Specification and Estimation of the Real Options Markup: The Case of Tanker Markets *

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Abstract

We propose structural models of investment for the econometric estimation of the real option markup. Count data models offer flexible specifications for bringing real option investment models to aggregate market data. The empirical results for oil tanker investment data are supportive for the proposed structural models, as well as the real option hypothesis. We find that the sensitivity of investment to the real option rule is much higher than expected. Finally, this framework may be applied for any industry and provides a "trading volume" model for investment activity.

JEL Codes: C21, C31, C51 and C52, D21, D53

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1 Introduction

In the last years option theory has been important for economics and investment decisions. After the introduction of the "real option" value, implicit in investment decisions by McDonald and Siegel (1984), it has been well understood that uncertainty has a key role in investment. Under uncertainty and irreversibility (Dixit and Pindyck, 1994, p.142) the Net Present Value (NPV) rule is incorrect for evaluating investment decisions; uncertainty and irreversibility drive a wedge between the critical value of the project and the direct or tangible cost of investment. A great deal of theoretical work has stressed their role on investment behavior. Furthermore, there has been considerable research in the application of real options in entry and exit decisions.

However, few applications to specific investment models have been derived in this framework and empirical research has lagged considerably behind the theoretical contributions in this literature. Moel and Tufano (2002) use the real options model as a descriptor of exit decisions in the mining business. Research has also included empirical evidence on applications of real options with firm-level data, such as the explanation of asset prices, e.g. Quigg (1993), Berger, Ofek, and Swary (1996).

Moel and Tufano (2002) use firm specific data to test whether real options are a sufficient statistic for entry and exit decisions. However they forego issues of industry equilibrium, allow for subjectivity in the choice of the parameters, as well as firm heterogeneity. Introducing firm heterogeneity and parameter subjectivity casts doubt on the "survival" of the real option hypothesis under industry competition (Dixit and Pindyck (1994)).

Due to significant problems of aggregation the theory of optimal investment decisions has mainly been applied directly to a firm or an individual decision maker. There has been limited empirical work on issues of specification and estimation of real options investment models. The threshold rules derived for the the decision unit may not be invalidated if allowing for competition or endogenous equilibrium price processes. Furthermore, different firms may have different action thresholds and the implications of the theory at the industry level depend crucially on the market structure of the industry. Any real option ivestment model brought to empirical data - either on firm level or with aggregate market data - is therefore sensitive to the specification of the empirical model and the market assumptions.

In this paper we offer flexible structural econometric models for estimating the real option markup with industry level aggregate data. The price to be paid for the use of aggregate data is that the estimated markup depends on the model specification. This is demonstrated in the empirical part of our analysis where we bring our models to investment data in oil tanker carriers. Our choice of the tanker market is motivated by (Dixit and Pindyck, 1994, p. 237) and its competitive structure that leads to closed form parametric specifications for our models.

We believe we make a threefold contribution: we use the underlying theory in a proper empirical context (data and methods); we use a structural approach for modeling investment activity; the specification of our empirical models accommodate the estimation of the investment threshold and real options; we do all this in an encompassing framework, in the sense that our specification and estimation are well-defined within the context of our empirical model and the empirical model itself is well-defined within the context of economic theory. Furthermore, the merit of the approaches that we propose in this paper is that they maintain the use of industry level data as indicators of investment activity, and they accommodate structural estimation methods.

The rest of the paper is organized as follows. In section 2 we lay out the specification of our models of aggregate investment behavior; in section 3 we describe our data set and the specific characteristics of the tanker industry; in sections 4 we bring the model to the data discuss a variety of empirical results; we offer some concluding remarks and extensions to the current research in section 5.

2 Aggregate Investment Behavior and Econometric Specification

Investment orders are regularly provided in discrete count form. Furthermore, missing values at the industry level make the count data specification a natural choice. Introduced by Hausman, Hall and Griliches (1984) the latter offer a flexible specification that accommodates several market structures and issues of aggregation: the total number of investment orders (i.e. the total number of tanker vessels ordered in each period, houses constructed, machines ordered, say o_t) may be well assumed to follow a generalized Poisson process $\mathcal{P}(\lambda_t) \equiv \mathcal{P}(o_t; \lambda_t)$ with intensity depending on a set of factors, i.e. $\lambda_t \stackrel{\text{def}}{=} \lambda(\boldsymbol{X}_t)$. This parametric model may be estimated using the conditional Poisson model introduced by Hausman, Hall and Griliches (1984). This specification has been used by Becker and Henderson; following the "bottom-up" approach to investment decisions, Becker and Henderson (2000) argue that at each point in time, there is a supply of agents. This supply relation is upward sloping in positive NPV values. In our real options framework, NPV does not provide the correct rule under uncertainty and irreversibility and the supply of agents willing to commit themselves to investment decisions is a positive function of the optimal value under uncertainty, as derived by Dixit and Pindyck (1994) and Hausman (1999). As one moves up the supply curve, the mass of agents investing in projects has to be an increasing function of the difference between actual prices and from this critical value that triggers investment.

The reduced form equation for the count of investments b_{jt} in each period t for each agent j is a function of his value V_{jt}, which equals the value of the project minus the option to wait, namely:

$$b_{jt} \stackrel{\text{def}}{=} b(V_{jt}) \tag{1}$$

Then, the observable count of firm orders in each period t is the sum of the count decisions of each agent:

$$o_t \stackrel{\text{def}}{=} \sum_j b(V_{jt}) \tag{2}$$

Motivated by their discrete nature, we model the count of investment orders each period as a generalized Poisson process. Let us now assume that the probability that the most efficient operator $j = E$ will not undertake investment is given by:

$$P(V_{E,t} < 0) = 1 - P(V_{E,t} \geq 0) \equiv \frac{1}{1 + \exp(V_{opt,t})} \tag{3}$$

where $V_{opt,t}$ is the observable to the econometrician and stands for his entry value which is positive if the value of the cash of the project exceeds the option to wait and zero otherwise. The structural error that determines the specification of the above probability is due to the unobservables. Naturally this probability of no entry is a diminishing function of $V_{opt,t}$.

In a model of ordered entry where entry order is determined by value, the probability of the event "no new investment is observed in this period" is pinned down by the most efficient operator. If he doesn't undertake investment, no other operator will do so.[1] The above probability equals the probability of zero investment for the aggregate data that is implied by the Poisson specification

[1] The same argument is used by Berry (1992) in his study of entry decisions in airport hubs, where he defines the structural error that generates this specification as "ordered heterogeneity".

with intensity λ_t. From the Poisson specification, the probability that a zero investment count will be observed at time t is given by:

$$P(o_t = 0) = \mathcal{P}(0, \lambda_t) = \exp(-\lambda_t) \tag{4}$$

Equating equations (3) and (4) we obtain the following parametric form for the intensity:

$$\lambda_t = -\ln\left[P(V_{E,t} < 0)\right] = \ln\left[1 + \exp(V_{opt,t})\right] \tag{5}$$

Aggregate investment orders each period (which may correspond to entry decisions) are a count variable: Having assumed they follow a generalized Poisson process and that there exists ordering in entry we have derived a structural interpretation between the intensity of investment flows and the value function of the most efficient investor. Most importantly it offers a flexible framework for estimating the value function that triggers investment allowing for a variety of specifications of this value (parametric or semi parametric).

The model is simple, tractable and is similar to the "observed heterogeneity" model introduced by Berry (1992, p.899), where the probability that N agents invest is equal to the probability that N agents have a positive investment rule. The above approach is of generic applicability to any partial equilibrium model involving entry and exit decisions, provided that the conditions in Berry are satisfied. Specific assumptions on market organization and equilibrium pin down the appropriate investment rule for $V_{opt,t}$ and λ_t respectively.

Although the observed heterogeneity model offers a structural interpretation into the intensity of investment counts it requires the specification of the investment rule of the agent with the highest value. Let us now relax this assumption. We consider an equilibrium investment value observable to the econometrician (i.e. the outcome of a general equilibrium model) and the following probability of investment $P_{invest,t}$ due to the econometric error arising from unobservables:

The count of investment orders in each period o_t remains the sum of individually placed orders:

$$o_t = \sum_{j=1}^{n_t} b_{jt} \tag{6}$$

for a total number of n_t agents considering investment at time t. Assuming that n_t (which is random) follows a Poisson process $n_t \sim \mathcal{P}(n_t, \lambda_n(V_{opt,t})$, and that each new investment decision b_{jt} is an identically distributed Bernoulli trial $b_{jt} \sim Bernoulli(P_{invest,t})$, then the total number of investment orders o_t will follow a Poisson process with intensity λ_t, i.e. $o_t \sim \mathcal{P}(o_t, \lambda_t)$, where $\lambda_t = \lambda_n \cdot P_{invest,t}$; the full derivation of this result is given in the appendix. This specification allows a more flexible parametrization of the aggregate Poisson count model, since the number of agents, may depend on other variables, too. Then, the intensity of the Poisson process governing the total number of new orders o_t may be expressed in reduced form as:

$$\lambda_t = \exp(\ln(P_{invest,t}) + \boldsymbol{X}_t^{\top}\boldsymbol{\beta} + \gamma V_{opt,t}) \tag{7}$$

where we separate the effect of $V_{opt,t}$ and assign it a distinct coefficient γ for clarity. This model provides us a very straightforward parametrization of the Poisson model, which is the familiar exponential specification of the mean, and the main common practice in most empirical studies that deal with count data. This model provides the exponential specification for the intensity with a structural interpretation for the estimated parameters.

3 Real Option Markup Estimation: Tanker Investment Orders

3.1 The Tanker Industry

Having introduced the benefits of the count data specification for investment modeling and the sensitivity of the estimated parameters to the aggregating assumptions we focus on the problem at hand: employ the models for estimating the real options markup. We will do so by using for $V_{opt,t}$ (the value function observable to the econometrician) the specification of the real options framework.

The tanker industry offers a challenging framework for accommodating our objectives. The ship is the firm and shipping firms produce only one homogenous good (transportation services for oil), which they sell in the fully competitive freight rate market at market clearing prices. Tanker freight rates determine the revenue a ship earns for servicing a particular contract for a specified period of time; rates vary with duration and vessel type. However, they are fairly standardized and the market for one year time-charter contracts is fairly liquid. Time charter rates depend on the equilibrium between the supply of transportation capacity and the demand for transportation. To take account of the distance oil is carried ("average haul"), it is usual to measure sea transport demand and supply in terms of "ton miles". Both are quoted in terms of transported tonnage multiplied by miles (distance) and do not depend solely on the cargo shipped, but also on the average distance that goods must be transported. A ton of oil transported from the Middle East to Western Europe via the Cape creates two or three times as much demand for sea transport as the same tonnage of oil shipped from Libya to Marseilles. This distance effect corresponds to the average distance which explains why sea transport demand and supply is quoted in ton-miles. Demand in the tanker industry is exogenous, as transportation costs are a very small fraction of the value of the transported good and derived from the demand for oil. Finally, the projects are almost finitely divisible, as firm operators can adjust their transportation supply, by adjusting speed, demand is continuous and returns to scale are not increasing.

Although it may seem that significant real risks are associated with the operation of a tanker vessel (such as the loss of a tanker due to war, or running up on a shoal) the owner of the tanker may reduce risk by choosing to "fix" his vessel under a *time charter* contract. As discussed in Stopford (1991) "a time charter gives the charterer operational control of the ships carrying his cargo, while leaving ownership and management of the vessels in the hands of the owner." When on charter, the owner (investor) is liable only for the operating costs (crew, maintenance and repair) and the charterer directs the commercial operations and pays all voyage expenses. With a time charter, the investor has a clear basis for evaluating the value of the vessel, as well as his option to wait. The duration of a time charter contract varies, but since the most liquid contract is the one year rate, we assume that investors undertake their calculations, using the one year contract. Since the payoff of operating a ship is fairly straightforward (it is determined by the time charter rate minus the operating costs, defined precisely in Stopford (1991) and time charter risk is spanned in financial markets, the assumption of complete markets, seems realistic. The value of the vessel and the option to wait, are then fully determined by the assets traded in financial markets. The ship is the firm and firm heterogeneity arises from differences in running costs among heterogenous operators, as well as the ability of the manager to achieve a long term time charter rate for the ship, before placing the order to the shipyard[2]. Heterogeneity in operating costs (especially crew and repair) are unobservables to the econometrician and account for the presence of the structural error, that makes entry decisions in this market non degenerate.

A vessel under time charter hire will supply transportation capacity, and receive in exchange

[2]This method was introduced by Aristotle Onassis: He first agreed on a long term fixed rate from the shipper and then ordered the ship. In some sense this was one of the earliest collateralized debt obligation structures.

a profit flow $P(t)$, which depends on the time charter rate and the operating costs of each vessel. Time charters differ only across categories (we will define five categories of vessels based on category classification later on), they are standardized and quoted by fully organized brokers in a very competitive environment. Ship owners differ only in operating costs, and they are price takers.

The source of our proprietary data is Marsoft, (Boston) Inc. and it is the same source used by (Dixit and Pindyck, 1994, p.238).[3] Marsoft provided the *orderbook* (the orders placed for the construction of new vessels) for tanker ships (crude oil carriers). This data set is accurate and precise. The data set is in quarters from 1980 until 2002. We are given 91 observations for each type of tanker carrier. Given the five different categories for tanker vessels we have 455 observations. For this time period the data on time charter rates (R_t, the revenue earned per day under a on year time charter contract in U.S. dollars) are fully available and precise, as well as the prices of new vessels, I_t. As we discussed earlier, the operating costs (C_t, the expenses per day for operating a new ship in U.S. dollars (fuel costs, etc. are not paid by the owner under a time charter hire)) are fairly straightforward, but differ significantly among different operators. We use a representative average for operating costs, based on estimates of different consulting firms in the industry.

3.2 Real Option Investment Model Specification

The specification of $V_{opt,t}$ depends on the profit flow $P(t)$, which follows a geometric Brownian motion with growth rate α. The profit flow equals the prevailing one-year time charter rate for each category minus the estimates of different consulting firms for a representative level of operating costs. In line with standard real options analysis (Dixit and Pindyck, 1994) we assume the existence of a yield δ on a traded asset that replicates the "convenience yield" in $P(t)$. Furthermore, following the analysis in Dixit and Pindyck (1994, p.201) we assume exponential decay (which is standard in this industry) and a life span of the vessel of 30 years, which pins down the depreciation rate λ. Then the level of the profit flow that triggers investment becomes:

$$P(t^*) = (\delta + \lambda)\mu I(t^*) \tag{8}$$

where I_t is the cost of the project and μ is the real option markup which is bigger than one. Then

[3] The data were kindly provided by Dr. Arie Sterling, President of Marsoft, and Kevin Hazel.

the value function introduced in the previous section is a linear combination of profit flow and investment:

$$V_{opt,t}(t) = \theta P(t) - \mu I(t) \tag{9}$$

with $\theta \stackrel{\text{def}}{=} (\delta + \lambda)^{-1}$. The real option hypothesis in industry equilibrium suggests that $V_{opt}(t)$ should remain negative for all periods with zero investment and strictly equal to zero, only when some investment activity is observed. The rule $V_{opt,t}(t^*) = 0$ determines the price level that triggers entry. As this is clearly not the case we should reject the model with probability one.[4] However, unobservables in the technology of each firm (operating costs) leave space for the econometric error that makes estimation non-degenerate.

In the context of our model, we jointly estimate the model and the real options markup. This highlights the sensitivity of our estimates to model specification and the underlying aggregation assumptions. Our main motivation behind the choice of the tanker industry for estimation the real options markup is that most underlying assumptions made so far hold in the tanker industry, something that should make our results more palatable. Specifically, note:

- the perfectly competitive nature of this market, necessary for the validity of the myopic equivalence theorem;
- the existence of organized markets, necessary for completeness;
- the simple structure of pay-offs (time charter rates minus operating expenses) $P(t)$;
- the sunk nature of the costs of investing in a new vessel $I(t)$;
- the number of publicly traded shipping companies, which accommodates spanning of risks.

In line with the specific characteristics of this industry $V_{opt,t}$ will be hereafter the representative measure of the real option hypothesis investment rule observed by the econometrician:

$$V_{opt,t} = \theta_t P_t - \mu I_t \tag{10}$$

[4]This argument is similar with the econometric testing of the Black and Scholes formula for option pricing; only one price that departs from the BS formula suffices for rejecting the theory with probability one.

where P_t is the profit flow (time charter minus operating expenses) and I_t the investment cost for the new vessel. For each of the five category of ships the econometrician observes the sunk cost for investing in a new vessel I_t, a proportional dividend ratio δ_t (depreciation is predetermined from regulators for 30 years and thus $1/\theta_t = \delta_t + \lambda$), the time charter rate R_t for one year (which is publicly quoted) and an estimate for a representative level of operating costs, C_t. The difference of the latter two determines the profit flow $P_t \stackrel{\text{def}}{=} R_t - C_t$. According to the previous analysis, each firm, given its cost structure, will enter the market when $V_{opt,t}$ becomes equal to zero. However, since the operating costs are unobserved, this opens space for the econometric error, which is necessary for making econometric estimation non-degenerate: we assume that each firm has a threshold function that is contaminated by noise given by:

$$V_{jt} = V_{opt,t} + \epsilon_{jt} \tag{11}$$

To progress on the specification of equation (11) we proceed under the additional assumption that the marginal distribution of ϵ_{jt} is Type I extreme value; it is then well known, e.g. McFadden (1974), Rust (1987), that the choice probabilities of entry are given by the standard logit formula:

$$P(V_{jt} \geq 0) = \frac{\exp(V_{opt,t})}{1 + \exp(V_{opt,t})} \tag{12}$$

From the Poisson specification, the probability that a zero investment count will be observed at time t is given by:

$$P(o_t = 0) = \mathcal{P}(0, \lambda_t) = \exp(-\lambda_t) \tag{13}$$

Assumptions on the unobservables determine the probability of entry and the flow of entering firms in this partial equilibrium. Assuming firms are ordered in increasing costs and all of them face the same time charter rate (demand function) we build on the special case of Berry (1992) and consider ordered entry. As noted in Berry "such assumptions allow for probability statements on the order of entering firms. If more profitable firms enter first, then any ambiguity as to which firm will enter is decided in favor of the most profitable firm." Using Berry's model, according to which the most profitable firm moves first we derive the efficient operator specification, which provides the estimation and identification condition for the intensity of the Poisson process, as discussed in the previous section and an intuitive model of entry. On the other extreme, the econometric error is common across firms and consequentially the probability of entry is assumed the same for all investors, in the eyes of the econometrician. For the "ordered heterogeneity" model of entry introduced in the previous section, we derive the structural intensity of investment flows with the real option specification for the value function:

$$
\begin{aligned}
P(o_t = 0) &= P(V_{jt} \leq 0) \Rightarrow \\
\exp(-\lambda_t) &= \tfrac{1}{1+\exp(V_{opt,t})} \Rightarrow \\
\lambda_t &= \ln(1 + \exp(V_{opt,t})) \Rightarrow \\
\lambda_t &= \ln(1 + \exp(\theta_t P_t - \mu I_t))
\end{aligned}
\tag{14}
$$

note that the above specification implies several useful derivatives since we have that:

$$
\begin{aligned}
\partial\lambda_t / \partial V_{opt,t} &= P(V_{jt} \geq 0), \\
\partial\lambda_t / \partial P_t &= P(V_{jt} \geq 0) \cdot \theta_t, \\
\partial\lambda_t / \partial I_t &= - P(V_{jt} \geq 0) \cdot \mu
\end{aligned}
\tag{15}
$$

which connect the intensity of new orders with the markup μ and the dividend rate δ_t, which determines θ_t. Thus, market investment activity is an increasing function of the excess value implicit in investing in a new vessel (project), which is in line with our economic intuition.

The above specification is a structural link between the investment dynamics of aggregate level industry data with the parameters of the real option value. Furthermore it accommodates their estimation in a structural framework and demonstrates the flexibility offered by count data models. It should be noted that the specification is sensitive to the market and aggregating assumptions. Therefore, rather proceeding with the direct estimation of θ and μ we will test the specification of the model.

At this point it should be noted that although the real options investment rule depends on the market assumptions and characteristics, the econometrics models proposed in the next sections do not depend on the specification of the real option value and therefore may be easily generalized for the estimation of the structural value function in entry decisions.

For testing the models we will use $V_{opt,t}$ as an exogenous variable and then test the linear restriction imposed by the real option value on the parameters θ and μ. Let us now revert to the specification of the investment value, $V_{opt,t}$. We have followed closely Dixit and Pindyck (1994, p.238) and their discussion on tankers. We have implicitly assumed that the revenue process ($P_t = R_t - C_t$, charter rate minus operating expenses) follows a continuous time log-normal process. The drift of the process does not enter directly the value formula and the volatility of the process is the determinant of the real option multiple. The "discount rate" for the value of the project is the difference between the market risk-adjusted expected rate of return on the revenue process and the drift rate. This is explicitly discussed in Dixit and Pindyck (1994, p.174) and this difference δ is an opportunity cost of keeping the option to invest alive. Following Dixit and Pindyck we take the discount factor δ to be the basic parameter and let the drift and risk-adjusted rate of return adjust accordingly.

We start withe the following values for the parameters of $V_{opt,t}$: δ is taken equal to $\delta = 2\%$ and the depreciation rate λ is equal to $\lambda = 3\%$, since ships have an official life time of 30 years. There is, however, significant evidence that depreciation rates depend on market conditions in this industry. Dixit and Pindyck use a real option markup of $\mu = 2.5$ in their discussion, but this markup is correct only if depreciation is omitted. As pointed out in their table in page 204, the existence of depreciation lowers the markup. Therefore, for $\sigma = 0.2$ and the above parameters, the correct choice for the markup seems to be $\mu = 1.30$. Later on, we shall not impose any specific values on these parameters and instead we shall estimate the implied parameters. If the real option hypothesis holds, the implied parameters have to generate a μ at least higher than 1.

The specification in the construction of $V_{opt,t}$ imposes a linear restriction on the revenue and the price of a new vessel, $V_{opt} = \theta P_t - \mu I_t$. Once we have derived a correctly specified model, estimating θ and μ corresponds to testing the robustness of this linear restriction implied by the real option theory. Before proceeding with the first model we should note that the number of ships ordered each quarter t from 1980 until 2002 is split in five different categories: Handymax, Panamax, Aframax, Suezmax and VLCC's are the five different categories, classified on the transportation capacity of each category. The existence of different categories is mainly due to technical restrictions on size and draft for specific routes and does not have economic implications.

4 Estimation and Results

4.1 Model I

In the first model investment is observed only if the most efficient operator places an order. Assuming that the total number of vessels ordered follows a Poisson process, the intensity of the process is equal with the negative logarithm of the probability, that the most efficient investor does not enter. This probability is fully determined by the real option formula. Given the efficient operator identification condition, the probabilities defined in (12) and (13) are equal and determine the structural intensity λ_t of the Poisson process of new investment orders. Since we observe quarterly data and we do not know the decision-making frequency of the most efficient operator, we add a constant term in the exponential specification. This model is restrictive since it imposes a coefficient of unity for the negative logarithm of the probability of zero investment. We proceed with estimation by pooled maximum likelihood estimation, in line with Hausman, Hall and Griliches (1984). The data on new orders contain 455 observations with 65 zero counts and the maximum value of ships ordered in one single period is 66 (for small size Handymax vessels). Although our data set contains a significant number of zero orders, the average of ordered ships is 7.55 and the associated average DWT (deadweight tonnage) is 0.71 million tons. There are two interesting observations: On the one hand, the larger the tonnage category of the ship, the less the order counts observed in each period, and on the other hand in the two "bull" regimes of particularly high freight rates investment "counts" appear to be high. This is the main reason why, despite the big number of zero counts (approximately fifteen percent) the average number of ships ordered is 7.55 . Another crucial fact is that for all our observations, time charter rates are always significantly higher than operating costs. *However investment counts are positive, only when charter rates are significantly higher than operating costs.* This indicates that uncertainty has a significant effect on investment decisions and provide supportive preliminary evidence for choosing the real option value as an investment statistic.

Insert Table 1 here

Results of estimation are displayed in Table 2. We perform pooled Poisson maximum likelihood (MLE) using as a regressor the negative logarithm of the "no-investment most efficient operator" probability and compare it with the Non Linear Least Squares (NLLS hereafter) estimates under the exponential specification and with robust standard errors.

Insert Table 2 here

The use of QMLE leads to a significant improvement of the fit of the model; a Hausman specification test, Hausman (1978), between the two estimators (NLLS and MLE) yields a test value of 1.65. To allow for possible overdisperion and unequal conditional mean and variance, we then estimate the parameters using a Negative Binomial (NB) specification, which improves the likelihood even more. Performing some diagnostic tests we find that the Poisson specification fails to capture both the zero counts, as well as the excess counts observed for very high investment values observed in our data. The appropriate Pearson statistic normalized for the 454 degrees of freedom yields a value of 74.92, which is supportive for the excess overdispersion of the data set. Furthermore, the "Goodness-of-fit" statistic is 3447.15, and rejects the Poisson specification with a p-value of 0 (to four decimals). Finally, the likelihood ratio for the parameter of overdisperion of the negative binomial, rejects the null hypothesis of no-overdisperion and estimates the relevant parameter of the NB distribution equal to $\alpha = 1.08$.

Before proceeding with testing the second model, we consider fixed and random effects models.[5] The fixed effects model introduces a constant term for each of the five categories of ships. Intuitively, this implies that the frequency of investing orders differs among category. The random effects model assumes heterogeneity among category. Following Hausman, Hall and Griliches (1984), a Beta random effect specification is adopted, that leads to a closed form formula for the maximum likelihood. The introduction of multiplicative effects across different categories corresponds to an intercept shift, which holds only for the exponential mean specification and occurs due to different frequencies of decision-making. Results are displayed in Table 3, where standard errors are reported. For a more formal derivation of the Fixed and Random Effects Specification see Cameron and Trivedi (1998, p.275).

Insert Table 3 here

The coefficient of the inverse probability is now slightly higher than in the previous specification and the Log-likelihood is significantly higher. All estimated coefficients remain statistically significant. The Hausman test between Poisson Random and Fixed effects does not reject the Random Effects specification,and the same result is verified for the Negative Binomial Random and Fixed effects specification. The Likelihood Ratio test of the Negative Binomial Random Effects specification versus the pooled estimates follows a $\chi^2(1)$ with value 223.30, which indicates that the NB specification is far more suitable. Finally, by inspecting the predictions of the model it is clear that it captures successfully the low and zero counts, but it systematically fails to predict the excess counts observed at the peak of the shipping cycle. Although the coefficient of the

[5] For a detailed discussion of fixed and random effects see Cameron and Trivedi (1998).

inverse probability is statistically significant, the model does not explain the data and therefore it cannot be inferred whether it accepts or rejects the real options markup hypothesis. We therefore proceed with the estimation of Model II.

4.2 Model II

It is assumed that the probability of entry (namely of observing a positive count) is equal among all operators. As a consequence, the specification of the Poisson model has the form obtained from equations (6) and (7). Regarding the exogenous variables $\boldsymbol{X}_t$ that determine the expected number of investors, we use the following:

- $ship1$ a lag of the number of ships ordered one quarter before
- V_{opt}^2 the squared value of V_{opt}
- *accident* a dummy variable for the accident of *Erika* in December 1999[6]
- I the price of new vessels
- *lrate* since the predominant source of ship finance is the bank we also include the lending rate in the regressors
- $V_{opt,lag}$ a lag of V_{opt}

We now run Poisson likelihood estimation(with robust standard errors), NLLS, Negative Binomial with Random Effects and Ordinary Least Squares with robust errors. Results are reported in Table 4.

Insert Table 4 here

It is clear that the real option value appears statistically significant for the above specification. Conducting some diagnostic tests we find results similar to those for Model I: we reject the Poisson specification, there is still overdispersion un-accounted for by the Poisson specification, and there is some failure of the NB to predict the zero counts as well as some excess counts, especially for

[6] The accident of Erika in December 1999, which led to one of the largest oil spills in Europe, had a huge impact on the technical regulations on newbuilding vessels.

the lighter categories, where the most "excess events" are observed. What is even more puzzling is that V_{opt}^2 and I are statistically significant, which should not be the case under the hypothesis that V_{opt} is a sufficient statistic. As the model does not fully explain the data, before proceeding with Random and Fixed effects specifications, we relax the specification of V_{opt} and the dependency of our results on the associated parameters of δ and μ. V_{opt} is calculated as the profits from the one year time charter rates minus the operating costs discounted by the "dividend payout ratio" and the depreciation rate minus the newbuilding price, times the "real option" markup. As discussed earlier, it imposes a linear restriction on the time charter rate, the operating expenses and the price of new vessels, which is consistent to the real option multiple hypothesis, as long as the "discounted" value of operating income exceeds the tangible cost by a factor greater than one. This implies, that if we re-estimate the parameters of the above model, including the one year time charter rate, the operating costs and the newbuilding prices in the regressors, the estimated parameters for rates and costs should be of the same magnitude. It will then be checked if the implied estimated parameters are consistent with the real option multiple specification in equation (9) and the parameters we choose. This will provide the necessary robustness check with respect to the values we used for the specification of the real option formula, as well as the necessary intuition, before proceeding with more complicated models.

Insert Table 5 here

The results of the four different specifications, without imposing the linear restriction of equation (12) are presented in Table 5. It becomes apparent that for all four specifications, with the three variables that determine V_{opt} (the one year time charter rate, the operating expenses and the price of the new vessel), included in the regressors, are statistically significant. R_t is always positive and the other two variables are negative as expected. The magnitude of the coefficient of the operating expenses is of the same significance and slightly higher than the corresponding coefficient of the time charter rates, since costs incur, even when the ships does not earn revenue (in the port, dry-dock, etc.). Furthermore, R_t and C_t are on a $per-day$ basis. Thus if we calculate the difference of these two coefficients and multiply it by 365 days, the number we get is of the same significance as the coefficient of the newbuilding price I_t, but almost three times less, **exactly as predicted by the real option literature**. In order to make this point clear the estimation is repeated and instead of using R_t and C_t as regressors we use the value of the project Val (the discounted expected revenue for the geometric Brownian motion), which is given by the formula $V_{al} = \frac{R_t \cdot 365 - C_t \cdot 365}{\delta + \lambda}$ and then the coefficient of this variable is compared with the coefficient of I_t; the results are in Table 6. According to the real option multiple hypothesis, the coefficient of I_t has to be higher than the coefficient of Val, which is exactly the case. As observed by the results, the real option markup implied by the data (the ratio of the coefficient of I_t with V_{al}) indicates a value for μ much higher than 1, which either corresponds to an implied volatility for the underlying profit flow process much higher than 0.20, or implies a smaller discount factor δ and a smaller depreciation rate λ. For the exponential mean specification the Akaike information criterion (AIC) indicates that the model performs better when the real option value is used as a regressor (with a markup of 1.3 for the excess option value) than using R_t, C_t and I_t as separate regressors. It is now clear that on the one hand the optimal combination between the variables that determine the value of the project and the option to wait, is the one predicted by the real option literature and on the other hand, not much can be gained by assuming a time varying markup specification or different parameters for the specification of V_{opt}.

Insert Table 6 here

However, we still reject the Poisson specification in favor of the Negative Binomial; the corresponding Likelihood ratio test yields a statistic of 20.33. Before going on with Fixed effects and Random effects models, we will add some non-linear variables and check the robustness of the previous findings. If V_{opt} is indeed sufficient to explain the effect of revenues and cost on investment activity, non-linear transformations should not really add any explanatory power. Furthermore, it is argued that if the underlying process does not follow a lognormal distribution, then the excess option value is a non-linear function of the variables of the project. We thus include a number of additional regressors. Finally, in order to account for category-specific effects we repeat our estimation and include a dummy variable for the each of the five different categories (dwg dummy). The dummy takes a value of one if the data of the related category are used for estimation and zero otherwise. These results are displayed in Table 7 and reconfirm the robustness of our previous findings.

Insert Table 7 here

The intuition for including additional lags of ordered ships is the following: Previous lags (one quarter and four quarters ago, respectively) of orders are an indicator of the total tonnage on order. Especially since construction lags differ among shipyards we do not have a precise estimate of the tonnage on order. Tonnage on order is a good proxy for the number of agents in this industry. We therefore include previous lags in our regressors. Therefore *ship*1 and *ship*4 appear explanatory variables for the intensity of investors λ_n. What is impressive is that the magnitude of the coefficient of operating expenses is of the same order as the corresponding coefficient of time charter rates, which is in line with the real option linear restriction; finally all three variables that determine V_{opt} have the right sign and the hypothesis that the implied markup $\mu = 1$ is rejected with probability 1. Diagnostic tests still reject the Poisson specification, due to overdispersion. The Likelihood Ratio of the Negative Binomial Random Effects versus the pooled is still in favor of the NB-RE model. However, all Likelihood Ratio tests are supportive to the presence of the additional variables and the relationship between time charter rates, operating expenses and newbuilding prices is exactly the one predicted by the real option theory and with an implied average markup being close to 1.35[7]. Finally the fourth lag of ships ordered (one year ago) and the dummy for deadweight category appear very significant, as well as the square of the real option value. The significance of the weight dummy implies that carrier capacity has a negative impact on the demand for new ships and is in line with the absence of economies of scale in this industry. Different categories exist due to technical restrictions on draft and not due economies of scale. Having derived these encouraging results for the different re-parametrizations of the underlying theory, we go on with the negative binomial specification and Random versus Fixed effects tests.

Insert Table 8 here

We perform a Hausman specification test between the NB Fixed and NB Random effects specification, displayed in Table 8. If the RE model is correctly specified, then both FE and RE models are consistent, while if the RE are correlated with the regressors, then RE loses its consistency. The difference between these two estimators can be used as a basis for a Hausman test.[8] The statistic is $\chi^2(6)$ distributed and has a value 34.84 and we reject the RE specifica-

[7]The implied markup for the full parametrization is time varying and is calculated using the value of the project, the newbuilding price and the time charter rate.

[8]This test was introduced by Hausman (1984, p.921-928). For a detailed application of Hausman tests in count data methods see Cameron and Trivedi (1998).

tion. The NB-FE specification implies that there is a time varying effect, which accounts for the overdisperion of the data. The previous lags of ordered ships are statistically significant, as well as the time charter and operating expenses coefficients. The dummy for the *Erika* accident appears statistically significant and negative. This implies that new regulations for the construction of new tankers, imposed after the Erika accident, had a negative impact on investments in new tankers. This provides supportive evidence for the real option theory; regulation uncertainty increases the value of the option to wait and defers investment. Without taking into account the impact of regulatory uncertainty on the value of waiting, regulators and analysts expected that the new regulations would have a positive effect on the construction of new double-hull vessels, since all older vessels, past a certain age, were not allowed any more to operate in U.S. ports any longer. What appears statistically insignificant and makes the real option multiple hypothesis questionable, is the coefficient of the price of new vessels. There are two explanations for this finding. On the one hand it is possible that I_t has errors in variables. The price reported by the agencies is the average price of the ships ordered and it is reported by the shipyards. Since shipbuilding is heavily subsidized, it is possible that the reported prices do not include rebates or other "under the table" agreements. Another potential explanation is the endogeneity of I_t, as we explicitly discussed during the analysis of the supply side in our introduction. Both would lead to inconsistent estimates for the Negative Binomial specification. In order to test for endogeneity we use a set of instruments for the log of the price of new vessels and we then include the prediction error from this regression in the NB-FE specification. Finally we shall test for both endogeneity as well as autocorrelation. Both tests are Hausman specification tests and are fully discussed in (Wooldridge (2002), p.663)The set of instruments we use include the Standard and Poor's Oil Price index *spoil*, the crude oil price *oil*, the Standard and Poor's Air Transportation Index *air* and all other exogenous regressors. The reason we include the transportation air index is the following: on the one hand it is correlated with economic, trade growth and their associated transportation networks, but uncorrelated with the demand for new vessels and on the other hand it is a proxy for alternative modes of transportation.

We then repeat the estimation of the model under the NB-FE specification and we include the residuals of the projection of the price of new vessels on all the instruments and the exogenous variables in the regressors. The results are displayed in Table 9.

Insert Table 9 here

In order to account for possible autocorrelation we also include the lag of the predicted residuals. Under the hypothesis of non-autocorrelated errors, the lag of the estimated residuals is included in the regressors; a non-significant coefficient implies that the null should not be rejected. Results are displayed in Table 10.

Insert Table 10 here

Since both the residuals of the instruments, as well as the lag of the predicted residuals appear statistically insignificant, endogeneity, is rejected. Although the coefficient of I has increased significantly and the markup has been restored above one, the price of new vessels still appears statistically insignificant. In both Table 9 and Table 10 we have included the square of V_{opt}. If our claim is correct that the three variables that determine V_{opt} suffice to explain the number of orders, then any non-linear combination should appear statistically insignificant, which is the case indeed and may cast doubt on the linear restriction imposed. Having concluded on the econometric model that sufficiently explains our data we proceed with our main task; a specification test for the validity of the real option linear restriction. We therefore proceed and estimate the NB model using V_{opt} as an exogenous variable, instead of the price of new ships, time charter rates and operating expenses. This will allow us to compare the performance of the NB-RE and FE parametrization. The results appear in Table 11.

Insert Table 11 here

Now that we have derived the NB-RE and FE specification with V_{opt} as an exogenous variable we conduct a Hausman test, that clearly rejects the NB-RE specification. Having verified the significance of the terms that determine V_{opt}, as well as the specification of the model, we will test whether the linear restriction imposed by V_{opt}, is consistent. This is the final and most crucial step, in order to verify that μ is higher than one and the chosen parameters in the specification are supported by the data. Since we have specified the NB-FE both with V_{opt} in the regressors, as well as with the full parametrization of R_t, C_t and I_t (which does not depend on the particular parameters we choose in the specification of V_{opt}), we will test the imposed real option multiple hypothesis linear restriction. It is known from econometric theory, that if V_{opt} is correctly specified (in other words we have the correct relationship between R_t, C_t and I_t, namely the one derived in equation (9)) the estimates displayed in Table 11 are efficient. The full parametrization (Table

9, Table 10) is consistent under the alternative parametrization, where V_{opt} is not the optimal combination. We therefore conduct a Hausman test and the statistic is $\chi^2(6)$ and 1.62. We repeat this test for perturbations in the parameters that determine V_{opt} (namely δ and μ) and our results remain supportive for the real option linear restriction, especially for small distortions around our initial choices, which are consistent to the data in this industry. We therefore accept that the optimal combination is the one derived by the real option literature and accept the hypothesis, that namely the real option multiple and the empirical parameters used in our analysis of the tanker industry determine the rule that fully determines economic activity in this industry.

5 Conclusions

We propose count data models for aggregate investment activity with firm level data, with the real option value as a measure for investment flows. Specification and estimation of these models provide ample empirical evidence in favor of the real option multiple value for the tanker market industry: the value of a project as spanned in complete financial markets, once adjusted for the option to wait, is a sufficient statistic for characterizing investment decisions. In the case of irreversibility and investment under uncertainty, the correct specification for this value is the one expected by the real options literature. The value of the project not only has to exceed the investment cost, but also the option to wait. In the case of the competitive market for new tankers, the statistical results for the last 22 years have verified both these hypotheses. Furthermore we offer an empirical framework for estimating the value of waiting and the real options value markup.

We apply count data-based specifications that allow us to test the validity of the theory within a structural framework. Entry and exit decisions are by nature count data decisions. We proposed a consistent methodology for applying count data techniques for the empirical analysis of investment decisions with industry level assumptions. A partial equilibrium “ordered heterogeneity” model and a Poisson specification for aggregate decisions, suffice for the derivation of a structural intensity of entry. The derivation of the value function is left to the choice of the econometrician, but the proposed methodology remains intact. The implications of the theory are in the form of a unique linear restriction on the value function of a new vessel (risk discounted output prices (freight rates) minus costs) and the sunk cost, which is tested via a Hausman specification test. Our results lend ample support to the real option theory for this industry and are robust across a variety of different specifications.

Although the estimation is sensitive to model specification, market structure and aggregating assumptions, the methodology proposed is flexible and provides a general framework for deriving "trading volume" models of investment activity based on structural investment thresholds.

6 Appendix A

Let X be a random variable with Poisson distribution given by:

$$X \sim P(\lambda) = e^{-\lambda} \cdot \frac{\lambda^x}{x!}$$

The associated Moment Generating Function (MGF) of the Poisson distribution is given by:

$$M_x(t) = e^{\lambda(e^t - 1)}$$

Consider a new random variable, say Y, that is the sum of d i.i.d. Poisson random variables as in $Y = \sum_{j=1}^{d} X_j$. We then have that the MGF of Y is given by:

$$M_y(t) = \mathsf{E}e^{-tY} = \prod_{j=1}^{d} M_x(t) = e^{\lambda d(e^t - 1)}$$

which immediately shows that the distribution of Y is also Poisson with intensity equal to the sum of the intensities of the X_j's. Note that the same result would hold even if the X_j's were only independent but not identically distributed.

Consider now the case where you have d i.i.d. Bernoulli random variables with probability p, say $B_j \sim Bernoulli(p)$. If Y is again defined as the sum of B_j's as $Y = \sum_{j=1}^{d} B_j$ then we can use the above argument to find the MGF of Y. The case that interests us is when the number of Bernoulli random variables being summed is also a random variable that follows a Poisson distribution. We write $d \sim P(\lambda)$. Then, we have the following:

$$M_y(t) = \mathsf{E}e^{-tY} = \mathsf{E_d}\mathsf{E_{Y|d}} = \mathsf{E_d} \prod_{j=1}^{d} M_x(t) = \mathsf{E_d}((1-p) + pe^t)^d$$

Now set $\beta = (1-p) + pe^t$ and:

$$\mathsf{E_d}\beta^d = \sum_{k=0}^{\infty} \beta^k \lambda^k \frac{e^{-\lambda}}{k!} = \sum_{k=0}^{\infty} (\beta\lambda)^k \frac{e^{-\lambda}}{k!} e^{-\lambda\beta} e^{\lambda\beta} = e^{\lambda(\beta-1)}$$

Combining the previous two results we get the following specification for the MGF:

$$M_y(t) = e^{\lambda p(e^t - 1)}$$

which implies that the distribution of Y is given by $Y \sim P(\lambda p)$.

Table 1.-DEPENDENT VARIABLE Y DESCRIPTIVE STATISTICS

Dependent Variable	Obs	Mean	Std. Dev.	Min	Max
Ships ordered	455	7.56	9.30	0	66
Deadweight Tonnage	455	0.71	0.93	0	7.44

"Ships ordered" is the observed number of orders for each quarter and "Deadweight Tonnage" stands for the total carrying capacity in tonnes of the orders.

Table 2.-MODEL 1 REGRESSION ESTIMATES

	Estimation Method			
Variable	NLLS	PQMLE	NB	OLS
Negative of Log-probability	.32	.29	.35	2.70
	(.012)	(.028)	(.040)	(.35)
Constant	1.55	1.62	1.52	4.47
	(.027)	(.067)	(.071)	(.38)
Log likelihood	-2413	-1623	-1358	n.a.
Pseudo R^2	0.13	n.a.	0.026	0.14

Notes: Asymptotic, robust standard errors in parentheses.

Table 3.-MODEL 1 WITH FIXED AND RANDOM EFFECTS

	Estimation Method			
Variable	NB Fixed	NB Random	Poisson FE	Poisson RE
Negative of Log-probability	.38	.38	.39	.39
	(.027)	(.027)	(.014)	(.014)
Constant	.21	.21	n.a.	1.47
	(.11)	(.11)	n.a.	(.31)
Log likelihood	-1201	-1237	-1491	-1528

Notes: Asymptotic, robust standard errors in parentheses.

Table 4.-MODEL 2 REGRESSION ESTIMATES

	Estimation Method			
Variable	PQMLE	NLLS	NB(RE)	OLS
ship1	.036	.024	.061	.62
	(.0051)	(.0057)	(.0067)	(.081)
V_{opt}	.014	.015	.013	.072
	(.0021)	(.0050)	(.0029)	(.021)
V_{opt}^2	-2.57 e-05	-2.66 e-05	-2.64 e-05	-1.19 e-04
	(0.65) e-05	(0.10) e-05	(0.65) e-05	(0.43) e-04
I	-.016	-.030	-.011	-.055
	(.0037)	(.013)	(.0027)	(.017)
accident	-.15	.085	-.36	1.41
	-(.15)	(.16)	-(.18)	(1.72)
lrate	-.024	.0060	-.032	.062
	(.018)	(.019)	(.021)	(.13)
$V_{opt,lag}$	-.0021	-.0021	-.00084	-.029
	(.0012)	(.0015)	-(.0021)	(.013)
Constant	2.44	2.79	2.10	4.74
	(0.20)	(.40)	(.24)	(1.54)
Log Likelihood	-1758	-1497	-1255	n.a.
Pseudo R^2	0.36	n.a.	0.098	0.53

Notes: Asymptotic, robust standard errors in parentheses.

Table 5.-MODEL 2 WITHOUT THE LINEAR RESTRICTION OF V_{opt}

	Estimation Method			
Variable	NLLS	PQMLE	NB(RE)	OLS
ship1	.028	.039	.049	0.62
	(0047)	(.0054)	(.0034)	(0.080)
R	3.47 e-05	4.37 e-05	3.58 e-05	2.65 e-04
	(0.90) e-05	(0.88) e-05	(0.54) e-05	(0.83) e-04
C	-3.83 e-05	-2.68 e-05	-2.65 e-05	-1.755 e-04
	(1.87) e-05	(1.83) e-05	(1.50) e-05	(1.09) e-04
I	-.029	-.023	-.017	-.11
	(.0082)	(.0046)	(.0032)	(.030)
lrate	-.0013	-.036	-.059	.025
	(.019)	(.017)	(.017)	(.13)
accident	.22	-.19	-.40	.46
	(.21)	-(.17)	(.19)	(1.70)
Constant	2.64	2.39	1.12	4.70
	(.29)	(.21)	(.26)	(1.78)
Log Likelihood	-1515	-1820	-1257	n.a.
Pseudo R^2	n.a.	0.34	n.a.	0.52

Notes: Asymptotic, robust standard errors in parentheses.

TABLE 6.-MODEL 2 WITH A LINEAR RESTRICTION ON V_{al}

	Estimation Method			
Variable	NLLS	PQMLE	NB(RE)	OLS
ship1	.028	.040	.049	.62
	(.0049)	(.0054)	(.0034)	(.0800)
V_{al}	.0049	.0060	.0049	.035
	(.0012)	(.0012)	(.00070)	(.011)
I	-.029	-.022	-.016	-.11
	(.0084)	(.0046)	(.0032)	(.029)
lrate	-.0015	-.036	-.060	.0081
	(.019)	(.018)	(.018)	(.12)
accident	.21	-.16	-.37	.65
	(.21)	(.16)	(.19)	(1.67)
Constant	2.63	2.48	1.18	5.35
	(.27)	(.19)	(.25)	(1.53)
Pseudo R^2	n.a.	0.3387	n.a.	0.5189
Log L	-1515	-1823	-1258	n.a.

Notes: Asymptotic, robust standard errors in parentheses.

As defined in (10), $V_{opt,t} = \theta_t P_t - \mu I_t$ and $V_{al} = \theta_t P_t$. Dividing the coefficient of I with the coefficient of V_{al} gives us an estimator for μ, provided the model is not misspecified. For all methods of estimation $\hat{\mu}$ appears significantly higher than 1. We proceed with robustness checks and specification tests.

TABLE 7.-FULL MODEL WITHOUT THE LINEAR RESTRICTION ON V_{opt}

	Estimation Method			
Variable	NLLS	PQMLE	NB(RE)	OLS
ship1	.0090	.020	.027	.47
	(.0064)	(.0057)	(.0034)	(.10)
ship4	.0042	.013	.023	.17
	(.0036)	(.0035)	(.0039)	(.0551)
R	11.2 e-05	7.19 e-05	4.58 e-05	55.93 e-05
	(9.72) e-05	(3.16) e-05	(1.39) e-05	(30.33) e-05
C	-10.82 e-05	-7.43 e-05	-4.20 e-05	-42.37 e-05
	(3.28) e-05	(2.14) e-05	(1.45) e-05	(16.6) e-05
I	-.029	-.012	-.010	-.044
	(.024)	(.0056)	(.0049)	(.032)
V_{opt}^2	-3.85 e-05	-4.93 e-05	-2.11 e-05	6.59 e-04
	(5.88) e-05	(1.80) e-05	(1.68) e-05	(1.34) e-04
R^2	4.32 e-10	8.89 e-10	-1.89 e-10	-6.00 e-09
	(2.34) e-09	(7.61) e-10	(6.45) e-10	(6.50) e-09
accident	.030	-.18	-1.19	.45
	(.20)	(.15)	(.19)	(1.70)
lrate	.029	-.0017	-.076	.11
	(.014)	(.016)	(.017)	(.15)
dwg	-.015	-.010	-.0068	-.035
	(.0025)	(.0020)	(.0014)	(.013)
Constant	2.87	2.30	1.55	3.32
	(.37)	(.31)	(.32)	(2.76)
Log Likelihood	-1426	-1568	-1232	n.a.
Pseudo R^2	n.a.	0.43	n.a.	0.56
Average Markup	1.90	1.26	1.57	n.a.

Notes: Asymptotic, robust standard errors in parentheses.

The average markup is calculated as the implied markup $\hat{\mu} = \frac{\hat{I} \cdot V_{al}}{\hat{R} \cdot R + \hat{C} \cdot C}$.

TABLE 8.-FULL MODEL II NEGATIVE BINOMIAL SPECIFICATION

	Estimation Method	
Variable	NB Random Effects	NB Fixed Effects
ship1	.027	.032
	(.0034)	(.0047)
ship4	.023	.029
	(.0039)	(.0050)
R	4.58 e-05	8.33 e-05
	(1.39) e-05	(3.22) e-05
C	-4.20 e-05	-4.89 e-05
	(1.45) e-05	(1.61) e-05
I	-.010	-.0043
	(.0049)	(.0070)
V_{opt}^2	-2.11 e-05	-4.36 e-04
	(1.68) e-05	(1.96) e-04
R^2	-1.89 e-10	3.62 e-10
	(6.45) e-10	(7.87) e-10
accident	-1.19	-1.27
	(.19)	(.41)
lrate	-.076	-.028
	(.017)	(.050)
dwg	-.0068	(.0020)
	(.0014)	(.0020)
Constant	1.55	.95
	(.32)	(.67)
Log Likelihood	-1232	-821
Average Markup	1.57	1.611

Notes: Asymptotic, robust standard errors in parentheses.

Having concluded on the Negative Binomial specification we perform estimation with Random and Fixed Effects. The squares of V_{opt} and R appear now statistically insignificant. We proceed with robustness and specification checks.

TABLE 9.-ROBUSTNESS CHECKS: EXOGENEITY TEST

	Negative Binomial with Fixed Effects			
Variable	Estimates	Std.Errors	z-test	p-value
ship1	.033	.0047	6.92	0.000
ship4	.029	.0049	5.85	0.000
R	8.39e-05	3.21e-05	2.61	0.009
C	-4.25e-05	1.92e-05	-2.22	0.027
I	-.0087	.010	-0.86	0.39
V_{opt}^2	-4.82e-05	2.09e-05	-2.30	0.021
R^2	5.44e-10	8.40e-10	0.65	0.51
accident	-1.32	.42	-3.14	0.002
lrate	-.018	.054	-0.33	0.74
dwg	-.0073	.0023	-3.17	0.002
residuals	.0035	.026	0.14	0.89
Constant	.89	.68	1.30	0.19

Notes: Asymptotic, robust z-statistics.

TABLE 10.-ROBUSTNESS CHECKS: AUTOCORRELATION AND EXOGENEITY TEST

	Negative Binomial with Fixed Effects			
Variable	Estimates	Std.Errors	z-test	p-value
ship1	.033	.0088	3.73	0.000
ship4	.030	.0049	5.99	0.000
R	8.12e-05	3.21e-05	2.53	0.009
C	-4.32e-05	1.92e-05	-2.22	0.027
I	-.0096	.010	-0.96	0.34
V_{opt}^2	-5.08e-05	2.10e-05	-2.41	0.016
R^2	6.36e-10	8.40e-10	0.76	0.45
accident	-1.346	.42	-3.24	0.001
lrate	-.029	.054	-0.55	0.58
dwg	-.0071	.0023	-3.01	0.003
residuals	.0038	.063	0.06	0.95
lagged residuals	-.00080	.0091	-0.10	0.92
Constant	1.030	.681	1.51	0.13

Notes: Asymptotic, robust z-statistics.

TABLE 11.-MODEL II NEGATIVE BINOMIAL SPECIFICATION WITH THE V_{opt} LINEAR RESTRICTION

	Estimation Method	
Variable	NB Random Effects	NB Fixed Effects
ship1	.033	.027
	(.0047)	(.0041)
ship4	.029	.023
	(.0050)	(.0046)
V_{opt}	.0069	.0088
	(.0017)	(.0018)
V_{opt}^2	-6.27 e-05	-7.11 e-05
	(1.18) e-05	(1.12) e-05
R^2	1.24 e-09	1.41 e-09
	(2.85)e-10	(2.82)e-10
accident	-1.28	-1.20
	(.40)	(.22)
lrate	-.047	-.074
	(.046)	(.021)
dwg	-.0068	-.0065
	(.0012)	(.0013)
Constant	1.48	1.52
	(.48)	(.23)
Log Likelihood	-822	-1271

Notes: Asymptotic, robust standard errors in parentheses.

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