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DETECTION AND IMPACT OF INDUSTRIAL SUBSIDIES:
THE CASE OF WORLD SHIPBUILDING

Myrto Kalouptsidi

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ABSTRACT

This paper provides a model-based empirical strategy to, (i) detect the presence and magnitude of government subsidies and (ii) quantify their impact on production reallocation across countries, industry prices, costs and consumer surplus. I construct and estimate an industry model that allows for dynamic agents in both demand and supply and apply my strategy to world shipbuilding, a classic target of industrial policy. I find strong evidence consistent with China having intervened and reducing shipyard costs by 15-20%, corresponding to 5 billion US dollars between 2006 and 2012. Standard detection methods employed in subsidy disputes yield less than a third of this magnitude. The subsidies led to substantial reallocation of ship production across the world, with Japan in particular losing significant market share. They also misaligned costs and production, while leading to minor surplus gains for shippers. Finally, I find that production subsidies had a stronger impact than capital subsidies.

Myrto Kalouptsidi
Department of Economics
Princeton University
315 Fisher Hall
Princeton, NJ 08544
and NBER
myrto@princeton.edu

1 Introduction

Government subsidies to industries have been prevalent throughout economic history and in several countries have steered industrialization and growth. An important and open question is what is their impact on production allocation across countries, industry prices, costs and surplus. A significant challenge in this task is that government subsidies to industries are notoriously difficult to detect. Indeed, partly because WTO agreements prohibit direct and in-kind subsidies other than infrastructure,[1] the existence and magnitude of such subsidies is often unknown.[2]

This paper offers two contributions to the effort of assessing the consequences of subsidies. First, it provides a model-based empirical strategy to detect the presence and gauge the magnitude of government subsidies. Second, it quantifies the impact of these subsidies on industrial evolution.

I apply this strategy to the world shipbuilding industry, a prototypical example of an industry in which subsidies are believed to play a prominent role. Shipbuilding in the 2000's is a particularly interesting case because a striking reallocation of production took place: in a single year (2006), China doubled its market share from 25% to 50%, leaving Japan, S. Korea and Europe trailing behind. In 2006, China launched a capital subsidization plan; these capital subsidies are known, observed and not prohibited. However, many asserted that China's rapid rise was also driven by government production subsidies, which are not known, unobserved and prohibited; here I disentangle the contributing factors (e.g. differentiated products, inherent cost differences, and most importantly, capital and production subsidies).

I develop and estimate a model of the shipbuilding industry, providing one of the first empirical analysis in industrial organization looking at dynamic agents on both the demand and the supply side. A large number of shipyards offer durable, differentiated ships. Their production decisions are subject to a dynamic feedback because of time to build: shipyards accumulate backlogs, which affect their future ability to accept new ship orders. Production is also subject to an aggregate stochastic

[1] In its Agreement on Subsidies and Countervailing Measures, the WTO defines a subsidy as an unrequited financial contribution by a government to enterprises in the form of: (i) direct transfer of funds, (ii) foregone revenue that is otherwise due, (iii) provision of goods or services, except infrastructure, (iv) payments to a funding mechanism to carry out one or more of the type of functions illustrated in (i) to (iii).

[2] The Department of Commerce and the US International Trade Commission devote many resources to detection of dumping and subsidies. See for example Haley and Haley (2013)' book, which is devoted to the difficulties in detecting subsidies.

cost shock, summarized in the price of steel, a key production input. Every period a large number of identical potential shipowners decide to enter the freight market by buying a new ship from world shipyards. Demand for new ships is driven by demand for international sea transport, which is uncertain and volatile. As ships are long-lived investments for shipowners, demand for new ships is dynamic.

The model primitive of interest is the cost function of potentially subsidized firms. As in many industries, however, costs of production are not observed. My strategy amounts to estimating costs from demand variation, as is common in empirical industrial organization, but in a framework of dynamic demand and supply. In the simplest example of a static, perfectly competitive framework, marginal cost is recovered directly from prices. In that case, the detection strategy amounts to testing for a break in observed ship prices in 2006 when China launched its capital subsidization plan. In my setup, there are two complications: (i) new ship price data are scant, and (ii) the shipbuilding production decision is subject to dynamic feedbacks. To address (i), I add used ship prices; to address (ii) I use the shipyard's optimality conditions resulting from its dynamic optimization. In summary, my estimation strategy first uses new and used ship prices to estimate the willingness to pay for a new ship and then inserts it into the dynamic optimization problem of shipbuilders. The first step is an extension of Kalouptsidi (2014); the second step forms a hybrid approach, inspired by the recent literature on the estimation of industry dynamics models (e.g. Bajari, Benkard and Levin (2007), Pakes, Ostrovsky and Berry (2007)). Finally, the estimation treats China's 2006 government plan as an unexpected and permanent change from the point of view of industry participants: expectations and value functions are estimated separately before and after 2006.

The first objective of the empirical analysis is to detect and measure changes in costs that are consistent with subsidies. I find a strong significant decline in Chinese costs, consistent with subsidies equal to about 15-20% of costs, or 5 billion US dollars at the observed production levels. A concern may be that this decline is not driven by subsidies, but rather by technological change, or learning-by-doing. To address this concern, I perform several robustness checks. I find that the results are robust to many specifications that control flexibly for time-variation. I also provide evidence that costs did not change in other countries. Most convincingly, the results hold when I estimate costs on the subset of shipyards that existed prior to 2001. These shipyards are no longer learning-by-doing, nor did their technology change (though bulk ship production is not characterized by technological innovations to begin with). My identification relies heavily on China's rapid expansion in market share. Using market share and price data to detect subsidies is in fact different from current methods used by the WTO and the US ITC, who rely exclusively on prices. To illustrate, I compare my detection method to the price-gap approach used in WTO cases; the latter recovers subsidies equal to 4-7%, less than a third of the retrieved magnitude here.

The second objective of the empirical analysis it to use the estimated model to quantify the impact of China's subsidies on ship prices, production reallocation across countries, as well as industry costs and shipper surplus. I also ask whether this impact varies by different types of subsidies (capital or production subsidies). Here is a brief summary of my main four findings.

First, I find that subsidies lead to substantial reallocation in production: if production subsidies are removed, China's market share is cut to half, while Japan's share increases by 50%. Interestingly, production subsidies seem to have a much larger impact than capital subsidies. The dynamic feedback in production, captured by the dependence of costs on backlog, is responsible for about 7% of this reallocation.

Second, ship prices experience moderate increases in all countries; this is not surprising, given that China's subsidization shifted supply outward.

Third, freight rates decrease moderately because of the larger fleet between 2006 and 2012 and more so over time due to time to build. As a result, cargo shippers benefit from Chinese subsidies and gain about 250 million US dollars in shipper surplus in that time period. Comparing this gain to the 5 billion US dollar cost of production subsidies implies that the benefits of subsidies within the maritime industries are minimal and perhaps the Chinese government is aspiring to externalities to different sectors (e.g. steel, defense).

Fourth, the subsidies create a wedge in the alignment of market share and production costs: net of subsidies, they lead to a large increase in the industry average cost of production by shifting production away from low-cost Japanese shipyards towards high-cost Chinese shipyards.

This paper contributes to the long theoretical (e.g. Jovanovich (1982), Hopenhayn (1992), Ericson and Pakes (1995)) and recent empirical (e.g. Aguirregabiria and Mira (2007), Jofre-Bonet and Pesendorfer (2003), Benkard (2004), Ryan (2012), Collard-Wexler (2013), Xu (2008), Sweeting (2013)) literature on industry dynamics. Methodologically, it lies closest to Hotz and Miller (1993), Pakes, Ostrovsky and Berry

(2007) and Bajari, Benkard and Levin (2007), yet this literature considers either single agent dynamics or dynamic firms and static consumers. To tackle the difficulty of having dynamic consumers (shipowners) and dynamic producers (shipbuilders), we resort to second-hand sale transactions, extending Kalouptsidi (2014). Such transaction prices may be helpful in other markets of durable goods which are characterized by dynamics in both demand and supply; such setups have scarcely been studied (one example is Chen, Esteban and Shum (2013)).

The paper also naturally contributes to the trade literature on the impact of industrial policies. Grossman (1990) provides an excellent survey of the relevant literature. Not surprisingly, there is little empirical work given the constraints in subsidy data availability. Baldwin and Krugman (1987*a*) and (1987*b*) explore the impact of trade policies in the wide-bodied jet aircraft and the semiconductor industries, while Baldwin and Flam (1989) in the 30-40 seat commuter aircraft industry. They all discuss the lack of knowledge regarding both the presence and magnitude of subsidies and other policies and compute industrial evolution under different hypothetical scenarios. Another strand of literature explores the impact of anti-dumping rulings on industry (e.g. Blonigen and Wilson (2005) focus on the steel industry, but do not address the detection of dumping). Finally, there is a long literature on China's expansion and trade policy in several industries (e.g. Roberts, Fan, Xu and Zhang (2011)).

The remainder of the paper is organized as follows: Section 2 provides a description of the industry. Section 3 presents the model. Section 4 describes the data used and provides some descriptive evidence. Section 5 presents the empirical strategy and the estimation results. Section 6 provides the counterfactual experiments and Section 7 concludes.

2 Industry Description

Shipbuilding is often seen as a "strategic industry" as it increases industrial and defence capacity, generates employment, accelerates regional development and can have important spill-overs to the iron and steel, electronic, and machinery manufacturing industries (OECD (2008)). Indeed, several of today's leading economies developed their production technologies and human capital through a phase of heavy industrialization, in which shipbuilding was one of key pillars, along with steel and petrochemicals. In the 1850's, Britain was the world leading shipbuilder, until it was overtaken by Japan in the 1950's, which in turn lost its leading position to Korea, in the 1970's. Japan used its shipbuilding industry to rebuild its industrial capability motivated by its strong maritime tradition, while Korea saw shipbuilding as a strategic core for its economic development and gave it an exporting orientation (OECD (2008)). Over the years, several disputes regarding subsidies have occurred.[3] Until recently, China was a small player and was regarded as a risky place to build new ships, while Chinese built vessels commanded a discount in both the new-building and second-hand market (Stopford (2009)).

China's[4] "Long and Medium Term Plan for the Shipbuilding Industry 2006-2015" "implements plans to strengthen and upgrade the overall shipbuilding industrial capability through the construction of shipyards, while also upgrading existing shipbuilding facilities" (Collins and Grubb (2008)). Nevertheless, it is claimed that the government is not involved in general business operations of individual companies (OECD (2008)), while even state-owned "shipyards largely function as independent corporate entities and handle day-to-day operations and contract bids" (Collins and Grubb (2008)). Finally, China's shipbuilding is mostly geared towards export sales which comprised about 80% of its orderbook in 2006 (Collins and Grubb (2008)). Figure 1 shows China's rapid expansion in capital infrastructure as measured by shipbuilding dry docks.

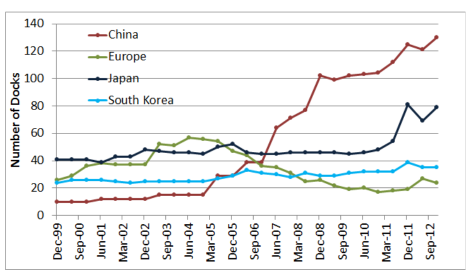

Figure 1: Shipbuilding dry docks.

[3] A recent example was Europe's accusation for Korean subsidies in 2001, which was not accepted by the WTO: "No progress was achieved, as the Korean Government claimed that it had no influence on the shipyards (...) and further said that it was convinced business was conducted along free market principles". (EU Commission)

[4] In recent years, China has been a target of trade disputes in many industries (see Haley and Haley (2013) for an overview) that have trickled down to the press. A good example, is "Perverse Advantage", published in The Economist, April 2013: "China is the workshop to the world. It is the global economy's most formidable exporter and its largest manufacturer. The explanations for its success range from a seemingly endless supply of cheap labour to an artificially undervalued currency. (...) another reason for China's industrial dominance: subsidies".

Commercial ships are the largest factory produced product. Based on Stopford (2009), a $30,000$ DWT bulk carrier might contain $5,000$ tons of steel and $2,500$ tons of other components (e.g. the main engine and numerous minor components such as cabling, pipes, furniture and fittings). Materials account for about half the cost of the ship (steel is about 13%) and labor about 17% of total cost. A shipyard constructs the steel hull and conducts the outfitting of the hull with machinery, equipment services and furnishings (Stopford (2009)); many of these operations are conducted simultaneously, with individual tasks not requiring highly technical skills.

Shipbuilding demand is determined by entry in the shipping industry. In this paper I focus on cargo transportation and in particular, bulk shipping, which concerns vessels designed to carry a homogeneous unpacked dry or liquid cargo, for individual shippers on non-scheduled routes (see Kalouptsidi (2014) for a detailed description of the bulk shipping industry). The entire cargo usually belongs to one shipper and it involves mostly raw materials, such as iron ore, steel, coal and grain. The bulk shipping market consists of a large number of small shipowning firms. Demand for shipping services is driven by world seaborne trade and is thus subject to world economy fluctuations. In the short run, the supply of shipping services is determined by the number of voyages carried out by shipowners and is rather inelastic. In the long run, the supply of cargo transportation adjusts via the building and scrapping of ships. Exit in the industry occurs when shipowners scrap their ships by selling them to scrapyards where they are dismantled and their steel hull is recycled.

3 Model

In this section, I present a dynamic model of the market for new ships, which lies within the general class of industry dynamic models studied in Ericson and Pakes (1995) and Hopenhayn (1992). Time is discrete and the horizon is infinite. Shipowners create demand for shipbuilders, who respond by supplying new ships. I begin by describing shipowner behavior, then turn to shipbuilders. I also discuss how government subsidies enter.

3.1 Demand for New Ships (Shipowners)

There is a finite number of incumbent shipowners (the fleet) and a large number of identical potential entrant shipowners. I assume constant returns to scale, so that a firm is a ship. Ships are long-lived. The state variable of ship i at time t, s_{it}, includes its:

1. age, $a_{it} \in \{0, 1, ..., A\}$
2. country where built, $c_i \in \mathcal{C}$

while the industry state, s_t, includes:

1. the distribution of characteristics in s_{it} over the fleet, $S_t \in \mathbb{R}^{A \times ||\mathcal{C}||}$
2. the backlog $b_t \in \mathbb{R}^{J \times \overline{T}}$, whose $(j,k)^{th}$ element is the number of ships scheduled to be delivered at period $t+k$ by shipyard j and $\overline{T}$ the maximum time to build
3. the aggregate demand for shipping services, $d_t \in \mathbb{R}^+$
4. the price of steel, $l_t \in \mathbb{R}^+$.[5]

In period t, each shipowner i chooses how much transportation (i.e. voyages travelled) to offer, q_{it}. Shipowners face the inverse demand curve:

$$P_t = P(d_t, Q_t) \tag{1}$$

where P_t is the price per voyage, d_t defined above includes demand shifters, such as world industrial production and commodity prices and Q_t denotes the total voyages offered, so that $Q_t = \sum_i q_{it}$. Voyages are a homogeneous good, but shipowners face heterogeneous convex costs of freight, $c^F(q_{it}, s_{it})$. Ship operating costs increase with the ship's age and may differ based on country of built because of varying quality.

I assume that shipowners act as price-takers in the market for freight. Their resulting per period payoffs are $\pi(s_{it}, S_t, d_t)$.

A ship lives a maximum of A periods. At the same time, a ship can be hit by an exit shock each period. In particular, I assume that a ship at state (s_{it}, s_t) exits with probability $\delta(s_{it}, s_t)$ and receives a deterministic scrap value $\phi(s_{it}, s_t)$. Note that $\delta([a_{it}, c_i], s_t) = 1$, for $a_{it} \geq A$ and all c_i, s_t.[6]

[5] The steel price is part of the state because it: (i) is a key determinant of shipyard production costs; (ii) determines the ship's scrap value.

[6] Generalizing to endogenous exit is straightforward (see Kalouptsidi (2014)).

The only dynamic control of shipowners is entry in the industry: each period, a large number of identical potential entrants simultaneously make entry decisions. There is time to build, in other words, a shipowner begins its operation a number of periods after its entry decision. To enter, shipowners purchase new vessels from world shipyards. Shipyard j in period t can build a new ship at price P_{jt}^{NB} and time to build T_{jt}. The assumption of a large number of homogeneous potential shipowners implies that shipyard prices are bid up to the ships' values and shipyards can extract all surplus. One can also think of this as a free entry condition in the shipping industry where the entry cost is equal to the shipyard price. Therefore, the following equilibrium condition holds:

$$P_{jt}^{NB} = E\left[\beta^{T_{jt}} V\left(s_{it+T_{jt}, s_{t+T_{jt}}}\right) | s_{it}, s_t\right] \tag{2}$$

where β is the discount factor and s_{it} in this case involves $a_{it} = 0$ and the country of yard j, while the value function $V(s_{it}, s_t)$ satisfies the Bellman equation:

$$V(s_{it}, s_t) = \pi(s_{it}, s_t) + \delta(s_{it}, s_t)\phi(s_{it}, s_t) + (1 - \delta(s_{it}, s_t))\beta E\left[V(s_{it+1}, s_{t+1}) | s_{it}, s_t\right] \tag{3}$$

In words, the value function of a ship at state (s_{it}, s_t) equals the profits from cargo transport plus the scrap value which is received with probability $\delta(s_{it}, s_t)$ and the continuation value $E\left[V(s_{it+1}, s_{t+1}) | s_{it}, s_t\right]$, which is received with probability $1 - \delta(s_{it}, s_t)$.

In practice, shipowners can also buy a used ship. In this model, ships are indistinguishable from their owners and therefore, transactions in the second-hand market do not affect entry or profits in the industry. In addition, since there is a large number of identical shipowners who share the value of a ship, the price of a ship in the second hand market, P_{it}^{SH}, equals this value and shipowners are always indifferent between selling their ship and operating it themselves. Therefore, in equilibrium:

$$P_{it}^{SH} = V(s_{it}, s_t) \tag{4}$$

I revisit sales in the empirical part of the paper, where both second-hand and new ship prices are treated as observations on the value function.

3.2 Supply of New Ships (Shipyards)

There are J long-lived incumbent shipbuilders. The state variable of shipyard j at time t, y_{jt}, includes its:

1. backlog $b_{jt} \in \mathbb{R}^{\overline{T}}$
2. country $c_j \in \mathcal{C}$
3. other characteristics, such as: age, capital equipment (number of docks and berths, length of largest dock), number of employees.

Shipyards also share the industry state, s_t.

In period t, shipyard j draws a private iid (across j and t) production cost shock $\varepsilon_{jt} \sim N(0, \sigma)$ and makes a discrete production decision $N_{jt} \in \{0, 1, ..., \overline{N}\}$.[7] Shipyard j faces production costs, $C(N_{jt}, y_{jt}, s_t, \varepsilon_{jt})$. Even though N_{jt} is an integer I assume that the cost function $C(N_{jt}, \cdot)$ can be defined over $[0, \overline{N}]$ and that as such it is convex in N_{jt}. I also assume that the cost shock ε_{jt} is paid for each produced unit, so that:

$$C(N_{jt}, y_{jt}, s_t, \varepsilon_{jt}) = c(N_{jt}, y_{jt}, s_t) + N_{jt}\varepsilon_{jt} \tag{5}$$

In this model N_{jt} corresponds to the number of ships ordered in period t at shipyard j. These ships enter the shipyard's backlog b_{jt} and are delivered a number of years later.[8] Under demand uncertainty, therefore, undertaking a ship order becomes a dynamic choice. To capture this dynamic feedback, I assume that the cost function depends on the shipyard's backlog. As in Jofre-Bonet and Pesendorfer (2003), there are two opposing ways the backlog can impact costs: on one hand, increased backlogs can raise costs because of capacity constraints (e.g. less available labor); on the other hand, increased backlogs can lower costs because of economies of scale (e.g. in ordering inputs) or the accumulation of expertise.[9]

As discussed above, shipyard j sells its ships at a price equal to the shipowners' entry value:[10]

[7] Allowing for serially correlated unobserved state variables is a difficult issue that the literature has not tackled yet.

[8] I consider the number of orders as the relevant choice variable (as opposed to using the number of deliveries or smoothing orders) because the observed ship prices are paid at the order date and may be dramatically different from the prevailing prices at the delivery date.

[9] Here, the shipyard's backlog also affects its demand, as it increases the time to build offered.

[10] Note that the willingness to pay for a new ship from yard j depends only on its country of origin, not j itself. Even though it is straightforward in the model to allow a ship's value to change with j,

$$VE_j\left(s_t\right) \equiv E\left[\beta^{T_{jt}} V\left(s_{it+T_{jt}}, s_{t+T_{jt},}\right) | s_{it}, s_t\right] \tag{6}$$

where s_{it} has $a_{it} = 0$ and the country of yard j. Time to build is shipyard-specific and in particular, $T_{jt} = T\left(y_{jt}, s_t\right)$. Note that $VE_j\left(s_t\right)$ does not explicitly depend on period t's production, N_{jt}; in other words yards do not face a downward sloping demand curve. Indeed, N_{jt} affects the willingness to pay for the ship by entering into the total backlog b_t and from there into the fleet after T_{jt} periods. Typically, N_{jt} is a small integer, while the total fleet is a large number in the order of thousands. Therefore each shipyard, when making its production decision, can ignore the impact it has on $VE_j\left(s_t\right)$; note however, that aggregates do matter so that as the total fleet increases, shipowners' willingness to pay falls, all else equal.

Shipyard j chooses its production level to solve the Bellman equation:

$$W\left(y_{jt}, s_t, \varepsilon_{jt}\right) = \max_{N \in \left\{0,1,\ldots,\overline{N}\right\}} VE_j\left(s_t\right) N - c\left(N, y_{jt}, s_t\right) - N\varepsilon_{jt} + \beta E\left[W\left(y_{jt+1}, s_{t+1}, \varepsilon_{jt+1}\right) | N, y_{jt}, s_t\right] \tag{7}$$

To ease notation, I also define the continuation value:

$$Q\left(y_{jt}, s_t, N\right) \equiv E\left[W\left(y_{jt+1}, s_{t+1}, \varepsilon_{jt+1}\right) | N, y_{jt}, s_t\right] \tag{8}$$

The expectation in (7), as well as (2) and (3) is over demand for shipping services, d_t, steel prices, l_t and shipyard production N_{jt}, all j. The demand state variable d_t and steel prices l_t evolve according to a first order autoregressive process with trend (see Section 5.1.1). Period t production, N_{jt}, enters j's backlog, b_{jt}, at position T_{jt}, while the remaining elements of b_{jt} move one period closer to delivery with its first element being delivered. Note that the evolution of all other states is deterministic (see Section 5.1.1). The trend component in demand and steel prices implies that time t is explicitly part of the state (in other words, the state notation $\{s_{it}, y_{jt}, s_t\}$ incorporates t). Allowing for time to enter the agents' decision-making offers some generality and is important in this application, as my empirical analysis of detecting government subsidies hinges on allowing time-varying factors to affect costs.

Under convex costs, the shipyard's optimal policy amounts to comparing each production level n to $n + 1$ and $n - 1$, as stated in the following intuitive lemma:

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the hundreds of shipyards encountered in the data make this generalization impossible.

Lemma 1 *If the shipbuilding cost function $C(n, \cdot) : [0, \overline{N}] \to \mathbb{R}$, is convex in n, then the shipyard's optimal policy is given by:*

$$N^*(y_{jt}, s_t, \varepsilon_{jt}) =$$

$$= \begin{cases} 0, \quad \text{if } \varepsilon_{jt} \geq VE_j(s_t) + c(0, y_{jt}, s_t) - c(1, y_{jt}, s_t) + \beta(Q(y_{jt}, s_t, 1) - Q(y_{jt}, s_t, 0)) \\ n, \quad \text{if } \varepsilon_{jt} \in \begin{bmatrix} VE_j(s_t) + c(n, y_{jt}, s_t) - c(n+1, y_{jt}, s_t) + \beta(Q(y_{jt}, s_t, n+1) - Q(y_{jt}, s_t, n)), \\ VE_j(s_t) + c(n-1, y_{jt}, s_t) - c(n, y_{jt}, s_t) + \beta(Q(y_{jt}, s_t, n) - Q(y_{jt}, s_t, n-1)) \end{bmatrix} \\ \overline{N}, \quad \text{if } \varepsilon_{jt} \geq VE_j(s_t) + c(\overline{N}-1, y_{jt}, s_t) - c(\overline{N}, y_{jt}, s_t) + \beta(Q(y_{jt}, s_t, \overline{N}) - Q(y_{jt}, s_t, \overline{N}-1)) \end{cases} \tag{9}$$

Proof. See the Online Appendix. ■

The timing in each period is as follows: incumbent and potential entrant shipowners observe their state (s_{it}, s_t), while shipbuilders observe their state (y_{jt}, s_t). Shipowners are hit by exit shocks and shipbuilders observe their private production cost shocks. Shipyards make production decisions. Next, shipowners receive profits from freight services and shipyards receive profits from new ship production. Exiting ships receive their scrap value $\phi(s_i, s)$. Finally, states are updated.

I consider a competitive equilibrium which consists of an optimal production policy function $N^*(y_{jt}, s_t, \varepsilon_{jt})$ that is given by (9), as well as value functions $W(y_{jt}, s_t)$ and $V(s_{it}, s_t)$ that satisfy (7) and (3) respectively, while all expectations employ $N^*(y_{jt}, s_t, \varepsilon_{jt})$. Existence of equilibrium follows from Doraszelski and Satterthwaite (2010), Hopenhayn (1992), and Jovanovic (1982).

Finally, I assume that China's 2006 subsidization program was an unexpected, one-shot, permanent and immediate change from the point of view of industry participants. Explicitly modeling expectations with regard to policy interventions is extremely complicated and would rely on strong and perhaps ad hoc assumptions. Within my model, the before and after 2006 worlds differ in the number of shipyards, shipbuilding infrastructure (found in y_{jt}) and China's cost function. I also assume that shipyards do not make entry or capital expansion decisions. On one hand, outside of China there is not much action (see Figure 1), while within China, these decisions are determined by government policy.

4 Data and Descriptive Evidence

Data All data I use come from Clarksons. I employ five different datasets.

The first, reports shipbuilding quarterly production (i.e. orders) between Q1-2001 and Q3-2012. For each shipyard and quarter I observe its bulk ship production in tons and numbers, as well as the yard's backlog and average time to build. There are 192 yards that produce Handysize vessels (the segment on which my empirical analysis will focus), of which 119 are Chinese, 41 are Japanese, 21 are S. Korean and 11 are European. The majority of bulk ship production occurs in China and Japan; hence even though I include Europe and S. Korea in the estimation and counterfactuals, most comparisons will be made between China and Japan.

The second dataset is a sample of shipbuilding contracts, between August 1998 and August 2012. It reports the order and delivery dates, the shipyard and price in million US dollars. Unfortunately, prices are reported for only a fraction of contracts. I illustrate this in Figure 2, which plots the average reported new ship price per country and quarter. Note that several quarters, especially in the pre-2006 period involve missing prices. In addition, for shipyard-quarter combinations that involve zero production, the corresponding price does not exist by default.

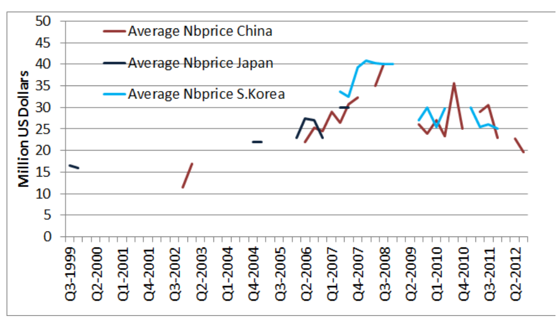

Figure 2: Reported new ship prices.

To deal with these issues, I introduce a dataset of second-hand ship sale transactions, between August 1998 and August 2012. The dataset reports the date of the transaction, the name and age of the ship, as well as the price in million US dollars. I end up with 418 observations of new ship contracts and 2016 observations of second-hand sale contracts (2434 total), of which 1173 are pre-2006 and 1261 are post-2006.

The fourth dataset employed reports shipyard characteristics in 2013 and includes:

each shipyard's first year of delivery, location, number of dry docks and berths, length of its largest dock, number of employees, total past output and total TEU (i.e. container ships) produced. The first year of delivery is used to compute the shipyard's age.[11] The number of docks and berths are a crude measure of capacity, since production bottlenecks occur during the assembly operations done on the docks/berths. The length of a dock determines the size of the ships built and it is a proxy not only for capacity, but also for overall productivity, since bigger bulk carriers are more complicated versions of smaller ones. Similarly, a shipyard that builds containers is more likely to be overall more efficient (when looking at shipyards that produce Handysize vessels only 5% also produces containers). This dataset is not ideal and several shipyards have missing observations. To allow the infrastructure of yards (i.e. docks/berths and length) to be different before and after 2006, I employ Clarksons's monthly "World Shipyard Monitor" which reports the number of docks, berths and largest dock length for the largest shipyards (about 150 per month) beginning in 2001. I use this information to create a pre-2006 level, while the post-2006 level is taken from the 2013 snapshot.[12]

Finally, the fifth dataset consists of quarterly time-series for the orders of new ships, deliveries, demolitions, fleet and total backlog. I also obtain time-series of Japan's steel ship plate commodity price in dollars per ton.[13]

Descriptive Evidence What patterns of the raw data are consistent with the presence of subsidies? One might expect that new ship prices should react in 2006. As Figure 2 shows, the sparsity of new ship prices makes it impossible to explore this. Used ship prices, however, should also display a reaction. I, therefore, run a hedonic regression of second hand prices on ship characteristics (age and country where built) and quarter dummies. Figure 3 shows that indeed there is a short-lived

[11] Some shipyards took orders before having ever delivered ("greenfields") during the 2007 boom, implying negative shipyard age. I subtract a number of years from every first delivery year of all shipyards, after consulting with Clarksons's analysts. The results I report subtract 3 years (similar findings were obtained when 6 years are subtracted).

[12] I do not create a quarterly measure of capital infrastructure (docks, berths, largest dock) for several reasons. First, this changes extremely slowly (and not much outside of China). Second, the information retrieved from the World Shipyard Monitor is rather noisy: there are several missing observations across quarters, the matching between shipyards in the several datasets is sometimes difficult and numbers may be fluctuating (or even decreasing) out of obvious measurement error. The pre-2006 snapshot I manually create overcomes these issues.

[13] Due to space limitations, some summary statistics are reported in the Online Appendix.

drop in 2006, in a period when ships prices are trending upward due to increased demand for freight. Of course this finding is not proof of production subsidies; even the announcement of the capital infrastructure subsidies should lead to a temporary drop in prices since shipowners now expect higher competition in the future.[14] Yet if no drop were observed, one may have been concerned about the impact of this policy.

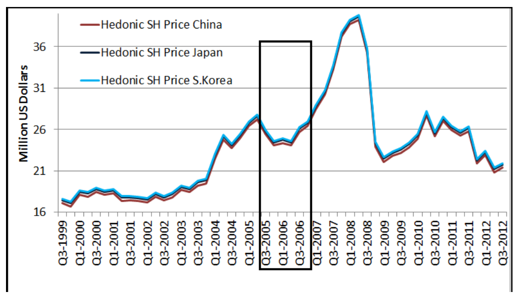

Figure 3: Hedonic regression of used ship prices on ship age, country and quarter dummies.

Despite the importance of a price response, the main insight of this paper in terms of identifying subsidies is that production patterns are equally important. Figure 4 depicts the evolution of China's market share. Between 2005 and 2006, China experiences a large, rapid increase in market share. In this paper, I employ precisely this rapid increase in production to identify changes in costs that are consistent with the presence of subsidies. When I come to results, I discuss alternative explanations for this pattern (e.g. productivity or learning by doing) and claim that they are less plausible than subsidies. To my knowledge, this is the first paper in the subsidy and dumping detection literature to employ a combination of price and quantity data, rather than just prices.

[14] I have unsuccessfully searched extensively in industry magazines for alternative explanations.

Figure 4: China's market share.

5 Model Estimation and Detection of Subsidies

To see the main idea behind the subsidy detection method, consider a static, perfectly competitive market, so that $P_{jt}^{NB} = MC_{jt}$ for all j and t. In that case, to detect subsidies one would simply look for a break in observed prices in 2006, since prices are in fact the marginal costs. In my setup, there are two complications: (i) I do not observe enough prices of new ships, and (ii) there are dynamics in the production decision. To address (i), I complement with used ship prices; to address (ii) I use the shipyard's first order condition from its dynamic optimization.

The proposed strategy proceeds in two steps. In the first step, I recover the demand curve that shipbuilders face, which coincides with the value that shipowners place on entering the shipping industry. Retrieving this willingness to pay for a new ship amounts to estimating the value function for a new ship, as well as shipowner expectations. The second step inserts the estimated willingness to pay for a ship into the optimization problem of shipbuilders to recover their costs.

5.1 Estimation of the Willingness to Pay for a New Ship

In this step, I estimate ship value functions and state transitions. All ship states are directly observed in the data except for the demand for shipping services, d_t. I construct d_t as in Kalouptsidi (2014) by estimating a demand curve for shipping services and using the intercept. The analysis is replicated in the Appendix, for completeness. Each estimation task is described below and followed by the results. All results presented are for Handysize vessels. A time period is a quarter.

5.1.1 State Transitions

In order to compute the value of entering the shipping industry, defined in (6), I need shipowner expectations over (s_{it}, s_t). The transition of s_{it} is known (age evolves deterministically, while country of built is time invariant). The transition of s_t is computationally complex: on one hand the dimension of the state space is enormous (S_t has dimension $4 \times A$ -where A is a ship's maximum age- in the case of four countries, while b_t has dimension $J \times \overline{T}$ which in my sample is in the order of several thousand); on the other hand, updating b_t requires optimal production policies for all shipyards. Instead of working with the true transitions (as in Kalouptsidi (2014)) I follow Jia Barwick and Pathak (2012) who assume that s_t follows a vector autoregressive (VAR) model. This approach is equivalent to the first step of two-step estimation procedures for dynamic games (e.g. Bajari, Benkard and Levin (2007) and Pakes, Ostrovsky and Berry (2007)).

To deal with the state dimension, I make the following simplifying assumptions. First, I replace the fleet distribution, S_t, with two age groups (S_t^1, S_t^2): the number of ships below 20 years old and the number of ships above 20 years old.[15] I do not use the distribution of the fleet over country of built because its evolution is extremely slow and it remains practically flat for a big part of the sample. In addition, I replace the backlog, b_t, with the total backlog $B_t = \sum_{j,l} b_{jtl}$.[16]

I have experimented with several variations of the general time varying vector autoregression (VAR) model:

$$s_t = C_t + R_t s_{t-1} + \xi_t$$

where $\xi_t \sim N(0, \Sigma)$. I allow the VAR parameters (C_t, R_t) to be different before and after 2006: since state transitions are not modeled explicitly, the VAR model embraces equilibrium features of agents' expectations that are likely to change after China's intervention. In particular, since post-2006 shipbuilding capital infrastructure increases, shipowners know that all else equal the supply of ships has permanently increased. This change affects their ship valuations and therefore captures any changes in demand for new ships, brought by China's policies.

[15] I have also worked with statistics of the fleet age distribution (total fleet, mean age, variance of age) and found the results to be robust.

[16] Ideally, the distribution of shipyards over their characteristics y_{jt} would be part of the state. Maintaining computational tractability does not allow for such a large state space.

I examined several specifications where (C_t, R_t) vary deterministically (e.g. time trend) or randomly with time (random walk model for R_t determined by the Kalman filter), or are time-invariant. The baseline specification is:

$$\begin{bmatrix} S_t^1 \\ S_t^2 \\ B_t \\ d_t \\ l_t \end{bmatrix} = \begin{bmatrix} c^{S_1} \\ c^{S_2} \\ c^B \\ c^d \\ c^l \end{bmatrix} 1\{t \leq 2006\} + \begin{bmatrix} c^{S_1\prime} \\ c^{S_2\prime} \\ c^{B\prime} \\ c^d \\ c^l \end{bmatrix} 1\{t > 2006\} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ a^d \\ a^l \end{bmatrix} t + \begin{bmatrix} \rho^{S_1S_1} & \rho^{S_1S_2} & \rho^{S_1B} & \rho^{S_1d} & \rho^{S_1l} \\ \rho^{S_2S_1} & \rho^{S_2S_2} & \rho^{S_2B} & \rho^{S_2d} & \rho^{S_2l} \\ \rho^{BS_1} & \rho^{BS_2} & \rho^{BB} & \rho^{Bd} & \rho^{Bl} \\ 0 & 0 & 0 & \rho^d & 0 \\ 0 & 0 & 0 & 0 & \rho^l \end{bmatrix} s_{t-1} + \xi_t \tag{10}$$

and Σ is diagonal. Note that as discussed above, d_t and l_t are exogenous to the model and are unaffected by the pre/post-2006 regime. In contrast, I allow (S_t^1, S_t^2, B_t) to be affected by all variables to account for ship entry and exit. The baseline specification allows only C to change before and after 2006. Even though t appears explicitly only in the exogenous variables, it affects (S_t^1, S_t^2, B_t) through their dependence on (d_t, l_t). I estimate the parameters of interest (C, R, Σ) via OLS separately for each variable (note that separate OLS yields identical estimates to Maximum Likelihood estimation) and work with natural logarithms for (S_t, B_t). Table 1 reports the results. All variables are persistent. Signs are also in general as expected: S_1 is increasing in the backlog and demand and decreasing in steel prices (as steel prices increase, exit increases); S_2 is decreasing in S_1 as more young ships increase exit and increasing in demand which leads to less exit; the backlog is increasing in demand. All eigenvalues of R lie inside the unit circle so that the model is stationary conditional on the trend. Finally, the post-2006 world's steady state has significantly higher fleet.[17]

5.1.2 Ship Value Function

The main object entering the willingness to pay for a new ship in (6), is the ship's value function. In order to estimate it, I treat prices of new and used ships as observations

[17] I also experimented heavily with restrictions on C and R both in terms of before and after 2006, allowing Σ to be full, as well as parameter restrictions (e.g. time to build might imply that $\rho^{S_1d} = 0$ ignoring ship exit). I also employed LASSO in a model where all parameters can change in 2006 to choose the relevant terms. Finally, I allowed d_t to be an $AR(2)$. My main findings are in general robust to many of these experiments. The chosen specification combines the following desired properties: it is parsimonious, stationary (conditional on the trend) and takes into account the 2006 break.

c^d	a^d	ρ^d	c^l	a^l	ρ^l
0.4118	0.0077	0.688	0.695	0.0209	0.796
$(0.1656)^*$	(0.0051)	$(0.113)^*$	(0.395)	(0.015)	$(0.091)^*$

	c^{S_1}	c^{S_2}	c^B
pre-2006	-1.47	2.53	-8.49
	(0.97)	$(1.03)^*$	(7.31)
pre-2006	-1.46	2.525	-8.503
	(0.976)	$(1.037)^*$	(7.348)

$\rho^{S_1S_1}$	$\rho^{S_1S_2}$	ρ^{S_1B}	ρ^{S_1d}	ρ^{S_1l}
1.104	0.0802	0.021	0.0046	-0.003
$(0.04)^*$	(0.094)	$(0.0044)^*$	(0.0035)	$(0.00097)^*$
$\rho^{S_2S_1}$	$\rho^{S_2S_2}$	ρ^{S_2B}	ρ^{S_2d}	ρ^{S_2l}
-0.146	0.806	-0.0068	0.0041	0.0022
$(0.043)^*$	$(0.1)^*$	(0.0047)	$(0.0037)^*$	$(0.001)^*$
ρ^{BS_1}	ρ^{BS_2}	ρ^{BB}	ρ^{Bd}	ρ^{Bl}
0.158	1.066	0.87	0.0754	-0.0094
(0.303)	$(0.707)^*$	$(0.033)^*$	(0.026)	(0.0073)

σ^{S_1}	σ^{S_2}	σ^B	σ^b	σ^d
0.0001	0.0001	0.004	0.141	1.225

Table 1: VAR parameter estimates. Stars indicate significance at the 0.05 level.

of the value of entry and the value function respectively. In particular, under the assumption of a large number of identical potential entrant shipowners, ship prices are bid up to valuations. The empirical versions of the equilibrium conditions (2) and (4) are:

$$P_{jt}^{NB} = E\left[\beta^{T_{jt}} V\left(s_{it+T_{jt}, s_{t+T_{jt}}}\right) | s_{it}, s_t\right] + \zeta^{nb} \tag{11}$$

$$P_{it}^{SH} = V\left(s_{it}, s_t\right) + \zeta^{sh} \tag{12}$$

where ζ^{sh} and ζ^{nb} are measurement error. Kalouptsidi (2014) employes used ship prices alone to nonparametrically estimate ship value functions and provides an extensive discussion on the merits and caveats of this approach, as well as direct and suggestive evidence against worries of sample selection. To this approach I add here the new ship contracts dataset and in order to combine (11) and (12) in a single estimation step I follow a different methodology.[18] In particular, I use a flexible linear sieve approximation for the value function:

$$V\left(s_{it}, s_t\right) = \gamma f\left(s_{it}, s_t\right)$$

where $f(\cdot)$ is a polynomial function in the ship state (s_{it}, s_t) and γ is a (sparse) parameter vector. Then:

$$P_{jt}^{NB} = \gamma\beta^{T_{jt}} E\left[f\left(s_{it+T_{jt}}, s_{t+T_{jt}}\right)|s_{it}, s_t\right] = \tag{13}$$

$$= \gamma\beta^{T_{jt}} \int f\left(s_{it+T_{jt}}, s_{t+T_{jt}}\right) dP\left(s_{it+T_{jt}}, s_{t+T_{jt}}|s_{it}, s_t\right) \equiv \gamma f_{NB}\left(s_{it}, s_t\right)$$

$$P_{it}^{SH} = \gamma f\left(s_{it}, s_t\right) \tag{14}$$

$P\left(s_{it+1}, s_{t+1}|s_{it}, s_t\right)$ is the state transition and is given by the VAR estimated above. The parameters γ enter (13) and (14) linearly; yet even though (14) can be estimated in a straightforward manner, (13) requires the computation of the right-hand side integrals. Indeed, (13) involves the expectation of higher order terms of the following vector:

$$s_{t+T} = R^T s_t + \sum_{k=t+1}^{t+T} R^{t+T-k}(C_k + ak + \xi_k) \tag{15}$$

I derive closed-form expressions for the integrals of up to third order terms in the industry state s_t in the Appendix.

As the dimensionality of the state (s_{it}, s_t) is large, computing high order polynomial terms quickly leads to a very large number of regressors in (13) and (14). I therefore use the LASSO, a method appropriate for sparse regression problems, i.e. problems that involve a large number of potential regressors, only a small subset of whom is important in capturing the regression function accurately. LASSO identifies the relevant regressors by performing a modified OLS procedure which penalizes a large number of nonzero coefficients, through regularization by a penalty based on

[18] Alternatively, approach one could work only with estimated expectations and used ship prices to estimate the value function and then use new ship prices for external validation. Kalouptsidi (2014) shows that the three objects are indeed consistent, albeit using only an average new ship price (taken exogenous).

the $\mathcal{L}_1$ norm of the parameter. Thus γ is estimated from :

$$\min_{\gamma}\left\{\sum_{j,t}\left(P_{jt}^{NB}-f_{NB}\left(s_{it},s_t\right)'\gamma\right)^2+\sum_{i,t}\left(P_{it}^{SH}-f\left(s_{it},s_t\right)'\gamma\right)^2+\lambda\left|\gamma\right|_1\right\}$$

In this application, the regressors $f(s_{it}, s_t)$ and $f_{NB}(s_{it}, s_t)$ are third order polynomials in s_t and s_{it}, as well as interactions of s_{it} and s_t. The discount factor is set to 0.9877 which corresponds to 5% annual interest rate.

The flexible nature of this empirical approach implies that the parameters γ embody equilibrium features which are likely to change in 2006 as agents' valuations are altered. For example, China's capital and/or production subsidies may have led potential shipowners to expect a large increase in the fleet in the coming years, thus reducing the price of ships today. Therefore, in analogy with the VAR formulation, I allow the value function to change before and after 2006, by adding all monomials multiplied by a post-2006 dummy variable. Figure 5 depicts the estimated value function on the observed states for zero year old ships (the relevant value function for the value of entry). Consistent with the raw data, Chinese ships are of lower value, with Japanese ships being of higher value; yet the differences are small.[19]

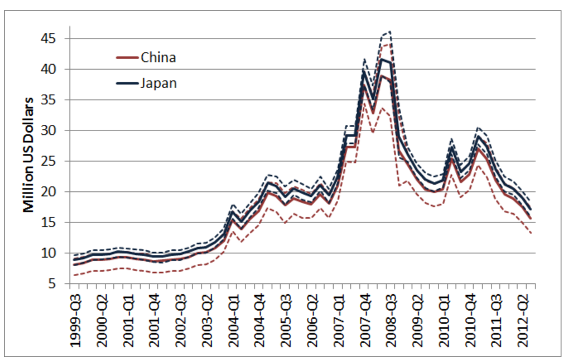

Figure 5: Value function of a 0 year old ship. 0.95 bootstrap confidence intervals.

5.2 Shipbuilding Production Cost Function

I next turn to estimating the shipbuilding cost function. I begin with the simple case where shipbuilders are static and present the estimation results along with several

[19]Pointwise confidence intervals are computed via 500 bootstrap samples, with the resampling done on the error.

robustness exercises. I then proceed to the case of dynamic shipbuilders.

5.2.1 Static Shipbuilders

If shipyard j is myopic it solves:

$$\max_{N_{jt}\in\left\{0,1,\ldots,\overline{N}\right\}} VE_j\left(s_t\right)N_{jt} - c\left(N_{jt}, y_{jt}, s_t; \theta\right) - \sigma\varepsilon_{jt}N_{jt}$$

where $\varepsilon_{jt} \sim N\left(0,1\right)$. This is essentially an ordered choice problem and to estimate the cost function parameters, I maximize the following likelihood function:

$$\prod_{j,t:N_{jt}=0}\Pr\left(N_{jt}=0|y_{jt},s_t;\theta\right)\prod_{j,t:N_{jt}=\overline{N}}\Pr\left(N_{jt}=\overline{N}|y_{jt},s_t;\theta\right)\prod_{n}\prod_{j,t:N_{jt}=n}\Pr\left(N_{jt}=n|y_{jt},s_t;\theta\right) \tag{16}$$

I assume that the shipbuilding cost function takes the following form:

$$c\left(N_{jt}, y_{jt}, s_t; \theta\right) = c_1\left(y_{jt}, s_t; \theta\right)N_{jt} + c_2\left(y_{jt}, s_t; \theta\right)N_{jt}^2$$

with $c_2\left(y_{jt}, s_t; \theta\right) > 0$ and $\left(\theta, \sigma\right)$ are the cost parameters of interest. The baseline specifications involve

$$\begin{aligned} c_1\left(y_{jt}, s_t; \theta\right) &= \theta_0^{ch}1\left\{\text{China}\right\} + \theta_0^{ch,post}1\left\{t \geq 2006, \text{China}\right\} \\ &\quad +\theta_0^{EU}1\left\{\text{Europe}\right\} + \theta_0^{J}1\left\{\text{Japan}\right\} + \theta_0^{K}1\left\{\text{S.Korea}\right\} + \theta_1 g(y_{jt}, s_t, t) \end{aligned}$$

and

$$c_2\left(y_{jt}, s_t; \theta\right) = c_2$$

where $g(y_{jt}, s_t, t)$ is a (flexible) function of the shipyard's characteristics y_{jt}, the industry state (steel price in particular) s_t and time, t. Testing that $\theta_0^{ch,post} \neq 0$ provides evidence of a structural change in China's cost function, for any value of y, s and N. I follow Amemiya (1984) and maximize the likelihood over $\left(\frac{1}{\sigma}, \frac{\theta}{\sigma}\right)$ rather than $\left(\theta, \sigma\right)$. I consider Q3-2005 as the first quarter of the post-2006 world, consistent with Figures 1 and 3 (results are robust to alternative thresholds around that date). Finally, I drop shipyards with missing capital measures (docks/berths) so that the end sample consists of 4741 observations (all results are robust if the full sample is used).[20]

Table 2 reports the baseline cost function estimates. In all specifications there is a strongly significant decline in China's cost after 2006 in the order of 15-20%, as indicated by the China-POST dummy. Multiplying this parameter with China's production, I find that between 2006 and 2012 China paid between 2.5 and 5 billion US Dollars in production subsidies. The estimates imply that the average cost of building a ship is 38.1 million US dollars, very close to an estimate provided in Stopford (2009) of 40.5 million US dollars. The results suggest that there is significant convexity in costs. Backlog is negative, implying cost declines due to economies of scale or expertise. This finding is consistent with industry participants' testimony, who claim that shipyards have incentives to produce ships similar to those they already have under construction. In addition, costs are decreasing in capital measures, as expected. Not surprisingly, Europe is the highest cost producer, while either Japan or China post-2006 are the lowest cost producer depending on the specification.

Specifications I and II are the simplest ones; they control for the shipyard's backlog, docks/berths, length of the largest dock, as well as a linear time trend.

It is important to control for time-varying factors adequately in order to alleviate the concern that the estimated cost declines may be driven by unobserved time variation. The results are robust to any parametric function of time I have tried (e.g. country specific time trends, polynomial trends); as an example, Specification III of Table 2 adds time trends specific to China and Japan. Specification IV moves away from parametric functions of time and adds year dummies; there is still a significant decline in Chinese costs, not surprisingly somewhat lower, at 14%. The most flexible specification in terms of time variation is to estimate China-year dummies. As expected, estimates (reported in the Online Appendix) are more noisy, yet as shown in Figure 6, there is a large drop in costs between 2005 and 2006. Perhaps more importantly, there seem to indeed be two regimes, before and after 2006, with the post regime involving lower costs. Clearly, one can argue that an arbitrary productivity process can also be consistent with these results; such a productivity process, however, needs to feature a discontinuity in 2006 in China alone. In addition, the production process of bulk carriers is old, without any important technological advances.

[20] As $VE_j(s_t)$ is estimated, to compute standard errors I create 500 bootstrap samples by redrawing (N_{jt}, y_{jt}, s_t) and combine them with the 500 samples drawn to compute confidence intervals for $VE_j(s_t)$. I have also used the block-boostrap where I drew shipyards with replacement, and standard errors are unaffected.

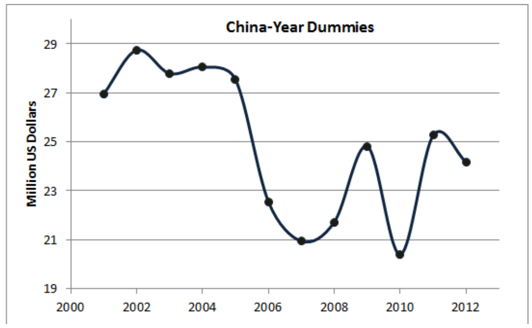

Figure 6: China-Year Dummies.

The assumption that the convexity parameter c_2 is constant is also not crucial. Specification V of Table 2 makes c_2 a linear function of docks/berths, to allow convexity to depend on capital measures. Results are robust. At the average number of docks/berths the convexity parameter becomes 1.1, close to most estimates. I also allow c_2 to be country specific; results are reported in the Online Appendix due to space limitations, and imply the same retrieved subsidies.

Specification VI of Table 2 shows that no significant changes occur in 2006 in other countries. Indeed, I add a Japan-post 2006 dummy and find that Japan's costs seem to increase slightly, but the coefficient is not significant (similar findings are obtained if other countries are used, with the caveat of having few observations on Europe and S. Korea to begin with).

Results are also robust to adding several covariates, such as the shipyard's: age, total TEU produced, total past production (capturing experience), dummy variables for young ages to capture learning by doing (documented in military ships in Thompson (2001)) somewhat more flexibly, administrative region, number of employees (reported only in a subset of yards).[21]

I next reestimate costs using only shipyards that already existed in 2001. Table 3 reports the results, which show that the same cost declines are retrieved when only old shipyards are considered. This finding, speaks to the following two concerns: (i) cost declines are driven by the new yards built in 2006 which perhaps are more modern and have entirely different production capabilities (though, to reiterate, bulk ship building technology is not subject to technological innovations often), (ii) cost declines are driven by firms' optimizing production under learning by doing (though in

[21] Working with tons produced, rather than ships, and thus using a tobit model also does not alter findings.

the next section I allow for a narrow form of expertise accumulation). Indeed, existing shipyards do not change technology and have already gone down their learning curve.

As regional governments in China can play an important role, I consider the possibility that they implement the national subsidization plan at different dates and magnitudes. As no official documentation was found on implementation dates, I consider the first quarter that new shipbuilding docks/berths come online and divide regions into three groups. I present results in the Online Appendix, which are similar to prior specifications. It seems that the last region to implement, also has the lowest subsidy level.

One may be concerned that the estimated cost declines are solely driven by the inherent discontinuity in the estimated $VE_j(s_t)$ due to the different VAR model and LASSO coefficients. To address this concern I estimate costs using the average quarterly price (across shipyards and countries) of a new ship, obtained from Clarksons. I find that estimated subsidies are significant and of the same magnitude.

Note that my model implies that the Chinese government gives the same subsidy to all yards. Suppose instead that the government gives subsidy $x + \xi_{jt}$ to yard j, where $\xi_{jt} \sim N(0, \sigma_\xi)$ across j and t. In that case, the estimated cost parameters θ are still consistent (Wooldridge (2001)) and the estimated subsidy, $\theta_0^{ch,post}$, is the average subsidy across yards (my estimate for σ, however, is no longer consistent). More complicated models of targeted subsidies are more difficult to handle.

	I	II	III	IV	V	VI
China	32.4 (5.75)**	33.34 (5.95)**	33.56 (5.8)**	31.23 (5.13)**	36.83 (6.81)**	32.23 (5.84)**
China,POST	-7.67 (2.42)**	-7.63 (2.54)**	-8.01 (3.82)**	-4.21 (1.85)**	-8.85 (3.06)**	-6.51 (2.63)**
Europe	33.14 (6.04)**	34.14 (6.31)**	36.23 (7.61)**	31.76 (5.31)**	37.21 (7.08)**	33.38 (5.99)**
Japan	25.4 (3.78)**	25.94 (3.78)**	26.02 (4.16)**	28.14 (3.62)**	30.02 (4.68)**	25.14 (3.58)**
Japan, POST						1.085 (1.47)
S. Korea	31.34 (5.52)**	32.41 (5.44)**	34.85 (7.3)**	32.46 (4.54)**	34.29 (5.85)**	32.22 (5.43)**
Backlog	-0.71 (0.18)**	-0.71 (0.18)**	-0.72 (0.18)**	-0.39 (0.17)**	-0.8 (0.202)**	-0.66 (0.17)**
Docks/Berths		-0.17 (0.17)**	-0.17 (0.18)			-0.16 (0.16)
Max Length		-0.0011 (0.0011)	-0.0011 (0.0012)			-0.001 (0.0011)
Steel price	0.38 (0.24)	0.38 (0.23)	0.38 (0.24)*	0.87 (0.5)**	0.44 (0.24)*	0.36 (0.22)
t	0.33 (0.06)**	0.33 (0.06)**	0.28 (0.084)**		0.36 (0.07)**	0.3 (0.06)**
China*t			0.068 (0.13)			
Japan*t			0.062 (0.09)			
c_2	1.31 (0.34)**	1.31 (0.35)**	1.33 (0.36)**	0.71 (0.32)**		1.22 (0.33)
$c_2 * (\text{Docks/Berths})$					0.32 (0.097)**	
σ	14.15 (3.48)	14.11 (3.85)	14.36 (3.59)	7.49 (3.3)	17.08 (4.15)	13.1 (3.27)
Year Dummies	NO	NO	NO	YES	NO	NO

Table 2: Baseline static cost function estimates. Time t measured in quarters. Countries refer to country dummy variables. Stars indicate significance at the 0.05 level. Standard errors computed from 500 bootstrap samples.

China	41.02
	(10.61)**
China,POST	-9.15
	(4.1)**
Europe	41.65
	(11.19)**
Japan	30.5
	(6.51)**
S. Korea	38.1
	(9.52)**
Backlog	-1.002
	(0.34)**
Docks/Berths	-0.375
	(0.26)
Max Length	0.0006
	(0.0023)
Steel price	0.36
	(0.36)
t	0.38
	(0.097)**
c_2	1.84
	(0.63)**
σ	18.69
	(6.16)

Table 3: Static cost function estimates with yards existing prior to 2001. Time t measured in quarters. Countries refer to country dummy variables. Stars indicate significance at the 0.05 level. Standard errors computed from 500 bootstrap samples.

5.2.2 Dynamic Shipbuilders

If shipyard j takes into account the dynamic feedback of the backlog, optimal production obeys (9). To estimate therefore the parameters (θ, σ), I maximize the likelihood (16) where the choice probabilities are (to ease notation, rename the shipyard state $x = (y_{jt}, s_t)$ and $x' = (y_{jt+1}, s_{t+1})$ and suppress (j, t)):

$$\Pr\left(N = 0|x;\theta\right) = 1 - \Phi\left(\frac{1}{\sigma}\left[VE\left(x\right) + c\left(0, x;\theta\right) - c\left(1, x;\theta\right) + \beta\left(Q\left(x, 1\right) - Q\left(x, 0\right)\right)\right]\right) \tag{17}$$

$$\Pr\left(N = \overline{N}|x;\theta\right) = \Phi\left(\frac{1}{\sigma}\left[VE\left(x\right) + c(\overline{N} - 1, x;\theta) - c\left(\overline{N}, x;\theta\right) + \beta\left(Q\left(x, \overline{N}\right) - Q\left(x, \overline{N} - 1\right)\right)\right]\right)$$

$$\begin{aligned}\Pr\left(N_{jt} = n|x;\theta\right) = \Phi\left(\frac{1}{\sigma}\left[VE\left(x\right) + c\left(n-1, x;\theta\right) - c\left(n, x;\theta\right) + \beta\left(Q\left(x, n\right) - Q\left(x, n-1\right)\right)\right]\right) - \\ -\Phi\left(\frac{1}{\sigma}\left[VE\left(x\right) + c\left(n, x;\theta\right) - c\left(n+1, x;\theta\right) + \beta\left(Q\left(x, n+1\right) - Q\left(x, n\right)\right)\right]\right), \quad \text{for } n = 1, ..., \overline{N} - 1\end{aligned}$$

Maximizing this likelihood function would be trivial if the continuation value $Q(x, n)$ were known. This is the standard difficulty of estimating dynamic setups and to address it, I adopt a hybrid approach based on the recent literature on estimation of dynamic setups. In particular, first I recover the shipyard's optimal policy $N^*(y_{jt}, s_t, \varepsilon_{jt})$ nonparametrically using choice probabilities, in analogy to the Hotz and Miller (1993) inversion and the first stage of Bajari, Benkard and Levin (2007). Then, I am able to obtain the ex ante optimal per period payoffs in closed-form, which allow me to recover the shipyard's value function. I next describe my approach in detail.

Let

$$A\left(x, n\right) \equiv \frac{1}{\sigma}\left[VE\left(x\right) + \left(c\left(n, x\right) - c\left(n+1, x\right)\right) + \beta\left(Q\left(x, n+1\right) - Q\left(x, n\right)\right)\right] \tag{18}$$

for $n = 0, 1, ..., \overline{N} - 1$. I rewrite the choice probabilities (17) as follows:

$$\Pr\left(N^* = 0|x\right) \equiv p_0\left(x\right) = \Pr\left(\varepsilon \geq A\left(x, 0\right)\right) \tag{19}$$

$$\Pr\left(N^* = n|x\right) \equiv p_n\left(x\right) = \Pr\left(\varepsilon \leq A\left(x, n-1\right)\right) - \Pr\left(\varepsilon \leq A\left(x, n\right)\right)$$

$$\Pr\left(N^* = \overline{N}|x\right) \equiv p_{\overline{N}}\left(x\right) = \Pr\left(\varepsilon \leq A\left(x, \overline{N}-1\right)\right)$$

The function $A(x, n)$ can be recovered from the observed choice probabilities using:[22]

$$A\left(x, n\right) = \Phi^{-1}\left(1 - \sum_{k=0}^{n} p_k\left(x\right)\right), \quad \text{for } n = 0, 1, ..., \overline{N} - 1 \tag{20}$$

where $\Phi(\cdot)$ is the standard normal distribution. Clearly, $A(x, n)$ is (weakly) decreasing in n. Most important, if $A(x, n)$ is known, so is the optimal policy: For any (x, ε),

$$N^*\left(x, \varepsilon\right) = \widehat{n}, \text{ such that } \varepsilon \in \left[A\left(x, \widehat{n}\right), A\left(x, \widehat{n} - 1\right)\right]$$

Once the optimal policy is known, the value function can be recovered. Indeed, consider shipyard j's Bellman equation (7) which I repeat here for convenience:

$$W\left(x, \varepsilon\right) = \max_{N \in \left\{0,1,...,\overline{N}\right\}} VE\left(x\right) N - c\left(N, x\right) - N\varepsilon + \beta E_{\varepsilon', x'}\left[W\left(x', \varepsilon'\right)|N, x\right]$$

where as a reminder,

$$E_{\varepsilon', x'}\left[W\left(x', \varepsilon'\right)|N, x\right] = Q\left(x, N\right)$$

Using the optimal policy $N^*(x, \varepsilon)$, the value function becomes:

$$W\left(x, \varepsilon\right) = VE\left(x\right) N^*\left(x, \varepsilon\right) - c\left(N^*\left(x, \varepsilon\right), x\right) - N^*\left(x, \varepsilon\right)\varepsilon + \beta E_{\varepsilon', x'}\left[W\left(x', \varepsilon'\right)|N^*\left(x, \varepsilon\right), x\right]$$

Similarly, the ex ante value function can be written as

$$E_\varepsilon W\left(x, \varepsilon\right) \equiv W\left(x\right) = E_\varepsilon\left[\pi\left(x, N^*\left(x, \varepsilon\right)\right) + \beta E_{\varepsilon', x'}\left[W\left(x', \varepsilon'\right)|N^*\left(x, \varepsilon\right), x\right]\right]$$

where

$$\pi\left(x, N^*\left(x, \varepsilon\right)\right) = E_\varepsilon\left[VE\left(x\right) N^*\left(x, \varepsilon\right) - c\left(N^*\left(x, \varepsilon\right), x\right) - N^*\left(x, \varepsilon\right)\varepsilon\right] \tag{21}$$

is the ex ante per period profit. If $\pi(x, N^*(x, \varepsilon))$ is known then one can solve for the

[22] To show this, begin with $p_0(x) = 1 - \Phi(A(x, 0))$, so that $A(x, 0) = \Phi^{-1}(1 - p_0(x))$. Next, $p_1(x) = \Phi(A(x, 0)) - \Phi(A(x, 1)) = 1 - p_o(x) - \Phi(A(x, 1))$, so that $A(x, 1) = \Phi^{-1}(1 - p_0(x) - p_1(x))$. The general case follows by induction.

ex ante value function from the following relationship:

$$W(x) = E_\varepsilon \pi(x, N^*(x, \varepsilon)) + \beta E_{\varepsilon, x'}[W(x') | N^*(x, \varepsilon), x] \tag{22}$$

Solving (22) can be done in several ways, such as state space discretization and matrix inversion, or parametric approximation; I opt for the latter because of the large dimension of the state space. In particular, I approximate the value function by a polynomial function, so that:

$$W(x) = \delta f(x)$$

then (22) becomes

$$\delta f(x) = E_\varepsilon \pi(x, N^*(x, \varepsilon)) + \delta\beta E_{\varepsilon, x'}[f(x') | N^*(x, \varepsilon), x]$$

or

$$(f(x) - \beta E_\varepsilon [f(x') | N^*(x, \varepsilon), x])\, \delta = E_\varepsilon \pi(x, N^*(x, \varepsilon)) \tag{23}$$

and I can therefore estimate δ via LASSO. I now only need to show how $E_\varepsilon \pi(x, N^*(x, \varepsilon))$ is computed.

Under the assumption of quadratic costs, ex ante per period payoffs become:

$$\begin{aligned}
\pi(x, N^*(x, \varepsilon)) &= E_\varepsilon \left[VE(x)\, N^*(x, \varepsilon) - c_1(x;\theta)\, N^*(x, \varepsilon) + c_2(x;\theta)\, N^*(x, \varepsilon)^2 - \sigma N^*(x, \varepsilon)\, \varepsilon\right] \\
&= (VE(x) - c_1(x;\theta))\, E_\varepsilon N^*(x, \varepsilon) + c_2(x;\theta)\, E_\varepsilon N^*(x, \varepsilon)^2 - \sigma E_\varepsilon [N^*(x, \varepsilon)\, \varepsilon]
\end{aligned}$$

I show in the Appendix that

$$E_\varepsilon N^*(x, \varepsilon) = \sum_{n=0}^{\overline{N}-1} \Phi(A(x, n)) \tag{24}$$

$$E_\varepsilon [N^*(x, \varepsilon)]^2 = 2 \sum_{n=1}^{\overline{N}} n \Phi(A(x, n-1)) - \sum_{n=0}^{\overline{N}-1} \Phi(A(x, n)) \tag{25}$$

$$E_\varepsilon [N^*(x, \varepsilon)\, \varepsilon] = - \sum_{n=0}^{\overline{N}-1} \phi(A(x, n)) \tag{26}$$

where $\phi(\cdot)$ is the standard normal density.

To sum up, the estimation proceeds as follows (further details are in the Appendix):

1. Estimate $A(x, n)$ using (20)

2. Compute the statistics of the optimal production in (24), (25) and (26)

3. At each guess of the parameters (θ, σ) in the optimization of the likelihood (16):

    (a) Solve for the approximate value function parameters δ from (23)

    (b) Using δ, compute the choice probabilities in the likelihood and update (θ, σ).

Table 4 gives the estimated cost function of dynamic shipyards. The implied subsidy is in the order of 20% or 5.6 billion US dollars paid between 2006 and 2012, similarly to the case of static shipyards. Also in analogy to static shipbuilders, costs are decreasing in the current backlog, consistent with economies of scale or accumulation of expertise. More docks/berths, as well as longer docks decrease costs. Interestingly, the estimated cost function of dynamic shipyards is significantly more convex than the one of static shipyards. Since accumulating a backlog decreases future costs, higher cost parameters are needed to justify the observed low production levels.

Finally, I compute the expected value of all new Chinese shipyards that are born between 2006 and 2012, which equals 8.5 billion US dollars. One can think of this amount as a rough estimate of the order of magnitude of the costs of building these shipyards, which may be close to the fixed cost subsidies of China's 2006 plan.

In summary, the static and dynamic formulations yield similar results in terms of subsidy detection. As discussed in the following section, however, the two models have different quantitative predictions regarding the implications of subsidies.

China	46.12 (9.08)**
China,POST	-8.9 (3.32)**
Europe	47.42 (9.62)**
Japan	35.88 (5.76)**
S. Korea	45.63 (8.31)**
Backlog	-0.84 (0.23)**
Docks/Berths	-0.22 (0.15)
Max Length	-0.002 (0.0014)
Steel price	0.36 (0.24)
t	0.25 (0.067)**
c_2	2.53 (0.69)**
σ	19.75 (5.26)**

Table 4: Dynamic cost function estimates. Time t measured in quarters. Countries refer to country dummy variables. Stars indicate significance at the 0.05 level. Standard errors computed from 500 bootstrap samples.

5.2.3 Comparison to the WTO Subsidy Detection Method

Before turning to the impact of subsidies on industrial evolution, I compare my detection approach to the price-gap approach, which is followed in WTO subsidy cases. The price-gap approach, compares product end-user prices to reference prices (i.e. prices that would prevail in markets without subsidies); yet the latter can be tough to compute.[23] In the case of ships, my understanding of the price-gap approach is that it would essentially compare Chinese to world prices. Table 5 presents results from a hedonic regression of (the few observed) new ship prices. The price-gap approach would detect a 7.3% subsidy (i.e. the discount of Chinese ships), less than half of my

[23]See Haley and Haley (2013) for a description of this approach and its caveats.

	New Ship Prices		Used Ship Prices	
	parameter	s.e.	parameter	s.e.
constant	15	(3.5)**	21.95	(1.36)**
China	-3.09	(0.52)**	-0.83	(0.67)**
Japan	-2.16	(0.93)**	-0.061	(0.52)**
Europe			-1.36	(0.59)**
delivery lag	-2.08	(0.61)**		
age			-0.78	(0.015)**
quarter dummies	YES		YES	

Table 5: Hedonic regression of new ship prices.

magnitude. As Haley and Haley (2013) point out, however, there would be efforts to correct for quality differences. Quality corrections are performed on a case by case basis; one thought would be to explore price differences in the second-hand market where prices may be reflecting quality differences only, rather than cost differences. Table 5 presents results from a hedonic regression of used ship prices and shows that Chinese ships are on average 3.5% cheaper in the second-hand market. My interpretation is that the price-gap approach would have now produced about 4% subsidies, which are dramatically lower from my robustly estimated 15-20%.

6 Quantifying the Implications of Subsidies

What is the impact of government subsidies on industry prices, production reallocation across countries, costs and consumer surplus? In addition, how do different types of subsidies (capital vs. production) affect the above? I answer these questions in the context of China's intervention in shipbuilding by using my model to predict the evolution of the industry in two counterfactual scenarios: first, no Chinese subsidies of any kind (i.e. no 2006 plan altogether); second, Chinese capital subsidies only (i.e. remove (prohibited) production subsidies alone and keep docks/berths expansions and new shipyards).

To implement the "no subsidies" counterfactual, I assume that shipowners maintain their pre-2006 expectations and ship value functions, while shipyards keep their pre-2006 capital structure (i.e. docks/berths and length) and costs. To implement the "capital subsidies only" counterfactual, I assume that shipowners switch to the post-2006 expectations and value functions. In other words, I assume that shipowners understand that a change occurred in 2006; yet they can't distinguish production vs. capital subsidies (which may be reasonable given production subsidies are secret). Shipyards keep their pre-2006 cost functions and their post-2006 capital structures. I feed the observed post-2006 values for shipping demand and steel prices into the model and simulate shipyard optimal production and ship prices. Details on the implementation of these counterfactuals can be found in the Appendix.

As shown in Table 6, both production and capital subsidies lead to substantial reallocation in production, by increasing China's market share and decreasing Japan's share. Interestingly, production subsidies seem to have a much larger impact than capital subsidies: if production subsidies are removed, China's market share is cut to half falling from 50% to 25%; if capital subsidies are removed on top, China's share drops to 18.5%. Similarly, Japan's share increases from 43% to 65% in the absence of Chinese production subsidies and to 74% in the absence of both production and capital subsidies. This finding is due to the high (convex) costs estimated, which rationalize the low observed production levels. Figure 7 plots China's total backlog in the three counterfactual worlds and tells the same story.[24] A further interesting feature of the post-2006 period is that demand for freight services boomed and led (at least in part) to a shipping investment boom (viewed in Figure 7, as well as ship values in Figure 5). The crisis in 2008 led in turn to a crash. Figure 7 implies that China's subsidies amplified the boom and bust in shipping investment in the last decade.

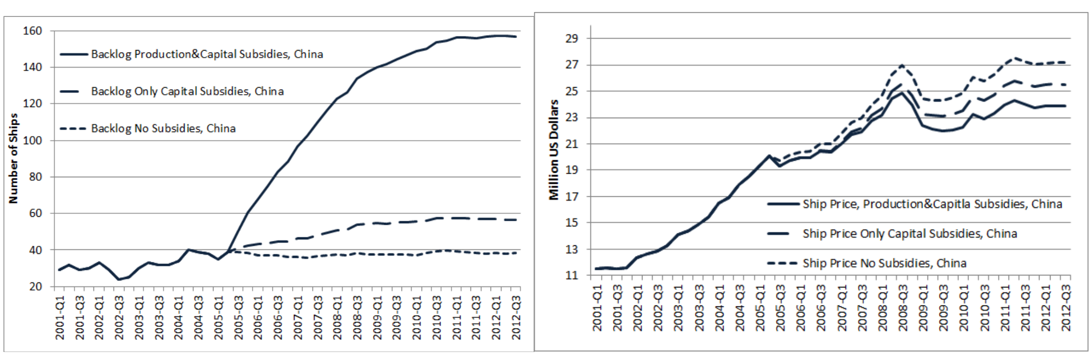

Figure 7: Backlog and Ship Price, China, Counterfactuals.

[24] This finding does not seem to depend on the assumption that c_2 is constant. I replicated the counterfactuals in the case of static shipyards under cost specification V of Table 2, where c_2 is linear in the number of docks/berths, and find that still production subsidies have a more substantial impact than capital subsidies.

	Capital & Production Subsidies	Capital Subsidies	No Subsidies
Market Share, China	50%	25.1%	18.4%
Market Share, Japan	43.4%	64.8%	73.9%
Ship Price, China	23.8	24.5	25
Ship Price, Japan	25.5	26.1	26.6
Japan, Shipyard Profits	95.1	101.3	105.4
Freight Rate (price per voyage)	1.25	1.27	1.28
Consumer Surplus (shippers)	5617	5378	5331
Industry AVC	0.42	0.54	0.65

Table 6: Counterfactual results. Prices, surplus and cost measured in million US Dollars. Profits and surplus refer to the total amount between 2006 and 2012.

Table 6 also compares ship prices in all counterfactual worlds and shows that ship prices are higher for all countries in the absence of China's subsidization plans (by about 2% and 5% in the two counterfactuals respectively). This is not surprising, given that China's subsidization shifted supply outward. Figure 7 plots ship prices for China (the behavior of Japanese ships' prices is very similar).

Next, I turn to costs, profits and shipper surplus, shown in the lower half of Table 6. Chinese subsidies decrease profits of other countries by moderate amounts; for example, Japan's profits fall by 6.5% (11%) because of Chinese production (production and capital) subsidies between 2006 and 2012. In this model, shipowners neither gain, nor lose from subsidies: because of the free entry condition in shipping, they are always indifferent between buying a ship or not. Shippers of cargo, however, gain from subsidies as they lead to higher shipbuilding production and thus to a larger fleet. I use the demand curve estimated in the Appendix to compute shipping prices and shipper surplus. This cargo shipping demand curve gives the price per voyage as a function of the total number of voyages. I assume that there is a constant fleet utilization rate to map the fleet into voyages. As shown in Table 6, the freight rate is moderately higher (by 2% and 3% respectively) in the absence of Chinese subsidies. The difference in prices, however, increases over time between 2006 and 2012: because of time to build it takes time until the different worlds lead to different fleet levels. Indeed, between 2009 and 2012 prices are higher by 4% and 5% respectively. As a result, cargo shippers benefit from Chinese subsidies; their consumer surplus is higher by 4% (5%) because of production (production and capital) subsidies and increases over time (between 2009 and 2012 consumer surplus is higher by 7% (8%)). Between 2006 and 2012 production subsidies cost about 5.6 billion US dollars and resulted in consumer surplus gains of 240 million US dollars. This calculation implies that the benefits of subsidies within the maritime industries are minimal and perhaps the Chinese government is aspiring to externalities to different sectors (e.g. steel, defense) or, even, national pride (Grossman (1990)).

Next, I turn to the cost implications of subsidies. I compute the average cost of a ship at the industry level and find that as expected, subsidies decrease costs of production. Thus, looking at the last row of Table 6 one might think that subsidies benefit the industry by better aligning market share and costs. If I decompose the average cost to subsidies and market share allocation, however, this picture is entirely different. Indeed, consider the cost function $c_j N + cN^2$, for $j \in \{\text{China, EU, Japan, S.Korea}\}$, which for $j =$China becomes $(c_{china} - s) N + cN^2$ post-2006. The change in the industry average cost because of subsidies is equal to a sum of two terms: the first is $s\frac{N_{China}}{N_{China}+N_{EU}+N_{Japan}+N_{SK}}$, while the second includes all other terms and is related to the reallocation of production and market share. As shown in Table 6, the change in industry average cost brought about by production subsidies is 0.12 million. The term $s\frac{N_{China}}{N_{China}+N_{EU}+N_{Japan}+N_{SK}}$ equals 4.44 million, implying a negative reallocation effect equal to $0.12 - 4.44 = -4.32$ million. In other words, the subsidization in costs should have led to a much larger decline in the industry average cost of production; but as subsidies shift production away from the low-cost Japanese shipyards towards the high-cost Chinese shipyards, the industry produces at a much higher average cost net of subsidies.

Finally, there are two questions of interest related to the importance of allowing for dynamics in shipbuilding production. First, how important is the interaction of subsidies and dynamics in production? To answer this question, I simulate the model setting the impact of backlog in the cost function equal to zero. I find that reallocation would have been somewhat lower in the absence of dynamics: about 7% of China's increase in market share can be attributed to the dynamic production feedback. As increased backlog decreases costs, market share gains multiply and lead to more reallocation favorable to China and unfavorable to Japan. The second question of interest, is whether the static model leads to the same counterfactual results. To answer, I use specification II of Table 2 to simulate the model. I find that even though the static and dynamic models yield similar results in terms of detecting subsidies, they lead to different predictions regarding the implications of subsidies. In particular, I find that the static model leads to significantly more reallocation than the dynamic model: China's loses 62% (73%) of its market share in the absence of production (production and capital) subsidies, while Japan's share almost doubles. This difference is mainly driven by the different cost function, which is higher and more convex in the case of dynamic shipyards.

7 Conclusion

Industrial trade policies can have a substantial impact on the evolution of industries. To understand this impact, one needs to first know what policies are in place. This paper detects production subsidies and quantifies their impact for the case of world shipbuilding. I find strong evidence consistent with China having subsidized the shipbuilding industry by decreasing firm production costs by 15-20%. In my model, the government gives subsidies because of "exogenous" reasons (i.e. there are no factors such as learning spillovers between Chinese firms). This may be reasonable because of shipbuilding's important externalities to other sectors, such as the steel industry or the readiness of the military sector. Yet, understanding the impact of subsidies when such considerations are in place, provides an interesting avenue for future research.

8 Appendix

8.1 Creation of shipping demand state

I estimate the inverse demand for shipping services via instrumental variables regression, to create the state d_t. The analysis follows Kalouptsidi (2014). The empirical analogue of the demand curve in (1) chosen is:

$$P_t = \alpha_0^d + \alpha_1^d X_t^d + \alpha_2^d Q_t + \varepsilon_t^d \tag{27}$$

where P_t is the average price per voyage observed in a quarter, X_t^d includes demand shifters, while Q_t is the total number of voyages realized. X_t^d includes the index of food prices, agricultural raw material prices and minerals prices (taken from UNCTAD), the world aluminum (taken from the International Aluminum Institute) and world grain production (taken from the International Grain Council), as well as the Handymax fleet (as a potential substitute). The first stage instruments include the total fleet and its mean age. Both instruments are key determinants of industry supply capacity, as ship operating costs are convex and depend on age. Instrumentation corrects both for endogeneity, as well as measurement error (I observe the number of voyages realized, rather than ton-miles).

	1st stage	2nd stage
	parameter	parameter/10^6
constant	-2731.3 (790.28)**	-1.403 (1.26)
food P	0.61 (0.693)	0.0051 (0.0038)
agr raw mat P	1.35 (0.48)**	0.0022 (0.0028)
mineral P	-0.43 (0.33)	0.0014 (0.0018)
aluminum prod	-0.28 (0.11)**	0.0012 (0.00057)**
grain prod	-0.86 (0.9)	0.0047 (0.0044)
subst fleet	0.38 (0.15)**	-0.0022 (0.00052)**
fleet	0.55 (0.22)**	
mean age fl	96.67 (18.5)**	
$\widehat{Q_t}$		-0.0033 (0.001)**

Table 7: Demand IV regression results.

Table 7 reports the results. The impact of all shifters is lumped into the state variable d_t (the residual $\widehat{\varepsilon_t^d}$ is included in d_t as it captures omitted demand shifters):

$$d_t = \widehat{\alpha_1^d} X_t^d + \widehat{\varepsilon_t^d}$$

8.2 Derivation of state expectations in ship value function

I derive the expressions required for the LASSO estimation of the value functions of Section 5.1.2. Remember that I approximate the value function with a polynomial function, so that:

$$V(x_t) = \gamma f(x_t) = \sum_{i=1}^{d} \gamma_i x_t^{(i)}$$

where $x_t = (s_{it}, s_t)$, and $x_t^{(i)}$ are Kronecker products, so that $x_t^{(2)} = x_t \otimes x_t$, $x_t^{(3)} = x_t^{(2)} \otimes x_t$, etc. Then, note that (13) can be written as:

$$P_{jt}^{NB} = \beta^{T_{jt}} \gamma E\left(f\left(x_{t+T_{jt}}\right)|x_t\right) = \beta^{T_{jt}} \sum_{i=1}^{d} \gamma_i E\left(x_{t+T_{jt}}^{(i)}|x_t\right) \tag{28}$$

The conditional expectation is only necessary for s_t since s_{it} evolves deterministically. I use the general VAR model (6) to get that:

$$s_{t+T} = \phi(t+T, t)\, s_t + \sum_{k=t+1}^{t+T} \phi(t+T, k)\,(C_k + \xi_k)$$

where

$$\phi(t+T, k) = \begin{cases} R_{t+T} R_{t+T-1} \ldots R_{k+1}, & \text{for } k < t+T \\ I, & \text{for } k = t+T \end{cases}$$

For example, since here I set $R_t = R$, all t, I get (15) of the main text.

The above expression takes the form:

$$s_{t+T} = A + v$$

where

$$
\begin{aligned}
A &= \phi\left(t+T,t\right)s_t + \sum_{k=t+1}^{t+T} \phi\left(t+T,k\right)C_k \\
v &= \sum_{k=t+1}^{t+T} \phi\left(t+T,k\right)\xi_k
\end{aligned}
$$

Note that conditional on s_t, A is constant. Moreover, v is zero-mean normal with covariance

$$
\Sigma_v = Ev'v = \sum_{k=t+1}^{t+T} R^{t+T-k}\Sigma\left(R'\right)^{t+T-k}
$$

Therefore, (28) becomes:

$$
P_{jt}^{NB} = \beta^{T_{jt}} \sum_{i=1}^{d} \gamma_i E\left(\left(A+v\right)^{(i)}|s_t\right)
$$

I next compute the conditional expectations for up to third order terms:

$$
\begin{aligned}
E\left(A+v|s_t\right) &= A \\
E\left(\left(A+v\right)^{(2)}|s_t\right) &= A^{(2)} + vec\left(\Sigma_v\right) \\
E\left(\left(A+v\right)^{(3)}|s_t\right) &= A^{(3)} + A\otimes vec\left(\Sigma_v\right) + vec\left(\Sigma_v\right)\otimes A + T_{mm^2}A\otimes vec\left(\Sigma_v\right)
\end{aligned}
$$

where $vec\left(x\right)$ denotes the vector formed by stacking the columns of x one after the other; given a $L\times n$ matrix A, T_{Ln} is an $Ln\times Ln$ matrix defined by $T_{Ln}vec\left(A\right) = vec\left(A'\right)$. The first of the above equations is straightforward. To prove the second, use:

$$
E\left(\left(A+v\right)^{(2)}|s_t\right) = E\left(\left(A+v\right)^{(2)}\right) = A\otimes A + A\otimes E\left(v\right) + E\left(v\right)\otimes A + Ev^{(2)}
$$

It is easy to see that $Ev^{(2)} = vec\left(Evv'\right) = vec\left(\Sigma_v\right)$ using the property

$$
vec\left(BXC\right) = \left(C'\otimes B\right)vec\left(X\right)
$$

Finally, I prove the third order equation. Note that

$$\begin{aligned} E\left((A+v)^{(3)}\,|s_t\right) &= A\otimes E\,(A+v)^2 + Ev\otimes (A+v)^2 \\ &= A\otimes \left(A^{(2)} + vec\,(\Sigma_v)\right) + E\,(v\otimes A\otimes v) + E\,(v\otimes v\otimes A) + Ev^{(3)} \end{aligned}$$

$Ev^{(3)}$ is zero since v is Gaussian. Moreover,

$$E\,(v\otimes A\otimes v) = T_{mm^2}\otimes Ev^{(2)}$$

Indeed, if B and C are matrices of dimensions (L,n) and (n,q) respectively, then

$$B\otimes C = T_{pl}\,(C\otimes B)\,T_{nq}$$

8.3 Statistics of the Optimal Production

To derive (24) I use (19) to get:

$$\begin{aligned} E_\varepsilon N^*\,(x,\varepsilon) &= \sum_{n=1}^{\overline{N}} np_n\,(x) = \sum_{n=1}^{\overline{N}-1} n\,[\Phi\,(A\,(x,n-1)) - \Phi\,(A\,(x,n))] + \overline{N}\Phi\left(A\left(x,\overline{N}-1\right)\right) \\ &= \sum_{n=0}^{\overline{N}-2} (n+1)\,\Phi\,(A\,(x,n)) - \sum_{n=1}^{\overline{N}-1} n\Phi\,(A\,(x,n)) + \overline{N}\Phi\left(A\left(x,\overline{N}-1\right)\right) \\ &= \Phi\,(A\,(x,0)) + \sum_{n=1}^{\overline{N}-2} \Phi\,(A\,(x,n)) + \Phi\left(A\left(x,\overline{N}-1\right)\right) = \sum_{n=0}^{\overline{N}-1} \Phi\,(A\,(x,n)) \end{aligned}$$

Equation (25) follows similarly. Finally, let $\phi\,(\varepsilon)$ denote the standard normal density. Then,

$$\int_a^b \varepsilon\phi\,(\varepsilon) = -\frac{1}{2\sqrt{\pi}}\int_a^b de^{-\frac{1}{2}\varepsilon^2} = \phi\,(a) - \phi\,(b)$$

and therefore:

$$\begin{aligned} E_{\varepsilon}\varepsilon N^{*}(x,\varepsilon) &= \int \varepsilon N^{*}(x,\varepsilon)\,\phi(\varepsilon)\,d\varepsilon = \\ &= \sum_{n=1}^{\overline{N}-1} n \int_{A(x,n)}^{A(x,n-1)} \varepsilon\phi(\varepsilon) + \overline{N}\int_{-\infty}^{A\left(x,\overline{N}-1\right)} \varepsilon\phi(\varepsilon) \\ &= \sum_{n=1}^{\overline{N}-1} n\left[\phi(A(x,n)) - \phi(A(x,n-1))\right] - \overline{N}\phi\left(A\left(x,\overline{N}-1\right)\right) \\ &= -\sum_{n=0}^{\overline{N}-1} \phi(A(x,n)) \end{aligned}$$

8.4 Estimating costs for dynamic shipbuilders: Details

I provide details on each step performed when estimating the cost function of dynamic shipyards.

Step 1: *Estimate* $A(y,s,n)$ *using* (20). In this step, I first compute the choice probabilities $\{p_n(y_{jt},s_t)\}_{n=0}^{\overline{N}}$ from observed frequencies. I also include a post-2006 dummy in the state to capture differences in the policy function before and after 2006. As is common in dynamics applications, there are not many observations for all $n = 0,1,...,\overline{N}$ at each state (y_{jt},s_t). To overcome this sparsity, I first cluster the data finely, using the kmeans algorithm, and compute frequencies on this subset of states. Second, I smooth the frequency matrix using kernels. In particular, to compute the choice probability $p_n(x)$ at state $x = (y_{jt},s_t)$, I use the following formula:

$$p_n(x) = \sum_{x'} w(x'-x)\,\widetilde{p}_n(x')$$

where $\widetilde{p}_n(x)$ is the observed frequency count of n at state x and $w(\cdot)$ is a kernel that appropriately weights the distance of x from every other state x'. For numerical states (backlog, docks/berths, length, time, fleet, total backlog, demand, steel price) I use normal kernels with diagonal covariance. For categorical states (country and post-2006 dummy) I use the following kernel:

$$w(x'-x) = \begin{cases} 1-h, & \text{if } x'=x \\ h/k_x, & \text{if } x'\neq x \end{cases}$$

where k_x is the number of values that x can take (in the case of country it's 4, in the case of the post dummy 2) and h represents the bandwidth of the kernel. As h gets close to 0, this kernel weights states that share the same variable x. I also experimented with parametric specifications for $A(y,s,n)$. In particular, I estimated an ordered probit model using directly the production data, so that:

$$A(x,n) = \beta f(x) + \gamma_n$$

while the observed variables are the production values given by

$$N^*(x,\varepsilon) = \widehat{n}, \text{ such that } \varepsilon \in [A(x,\widehat{n}), A(x,\widehat{n}-1)]$$

I estimate β and γ_n for $n = 0, ..., \overline{N}-1$ via Maximum Likelihood. This specification is flexible in terms of n but less so in terms of (y,s).[25] It overall gives similar results to the nonparametric specification above. Finally, I chose $\overline{N} = 10$, since 99.75% of observations involve $N \leq 10$.

Step 2: *Compute the terms* EN^*, EN^{*2}, $E\varepsilon N$ using (24), (25) and (26)

Step 3: *At each guess of the parameters* (θ,σ) *in the optimization of the likelihood* (16):

Step 3a: *Solve for the approximate value function parameters* δ *from* (23). Note that the choice probabilities require the continuation value $Q(x,n) = \delta E[f(x')|n,x]$. To estimate δ from (23) I need

$$E_{\varepsilon,x'}[f(x')|N^*(x,\varepsilon),x] = \delta \sum_{n=0}^{\overline{N}} p_n(x) E_{x'}[f(x')|n,x] \tag{29}$$

I use polynomials of third order in all variables (I have also tried fourth order which doesn't alter the results). The industry state s evolves by the estimated VAR model described in Section 5.1.1, while the expectations of its polynomial powers are given in Appendix 8.3. I assume that the shipyard's individual backlog, b_{jt}, transitions as

[25] The plot of γ_n with respect to n exhibits small deviation from linearity. This is consistent with the static model where

$$A = \Phi^{-1}\left(\frac{1}{\sigma}(VE - c_1 - c_2(2n+1))\right)$$

This is relevant in case one thought that (in the static case) imposing both a distributional assumption on ε's, as well as a parametric form on $c(n)$ is restrictive.

follows:

$$b_{jt+1} = (1 - \delta)\, b_{jt} + n$$

δ% of the backlog is delivered and period t's orders n enter the backlog. I experimented *extensively* with the above transition rule. In particular, I've tried models of time-varying δ (e.g. δ is drawn from a beta distribution estimated from the data whose mean can depend on the shipyard's current backlog, docks/berths or length; alternately, δ is taken as a discrete random variable with probabilities estimated from the data; in other experiments, I used deliveries, instead of δ, described by a binomial random variable whose parameters can again depend on shipyard observables). It was found that the simplest model where δ is taken constant over shipyards and time and equal to the sample mean (which is 10%) performs equally well to more complex models (and even better than several). Given the state transitions it is straightforward to compute (29). I estimate (23) using the LASSO in two ways. First, call the LASSO within the likelihood maximization with the regularization parameter chosen using Belloni and Chernozhukov (2011). Second, estimate (23) with LASSO using profits obtained from the static cost estimates. The goal here is to recover which polynomial terms should be kept. I then run OLS within the likelihood with only these terms (and repeat the estimation for many values of the regularization parameter). Results are overall robust to all of the above.

Step 3b: *Using δ, compute choice probabilities in the likelihood and update (θ, σ).*

A concern in two-step approaches to dynamic frameworks is that the first stage policy functions (in this case, the nonparametric $A(x, n)$ that I recover) may be different from the optimal policy computed using the true parameters and value function, i.e. from (18). To check this, I compute $A(\cdot)$ from (18) and find that it is close to the its first stage estimate. I then re-optimize the likelihood using the new $A(\cdot)$. The parameters that I report result from this loop.

8.5 Counterfactual Computation

There are two steps in the implementation of the counterfactual scenarios presented in Section 6. First, I compute the equilibrium of the model in each scenario (if shipyards are static this step is skipped). Second, I simulate the model using the observed paths of demand and steel prices which are exogenous. Note that if one is only interested in the "no subsidies" counterfactual, one can simply use the pre-2006 expectations and value functions and simulate the model.

To predict how the industry would evolve under different counterfactual scenarios I need to obtain shipyards' optimal policies and value functions under each scenario. I can no longer use the estimated VAR for state transitions, since this formed an approximation to expectations that hid equilibrium features. I therefore turn to the following state transitions for (S_t^1, S_t^2, B_t), where S_t^1 is the number of ships younger than 20 years old, S_t^2 is the number of ships older than 20 years old and B_t is the total backlog:

$$\begin{aligned} S_{1t+1} &= \delta B_t + (1-\rho_{1t}) S_{1t} && (30) \\ S_{2t+1} &= S_{2t} + \rho_{1t} S_{1t} - \zeta(s_t) \\ B_{t+1} &= (1-\delta)B_t + \sum_j N_{jt} && (31) \end{aligned}$$

where $\zeta(s_t)$ is the number of ships that exit at state s_t, ρ_{1t} is the percentage of ships that transit from 19 years old and 3 quarters to 20 years old and δ is the percentage of the backlog that is delivered, consistent with the individual backlog transition used in the estimation and described in Appendix 8.5. In words, the number of young ships S_{t+1}^1 equals last period's young ships plus deliveries from the total backlog, minus exiting ships (as documented in Kalouptsidi (2014) there is virtually no exit in ships younger than 20 years old). The number of old ships S_{t+1}^2 equals last period's old ships plus the aging ships minus exiting ships. Finally, total backlog B_{t+1} equals last period's total backlog minus deliveries, plus total new ship orders. I calibrate ρ_{1t} to 3% which is the sample average. To predict ship exit $\zeta(s_t)$ I follow Kalouptsidi (2014) where the number of exiting ships is regressed on the industry state (in particular, $\log \zeta_t = \beta_\zeta s_t$); note that exit rates are extremely low (even during the 2008 crisis). Demand d_t and steel price l_t retain their original transition processes, since these are exogenous to this model.

To find the equilibrium of the model in any of the counterfactual worlds I use a standard fixed point algorithm with the goal of recovering the shipyard's optimal policy function $p_n^*(x)$, for all n and $x = (y, s)$, as well as the shipyard's value function $W^*(x)$. At each iteration l I use the policies $p_n^l(x)$ to update to $p_n^{l+1}(x)$ and I keep iterating until $||p_n^{l+1}(x) - p_n^l(x)|| \leq eps$. Each iteration performs the following steps:

Step 1: Update the value function using a sparse parametric approximation and LASSO (third order polynomials are used). The estimation of δ relies on the approximate Bellman equation:

$$\left(f\left(x\right)-\beta E\left[f\left(x'\right)|p_n^l\left(x\right),x\right]\right)\delta^{l+1}=\pi\left(x,p_n^l\left(x\right)\right)$$

where:

Step 1a: Ex ante profits are computed by:

$$\pi\left(x,p_n^l\left(x\right)\right)=\left[VE\left(x\right)-c_1\left(x\right)\right]\sum_{n=0}^{\overline{N}}np_n^l\left(x\right)-c_2\sum_{n=0}^{\overline{N}}n^2p_n^l\left(x\right)+\sigma\sum_{n=0}^{\overline{N}-1}\phi(A^l\left(x,n\right))$$

where $A\left(x,n\right)=\Phi^{-1}\left(1-\sum_{k=0}^{n}p_k^l\left(x\right)\right)$, $n=0,1,...,\overline{N}-1$. To derive the above, use (21) and (26).

Step 1b: To compute $E\left[f\left(x'\right)|p_n^l\left(x\right),x\right]$, I simulate d_t and l_t one period forward since these are the only stochastic states now. I compute next period's (S_t^1,S_t^2,B_t) using the deterministic transitions (30). Due to computational constraints I have assumed throughout that shipyards keep track of the total backlog rather than the distribution of backlogs. Therefore, at this stage shipyards don't have the full information to predict total orders accurately. To circumvent this issue I make the simplifying assumption that shipyards believe they are all at the same state and can predict total orders using the total number of firms.

Step 2: Update the choice probabilities:

$$\begin{aligned}
p_0^{l+1}\left(x\right) &= 1-\Phi\left(\frac{1}{\sigma}\left(VE\left(x\right)-c_1\left(x\right)-c_2+\beta\left(W^{l+1}\left(1\right)-W^{l+1}\left(0\right)\right)\right)\right)\\
p_n^{l+1}\left(x\right) &= \Phi\left(\frac{1}{\sigma}\left(VE\left(x\right)-c_1\left(x\right)-c_2\left(2n-1\right)+\beta\left(W^{l+1}\left(n\right)-W^{l+1}\left(n-1\right)\right)\right)\right)-\\
&\quad -\Phi\left(\frac{1}{\sigma}\left(VE\left(x\right)-c_1\left(x\right)-c_2\left(2n+1\right)+\beta\left(W^{l+1}\left(n+1\right)-W^{l+1}\left(n\right)\right)\right)\right)\\
p_{\overline{N}}^{l+1}\left(x\right) &= 1-\sum_{n=0}^{\overline{N}-1}p_n^{l+1}\left(x\right)
\end{aligned}$$

I solve the above fixed point under three scenarios: the true post-2006 world, a world with no China interventions and a world with only China's capital interventions. These worlds differ in the shipyard cost function, the set of active shipyards and the shipyard capital structure. I perform the fixed point on all data (as a robustness I have also used a set of states chosen by the kmeans algorithm, as well as the pre-2006 data alone for the relevant counterfactuals).

Finally, to simulate the model, I draw cost shocks ε and obtain the corresponding optimal production using (9) which in turn relies on the value function computed using the parameters δ retrieved by the fixed point algorithm. At each state visited I still need to compute $E\left[f\left(x'\right)|p_n^*\left(x\right),x\right]$ which I do as above, using the retrieved equilibrium choice probabilities.

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