Inverse System Dynamics in Competitive Economic Modelling: The case of Tanker Freight Rates

George Dikos *
Eugenides Group
and Hellenic Air Force

Henry S. Marcus †
Massachusetts Institute of Technology

Martsin Panagiotis Papadatos ‡
University of Cambridge
Judge Institute of Management

Vassilis Papakonstantinou §
Eugenides Group

June 22, 2005

*gdikos@alum.mit.edu
†hsmarcus@mit.edu
‡m.papadatos@jims.cam.ac.uk
§vpap@alum.mit.edu

Abstract

A system dynamics approach is used in order to model and identify the structural relationship between freight rates in the tanker industry and a set of exogenous inputs. Our motivation results from the limited data availability and the prohibitive theoretical complexity of economic models for the evaluation of managerial decisions and risk management. The combination of statistical analysis and economic insight leads to an innovative multidisciplinary approach for modelling competitive economic systems. We calibrate the model with real data from 1980-2002, achieve estimation and identification of the system and fully track the directional changes in freight rates. After conducting performance evaluation an innovative hybrid model is introduced and system performance is maximized both within and out-of-sample. Finally we discuss potential uses of this model for policy analysis, managerial investment decisions and risk management.

1 Introduction

There are two main contributions of this paper: (1) The development of a structural model for time charter rates in the oil tanker industry, that improves the ability of agents and policy makers to undertake decisions in this industry and (2) the demonstration of innovative techniques for the modelling of competitive economic systems. While pursuing this task we discuss how system dynamics and identification techniques can effectively represent complex environments, where agents undertake economic actions and ultimately challenge the widespread perception that structural models consistently under-perform statistical models.

Since the seminal work of Lucas and Prescott (1989) the General Equilibrium approach has been the predominant trend for analyzing investments under perfect competition. Due to the assumptions concerning the rationality of agents and their ability to commit themselves to fully rational decisions, the General Equilibrium approach has strict implications on price dynamics, especially when we try to compute the equilibrium in sophisticated markets, such as the oil tanker industry. Despite the limited empirical success of such models (Rust 1995), economists have been particularly cautious with approaches that build on the general principles of systems. Besides the inability of most structural models to outperform statistical models, economists have been suspicious of "black-box" type methodologies that do not take into account the ability of agents to "learn" rationally and adapt their optimal policies dynamically. After what is formally known as Lucas' critique (1989), recursive dynamic programming methods have been the standard approach.

Furthermore, from an empirical and applied point of view, most models derived from the principles of structural systems have not outperformed statistical approaches, such as the Generalized Autoregressive Conditional Heteroscedastic family (Engle et al. 1994). Due to the dynamic response of agents to shifts in policy and external shocks, economic systems are *time varying*, which implies that the dimension of the system may evolve over time. Non-parametric solutions may lead to over-parameterization of the system and in some sense, if we attempt to fully identify the system non-parametrically, there is no need for conceptual or scientific intuition. In this paper, besides the accomplishment of our main objective, we demonstrate that any attempt to model economic systems without theory and first principles in the background, leads to over-parameterization; on the other hand system theory coupled with economics may provide a useful and intuitive alternative towards the understanding and modelling of complex economic systems, *especially when the availability of data is prohibitive for the employment of classical or computationally intense methodologies.* In the final section we present a hybrid model that clearly outperforms statistical models, allowing for controlling external events. This is particularly relevant for evaluating managerial and policy decisions in this market, especially when one takes into account the interaction of different inputs.

The paper is organized as following:

In Section 2 we introduce the tanker industry and the economic laws of motion that govern the industry. In Section 3 we re-address the theoretical issues of the system and their empirical relevance with regards to the specific market for time charter freight rates. Several shortcomings are analyzed, which are mainly accountable for preventing system dynamics to become the main device towards the modelling of complex economic systems of interacting agents, despite the natural tendency of economic systems to seem consistent with system modelling. Whilst proceeding with identification and estimation, several techniques are introduced, which provide the intuition and theoretical relevance that allows us to overcome some of the restrictions and shortcomings imposed by rational expectations equilibriums. The combination of system principles, econometrics and economic theory provides a hintful insight. We calibrate the system and in Section 4 we test its performance and discuss issues of data updating and learning. In Section 5 an innovative technique that maximizes performance is proposed. Finally we highlight possible uses of the model for policy making, evaluation of managerial decisions in the tanker industry and the extension of this approach to competitive economic markets.

2 The Tanker Industry: Economic Principles of the System

A tanker is a vessel designed to carry liquid cargoes. Refined oil products and crude oil are the most common types of cargo carried in such vessels. Tankers may rarely be employed for the transportation of chemicals, wine, vegetable and other food oils [1]. The tanker freight market may be perceived as the place where the buyers and sellers of shipping services come together to strike a deal, regarding the transportation of a specific tonnage of oil from one place to another. In exchange for their service, carriers receive a time charter rate per day (freight rate hereafter). Tanker freight rates determine the revenue a ship earns for servicing a particular contract for a pre-specified period of time and vary with duration and vessel type. However, the procedures involved are fairly standardized and the market for one-year time charter contracts is well organized and liquid. Time charter rates correspond to price in the transportation supply function, which is determined by the existing fleet, the orders for new vessels and the number of scrapped vessels. Furthermore, ship owners have the option to lay-up a fraction of the available capacity. Additionally, in order to reduce fuel and maintenance costs, they have the option to adjust their velocity and the productive operational days, given the economic conditions prevailing in the market. In order to obtain an

[1] For a detailed description of the tanker industry the reader should consult (Strandenes 2002) or (Frankel and Marcus 1973).

estimate for the transportation supply function we have to determine the ordered tonnage in each period, the tonnage scrapped and the fraction of tonnage in lay-up, as well as the productivity of the total fleet. The above modules of the transportation supply function depend on the prevailing time charter rate. Demand is derived from the demand for oil and is considered as freight rate inelastic, in the short-term at least (Stopford 1991). This is discussed later on, as it is of profound impact on the specification and identification of the system. The key determinants of demand for sea transport are: the distance and the volume or quantity of the cargo to be transported.

The active merchant fleet may be perceived as the state variable of the system that takes into account the inflows and outflows of tonnage, whereas the average fleet productivity is a transformation device that incorporates decisions of operations management in this industry. Later on all variables are explicitly defined, in a consistent fashion related to the economic principles of the tanker industry. Furthermore, most competitive economic systems display similar dynamics and characteristics with the tanker industry. This observation makes the methodology and insight in this paper extendable to most markets governed by conditions of intense competition.

The specific characteristics of each market provide the essential contextual knowledge for the design of a system counterpart that will generate the observed market dynamics, given a set of inputs. In the tanker market industry there are two facts that reduce the complexity of the problem. *Demand* for transportation capacity is freight rate inelastic (at least in the short term), as transportation costs (freight rates) are a very small fraction of the price of the transported product. This allows us to consider demand exogenous and identify it with the input of the system. On the other side, supply (which consists of the aggregate tonnage capacity and the notion of *productivity*) will be the main driving force of the freight rate innovations and we identify it with the system.

The most important task, before proceeding with the structural determination of the time charter rate given a set of relevant inputs, is the precise definition of the transportation supply function and demand. In this section we follow closely the notation and discussion in "Maritime Economics", the authoritative tome by Martin Stopford (1991). Stopford discusses a similar model for the determination of the short term time charter rate, with perfect foresight and no structural interpretation into the modules of entry, exit and lay-up, which determine the active tonnage that exists in this market. Once we have specified the aggregate exit, entry and lay-up equations, the rate will be determined by the interaction of supply and demand. The most crucial aspect is that demand and supply do not solely depend on the available deadweight or tonnage, but also on the average haul that goods have to be transported. A ton of oil transported from the Middle East to Western Europe via the Cape generates 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 haul** which explains why sea transport demand and supply is measured in **ton-miles**. Following the definition by Stopford (1991) it is "the tonnage of cargo shipped, multiplied by the average distance over which it is transported." The effect of changes in the average haul on transportation capacity is dramatic and significant movements in spot and time charter prices are often due to political events that have a direct effect on the average haul. A recent example with a severe impact on the haul is the Iraq war.

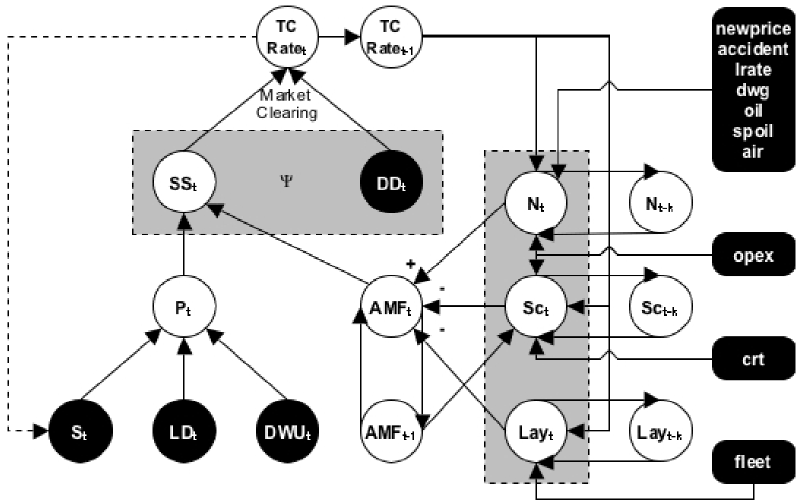
On the supply side, although at each point of time the fleet is fixed in terms of deadweight or tonnage, the **productivity** of the ships determine the transportation supply function. Tanker productivity adds an element of flexibility to the specification of the transportation supply function, but it is impossible to measure it directly since there are no available data on the productivity of each specific vessel. Most of our efforts in identifying the system will be devoted to the specification of an appropriate productivity function and are motivated by the lack of data on the productivity of each vessel. All the equations and notation in this section are presented and discussed by Stopford (1991) in his "Introduction to Ship Market Modelling" ((Stopford 1991), p.515). Although the system equilibrium modelling of ship markets is inherent in the pioneering Zannetos (1966) monograph, to the knowledge of the authors, this paper is the first published study that introduces a hybrid device for the modelling of competitive economic environments. Motivated from the economics of this particular market, the key idea between the supply and demand representation of spot and short term charter rates, remains unchanged. The interaction of the different modules, input and output variables is visualized in Figure 1, which summarizes all the different equations and notation we introduce in this section. In the remainder of this section and in the next we will explicitly analyze the motivation behind these interactions, as well as the necessary assumptions and limitations.

We now define the laws of motion that govern the system, such as the tonnage supply function and the average productivity of fleet. Staying consistent to Stopford's notation P_t stands for **aggregate** productivity at time t, S_t the average operating speed per hour, LD_t the loaded days at sea per annum, DWU_t the deadweight utilization and r_t the time charter rate. Then:

$$P_t(r_t) = 24 \cdot S_t(r_t) \cdot LD_t(r_t) \cdot DWU_t \tag{1}$$

The transportation supply function in ton-miles is denoted SS_t, the active merchant fleet AMF_t and the average productivity P_t. Both the average merchant fleet and the productivity are determined by the time charter rate r_t and some set of exogenous variables x_t, which we have suppressed in the above equation. The active merchant fleet is equal to the existing fleet during the previous period, plus any new deliveries, minus scrapped tonnage and vessels in lay-up and may be perceived

Figure 1: System Modelling of Time Charter Freight Rates



as the "state variable" of the system. The transportation supply function is the product of the active tonnage (AMF) and the productivity of the fleet (P):

$$SS_t(r_t) = AMF_t(r_t) \cdot P_t(r_t) \tag{2}$$

The equilibrium time charter rate is determined by bringing supply $SS_t(r_t)$ to demand DD_t, where demand is measured in ton-miles and is assumed completely exogenous. Then, assuming there is an unknown functional relationship Ψ between supply and demand:

$$\Psi(SS_t(r_t), DD_t) \tag{3}$$

Having discussed the key characteristics of the Tanker Industry and the equations that govern the demand and supply of transportation capacity, we proceed with the estimation and identification of the system.

3 Tanker Freight Rate Dynamics: A system dynamics Problem

This section is structured in three parts. First, we discuss the theoretical "inconsistency" between the system dynamics approach and modern economic theory, which is formally known as Lucas' critique. Second, we provide the necessary behavioral motivation for our innovative approach of analyzing economic systems. Third, we state the problem formally and proceed with the identification of the system and argue that the performance is very good.

3.1 Lucas' critique

At this point one might find it hard to understand why and what is particularly difficult in estimating the laws of motion introduced in the previous section. Given a set of inputs and data why is it difficult to estimate the transportation supply equation? And once specified, may we simulate the effects of different policies by simply changing the inputs? The answer to these two questions is interrelated and, according to Economic Theory, it is "no" to both of them.

The system modelling approach is surrounded by the suspicion that arises from the criticism Lucas initiated in the 70s (1975). Traditional model building that uses historical data for the calibration of abstract econometric models does not take into account the response of agents to changes in policy regimes. Under Rational Expectations, agents assume a process for the freight rates r_t and then make their optimal decisions regarding entry, exit and lay-up. Their responses simultaneously determine the average merchant fleet and productivity. Demand is fully satisfied in equilibrium and the observed process has the same dynamics with the assumed process. The theory of Rational Expectations assumes that agents are forward looking and do not act upon historical data. This implies that on the one hand historical data should not be used for estimating the equation without incorporating the role of expectations and on the other hand, models estimated solely on historical time series should not be employed for evaluating the effects of different policies. The role of Lucas' critique on models of time charter rates has also been addressed in a seminal paper by Magirou, Psaraftis and Christodoulakis (1992). These two reasons may provide additional reasons for "why systems thinking has struggled to influence strategy and policy formulation"; a question recently addressed by Warren (2004). A third reason that is also accountable for the limited usage of the system modelling approach of competitive economic systems is the relatively low performance of such models in comparison to econometric models. In this paper we do not attempt to provide the necessary behavioral assumptions (such as bounded rationality) for making system thinking to overcome Lucas' critique; however, we will show the importance and necessity of economic thinking for designing the system, as well as the unique performance of these techniques for explaining the dynamics of time charter rates.

Additional motivation towards the system analysis stems from the complexity of the Rational Expectations approach. Under uncertainty, the derivation of a competitive equilibrium requires that the **whole stochastic process** is determined endogenously as a fixed point of the system[2] (Dixit and Pindyck 1994), whilst preserving the necessary economic structure. In order to avoid the

[2]Dixit and Pindyck (1994) extend the Lucas investment model under uncertainty and irreversibility. For an excellent discussion regarding the tight connection between the competitive equilibrium and finding a fixed point in uncountable infinite dimensional spaces see (Dixit and Pindyck 1994, p. 253).

search for a **fixed point** in the functional space of processes, we employ the structural equations that depend only on the current value of the variable, which is then determined endogenously by the outcome of the system. Ultimately, the performance of the system will be an indirect joint test of the underlying structural assumptions and our belief that the approach we undertake can shed light into the dynamics of tanker freight rates. To avoid the complications of solving for a fixed point in functional spaces, we now proceed with a sketch of assumptions regarding the way agents undertake their decisions. This allows the decomposition of the average merchant fleet function into the entry, exit and lay-up modules and the simplification of our calculations, and highlights the importance of the behavioral background of the model on our interpretation and understanding of the results. The validity of the method will be tested by the performance of the system.

3.2 The Principle of Decomposition

In contrast to financial markets, data in this industry are not fully available, especially for the productivity of vessels and consequentially the average productivity of the fleet. This limitation makes the need for the introduction of an innovative technique even stronger. In the next section we will demonstrate that the system modelling approach may provide significant insight in such cases of limited data, where we are essentially addressing a problem of "blind" identification. However, Economic Theory will provide the necessary intuition for the inclusion of the relevant variables and for the assessment of the estimated implied equations and parameters.

Having foregone the rationality assumptions underlying the general equilibrium, the derived price process does not have to be consistent to the one that rational agents assume. This reduces the complexity of the problem. By employing independence of actions and the principle of decomposition[3] (Rust 1997), as well as a mild assumption on the exogeneity of the price process with respect to entry and exit decisions, we provide an alternative and innovative approach. Furthermore, if we are willing to relax some of the behavioral assumptions, "backward looking" might seem more permissible. The behavioral intuition behind the decomposition principle is the following: Instead of assuming that agents learn and respond fully rationally from prices, we assume that agents "solve" the sub-problems of entry, exit and temporary suspension, instead of the full dynamic programming problem. In some sense, we assume that agents learn, but not perfectly, as implicitly assumed in a Rational Expectations General Equilibrium. This approach allows us to break down the average merchant fleet into three different flows, by assuming that agents perceive the *endogenous* price process as exogenous, when they determine their optimal actions. In this paper we do not attempt to provide the necessary set of behavioral assumptions that will allow

[3] Rust is the first one who introduces decomposition in order to deal with the complexity of economic systems.

us to forego the suspicions that surround black-box modelling approaches. Our main focus will be on the successful calibration of the model. However, any approach to design an economic system has to take into account the economic structure of the underlying market and remain consistent to the underlying behavioral assumptions. On the one hand this reduces the dimensionality of the problem and on the other hand it may enhance system thinking to influence strategy and policy evaluation.

The transportation supply function characterizes the formation of time charter freight rates, especially in this market, where demand is freight rate inelastic (at least in the short term) (see Frankel and Marcus, 1973, for a detailed discussion). Using the principle of decomposition (Rust 1997) we “break-down” the transportation supply function and estimate separately the mass of new and exiting tonnage, as well as the lay-up dynamics. We then bring them together and compute the structural transportation supply function, which determines the spot price and, consequently, the short term time charter price once set equal to demand. From this highly nonlinear approach it is obvious that the dynamics of the time charter process will not always be consistent to the expectations heterogeneous agents adopt on the process. We avoid this complication by disregarding the ability of agents to learn in competitive markets with the hope to achieve more complex feedback mechanisms and a more realistic description of price dynamics. This is the **system theoretical** approach we adopt, that will ultimately allow us control over the input of the system, which in this case is the exogenous demand for transportation capacity. The main drawback of this approach is that it is still subject to Lucas’ critique: rational agents in equilibrium should respond to exogenous shifts and update their supply of capacity. By using the equations for new vessels, scrapped vessels and lay-up, in order to determine the transportation supply function, we do not take fully into account optimal reactions of agents to external shifts, nor their change of optimal actions with respect to shifts in policies. A rather strong implication is that in the long-run the model may not fully reflect the impact of different policies, unless we make some *ad hoc* modifications to the micro-foundations of the three different building blocks of the transportation supply functions. Whatever approach we undertake our understanding of the economic principles of the system is essential for its effective representation.

Having discussed our motivation and intuition behind the **decomposition** and **exogeneity** assumptions, as well as the laws of motion that govern this market, we proceed with the specification and identification of the system.

3.3 The system dynamics Approach

Starting with the integration of each estimated module towards a complete system, our key problem is a problem of system dynamics. We suppress the time index and assume an exogenous demand

$$DD$$

in ton-miles, which has been kindly provided by Marsoft, (Boston) Inc. and the demand data in the book of Martin Stopford (1991). The key equation that determines the time charter rate r is the unknown functional relation Ψ that relates supply

$$SS(r, x)$$

with demand (x stands for the vector of all exogenous variables hereafter, such as operating expenses $opex$ and all other "system inputs" introduced diagrammatically in Figure 1 and defined in the Appendix):

$$\Psi(SS(r, x), DD) = 0 \tag{4}$$

Furthermore, supply is determined by the active merchant fleet (tonnes) times the average productivity of the fleet, as defined in the previous section:

$$SS(r, x) = AMF(r, x) \cdot P(r, x) \tag{5}$$

And finally, the innovation of the state variable of AMF each period is determined by the previous value of the state variable, the new deliveries $N(r, x)$ (entry), the scrapped levels $Sc(r, x)$ (exit) and the tonnage in lay-up $Lay(r, x)$:

$$AMF_{t+1}(r, x) = AMF_t(r, x) + N(r, x) - Sc(r, x) - Lay(r, x) \tag{6}$$

We are facing a non linear problem with three unknowns and three equations. What complicates the problem is that our unknowns are **functions**, namely: the fraction of the lay-up function $Lay(r, x)$ for each category of tankers[4], the productivity $P(r, x)$ and the functional relation Ψ between supply and demand. Based on the principle of decomposition we will employ category specific estimates for the entry and exit functions (namely $N(r, x)$ and $Sc(r, x)$) derived in different settings (Zannetos 1966), (Dikos 2004), whose form is discussed in the Appendix.

[4]Although we have data to derive the Lay-Up function for aggregate data, the task of deriving the fraction for each tanker category is part of the calibration process, due to the lack of category specific data.

Regarding the Ψ function that determines the relationship between supply and demand, we start with the simplest form, which stems from the neoclassical assumption that requires markets to clear and bring supply equal to demand. This specification contradicts the discussion in the seminal monograph by Zannetos ((1966), Chapter 8), where Zannetos speculates that the price (spot and time charter) generating mechanism is far more complicated than equality, due to the "Cobweb" Theorem and the elasticity of expectations. At this point the reader may question the ability of the system to generate such volatile price outputs (hereafter price stands for the spot and time charter rate), since the input of the system (demand) is far less volatile and relatively stable. As it will turn out, market clearing modelling of prices will be sufficient for the specification of the system.

Let us now discuss the lay-up function, which consists of our second functional unknown. Using the principle of similarity we assume that the parametric form of the lay-up function is the same across size categories. We therefore proceed and use the well-established functional form[5] for lay-up, which we estimate with aggregate data and present in the Appendix. It then becomes part of the system calibration process to assign the optimal fraction of lay-up for each category, by employing simulation techniques. This assignment is a critical part of the system calibration process and the algorithm we use in order to calibrate the system will be thoroughly discussed, once we have addressed the final and most crucial unknown, which is the average productivity of the fleet.

Stopford ((1991), Appendix 1) derives the implied average fleet productivity that satisfies market clearing (supply equals demand). There are two limitations with the numbers presented by Stopford: These numbers are annual, which does not leave them enough space to account for the volatility observed in each quarter, and they are averaged across size categories. However they may provide preliminary guidance towards the parametric form of productivity. Consequentially, the estimation of the parameters becomes a part of the calibration process.

We now proceed with the presentation of the "calibration" algorithm. To account for the effects of category and size we consider three different size categories (j is a category index): The first one is for tankers with deadweight tonnage between 10.000 and 60.000 ($10 - 60K$ DWT), the second $70 - 140K$ and the last one is $200 + K$ DWT. The average merchant fleet for each category is determined by the recursive state defined as in (6):

$$AMF_{t+1,j}(r, x; \beta_j) = AMF_{t,j}(r, x) + N_j(r, x) - Sc_j(r, x) - Lay(r, x; \beta_j) \tag{7}$$

[5]Zannetos proposes a functional relation between tonnage in lay-up and the inverse square of the time charter rate. This functional relation has been re-estimated in (Dikos 2004) and is strongly supportive of to the Zannetos specification.

where j now stands for each one of the three categories.

Using the principle of decomposition our identification strategy is the following: We employ structural equations that determine the flow of new vessels ($N_j(r,x)$), the flow of scrapped vessels ($Sc_j(r,x)$) and the tonnage in lay-up, up to the unknown parameters for each category β_j. These equations have been estimated from historical data and their form is discussed in the Appendix. With these estimates we proceed with the calculation of estimates for the average merchant fleet. The success of the integration of the modules and our modelling approach depends on the successful identification of the relationship between supply and demand and the productivity function.

The equations in (7), for the newbuildings $N_j(r,x)$ (Module 1), the scrapped tonnage $Sc_j(r,x)$ (Module 2) and the tonnage in lay-up status are presented in Appendix. The parametric form of the lay-up equation has been determined from aggregate data, but has to be re-calibrated for each category: therefore, it is known only up to the parameter β_j, where j stands for the three different categories. Preliminary insight into the parametric form of the productivity function $P(r,x,\theta_j)$ and the explanatory exogenous variables x is based on the Stopford productivity data set. Regarding the third unknown Ψ we start with the market clearing approach that imposes a linear relation that requires supply to be equal to demand.

In order to choose the parameters β_j, θ_j optimally for each category and calibrate the system (within the sample) we use as input the real prices r, exogenous variables x and exogenous demand DD observed in our historical data set and choose for each of the three categories the parameters that minimize the mean squared error between supply and demand:

$$\frac{1}{N-1}\sqrt{\sum_{t=0}^{N}}(AMF_{t,j}(r_t,x_t;\beta_j)\cdot P(r_t,x_t,\theta_j)-DD_{jt})^2, j=1,2,3 \tag{8}$$

The calibration process is essential but not particularly interesting. Despite its profound impact on the performance of the system the specification of the productivity function remains subtle. The next section will be devoted to the derivation of the parametric form of the average productivity and the presentation of the outcome of the calibrated system.

3.4 Integrating the Modules

Using the three modules (presented in Appendix) that determine the active merchant fleet in (7), we may observe that the average merchant fleet is far less volatile than the observed spot and time charter rates.

Demand, which is an exogenous input and the main "driving force" of the system, is far less volatile than the time charter rates. This observation implies that **in a market clearing model, average productivity of fleet is the only mechanism that can generate the observed**

price volatility. This observation leads us to the consequence that productivity **has to be a function of the price**, if there is any value in attempting to model the price process as the outcome of the interaction of supply and demand. If productivity is completely exogenous, then any set of prices may well satisfy market equilibrium, since for every r there will be a P that satisfies equation (4) for any Ψ; if it is to make the system non-degenerate, then productivity has to be a function of time charter rates and potentially of other variables, too.

In our market clearing specification, where supply equals demand in (4), the most important unknown is the average fleet productivity function as defined in (5). In order to identify the parametric form of the productivity function and optimize accordingly we will use the following strategy, which is the one introduced by Stopford ((1991), Appendix 1). Stopford uses the actual active merchant fleet and solves for the **implied average fleet productivity**, that equilibrates supply with demand. In order to stay consistent to our approach we may use the predicted active merchant fleet (which does not depart significantly from the true active merchant fleet) and solve for the implied average fleet productivity. The ability of the system to generate accurate time charter estimates **depends crucially on the level of correlation between the estimated implied average productivity and the observed prices**. To make this point clear, let us assume that average productivity is totally random; then an infinite set of prices satisfies the three equations presented in the previous section. If productivity is fully determined by some (unknown) functional dependence with prices, then we may equate supply as defined in (5) with demand and solve for the implied productivity ($\frac{DD_t}{AMF(r_t)} = P(r_t)$) that brings the system in equilibrium and has a straightforward solution, and then solve for the unknown price. Stopford (1991) follows this approach and derives average fleet productivity, by dividing the demand in ton-miles with the average merchant fleet in each period from $1980 - 1995$ on an annual basis. Although his data for the total fleet do not differ across categories and are quoted on an annual basis, we use them as a benchmark, in order to generate a first estimate of the parametric form of the average productivity function.

By regressing the levels of implied productivity on the logarithm of rates, we acquire a fit of 0.7869, which although significant, is not sufficient enough to capture the co-movement of productivity and rates. The average fleet productivity function, derived on aggregate data, has the following parametric form, which guarantees the non-negativity of the time charter rate:

$$P(r_t) = \theta_{1,j} \cdot \ln(r_t) - \theta_{2,j} \tag{9}$$

We now proceed with the presentation of the calibration algorithm that will allow us to estimate the unknown parameters of the lay-up and productivity function, β and θ in equation (8) respectively, as well as, any "hidden" functional relationships that will improve the system. This algorithm is in a sense a typical learning algorithm that reduces significantly the **dimensionality** of the identification problem. We start with the smallest number of parameters and increase the dimensionality only when a higher performance is accomplished.

Calibration Algorithm

- Using the real numbers for ships in lay-up, scrapped tonnage and new orders we derive the active average merchant fleet. We assume equilibrium, divide the exogenous demand with the AMF_t and derive the implied average fleet productivity P_t. We start with the actual numbers for AMF_t and DD and not with their structural estimates.

- We regress the implied productivity for each category with the actual prices (time charter rates r_t) and estimate the unknown parameters θ_j for the productivity function, for each category as in (9). The performance of the system depends on the level of fit acquired in this step. We have now obtained an estimate of the productivity function $\widehat{P(r_{t,j}, \theta_j)}$.

- We repeat Step 1, but instead of solving for P_t we use $\widehat{P(r_t, \theta)}$ (we suppress the category index j) and solve for $\widehat{r_t}$ that clears the market in (5). The mean squared error between the actual prices r_t and the output of the system, $\widehat{r_t}$ is calculated. If this error is acceptable we proceed to the following step; if not, we try to improve the estimation and specification in the previous step, by adding exogenous variables x_t in the specification of the productivity function.

- Having an acceptable estimate of the implied productivity we proceed with full system estimation. Instead of using the actual active merchant fleet AMF_t, we employ the structural functional forms of the modules that determine (7) and minimize the mean squared error between the estimated transportation supply function and the exogenous demand:

$$\frac{1}{N-1}\sqrt{\sum_{t=0}^{N}}(AMF_{t,j}(r_t, x_t) \cdot P(r_t, x_t, \theta_j) - DD_{jt})^2, j = 1, 2, 3 \tag{10}$$

  where $DD_{t,j}$ and x_t are the exogenous inputs to the system and presented in the Appendix for the modules that determine the average merchant fleet. The choice of the exogenous inputs that determine the productivity function is part of the system identification process. Solving for the equilibrium rate $\widehat{r_{t,j}}$ we achieve all the goals set: We derive the forecast for prices and fully determine the new orders and scrapped vessels. We then calculate the mean squared error between the new estimates and the actual prices for the parameters θ_j, β_j that minimize the error. This allows an endogenous determination of the average transportation supply and the interrelated modules. At this point the estimates of θ_j may differ significantly from the estimates in the previous step.

- If the mean squared error is acceptable, we stop. If not, we go back to Step 2, add some of the exogenous variables to the specification of the productivity function and repeat all the steps. If this action is insufficient then we depart from the market clearing assumption and search for a non-linear relationship between supply and demand in (4).

We now proceed as discussed in the calibration algorithm and start with the simplest linear specification; we start directly from Step 3 by replacing the parameters $\theta_{1,j}$ and $\theta_{2,j}$ in (9), with estimates from the annualized average productivity data set derived by Stopford ((1991), Appendix 1). To gain insight regarding the performance of the system we start with a productivity function that does not differ across categories and is a linear function of the logarithm of time charter rate. The generated outcome captures the main trend of the actual market prices, but is far below the performance of the statistical models and is much less volatile than the real market prices. Furthermore, especially in the region of low rates, the implied productivity values do not guarantee the non-negativity of the price process and the output of the system generates negative values for the estimated time charter process. The results are encouraging, but fail systematically especially for the larger categories. The failure of the outcome may be attributed to two other basic reasons: Either the market clearing assumption does not hold, or productivity differs significantly across categories. We therefore abandon the aggregate annual productivity specification, and proceed with the implementation of all steps of the calibration algorithm, where productivity is estimated endogenously for each category, as the ratio of the demand in ton-miles with the estimated active merchant fleet, which accounts for heterogeneity across categories.

The full algorithm is re-implemented and the different parameters for the productivity function across categories are derived. The results are improved, but still lack the necessary volatility observed in actual market prices. As discussed earlier, the dynamics of the actual merchant fleet and the exogenous demand, are far less volatile than the spot and time charter rates observed in the markets. This implies that we have two key expectations from the productivity function, if we want to achieve an acceptable performance for our system: we expect productivity to be a function of the price and generate through the system the volatility observed in real data. We proceed as discussed in the last step in the algorithm by adding a set of exogenous variables that will hopefully identify the structural relationship between the implied productivity and charter rates.

In order to improve the performance of the system, without abandoning the market clearing approach, we will derive the aggregate average fleet productivity, based on microfoundations with the hope that the structural approach will provide us the necessary insight in including the “missing” variables, that will improve the identification process. As it will turn out, there will be one variable that will totally “boost” the performance of the system.

Let us start from explaining and understanding productivity for one specific vessel: On a ship basis, the ship has a non-zero productivity only if it is in a non lay-up status. If the ship is in lay-up or used for purposes of storage (a recent example is the employment of VLCC's in the 1991 Kuwait War) then it has zero speed S_t and consequently from (1) zero productivity. Once rates are sufficiently high, then the ship has a positive productivity. The speed increases with the prevailing prices, but the loaded days at sea and capacity utilization remain ambiguous. This observation implies that in the region of low rates, only the younger and most efficient ships contribute to the average fleet productivity. At higher rates even the more obsolete and old vessels contribute to the *average* fleet productivity, which reduces the effects of higher rates on the average speed of the fleet. Due to the adverse effects we expect average productivity to remain relatively stable in the region of high rates. Higher prices **have a positive impact on the optimal speed of each vessel and a negative impact on the quality and average performance of the active fleet.** Therefore, the implied productivity of the system does not possess the necessary volatility we have hoped for and cannot solely account for the volatile pattern observed in prices. In order to model average productivity effectively we have to combine two adverse forces: on the one hand, high rates have to contribute in a positive sense and on the other hand, we must identify the necessary state variable that will account for the negative contribution of high prices on the quality and age distribution of the fleet. We choose tonnage in lay-up as the associated quality explanatory state variable for the following reason: High rates induce high productivity and less tonnage in lay-up, whereas low rates reduce speed and potentially the days spent at sea (owners are willing to undertake dry-docking and repair activities in depressed markets), but increase lay-up. These two adverse factors that account for speed, days at sea and fleet quality seem more intuitive for modelling productivity. We now choose the following parametric form for the $P(r_t, Lay)$ function:

$$P(r_t) = \theta_{1,j} \cdot \ln(r_t) - \theta_{2,j} + \theta_{3,j} \cdot Lay \tag{11}$$

We now repeat all the steps of the calibration algorithm. The parameters θ of the productivity function and the mean squared error and average error between the system output and the observed rates are presented in $TableP$. The results are displayed in Figure 2 and are remarkable indeed verifying Vapnik's assertion (1995) that “there is nothing more practical than a good theory”. The outputs of the system are marked with arrows. In periods of low rates, the system output is below the actual market prices, which implies that supply potentially exceeds demand, when the market

Table P: Implied Productivity Parameters

Categories	200K	90-140K	30-70K
theta1	5500	6150	6500
theta2	29050	19000	10300
theta3	2300	2000	1150
Mean Squared Error	6068.93	3165.77	2273.25
Average Error	-0.2507	-0.1981	-0.1235

is in recession. In periods of high rates our forecast tracks the innovations of the true prices even in the most volatile and adverse movements. The performance of the system is not only optimized but follows the direction of the actual prices with the utmost precision.

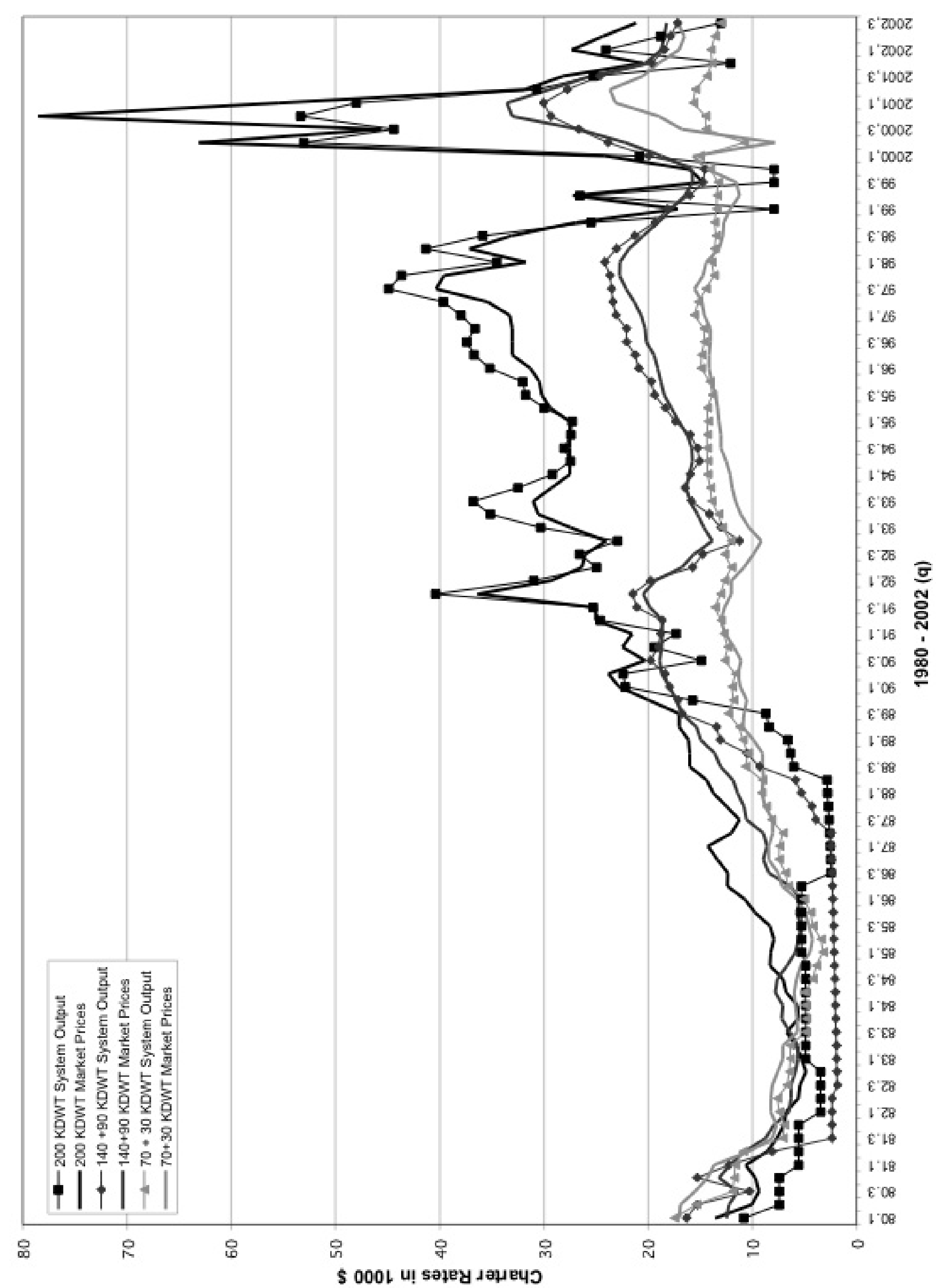
Having completed the specification and estimation of the model, we proceed with discussing the results. Despite the remarkable fit achieved, let us give a structural interpretation into the estimated parameters.

In equilibrium, average fleet productivity for each category is $\widehat{P} = \frac{DD_t}{AMF_t}$ and using the final formula for productivity, we solve for the rate and plug in the derived productivity. We then obtain the following structural equation for the rate:

$$r_t = \exp(\frac{1}{\theta_1} \cdot (\frac{DD_t}{AMF_t} + \theta_2 - \theta_3 \cdot Lay)) \tag{12}$$

Taking the partial derivatives with respect to demand DD, we expect the derivative to be positive; whereas we expect it to be negative with respect to the average merchant fleet, which is the case if and only if $\theta_1 > 0$. Taking the partial derivative with respect to the tonnage in lay-up Lay, we expect the partial derivative to be negative, which requires $\theta_3 > 0$. The derived parameters θ **are all positive** and verify the requirements imposed by economic theory and intuition. What is particularly interesting is that in the periods of high volatility, the fit provided by the **deterministic** equation (12) is more than 0.93, which implies that a deterministic equation can provide the rich price dynamics, that are very sympathetic to stochastic specifications. This argument verifies the assertion of Chaos Dynamics Theorists, that namely deterministic equations can generate patterns that resemble stochastic processes.

Figure 2: system dynamics Output: Final Results



4 Performance Evaluation and Learning

All the analysis, identification and estimation has been carried out within the full sample until now. There are two particular reasons supportive to this specific approach: on the one hand our data consists of only 91 observations for each category and on the other hand, we have been mainly interested in assessing the validity of our basic identification assumptions, such as the equality between supply and demand and the exogeneity of the time charter rate for newbuilding and scrapping decisions. Furthermore, we have been particularly interested in the economic interpretation of the structural parameters, which have been in line with economic theory and supportive to the integration of the three sub-modules.

Having verified the validity of the market clearing approach, as well as the success of the integrated equilibrium price model, we now address issues interrelated to the ability of the model to generate accurate forecasts. In order to address potential concerns on over-fitting, we use the following training rule: we split the sample and use a fraction of the available observations in order to "train" the system (identify the parameters) and the remaining fraction, in order to generate the forecasts **with the parameters obtained from the "training" sub-sample** and compare the relative performance of the system, with respect to the "full sample" performance. This is an essential step for evaluating the performance of the system, when data arrive dynamically and from a theoretical point of view, it is interrelated to the consistency of the learning process (Vapnik, (1995), p. 35). More specifically, the estimation of the parameters β, θ in (10) is performed for a fixed sample. When data arrive dynamically an iterative "learning" procedure is used for updating the parameters. Viewing the square of the distance between the estimated supply function and demand as the empirical risk function, we may rigorously apply the entire asymptotic learning theory. The smooth properties of the functions that determine transportation supply, guarantee the consistency of the learning process, i.e. that the estimated parameters behave smoothly and converge to the true parameters, regardless of the choice of sample and dynamic updating of data. The rigorous application of the theory is beyond the scope of this paper. However, we estimate the parameters for different sub-samples in order to provide empirical evidence with regards to the stability and forecast ability of the system.

In order to perform the training and forecasting approach for the System Dynamics output we consider several sub-samples (deterministic and random) and perform parameter estimation "within the sub-sample" and forecasting "out-of-sample". Finally we evaluate the performance of the system by undertaking an adaptive learning approach: namely, we increase in each step the training sub-sample by one observation and decrease the remaining forecasting sub-sample by one observation.

Once we forego the first quarter of observations (which corresponds to a “bear” market), the estimated parameters and the associated “out-of-sample” performance display remarkable stability and appear to converge to the “full sample” parameters and mean squared error. The results are indicative of the stability of the system and provide supportive evidence for the “out-of-sample” ability of the system to track changes, both in direction and magnitude. Once the two thirds of the sample approximately are used to calibrate the system, all changes of directions are tracked successfully and the “out-of-sample” mean square error does not differ significantly from the one achieved with the entire 91 observations. Our results provide firm empirical evidence that the system is not over-parameterized and that convergence of the system is achieved within a relatively small fraction of the total sample. Results for different ratios of fitting/forecasting data resemble very similar patterns, especially after the first quarter of observations is used for calibration and estimation. This performance evaluation approach is interrelated to the learning properties of the system and the consistency of the learning process, when the system is updated with dynamic data and the parameters are re-calibrated dynamically.

5 A Hybrid Model

In this section we evaluate the performance of the system within a statistical framework. The results derived in the previous sections correspond to the output of a **structural** system, whereas the Generalized Autoregressive Conditional Heteroscedasticity model (GARCH) ((Engle et al. 1994), Appendix 2), which is the main statistical model employed in financial modelling and time charter rate modelling specifically (Kavussanos 2002), corresponds to the **statistical** approach. In his influential series of papers, Kavussanos ((Kavussanos 2002), (Kavussanos 1996)) applied models of the GARCH family for the representation of risk and uncertainty in the tanker industry. To the knowledge of the authors this has been a unique application of models usually employed in high frequency financial data, in Industrial Organization. In this section we address the question, to which extent each model can benefit from the other and proceed with the estimation of “hybrid” models that optimize the performance of our system, combining the complex statistical modelling of volatility (uncertainty) with the structural output of the supply and demand approach, which allows us to control for exogenous events.

The first step towards the evaluation of our system dynamics outputs is the following: Since the output of the system displayed in Figure 2 (*busp* hereafter) incorporates all economic information on demand and prices, the key assertion is that it should be a sufficient statistic for all the exogenous variables used in the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) [6] models as defined in (Engle, Bollerslev and Nelson, 1994, p.10-11) where the dependent variable is the first difference (denoted D. hereafter) of the time charter rate r_t and the exogenous variables X_t' is the first difference of the output of the system *busp*, as displayed in Figure 2.

The output of our system, *busp*, is a sufficient statistic indeed, if it improves the Log Likelihood function, once it replaces the commonly employed exogenous variables: demand for transportation *dmd*, oil prices *oil* and the index for air transportation *air*. We perform estimation and specification of the model with *busp* as the main exogenous variable and report the results in *Table I.*

The results verify our assertion that the output of the system aggregates all **economic information**. The Log Likelihood has been increased with a smaller number of variables, which results in a significant increase in the Akaike information ratio and the parameter of *busp* displays a huge t-statistic of $t_{busp} = 121.92$, which verifies the high impact of the system output on the statistical model. Finally, the category effect appears insignificant here, which is intuitive, since all information aggregate or category specific is aggregated in *busp*. Having estimated the GARCH model with the output of the System Dynamics model as an input to the (GARCH) specification, we have accomplished two diverse, but complementary tasks: on the one hand we have verified that the variable created in the previous two paragraphs indeed aggregates all economic information and on the other hand this hybrid model takes advantage of the dynamics of any information "left out" by the System Dynamics approach, or simply by imposing statistical structure on the deterministic market clearing model.

We now proceed with imposing some more structure on our hybrid model and repeat estimation of the GARCH model for the logarithm of the time charter rate, as indicated by the exponential specification we derived in (12) and display the results in *Table II.*

The mean squared error across each category ranges from 0.143611 to 0.22187 and the average error from 0.00675 to 0.018272, which is less than two percent and is very low, given the small numbers of inputs used. In order to test if any information is "left out" in the residuals, we employ white noise tests (which are typical in system identification) and the Portmanteu (1983) statistic is $\chi^{40} = 26.7704$ and does not reject the null, namely that residuals are white noise. Having combined

[6]

$$y_t = \sum_{j=1}^{p} arLj \cdot y_{t-j} + X_t' \cdot \beta + \sum_{k=0}^{q} maLk \cdot \epsilon_{t-k}, \epsilon_t \sim N(0, \sigma_t^2) \tag{13}$$

and

$$\ln \sigma_t^2 = \sum_{j=1}^{p} earchLj \cdot \ln \sigma_{t-j}^2 + Z_t' \cdot het_{factors} + \sum_{k=0}^{q} egarchLk \cdot z_{t-k}, z_t \sim N(0, \sigma^2) \tag{14}$$

Table I Hybrid EGARCH Full System

D.tcrate	Coef.	Std.Err.	z	p-0
D.busp	.5947561	.0048782	121.92	0.000
cat	-.0544945	.3609009	-0.15	0.880
cst	89.67948	39.91656	2.25	0.025
arL1	1.605983	.1200491	13.38	0.000
arL2	-.7344997	.1003696	-7.32	0.000
maL1	-1.57367	.130966	-12.02	0.000
maL2	.6588982	.1171024	5.63	0.000
D.busp	.0000316	3.67e-06	8.63	0.000
hetcat	.0001946	.0005558	0.35	0.726
hetcst	.7213303	.2043463	3.53	0.000
earchL1	.2120146	.0515153	4.12	0.000
earchL2	.0765114	.041925	1.82	0.068
earchaL1	.5955742	.0587514	10.14	0.000
earchaL2	.8173896	.056611	14.44	0.000
egarchL1	.0493823	.036764	1.34	0.179
egarchL2	.9088119	.0315344	28.82	0.000
LogL	-3856.066			

Table II Hybrid EGARCH Full System

D.ln(tcr)	Coef.	Std.Err.	z	p-0
D.ln(busp)	.4394877	.0085786	51.23	0.000
cat	8.68e-07	.000012	0.07	0.942
cst	.0015319	.0016221	0.94	0.345
arL1	.8382046	.5109495	1.64	0.101
arL2	.0170225	.4519416	0.04	0.970
maL1	-.8280828	.5218845	-1.59	0.113
maL2	-.1203292	.5073313	-0.24	0.813
D.ln(busp)	.1340466	.0789613	1.70	0.090
hetcat	.000816	.0007054	1.16	0.247
hetcst	-.3673754	.1639719	-2.24	0.025
earchL1	-.0398744	.0413473	-0.96	0.335
earchL2	.0554082	.0363861	1.52	0.128
earchaL1	.6983358	.057588	12.13	0.000
earchaL2	.8875543	.047151	18.82	0.000
egarchL1	-.0305064	.0193224	-1.58	0.114
egarchL2	.9381737	.0149055	62.94	0.000
LogL	516.61382			

all available forces for the calibration of the system this hybrid GARCH-System Dynamics model has achieved three different tasks:

- It incorporates all economic theory and information in a market clearing environment, since it uses as an input the output of a market clearing system.
- It takes advantage of the rich character of GARCH models, by imposing structure on the dynamics of the residuals and combines system dynamics and identification with statistical modelling.
- Finally, we have proposed a hybrid model and a calibration algorithm that aggregates statistical models with engineering type models.

The results of the hybrid model and the actual prices are displayed in Figure 3, which needless to say speaks for itself.

6 Conclusions and Further Research

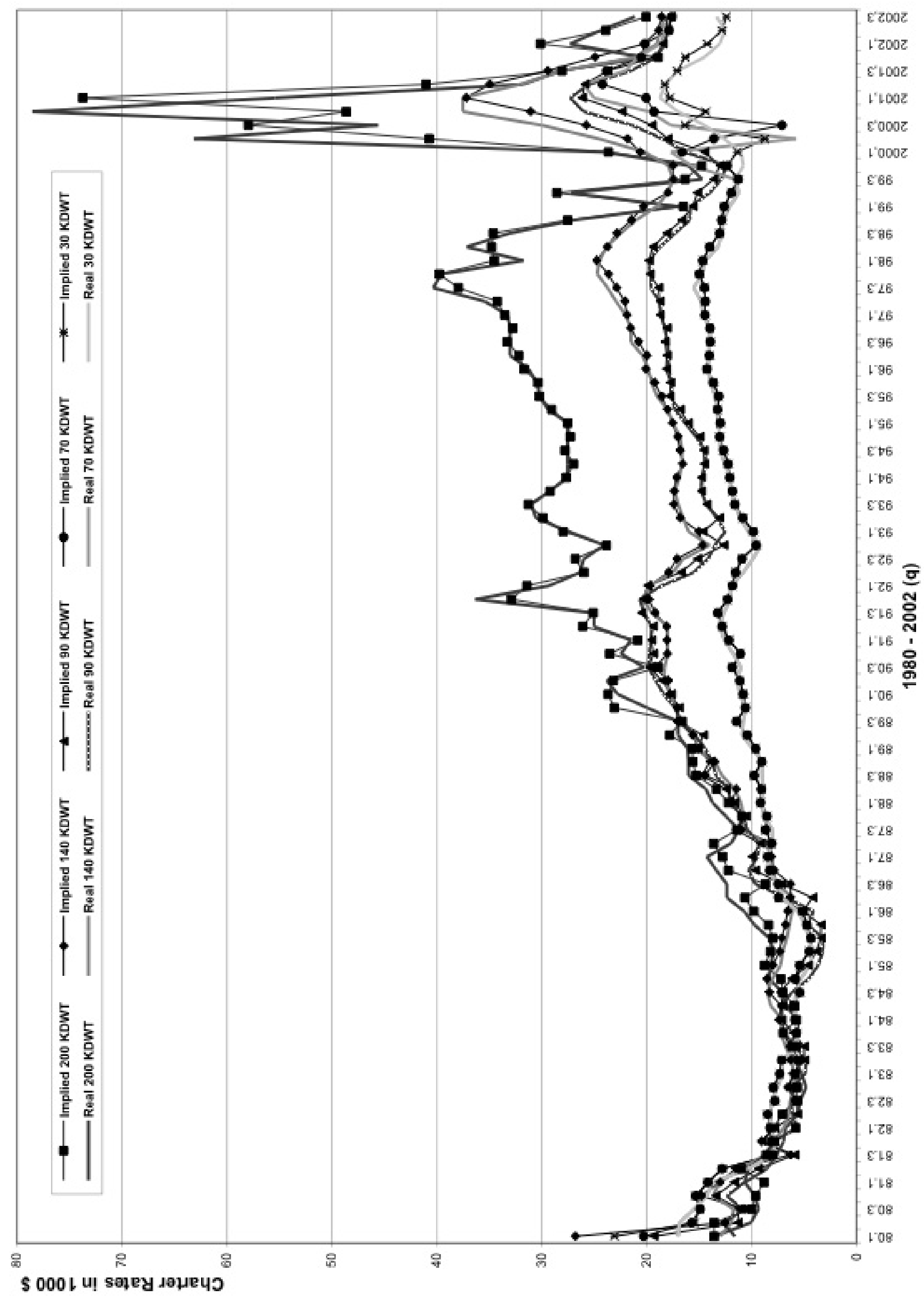
Besides our main goal of describing an innovative approach for the modelling of the competitive market for tanker rates, we have demonstrated the importance of behavior, economics and statistical modelling towards a system synthesis and identification of the relevant variables in a competitive economic environment.

We focused on the structural relationship between freight rates in the tanker industry and a set of exogenous inputs. We have successfully challenged the assertion that statistical models systematically outperform structural or system dynamics models and presented an innovative approach for the modelling of the competitive market for tanker rates. Subsequently, this model captures the essential features of several shipping industry situations and allows us to identify analytically conditions that influence bidirectional changes imposed on time charter rates. The amalgamation of a structural system and a statistical framework give us the necessary insights in this specific market, while remaining consistent to economic principles.

Further applications of our model leads to the support of managerial decisions, both quantitative and qualitatively in risk management and decision making.

The innovative techniques introduced in this paper, may be applied to the analysis and modelling of any competitive economic system. A final route of future research that is worth exploring is to embed our estimation procedure into other transportation-related industries that exhibit similar patterns or the real estate industry.

Figure 3: Hybrid GARCH-system dynamics Output



7 Appendix

For the function of the flow of new building vessels that corresponds to the tonnage inflow $N(r, x)$, we employ the estimates in Dikos (Dikos, 2004, p. 54). The number of new vessels in each period follows a Negative Binomial process (Hausman, Hall and Griliches, 1984) (an extension of a Poisson process) and the set of exogenous inputs x that determine the intensity of the process are the following:

- ship$k$: lags of ships of order k
- tcrate: one year time charter rate r_t (source: $Marsoft$, $Clarksons$)
- newprice: the price of new vessels (source: $Clarksons$)
- accident: a dummy for accidents
- lrate: the FED lending rate (source: *Datastream*)
- opex: operating expenses (source: $Clarksons$, $Marsoft$, etc.)
- tcs: $tcrate^2$
- dwg: a deadweight dummy variable
- oil: prices of crude oil (source: *Datastream*)
- spoil: Standard and Poor's oil price index (source: *Datastream*)
- air: Standard and Poor's index of air transportation (source: *Datastream*)

For the function of of the flow of scrapped tonnage that corresponds to the tonnage outflow $Sc(r, x)$, we employ the estimates in Dikos (Dikos, 2004, p. 77). The number of vessels scrapped each period follows a Negative Binomial process and the set of exogenous inputs x that determine the intensity of the process are:

- scr$k$: lags of the scrapped tonnage *scr* of order k
- crt: capital replacement time calculated in equilibrium
- tci, opi: *tcrate* and *opex* category weighted indexes

For the fraction of tonnage in Lay-Up $Lay(r, x)$ we employ the functional form estimated by Zannetos (1966) and Dikos (2004). Although estimates of the Lay-Up function with aggregate data exist, size category specific estimates do not exist. Therefore the parametric form is presented up to the unknown parameter β_j. Estimating the parameters for each category is part of the calibration process.

$$Lay_t(r_t, x) = \frac{\beta_{j0}}{r_t^2} + \beta_{j1} \cdot x_t \tag{15}$$

The set of exogenous inputs x are the following:

- lay$k$: lag of the tonnage in lay-up lay of order k
- fleet: total fleet in tonnage (source: $Marsoft$)

Acknowledgments

George Dikos is grateful to Professor Nick Patrikalakis and Professor Victor Chernozhukov for their support and encouragement. Part of this paper appears in his Doctoral Thesis. Special thanks to the Hellenic Air Force for its hospitality during the write up of the paper. We are all grateful to the Eugenides foundation and especially Mr Eudenides Dimitriadis for financial assistance and his belief in our work.

References

Coyle, R. G. 1978. "A System Dynamics Case Study". *Journal of Operational Research* 2, 2, pp. 86-96.

Dahleh, M. A., Sontag, E. D., Tse, D. N. C. and J. N. Tsitsiklis 1995. "Worst-Case Identification of Nonlinear Fading Memory Systems". *Automatica*, 31, pp. 503-508.

Dikos, G. 2004. "Decisionmetrics: Dynamic Structural Estimation of Shipping Investment Decisions". *Unpublished PhD Thesis*, Department of Ocean Engineering, Massachusetts Institute of Technology.

Dixit A. and R. Pindyck 1994. "Investment under Uncertainty". *Princeton University Press.*

Engle, R., Bollerslev, T. and D. B., Nelson 1994. "ARCH Models". *Handbook of Econometrics*, edited by R. F. Engle and D. L. McFadden, Elsevier.

Frankel, E. and H. S. Marcus 1973. *Ocean Transportation*, MIT Press, Cambridge, MA.

Größler, A. 2004. "A Content and Process View on Bounded Rationality". *Systems Research and Behavioral Science* 21, pp. 319-330.

Hausman, J., Hall, B. and Z. Griliches (1984). "Econometric Models for Count Data with an Application to Patents-RD Relationship". *Econometrica* 52, pp.909-938.

Kavussanos, M. 2002. "Business Risk Measurement and Management in the Cargo Carrying Sector of the Shipping Industry" in C. Th. Grammenos editor. *The Handbook of Maritime Economics and Business*, LLP Press.

Kavussanos, M. 1996. "Price Risk Modelling of Different Size Vessels in the Tanker Industry using ARCH Models". *The Logistcis and Transportation Review* 32, 2, pp. 161-176.

Khaled, A., AbbasMichael G. and H. Bell 1994. "System Dynamics Applicability to Transportation Modelling". *Transportation Research Part A: Policy and Practice* 28, 5, pp. 373-390.

Lucas. R. Jr. 1975. "Econometric Policy Evaluation: A Critique" in K. Brunner and A. Meltzer, eds. *The Phillips Curve and Labor Markets*, North-Holland.

Mageirou, E., H. Psaraftis and N. Christodoulakis 1992. "Quantitative Methods in Shipping: A Survey of Current Use and Future Trends". *Working Paper*, Report No. E115, Athens University of Economics and Business.

Rust, J. 1995. "Optimal Replacement of GMC Bus Engines: An Empirical Model of Harold Zurcher". *Econometrica* 55, pp. 999-1033.

Rust, J. 1997. "Dealing with the Complexity of Economic Calculations". *Working Paper*, Departemnt of Economics, University of Maryland.

Sharp, J. and D.H.R. Price 1984. "System Dynamics and Operational Research: An Appraisal". *European Journal of Operational Research* 16, pp. 1-12.

Stokey, L. N., Lucas, R. Jr. with E. Prescott 1989. *Recursive Methods in Economic Dynamics*, Harvard University Press.

Stopford, M. 1991. *Maritime Economics*, Routledge, London.

Strandenes, S. P. 2002. "Economics of the Markets for Ships" in C. Th. Grammenos editor. *The Handbook of Maritime Economics and Business*, LLP Press.

Tong, H. 1983. *Threshold Models in Non-linear Time Series Analysis*, Lecture Notes in Statistics, Springer Verlag.

Vapnik, V. 1995. *The Nature of Statistical Learning Theory*, New York , Springer Verlag.

Vives, X. 1993. "How Fast Do Rational Agents Learn?". *Review of Economics and Statistics* 60, pp. 329-347.

Warren, K. 2004. "Why Has Feedback Systems Thinking Struggled to Influence Strategy and Policy Formulation? Suggestive Evidence, Explanations and Solutions". *Systems Research and Behavioral Science* 21, pp. 331-347.

Zannetos, Z. 1966. *The Theory of Oil Tankership Rates*, M.I.T. Press.