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ABSTRACT

This paper provides a model-based empirical strategy to, (i) detect the presence and gauge the 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. 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.

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An online appendix is available at:
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1 Introduction

In recent years, Chinese firms have extremely rapidly dominated a number of capital intensive industries, such as steel, auto parts, solar panels, shipbuilding.[1] Government subsidies are often evoked as a possible contributing factor to China's expansion.[2] Yet, even though industrial subsidies have steered industrialization and growth in several countries (e.g. in East Asia) throughout economic history, little is known about their quantitative impact on production reallocation across countries, industry prices, costs and surplus. A significant challenge in this task is that government subsidies to industries are notoriously difficult to detect and measure; and in China even more so. Indeed, partly because international trade agreements prohibit direct and in-kind subsidies, "systematic data are non-existent"[3] and thus the presence and magnitude of such subsidies is often unknown.

This paper assesses the consequences of government subsidies on industrial evolution, focusing on the unparalleled and timely Chinese expansion. Since measuring subsidies is a prerequisite for this analysis, I provide a model-based empirical strategy to detect their presence and gauge their magnitude. I apply my empirical strategy to the world shipbuilding industry, a classic target of industrial policy. In 2006, China identified shipbuilding as a "strategic industry" and introduced a plan for its development.[4] Within a short time span, its market share doubled from 25% to 50%, leaving Japan, S. Korea and Europe trailing behind. Many asserted that China's rapid rise was driven by hidden government subsidies that reduced shipyard production costs, as well as by a number of new shipyards constructed through the government plan; here I assess the relative contribution of these interventions.

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,

[1]The share of labor intensive products in Chinese exports fell from 37% to 14% between 2000 and 2010. On a monthly basis, in 2011 the US imported advanced-technology products from China 560% more than it exported to China. By contrast, the monthly US-China trade surplus in scrap (used as raw material) grew by 1187% between 2000 and 2010. (U.S.-China Economic and Security Review Commission (2011)).

[2]"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 [include the] seemingly endless supply of cheap labour (...) another reason for China's industrial dominance: subsidies." ("Perverse Advantage", The Economist, April 2013).

[3]WTO (2006).

[4]Section 2 provides details.

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 cost is also subject to an aggregate stochastic 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 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 when China launched its shipbuilding 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.

My estimation strategy can be summarized as follows. To estimate shipyard costs, I adopt a novel approach that is inspired by the literature on estimation of dynamic setups, e.g. Hotz and Miller (1993), Bajari, Benkard and Levin (2007) and Pakes, Ostrovsky and Berry (2008): I first invert observed choice probabilities to obtain directly the optimal policy thresholds nonparametrically in an ordered-choice dynamic problem; I then show that the latter lead to a closed-form expression for ex ante optimal per period payoffs, which in turn are sufficient to obtain shipyard value functions. To recover demand for new ships I estimate the willingness to pay using new and used ship prices, as well as shipowner expectations (similar to Kalouptsidi (2014)). The estimation allows expectations and value functions to be different before and after 2006, consistent with China's intervention. Finally, in estimating dynamics, I employ sparse approximation techniques (LASSO) that allow for a very large state space, as well as significant flexibility. Solving value functions via LASSO, which to my knowledge has not be used before, can be very useful to other applications with dynamic agents and a large state space.

I use my framework 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 (bulk ship production is not characterized by technological innovations to begin with).

Next, I use my framework to quantify the contribution of government interventions in China's seizing of the market. My main counterfactual predicts industry evolution (production reallocation across countries, ship prices, industry costs and shipper surplus) in the absence of China's government plan altogether; note that both cost subsidies and new shipbuilding facilities would violate international trade agreements. Moreover, I assess the relative contribution of the new shipbuilding facilities constructed through China's plan in a second counterfactual that removes the new facilities, but maintains the cost subsidies detected above. Here is a brief summary of my main four findings from these counterfactuals.

First, I find that the interventions led to substantial reallocation in production: in the absence of China's government plan, its market share is cut to half, while Japan's share increases by 50%. If only new shipyards are removed, China's share falls from 50% to 40%, suggesting that they played an important, but not the predominant part in China's expansion. 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 in the absence of China's plan, as the latter 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, compared to a world without China's intervention. As a result of China's plan, cargo shippers gain about 290 million US dollars in shipper surplus over that time period. Comparing this gain to the 5 billion US dollars of cost subsidies alone 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, subsidies create a wedge in the alignment of market share and production costs: they lead to a large increase in the industry average cost of production (net of subsidies) by shifting production away from low-cost Japanese shipyards towards high-cost Chinese shipyards.

This paper contributes to the long theoretical (e.g. Jovanovic (1982), Hopenhayn (1992), Ericson and Pakes (1995)) and recent empirical (e.g. Aguirregabiria and Mira (2007), Xu (2008), Jofre-Bonet and Pesendorfer (2003), Benkard (2004), Ryan (2012), Collard-Wexler (2013), Sweeting (2013)) literature on industry dynamics. Methodologically, it lies closest to Hotz and Miller (1993), Bajari, Benkard and Levin (2007) and Pakes, Ostrovsky and Berry (2007). This literature typically considers either single agent dynamics or dynamic firms and static consumers (one exception is Chen, Esteban and Shum (2013)). In contrast, this paper allows for dynamics in both demand and supply.

The paper also naturally contributes to the literature on trade policies. Goldberg (1995) and Berry, Levinsohn and Pakes (1999) consider the impact of voluntary export restraints in the automobile industry. Grossman (1990) provides an excellent survey of the relevant trade literature, while Brander (1995) is a classic reference on the long theoretical literature of strategic trade.[5] Not surprisingly, given the constraints in subsidy data availability, there is little empirical work, most of which is in the form of model calibration. 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 small 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.

The remainder of the paper is organized as follows: Section 2 provides a description of the environment under study including subsidy regulations and features 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.

[5] See also Bagwell and Staiger (2001) and Maggi (1996), as well as references within Brander (1995).

2 Environment

Subsidy Disputes Subsidy disputes are handled both bilaterally (e.g. in the US the relevant agencies are the Department of Commerce and the International Trade Commission (ITC)), as well as internationally through the WTO. They often lead to retaliating measures (countervailing measures or subsidy wars), which may spiral the effects of the original subsidies and further the reallocation.[6] Deciding on subsidy complaints is difficult for two reasons; first, "systematic data (on industrial subsidies) are non-existent; reliable sources of information are scarce and mostly incomplete [...] because governments do not systematically provide the information" (WTO (2006)). Therefore, detecting and measuring subsidies becomes a difficult task and plaintiffs need to base their allegations mostly on available self-reported data.[7] The second difficulty concerns (dis)proving "injury caused" by the alleged subsidies.[8] Ideally, the question to be answered is "how would have this industry evolved absent the alleged subsidies?"; this is clearly a difficult question which is answered based on a mostly qualitative analysis of industry indicators on a case by case basis.

China has had more trade conflicts than any other country in the world, in more industries and with more countries.[9] China provides industry subsidies in the form of free or low-cost loans, as well as subsidies for inputs (including energy), land and technology. Because of institutional and strategic reasons, the information on subsidies that the Chinese government provides has rampant missing and misreported

[6] "The ITC received a total of 1,606 antidumping and countervailing duty petitions during 1980-2007. These cases involved over $65 billion in imports. Thirty-eight percent of the petitions resulted in affirmative determinations by the Commission and Commerce, culminating in the issuance of an antidumping or countervailing duty order." (ITC (2008))

[7] One possible source of information (other than e.g. national accounts or individual government measures (Sykes (2009))) are subsidy "notifications" required by the WTO under SCM; however "the data contain many gaps and shortcomings. Not all Members fulfil the notification requirements. 29 of the currently 149 WTO Members have so far not submitted any notification. [...] Other Members do not provide quantitative information on subsidy programmes or do not provide this information systematically. In most years, information is available for less than half of the WTO membership." (WTO (2006))

[8] For example, in the US "an interested party may file a petition with ITC and Commerce alleging that an industry in the United States is materially injured or threatened with material injury, or that the establishment of an industry is materially retarded, by reason of imports that are being subsidized" (ITC (2008)). "Material injury" amounts to observing the volume of imports, as well as their impact on the domestic industry's prices and production. WTO's SCM has similar provisions: complaining countries must provide evidence of adverse trade effects in their own or third country markets (as well as evidence on the existence and nature of subsidies as mentioned above).

[9] The rest of the section draws from Haley and Haley (2008).

data.[10] These subsidies are often transferred through financial institutions, most of which are directed by the central and provincial governments.

Shipbuilding and China's Plan[11] Shipbuilding is one of the major recipients of subsidies globally, along with e.g. the steel, mining and automotive industries. It is often seen as a "strategic industry" as it increases industrial and defence capacity, generates employment and has important spill-overs to other industries (e.g. iron and steel). 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. 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 (4.5% of its GDP today).

China's 11^{th} National 5-year Economic Plan 2006-2010 was the first to appoint shipbuilding as a "strategic industry" in need of "special oversight and support"; the central government "unveiled an official shipbuilding blueprint to guide the medium and long-term development of the industry". The overwhelming majority of Chinese shipbuilding production[12] occurs at (i) a number of shipyards under the umbrella of two major state-owned enterprises directly administered by the Chinese central government (CSSC and CSIC); (ii) numerous shipyards administered by provincial and local governments.

Many asserted that China's plan provided subsidies to production costs, as well as expanded capital infrastructure. Consistent with this assertion, Figure 1 shows China's rapid expansion in shipbuilding dry docks, the majority of which (82%) was realized through the construction of new facilities. In contrast to the capital expansion, which is observed, subsidies that reduce operating costs are not observed. The two measures also differ in their implementation. Entry/Capital expansion decisions are not taken at the shipyard level, but rather at the higher administrative level (i.e. CSSC, CSIC, regional governments). Indeed, a significant portion of CSSC and CSIC

[10] In its 2014 report the US-China Economic and Security Commission (a US government body established to monitor and investigate national security implications of the bilateral trade and economic relationship between the United States and China) states that "a full identification of support programmes was not possible for the Secretariat, as they are often the result of internal administrative measures that are not always easy to identify and generally only available in Chinese. In addition, the budget is not a public document hence it is not possible to identify outlays."

[11] This section draws from OECD (2008), Collins and Grubb (2008) and Stopford (2009).

[12] China's shipbuilding is mostly geared towards export sales which comprised about 80% of its production in 2006.

financial resources have been devoted to expanding China's shipbuilding infrastructure.[13] In contrast, the day-to-day operations and contract bids are handled directly by the individual shipyards. This distinction is taken into account in the model and is discussed further in Sections 3 and 5. Finally, it is important to note that both types of interventions would violate trade agreements; the relevant question of interest to disciplining authorities is how the industry would evolve in the absence of all measures.

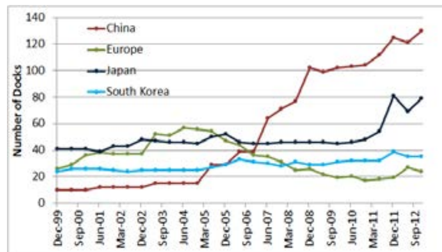

Figure 1: Shipbuilding dry docks.

Commercial ships are the largest factory produced product. Materials account for about half the cost of the ship (steel is about 13%) and labor (mostly low skill tasks) about 17% of total cost. This paper focuses on cargo transportation and in particular, dry bulk shipping, which concerns vessels designed to carry a homogeneous unpacked cargo (mostly raw materials), for individual shippers on non-scheduled routes. The bulk shipping market consists of a large number of small shipowning firms (largest firm has share 3%).[14]

3 Model

In this section, I present a dynamic model for world shipbuilders. A key input is demand for new ships, which stems from the decisions of shipowners to purchase new vessels. I therefore begin this section by describing shipowner behavior. Next, I turn to shipbuilder behavior, which is the focus of this paper. I also discuss how government subsidies enter. Variables with superscript "o" refer to shipowners and "y" to yards, while subscripts i and j refer to a particular owner and yard respectively.

[13] As an example, "CSSC had multibillion-dollar projects under way to build new shipyards on Changxing Island in Shanghai and Longxue Island in Guangzhou".

[14] See Kalouptsidi (2014) for a detailed description of the bulk shipping industry.

In the model, shipyards do not make entry or capital expansion decisions: as discussed above, in China these decisions are not made by individual shipyards, but rather by the central government through either the state conglomerates, or regional authorities. Moreover, no significant changes in docks are observed in other countries; see Figure 1. I discuss this further in the estimation results.

3.1 Demand for New Ships (Shipowners)

Time is discrete and the horizon is infinite. 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 shipowner is indistinguishable from his ship. Ships are long-lived. The state variable of ship i at time t, s^o_{it}, includes its:

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

while the industry state, s_t, includes the:

1. distribution of characteristics in s^o_{it} over the fleet, $\overline{s^o_t} \in \mathbb{R}^{A \times ||\mathcal{C}||}$
2. 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 $t+k$ by shipyard $j = 1, ..., J$ and $\overline{T}$ the maximum time to build
3. aggregate demand for shipping services, $d_t \in \mathbb{R}^+$
4. price of steel, $l_t \in \mathbb{R}^+$.[15]

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

$$P_t = P\left(d_t, Q^o_t\right) \tag{1}$$

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^o_t denotes the total voyages offered, so that $Q^o_t = \sum_i q^o_{it}$. Voyages are a homogeneous good, but shipowners face

[15] 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.

heterogeneous convex costs of freight. 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 $\pi^o\left(s_{it}^o, s_t\right)$.[16]

A ship lives a maximum of A periods. At the same time, a ship can be hit by an exit shock each period.[17] In particular, I assume that a ship at state $\left(s_{it}^o, s_t\right)$ exits with probability $\delta\left(s_{it}^o, s_t\right)$ and receives a deterministic scrap value $\phi\left(s_{it}^o, s_t\right)$. Note that ships exit with certainty at age A.[18]

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:

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

where β is the discount factor and s_{it}^o in this case involves ship age equal to zero and the country of yard j, while the value function $V^o\left(s_{it}^o, s_t\right)$ satisfies the Bellman equation:

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

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

[16] More accurately, ship profits from freight are $\pi^o\left(s_{it}^o, \overline{s_t^o}, d_t\right)$; even though the backlog and steel prices do not affect current payoffs, they affect state transitions and scrap values and are thus part of the state.

[17] Shipowners scrap their ships by selling them to scrapyards where they are dismantled and their steel hull is recycled.

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

$\delta(s^o_{it}, s_t)$.

In practice, shipowners can also buy a used ship. In this model, since ships are indistinguishable from their owners, 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^{SH}_{it}, equals this value and shipowners are always indifferent between selling their ship and operating it themselves. Therefore, in equilibrium:

$$P^{SH}_{it} = V^o\left(s^o_{it}, s_t\right) \tag{4}$$

I revisit sales in the empirical part of the paper, where both second-hand 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, s^y_{jt}, includes its:

1. backlog $b_{jt} \in \mathbb{R}^{\overline{T}}$
2. country
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 ε_{jt}, with $\sigma\varepsilon_{jt} \sim N(0,1)$, and makes a discrete production decision $q_{jt} \in \{0, 1, ..., \overline{q}\}$.[19] Shipyard j faces production costs, $C\left(q_{jt}, s^y_{jt}, s_t, \varepsilon_{jt}\right)$. Even though q_{jt} is an integer I assume that the cost function can be defined over the real interval $[0, \overline{q}]$ and that as such it is convex in q_{jt}. I also assume that the cost shock ε_{jt} is paid for each produced unit, so that:

$$C\left(q_{jt}, s^y_{jt}, s_t, \varepsilon_{jt}\right) = c\left(q_{jt}, s^y_{jt}, s_t\right) + \sigma q_{jt}\varepsilon_{jt} \tag{5}$$

In this model q_{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

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

later.[20] 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.[21]

As discussed above, shipyard j sells its ships at a price equal to the shipowners' entry value:[22]

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

where $s^o_{it+T_{jt}}$ has zero ship age and the country of yard j. Time to build is shipyard-specific and in particular, $T_{jt} = T\left(s^y_{jt}, s_t\right)$. Note that $VE_j^o(s_t)$ does not explicitly depend on period t's production, q_{jt}; in other words yards do not face a downward sloping demand curve. Indeed, q_{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, q_{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 $VE_j^o(s_t)$; 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:

$$V^y\left(s^y_{jt}, s_t, \varepsilon_{jt}\right) = \max_{0 \le q \le \bar{q}} VE_j^o(s_t)\, q - c\left(q, s^y_{jt}, s_t\right) - \sigma q \varepsilon_{jt} + \beta E\left[V^y\left(s^y_{jt+1}, s_{t+1}, \varepsilon_{jt+1}\right) | s^y_{jt}, s_t, q\right] \tag{7}$$

[20] 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.

[21] Here, the shipyard's backlog also affects its demand, as it increases the time shipowners have to wait for delivery.

[22] 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, the hundreds of shipyards encountered in the data make this generalization impossible in this empirical application.

To ease notation, I also define the continuation value:

$$CV^y\left(s_{jt}^y, s_t, q\right) \equiv E\left[V^y\left(s_{jt+1}^y, s_{t+1}, \varepsilon_{jt+1}\right) | s_{jt}^y, s_t, q\right] \tag{8}$$

The expectation in (7), as well as in ship value functions (2) and (3), is over demand for shipping services, d_t, steel prices, l_t, shipyard production q_{jt}, all j and j's future cost shocks. 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, q_{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. 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 $\left\{s_{it}^o, s_{jt}^y, s_t\right\}$ 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 q to $q+1$ and $q-1$, as stated in the following intuitive lemma:

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

$$q^*\left(s_{jt}^y, s_t, \varepsilon_{jt}\right) = \begin{cases} 0, & \text{if } \varepsilon_{jt} \geq A\left(s_{jt}^y, s_t, 0\right) \\ q, & \text{if } \varepsilon_{jt} \in \left[A\left(s_{jt}^y, s_t, q-1\right), A\left(s_{jt}^y, s_t, q\right)\right] \\ \overline{q}, & \text{if } \varepsilon_{jt} \leq A\left(s_{jt}^y, s_t, \overline{q}-1\right) \end{cases} \tag{9}$$

where

$$A\left(s_{jt}^y, s_t, q\right) \equiv \frac{1}{\sigma}\left[\begin{array}{c} VE_j^o\left(s_t\right) + \left(c\left(q, s_{jt}^y, s_t\right) - c\left(q+1, s_{jt}^y, s_t\right)\right) + \\ +\beta\left(CV^y\left(s_{jt}^y, s_t, q+1\right) - CV^y\left(s_{jt}^y, s_t, q\right)\right) \end{array}\right]$$

for $q = 0, 1, ..., \overline{q}-1$, are the optimal policy thresholds.

Proof. See the Online Appendix. ■

The timing in each period is as follows: incumbent and potential entrant shipowners observe their state (s_{it}^o, s_t), while shipbuilders observe their state $\left(s_{jt}^y, s_t\right)$. 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 $\phi(s_{it}^o, s_t)$. Finally, states are updated.

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

Finally, I assume that China's plan 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 undoubtedly ad hoc assumptions. Within my model, the before and after 2006 worlds differ in the set of shipyards, China's cost function and shipbuilding infrastructure (found in s_{jt}^y).

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.

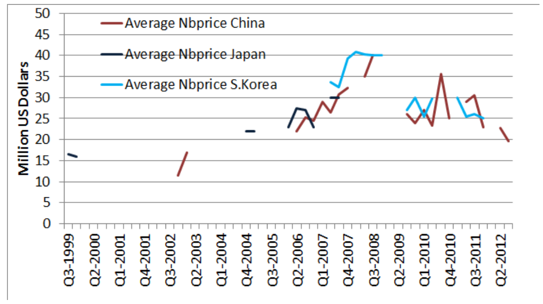

Figure 2: Average quarterly new ship price.

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 is a snapshot of shipyard characteristics in 2012, such as shipyards' first year of delivery, location, number of dry docks and berths, length of largest dock, number of employees, total past output. Several shipyards have missing observations. The first year of delivery is used to compute the shipyard's age.[23] The number of docks and berths is a measure of capacity, since production bottlenecks occur during the assembly operations done on the docks/berths. I allow the capital infrastructure of yards (i.e. docks/berths and length) to be different before and after China's plan by collecting data from a Clarksons publication ("World Shipyard Monitor"). The adoption of a pre- and post-2006 capital infrastructure level is consistent with the modeling assumption of two equilibria before and after China's plan. I drop shipyards with missing capital measures (docks/berths) so that the end shipyard sample (production and characteristics) consists of 4741 shipyard-quarter observations (all results are robust if the full sample is used).

Finally, the fifth dataset consists of quarterly time-series between 1998 and 2012

[23] Because of time to build, I subtract a number of years from every first delivery year of all shipyards, after consulting with Clarksons' analysts. The results I report subtract 3 years (similar findings were obtained when I vary the number of years subtracted).

for the fleet, total backlog, orders of new ships, deliveries, demolitions between 1998 and 2012. This dataset is used to create the states and estimate their transition. I also obtain quarterly time-series of Japan's steel ship plate commodity price in dollars per ton during the same time period.[24]

Descriptive Evidence What patterns of the raw data are consistent with the presence of subsidies? One might expect that new ship prices should react around 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 drop in 2006, in a period when ship prices are trending upward due to increased demand for freight (shifts in demand are also the reason the price decline is not permanent in the raw data).[25] Of course, this finding is not proof of cost subsidies; yet if no drop were observed, one may have been concerned about the impact of this policy.

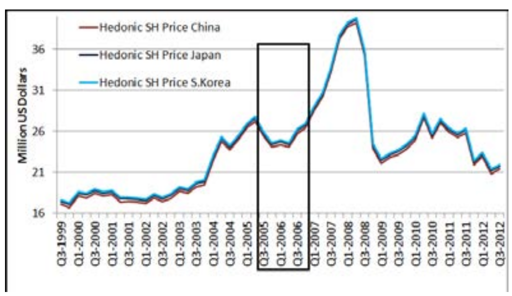

Figure 3: Hedonic regression of used ship prices on ship age, country and quarter dummies.

Despite the importance of a price response, the main insight of this paper, in terms of identifying/measuring 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 (in combination with prices) to identify changes in costs that are consistent with the presence of subsidies. At the same time, the constructed model can control for the different factors leading to this increase

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

[25] I have unsuccessfully searched extensively in industry publications for alternative explanations.

and provide a measurement of the alleged subsidies, a fundamental input into subsidy disputes. When I come to the results, I discuss alternative explanations for this pattern (e.g. productivity changes/technological improvements or learning by doing) and argue that they cannot account for the observed patterns.

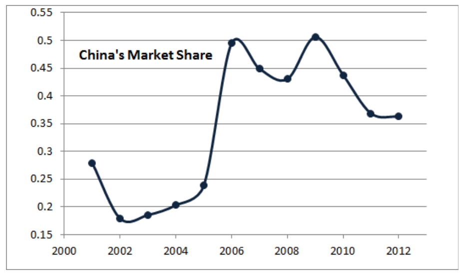

Figure 4: China's market share.

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.

Each estimation task is described below and followed by the results. A time period is a quarter. All results presented are for bulk vessels, in particular, Handysize. There are three good reasons to focus on bulk carriers: China was already an important player before 2006; their production process is not characterized by significant technological advances; product differentiation is limited.[26]

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 following Kalouptsidi (2014) by estimating a demand curve for shipping services and using the intercept. The analysis is presented in the Appendix.

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^o_{it}, s_t). The transition of s^o_{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 ($\overline{s^o_t}$ has dimension $4 \times A$ -where A is a ship's maximum age- in the case of four countries, while the backlog 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 is similar 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, $\overline{s^o_t}$, with two age groups $\left(\overline{s^o_{1t}}, \overline{s^o_{2t}}\right)$: the number of ships below 20 years old and the number of ships above 20 years old.[27] I do not use the distribution of the fleet over country of built because its evolution is extremely slow. Second, I replace the backlog, b_t, with the total backlog $B_t = \sum_{j,l} b_{jtl}$.[28]

I have experimented with several variations of the general time varying vector

[26] Looking at other ship types (and even different aggregations across types) reveals that virtually all experience the same market evolution, with China displacing other countries (e.g. Figure 4 is very similar across types); therefore concerns that perhaps countries started specializing in different ships are put to rest.

[27] 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.

[28] Ideally, the distribution of shipyards over their characteristics s^y_{jt} would also be part of the state; it is omitted for computational tractability.

autoregression (VAR) model:

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

where $\xi_t \sim N(0, \Sigma_\xi)$. I allow the VAR parameters (R_{ot}, 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, shipowners are likely to believe that all else equal the supply of ships is permanently higher post 2006. This change affects their ship valuations today and therefore captures any changes in demand for new ships, brought by China's policies. I consider Q3-2005 as the first quarter of the post world (for all empirical tasks in the paper), consistent with Figures 1 and 3; all results are robust to alternative thresholds around that date.

I examined several specifications where (R_{ot}, R_t) vary deterministically (e.g. time trend, so that $R_{ot} = R_o + R_\tau t$) or randomly with time (random walk model for R_t determined by the Kalman filter), or are time-invariant; end results are very robust. The baseline specification is:

$$\begin{bmatrix} \overline{s^o_{1t}} \\ \overline{s^o_{2t}} \\ B_t \\ d_t \\ l_t \end{bmatrix} = \begin{bmatrix} r_o^{s_1} \\ r_o^{s_2} \\ r_o^{B} \\ r_0^{d} \\ r_0^{l} \end{bmatrix} 1\{t \leq 2006\} + \begin{bmatrix} r_o^{s_1\prime} \\ r_o^{s_2\prime} \\ r_o^{B\prime} \\ r_o^{d} \\ r_o^{l} \end{bmatrix} 1\{t > 2006\} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ r_\tau^{d} \\ r_\tau^{l} \end{bmatrix} t + \begin{bmatrix} r^{s_1 s_1} & r^{s_1 s_2} & r^{s_1 B} & r^{s_1 d} & r^{s_1 l} \\ r^{s_2 s_1} & r^{s_2 s_2} & r^{s_2 B} & r^{s_2 d} & r^{s_2 l} \\ r^{B s_1} & r^{B s_2} & r^{BB} & r^{Bd} & r^{Bl} \\ 0 & 0 & 0 & r^{d} & 0 \\ 0 & 0 & 0 & 0 & r^{l} \end{bmatrix} s_{t-1} + \xi_t \tag{10}$$

and Σ_ξ is diagonal and I work with natural logarithms for $\left(\overline{s^o_{1t}}, \overline{s^o_{2t}}, B_t\right)$. Note that as discussed above, demand d_t and steel price l_t are exogenous to the model and are unaffected by the pre/post-2006 regime. In contrast, I allow $\left(\overline{s^o_{1t}}, \overline{s^o_{2t}}, B_t\right)$ to be affected by all variables to account for ship entry and exit. The baseline specification allows only R_0 to change before and after 2006. Even though t appears explicitly only in the exogenous variables, it affects $\left(\overline{s^o_{1t}}, \overline{s^o_{2t}}, B_t\right)$ through their dependence on (d_t, l_t). I estimate the parameters of interest (R_0, R, Σ_ξ) via OLS separately for each variable (note that separate OLS yields identical estimates to Maximum Likelihood estimation). Table 1 reports the results. All variables are persistent. Signs are also in general as expected: $\overline{s^o_{1t}}$ is increasing in the backlog and demand and decreasing in steel prices (as steel prices increase, exit increases); $\overline{s^o_{2t}}$ is decreasing in $\overline{s^o_{1t}}$, as more young ships increase exit, and also $\overline{s^o_{2t}}$ is 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.[29]

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 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:

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

$$P^{SH}_{it} = V^o\left(s^o_{it}, s_t\right) + \zeta^{SH}_{it} \tag{12}$$

where ζ^{SH}_{it} and ζ^{NB}_{jt} are measurement error. Kalouptsidi (2014) employes used ship prices alone to nonparametrically estimate ship value functions (via local linear regression) 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. Here, however, the addition of the new ship contracts dataset requires the combination (11) and (12) in a single estimation step, which is not straightforward. To do so, I take a different approach. In particular, I use a flexible linear sieve approximation for the value function:

$$V^o\left(s^o_{it}, s_t\right) = \ {}^o f^o\left(s^o_{it}, s_t\right)$$

where $f^o(\cdot)$ is a polynomial function in the ship state (s^o_{it}, s_t) and ^{o} is a (sparse) parameter vector.

[29] I also experimented heavily with restrictions on R_0 and R both in terms of before and after 2006, allowing Σ_ξ to be full, as well as parameter restrictions (e.g. time to build might imply that $r^{s_1 d} = 0$ 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 robust to 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.

$r_o^{s_1}$, pre	-1.47 (0.97)	$r^{s_1 s_1}$	1.104 $(0.04)^*$
$r_o^{s_2}$, pre	2.53 $(1.03)^*$	$r^{s_2 s_1}$	-0.15 $(0.04)^*$
r_o^{B}, pre	-8.49 (7.31)	$r^{B s_1}$	0.16 (0.3)
$r_o^{s_1}$, post	-1.46 (0.98)	$r^{s_1 s_2}$	0.08 (0.094)
$r_o^{s_2}$, post	2.53 $(1.04)^*$	$r^{s_2 s_2}$	0.81 $(0.1)^*$
r_o^{B}, post	-8.5 (7.35)	$r^{B s_2}$	1.07 $(0.71)^*$
r_0^d	0.41 $(0.17)^*$	$r^{s_1 B}$	0.021 $(0.0044)^*$
r_τ^d	0.008 (0.005)	$r^{s_2 B}$	-0.007 (0.0047)
r^d	0.69 $(0.11)^*$	r^{BB}	0.87 $(0.03)^*$
r_0^l	0.7 (0.4)	$r^{s_1 d}$	0.0046 (0.0035)
r_τ^l	0.021 (0.015)	$r^{s_2 d}$	0.004 $(0.0037)^*$
r^l	0.8 $(0.09)^*$	r^{Bd}	0.075 (0.026)
$\sigma_\xi^{s_1}$	0.0001	$r^{s_1 l}$	-0.003 $(0.001)^*$
$\sigma_\xi^{s_2}$	0.0001	$r^{s_2 l}$	0.002 $(0.001)^*$
σ_ξ^{B}	0.004	r^{Bl}	-0.0094 (0.007)
σ_ξ^{b}	0.14		
σ_ξ^{d}	1.23		

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

Then:

$$P_{it}^{SH} = \ ^{o} f^{o}\left(s_{it}^{o}, s_{t}\right) + \zeta_{it}^{SH} \tag{13}$$

while

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

$$= \ ^{o} \beta^{T_{jt}} \int f^{o}\left(s_{it+T_{jt}}^{o}, s_{t+T_{jt}}\right) dP\left(s_{it+T_{jt}}^{o}, s_{t+T_{jt}} | s_{it}^{o}, s_{t}\right) + \zeta_{jt}^{NB} \equiv \ ^{o} f_{NB}\left(s_{it}^{o}, s_{t}\right) + \zeta_{jt}^{NB} \tag{14}$$

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

$$s_{t+T} = R^{T} s_{t} + \sum_{k=t+1}^{t+T} R^{t+T-k}\left(R_{ok} + R_{\tau} k + \xi_{k}\right) \tag{15}$$

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

As the dimensionality of the state (s_{it}^{o}, s_{t}) is large, computing high order polynomial terms quickly leads to a very large number of regressors in (14) and (13). I therefore use LASSO, a method appropriate for sparse regression problems, i.e. problems that involve a large number of potential regressors, only a small subset of which 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 the $\mathcal{L}_1$ norm of the parameter of interest. Thus ^{o} is estimated from :

$$\min_{o}\left\{\sum_{j,t}\left(P_{jt}^{NB} - \ ^{o} f_{NB}\left(s_{it}^{o}, s_{t}\right)\right)^{2} + \sum_{i,t}\left(P_{it}^{SH} - \ ^{o} f^{o}\left(s_{it}^{o}, s_{t}\right)\right)^{2} + \lambda \left| \ ^{o}\right|_{1}\right\}$$

In this application, the regressors $f^{o}\left(s_{it}^{o}, s_{t}\right)$ and $f_{NB}\left(s_{it}^{o}, s_{t}\right)$ are third order polynomials in s_t and s_{it}^{o}, as well as interactions of s_{it}^{o} 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 ^{o} embody equilibrium features which are likely to change in 2006 as agents' valuations are altered (mainly because of the permanently higher fleet and thus competition). 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.[30]

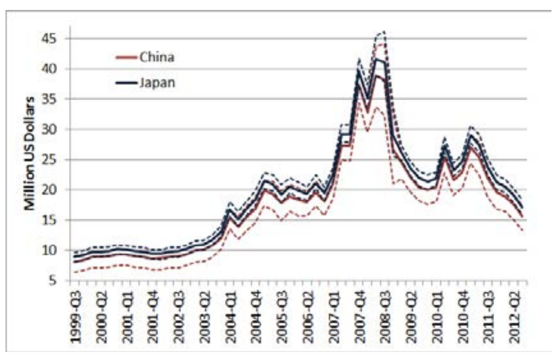

Figure 5: Value function of a ship at age zero. 0.95 bootstrap confidence intervals.

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 to illustrate the estimation strategy followed. I present the estimation results along with several robustness exercises. I then proceed to the case of dynamic shipbuilders.

5.2.1 Static Shipbuilders

If shipyard j is myopic it solves:

$$\max_{0\leq q\leq \bar{q}} VE^{o}_{j}\left(s_t\right) q - c\left(q, s^{y}_{jt}, s_t;\theta\right) - \sigma\varepsilon_{jt} q$$

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

This is essentially an ordered choice problem, so in order to estimate the cost function parameters, I maximize the following likelihood function:

$$\prod_{j,t:q_{jt}=0} \Pr\left(q_{jt} = 0|s^y_{jt}, s_t; \theta\right) \prod_q \prod_{j,t:q_{jt}=q} \Pr\left(q_{jt} = q|s^y_{jt}, s_t; \theta\right) \prod_{j,t:q_{jt}=\overline{q}} \Pr\left(q_{jt} = \overline{q}|s^y_{jt}, s_t; \theta\right) \tag{16}$$

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

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

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

$$\begin{aligned} c_1\left(s^y_{jt}, s_t; \theta\right) \quad &= \quad \theta^{ch}_0 1\{\text{China}\} + \theta^{ch,post}_0 1\{t \geq 2006, \text{China}\} \\ &\quad +\theta^{EU}_0 1\{\text{Europe}\} + \theta^{J}_0 1\{\text{Japan}\} + \theta^{K}_0 1\{\text{S.Korea}\} + \theta_1 g(s^y_{jt}, s_t, t) \end{aligned}$$

and

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

where $g(s^y_{jt}, s_t, t)$ is a (flexible) function of the shipyard's characteristics s^y_{jt}, the industry state s_t (steel price in particular) and time, t. Testing that $\theta^{ch,post}_0 \neq 0$ provides evidence of a structural change in China's cost function, for any value of s^y_{jt}, s_t and q. I follow Amemiya (1984) and maximize the likelihood over $\left(\frac{1}{\sigma}, \frac{\theta}{\sigma}\right)$ rather than (θ, σ).[31]

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 Chinese subsidies cost between 2.5 and 5 billion US Dollars. The estimates imply that the average cost of building a ship is 38.1 million US dollars across countries, 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

[31] As $VE^o_j(s_t)$ is estimated, to compute standard errors I create 500 bootstrap samples by redrawing $\left(q_{jt}, s^y_{jt}, s_t\right)$ and combine them with the 500 samples drawn to compute confidence intervals for $VE^o_j(s_t)$. I have also used the block-boostrap where I drew shipyards with replacement, and standard errors are unaffected.

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 for 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. One could argue that an arbitrary productivity process or technological improvements can also be consistent with these results. The production process of bulk carriers is old, however, without frequent technological advances. In addition, such a productivity process would have to feature a discontinuity in 2006 in China alone.

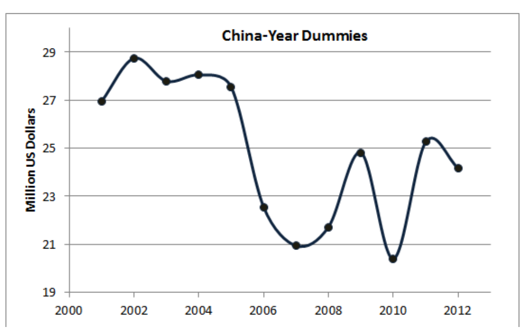

Figure 6: China-Year Dummies.

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, in addition to the China post 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 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).

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

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 facilities built through China's plan, which perhaps are more modern and have entirely different production capabilities (though, to reiterate, bulk shipbuilding technology is not subject to frequent technological innovations), (ii) cost declines are driven by firms' optimizing production under learning by doing (though in 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 (see Section 2), I consider a specification where they implement the national 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 somehow driven by the estimated willingness to pay, $VE_j^o(s_t)$, (for instance due to the different pre and post expectations -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, which is reported by Clarksons. I find that estimated subsidies are significant and of the same magnitude.

Finally, note that when shipyards choose production in a static fashion, the assumption that dock development is determined by higher administration rather than the yards themselves, does not bias cost (and thus subsidy) estimates in this model (the first order condition for optimal production is unaffected by shipyard dock choice).[32] When shipyards take into account production dynamics, however, this assumption is important; if yards were to choose both production and docks, the first order conditions are no longer decoupled, since firms consider the future impact of all their actions.

[32] If shipyards were choosing docks themeselves and the government provided subsidies to both operating costs, as well as dock building costs, it is easy to show that both cost and dock building subsidies can be separately identified. In addition this does not hinge upon the specific cost function employed here, but rather it holds under fairly general cost function specifications.

	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)
$c_2 *$ (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

I now examine the case where shipyards take into account the dynamic feedback of their current production choice to their future operating costs, as well as the durability of their product. The shipyard's optimal production now obeys (9). To ease notation, rename the shipyard state $x = \left(s^y_{jt}, s_t\right)$ and $x' = \left(s^y_{jt+1}, s_{t+1}\right)$ and suppress (j, t). Recall the optimal policy thresholds that define the shipyard's optimal production (see Lemma 1):

$$A(x,q) = \frac{1}{\sigma}\left[VE^o(x) + (c(q,x) - c(q+1,x)) + \beta\left(CV^y(x,q+1) - CV^y(x,q)\right)\right] \tag{17}$$

for $q = 0, 1, ..., \overline{q} - 1$. To estimate the parameters (θ, σ), I maximize the likelihood (16) with choice probabilities:

$$\Pr(q^* = 0|x) \equiv p_0(x) = \Pr(\varepsilon \geq A(x,0)) \tag{18}$$

$$\Pr(q^* = q|x) \equiv p_q(x) = \Pr(\varepsilon \leq A(x,q-1)) - \Pr(\varepsilon \leq A(x,q))$$

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

Maximizing this likelihood function would be trivial if the continuation value $CV^y(x,q)$ were known. This is the standard difficulty of estimating dynamic setups and to address it, I adopt a novel approach that proceeds in two steps (following the recent literature, e.g. Hotz and Miller (1993) and Bajari, Benkard and Levin (2007)). First, I invert observed choice probabilities to directly obtain the optimal policy thresholds nonparametrically. Second, I show that the latter lead to a closed-form expression for ex ante optimal per period payoffs, which in turn are sufficient to obtain the value function. I next describe my approach in detail.

For the first step, note from (18) that clearly, the choice probabilities are a one-to-one function of the optimal policy thresholds $A(x,q)$. Therefore the latter can be recovered from the observed choice probabilities using[33]:

$$A(x,q) = \Phi^{-1}\left(1 - \sum_{k=0}^{q} p_k(x)\right), \quad \text{for } q = 0, 1, ..., \overline{q} - 1 \tag{19}$$

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

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

For the second step, I show that once the optimal policy is known, the value function can be recovered in a straightforward manner. Indeed, consider shipyard j's Bellman equation (7) which I repeat here for convenience:

$$V^y(x,\varepsilon) = \max_{0 \leq q \leq \overline{q}} \pi^y(x,q,\varepsilon) + \beta E_{\varepsilon',x'}[V^y(x',\varepsilon')|x,q]$$

where $\pi^y(x,q,\varepsilon) \equiv VE^o(x)q - c(q,x) - \sigma q\varepsilon$. The ex ante value function under the recovered optimal policy becomes:

$$V^y(x) \equiv E_\varepsilon V^y(x,\varepsilon) = E_\varepsilon[\pi^y(x,q^*(x,\varepsilon),\varepsilon) + \beta E_{\varepsilon',x'}[V^y(x',\varepsilon')|x,q^*(x,\varepsilon)]] \tag{20}$$

If the ex ante per period profit, $E_\varepsilon \pi^y(x,q^*(x,\varepsilon),\varepsilon)$, were known, then one could solve for the ex ante value function from (20). This 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 of the state, so that:

$$V^y(x) = \ {}^y f^y(x)$$

then (20) becomes

$$(f^y(x) - \beta E_\varepsilon[f^y(x')|x,q^*(x,\varepsilon)])\ {}^y = E_\varepsilon \pi^y(x,q^*(x,\varepsilon),\varepsilon) \tag{21}$$

It is now possible to estimate the approximating parameters $\ {}^y$ by ordinary regression,

[33] 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.

provided the ex ante profit can be computed. Note, however, that the large number of states leads to an exploding number of possible terms in $f^y(x)$; in addition, choosing which terms to include in $f^y(x)$ can be an arduous process. Instead, I estimate the sparse vector ^{y} via LASSO, which circumvents these issues. Using LASSO to solve for approximate value functions can be useful to the many empirical applications of dynamic setups.

I now only need to show how $E_\varepsilon \pi^y(x, q^*(x,\varepsilon), \varepsilon)$ is computed. Under the assumption of quadratic costs, ex ante per period payoffs become:

$$E_\varepsilon \pi^y(x, q^*(x,\varepsilon), \varepsilon) =$$

$$\begin{aligned} &= E_\varepsilon\left[VE^o(x)\, q^*(x,\varepsilon) - c_1(x;\theta)\, q^*(x,\varepsilon) + c_2(x;\theta)\, q^*(x,\varepsilon)^2 - \sigma q^*(x,\varepsilon)\,\varepsilon\right] \\ &= \left(VE^o(x) - c_1(x;\theta)\right) E_\varepsilon q^*(x,\varepsilon) + c_2(x;\theta)\, E_\varepsilon q^*(x,\varepsilon)^2 - \sigma E_\varepsilon\left[q^*(x,\varepsilon)\,\varepsilon\right] \end{aligned} \tag{22}$$

I show in the Appendix that

$$E_\varepsilon q^*(x,\varepsilon) = \sum_{q=0}^{\bar{q}-1} \Phi\left(A(x,q)\right) \tag{23}$$

$$E_\varepsilon\left[q^*(x,\varepsilon)\right]^2 = 2\sum_{q=1}^{\bar{q}} q\Phi\left(A(x,q-1)\right) - \sum_{q=0}^{\bar{q}-1} \Phi\left(A(x,q)\right) \tag{24}$$

$$E_\varepsilon\left[q^*(x,\varepsilon)\,\varepsilon\right] = -\sum_{q=0}^{\bar{q}-1} \phi\left(A(x,q)\right) \tag{25}$$

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

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

1. Estimate the policy thresholds $A(x,q)$ using (19)

2. Compute the statistics of the optimal production in (23), (24) and (25)

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

(a) Solve for the approximate value function parameters ^{y} from (21)

(b) Using ^{y}, compute the choice probabilities and update (θ, σ).

Table 4 gives the maximum likelihood estimate of the 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 and yards take this into account, 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 through China's government plan, 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.

In summary, the static and dynamic formulations yield similar results in terms of subsidy detection, with the dynamic model having a higher likelihood. 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.

6 Quantifying the Implications of Subsidies

I quantitatively assess the degree to which industrial subsidies contribute to China's rapid emergence as a world leader in the shipbuilding industry. In particular, I evaluate the impact of government interventions on industry prices, production reallocation across countries, costs and consumer surplus. I use my model to predict the evolution of the industry in the absence of China's government shipbuilding plan, by removing both the cost subsidies retrieved in Section 5, as well as the new shipbuilding facilities that were built through the plan. This counterfactual quantifies the adverse trade effects from these two interventions, which are considered actionable by the WTO. Moreover, I assess the relative contribution of the new shipyards to industrial reallocation and surplus by performing a counterfactual that removes the new facilities but maintains the detected cost subsidies.

To implement the main counterfactual of "no interventions", I assume that shipowners maintain their pre-2006 expectations and ship value functions, shipyards keep their pre-2006 costs and capital structure (i.e. docks/berths and length) and new shipyards are removed. To implement the "no entrants" counterfactual, new shipyards are removed and existing shipyards keep their post-2006 cost functions and capital structures. Also, I assume that shipowners switch to the post-2006 expectations and value functions. In other words, shipowners understand that a change occurred; yet they can't distinguish between different policies. I feed the observed post-2006 values for shipping demand and steel prices into the model and simulate shipyard optimal production and ship prices. Computing the equilibrium to the model is not straightforward and thus details on the implementation of these counterfactuals can be found in the Appendix.

As shown in Table 5, the industrial subsidies lead to substantial reallocation in production, by increasing China's market share and decreasing Japan's share: if the plan is removed, China's market share falls from 50% to less than 20%. Japan's share increases from 43% to 74% in the absence of China's intervention.[34] If only the new shipyards are removed, China's share falls from 50% to 40%, revealing that new facilities played an important but not the predominant part in China's expansion.

Table 5 also compares ship prices in the baseline and counterfactual worlds and shows that ship prices are higher for all countries in the absence of China's subsidization plans (by about 5%). This is not surprising, given that China's subsidization shifted supply outward.

Next, I turn to costs, profits and shipper surplus, shown in the lower half of Table 5. China's government plan decreased profits of other countries by moderate amounts; for example, Japan's profits fell by 11% because of Chinese 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 (existing shipowners do lose, however, because of the unexpected negative shock to their asset value). Shippers of cargo, however, gain from subsidies as they lead to higher shipbuilding production and thus to a larger fleet. I use the demand

[34]Counterfactual results are robust to 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.

	Baseline	No Interventions	No New Facilities
Market Share, China	50%	18.4%	40%
Market Share, Japan	43.4%	73.9%	54.7%
Ship Price, China	23.8	25	24.2
Ship Price, Japan	25.5	26.6	25.95
Japan, Shipyard Profits	95.1	105.4	102.8
Freight Rate (price per voyage)	1.25	1.28	1.27
Consumer Surplus (shippers)	5617	5331	5446
Industry AVC	0.42	0.65	0.54

Table 5: Counterfactual results. Prices, surplus and average variable cost (AVC) measured in million US Dollars. Profits and surplus refer to the total amount between 2006 and 2012.

curve estimated in the Appendix to compute shipping prices and shipper surplus.[35] As shown in Table 5, the freight rate is moderately higher (by 3%) 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 5%. As a result, cargo shippers benefit from Chinese subsidies; their consumer surplus is higher by 5% because of subsidies and increases over time (between 2009 and 2012 consumer surplus is higher by 8%). Note that between 2006 and 2012 the cost subsidies alone (i.e. ignoring the additional costs of building new yards), cost the government about 5.6 billion US dollars and resulted in consumer surplus gains of 286 million US dollars. This calculation implies that a frequent assertion that China developed shipbuilding to benefit from low freight rates for its trade seems to be unsubstantiated; indeed, 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, see last row of Table 5. If I decompose the average cost to subsidies and market share allocation, however, this picture is entirely different. Indeed, consider

[35] The 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.

the cost function $c_j q + cq^2$, for $j \in \{$China, EU, Japan, S.Korea$\}$, which for $j =$China becomes $(c_{china} - s)\, q + cq^2$ post-2006. The change in the industry average cost because of subsidies is equal to a sum of two terms: the first is $s\frac{q_{China}}{q_{China}+q_{EU}+q_{Japan}+q_{SK}}$, while the second includes all other terms and is related to the reallocation of production and market share. As implied by the numbers in Table 5, the change in industry average cost brought about by production subsidies is 0.23 million. The term $s\frac{q_{China}}{q_{China}+q_{EU}+q_{Japan}+q_{SK}}$ equals 4.44 million, implying a negative reallocation effect equal to $0.23 - 4.44 = -4.21$ 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? In the case of production dynamics, increased backlog decreases costs and thus market share gains multiply and may lead to more reallocation favorable to China and unfavorable to Japan. Indeed, when 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. The second question of interest, is whether the static model leads to different 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 73% of its market share in the absence of 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

The role of industrial policy in China's rapid takeover, especially in industries that are capital intensive, is still an open question. To answer, one needs to first know what policies are in place. This paper measures subsidies and quantifies their impact for the striking example of the world shipbuilding industry. I find strong evidence consistent with subsidies that decreased shipyard costs by 15-20%. The interventions led to a substantial reallocation of production across countries with no significant surplus gains. Therefore, subsidies may be justified by shipbuilding's important externalities to other sectors, such as the steel industry or the readiness of the military sector. Yet, understanding government objectives is 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:

$$P_t = \alpha_0^d + \alpha_1^d X_t^d + \alpha_2^d Q_t^o + \varepsilon_t^d \tag{26}$$

where P_t is the average price per voyage observed in a quarter, X_t^d includes demand shifters, while Q_t^o is the total number of voyages realized (see Kalouptsidi (2014) for a detailed data description). 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).

Table 6 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):

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

	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)**	
$\widehat{Q_t^o}$		-0.0033 (0.001)**

Table 6: Demand IV regression results.

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:

$$V^o(x_t) = \; {}^o f^o(x_t) = \sum_{i=1}^{d} \; {}^o_i x_t^{(i)}$$

where $x_t = (s_{it}^o, s_t)$, and $x_t^{(i)}$ are Kronecker products, so that $x_t^{(2)} = x_t \quad x_t$, $x_t^{(3)} = x_t^{(2)} \quad x_t$, etc. Then, (14) can be written as:

$$P_{jt}^{NB} = \beta^{T_{jt}} \; {}^o E \; \square f^o \; \square x_{t+T_{jt}}) \, |x_t) = \beta^{T_{jt}} \sum_{i=1}^{d} \; {}^o_i E\left(x_{t+T_{jt}}^{(i)} | x_t\right) \tag{27}$$

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

$$s_{t+T} = \phi(t+T,t)\, s_t + \sum_{k=t+1}^{t+T} \phi(t+T,k)\,(R_{0k} + \xi_k)$$

where

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

I denotes the identify matrix. In the time invariant case, $R_t = R$, all t, I get (15) of the main text.

Next, I focus on the time invariant case. The above expression takes the form:

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

where

$$\begin{aligned} A &= R^T s_t + \sum_{k=t+1}^{t+T} R^{t+T\square k} R_{0k} \\ v &= \sum_{k=t+1}^{t+T} R^{t+T\square k} \xi_k \end{aligned}$$

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

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

Therefore, (27) becomes:

$$P_{jt}^{NB} = \beta^{T_{jt}} \sum_{i=1}^{d} \; {}^{o}_{i} E\left((A+v)^{(i)} \,|x_t \right)$$

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

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

where $vec\,(x)$ denotes the vector formed by stacking the columns of x one after the other; the matrix T_{mm^2} is defined as the following linear operator: given a $L \times n$ matrix A, T_{Ln} is an $Ln \times Ln$ matrix specified by the assignment $T_{Ln} vec\,(A) = vec\,(A')$, ($A'$ stands for transpose). The first of the above equations is straightforward. To prove the second, use:

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

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

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

Finally, I prove the third order equation. Note that

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

$Ev^{(3)}$ 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, k) respectively, then

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

8.3 Statistics of the Optimal Production

To derive (23), I use (18) to get:

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

Equation (24) 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:

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

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 $A(x,q)$ using (19). In this step, I first compute the choice probabilities $\{p_q(x)\}_{q=0}^{\overline{q}}$ 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 dynamic applications, there are not many observations for all $q = 0, 1, ..., \overline{q}$ at each state x. Therefore, I first cluster the data finely, using the kmeans algorithm, and then compute frequencies on this subset of states. Second, I smooth the frequency matrix using kernels. In particular, I compute the choice probability $p_q(x)$ at state x using the following formula:

$$p_q(x) = \sum_{x'} w(x' - x)\,\widetilde{p}_q(x')$$

where $\widetilde{p}_q(x)$ is the observed frequency count of q 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 kernel:

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

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 $A\left(x, q\right)$. In particular, I estimated an ordered probit model using directly the production data, so that:

$$A\left(x, q\right) = \beta f\left(x\right) + \quad {}_q$$

while the observed variables are the production values given by

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

I estimate β and $\quad {}_q$ for $q = 0, ..., \overline{q} - 1$ via Maximum Likelihood. This specification is flexible in terms of q but less so in terms of x.[36] It overall gives similar results to the nonparametric specification above. Finally, I chose $\overline{q} = 10$, since 99.75% of observations involve $q \leq 10$.

Step 2: Compute the terms Eq^*, Eq^{*2}, $E\varepsilon q$ using (23), (24) and (25).

Step 3: At each guess of the parameters (θ, σ) in the optimization of the likelihood (16) the following calculations are performed:

Step 3a: Solve for the approximate value function parameters $\quad {}^y$ from (21). Note that the choice probabilities require the continuation value $CV^y\left(x, q\right) = \quad {}^y E\left[f^y\left(x'\right)|x, q\right]$. To estimate $\quad {}^y$ from (21) I need

$$E_{\varepsilon, x'}\left[f^y\left(x'\right)|x, q^*\left(x, \varepsilon\right)\right] = \quad {}^y \sum_{q=0}^{\overline{q}} p_q\left(x\right) E_{x'}\left[f^y\left(x'\right)|x, q\right] \tag{28}$$

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[36] The plot of $\quad {}_q$ with respect to q is close to a linear graph. This is consistent with the static model where

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

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 $c\left(q\right)$ is restrictive.

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 follows:

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

i.e. δ% of the backlog is delivered and q orders of period t enter the backlog. I experimented extensively with the above transition rule. In particular, I have conducted experiments with time-varying δ; for example, δ drawn from a probability distribution estimated from the data (e.g. beta distribution whose mean can depend on the shipyard's current backlog, docks/berths or length; δ taken as a discrete random variable with probabilities estimated from the data); alternatively other experiments employed deliveries, instead of δ, described by a binomial random variable whose parameters can again depend on shipyard observables. It was found that the simple model where δ is constant over shipyards and time and equal to the sample mean (which is 10%) performs equally well compared to more complex models. Given the state transitions it is straightforward to compute (28). I estimate (21) using LASSO in two ways. First, call the LASSO within the likelihood maximization with the regularization parameter chosen using Belloni and Chernozhukov (2011). Second, estimate (21) 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 ^{y}, 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 $A(x, q)$ that I recover) may be different from the optimal policy computed using the true parameters and value function, i.e. from (17). To check this, I compute $A(\cdot)$ from (17) and find that it is close to 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 interventions" 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 $\left(\overline{s^o_{1t}}, \overline{s^o_{2t}}, B_t\right)$, where $\overline{s^o_{1t}}$ is the number of ships younger than 20 years old, $\overline{s^o_{2t}}$ is the number of ships older than 20 years old and B_t is the total backlog:

$$\overline{s^o_{1t+1}} = \delta B_t + (1 - \rho_{1t})\,\overline{s^o_{1t}} \tag{29}$$

$$\overline{s^o_{2t+1}} = \overline{s^o_{2t}} + \rho_{1t}\overline{s^o_{1t}} - \zeta(s_t)$$

$$B_{t+1} = (1 - \delta)B_t + \sum_j q_{jt} \tag{30}$$

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 $\overline{s^o_{1t+1}}$ 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 $\overline{s^o_{2t+1}}$ 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 I use a fixed point algorithm with the goal of recovering the shipyard's optimal policy function $p_q^*(x)$, for all production levels q and states $x = (s^y, s)$, as well as the shipyard's value function $W^*(x)$. At each iteration l I use the policies $p_q^l(x)$ to update to $p_q^{l+1}(x)$ and I keep iterating until $||p_q^{l+1}(x) - p_q^l(x)|| \leq eps$. 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 the value function approximating parameters, $^{\sim y}$, relies on the approximate Bellman equation:

$$\left(f^y(x) - \beta E\left[f^y(x')\,|p_q^l(x), x\right]\right)^{\sim y, l+1} = E_\varepsilon\left[\pi^y(x,q,\varepsilon); p_q^l(x)\right]$$

where ex ante profits are computed by:

$$E_\varepsilon\left[\pi^y(x,q,\varepsilon); p_q^l(x)\right] = \left[VE(x) - c_1(x)\right]\sum_{q=0}^{\bar{q}} q p_q^l(x) - c_2 \sum_{q=0}^{\bar{q}} q^2 p_q^l(x) + \sigma \sum_{q=0}^{\bar{q}-1} \phi(A^l(x,q))$$

where $A(x,q) = \Phi^{-1}\left(1 - \sum_{k=0}^{q} p_k^l(x)\right)$, $q = 0, 1, ..., \bar{q} - 1$. To derive the above, use (22) and (25).

Moreover, to compute $E\left[f(x')\,|p_q^l(x), x\right]$, I simulate d_t and l_t one period forward since these are the only stochastic states now. State transitions are computed via (29). 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:

$$\begin{aligned}
p_0^{l+1}(x) &= 1 - \Phi\left(\frac{1}{\sigma}\left(VE^o(x) - c_1(x) - c_2 + \beta\left(CV^{y,l+1}(1) - CV^{y,l+1}(0)\right)\right)\right) \\
p_q^{l+1}(x) &= \Phi\left(\frac{1}{\sigma}\left(VE^o(x) - c_1(x) - c_2(2q-1) + \beta\left(CV^{y,l+1}(q) - CV^{y,l+1}(q-1)\right)\right)\right) - \\
&\quad -\Phi\left(\frac{1}{\sigma}\left(VE^o(x) - c_1(x) - c_2(2q+1) + \beta\left(CV^{y,l+1}(q+1) - CV^{y,l+1}(q)\right)\right)\right) \\
p_{\bar{q}}^{l+1}(x) &= 1 - \sum_{q=0}^{\bar{q}-1} p_q^{l+1}(x)
\end{aligned}$$

I solve the above fixed point under three scenarios: the true post-2006 world, a world with no China intervention and a world without the Chinese new shipyards. 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 $^{\sim y}$ retrieved by the fixed point algorithm. At each state visited I compute $E\left[f\left(x'\right)|p_q^*\left(x\right), x\right]$ using the retrieved equilibrium choice probabilities.

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