, it is difficult to deem if their effect is caused by random noise or not.
When comparing the inter-grade effects between lots, it is notable that a grade B lot will on average receive a higher premium than a grade A lot (around 18-9% depending on the rent to guide price), except when the guide price indicate a high rent/guide price ratio where a slight negative effect (-0.43%) on the premium is notable. When comparing inter-grade effects between grade-A and vacant lots, the effect is the opposite; for mean- to high- rent to guide price lots, a vacant lot receives 11.6%-26.2% lower premiums than a grade-A lot, and for low rent/guide price ratios vacant lots will actually receive a slight 3% premium above the guide price as compared to a grade-A lot. It is quite important to note that an absolute majority of vacant lots transacts in the interval of ex-ante 0-3% rent to guide price, thus the marginal effect of the inter-grade comparison should be analysed at those levels, where the average premium is close to 15% higher than for a grade-A lot.

4.4 Other independent variables

As explained in Method, a number of variables were also included in the models in order to control for exogenous factors and increase the explanatory power. As seen in the below extract of the regression tables (table 12 and 13), following control variables was included: dummy variables for time and auction venue, the lot number (a.k.a. lotno – a variable telling when during the auction the lot was auctioned), as well as a property macro index based on the all property IPD index in the UK area (which is an index of property returns of directly held properties).
Table 12. Marginal Effects of the control variables, excluding the time dummies

<table>
<thead>
<tr>
<th>Variable</th>
<th>Regression 1: Sale Probability</th>
<th>Significance</th>
<th>Regression 2: Net Initial Yield</th>
<th>Significance</th>
<th>Regression 3: Price Premium</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>lotno</td>
<td>-0.000357</td>
<td>***</td>
<td>-1.59E-06</td>
<td></td>
<td>0.000782</td>
<td>***</td>
</tr>
<tr>
<td>previous_auction_liquidity</td>
<td>9.21E-09</td>
<td>***</td>
<td>2.68E-11</td>
<td></td>
<td>1.18E-09</td>
<td></td>
</tr>
<tr>
<td>property_macro_index</td>
<td>-0.029676</td>
<td>***</td>
<td>0.0002286</td>
<td>***</td>
<td>-0.0028569</td>
<td></td>
</tr>
<tr>
<td>Venue: Le_Meridien</td>
<td>-0.332105</td>
<td>***</td>
<td>0.001133</td>
<td></td>
<td>-0.0319763</td>
<td></td>
</tr>
<tr>
<td>Venue: The_Berkeley_Wilton</td>
<td>-0.1382337</td>
<td>*</td>
<td>-0.0066376</td>
<td>*</td>
<td>-0.0445249</td>
<td></td>
</tr>
<tr>
<td>Venue: The_Cafe_Royal</td>
<td>0.4738799</td>
<td>***</td>
<td>0.0034124</td>
<td>*</td>
<td>-0.0261218</td>
<td></td>
</tr>
</tbody>
</table>

**Lotno**

The lotno, or the number at which the respective property was being sold at during the auction, proved to be a significant factor at the 1%-level in determining the probability if sale as well as the price premium. An increase in lotno, that is – the later the lot is being called during the auction-event – the lower the probability of it becoming sold. A lot that is being called out as number 100 has a 3.5% lower probability than the first lot of getting sold, on average. At the same time, the number 100 receives on average a 7.8% higher price premium.

**Property Macro Index**

**Picture 5. Auction Net Initial Yields and the IPD index and Auction Transaction Volume from Allsop’s auctions**
The UK IPD property macro returns index was another variable that was included in order to take into account the effects of macro property returns and proved to be significant at the 1%-level both in determining sale probability as well as the initial yield for the lot at auction. The index was designed to start at 100 at the first auction event of 7th of February 2007. An increase of the index by 1 would on average decrease the sale probability by approximately 3%, while it would increase the average net initial yield by 0.2‰.

*Previous Auction Liquidity*

The previous auction liquidity, which is a variable of the total amount raised during the last event, proved to be significant in explaining the sale probability. The larger the volume of last event, the higher the probability of sale during this event. A change in £5,000,000 is on average affiliated with a increase in probability of a successful auction by approximately 5%.

*Auction Venue*

The auction venue variable is a dummy variable of the location of the auction event, and was implemented in order to control for external effects linked with changing the locale of the event. As indicated in table 12, the auction venue do in fact significantly (at 1% alpha level) affect the probability of sale. The effect of having the auction at Le Meridien instead of the Park Lane Hotel, the probability of sale went down almost 33%, and when the for the similar comparison of moving to The Cafe Royal comparable probability went up 47% on average. However, it is important to note that the data only contain two auction-occasions at Le Meridien with 118 auctions in total.
Time Effects

Table 13. Regression coefficient results of the time dummy variables

<table>
<thead>
<tr>
<th>Date</th>
<th>Regression 1: Sale Probability Coefficient</th>
<th>Regression 2: Net Initial Yield Coefficient</th>
<th>Regression 3: Price Premium Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Significance</td>
<td>Significance</td>
<td>Significance</td>
</tr>
<tr>
<td>okt-12</td>
<td>0.2731481 ***</td>
<td>-0.001532</td>
<td>0.122207</td>
</tr>
<tr>
<td>jul-12</td>
<td>0.2271521 **</td>
<td>-0.0005512</td>
<td>0.0683809</td>
</tr>
<tr>
<td>maj-12</td>
<td>0.0749303</td>
<td>-0.0031095 *</td>
<td>0.1146489</td>
</tr>
<tr>
<td>mar-12</td>
<td>0.2570261 ***</td>
<td>0.001202</td>
<td>0.0731756</td>
</tr>
<tr>
<td>feb-12</td>
<td>0.2229581 **</td>
<td>-0.0004585</td>
<td>0.0662421</td>
</tr>
<tr>
<td>dec-11</td>
<td>-0.0624624</td>
<td>0.0029908</td>
<td>0.0577792</td>
</tr>
<tr>
<td>okt-11</td>
<td>-0.0587644</td>
<td>0.0002118</td>
<td>-0.0402771</td>
</tr>
<tr>
<td>jul-11</td>
<td>0.0537946</td>
<td>-0.00033</td>
<td>-0.0031064</td>
</tr>
<tr>
<td>mar-11</td>
<td>-0.138123 **</td>
<td>0.0007604</td>
<td>-0.0019491</td>
</tr>
<tr>
<td>feb-11</td>
<td>-0.1952306 ***</td>
<td>-0.0026805 *</td>
<td>0.0332928</td>
</tr>
<tr>
<td>dec-10</td>
<td>-0.3588423 **</td>
<td>-0.0012574</td>
<td>-0.0384984</td>
</tr>
<tr>
<td>okt-10</td>
<td>-0.2524127 **</td>
<td>0.0017758</td>
<td>-0.0277565</td>
</tr>
<tr>
<td>maj-10</td>
<td>-0.2779871 **</td>
<td>0.003223 **</td>
<td>-0.0737768 **</td>
</tr>
<tr>
<td>mar-10</td>
<td>-0.3558078 **</td>
<td>0.0015459</td>
<td>0.0551073</td>
</tr>
<tr>
<td>feb-10</td>
<td>-0.6085494 ***</td>
<td>0.0000526</td>
<td>-0.0260789</td>
</tr>
<tr>
<td>dec-09</td>
<td>-0.9122964 ***</td>
<td>0.0060865 ***</td>
<td>-0.1595778 ***</td>
</tr>
<tr>
<td>okt-09</td>
<td>-0.7919611 **</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>maj-09</td>
<td>-0.5882972 ***</td>
<td>0.0117583 **</td>
<td>-0.0280931</td>
</tr>
<tr>
<td>mar-09</td>
<td>-0.6652156 ***</td>
<td>0.0033017</td>
<td>-0.0076249</td>
</tr>
<tr>
<td>feb-09</td>
<td>-0.4348919 **</td>
<td>0.0031053</td>
<td>0.0047497</td>
</tr>
<tr>
<td>dec-08</td>
<td>-0.4421735 ***</td>
<td>-0.0009204</td>
<td>-0.009691</td>
</tr>
<tr>
<td>okt-08</td>
<td>-0.3914365 ***</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>jul-08</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>maj-08</td>
<td>-0.6644394 ***</td>
<td>-0.0035365</td>
<td>-0.0900878</td>
</tr>
<tr>
<td>mar-08</td>
<td>-0.351759 ***</td>
<td>-0.0050362 ***</td>
<td>0.0138668</td>
</tr>
<tr>
<td>feb-08</td>
<td>-0.5160527 ***</td>
<td>-0.0064106 ***</td>
<td>-0.008529</td>
</tr>
<tr>
<td>dec-07</td>
<td>0</td>
<td>-0.0088558 ***</td>
<td>-0.019979</td>
</tr>
<tr>
<td>okt-07</td>
<td>0.2917416 ***</td>
<td>-0.001512</td>
<td>0.0461499</td>
</tr>
<tr>
<td>jul-07</td>
<td>0.325015 ***</td>
<td>0.0027123 *</td>
<td>-0.0686358</td>
</tr>
<tr>
<td>maj-07</td>
<td>0.1219359 ***</td>
<td>0.0010973</td>
<td>-0.0507256</td>
</tr>
<tr>
<td>feb-07</td>
<td>0.3385313 ***</td>
<td>0.0011919</td>
<td>0.1584829</td>
</tr>
<tr>
<td>dec-06</td>
<td>0.5748787 ***</td>
<td>0.0021987</td>
<td>-0.1319475 ***</td>
</tr>
<tr>
<td>okt-06</td>
<td>-0.0351678 ***</td>
<td>0.0023011 *</td>
<td>-0.0529438</td>
</tr>
<tr>
<td>jul-06</td>
<td>-0.1353303 ***</td>
<td>0.0033095 ***</td>
<td>-0.0773817 *</td>
</tr>
<tr>
<td>maj-06</td>
<td>-0.1401847 ***</td>
<td>0.0049424 *</td>
<td>-0.0206332</td>
</tr>
<tr>
<td>mar-06</td>
<td>-0.0782384 ***</td>
<td>0.0049076 *</td>
<td>0.0371626</td>
</tr>
</tbody>
</table>

Red: time effects are positive, green: time-effects are negative or small

The time dummy variables were included in order to control for time-effects. In the sale probability regression (1), the time effects are quite big, and in general very significant, as compared to regression 2 and 3. Especially at the time period during the financial crisis - starting September 2008, peaked during late -08 and 2009 and continued on into 2010 – it is notable that the coefficients during that time is consistently negative (marked in green) with large negative effects on probability of sale, peaking at December 2009 with a negative 91% as compared to December 4 2012. The same positive/neutral effect (marked in red/white) can be noted before and after that period. Meanwhile, the other two regressions does not provide the same pattern, suggesting that they are not as exposed to external effect over time.
5. Discussion

In this discussion the results will be analysed, and a discussion regarding the implications, applicability, validity and future research will be conducted.

Causality

Regarding the reliability of logical causality regression results one must see to the different effects the variables have on one another. The INUS (Insufficient, but Necessary part of an Unnecessary but Sufficient condition) conditions for a necessary cause poses that the effects in the independent variable X are necessary causes of the effects in the dependent variable Y, however the reverse implication does not apply. For a sufficient cause, an effect in X is sufficient (but not necessary) for an effect in Y, for there may be another variable Z that causes Y to move (Mackie, 1965). This is also what is referred to as omitted variables.

Since the regression models 1-3 cannot explain all movements in the sale results there are either omitted variables - suggesting that the variables included (investment grade and guide price) are an unnecessary but sufficient complex of the movements in sale probability, initial yield and price premium – or random noise causing the models not be perfect in explaining the sale metrics. However, it is always difficult to say if the effects on the dependent variable just happen to correlate, if there is a causal connection or if there is some of both. If, for example, the guide price yield and the resulting yield would be a case of non-causal correlation, then the pricing of the bidders would not change at all if that information (guide prices) would be omitted. The way to check for this is through an out-of-sample prediction. However, as this is not a study focused on predictions, this research does not include such predictions. However, one can with understanding assume that the independent variables do have causal effect on the yield: The more info that is omitted about the object to the bidder, the more the bid become a ‘guess’ for the bidder, and therefore it is likely that this would result in more dispersed reservation prices of the bidders. In the extreme, (where the bidders receive no/very little info about the lot) the bidders price distribution would assumingly almost completely flat, due to the ambiguous nature of such auction, as the valuation assessment of the object now would be much more difficult (similar to a lottery-situation). In this case it would make sense that sheer correlation to occur through such vast amount of observations is unlikely. Thus, the conclusion is that the author in the Discussion section can assume causality, and not only spurious correlation.
The Guide Price Yield/Rent to Guide Price ratio

As explained in the methods section, the rent to guide price – ratio was created in order to make the data relevant as a relative ratio instead of an absolute measure, since the latter doesn’t really indicate if the valuation is relatively high or low compared to rental income. Just as with the metric “yield”, or “cap-rate” in property valuation, the rent to guide price ratio should reasonably be interpreted as a measure of risk and growth, since it inherently capture both performance value and income as derived by the Gordon formula\(^7\) of perpetual income streams.

The Investment Grades

Since the investment grades were constructed as dummy variables (as opposed to parameterized variables), their coefficients’ interpretation is how a grade B, grade C, multilet or vacant property compares to an A-graded property, while everything else is equal. Furthermore, it is important to note that the label Multilet and Vacant is not an actual grade, but rather a label of the buildings present tenant-state. So far, it has been assumed that these two are at the “bottom” of the grade scale (meaning highest risk investment). However, their average transaction yield poses that Multilet buildings are viewed as more “safe” from an investor perspective, as their average yield from the transaction lies between grade B and grade C (yet, they have still the lowest probability of sale). The same comparison is not adequate to do with vacant buildings, since their yield will inherently be low due to completely or partial lack of rental income. Furthermore, vacant-labelled buildings had very high premiums and high probability of sale, which is indicating a discrepancy between guide-price yields and transaction yields.

5.1 Regression 1

When addressing regression 1, it is quite important to sort out what sale probability means. In a general sense it is the probability that someone in the population of bidders have a reservation price above the sellers ditto, and therefore makes the decision to bid. Intuitively, it would therefore make sense to include the size of the population of bidders that are attending the auction. Unfortunately that data is not available, but it would certainly turn out to be an important factor, as earlier studies have suggested.

\[ PV = \frac{CP}{r-g}, \text{ where } r-g = \text{yield} \] (Gordon & Shapiro, 1956)
As seen in the results from regression 1, an increase in the guide price yield by one percent lowers the probability of sale for grade-A, Grade-B and vacant buildings, while it increases the probability for grade C and Multilet buildings. Since the different grades on average transact at different indicated guide price yield – as depicted in picture 6, the average yield is distributed as following (in increasing order): Vacant, Grade A, Grade B, Multilet and lastly Grade C – it seems as though the negative marginal effect of an increased guide price yield decreases and starts to increase between 7-8% (i.e. between the average rent/guide price – ratio of grade B and Multilet buildings. The implication of this is that the function is not linear inter-grade wise and as can be observed in picture 6; the highest probability of sale is for an A-graded lot with a low implicit guide price yield, while the lowest sale probability is for a Multilet lot with a signalled guide price yield of around 7%.

Still, when comparing lots at the same guide price-yields, downgrading a lot from A to any of the other will always lower the probability of sale. This either means that the bidder in most cases prefer to bid on a property with the highest grade and (for the most cases) low yields (i.e low-risk objects), or it means that the sell side (auctioneer and seller) are consistently better in selling an A-graded property (through e.g. pricing strategy and marketing). Whether this is due to inefficient ex-ante pricing (i.e. lower graded objects have a too high guide price, or A-
graded objects a too low pricing), time on the market, marketing costs etc. is difficult to say, however it is a clear indication that the sell side is doing a better job in auctioneering A-graded properties.

When looking at bidder behaviour in terms of probability of sale, it is interesting that the bidder seem to react on external factors, such as the auction location, when during the auction the object in question is called, property macro market effects as well as time effects. All those were significant in explaining bidding behaviour providing evidence that the bidder might be making a contextual analysis of owning the object.

5.2 Regression 2

It is clear from the results from regression 2 that an increase in ex-ante guide price yield will on average result in an increase of the net initial yield, regardless of the grade (even though the effect is different within different grade, as well as inter-grade wise). The result gives a clear indication that the bidders’ response of the value signal is very important when determining their individual value. The effect of a 1%-change in rent/guide price –ratio is around 0.8%, which raises the question why the effect is not a 1:1 ratio. What is clear though, is that the ratio comes closer to a 1:1 relationship (actually the relationship is 100:87) for a lot with relatively low rent to guide price (when around 0-5%), and decreases to almost a marginal effect of 0.7% of initial yield per each 1%-increase in guide price yield. In other words, the marginal effect of an increase in guide price yields stagnates a little when increasing. This might be an effect of that the bidders are listening less on the valuation by the auctioneer on relatively risky objects than when they bid on a “low-risk” object.

Equivalently, an A-graded property will on average sell for a lower yield than a property with a B-grade, C-grade, a multilet property or a vacant property. However the difference in marginal effects on the yield is very close to zero for vacant properties and for properties with high ex-ante rent to guide price ratios. This effect is quite expected since vacant and grade-A lots both transact at low guide price yields, and the other grades transact on average at higher rent/guide price-ratios. These results indicate that the winning bidders do trust the grade when determining their price, however, only when they simultaneously assess the guide price yield (note that the significance in table 3 is not very convincing except for grade B and –C lots as compared to the rent to guide price).
5.3 Regression 3

A price premium is the difference of the final auction price, which the bidder pay the seller, less the guide price given by the auctioneer and seller. The resulting allocation of the surpluses determines if the auction is a case of the winners curse or arbitrage, and if the pricing strategy was effective. If it is the winners curse, the winning bidder paid more than the market value, and the arbitrage occurs when the winning bidder has information about the object that the market doesn’t, which increases it’s inherent value, in which case the market and the auctioneer was undervaluing the object and the winning bidder receives a positive NPV. In this case both the seller and the buyer perceives a received surplus, due to the asymmetric information.

Receiving a price premium is never the final incentive of the sell-side, since both the seller and auctioneer maximises their surplus by maximising the total amount by which the lot sell, and not by maximising the auction price premium. The price premium is (partly) rather a result of the pricing strategy, which is set in place in order to get the lot sold with an as beneficial outcome as possible. There are a number of strategies, such as the “loss-leading”, predatory pricing, premium pricing etc. (Monroe & Della Bitta, 1978). This report aims not to study which one is utilized or most efficient, but simply to state how the price premium was affected by the initial value signals.

As suggested by the F-tests in section 4, the price premium is less significantly explained than the sale metrics modelled in regression 1 and 2. The only occasions that fulfilled statistical significance was the simultaneous marginal effect of the rent to guide price and a grade B lot, as well as the simultaneous marginal effect of the rent to guide price and a Vacant lot simultaneously. Otherwise one could not reject that the marginal effect on price premiums from a grade-shift or a rent to guide price change was zero, on average. With this being said, the implications of the coefficients are that an increase in rent to guide price within the grades B and Vacant were strongly negative on the price premiums. At the same time, comparing the price premiums of an A-graded property with that of a grade-B property, the premiums increased by 10-20% when switching to the latter for rent to guide prices in mid-low ranges (see table 8). A positive effect was also notable for the similar comparison between a vacant and a grade-A lot (at low rent to guide price-ratios). This could be an indication that the bidders perceives a surplus opportunity in these particular lots; properties graded B with low indicated rent to guide price, as well as vacant lots at low ex-ante guide price yields. It could
also be an indication that the sell-side on average has a strategy for these particular lots that effectively is working.

5.4 Applicability and Validity
When determining to which datasets for which these models are externally valid, it is important to know what data was used and how. As described in the Data section, only commercial properties sold on auctions in the UK was used. Thus, it is adequate to apply the model predicting future results for the same type of transactions. However, whether or not the auction has to be in the UK for the models to be externally valid is more difficult to answer, since it may be problematic to deem whether bidders in the UK compared to elsewhere behaves differently, due to cultural reasons or risk behavioural reasons (etc.).

When it comes to the applicability of the model, the R-squared measure is quite important, as it tells us how far from the actual values the model estimations are. The higher the R-squared, the better the model estimation. As stated earlier in the Results-section, this means that regression 1 & 3 are not that good in estimating results, whereas regression 2 is much better in estimating yield movements.

Bias: Simultaneous causality, Sample Selection, Error-in variables and Functional Form
When it comes to the validity of the study, a majority of the established threats can be neglected due to the source of sampling. For example, Simultaneous causality bias is highly unlikely as the chronological order of the variable-generation is quite intuitive; first the investment grade and guide price is generated, and then the price at auction is established. Error in variable-bias is another bias that can be more or less ignored, as the data is not a questionnaire where the respondent has room to generate errors (there should be no incentives in destroying information during the data gathering). Surely, there might be some errors in creating the data-spread sheets, such as typos or equivalent, but due to the amount of data such errors have quite small effects. One could also discuss if there is a sample selection bias, as the data was collected during a market top, a crash and then proceeded through the current bull-market situation. However, this was controlled for with the IPD variable, which in any case seemed uncorrelated with the auction variables, which should conclude that it brings little useable information that should be added to the model.
Due to the number of variables that were included, the linear OLS is the functional form with the most intuitive explanation when assessing the marginal change in Y for a one-unit change in X. When it comes to the probability of a successful sale at auction, the probit model is a commonly utilized model in academia, and one of the most appropriate models to apply as it fits the probability of a binary variable better than a straight line.

*Omitted Variables Bias*

The low explanatory power of regressions 1 & 3 suggests that the investors’ decision in whether or not to invest (that is, whether or not to make a bid) is little influenced by the guide price or investment grades signalled by the auctioneer and/or seller. The regressions do show, however, in which way these factors push the sale probability on average. Now, it is important to note that the low R-squared is not entirely due to omitted variables: another important factor is random noise, i.e. the random fluctuations in prices.

As suggested by earlier studies, one such omitted variable might be number of attendees at the auction. Another variable, which would be easier to quantify, could be the amount of marketing of the lot put forth by the owner, which suggestively would increase the probability of sale.

By the yield regression (2), the results suggested that the bidder does in fact take the guide price into account when making up his individual pricing. However, the model predicting the price premium (3) didn’t explain its movements very well, as shown from its low $R^2$ metric. Similarly to the sale probability model, there are other factors, omitted in this model due to lack of data, which are driving and influencing the price premium, i.e. the valuation when the winning bidder puts his bid above the guide price opinion.

**5.5 Future Research**

When assessing future research, it is important (as always) to determine the purpose of the research. When examining the sellers’ signals or marketing, and the auctioneers’ valuation; including as many variables as possible is always important (as long as multicollinearity is avoided). One of the biggest challenges is the lack of substitutability for properties due to their individuality. Quantifying this factor is quite difficult and may even not be possible. One of the conventional way of dealing with this problem is to use appraisals made by professional
appraisers, which in this research have been the case to the extent possible (since the guide price is not really the same as an appraisal).

One factor that more easily can be included in order to control for exogenous factors is the marketing cost incurred with the auction for the seller, which is a factor independent from the valuation that should affect the resulting price. Another such factor is the amount of attending bidders during the event or amount of bidders for the particular lot being called (as done in the study by Hungria-Gunnelin (2012)). Furthermore, different bidding tactics can affect price premiums, thus the quantifications and implementation of these in a study might also be useful (Cremer & McLean, 1988).

Of course, future studies examining more qualitative aspects of the auction could include interviews of the sellers as well as the buyers in order to establish which incentives that drives the bidding, and studies examining not only statistical but also behavioural aspects would add to the existing body of knowledge (such as the study by Dholakia & Soltysinski (2001))
6. Conclusion

The highest probability of sale is for an A-graded lot with a low implicit guide price yield, while the lowest sale probability is for a Multilet lot with a signalled guide price yield of around 7%. This either means that the bidder in most cases prefer to bid on a property with the highest grade and (for the most cases) low yields (i.e low-risk objects), or it means that the sell side (auctioneer and seller) are consistently better in selling an A-graded property. Furthermore, the bidder seem to react on external factors, such as the auction location, when during the auction the object in question is called, property macro market effects and time effects.

The buying bidders’ pricing follows the sell-side signalled valuations (the guide-prices) with strong correlation. Furthermore, an A-graded property will on average sell for a lower yield than a property with a B-grade, C-grade, a multilet property or a vacant property. The effect on yield of a 1% change in ex-ante rent/guide price ratio is around 0.8%, which raises the question why the effect is not a 1:1 ratio; i.e. For two similar objects having difference in signalled guide-price, the bidders dare not change their valuation as much as the sell-side have indicated that they think they should. Another effect is that the bidders are listening less on the valuation by the auctioneer for more risky objects than when they bid on a “low-risk” object.

An increase in rent to guide price within the grades B and Vacant have a strongly negative impact on the price premium. At the same time, comparing the price premiums of an A-graded property with that of a grade-B property, the premiums increased by 10-20% when switching to the latter by around, depending on the size of the rent/guide price-ratio. A positive effect was also notable for the similar comparison between a vacant and a grade-A lot (at low rent/ guide price-ratios). This could be an indication that the bidders perceives a surplus opportunity in these particular lots; properties graded B with low indicated rent to guide price, as well as vacant lots at low ex-ante guide price yields. It could also be an indication that the sell-side on average has a strategy for these particular lots that effectively is working.

All in all, it is definitely preferable to receive the grade A when you are selling your lot, and it seems as many investors tend to see possibilities (rather than risks) in vacant lots. This
reasoning, however, assumes that high price premium also implies high price over true market value, i.e. that the guide prices are on average the same as market value or constantly a fraction of the market value.

Works Cited


