China’s Industrial Policy: an Empirical Evaluation

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Abstract

Industrial policies, broadly defined as policies that shape a country’s or region’s industry structure by either promoting or limiting certain industries or sectors, have been widely used in developed and developing countries. Despite their importance, few empirical studies directly evaluate the welfare consequences of these policies using micro-level data. This study examines an important industrial policy in China – the policy to develop the country’s shipbuilding industry to the largest worldwide in the 2000s. Using comprehensive data on shipyards worldwide, we quantify the magnitude of China’s industrial policies in supporting its domestic shipbuilding industry using a dynamic model. Our estimates suggest that the combined policy support exceeded 500 billion RMB from 2006 to 2013, boosted China’s domestic investment and entry by 270% and 200%, respectively, and enhanced its world market share by 40%. On the other hand, the policy created sizable distortions and led to increased fragmentation and idleness. Production and investment subsidies can be justified based on market share considerations, but entry subsidies are wasteful. The distortions induced by industrial policy could have been significantly reduced by implementing counter-cyclical policies and by targeting subsidies towards more productive firms. Finally, we find little evidence in support of the traditional justifications for industrial policies. Our results point to the importance of non-economic considerations in contributing to the policy design.

Keywords: Industrial Policy, Dynamic, Subsidies, Investment, Welfare

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1 Introduction

Industrial policies, broadly defined as policies that shape a country’s or region’s industry structure by either promoting or limiting certain industries or sectors, have been widely used in developed and developing countries. Examples include U.S. and Europe after the World War II, Japan in the 1950s and 1960s (Johnson, 1982; Ito, 1992), South Korea and Taiwan in the 1960s and 1970s (Amsden, 1989), China, India, Brazil, and other developing countries in the last couple of decades (Stiglitz and Lin, 2013). As Rodrik (2010) puts it, “The real question about industrial policy is not whether it should be practiced, but how.”

The theoretical literature on industrial policies is divided into two camps. Proponents argue that government intervention via industrial policies can help correct for externalities that are not internalized by individual firms or mitigate negative consequences of inherent wedges in the economy that distort firm decisions (Hirschman, 1958; Wade, 1990; Greenwald and Stiglitz, 2013; Liu, 2018). On the other hand, opponents caution against the potential adverse consequences of industrial policies due to asymmetric information, regulatory capture, and other political economy constraints (Baldwin, 1969; Krueger, 1990).

Despite the contentious debate in the literature and the prevalence of industrial policies in practice, there are remarkably few empirical studies that directly evaluate the costs and benefits of these policies using micro level data. There seems a major disconnect between the vast theoretical literature and the empirical analysis that has largely focused on describing what happens to the benefitting industries (or countries) in terms of output, productivity, growth rate, and has been silent on the welfare consequences (see Harrison and Rodriguez-Clare (2010) for an excellent review).

This study fills this hole in the literature by analyzing an important industrial policy in China – the policy to develop the country’s infant shipbuilding industry to be the largest worldwide in the early 2000’s. China’s shipbuilding industry was nascent at the turn of this century and accounted for less than 10% of the world production.1 During the 11th National Five-Year Plan (2006-2010), shipbuilding was dubbed as a strategic industry in need of “special oversight and support”. Since then, an unprecedented number of national policies were issued. In the Eleventh (2006-2010) and Twelfth (2011-2015) Five-Year plans, shipbuilding was identified as a pillar or strategic industry by twelve and sixteen provinces, respectively. By 2009, China became the largest shipbuilding country in terms of volume, overtaking Japan and South Korea.

Having identified an important historical event, we ask the following questions: how has China’s industrial policy shaped its domestic and the world shipbuilding industry? What are the welfare consequences of this policy? How do different policy instruments interact with each other? What are the general lessons and insights that can be gleaned from this study and applied to other

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1 Data source: Clarkson Ltd. Small ships used for inland navigation within a country are excluded throughout this analysis.
contexts? To answer these questions, we provide to our knowledge the first attempt to collect comprehensive micro data on all firms in the global shipbuilding industry from 1998 to 2014. Then we quantify the impact of policy support on targeted firms’ production, investment, entry and exit, using a dynamic model that incorporates economies of scale in firm production and accommodates private investment shocks. Finally, we conduct counter-factual analyses to examine the welfare consequences of this policy that spurred the growth of China’s shipbuilding industry.

Our analysis delivers four sets of main findings. First, like other policies unleashed by China’s central government in the past several decades, the scale of the policy is massive (relative to the size of this industry). Our estimates suggest that the policy support is equivalent to 550 billion RMB during our sample period. It boosted China’s domestic investment and entry by 270% and 200%, respectively, and enhanced its world market share by 40%. However, the policy created sizable distortions and generated merely 145 billion RMB of net profit gains to domestic producers and 230 billion RMB of worldwide consumer surplus. The policy attracted a large number of inefficient producers, exacerbated the extent of excess capacity, and did not translate into significantly higher industry profits over the long run.

Turning to the various components of the industrial policy, the effectiveness of different policy instruments is mixed. Production and investment subsidies can be justified based on market share considerations, but entry subsidies are extremely wasteful and lead to increased industry fragmentation and idleness. Production subsidy is more effective at achieving output targets, while investment subsidy is less distortive over the long run. In addition, welfare losses are convex and deteriorate when multiple policies interact and induce firms to make decisions further away from the margin.

Our analysis suggests that the effectiveness of industrial policy is significantly affected by the presence of the boom-and-bust cycles and heterogeneity in firm efficiency, both of which are key features of the shipbuilding industry. A counter-cyclical policy would have out-performed the pro-cyclical policy actually adopted by a large margin, partly because of a composition effect (there are more high-cost firms in a boom than in a bust) and partly because of the more costly production expansion during the boom. In a similar vein, had the government targeted subsidies towards a more efficient set of firms, the policy distortions would have been considerably lower.

Finally, our results provide limited evidence that the shipbuilding industry generates significant spillovers to the rest of the economy. Nor do we find supporting evidence for other standard rationales for industrial policies, such as the infant industry argument, industrywide learning-by-doing (Marshallian externalities), or strategic trade considerations. Our results suggest that non-economic arguments, such as national security, military considerations, and the desire to be world number one, might be more important in the design of this policy.

We make three contributions to the existing literature. This is the first empirical analysis of the
welfare consequences of a large-scale industrial policy using micro-level data that cover the entire global industry. Second, methodologically, we extend the existing literature on firm investment and incorporate private shocks to the marginal cost of investment that better explain heterogeneous investing behavior among observably similar firms. Third, our results are relevant to policy makers in both developing and developed countries and highlight the importance of taking firm heterogeneity into consideration in policy designs.

The rest of the paper is organized as follows. Section 2 gives an overview of China’s shipbuilding industry and discusses the relevant industrial policy and our data sets. Section 3 incorporates industrial policy into a market equilibrium model of ship demand and supply. Section 4 describes our strategy for estimating each component of the model. The estimation results are presented in Section 5. Section 6 quantifies the welfare impact of the industrial policy and compares different policy instruments. Section 7 concludes.

2 Literature Review, Industry Background, and Data

2.1 Literature Review

The traditional justification for government intervention via industrial policies is the existence of externalities that are not internalized by individual firms. For example, externalities to either upstream or downstream sectors generated by “advanced” sectors call for protection for infant-industries (Hirschman, 1958), knowledge spillovers from foreign firms or exporting provide the basis for FDI tax breaks and export subsidies (Krugman, 1991), and productivity-enhancing knowledge as a joint-product of goods production lends support for industrial policies that enhance and promote these activities (Greenwald and Stiglitz, 2013; Stiglitz et al., 2013). Recent papers point out that industrial policies, properly designed, might help mitigate negative consequences of inherent wedges in the economy including financial or production frictions (Liu, 2018; Itskhoki and Moll, 2019). In the meantime, another strand of the literature (Baldwin, 1969; Krueger, 1990) has cautioned against the potential disastrous consequences of industrial policies due to various political economy constraints.

Earlier empirical literature on industrial policies mostly focuses on describing what happens to the benefiting industries (or countries) regarding output, revenue, and growth rate (Baldwin and Krugman, 1988; Hansen et al., 2003; Head, 1994; Luzio and Greenstein, 1995; Irwin, 2000). Recent studies recognize the importance of measuring the impact on productivity and allocation efficiency. For example, Aghion et al. (2015) uses the Chinese manufacturing survey from 1998 to 2007 and finds evidence that sectoral policies that are competition-friendly may enhance productivity and productivity growth. Lane (2017) empirically analyses the effect of industrial policy
in South Korea in the 1970s and demonstrates that targeted sectors grow significantly more than non-targeted sectors with spillover benefits to downstream industries connected to the targeted industries. There is also a related literature that analyzes trade policies, in particular export subsidies (e.g., Das et al. (2007)), R&D subsidies (Hall and Van Reenen, 2000; Bloom et al., 2002; Wilson, 2009), place-based policies targeting disadvantaged geographical areas (Neumark and Simpson, 2015; Criscuolo et al., 2019), and environmental subsidies (e.g., the effectiveness of renewable energy subsidies, Yi et al. (2015); Aldy et al. (2018)). To the best of our knowledge, our paper provides the first (global) welfare analysis of a large-scale industrial policy and comparison of different policy instruments using firm-level data.

Our paper is also related to the public finance literature that study the effectiveness of different subsidy policies. Parish and McLaren (1982) argue using a theoretical model that investment subsidies or input subsidies could yield greater output per dollar of public funds spent if the production function is characterized by decreasing returns to scale. Very few empirical studies exist that compare production and investment subsidies. One exception is Aldy, Gerarden, and Sweeney (2018) that uses natural experiments to show that wind farms claiming investment subsidies produce 10-12% less power than wind farms claiming the output subsidy. Our findings in this paper suggest that while production subsidies are more effective at boosting output, investment subsidies can be less distortive and register a higher rate of return.

Our study is also related to a small and growing literature on the shipbuilding and shipping industry. Thompson (2001) studies learning in the shipbuilding industry, using as a case study the Liberty shipbuilding program during World War II. Greenwood and Hanson (2015) study the dry bulk shipping industry and argue that investors overpay for new ships during booming periods, while Jeon (2018) examines the role played by information and learning in investment in container shipping. Kalouptsidi (2017) is closely related to this paper and detects evidence of production subsidies by the Chinese government in the handysize segment within the bulk sector. In addition to analyzing the entire shipbuilding industry that includes all bulk ships, tankers, and containers, we conduct a positive analysis of the welfare consequences of different policies (including entry, production, and investment subsidies) used by the government. An important element in this study is investment and entry/exit, which is abstracted away in the previous study.

Methodologically, we build on the literature on dynamic estimation, including (Bajari et al., 2007; Ackerberg et al., 2007; Pakes et al., 2007; Xu, 2008; Aw et al., 2011; Ryan, 2012; Collard-Wexler, 2013; Sweeting, 2013; Barwick and Pathak, 2015; Fowlie et al., 2016), as well as the macro literature on firm investment (Abel and Eberly, 1994; Cooper and Haltiwanger, 2006). In contrast to the macro literature that focuses on inaction (zero investment) and adjustment costs, our approach can rationalize different investment levels chosen by observably similar firms while at the same time accommodate inaction and various adjustment costs. Our analysis on firm investment
extends Ackerberg et al. (2007) and provides one of the first empirical applications of this model, which can be used in a variety of settings where heterogeneity in investment levels is an important economic consideration.

2.2 Industry Background

Shipbuilding is a classic target of industrial policies, as it is often seen as a strategic industry for both commercial and military purposes. During the late 1800s and early 1900s, the UK and Europe were the dominant ship producers. After World War II, Japan subsidized shipbuilding along with several industries to rebuild its industrial base and became the world’s leader in ship production. South Korea went through the same phase in the 1970s and 1980s. In the 2000s, China followed Japan and South Korea and supported the shipbuilding industry via a broad set of policy instruments.

The scope and frequency of national policies issued in China in the 2000s, especially after 2005 to support its domestic shipbuilding industry is unprecedented. In 2002, when former Premier Zhu inspected China State Shipbuilding Corporation (CSSC), one of the two largest shipbuilding conglomerates in China, he pointed out that “China hopes to become the world’s largest shipbuilding country (in terms of dead weight tons) ... by 2015.” Soon after, the central government issued the 2003 National Marine Economic Development Plan and proposed constructing three shipbuilding bases centered at the Bohai Sea area (Liaoning, Shandong, and Heibei), the East Sea area (Shanghai, Jiangsu, and Zhejiang), and the South Sea area (Guangdong).

The 11th National Five-Year Economic Plan (2006-2010) dubbed shipbuilding as a strategic industry. Since then, the shipbuilding industry, together with the marine equipment industry and the ship-repair industry, has received numerous supportive policies. Zhejiang was the first province that identified shipbuilding as a provincial pillar industry, with the first major policy released in 2004. Jiangsu is the close second, and set up dedicated banks to provide shipbuilding companies with favorable financing terms. In the 11th (2006-2010) and 12th (2011-2015) Five-Year plans, shipbuilding was identified as a pillar, or strategic industry by twelve and sixteen provinces, respectively. Besides these Five-Year Plans, the central government issued a series of policy documents with specific production and capacity quotas. For example, as part of the 2006 Medium and Long Term Development Plan of Shipbuilding Industry, the government set an annual production goal of 15 million deadweight tonnes (DWT) to be achieved by 2010, and 22 million DWT by 2015. Both goals were met several years in advance. Table 1 documents major national policies issued during our sample period.

Government interventions affect firms’ decisions along several dimensions. We group policies that supported the Chinese shipbuilding industry into three categories: production, investment, and
entry subsidies. Production subsidies lower the marginal cost of producing ships. Steel is an im-
portant input for shipbuilding. Government-butressed domestic steel industry provides cheap input for
the shipbuilding industry. Besides subsidized input material and export credits (Collins and Grubb,
2008)\(^2\), buyer financing in the form of collateral loans provided by local banks constitutes another
important component of production subsidies. Ships are the largest commercial factory-produced
products and can cost millions of dollars. To help attract buyers, shipyards have traditionally of-
fered loans and various financial services to facilitate purchasing payment. A 2017 OECD report
attributes favorable terms on buyer financing from local banks as one of the key factors that fueled
the production expansion among Chinese shipyards. Investment subsidies take the form of low-
interest long-term loans and other favorable credit terms that reduce the cost of investment as well
as preferential tax policies that allow for accelerated capital depreciation. Finally, shortened pro-
cessing time and simplified licensing procedures, as well as heavily subsidized land prices along
the coastal region, greatly lower the cost of entry for potential shipyards.

An often explicitly-stated goal of China’s industrial policy is to create large successful firms
that can compete against international conglomerates. In the aftermath of the 2008 economic crisis
that led to a sharp decrease in global ship prices, the government promoted consolidation policies.
The Plan on Adjusting and Revitalizing the Shipbuilding Industry, implemented in 2009, resulted
in an immediate moratorium on entry with increased investment subsidies to existing firms. The
most crucial policy for achieving consolidation objectives was the Shipbuilding Industry Standard
and Conditions (2013), which instructed the government to periodically announce a list of selected
firms which “meet the industry standard” and thus receive priority in subsidies and bank financing.\(^3\)
The so called “White List” included sixty firms in 2014 upon announcement.

In this paper, we focus on dry bulk, tankers, and containerships, which account for more than
90% of world orders in tons in our sample period. Dry bulk ships transport homogeneous and
unpacked goods and raw materials, such as iron ore, grain, coal, steel, etc., for individual shippers
on non-scheduled routes. Tankers carry chemical, crude oil, and other oil products. These two types
of ships account for 85% of the world seaborne trade in tons (UNCTAD, 2018). Containerships
carry containerized cargos from different shippers in regular port-to-port itineraries. As these types
of ships carry entirely different commodities, they do not compete with each other for shippers. We
thus treat them as operating in separate markets.

Shipbuilding worldwide is concentrated in three countries: China, Japan, and South Korea,
which collectively are responsible for over 90% of the world production. We limit our empirical
analysis to shipyards in these three countries.

\(^2\)Until 2016, the Chinese government provided a range of subsidies for exporters, including reduced corporate income
tax, refund of the value-added-tax, etc. Shipbuilding companies benefit from export subsidies since most of their
products are traded internationally.

\(^3\)In practice, favorable financing terms and capital market access are often limited to firms on the white list post 2014.
2.3 Data

Our empirical analysis draws on a number of datasets. The first dataset comes from Clarksons, which is a leading ship brokerage firm. This dataset contains quarterly information on all shipyards worldwide that produce ships for ocean transport between the first quarter of 1998 and the first quarter of 2014. We observe each yard’s orders, deliveries, and backlog (which are undelivered orders that are under construction) measured in Compensated Gross Tonnage (CGT), for all of the major ship types, including bulk, tankers, and containers. Compensated Gross Tonnage, which is a widely used measure of size in the industry, takes into consideration production complexities of different ships and is comparable across types. The entry year for a shipyard is defined as the first year it takes an order or two years prior to the first delivery, whichever is earlier. We subtract two years from the first year of delivery to account for the time it takes to build a ship.4

The second data source is the annual database compiled by the National Bureau of Statistics (NBS) on Chinese manufacturing firms with annual sales above five million RMB. For each shipyard and year, we observe its location (province and city) and ownership status: state-owned enterprises (SOEs), privately owned, or joint ventures with foreign investors. We differentiate SOEs that are part of China State Shipbuilding Corporation (CSSC) and China Shipbuilding Industry Corporation (CSIC), the two largest shipbuilding conglomerates in China, from other SOEs. We link firms over time and construct their real capital stock and investment following the procedure described by Brandt et al. (2012). We also observe the annual accounting operation costs for each shipyard. The NBS database has some limitations. Most importantly, data for 2010 is missing. This prevents us from constructing the firm-level investment in either 2009 or 2010, since investment is imputed from changes in the capital stock. We merge these datasets to obtain a quarterly panel of Chinese, South Korean, and Japanese shipyards ranging from 1998 to 2013.

In addition to these yard-level variables, we collect a number of aggregate variables for the shipbuilding industry, including quarterly global prices per CGT for each of the three ship types.5 The steel ship plate price serves as a proxy for changes in the production cost, as steel is a major input in shipbuilding.

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4For 90% of Chinese firms, we successfully extracted their registration information (date and business scope) from the Trade and Industry Bureau database. The registration data is an imperfect measure of entry since firms often register with a wide business scope (ship building and repairs, marine equipment, marine engineering, etc.), and it is difficult to identify firms whose core business is shipbuilding from the registration data alone. In addition, some firms switch from ship repairs and marine equipment to shipbuilding years after registering with the Trade and Industry Bureau. As such, we use the entry year from the Clarkson’s database in our main analysis. Nonetheless, the overall entry pattern is similar across these two measures: entry peaked in 2005-2007 and became minimal post 2009.

5We experiment with two price indices, real RMB/CGT vs. USD/CGT, and obtain nearly identical results, suggesting that exchange rate fluctuations are not first-order in our analysis.
2.4 Descriptive Evidence and Summary Statistics

Similar to many other manufacturing industries in China, the shipbuilding industry experienced exponential growth since the mid 2000s. Indeed, China became the largest shipbuilding country in terms of deadweight tons in 2009, overtaking South Korea and Japan. Figure 1 plots China’s rapid ascent into global influence from 1998 to 2013. At the same time, a massive entry wave of new shipyards occurred along China’s coastal area. Figure 2 plots the total number of new shipyards by year for China, Japan, and South Korea. The number of entrants is modest for Japan (1.4 per year) and South Korea (1.2 per year), partly due to a lack of greenfield sites to build new ports. In contrast, the number of new shipyards in China registered a historic record and exceeded 30 during the boom years when the entry subsidy was in place. Entry dropped to 15 in 2009 and became minimal within a couple of years of the implementation of the 2009 entry moratorium, as part of the Plan on Adjusting and Revitalizing the Shipbuilding Industry.6

The rise in entry was accompanied by a large and unprecedented increase in capital expansion (Figure 3). The year of 2006 alone witnessed a steep four-fold increase in investment. The capital expansion was universal across both entrants and incumbents and among firms with different ownership status. For example, entrants account for 43% of the aggregate investment from 2006 to 2011, with the rest implemented by incumbents. Private firms, joint ventures, and SOEs account for 25%, 36%, and 38% of total investment, respectively. In addition, the capital expansion was spread out across provinces, though Jiangsu accounted for a disproportionate share of 40% of the aggregate investment between 2006 and 2011.

The rapid rise in China’s production, entry, and investment coincided with the introduction of China’s industrial policies for the shipbuilding industry. The global shipbuilding industry went through a boom in the mid-2000s, roughly concurrent with China’s initial expansion. As Figure 4 shows, ship prices began rising around 2003 and peaked in 2008, before collapsing in the aftermath of the financial crisis and remaining stagnant from 2009 through to 2013. China’s production and investment, on the other hand, continued to expand well after the financial crisis.

Table 2 contains summary statistics on key variables of interest. There are a large number of firms, with 266 Chinese shipyards, 108 Japanese shipyards, and 46 Korean shipyards. Industry concentration is low, with a world HHI that varies from 230 to 720 during the sample period.

An important feature of ship production is that shipyards take new orders infrequently, about 23% of the quarters for bulk and less frequently for tanker and containerships. From 2009 onwards, during a prolonged period of low ship prices, the frequency with which yards took new orders was significantly lower. This lumpiness in ship orders, combined with Chinese shipyards becoming

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6No new applications were processed post 2009, but projects already approved were allowed to be completed. In addition, firms registered prior to 2009 but engaged in repairs and marine engineering could ‘enter’ and produce ships post 2009. Both account for the entry (though at a far reduced rate) that we see in Clarksons from 2009 onward.
increasingly vulnerable to long periods of inaction in the latter part of our sample, is a key feature of the shipbuilding industry that informs our modeling choices in Section 3.

About 52% of firms in our sample produce one ship type, a pattern that holds across countries. The fraction of ships that produce all three types is higher in South Korea (28%) and Japan (16%) and lower in China (14%). If a shipyard never takes orders for a certain ship type throughout our sample, it is assumed not to produce this ship type.

3 Model

In this section, we introduce a dynamic model of firm entry, exit, and capital investment. In each period, incumbent firms make static production decisions to maximize their variable profit taking global ship prices as given. Then they choose whether or not to exit, and conditional on staying, how much to invest. A pool of potential entrants make one-shot entry decisions based on their expected discounted stream of profits as well as the cost of entry. At the end of the period, entry, exit, and investment decisions are implemented and the state evolves to the next period.

Time is discrete and is a quarter. In period $t$, there are $J_t$ firms in the world that produce ships. There are $M$ types of ships, such as dry bulkers, tankers, and containerships. Ships within a type are homogeneous.

Ship Demand  In each period, the aggregate inverse demand for ships of type $m$ is given by the function,

$$ P_{mt} = P (Q_{mt}, d_{mt}) $$

for $m = 1, ..., M$, where $P_{mt}$ is the market price of ship type $m$ in period $t$, $Q_{mt}$ is the total tonnage of type $m$ demanded, and $d_{mt}$ are demand shifters, such as freight rates and aggregate indicators of economic activity.

Ship Production  Firm $j$ produces $q_{jmt}$ tons at cost:

$$ C(q_{jmt}, s_{jmt}, \omega_{jmt}) = c_0 + c_m(q_{jmt}, s_{jmt}, \omega_{jmt}) $$

where $c_0$ is a fixed cost that is incurred even when shipyards have zero production. Fixed costs are often abstracted away in empirical studies, but are first-order in later periods of our sample when the aggregate demand for new ships plummeted and many shipyards reported prolonged periods with zero production. They capture wages and compensation for managers, capital maintenance, land usage, costs of searching for buyers (broker fees), etc.
The second term, $c_m(q_{jmt}, s_{jmt}, \omega_{jmt})$, is the standard production cost. We use $s_{jmt}$ to denote firm characteristics (e.g. capital, backlog, age, location, ownership status) and aggregate cost shifters that affect all shipyards (e.g. government subsidies, steel prices). In addition, production costs depend on a shock $\omega_{jmt}$: the larger $\omega_{jmt}$ is, the less productive the firm is. The marginal cost of production is given by $MC(q_{jmt}, s_{jmt}, \omega_{jmt})$.

Firms are price takers and choose how many tons to produce for ship type $m$, $q_{jmt}$, to maximize their profits:

$$\max_{q_{jmt}} \pi(s_{jmt}, \omega_{jmt}) = P_{mt}q_{jmt} - C(q_{jmt}, s_{jmt}, \omega_{jmt})$$

If the optimal production tonnage for type $m$, $q^*_{jmt}$, is positive, it satisfies the following first order condition:

$$P_{mt} = MC_m(q^*_{jmt}, s_{jmt}, \omega_{jmt})$$

(2)

Let $s_{jt} = \{s_{j1t}, ..., s_{jMt}\}$ and $\omega_{jt} = \{\omega_{j1t}, ..., \omega_{jMt}\}$ denote the union across ship types of observed state variables and unobserved cost shocks, respectively. Note that with a slight abuse of notation, we now use $s_{jmt}$ to denote all observed payoff relevant variables, which include ship prices in addition to cost shifters. A firm’s total expected profit from all types, before the cost shocks are realized, is given by:

$$\pi(s_{jt}) = E_{\omega_{jt}} \sum_{m=1}^{M} \pi(s_{jmt}, \omega_{jmt})$$

Finally, in each period, the prevailing ship price, $P_{mt}$, equates aggregate demand and supply, where the aggregate supply is the sum of $q^*_{jmt}$ defined in (2).

**Investment and Exit** Once firms make their optimal production choice, they observe a scrap or sell-off value, $\phi_{jt}$, that is distributed i.i.d. with distribution $F_{\phi}$ and decide whether to remain in operation or exit. If a firm chooses to exit, it receives the scrap value. If it remains active, it observes a firm-specific random investment cost shock, $v_{jt}$, that is distributed i.i.d. with distribution $F_{v}$ and chooses investment $i_{jt}$ at cost $C^i(i_{jt}, v_{jt})$. The amount invested $i_{jt}$ is added to the firm’s capital stock tomorrow, which in turn affects its future production costs.

The value function for incumbent firm $j$ is:

$$V(s_{jt}, \phi_{jt}) = \max \left\{ \phi_{jt}, E_{v_{jt}} \left( \max_i \left( -C^i(i, v_{jt}) + \beta E [V(s_{j+1}t)|s_{jt}, i] \right) \right) \right\}$$

(3)

$$= \pi(s_{jt}) + \max \left\{ \phi_{jt}, CV(s_{jt}) \right\}$$

$$CV(s_{jt}) \equiv E_{v_{jt}} \left( -C^i(i^*, v_{jt}) + \beta E [V(s_{j+1}t)|s_{jt}, i^*] \right)$$

(4)

where $CV(s_{jt})$ denotes the continuation value, which includes the expected cost of optimal invest-
ment and the discounted future stream of profits. Crucially, \( E_{\nu_{jt}} \) is the expectation with respect to the random investment cost shock \( \nu_{jt} \) and \( i^* \) denotes the optimal investment policy \( i^* = i^*(s_{jt}, \nu_{jt}) \).

The optimal exit policy is of the threshold form: the firm exits the market if the drawn scrap value \( \phi_{jt} \) is higher than its continuation value \( CV(s_{jt}) \). Since the scrap value is random, the firm exits with probability, \( p^x(s_{jt}) \), defined by,

\[
p^x(s_{jt}) \equiv \Pr \left( \phi_{jt} > CV(s_{jt}) \right) = 1 - F_{\phi} \left( CV(s_{jt}) \right)
\]

(5)

where \( F_{\phi} \) is the distribution of \( \phi_{jt} \).

Conditional on staying, firm \( j \) observes its investment shock, \( \nu_{jt} \). Its optimal investment \( i^* = i^*(s_{jt}, \nu_{jt}) \), which is non-negative, satisfies the first-order condition:

\[
\beta \frac{\partial E \left[ V(s_{jt+1}) | s_{jt}, i^* \right]}{\partial i} \leq \frac{\partial C^i(i^*, \nu_{jt})}{\partial i}
\]

(6)

with equality if and only if the optimal investment is strictly positive. When the investment costs are prohibitively high, firm \( j \) opts for no investment. Capital depreciates at a rate \( \delta \) that is common to all firms.

We assume that the cost of investment, \( C^i(i^*, \nu_{jt}) \) has the following form:

\[
C^i(i^*, \nu_{jt}) = c_1 i_{jt} + c_2 i_{jt}^2 + c_3 \nu_{jt} i_{jt} + c_4 T_t i_{jt}
\]

(7)

This (quadratic) specification borrows from the macro literature on investment costs (Cooper and Haltiwanger, 2006) with two important differences. First, investment costs depend on an unobserved marginal cost shock \( \nu_{jt} \). Much of the existing literature has focused on the lumpy nature of investment (inaction) and adjustment costs, but has shied away from modeling heterogeneous investment decisions among observationally similar firms. Here, we tackle this heterogeneity by introducing \( \nu_{jt} \) that shifts the marginal cost of investment across firms. Note that \( \nu_{jt} \) can also explain inaction: firms with unfavorably large \( \nu_{jt} \) will choose not to make any investment. In practice, there are many factors that influence firms’ investment decisions. Some firms have political connections that grant them favorable access to the capital market (Magnolfi and Roncoroni, 2018), and others might be experienced at sourcing from equipment suppliers at low costs. Once we control for \( \nu_{jt} \), additional adjustment costs, such as \( \frac{i_{jt}^2}{k_{jt}} \) and/or a (random) fixed cost, contribute little to the model fit. A second difference from the literature, is that we allow government policies \( T_t \) to

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7 Notable exceptions include Ryan (2012) that models firm investment decisions as following a S-s rule and Collard-Wexler (2013) that analyzes discrete investments.

8 The estimated fixed cost of investment, once included, is economically small. Fixed cost is associated with an inaction region where firms make no investments. The larger the fixed cost, the larger the inaction region. In our data, firms frequently make small investments, which is inconsistent with a large fixed cost.
directly affect the marginal cost of investment.

**Entry**  In each period $t$, $\bar{N}$ potential entrants observe the payoff relevant state variables and their own entry cost $\kappa_{jt}$, which is i.i.d., and make a one-time entry decision. If entrant $j$ decides not to enter, it vanishes with a payoff of zero. If it enters, it pays the entry cost and continues as an incumbent next period. In addition, the entrant is assumed to be endowed with a random initial capital stock that is realized next period when it becomes an incumbent and begins operation.

Potential entrant $j$ solves,

$$\max \{0, -\kappa_{jt} + E \left[ -C^i(k_{jt+1}) + \beta E \left[ V(s_{jt+1} | s_t) \right] \right] \}$$

where $\kappa_{jt}$ is the entry cost, $k_{jt+1}$ is entrant $j$’s initial capital stock in period $t + 1$ after paying a cost of $C^i(k_{jt+1})$. The expectation is taken over entrant $j$’s information set at time $t$, which includes all aggregate state variables.

Similar to the exit decision, the optimal entry policy is of the optimal threshold form: a potential entrant enters the market if the entry cost $\kappa_{jt}$ drawn is lower than the value of entering, i.e.

$$\kappa_{jt}(T_t) \leq VE(s_{jt}) \equiv E \left[ -C^i(k_{jt+1}) + \beta E \left[ V(s_{jt+1} | s_t) \right] \right]$$

where $\kappa_{jt}(T_t)$ makes it explicit that government policy affects the entry cost. Since $\kappa_{jt}$ is random, the potential entrant enters with probability, $p^e_t$, defined by,

$$p^e_t \equiv Pr(\kappa_{jt} \leq VE_{jt}) = F_\kappa(VE(s_{jt}))$$

where $F_\kappa$ is the distribution of $\kappa$.

**Industrial Policy**  Industrial policies affect costs of production, investment, and entry and are part of the payoff relevant state variables, $s_{jt}$. We assume that these policies are unexpected and perceived as permanent by all shipyards once they are in place. This is consistent with the empirical patterns documented in Section 2.4, where the spike in entry and investment coincides remarkably with the timing of these policies.

**Equilibrium**  The Markov Perfect Equilibrium (MPE) of this model is defined as follows:

**Definition 1.** An equilibrium of this model consists of policies, $\{q_{jmt}\}_{m=1}^M$, $i^x(s_{jt}, v_{jt})$, $p^x(s_{jt})$, $p^e_{jt}$, value function $V(s_{jt})$ and prices $P_{mt}$, such that the production quantity satisfies (2) and maximizes

\[\text{Here we follow the bulk of the empirical literature on industry dynamics (Ericson and Pakes, 1995; Ryan, 2012). Under this assumption, the entry decision involves a simple comparison between the value from entering the market and the random entry cost.}\]
the period profit, the investment policy satisfies (6), the exit policy satisfies (5), the entry policy satisfies (8), and ship prices clear the market each period so that aggregate demand equals total supply. Moreover, the incumbent’s value function satisfies (3) and firms employ the above policies to form expectations.

The key assumption in invoking the MPE concept is that the transition processes of all payoff relevant state variables (including ship prices) satisfy the Markovian property pre and post the policy intervention. Consequently, the equilibrium is stationary conditioning on our state variables (which include dummy variables for different policies) and the value functions are not indexed by \( t \). While China’s market share increased substantially during our sample period, such an expansion can be explained by changes in the underlying demand and cost factors, which are controlled by the state variables.\(^{10}\)

**Discussion** We close this section with some brief discussions on our assumptions. We assume that shipyards are price-takers. This assumption is motivated by the large number of firms in the industry. As discussed above, there are more than four hundred shipyards globally and the market share of the largest firm is less than 5%. The market is sufficiently unconcentrated that market power is not a first order consideration. Nonetheless, we consider a variation of our model that incorporates market power with firms being Cournot competitors in the product market. In that case, the optimal production of firm \( j \) in period \( t \) (when positive) satisfies a variant of the first order condition (2) that includes a markup equal to \(-q_{jmt} \left[ \partial P(Q_{mt}, d_{mt}) / \partial q_{jmt} \right] \). Empirically, this term turns out to be small and the estimates are robust when replicated under the Cournot assumption. It is worth noting that on the ship buyer side (shipowners), monopsony power is not a first-order issue as the concentration among ship ownership is also very low.

Ships are assumed homogeneous within a type conditioning on size. In prior work (Kalouptsidi (2014), Brancaccio et al. (2018)), this assumption is substantiated for dry bulkers. These papers show that in secondary markets, the majority of price variation is accounted for by a ship’s age and aggregate indicators of economic activity. To further substantiate this assumption, we explore a small sample of new ship purchase contracts with detailed price information and ship attributes. Ship type, ship size (measured in Compensated Gross Tonnage), and quarter dummies explain most of the price variation: the \( R^2 \) of a hedonic price regression when they are the only regressors is 0.93 for bulk, 0.94 for tankers, and 0.75 for containers. Ship and shipyard characteristics (age, country, number of docks and berths, etc.) have limited explanatory power: adding shipyard fixed effects to the hedonic regressions adds little to the fit with the exception of containers where the \( R^2 \) increases.

\(^{10}\)Stationarity does not preclude business cycles, which is typical for the world shipbuilding industry. We use ship prices to capture the aggregate business cycles. Relaxing the stationarity assumption is a difficult but important topic for future research.
from 0.75 to 0.95.

We assume away any dynamic considerations in production. In practice, producing a ship takes time and the production decision is in general dynamic: production today affects the backlog tomorrow, which affects tomorrow’s operation costs and therefore production decisions. However, as documented in Kalouptsidi (2018), cost function estimates under static and dynamic assumptions are similar, especially the estimates that reflect the impact of policy intervention on firms’ production costs. This is partly because the amount of drastic production expansion seen in practice cannot be explained by the intertemporal considerations that arise with a dynamic production. Note that we allow backlogs to directly affect the marginal cost of production, which proxies for the dynamic considerations in production decisions in a reduced-form manner. Second, we model shipyards’ production decision in tonnage, rather than number of ships. Modeling the optimization decisions in both the number and size (tonnage) of ships is substantially more complicated. Since our main focus here is on entry, exit, and investment, we thus make the simplifying assumption that shipyards choose production in tonnage to maximize their static profits. This keeps the model tractable.

It is worth noting that our estimated production subsidies are consistent with those in Kalouptsidi (2018) that models the choice of the number of ships and focuses on shipyards producing a specific size category of dry bulkers, Handysize vessels.

We assume that the cost shocks $\omega_{jmt}$ are i.i.d. There are several reasons for our choice. First, $\omega_{jmt}$ is estimated to be moderately persistent, with a serial autocorrelation of 0.28 for bulk, 0.27 for tankers, and 0.39 for containerships. It is worth noting that our estimation procedure on production cost parameters accommodates persistence in $\omega_{jmt}$. Second, while it is straightforward to estimate the persistence of these shocks using observed quantity choices, incorporating a persistent time-varying unobserved state variable in a dynamic model raises considerable modeling and estimation challenges. For the same reason, the investment cost shocks $\nu_{jt}$ are assumed i.i.d. Given that aggregate investment increased by more than fourfold within a year upon the announcement of the 11th National Five-Year Plan (Figure 3) and that all firms expanded regardless of their efficiency level, firm-specific persistent investment shocks are unlikely a first-order contributing factor to the boom of the capital expansion observed in our sample.

Lastly, the government policies are perceived as permanent by all firms. This is likely a strong assumption, since China’s economy is experiencing a drastic transformation with a highly dynamic policy environment. This assumption, however, is standard in the literature (Ryan, 2012). Relaxing this assumption and estimating firms’ expectation and adaptation to a changing environment is a difficult but important topic for future research (Doraszelski et al., 2018; Jeon, 2018). One (imperfect) approach to proxy for a dynamic policy environment is to use high discount rates so that future profits are less relevant for today’s decisions. We test for the robustness of our results with different discount rates.
4 Estimation Strategy

In this section, we present the empirical approach undertaken to uncover the model parameters. The key primitives of interest are: the world demand function for new ships, the shipyard production cost function, the investment cost function, the distribution of scrap values, and the distribution of entry costs. We estimate the heterogeneous production cost function for shipyards in all countries, but only analyze the dynamic decisions (entry, exit, and investment) for Chinese shipyards as there is little entry, exit, and capacity expansion in Japan and South Korea (OECD, 2015, 2016).

We proceed in three steps. In the first step, we estimate the demand curve for new ships, as well as shipyard production costs. We refer to the parameters of this step as “static parameters”. We use these estimates to construct firm profits in each period. In the second step, we estimate parameters governing investment costs and the scrap values for exiting firms, i.e. the “dynamic parameters”. This constitutes the bulk of our dynamic estimation where we adopt the two-step procedure in the tradition of Hotz and Miller (1993) and Bajari et al. (2007). In the final step, we estimate entry costs.11 We next describe each step in turn.

This section is self-contained and the reader may omit it and proceed to the result section if desired. Section 4.1 discusses estimation of the static parameters (demand and production costs). Section 4.2 focuses on the policy functions and state transition process. Section 4.3 illustrates the estimation of dynamic parameters (investment cost, scrap values, as well as entry costs).

4.1 Estimation of Static Parameters

Demand The demand curve (1) for ship type $m$ is parameterized as follows:

$$Q_{mt} = \alpha_0^m + \alpha_{pm}P_{mt} + d_{mt}'\alpha_{dm} + \varepsilon_{mt}$$

The demand shifters $d_{mt}$ include freight rates, the total backlog of type $m$, and some other type-specific variables. Demand for new ships is higher when demand for shipping services is high, reflected in higher freight rates.12 Conversely, a large backlog implies that more ships will be delivered in the near future, which reduces demand for new ships today. We also control for aggregate indicators of economic activity relevant for each ship type we consider: the wheat price and Chinese iron ore imports for bulk carriers; Middle Eastern refinery production for oil tankers; and world car trade for containerships. In some specifications, we allow for time trends as well. Finally, we allow the price elasticity to change before and after 2006, the main policy year.

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11Combining step two and three and estimating all of the dynamic parameters jointly is more efficient but computationally more challenging.
12The freight rate measures are the Baltic Exchange Freight Index for bulk shipping, the Baltic Exchange Clean Tanker Index for tankers, and the Containership Timecharter Rate Index for containerships.
Prices are instrumented by steel prices and steel production.\textsuperscript{13} Steel is a major input in shipbuilding and contributes to 13\% of the costs (Stopford, 2009). The identification assumption is that steel prices and steel production are uncorrelated with new ship demand shocks $\epsilon_{dt}^d$. This is a plausible assumption because only a modest portion of global steel production is used in shipbuilding and an increase in ship demand ($\epsilon_{dt}^d > 0$) is unlikely to have much impact on steel prices. In addition, internationally traded steel accounts for less than 8\% of the volume of goods transported by dry bulkers (UNCTAD, 2018). Thus, changes in the steel price that affects the amount of steel transported by sea are unlikely to directly affect demand for dry bulkers.

As there is a single global market for each ship type, the demand curves are estimated from time series variation. To improve the precision of parameter estimates, we restrict some parameters to be the same across ship types and estimate equation (9) jointly across the three types using GMM.

**Production Cost** We parameterize the marginal cost function for type $m$, $MC_m(q_{jmt}, s_{jmt}, \omega_{jmt})$, as follows:

$$MC_m(q_{jmt}, s_{jmt}, \omega_{jmt}) = \beta_0^m + s_{jmt}\beta_{sm} + \beta_{qm}q_{jmt} + \omega_{jmt}$$

(10)

where $q_{jmt}$ denotes tons of ship type $m$ chosen by firm $j$ in period $t$. It is worth noting that because of time to build, there is a difference between the orders placed in a period, the deliveries, and the production. We use orders as a measure of $q_{jmt}$, following Kalouptsidi (2018). We do so because the number of tons ordered is the relevant quantity decision made by the firm. In addition, our data source reports orders and deliveries instead of production and it is not straightforward to infer production from orders. Last but not least, the decision on orders corresponds to observed prices, while any constructed measure of production does not.

State variables $s_{jmt}$ include firm $j$’s capital and backlog of all ship types. Capital stock, together with investment, allows firms to achieve economies of scale and reduces (future) production cost. Backlogs capture economies of scale, learning by doing, and possibly capacity constraints. The vector $s_{jmt}$ also contains age and ownership status, region (for Chinese firms) and nationality, a dummy for large firms, the steel price, as well as polynomial terms of these state variables.\textsuperscript{14} Finally, $s_{jmt}$ includes dummies for the policy intervention between 2006 and 2008 and then from 2009 onwards. The production cost shock $\omega_{jmt}$ is assumed to be normally distributed with mean zero and variance $\sigma^2_{\omega m}$.

\textsuperscript{13} Other potential instruments include the aggregate number of shipyards, $J_t$, and the aggregate capital stock. These cost-side instruments shift the industry supply curve and are determined in period $t - 1$, before demand shocks in period $t$ are realized. Results are robust with or without these additional IVs.

\textsuperscript{14} Large firms are defined as the top firms that account for 90\% of the aggregate industry revenue from ship production throughout our sample period. There are fifty-five large Chinese shipyards. Adding this variable (on top of capital and other firm attributes) helps to capture unobserved differences across firms, like management skills, political connections, etc. and greatly improves the fit of our model.
The optimal production $q_{jmt}^*$, if positive, satisfies the first order condition that equates the marginal cost of production to the price:

$$q_{jmt}^* = \frac{1}{\beta_{q_m}} (P_{mt} - \beta_0 m - s_{jmt} \beta_{sm} - \omega_{jmt})$$

The yard chooses positive production if and only if:

$$\omega_{jmt} < P_{mt} - \beta_0 m - s_{jmt} \beta_{sm}$$

Besides observed shipyard attributes, zero production is driven by unfavorable cost shocks: firms with high cost shocks are more likely to stay idle.

The parameters characterizing shipyards’ production costs are $\theta_q \equiv \{\beta_0 m, \beta_{sm}, \beta_{qm}, \sigma_{\omega m}\}_{m=1}^M$ and are estimated via MLE. The sample likelihood of the Tobit model is:

$$L = \prod_{m=1}^M \prod_{q_{jmt}=0} \Pr(q_{jmt} = 0 | s_{jmt}; \theta_q) \prod_{q_{jmt}>0} f_q(q_{jmt} | s_{jmt}; \theta_q)$$

It is worth noting that $\theta_q$ is consistently estimated even when $\omega_{jmt}$ is correlated over time, despite the fact that this likelihood function assumes (erroneously) that $\omega_{jmt}$ is i.i.d. (Robinson, 1982). To obtain the standard errors allowing for autocorrelation in $\omega_{jmt}$, we use 500 block bootstraps.

Finally, it should be noted that a firm’s production decisions provide no information on its fixed cost $c_0$, since the firm incurs this cost regardless of whether it produces. However, unlike most empirical studies where fixed costs are assumed away, we take advantage of accounting cost data to calibrate $c_0$, exploiting the fact that firms report costs incurred even during periods when the production facility is idle. Details on this calibration procedure are reported in Appendix A. Normalizing the fixed cost to zero bias the counterfactual analyses (Aguirregabiria and Suzuki, 2014); we discuss this issue further in Section 6.1.

4.2 First Stage: Estimation of Policy Functions

Recall that the cost of investment, $C^i(i_{jt}, v_{jt})$, has the following form:

$$C^i(i_{jt}, v_{jt}) = c_1 i_{jt} + c_2 i_{jt}^2 + c_3 v_{jt} i_{jt} + c_4 T i_{jt}$$

As with production decisions that are driven by both observed firm attributes and a random cost shock, we allow for a random investment shock $v_{jt}$ which helps to rationalize different investment

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15Intuitively this is similar to how the OLS estimator in the standard linear regression model continues to be consistent (though not efficient) when the errors are non i.i.d.
decisions by observably similar firms. To our knowledge, this is one of the first empirical analyses that incorporates this feature in the context of continuous investments.

Optimal investment depends on the cost of investment and the future return associated with a larger capital stock. The former includes an unobserved investment shock $\nu_{jt}$, while the latter is determined by the shape of the value function. Estimating investment cost parameters requires us to tackle these two challenges: first, the optimal investment policy that depends on an unobserved investment shock $i^* = i^*(s_{jt}, \nu_{jt})$ is unknown; and second, the value function $V(s_{jt})$ that is defined in equation (3) is also unknown. Similarly, the exit policy depends on the unknown value function as well.

To tackle these challenges, we follow the tradition of Hotz and Miller (1993) and Bajari et al. (2007) (henceforth BBL) and estimate the parameters of dynamic models in two stages. In the first stage, we flexibly estimate investment and exit policy functions, as well as the transition process of state variables from the data. Then, we use these estimates to obtain a flexible approximation of the value function. Here we approximate the value function by a set of B-spline basis functions of the state variables, following Sweeting (2013), Barwick and Pathak (2015), and Kalouptsidi (2018). In the second stage, once we have an estimate of the value function, we formulate the likelihood of the observed investment and exit and recover the dynamic parameters of the investment cost function and scrap value distribution. We next describe each step. Appendix B contains additional details.

**Exit Policy Function** Estimating the exit policy function can be done via a number of different approaches (linear probability models, logit or probit, local polynomial regressions, etc.). Here, we perform a probit regression, though results appear robust across different specifications:

$$Pr(\chi_{jt} = 1|s_{jt}) = \Phi(h(s_{jt}))$$

where $\chi_{jt}$ equals 1 if firm $j$ exits in period $t$, $h(s_{jt})$ is a flexible polynomial of the states, and $\Phi$ is the normal distribution. We denote the first-stage estimate of the exit probability by $\hat{p}^X(s_{jt})$.

**Investment Policy Function** The optimal investment policy function $i^*_j(s_{jt}, \nu_{jt})$ is implicitly defined by the following first order condition:

$$\beta \frac{\partial E[V(s_{jt+1}|s_{jt}, i^*)]}{\partial i} \leq \frac{\partial C^i(i^*, \nu_{jt})}{\partial i}$$

with equality if and only if $i^*$ is strictly positive. Our goal is to flexibly estimate $i^*_j(s_{jt}, \nu_{jt})$. Under reasonable assumptions, one can show that the optimal investment is monotonically decreasing in
$v_{jt}$: firms with more favorable (smaller) cost shocks invest more, all else equal.\textsuperscript{16} As a result, conditioning on $s_{jt}$, the $j^{th}$ quantile of $v_{jt}$ corresponds to the $(100 - j^{th})$ quantile of $i_{jt}$ in the data. As shown in Bajari et al. (2007) and Ackerberg et al. (2007), we can recover the optimal investment policy function $i^*_j(s_{jt}, v_{jt})$ as follows:

$$F(i|s_{jt}) = Pr(i^*_j \leq i|s_{jt}) = Pr(v_{jt} \geq i^{-1}(i,s_{jt})|s_{jt}) = Pr(v_{jt} \geq v|s_{jt})$$

which implies

$$i^*|s_{jt} = F^{-1}(1 - F_v(v|s_{jt}))$$

(11)

where $F(i|s_{jt})$ denotes the empirical distribution of investment given the state variables and $F_v$ is the distribution of $v$. The data requirement for estimating this conditional distribution non-parametrically increases dramatically with the number of state variables and becomes challenging in our setting. Therefore, we make the simplifying assumption that the optimal investment function is additive in $v_{jt}$:

$$i^*_j = h_1(s_{jt}) + h_2(v_{jt})$$

where both $h_1(s_{jt})$ and $h_2(v_{jt})$ are unknown functions to be estimated. Moreover, since the distribution of $v_{jt}$ cannot be non-parametrically identified from $h_2(v_{jt})$, we assume that $v_{jt}$ is distributed as a standard normal. We first flexibly regress observed investment on the state variables to obtain an estimate of $h_1(s_{jt})$. Then we employ equation (11) to obtain an estimate of $h_2(v_{jt})$, treating $i^*_j - \hat{h}_1(s_{jt})$ as the relevant data.

We do not incorporate divestment in our analysis. Compared to the massive investment taken by Chinese shipyards, divestment is much less common and an order of magnitude smaller.\textsuperscript{17} Modeling the level of divestment with irreversible adjustment costs (firms only recoup a fraction of the nominal value of their capital goods when they sell them) introduces a kink in the cost function and makes the value function non-differentiable, which raises considerable computational challenges. As a result, we only model the probability that firms make zero or negative investment and abstract away from formulating the magnitude of divestment.

To address the issue that investment is non-negative, in addition to estimating the investment policy function using OLS with flexible state variables, we perform two robustness checks. The first is a Tobit model that assumes $h_2(v_{jt})$ is normally distributed. The second approach assumes that the median of $h_2(v_{jt})$ is zero and estimates $h_1(s_{jt})$ using the Censored Least Absolute Deviation

\textsuperscript{16}One sufficient condition for monotonicity is that the value function has increasing differences in investment and the negative of the investment shock.

\textsuperscript{17}The aggregate divestment is about 12% of the aggregate positive investment in the industry. We also drop 5% outliers with investments exceeding 250 million RMB or capital stocks exceeding 4 billion RMB.
estimator (CLAD) that was first proposed by Powell (1984) and later extended by Chernozhukov and Hong (2002). With an estimated $h_1(s_{jt})$ at hand, we non-parametrically estimate $h_2(v_{jt})$ using a modified version of (11) that takes advantage of the assumption that $i_{jt}^*$ is additively separable in $s_{jt}$ and $v_{jt}$. Appendix B provides more details.

**State Transition Process** Some of the state variables, $s_{jt}$, such as the province and ownership status, are fixed over time. The transition processes for age and government policies are deterministic. Capital ($k_{jt}$) depreciates at a common rate $\delta (k_{jt+1} = (1 - \delta)k_{jt} + i_{jt})$. We calibrate $\delta$ to 2.3% quarterly (Brandt et al., 2012), reflecting China’s high interest rates over our sample period. Similar to capital, the firm’s backlog in period $t+1$ is determined by orders and deliveries in period $t$. We assume backlog at time $t+1$ satisfies an AR(1) process: $b_{jmt+1} = (1 - \delta_{bm})b_{jmt} + q_{jmt}$, and calibrate $\delta_{bm}$ based on average deliveries.\(^{18}\)

Finally, we need to specify firm beliefs over the transition process of steel and ship prices. The steel price, which is perceived as exogenous to the industry, follows an AR(1) process. The equilibrium price for each ship type is a complicated object and determined by the intersection of aggregate demand and supply. Following the literature (Aguirregabiria and Nevo, 2013), we model shipyards’ beliefs about ship prices as an AR(1) process. This is a behavioral assumption: firms do not follow the production decisions of hundreds of rivals to predict future ship prices. They instead use the AR(1) process as a heuristic rule. The introduction of the Chinese government policies presents a permanent and unanticipated shock to the industry, which can potentially change the evolution of firm beliefs over prices. To capture this, we allow the AR(1) process to differ before and after 2006 when the policies came into effect.

**Value Function Approximation** Armed with estimates of the policy functions and state transitions, we now turn to the value function. Calculating the ex ante value function requires integrating out the scrap value $\phi_{jt}$. Assuming that $\phi_{jt}$ is distributed exponentially with parameter $1/\sigma$ (where $\sigma$ is the population average), $E(\phi|\phi > CV) = \sigma + CV$. We use this fact to obtain the ex ante value function:

$$
V(s_{jt}) = \pi(s_{jt}) + p^*(s_{jt})E\left(\phi_{jt} | \phi_{jt} > CV\left(s_{jt}\right)\right) + (1 - p^*(s_{jt}))CV(s_{jt})
$$

where $\pi_{jt}(s_{jt})$ and $p^*(s_{jt})$ denote firms’ static profit and exit probability, respectively, and $CV(s_{jt})$ denotes the firm’s continuation value as defined in equation (4).

The ex-ante value function in our context is smooth and can be approximated arbitrarily well\(^{18}\)The quarterly depreciation rate for backlog, $\delta_{bm}$, equals 6.8% for bulk, 6.3% for tankers, and 6.2% for containers.
by a set of B-spline basis functions of the state variables:

\[ V(s_{jt}) = \sum_{l=1}^{L} \gamma_l u_l(s_{jt}) \]

where \( \{u_l(s_{jt})\}_{l=1}^{L} \) are basis functions and \( \{\gamma_l\}_{l=1}^{L} \) are coefficients to be estimated. This approach has several advantages. First, this avoids discretization and approximation errors therein when the state space is large. Second, replacing an unknown function with a finite set of unknown parameters substantially reduces the computational burden. Third, the accuracy of the value function approximation can be controlled via appropriate choices of the basis functions and is directly benchmarked by the violation of the Bellman equation.\(^{19}\)

We search for \( \{\gamma_l\}_{l=1}^{L} \) that minimize the violation of the Bellman equation (12) given the dynamic parameters \( \theta^i \equiv \{\sigma, c_1, c_2, c_3, c_4\} \):

\[
\{\gamma_l\}_{l=1}^{L} = \arg \min_{\gamma} \left\| V(s_{jt}; \gamma) - \pi(s_{jt}) - \hat{p}^x(s_{jt})\sigma - CV(s_{jt}; \gamma) \right\|_2
\]

where \( \hat{p}^x(s_{jt}) \) and \( \hat{i}^*_{jt} \) are the estimated first-stage exit and investment policy functions, respectively, \( CV(s_{jt}; \gamma) = E_{\nu_{jt}} \{ -C(\hat{i}^*(s_{jt}, \nu_{jt})) + \beta E[V(s_{jt+1}; \gamma)|s_{jt}, \hat{i}_{jt}] \} \) is the continuation value evaluated at these estimated policy functions, and \( \| \cdot \|_2 \) is the \( L^2 \) norm. Equation (13) is imposed as a constraint in the estimation of dynamic parameters \( \theta^i \), as discussed below.

**Constructing Basis Functions** Note that several state variables enter the shipyard’s payoff as a single index \( s_{jmt} \beta_{sm} \) in the marginal cost of production (equation 10), including the shipyard’s region, ownership, size, age, and backlog. Instead of keeping track of each state individually, we collapse them into a single-dimensional state using the estimated coefficients:

\[
\bar{s}_{jt} = -\sum_{m} s_{jmt} \hat{\beta}_{sm}
\]

We use \( \bar{s}_{jt} \) as a measure of a firm’s observed cost efficiency: a higher \( \bar{s}_{jt} \) is associated with a lower marginal cost and a higher variable profit. Our approach of collapsing firm-level state variables into a single index is similar in spirit to Hendel and Nevo (2006) and Nevo and Rossi (2008) that use the “inclusive value” to capture the impact of changing product attributes on future profit streams. We further assume that \( \bar{s}_j \) evolves via a simple rule \( \bar{s}_{jt+1} = \alpha_0 + \alpha_1 \bar{s}_{jt} \), which almost perfectly forecasts \( \bar{s}_{jt+1} \) in period \( t \) since all but one of the variables in \( \bar{s}_{jt} \) are deterministic.

Therefore, the state variables we work with in the dynamic estimation are firms’ capital stock,\(^{19}\)

\(^{19}\)Another popular approach to calculate the value function is via forward simulation. The computational burden of our approach is comparable to forward simulation when the policy function is linear in parameters.
price for each ship type and steel, \( \delta_{jt} \) (which subsumes the remaining firm characteristics), and two policy dummies for the periods 2006-08 and post 2009, respectively. The basis functions are flexible third order B-splines (i.e. quadratic piecewise polynomials). Given our focus on investment, we use two knots (and have experimented with more knots) in forming the B-splines for capital. The total number of basis functions is 44.

### 4.3 Second Stage: Estimation of Dynamic Parameters

#### Investment and Exit

We estimate the dynamic parameters \( \theta^i \equiv \{ \sigma, c_1, c_2, c_3, c_4 \} \) via MLE. Our sample likelihood includes both the likelihood for exit decisions and the likelihood for investment decisions. The scrap value is assumed to follow an exponential distribution \( \phi_{jt} \sim F_{\phi}(\sigma) \), where \( \sigma \) is the mean of the scrap value. The investment cost shock is assumed to be a standard normal. The log-likelihood for exit is:

\[
L_1 = \sum_{j,t} \log(f(x_{jt})) = \sum_{j,t} \left[ (1 - x_{jt}) \log(1 - e^{-CV(s_{jt}; \gamma) / \sigma}) - x_{jt} \frac{CV(s_{jt}; \gamma)}{\sigma} \right]
\]

where \( x_{jt} = 1 \) if firm \( j \) exits in period \( t \) and \( f(x_{jt}) \) is the associated likelihood.

Optimal investment, \( i^*_jt = i^*(s_{jt}, \nu_{jt}) \), if positive, is defined by the first order condition:

\[
\beta \frac{\partial E[V(s_{jt+1}; \gamma) | s_{jt}, i^*]}{\partial i} = \frac{\partial C^i(i^*, \nu_{jt})}{\partial i}
\]

By construction, when \( i^*(s_{jt}, \nu_{jt}) \) is positive, it is strictly monotonic in \( \nu_{jt} \). Assuming it is also differentiable, the likelihood of positive investments can be written as follows:

\[
g(i_{jt}) = \frac{f_{\nu}(\nu_{jt})}{|i'(\nu_{jt})|}
\]

where \( f_{\nu}(\nu_{jt}) \) is the density of the cost shock \( \nu_{jt} \) and \( |i'(\nu_{jt})| \) is the absolute value of the derivative of \( i^*(s_{jt}, \nu_{jt}) \) with respect to \( \nu_{jt} \).

When receiving an unfavorable shock \( \nu_{jt} \), shipyards choose not to invest, so that \( i^*(s_{jt}, \nu_{jt}) \leq 0 \). The likelihood for these observations is:

\[
g(i_{jt}) = Pr(i^*(s_{jt}, \nu_{jt}) \leq 0) = Pr\left( \left[ \beta \frac{\partial E[V(s_{jt+1}; \gamma) | s_{jt}, i]}{\partial i} - \frac{\partial C^i(i, \nu_{jt})}{\partial i} \right]_{i=0} \leq 0 \right)
\]

\(^{20}\)The necessary condition for differentiability is that the value function is twice differentiable in investment, which holds since the value function is approximated using smooth spline basis functions.
Since the scrap values $\phi_{jt}$ and investment shocks $\nu_{jt}$ are assumed independent, the joint log-likelihood for exit and investment decisions is the sum of the two respective log-likelihoods:

$$L = L_1 + L_2 = \sum_{j,t} \log(f(\chi_{jt}; \theta_i)) + \sum_{j,t} \log(g(i_{jt}; \theta_i))$$

We maximize the sample log likelihood subject to the Bellman constraint (13).

**Entry Costs Parameters** Estimating the distribution of entry costs is straightforward once the investment cost and scrap value parameters are known. A potential entrant enters if their value of entry exceeds their random draw of the entry cost:

$$\kappa_{jt}(T_t) \leq VE(s_{jt}) \equiv E[-C_i(k_{jt+1}) + \beta E[V(s_{jt+1})|s_t]]$$

We first construct the value of entry $VE_{jt}$ using dynamic parameter estimates and then estimate the mean of the entry costs $\kappa_{jt}$ using the observed entry decisions via MLE.

One issue with the entry estimation is how to treat firms’ initial capital stock. As the initial capital is an order of magnitude larger than observed investment post entry, our investment model cannot rationalize the initial capital stock as an investment decision. Therefore, we assume that the cost of the initial capital equals $C(k_{t+1}) = c_1k_{t+1} + c_4T_tk_{t+1}$, where $k_{t+1}$ is drawn from the observed distribution of initial capital. Essentially, we assume that firms face no adjustment costs when choosing their initial capital so that $c_2k_{t+1}^2$ and $c_3\nu_{t+1}k_{t+1}$ do not apply.

## 5 Results

Our discussion in this section follows closely the sequence in Section 4. Section 5.1 presents estimates of the static parameters (demand and production costs). Section 5.2 discusses estimates of the policy functions and state transition process. Section 5.3 reports the dynamic parameter estimates (investment cost, scrap values, as well as entry costs).

### 5.1 Static Demand and Production Cost Estimates

**Demand** Table 3 reports estimates of the demand curve (Equation 9). Column (1) presents the simplest specification where the only demand shifter is the type-specific freight rate. Column (2) adds type-specific demand shifters. Column (3) further controls for a time trend while Column (4) allows the time trend to differ before and after 2006. In all specifications, we allow for a different

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21 The mean capital stock upon entry is 125 million RMB, compared to the average investment of 18.5 million RMB.
price coefficient before and after 2006, to capture changes in the slope of the demand curve after the introduction of Chinese subsidies. Given the limited number of observations for each type-specific aggregate demand, we restrict the price coefficient post 2006 and the coefficient on backlog to be the same across types. We instrument prices using steel prices and steel production and estimate the demand system using GMM. Adding demand shifters improves the fit, though time trends appear to matter little.\textsuperscript{22} As such we use Column (2) as our preferred specification.

Demand becomes less elastic post 2006. According to our preferred specification (Column 2), the price elasticity of demand prior to 2006 was 1.8 for bulk and tanker and 3.4 for containers, and decreased to 0.3 for bulk, 0.6 for tanker, and 1.7 for containers post 2006.\textsuperscript{23} As expected, demand is also responsive to backlog (which affects future competition shipowners face): a 1% increase in the backlog leads to a 1% decrease in the quantity of new ships demanded. The remaining shifters have the expected sign.\textsuperscript{24}

**Production Cost** In our baseline estimation, we estimate the marginal cost separately for China, Japan, and South Korea. Table 4 shows the estimated marginal cost parameters for Chinese yards for each ship type. Appendix B presents parameter estimates for Japan and South Korea. Standard errors are computed from 500 block bootstrap samples. We allow the key parameters that characterize the curvature of the production cost to be type specific (the coefficients on quantity, capital, backlog, and steel price), but restrict the coefficients on subsidy dummies and shipyard attributes to be the same across ship types, due to the large number of parameters. There are intuitive reasons for these restrictions. For example, the effect of scale economies from holding a large backlog, the return to capital (which proxies for capacity), and input intensity are likely to be different across ship types. On the other hand, it is not unreasonable to assume that subsidies are not earmarked for a particular ship type, as firms can produce different kinds of ships depending on the prevailing market conditions.

As the Chinese policies came into effect in 2006 and underwent major changes in 2009, we include separate dummies for Chinese yards in 2006-2008 and from 2009 onwards. The production subsidy between 2006-2008 is estimated to be 1,510 RMB/CGT, which is 10-13% of the average price. The subsidy from 2009 onwards is slightly smaller, at 1,380 RMB/CGT.\textsuperscript{25} Though our estimation method, sample period, and industry coverage are different from those in Kaloupt-

\textsuperscript{22}In addition, the time trends pose a challenge to the stationarity assumption of our dynamic setup and are difficult to deal with when extrapolating beyond our sample period in the counterfactual analyses.
\textsuperscript{23}Demand elasticity for new ships, which are durable, is driven by complicated dynamic considerations that include the composition of the existing fleet, expected number of new ships to be delivered in the near future, as well as belief of future freight rates and fuel costs. It could either increase or decrease post 2006.
\textsuperscript{24}The coefficient on wheat price is small, negative, and insignificant, consistent with the fact that a higher wheat price has an ambiguous effect on demand for bulk ships.
\textsuperscript{25}In robustness checks, we estimate the production subsidy separately for each region. It is higher in Jiangsu and Liaoning than in Zhejiang and the rest of China, although the differences are statistically insignificant.
sidi (2018), the estimated production subsidy is of a similar magnitude (with ours being slightly smaller), which is reassuring.

The parameter $\beta_q$ captures the increase in marginal cost (in 1000 RMB/CGT) from taking an additional order of 100,000 CGT. The larger $\beta_q$ is, the more convex the cost function is, and the less responsive supply is to changes in prices. On average, a 10% price increase causes bulk production to increase by 21%, tanker production, 28%, and container production, 22%. Higher capital is associated with a lower marginal cost of production, though at a diminishing rate (the coefficient on capital squared is positive). Increasing capital by 100 million RMB for an average firm with a capital of 400 million RMB reduces the annual marginal cost of production by 2.1% for bulk, 1.8% for tanker, and 1.7% for container. To put these numbers into context, the average firm’s per-period profits would decline by 38% if its capital stock were set to zero.

We find strong evidence of economies of scale in production in that it is cheaper to carry a backlog and produce multiple ships at the same time. The effect of backlog on marginal cost is sizable: increasing the backlog by 100,000 CGT reduces the marginal cost of production by 11% to 27% on average across ship types. As backlogs continue to increase, capacity constraints become binding and drive up marginal costs, as reflected in the positive coefficient (though much smaller in magnitude) on the backlog squared.

Firms located in Jiangsu, Liaoning, and Zhejiang provinces (the major shipbuilding regions in China) have lower marginal costs, by 18-22% for Jiangsu, 13-16% for Liaoning, and 10-12% for Zhejiang. The (additional) effect of ownership is limited. While private firms have the highest marginal costs, followed by small SOEs, CSSC/CSIC owned SOEs, and finally foreign JVs, none of these coefficients is statistically significant. As shipyards age, their marginal cost increases by about 1% each year. Finally, increases in the steel price raise the marginal cost for all types, as expected.

The fixed cost calibrated from the average of the NBS accounting data equals 15 million RMB per quarter, accounting for 15% of the industry profit on average. Thus setting it to zero, as is commonly done in the literature, would significantly overestimate per-period profits accruing to firms.

Our baseline specification (Table 4) estimates costs separately for each country, partly because we only observe the capital stock for Chinese shipyards. Table 5 displays parameter estimates when shipyards from all three countries are pooled together. We set the capital variable to zero for Japanese and South Korean yards and allow the constant term to differ by country. The key coefficients are qualitatively similar, though the subsidy for Chinese yards during 2006-08 is estimated to be somewhat larger relative to the baseline specification. We prefer the baseline specification, which allows more flexibility in capturing production differences across countries and delivers a
more conservative estimate of the subsidies.\footnote{Using the cost estimates that pool data from all three countries leads to qualitatively similar welfare results though the magnitude of subsidies is larger.}

Following Kalouptsdi (2018), we conduct a set of robustness checks and find similar patterns for the key coefficients of interest as reported there. Specifically, we use a time trend to capture technological advances in this industry, drop new shipyards, and test for firm- and industry-level learning-by-doing by controlling for firm and industry cumulative past production. The magnitude of subsidies is similar across specifications and there is no evidence of learning-by-doing once we control for backlog and firm attributes. We hence take the baseline estimates from Table 4 to the dynamic estimation and counterfactual analyses.

5.2 First Stage: Policy Functions

**Investment policy function** Table B1 in Appendix B reports the estimates for the investment policy function using OLS, Tobit with \( h_2(\nu) \) normally distributed, and CLAD that does not impose a specific distribution assumption on \( \nu \). Our preferred specification is the OLS regression, which delivers the highest model fit. Investment increases in ship prices and decreases in the steel price. Firms with higher \( \bar{s}_{jt} \) (i.e., more productive) invest more all else equal. As expected, the coefficients for both the 2006-08 and 2009+ policy dummies are positive. Moreover, investment is hump-shaped with respect to capital: it initially increases in the capital stock, reaches a peak when capital equals 1-1.5 billion RMB, and then falls with capital. Lastly, we invert the decreasing function \( h_2(\nu) \), which is necessary to calculate the expected investment cost that enters the sample likelihood.

**Exit policy function** We estimate the exit policy function via a probit regression. Table B2 in Appendix B presents two sets of estimates using linear terms of all states and capital squared, with and without region fixed effects. Firms with higher \( \bar{s}_{jt} \) are less likely to exit, which is intuitive as \( \bar{s}_{jt} \) is a measure of firm profitability. Exit probabilities are lower when subsidies are in place.

5.3 Second Stage: Dynamic Parameter Estimates

**Investment and exit** Following the literature on investment (Cooper and Haltiwanger, 2006), we assume that the unit investment cost is equal to one \( (c_1 = 1) \).\footnote{Monte Carlo evidence indicates it is difficult to identify all the cost parameters in equation (7).} Table 6 reports the rest of the cost estimates. Between 2006-2008, the subsidy is 0.25 RMB per RMB of investment, implying that 25% of the per-unit cost of investment (excluding adjustment costs) is subsidized. Post 2009, the subsidy nearly doubles and jumps to 0.49 RMB per RMB of investment, which helps to rationalize
the elevated investment among Chinese shipyards post the financial crisis with plummeting ship prices. In addition, the increase in subsidies post 2009 is consistent with the government policy change that shifted the focus towards consolidating the industry and supporting existing firms.

The coefficient on quadratic investment, $c_2$, is both economically and statistically significant. On average, adjustment costs account for 28% of total investment costs and exceed 50% for large investments over 50 million RMB. In addition, an estimated large value of $c_3$ implies that the shock $\nu_{jt}$ plays an important role in explaining investment. Finally, the mean of the scrap value distribution is estimated to equal 0.69 billion RMB. This is significantly lower than the estimated value of a firm ($V(s_{jt})$, which is around three to four billion RMB), as exit is a rare event and occurs in only 1% of the observations.

Figure 5 plots the distribution of the observed and the simulated investment. These two distributions are reasonably similar, though the actual distribution has a heavy-tail of large investments and fewer medium-sized investments. Table 7 compares the actual number of exits with the model’s estimates. Our model predicts fewer exits post 2006, with a total of 39 exits compared to a total of 48 exits observed in the sample.

**Entry cost estimates** Given the different number of entries across provinces (Zhejiang has the highest number of entries at 95), we estimate the entry cost separately for Liaoning, Jiangsu, Zhejiang, which collectively account for 70% of new shipyards, and the rest of China. The number of potential entrants is rarely observed in empirical studies. Here we follow the literature and assume that the number of potential entrants in a region in any quarter is equal to twice the maximum number of entrants ever observed in that region. At this level of potential entrants, the entry rate is 6.8%, leading to high estimated entry costs. In addition, we assume that the ship type produced by an entrant is a random draw from the observed distribution of product lines for entrants in that province and is realized post-entry. Finally, entry subsidies are assumed to begin in 2004 for Zhejiang when it identified shipbuilding as a pillar industry and in 2006 for all other provinces. This is consistent with the empirical pattern that entry peaked earlier in Zhejiang than the rest of the country.

Table 8 reports the estimates for $\kappa_{jt}$, the mean entry costs, across periods while Table 9 illustrates that the simulated number of entry is reasonably close to the actual number of entry in each policy period. The entry cost estimates range from 25 bn RMB to 91 bn RMB prior to 2006. Conditional on entering, the average entry cost paid is 2.3 billion RMB, close to a firm’s accounting value in the shipbuilding industry. Given the unprecedented entry boom from 2006 to 2008, it is not surprising that we find substantial entry subsidies, with the fraction of entry costs that is subsidized

varying from 49% in Liaoning to 64% in Jiangsu. Entry costs increased substantially in 2009 when the entry moratorium is put in place.

We have estimated the entry cost distribution under alternative assumptions on the number of potential entrants (the maximum number of entrants ever observed, or a large number such as 20 and 40). The higher the number of potential entrants, the higher the estimated $\kappa_{jt}$. While the estimates for $\kappa_{jt}$ vary, the estimated entry cost paid upon entering as well as the entry subsidies is remarkably robust, which is essentially determined by the actual number of entry observed in the sample.

6 Evaluation of China’s Industrial Policies

In this section, we carry out counter-factual exercises to evaluate the effects of China’s industrial policies. Doing so necessitates simulating the industry dynamics for a long period of time, as both entry and investment have dynamic consequences – the accumulated capital remains productive and new firms can continue operation long after the policy ends.\(^{29}\)

We implement the counterfactual analyses as follows. We simulate the world shipbuilding industry from 2006 when the Chinese government started subsidizing its domestic industry to 2099 (so that the discounted profit post 2099 is negligible), turning on and off the subsidies as needed for each analysis.\(^{30}\) In each period, Chinese firms make optimal production, investment, exit and entry decisions, taking both prices and government policies as given. Japanese and South Korean firms make production decisions, but don’t invest or enter/exit, since there is limited capacity expansion or entry/exit among these firms as discussed above. Equilibrium prices are determined each period by the intersection of the industry demand and supply curves. Appendix C contains more details on the implementation.

Section 6.1 firsts document the impact of subsidies before presenting the welfare implications of different subsidies. It also discusses the timing of subsidies. Section 6.2 evaluates the consolidation policies. Section 6.3 examines different rationales for industrial policy interventions.

\(^{29}\)Production subsidies also have dynamic consequences through backlogs that affect future cost of production, though these effects disappear when backlogs are converted to deliveries in a few years.

\(^{30}\)For each counterfactual, we carry out 50 simulations and average over these simulations. Further increasing the number of simulations makes little difference to the results. The discount rate is 0.02 per quarter, or 0.08 annually, reflecting the high interest rates in China (averaging 6% from 1996 to 2018). We have experimented with different subsidy duration (subsidies ending after a varying number of decades) and different discount rates. The results are qualitatively very similar.
6.1 Evaluation of Subsidy Policies

Magnitude of Subsidies Perhaps not surprisingly, subsidies had a significant impact on every outcome we examine: China’s world market share, overall production and business stealing from competing countries, prices, entry and exit, investment, profits, concentration and capital utilization.

Total subsidies handed out to Chinese shipbuilders were close to 540 billion RMB (or 90 billion USD) between 2006 and 2013 without discounting, with the lion’s share going to entry subsidies (330 billion RMB), followed by production subsidies (159 billion RMB) and investment subsidies (51 billion RMB). The subsidies are massive in comparison to the size of the domestic industry, whose revenue was around 1700 billion RMB during the same period.

These subsidies increased China’s world market share between 2006-13 by nearly 40%. The ascent in market share is most pronounced for bulk, since a large fraction of the new shipbuilders produce bulk and the cost advantage enjoyed by Japanese and South Korean firms is narrower for bulk. In the absence of subsidies, China’s production would still increase in absolute value, as a result of entry and production expansion in response to higher demands during the boom, but the increase would have been much less pronounced.31

In absolute terms, only one-fourth of China’s increased production translated into higher world industry output. The remaining three-fourths constitutes business-stealing, whereby Chinese production expanded at the expense of competing firms in other countries. As a consequence of Chinese subsidies, South Korea’s market share decreased from 47% to 38% and Japan’s market share from 24% to 21% during the 2006-2013 period, with profits earned by shipyards in these two countries down by 140 billion RMB.

The rising global supply induced by the subsidies led to substantial reductions in global ship prices: the price of bulk ships, oil tankers, and containers fell by 8.2%, 6.2%, and 3.1% from 2006 to 2008, respectively (Table 10). The price effect is most significant for bulkers, as Chinese shipyards account for a bigger market share in bulk and that the bulker demand is the most inelastic. As the effect of past subsidies accumulates through an increased production capacity for existing firms and a larger number of new firms, the price drop became more pronounced from 2009 to 2013 and reached 16.5% for bulk, 10.6% for tankers, and 3.7% for containers. Because of the reduction in ship prices, world ship owners benefit by 230 billion RMB from Chinese subsidies, though only a small proportion of these gains accrues to Chinese ship owners.32

Figure 6 compares the number of Chinese firms by year with and without subsidies. Govern-

31 Entry and expansion in Japan and South Korea were severely limited by the lack of suitable non-developed ports in these two countries.
32 According to Clarkson World Shipyard Monitor, orders by Chinese ship owners have been growing but still account for under 10% of world orders in 2010-2013.
ment support more than doubled the entry rate: 148 firms enter with subsidies vs. 65 without subsidies from 2006 to 2013. It also depresses exit (37 firms exit vs. 46) and changes the composition of exiting firms. With subsidies, a bigger fraction of exiting firms come from those that entered during the policy period, partly because subsidies attract small and relatively inefficient firms.

The most striking graph is Figure 8 that illustrates the effect of subsidies on investment, which skyrocketed post 2006. Total investment during 2006-2013 is 114 bill RMB with subsidies, compared to 42 bill RMB without subsidies. Finally, total subsidies handed out between 2006 and 2013 led to an estimated 145 billion RMB increase in the discounted lifetime profits for Chinese shipbuilders.

Entry subsidies induce entry of small inefficient firms. In addition, production and investment subsidies boost firms’ variable profit and retain unprofitable firms that should have exited. As a result, the industry became much more fragmented post the policy period. China’s domestic Herfindahl-Hirschman index (HHI) plummeted from 1,200 in 2004 to less than 500 in 2013 (Figure 7) with a significantly lower 4-firm concentration ratio. Despite a sizeable increase in China’s overall production, capacity utilization was much lower, particularly when demand was low. If China had not subsidized the shipbuilding industry, the ratio of production to capital (which proxies for capacity utilization) would have been 20% higher during the 2009-2013 recession.

Welfare Analysis and Effectiveness of Subsidies Subsidies led to a substantial increase in the number of firms, capacity, and production, but resulted in lower prices, lower capital utilization and a more fragmented industry structure. Our first goal in this section is to explore welfare implications. Since there is no market failure that the subsidies address, these interventions are necessarily welfare-reducing.\footnote{In the absence of market failures and non-internalized externalities, the best subsidy would be no subsidy. We return to this issue and examine rationales for industrial policies in Section 6.3.} What is less well-understood is how distortionary subsidies are and the magnitude of the welfare losses. Our second, and perhaps more important goal is to shed light on the effectiveness of different types of policy instruments, in particular the relative efficacy of production, investment, and entry subsidies and search for general lessons that can be applied in other contexts. Since China’s domestic consumer surplus accounts for a small fraction of the world consumer surplus as discussed earlier and is modest compared to the industry profit, we only briefly discuss the effect on consumer surplus when it is relevant.

In order to compare different types of policies, we carry out five counterfactual exercises with different subsidies in place: all subsidies (as in the data), only production subsidies, only investment subsidies, only entry subsidies, and no subsidies. When simulating the industry beyond 2013, we assume that the 2013 policy environment is propagated to the end of our simulation period unless otherwise noted. For example, in the scenario with all subsidies, entry subsidies run from 2006 to
2008, whereas production and investment subsidies run from 2006 to 2099.\textsuperscript{34}

The welfare effects are summarized in Table 11, which reports the discounted sums of industry revenue and profit, as well as the magnitude of different subsidies. The last three rows, “\(\Delta\)Revenue/Subsidy”, “\(\Delta\)(Profit-Inv. Cost)/Subsidy”, and “\(\Delta\)Net Profit/Subsidy”, constitute different measures of the effectiveness of the subsidies. “\(\Delta\)Revenue” is the revenue difference between subsidies and no subsidies. We report the ratio between the revenue increase and subsidy cost to evaluate the effectiveness of subsidies at promoting industry revenue. This is of interest, as China’s official government documents explicitly state production targets for the domestic shipbuilding industry. “\(\Delta\)(Profit-Inv. Cost)” is the difference in variable profit (revenue minus production cost) after subtracting investment costs. Finally, “\(\Delta\)Net Profit” is the difference in net profit which equals revenue plus the scrap value upon exiting, minus the costs of production, investment, and entry. We use “\(\Delta\)Net Profit/Subsidy” to measure the \textit{gross rate of return} of different subsidies. A rate lower than 100% indicates that the cost of subsidies exceeds the net benefits to the domestic industry and that subsidies are welfare reducing.

When each policy is in place in isolation, the return is 56% for production subsidies, 87% for investment subsidies, and 24% for entry subsidies, respectively. When all subsidies are effective, the rate of return is merely 18%, suggesting that the distortions induced by multiple subsidies are convex: i.e. the combination of all policies yields a considerably lower return compared to each policy in isolation. For example, entry subsidies attract inefficient entry. With the introduction of production and investment subsidies, the number of firms in operation is further inflated due to subsidized revenue and profit. The increase in firm take-up rates drives down the rate of return and makes the subsidies more distortionary in per-dollar terms.

An important factor contributing to the low returns are fixed costs. Indeed, firms incur fixed costs to stay in business even when they receive no orders from buyers. In volatile industries with cycles of booms and busts, this tends to be a common occurrence. If fixed costs are zero, the rate of return on subsidies would increase from 18% to 29%.

We now turn to the performance of each type of subsidy in isolation. If industry revenue is the object of interest, both production and investment subsidies are effective. On average, one RMB increase in the production and investment subsidy raises the industry’s revenue by 1.8 RMB and 2.3 RMB, respectively. This might justify the popularity of these subsidies in China, since quantity and revenue targets are often linked to local officials’ promotion (Jin et al., 2005). In addition, as discussed earlier, the government had set explicit output targets for ship production.

The investment subsidies appear less distortionary than the production subsidies (87% vs. 56%). However, this comparison is confounded by the larger magnitude of the production sub-

\textsuperscript{34}Another option is to shut down production and investment subsidies post 2013. This would constitute an unanticipated policy shock to firms and is shown in our simulations to produce lower returns.
sidies, as in our setting bigger subsidies are associated with more distortion. We reduce the per-
unit production subsidies by 75% and make the amount of these two subsidies comparable (44
bn RMB). The return to investment subsidies remains higher, though the difference is small (87% vs.
81%). On the other hand, production subsidies are slightly more effective at increasing rev-
ue: the increase in revenue per RMB of subsidy is 233% for production subsidies, versus 226%
for investment subsidies. Thus, depending on the policymaker’s objectives, there is potentially a
trade-off between production and investment subsidies. If the policymaker’s goal is to maximize
industry profits, perhaps investment subsidies are superior. However, if the goal is to achieve a
production/revenue target, then production subsidies might be preferred. In a similar vein, Aldy
et al. (2018) find that wind farms claiming output subsidies produced 10-11% more power than
wind farms claiming investment subsidies. Finally, for a government that cares about both industry
revenue and profit, a mix of production and investment subsidies may be more effective.

Entry subsidies are the least efficient policy instrument among the three by a large margin.
This is because the take-up rate for production and investment subsidies is higher among firms
that are more efficient, receive more orders (higher backlogs), and are more likely to invest. In
addition, production and investment subsidies increase backlogs and capital stocks that lead to scale
economies and drive down both current and future production costs. In contrast, the entry subsidies
predominantly attract the entry of small, high-cost firms that would not find it profitable to operate
in the absence of subsidies. The large number of additional entrants contributes little to industry
profits, while reduce ship prices and exacerbate excess supply.

Table 12 illustrates these points by decomposing subsidies that are taken up by firms above or
below the median efficiency (as measured by $\bar{s}_{jt}$, defined in equation 14). Subsidies are significantly
more effective when given to productive firms, both in terms of revenue and in terms of profits.
The subsidies accruing to productive firms has a net return rate of 29%, while those going to
unproductive firms is almost entirely wasted. Note that production and investment subsidies
are reasonably well-targeted, with between 70-84% of subsidies going to productive firms. In
comparison, less than 50% of entry subsidies are taken up by productive firms.

Business Cycles and Industrial Policy Like many other industries, cycles of booms and busts are
a fundamental feature of the shipbuilding industry. A rich macro and public finance literature ex-

\[ \text{35 Appendix D uses a simple static model to compare production and investment subsidies and illustrate that the rate}
\] of return is higher when taken up by efficient firms. In our empirical analysis, there are four margins of distortions:
entry, production, investment, and exits. Compared to efficient firms, inefficient firms are more likely to be distorted
in all four margins with subsidies. In addition, efficient firms enjoy considerable economies of scale as a result of
larger backlogs and capital stock relative to inefficient firms, which further widens the wedge in efficacy.

\[ \text{36 The rate of return for subsidizing unproductive firms is negative due to a general equilibrium effect: increased}
\] production drives down ship prices. Since these firms have high production costs, reduction in ship prices offsets
potential gains in quantity produced.
plores the optimal fiscal policy over the business cycle and generally recommends counter-cyclical fiscal policies, in order to smooth out intertemporal consumption (Barro, 1979), reduce the efficiency costs of business cycle fluctuations (Gali et al., 2007), and increase long-run investment by lowering volatility (Aghion et al., 2014). It is less well-understood, however, how industrial policy should be optimally designed in the presence of boom-and-bust cycles.

To explore whether the effectiveness of subsidies varies over the business cycle, we carry out two counterfactual simulations. The first simulation only subsidizes production and investment of all firms during the 2006-08 boom, while the second simulation only subsidizes production and investment during the 2009-13 bust. All subsidies are discontinued afterwards. The subsidy rates are calibrated so that the government spends the same amount in the two scenarios. This design allows us to explore the long-run implications of the pro-cyclical vs. counter-cyclical policies.

Strikingly, subsidizing firms during the boom leads to a net return of only 29%, whereas subsidizing firms during the downturn leads to a much higher return of 78%, as shown in Table 13. Therefore, What explains this large difference?

There are two main contributing factors: convex production and investment costs, and firm composition. In booming periods, the industry is operating close to full capacity. Further expansion is costly and entails utilization of high-cost resources. Firms that are already producing and investing may choose to engage in more rapid expansion than is efficient, incurring large adjustment costs. During a bust, on the other hand, the industry operates well below capacity and many production facilities remain idle. Subsidies mobilize underutilized resources, resulting in smaller distortions. The second contributing factor is the changing firm composition over the business cycle. Subsidies during a boom attract a higher fraction of inefficient firms, which pushes down the rate of return. As an illustration, Figure 9 plots the average $\bar{s}_{j,t}$ (a measure of profitability) over time for these two scenarios. Subsidies in the boom leads to a much lower average profitability than subsidies in the bust, as expected.

Despite the benefits of a counter-cyclical policy, the actual policy mix is overwhelmingly pro-cyclical: 442 billion RMB of subsidies were handed out between 2006 and 2008, vs. 106 billion RMB between 2009 and 2013. This echoes a more general finding in the literature showing that developing countries typically use pro-cyclical fiscal policies (Frankel et al., 2014), due to budget constraints, political considerations, etc. (Tornell and Lane, 1999; Barseghyan et al., 2013).

Discussion As a robustness check, we repeated our analysis assuming that firms are Cournot competitors rather than price takers. Parameter estimates are quantitatively similar to our main specification. The main difference is that estimated marginal costs become smaller and firm profits higher. As such, estimated entry subsidies are nearly 25% higher than in the baseline specification, as entry costs and entry subsidies are determined by the profitability of incumbents. In addition,
production subsidies are about ten to fifteen percent higher than in our baseline specification. Intuitively this is because Cournot competition causes the industry supply curve to become less elastic, which implies that larger subsidies are needed to rationalize the production increase post-policy. Investment subsidies are similar in magnitude to our baseline estimates. The counter-factual results, including both the return to industrial policies and the comparison of different subsidies, are unchanged when we allow for Cournot competition.

Our results suggest that entry subsidies are large in magnitude, amounting to 330 billion RMB in our sample period. While the number is large, it is consistent with a back-of-the-envelope calculation: entry subsidies induced the entry of 80-90 additional firms and each firm is worth a few billion RMB. Note that the entry costs we estimate include both the economic costs of entering (e.g. opportunity cost of land) and non-pecuniary costs of entry (e.g. lengthy bureaucratic approval process). Thus the monetary costs borne by the government in subsidizing entry may be lower than our estimates. Nonetheless, the key qualitative conclusions of our welfare analysis remain unchanged unless most entry subsidies (more than 90%) is non-monetary.

Our welfare analysis so far has abstracted away from changes in consumer surplus enjoyed by Chinese ship owners. Assuming that 10% (which is an upper bound) of the consumer surplus gains from reduced prices accrue to Chinese shippers, the rate of return only increases from 18% to 26%. For the total benefit of the subsidies to exceed the cost, China’s share of the global consumer surplus from new ships would need to be over 94%.

The analysis on consumer surplus depends on the elasticity of the demand curve. We repeat our counterfactual analyses under different elasticities. When demand is more elastic, the incidence of subsidies on producers is higher, as shown by a smaller reduction on prices, a smaller increase in consumer surplus, and a larger gain in producer surplus. Assuming that demand post 2006 is as elastic as pre 2006, the return on subsidies would increase from 18% to 25%.

Our model features dynamics only for Chinese yards. In practice, Chinese subsidies might induce exit in Japan and Korea, which could be important in a long time horizon and result in a larger gain to Chinese yards. On the other hand, our analysis does not take into account industrial policies that could be adopted by Japan and South Korea. If these governments respond in kind, the gains to Chinese shipbuilders from the subsidies would be reduced.

### 6.2 Evaluation of Consolidation Policies

One explicit goal of China’s industrial policies post the financial crisis is to facilitate consolidation and create large successful firms that can compete against international conglomerates. A crucial policy for achieving this objective was the 2013 *Shipbuilding Industry Standard and Conditions*, whereby the government announces a list of selected firms that meet the industry standard, the so
called “White List”. In this section, we ask the following questions. First, does the consolidation policy improve the return on subsidies, and if so by how much? Second, did the government choose the right set of firms for the White List?

Gains from Targeting In our first counter-factual exercise, we rank firms in 2013 based on their expected variable profits ($E[\pi_{jt}]$) in that year, and select the top 56 firms with the highest profitability to form the White List. These firms receive production and investment subsidies, while other firms receive no subsidies post 2013. We compare this policy to the one that subsidizes all firms after 2013, as well as the case with no subsidies.

As shown in Table 14, directing subsidies toward the best set of firms generates considerable gains. The net rate of return for targeted production and investment subsidies is 84%, whereas the return is 38% when all firms are subsidized. This pattern holds across all three measures of policy effectiveness, due to several reasons. First, subsidizing all firms encourages inefficient entry. The White List policy only subsidizes existing firms and does not distort entry. Second, subsidizing existing firms leads to lower exits than are socially optimal, but the set of firms on white list is unless likely to be subject to inefficient exit decisions. Lastly, as argued above, subsidizing productive firms leads to less distortions.

White List While subsidies are less distortionary when targeted towards efficient firms, it is unclear a priori whether the government targeted the right set of firms. Information asymmetries and regulatory capture might bias the process in favor of interest groups or “sunset sectors” (Lane, 2017).

To avoid confounding effects from subsidies and focus on the “White List” only, in this analysis we discontinue all subsidies post 2013 and examine profits post 2013 for the actual set of firms on the White List vs. firms included in our “optimal White List”. Note that our selection criterion focuses on short-run profitability and is not necessarily optimal in the long run. Thus this is a weak test: if the government chose the set of firms with the highest long-run profitability, then their selected firms should do at least as well as the set of firms we choose.

As shown in Figure 10, industry profits are significantly lower with the actual White List (the dashed blue line) than our White List (the solid red line). The difference in the long-run industry profits and revenue (the discounted sum from 2014 to 2099) is 14% and 10%, respectively. There appears a bias in favor of SOEs: 65% of firms selected by the government are SOEs, while 55% of our selected firms are SOEs. Out of the 56 firms chosen by the government, only 31 firms appear in our White List based on the short-run profitability.

---

Footnote: 37 Four firms on the official White List have missing values, so we focus on the remaining 56 firms in this analysis.
6.3 Rationales for the Industrial Policies

Our evaluation of China’s industrial policy in promoting the shipbuilding industry so far is mixed. The subsidies boosted production and investment, but contributed to the development of a fragmented industry, reduced the capital utilization rates, and to a large extent, were dissipated through inefficient entry/exit decisions. In this section, we assess traditional arguments in favor of industrial policies and evaluate the extent to which existing policies are effective in achieving these objectives.

A common rationale for industrial policies is related to economies of scale. In sectors with large entry costs or sectors deemed as “essential” to the national economy, the government may want to boost the formation of production capacities through subsidies. In developing countries, capital market inefficiencies and regulatory uncertainties may drive a wedge between privately and socially optimal firm entry (WTO, 2006). A combination of subsidies in the initial periods of the industry followed by consolidation could facilitate firm entry, induce a high growth rate, and allow the survival of the best performing firms post consolidation.

We assess this argument by simulating two scenarios. In the first scenario, the government subsidizes entry, production, and investment from 2006 to 2013, chooses the 56 best firms from the pool in 2014, and shuts down all other firms in the main time. In the second scenario, the industry evolves without any intervention and then the government chooses the same number of the best firms in 2014 and shuts down the remaining. In both scenarios, once the White List firms have been selected and the remaining firms removed, the industry is allowed to evolve with no further government intervention. We compare the long-run industry revenue and profits from 2014 onward.

Subsidizing the industry prior to consolidation does lead to 18% higher long-run industry revenue and profits, as shown in Figure 10. Since the number of firms is the same upon consolidation in 2014, the profit difference is driven by firm composition: firms are bigger and more productive with subsidies (solid red line) than in the scenario without subsidies (dashed green line). Nonetheless, the increase in the long-run industry profit is only 34% of the cost of subsidies from 2006 to 2013. Therefore, this argument does not provide a compelling justification for subsidizing the industry. In particular, entry subsidies are especially costly when combined with consolidation because a lion’s share of the entry subsidies goes to waste when new entrants exit post consolidation.

Another justification for subsidies is the presence of positive externalities (such as industry-wide learning-by-doing), as each firm produces less than what is socially optimal. As we discussed in Section 5.1, however, there is no evidence of significant spillover effects in this industry. One explanation is that much of the production by Chinese shipyards occurs in product sectors with mature technologies, where the scope for learning is limited.\textsuperscript{38}

\textsuperscript{38}There might be technological ‘catching-up’ and learning among Chinese shipyards for producing the latest generation ships (e.g., containerships or LNG’s), where most of the patents and ‘know-how’ are possessed by Japanese and especially South Korean firms. Unfortunately, there are few orders of these ships and our tests lack statistical power.
Our analysis focuses on the shipbuilding sector and does not account for benefits to other sectors. While spillovers to downstream sectors provide a rationale for subsidizing upstream industries (Liu, 2018), it is unlikely a justification for subsidies in the shipbuilding industry. Three-quarters of the output from this industry is used for final consumption (China’s 2012 Input-Output Table). Moreover, most of these ships are exported, reducing the share of benefits from subsidies that is captured domestically.

There are also potential spillovers to upstream sectors. Intermediate inputs from other sectors account for 63% of the value of ships produced. Steel in particular is an important input. One might argue that shipbuilding subsidies are partially designed to boost demand for steel, a strategic sector that has received many policy interventions. However, steel used in shipbuilding accounts for less than 1.5% of the total steel produced (China’s 2012 Input-Output Table). Moreover, even if subsidies to shipbuilding were large enough to have an appreciable effect on steel demand, they would lead to additional distortions since the increase in steel prices would reduce the amount of steel used in other industries.

Another justification for industrial policy is labor market consequences: subsidies could have welfare benefits if they increase employment and offset distortions that lead to depressed employment. However, even in the grand scheme of things, total employment in shipbuilding and related industries (ship repairs and marine equipments, etc.) accounts for less than 0.5% of national employment, suggesting that any potential labor market benefits would be modest.

In the presence of market power, there are in principle strategic trade benefits from subsidizing industries that compete with foreign firms (Krugman, 1986; Brander, 1995). Our main findings remain unchanged when we allow for firms to exercise market power in Cournot competition; indeed the returns to subsidies are nearly indistinguishable. Hence, the shipbuilding industry is unlikely a target for strategic trade policies.

These results suggest that economic justifications are unlikely the main factors in shaping the design of China’s industrial policy in the shipbuilding industry. Other considerations, including national security and military implications, as well as the desire to be the world leader in heavy industries (as stated in various government documents), might be more relevant in motivating these policies. Regardless of the motivation, our analysis provides cost estimates (and welfare losses) associated with implementing these policies, and can be used as a guidance for future polices.

7 Conclusion

We empirically evaluate China’s industrial policies, using the shipbuilding industry as a case study. While subsidies led to a significant increase in China’s world market share and buttressed China’s ascent into global influence, they are wasteful and entail substantial welfare distortions. Counter-
factual simulations indicate that the effective of subsidies can be improved substantially when targeted towards more productive firms or implemented counter cyclically. Our results provide a cautionary tale of industrial policies implemented in developing countries and highlight the importance of policy design.
References


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Fowlie, Meredith, Mar Reguant, and Stephen Ryan. “Market-Based Emissions Regulation and


**Jin, Hehui, Yingyi Qian, and Barry R. Weingast**, “Regional Decentralization and Fiscal Incen-


Yi, Fujin, C.-Y. Cynthia Lin Lawell, and Karen E. Thome, “A dynamic model of subsidies:
**Figure 1:** China’s Market Share Expansion

Source: Clarkson Research. Market shares computed from total quarterly ship orders.

**Figure 2:** Entry of New Shipyards

Source: Clarksons Research. Number of new shipyards.
Figure 3: Quarterly Investment by Chinese Shipyards

Source: NBS. Total quarterly investment.

Figure 4: Ship Prices

Source: Clarksons Research. Average price in US dollars per CGT.
Figure 5: Simulated vs. actual investment

Note: The simulated investment employed in the model: we use the estimated investment cost parameters and value function, randomly draw \( \nu \) for every observation, and calculate optimal investment.

Figure 6: Number of firms, with and without subsidies

Note: Total number of firms in the case of all subsidies (as in the data) and a counterfactual case with no subsidies.
Figure 7: HHI, with and without subsidies

Notes: The HHI reported in the above figure is calculated using all of the Chinese yards in any given year. It is thus a measure of concentration within the Chinese shipbuilding industry. The HHI for the global shipbuilding industry will generally differ from the HHI reported above.

Figure 8: Investment, with and without subsidies

Note: Total investment in the case of all subsidies (as in the data) and a counterfactual case of no subsidies.
Figure 9: Average firm cost-efficiency $\bar{s}_{jt}$ with subsidies during the boom vs. subsidies during the bust

![Figure 9: Average firm cost-efficiency $\bar{s}_{jt}$ with subsidies during the boom vs. subsidies during the bust](image)

*Note*: Average firm cost-efficiency, as captured by $\bar{s}_{jt}$, when subsidies are distributed during a boom vs. during a bust. Variable $\bar{s}_{jt}$ is defined in Section 4.2.

Figure 10: Industry Profits Under Different White Lists

![Figure 10: Industry Profits Under Different White Lists](image)

*Note*: In all scenarios, we pick a set of firms in the White List in 2013 and force all other firms to exit. In the scenario “Subsidies and Actual White List”, the government subsidizes the industry until 2013 and then keeps the observed White List. In the scenario “Subsidies and Simulated White List”, the government subsidizes the industry until 2013 and then chooses a White List based on observed profitability. In the scenario “No Subsidies and Simulated White List”, the industry does not receive any subsidies, and in 2013 a White List of firms is selected based on observed profitability.
Table 1: Shipbuilding National Industrial Policies

<table>
<thead>
<tr>
<th>Year</th>
<th>Shipbuilding National Industrial Policies</th>
<th>Plan Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>National Marine Economic Development Plan</td>
<td>2001-2010</td>
</tr>
<tr>
<td>2006</td>
<td>The 11th Five-Year Plan for National Economic and Social Development</td>
<td>2006-2010</td>
</tr>
<tr>
<td>2007</td>
<td>The 11th Five-Year Plan for the Development of Shipbuilding Industry</td>
<td>2006-2010</td>
</tr>
<tr>
<td>2007</td>
<td>Shipbuilding Operation Standards</td>
<td>2007-</td>
</tr>
<tr>
<td>2007</td>
<td>Plan on the Adjusting and Revitalizing the Shipbuilding Industry</td>
<td>2009-2011</td>
</tr>
<tr>
<td>2010</td>
<td>The 12th Five-Year Plan for National Economic and Social Development</td>
<td>2011-2015</td>
</tr>
<tr>
<td>2013</td>
<td>Plan on Accelerating Structural Adjustment and</td>
<td></td>
</tr>
<tr>
<td>2013</td>
<td>Shipbuilding Industry Standard and Conditions</td>
<td>2013-</td>
</tr>
</tbody>
</table>

Table 2: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Obs</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Observations (including zero orders)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bulk orders (1000 CGT)</td>
<td>10,101</td>
<td>17.1</td>
<td>51.9</td>
<td>0.0</td>
<td>968.2</td>
</tr>
<tr>
<td>Tanker orders (1000 CGT)</td>
<td>10,583</td>
<td>9.6</td>
<td>46.2</td>
<td>0.0</td>
<td>1119.0</td>
</tr>
<tr>
<td>Container orders (1000 CGT)</td>
<td>4,813</td>
<td>18.9</td>
<td>93.9</td>
<td>0.0</td>
<td>1644.1</td>
</tr>
<tr>
<td>Observations With Positive Orders</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bulk orders (1000 CGT)</td>
<td>2,316</td>
<td>74.6</td>
<td>86.5</td>
<td>3.9</td>
<td>968.2</td>
</tr>
<tr>
<td>Tanker orders (1000 CGT)</td>
<td>1,436</td>
<td>70.4</td>
<td>107.1</td>
<td>0.05</td>
<td>1,119.0</td>
</tr>
<tr>
<td>Container orders (1000 CGT)</td>
<td>625</td>
<td>145.3</td>
<td>222.7</td>
<td>2.3</td>
<td>1,644.1</td>
</tr>
<tr>
<td>Other Variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bulk backlog (1000 CGT)</td>
<td>10,101</td>
<td>171.4</td>
<td>329.3</td>
<td>0.0</td>
<td>2830.5</td>
</tr>
<tr>
<td>Tanker backlog (1000 CGT)</td>
<td>10,583</td>
<td>98.5</td>
<td>315.1</td>
<td>0.0</td>
<td>3840.8</td>
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<tr>
<td>Container backlog (1000 CGT)</td>
<td>4,813</td>
<td>206.6</td>
<td>670.5</td>
<td>0.0</td>
<td>7362.8</td>
</tr>
<tr>
<td>Investment (mill RMB)</td>
<td>4,386</td>
<td>18.5</td>
<td>88.9</td>
<td>-1,240.5</td>
<td>1,770.7</td>
</tr>
<tr>
<td>Capital (mill RMB)</td>
<td>6,157</td>
<td>392.0</td>
<td>806.9</td>
<td>0.3</td>
<td>8,203.3</td>
</tr>
</tbody>
</table>

1. The data on orders and backlog is for yards in China, Japan and Korea. There are a total of 14,455 observations, out of which 7,186 are for Chinese yards, 5,448 are for Japanese yards and 1,821 are for Korean yards.
2. 10,101 observations are for yards that produce bulkers, 10,583 observations are for yards that produce tankers, and 4,813 observations are for yards that produce containerships.
3. We observe investment and capital only for Chinese yards.
Table 3: Demand estimates

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>(1) Orders</th>
<th>(2) Orders</th>
<th>(3) Orders</th>
<th>(4) Orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price (bulk)</td>
<td>-2.34***</td>
<td>-1.67***</td>
<td>-2.07***</td>
<td>-2.12***</td>
</tr>
<tr>
<td></td>
<td>(0.77)</td>
<td>(0.64)</td>
<td>(0.69)</td>
<td>(0.75)</td>
</tr>
<tr>
<td>Price (tanker)</td>
<td>-2.66***</td>
<td>-1.46*</td>
<td>-1.80**</td>
<td>-1.76**</td>
</tr>
<tr>
<td></td>
<td>(0.60)</td>
<td>(0.88)</td>
<td>(0.78)</td>
<td>(0.89)</td>
</tr>
<tr>
<td>Price (container)</td>
<td>-4.85***</td>
<td>-2.44***</td>
<td>-3.39***</td>
<td>-3.39***</td>
</tr>
<tr>
<td></td>
<td>(0.91)</td>
<td>(0.85)</td>
<td>(1.01)</td>
<td>(0.99)</td>
</tr>
<tr>
<td>Price*Post2006</td>
<td>1.34***</td>
<td>1.00***</td>
<td>1.15***</td>
<td>1.34**</td>
</tr>
<tr>
<td></td>
<td>(0.18)</td>
<td>(0.14)</td>
<td>(0.15)</td>
<td>(0.55)</td>
</tr>
<tr>
<td>Backlog (log)</td>
<td>0.34</td>
<td>-1.00***</td>
<td>-0.78**</td>
<td>-0.81**</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.33)</td>
<td>(0.38)</td>
<td>(0.37)</td>
</tr>
<tr>
<td>Freight rate (bulk)</td>
<td>2.84***</td>
<td>3.27***</td>
<td>3.35***</td>
<td>3.33***</td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
<td>(0.56)</td>
<td>(0.57)</td>
<td>(0.56)</td>
</tr>
<tr>
<td>Freight rate (tanker)</td>
<td>4.04***</td>
<td>3.24***</td>
<td>2.94***</td>
<td>2.91***</td>
</tr>
<tr>
<td></td>
<td>(0.70)</td>
<td>(0.68)</td>
<td>(0.65)</td>
<td>(0.65)</td>
</tr>
<tr>
<td>Freight rate (container)</td>
<td>6.45***</td>
<td>4.47***</td>
<td>4.69***</td>
<td>4.60***</td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td>(0.73)</td>
<td>(0.77)</td>
<td>(0.75)</td>
</tr>
<tr>
<td>US Wheat price</td>
<td>-0.12</td>
<td>-0.10</td>
<td>-0.12</td>
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</tr>
<tr>
<td></td>
<td>(0.48)</td>
<td>(0.48)</td>
<td>(0.48)</td>
<td>(0.49)</td>
</tr>
<tr>
<td>Iron ore imports, China</td>
<td>2.62***</td>
<td>2.93***</td>
<td>3.01***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.90)</td>
<td>(0.89)</td>
<td>(0.92)</td>
<td></td>
</tr>
<tr>
<td>Middle East refinery production</td>
<td>1.37</td>
<td>1.84*</td>
<td>1.66*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.05)</td>
<td>(0.97)</td>
<td>(0.99)</td>
<td></td>
</tr>
<tr>
<td>World Car Trade</td>
<td>1.32***</td>
<td>2.08***</td>
<td>2.05***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.44)</td>
<td>(0.49)</td>
<td>(0.49)</td>
<td></td>
</tr>
<tr>
<td>Trend</td>
<td>-0.026**</td>
<td>-0.020</td>
<td></td>
<td>-0.0026</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.019)</td>
<td></td>
<td>(0.0076)</td>
</tr>
<tr>
<td>Trend*Post2006</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\[
R^2_{\text{bulk}} = 0.68 \quad 0.71 \quad 0.71 \quad 0.71 \\
R^2_{\text{tanker}} = 0.26 \quad 0.33 \quad 0.35 \quad 0.36 \\
R^2_{\text{container}} = 0.44 \quad 0.52 \quad 0.51 \quad 0.51
\]

* N equals 64 for bulk and container and 61 for tankers. The freight rate is the Baltic Exchange Freight Index for bulk ships, Baltic Exchange Clean Tanker Index for tankers, and the Containership Timecharter Rate Index for containerships. The demand shifters include the US wheat price and total Chinese iron ore imports for bulk, Middle East refinery production for tanker, and world car trade for containership. We instrument ship prices using steel production and the steel ship plate price. Parameters are estimated using GMM.
Table 4: Cost function estimates

<table>
<thead>
<tr>
<th>Type-specific</th>
<th>Bulk</th>
<th></th>
<th>Tanker</th>
<th></th>
<th>Container</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>T-stat</td>
<td>Coefficient</td>
<td>T-stat</td>
<td>Coefficient</td>
<td>T-stat</td>
</tr>
<tr>
<td>$\beta_q$</td>
<td>7.34</td>
<td>9.52</td>
<td>13.60</td>
<td>5.54</td>
<td>9.69</td>
<td>5.63</td>
</tr>
<tr>
<td>$\sigma_\omega$</td>
<td>8.49</td>
<td>10.43</td>
<td>14.40</td>
<td>7.08</td>
<td>12.14</td>
<td>5.71</td>
</tr>
<tr>
<td>Constant (1000 RMB/CGT)</td>
<td>19.26</td>
<td>15.88</td>
<td>36.58</td>
<td>9.18</td>
<td>32.30</td>
<td>8.39</td>
</tr>
<tr>
<td>Steel Price (1000 RMB/Ton)</td>
<td>1.55</td>
<td>7.49</td>
<td>1.10</td>
<td>3.04</td>
<td>0.63</td>
<td>1.65</td>
</tr>
<tr>
<td>Capital (bill RMB)</td>
<td>-2.43</td>
<td>-2.96</td>
<td>-2.61</td>
<td>-1.80</td>
<td>-2.19</td>
<td>-2.01</td>
</tr>
<tr>
<td>Capital$^2$</td>
<td>0.19</td>
<td>0.83</td>
<td>0.06</td>
<td>0.25</td>
<td>0.06</td>
<td>0.32</td>
</tr>
<tr>
<td>Backlog</td>
<td>-1.56</td>
<td>-5.29</td>
<td>-4.44</td>
<td>-5.04</td>
<td>-2.88</td>
<td>-3.34</td>
</tr>
<tr>
<td>Backlog$^2$</td>
<td>0.07</td>
<td>4.04</td>
<td>0.24</td>
<td>3.43</td>
<td>0.18</td>
<td>1.97</td>
</tr>
<tr>
<td>Backlog of Other Types</td>
<td>0.13</td>
<td>0.94</td>
<td>0.35</td>
<td>1.65</td>
<td>0.46</td>
<td>2.66</td>
</tr>
</tbody>
</table>

| Common                        |           |       |            |       |            |       |
|                               |           |       |            |       |            |       |
| 2006-2008                     | -1.51     | -2.62 |            |       |            |       |
| 2009+                         | -1.38     | -2.37 |            |       |            |       |
| Large firms                   | -3.85     | -6.97 |            |       |            |       |
| Jiangsu                       | -2.64     | -4.75 |            |       |            |       |
| Zhejiang                      | -1.42     | -2.80 |            |       |            |       |
| Liaoning                      | -1.87     | -2.05 |            |       |            |       |
| CSSC/CSIC                     | -0.77     | -1.20 |            |       |            |       |
| Private                       | 0.14      | 0.30  |            |       |            |       |
| Foreign JV                    | -0.78     | -1.45 |            |       |            |       |
| Age                           | 0.18      | 3.14  |            |       |            |       |

| N                             | 4886      | 4977  | 2504       |

* Standard errors bootstrapped using 500 bootstrap samples.
Table 5: Cost function estimates, pooling data across China/Japan/Korea

<table>
<thead>
<tr>
<th>Type-specific</th>
<th>Bulk</th>
<th>Tanker</th>
<th>Container</th>
</tr>
</thead>
<tbody>
<tr>
<td>MC (thousand RMB / CGT)</td>
<td>Coefficient</td>
<td>T-stat</td>
<td>Coefficient</td>
</tr>
<tr>
<td>$\beta_q$</td>
<td>9.10</td>
<td>12.94</td>
<td>11.04</td>
</tr>
<tr>
<td>$\sigma_\omega$</td>
<td>10.36</td>
<td>13.78</td>
<td>15.12</td>
</tr>
<tr>
<td>China (1000 RMB/CGT)</td>
<td>19.40</td>
<td>17.11</td>
<td>32.30</td>
</tr>
<tr>
<td>Japan (1000 RMB/CGT)</td>
<td>12.57</td>
<td>16.67</td>
<td>30.92</td>
</tr>
<tr>
<td>Korea (1000 RMB/CGT)</td>
<td>15.92</td>
<td>14.88</td>
<td>23.07</td>
</tr>
<tr>
<td>Steel Price (1000 RMB/Ton)</td>
<td>2.12</td>
<td>14.20</td>
<td>2.46</td>
</tr>
<tr>
<td>Capital (bill RMB)</td>
<td>-2.92</td>
<td>-3.06</td>
<td>-2.06</td>
</tr>
<tr>
<td>Capital$^2$</td>
<td>0.23</td>
<td>0.89</td>
<td>-0.01</td>
</tr>
<tr>
<td>Backlog</td>
<td>-2.09</td>
<td>-6.63</td>
<td>-4.50</td>
</tr>
<tr>
<td>Backlog$^2$</td>
<td>0.10</td>
<td>4.83</td>
<td>0.24</td>
</tr>
<tr>
<td>Backlog of Other Types</td>
<td>0.11</td>
<td>0.76</td>
<td>0.32</td>
</tr>
<tr>
<td>Common China 2006-2008</td>
<td>-2.79</td>
<td>-4.57</td>
<td></td>
</tr>
<tr>
<td>China 2009+</td>
<td>-0.90</td>
<td>-1.56</td>
<td></td>
</tr>
<tr>
<td>Large firms</td>
<td>-4.17</td>
<td>-6.84</td>
<td></td>
</tr>
<tr>
<td>Jiangsu</td>
<td>-2.93</td>
<td>-4.81</td>
<td></td>
</tr>
<tr>
<td>Zhejiang</td>
<td>-1.57</td>
<td>-2.79</td>
<td></td>
</tr>
<tr>
<td>Liaoning</td>
<td>-1.87</td>
<td>-1.88</td>
<td></td>
</tr>
<tr>
<td>CSSC/CSIC</td>
<td>-0.93</td>
<td>-1.28</td>
<td></td>
</tr>
<tr>
<td>Private</td>
<td>0.13</td>
<td>0.24</td>
<td></td>
</tr>
<tr>
<td>Foreign JV</td>
<td>-0.92</td>
<td>-1.61</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.26</td>
<td>6.14</td>
<td></td>
</tr>
</tbody>
</table>

N | 10013 | 10429 | 4661

* Standard errors bootstrapped using 500 bootstrap samples. We pool together Chinese/Japanese/Korean yards. We observe the capital stock only for Chinese yards. To account for the missing values, we set the capital variable to zero for Japanese and Korean yards, and allow the constant term to differ by country. We also allow the backlog coefficients to differ by country. (Backlog coefficients for Japan and Korea are not reported above).
Table 6: Estimates of investment cost and scrap value parameters

<table>
<thead>
<tr>
<th></th>
<th>Coeff.</th>
<th>T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma$</td>
<td>0.69</td>
<td>11.76</td>
</tr>
<tr>
<td>c1</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>c2</td>
<td>21.72</td>
<td>10.57</td>
</tr>
<tr>
<td>c3</td>
<td>1.55</td>
<td>8.27</td>
</tr>
<tr>
<td>$c_{4,2006-08}$</td>
<td>-0.25</td>
<td>-1.89</td>
</tr>
<tr>
<td>$c_{4,2009+}$</td>
<td>-0.49</td>
<td>-4.07</td>
</tr>
<tr>
<td>N</td>
<td>4286</td>
<td></td>
</tr>
</tbody>
</table>

* Standard errors bootstrapped using 500 block bootstrap samples.

Table 7: Actual vs. Simulated Exits

<table>
<thead>
<tr>
<th></th>
<th>1999-2005</th>
<th>2006-2013</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual exits</td>
<td>5</td>
<td>43</td>
<td>48</td>
</tr>
<tr>
<td>Simulated exits</td>
<td>9</td>
<td>30</td>
<td>39</td>
</tr>
</tbody>
</table>

1 We simulate the model 50 times from 1999 to 2013 under the baseline assumptions, and report the average number of exits across these simulations in the table above.

Table 8: Entry Cost Distribution (Mean), billion RMB

<table>
<thead>
<tr>
<th>Region</th>
<th>$\kappa_{pre}$</th>
<th>$\kappa_{post,06}$</th>
<th>% of pre costs</th>
<th>$\kappa_{post,09+}$</th>
<th>% of pre costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jiangsu</td>
<td>60</td>
<td>22</td>
<td>36%</td>
<td>69</td>
<td>114%</td>
</tr>
<tr>
<td>Zhejiang</td>
<td>91</td>
<td>37</td>
<td>41%</td>
<td>194</td>
<td>214%</td>
</tr>
<tr>
<td>Liaoning</td>
<td>56</td>
<td>29</td>
<td>51%</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Other</td>
<td>25</td>
<td>10</td>
<td>38%</td>
<td>44</td>
<td>172%</td>
</tr>
</tbody>
</table>

1 $\kappa_{pre}$ refers to the mean of the entry cost distribution prior to 2004 for Zhejiang, and prior to 2006 for Jiangsu, Liaoning and Other regions.
2 $\kappa_{post,06}$ refers to the mean of the entry cost distribution between 2006 and 2008 for Jiangsu, Liaoning and Other regions and between 2004 and 2008 for Zhejiang.
3 $\kappa_{post,09+}$ refers to the mean of the entry cost distribution from 2009 onwards.
4 We assume that $\bar{N}$, the number of potential entrants, equals twice the maximum number of potential entrants ever observed in the region.
### Table 9: Actual vs. Simulated Entries

<table>
<thead>
<tr>
<th></th>
<th>Pre</th>
<th>Post, Until 2008</th>
<th>Post, 2009+</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual entries</td>
<td>83</td>
<td>122</td>
<td>39</td>
<td>244</td>
</tr>
<tr>
<td>Simulated entries</td>
<td>69</td>
<td>125</td>
<td>38</td>
<td>232</td>
</tr>
</tbody>
</table>

1. "Pre" refers to the period prior to 2004 for Zhejiang, and prior to 2006 for Jiangsu, Liaoning and Other regions.
4. We simulate the model 50 times from 1999 to 2013 under the baseline assumptions, and report the average number of entries across these simulations in the table above.

### Table 10: Impact of Subsidies on Ship Prices

<table>
<thead>
<tr>
<th></th>
<th>Bulk</th>
<th>Tanker</th>
<th>Container</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subsidies, 2006-08</td>
<td>16.3</td>
<td>20.0</td>
<td>17.2</td>
</tr>
<tr>
<td>No subsidies, 2006-08</td>
<td>17.6</td>
<td>21.2</td>
<td>17.7</td>
</tr>
<tr>
<td>% difference</td>
<td>8.2%</td>
<td>6.2%</td>
<td>3.1%</td>
</tr>
<tr>
<td>Subsidies, 2009-13</td>
<td>8.8</td>
<td>8.1</td>
<td>9.2</td>
</tr>
<tr>
<td>No Subsidies, 2009-13</td>
<td>10.2</td>
<td>9.0</td>
<td>9.5</td>
</tr>
<tr>
<td>% difference</td>
<td>16.5%</td>
<td>10.6%</td>
<td>3.7%</td>
</tr>
</tbody>
</table>

1. Prices in 1000 RMB/CGT
Table 11: Comparison of Different Subsidies

<table>
<thead>
<tr>
<th></th>
<th>All Subsidies</th>
<th>Only Production</th>
<th>Only Investment</th>
<th>Only Entry</th>
<th>No Subsidies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime Revenue 2006-2099</td>
<td>2320</td>
<td>2091</td>
<td>1796</td>
<td>1830</td>
<td>1696</td>
</tr>
<tr>
<td>Lifetime Profits 2006-2099</td>
<td>854</td>
<td>788</td>
<td>618</td>
<td>590</td>
<td>570</td>
</tr>
<tr>
<td>Production subsidies</td>
<td>256</td>
<td>216</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Investment subsidies</td>
<td>86</td>
<td>0</td>
<td>44</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Entry subsidies</td>
<td>302</td>
<td>0</td>
<td>0</td>
<td>171</td>
<td>0</td>
</tr>
<tr>
<td>∆ Revenue/Subsidy</td>
<td>97%</td>
<td>183%</td>
<td>226%</td>
<td>78%</td>
<td></td>
</tr>
<tr>
<td>∆ (Profit-Inv. Cost)/Subsidy</td>
<td>44%</td>
<td>93%</td>
<td>148%</td>
<td>11%</td>
<td></td>
</tr>
<tr>
<td>∆ Net Profit/Subsidy</td>
<td>18%</td>
<td>56%</td>
<td>87%</td>
<td>24%</td>
<td></td>
</tr>
</tbody>
</table>

1 Each element in the table refers to the discounted sum from 2006 to 2099, averaged across all of the simulations. For example, “Lifetime Profits 2006” refers to the discounted sum of profits earned by firms from 2006 to 2099.
2 ∆Revenue/Subsidy equals the discounted sum of revenue in the scenario minus the discounted sum of revenue in the scenario with no subsidies, divided by the discounted sum of subsidies.
3 (Profit-Inv.Cost) refers to profits net of the cost of investment. ∆(Profit-Inv.Cost)/Subsidy equals the discounted sum of (profits-investment cost) in the scenario minus the discounted sum of (profits-investment cost) in the scenario with no subsidies, divided by the discounted sum of subsidies.
4 Net Profit = (Profits-Investment Cost+Scrap Value-Entry Cost). ∆Net Profit/Subsidy equals the discounted sum of net profits in the scenario minus the discounted sum of net profits in the scenario with no subsidies, divided by the discounted sum of subsidies.
5 In the scenarios “Only Production”, we maintain the same production subsidy as in the baseline estimation, but shut down entry and investment subsidies. The scenarios “Only Investment” and “Only Entry” are constructed in a similar fashion.
6 We assume for each scenario that the government policy from 2014 onwards remains frozen at the 2013 policy. This implies in particular that in the “Only Production” and “Only Investment” scenarios, the government continues to subsidize firms beyond 2013, whereas in the “Only Entry” scenario, there are no entry subsidies beyond 2013 (reflecting the fact that the government had already discontinued entry subsidies by 2013).
Table 12: Effect of subsidies on productive and unproductive firms

<table>
<thead>
<tr>
<th></th>
<th>Unproductive firms</th>
<th>Productive firms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime Revenue 2006-</td>
<td>406</td>
<td>1911</td>
</tr>
<tr>
<td>Lifetime Profits 2006-</td>
<td>70</td>
<td>779</td>
</tr>
<tr>
<td>Production subsidies</td>
<td>40</td>
<td>215</td>
</tr>
<tr>
<td>Investment subsidies</td>
<td>26</td>
<td>60</td>
</tr>
<tr>
<td>Entry subsidies</td>
<td>157</td>
<td>146</td>
</tr>
<tr>
<td>(\Delta) Revenue/Subsidies</td>
<td>71%</td>
<td>113%</td>
</tr>
<tr>
<td>(\Delta) (Profit-Invest Cost)/Subsidies</td>
<td>19%</td>
<td>58%</td>
</tr>
<tr>
<td>(\Delta) Net Profit/Subsidies</td>
<td>-4%</td>
<td>29%</td>
</tr>
</tbody>
</table>

1 We define “unproductive” firms as firms with initial \(\bar{s}_j\) (at the time the policy change first occurred) below the median, and “productive” firms as firms with initial \(\bar{s}_j\) above the median.
2 Each element in the table refers to the discounted sum from 2006 to 2099, averaged across all of the simulations. For example, “Revenue” refers to the discounted sum of scrap values earned by exiting firms from 2006 to 2099.
3 \(\Delta\)Revenue/Subsidy, \(\Delta\)(Profit-Inv.Cost)/Subsidy and \(\Delta\)Net Profit/Subsidy are defined as in Table 11.

Table 13: Pro-cyclical vs. counter-cyclical industrial policy

<table>
<thead>
<tr>
<th></th>
<th>Subsidize during boom</th>
<th>Subsidize during recession</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime Revenue 2006-</td>
<td>1792</td>
<td>1795</td>
</tr>
<tr>
<td>Lifetime Profits 2006-</td>
<td>609</td>
<td>624</td>
</tr>
<tr>
<td>Production Subsidies</td>
<td>34</td>
<td>35</td>
</tr>
<tr>
<td>Investment Subsidies</td>
<td>16</td>
<td>16</td>
</tr>
<tr>
<td>(\Delta) Revenue/Subsidies</td>
<td>222%</td>
<td>225%</td>
</tr>
<tr>
<td>(\Delta) (Profit-Invest Cost)/Subsidies</td>
<td>86%</td>
<td>126%</td>
</tr>
<tr>
<td>(\Delta) Net Profit/Subsidies</td>
<td>29%</td>
<td>78%</td>
</tr>
</tbody>
</table>

1 In the policy “Subsidize during boom”, the government offers production and investment subsidies during the boom of 2006-08, but discontinues the subsidies from 2009 onwards. In the policy “Subsidize during recession”, the government offers subsidies during the recession of 2009-13, but offers no subsidies before 2009 or after 2013. The subsidy rates are calibrated so that the subsidy budget is approximately the same in the two scenarios.
2 Each element in the table refers to the sum from 2014 to 2099, discounted back to 2006, averaged across all of the simulations. For example, “Scrap Value” refers to the discounted sum (in 2006) of scrap values earned by exiting firms from 2014 to 2099.
3 \(\Delta\)Revenue/Subsidy, \(\Delta\)(Profit-Inv.Cost)/Subsidy and \(\Delta\)Net Profit/Subsidy are defined as in Table 11.
Table 14: Targeting subsidies to White List firms

<table>
<thead>
<tr>
<th></th>
<th>Subsidize All Firms After 2013</th>
<th>Subsidize White List firms After 2013</th>
<th>No Subsidies After 2013</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lifetime Revenue 2014-</td>
<td>945</td>
<td>887</td>
<td>736</td>
</tr>
<tr>
<td>Lifetime Profits 2014-</td>
<td>416</td>
<td>395</td>
<td>278</td>
</tr>
<tr>
<td>Production subsidies</td>
<td>129</td>
<td>88</td>
<td>0</td>
</tr>
<tr>
<td>Investment subsidies</td>
<td>48</td>
<td>16</td>
<td>0</td>
</tr>
<tr>
<td>Entry subsidies</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>∆ Revenue/Subsidies</td>
<td>118%</td>
<td>144%</td>
<td></td>
</tr>
<tr>
<td>∆ (Profit-Invest Cost)/Subsidies</td>
<td>83%</td>
<td>109%</td>
<td></td>
</tr>
<tr>
<td>∆ Net Profit/Subsidies</td>
<td>38%</td>
<td>84%</td>
<td></td>
</tr>
</tbody>
</table>

1 Each element in the table refers to the sum from 2014 to 2099, discounted back to 2006, averaged across all of the simulations. For example, “Lifetime Profits 2014-” refers to the discounted sum (in 2006) of profits earned by firms from 2014 to 2099.

2 ∆Revenue/Subsidy, ∆(Profit-Inвест Cost)/Subsidy and ∆Net Profit/Subsidy are defined as in Table 11.
Appendix

Online Appendix. Not for Publication.

This appendix discusses the calibration of the fixed production cost, details for the dynamic estimation (e.g., estimates of the first-stage policy functions and state-variable transitions), and implementation of the counterfactual analyses.

A Calibrating Fixed Cost of Production

The NBS data include information on operation costs, which allows us to calibrate the fixed cost of production. A firm’s total production cost is equal to:

$$C_{jt} = c_0 + C(q_{jt})$$

where \(C(q_{jt})\) is the variable cost of taking \(q_{jt}\) orders that is estimated from the Clarkson data, as discussed in Section 4.1.

Let \(C_{NBS}^{\text{NBS}}\) denote the accounting operation costs, which includes the costs of both ship production and ship repairs, a common practice in this industry. We follow the standard assumption in the production literature that the cost share of ship production is the same as its revenue share and obtain the accounting operation cost of ship production as:

$$\hat{C}_{jt} = C_{NBS}^{\text{NBS}} \times \left( \frac{R_{Clarkson}^j}{R_{NBS}^j} \right)$$

where \(R_{Clarkson}^j = \sum_t R_{Clarkson}^j\) denotes \(j\)’s lifetime revenue from building new ships that is reported in Clarkson and \(R_{NBS}^j = \sum_t R_{NBS}^j\) denotes its lifetime revenue in NBS.

We use two approaches to estimate the fixed cost \(c_0\). Both deliver similar results. The first approach uses the quarters with zero production (so that the variable production cost is zero) and the accounting costs \(\hat{C}_{jt}\) (after adjusting for repairs) in the same periods to infer the fixed cost. The second approach uses the difference between a shipyard’s average operation costs and the average estimated variable cost of production:

$$c_0 = \frac{1}{T} \sum_t [\hat{C}_{jt} - C(q_{jt})]$$

Note that the calibrated fixed cost of operation is the same for all firms. While in principle we could allow the fixed cost to vary by firm characteristics, our data is not rich enough to deliver a precise estimate.
B Estimation Details

B.1 Estimating the Investment Policy Function

The investment policy function is assumed to be additive in observed state variables and the unobserved investment shock:

\[ I^*_jt = h_1(s_{jt}) + h_2(v_{jt}) \]
\[ I_{jt} = \max(I^*_jt, 0) \]

where the second equation makes it explicit that investment is non-negative. Powell (1984) showed that we can recover \( h_1(s) \) through the Censored Least Absolute Deviations estimator (CLAD) while normalizing the median of \( h_2(v_{jt}) \) to 0. Once we obtain the CLAD estimate \( \hat{h}_1(s) \), we treat \( I_{jt} - \hat{h}_1(s_{jt}) \) as data. The goal is to estimate \( h_2(v_{jt}) \) with truncated data:

\[ \tilde{i}_{jt} \equiv I_{jt} - \hat{h}_1(s_{jt}) = \max(h_2(v_{jt}), -\hat{h}_1(s_{jt})), \text{ or} \]
\[ \tilde{i}_{jt} = \max(h_2(v_{jt}), \bar{s}_{jt}) \]

where in the second equation we use \( \bar{s}_{jt} \) to denote \( -\hat{h}_1(s_{jt}) \).

Note that the level of truncation \( \bar{s}_{jt} \) varies across observations. We use the observed probability of truncation (zero or negative investment) to back out the level of investment shock that induces truncation, conditioning on the observed state variables (\( \Phi \) denote the CDF of a standard normal):

\[ Pr(\tilde{i}_{jt} > \bar{s}_{jt} | \bar{s}_{jt}) = Pr(h_2(v_{jt}) > \bar{s}_{jt}) = Pr(v_{jt} < h_2^{-1}(\bar{s}_{jt})) = Pr(v_{jt} < \bar{v}_{jt}) \]
\[ = \Phi(\bar{v}_{jt}), \text{ or} \]
\[ \bar{v}_{jt} = \Phi^{-1}(Pr(\tilde{i}_{jt} > \bar{s}_{jt} | \bar{s}_{jt})) \]

where \( Pr(\tilde{i}_{jt} > \bar{s}_{jt} | \bar{s}_{jt}) \) can be estimated either via kernel methods, or by approximating the cutoff value \( \bar{v}(\bar{s}_{jt}) \) by a flexible function of \( \bar{s}_{jt} \) and carrying out a probit regression.

To estimate \( h_2(v_{jt}) \), we categorize all the uncensored observations (where \( \tilde{i}_{jt} > \bar{s}_{jt} \)) into distinct bins. Specifically, suppose the thresholds are \( \{\bar{s}_1, \bar{s}_2, ..., \bar{s}_{R+1}\} \). Then any uncensored observation \( \tilde{i} \in (\bar{s}_r, \bar{s}_{r+1}] \) is placed in bin \( r \). We carry out the BBL inversion separately for each bin:

\[ F(i^* \mid i^* \in (\bar{s}_r, \bar{s}_{r+1}]) = Pr(\tilde{i} \leq i^* \mid i^* \in (\bar{s}_r, \bar{s}_{r+1})) \]
\[ = Pr(v \geq v^* \mid \bar{v}_{r+1} < v < \bar{v}_r) \]
\[ = \frac{\Phi(\bar{v}_r) - \Phi(v^*)}{\Phi(\bar{v}_r) - \Phi(\bar{v}_{r+1})} \]
In other words,

\[ i^* = F^{-1}\left( \frac{\Phi(\bar{v}_r) - \Phi(v^*)}{\Phi(\bar{v}_r) - \Phi(\bar{v}_{r+1})} \right) \text{ for } \bar{v}_{r+1} < v^* < \bar{v}_r \]

It is easy to verify that this estimator nests the uncensored example as a special case and allows us to better address censoring by increasing the number of bins. Monte Carlo simulations suggest that a small number of bins (say five) can lead to surprisingly well-behaved estimates with minimal bias in the estimated function \( h_2(v) \).

### B.2 First-stage Policy Function and State Transition Estimates

This section presents the first-stage estimates of the investment and exit policy functions, as well as the state transition process. Table B1 reports the estimated investment policy function using OLS, Tobin, and CLAD. Table B2 reports the estimated exit policy function. Table B3 presents estimates of the transition process for prices of bulk, tankers, containerships, and steel.

### B.3 State Space

As discussed in the main text, we approximate \( V(s_{jt}) \) via B-spline basis functions \( V(s_{jt}) = \sum_{l=1}^{L} \gamma_{0l} u_l(s_{jt}) \) and impose the Bellman equation as a constraint. Recovering \( \gamma_{0} \) requires specifying the set of state values on which to evaluate the Bellman constraint. We construct a sample that ensures sufficient variation in each of the state variables. First, we include all the \( N \) states observed in the sample. Second, we randomly draw \( N_{\text{add}} \) additional states to span the full range of the state variables. The coefficients \( \gamma_{0} \) are recovered using these \( N + N_{\text{add}} \) states. This approach is similar to Sweeting (2013).

These additional states are instrumental in getting a good approximation of the value function, for two reasons. First, some states (for example, ship prices and the steel price) are highly correlated in the data, which makes it challenging to separately identify the coefficients on basis functions formed from these state variables if we only use the observed states. Second, some regions of the state space have a limited number of observations. Both of these problems can be mitigated by adding randomly drawn states, which avoids multicollinearity between states and ensures sufficient data points across all regions of the state space.

### C Implementation of Counterfactual Analyses

Each of the counterfactual analyses involves two steps: first, solving for the new Bellman equation and policy functions, and second, simulating the industry forward till 2099. Here we briefly explain how to implement the first step through a fixed point algorithm:
<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) Tobit</th>
<th>(3) CLAD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.066</td>
<td>-12.2</td>
<td>-31.9***</td>
</tr>
<tr>
<td></td>
<td>(7.54)</td>
<td>(8.17)</td>
<td>(4.09)</td>
</tr>
<tr>
<td>B-spline 1 Capital</td>
<td>-69.7***</td>
<td>-63.8***</td>
<td>-69.6***</td>
</tr>
<tr>
<td></td>
<td>(22.0)</td>
<td>(17.2)</td>
<td>(1.67)</td>
</tr>
<tr>
<td>B-spline 2 Capital</td>
<td>-74.7***</td>
<td>-71.7***</td>
<td>-68.2***</td>
</tr>
<tr>
<td></td>
<td>(17.7)</td>
<td>(13.5)</td>
<td>(1.41)</td>
</tr>
<tr>
<td>2006-08</td>
<td>6.42***</td>
<td>4.59**</td>
<td>17.9***</td>
</tr>
<tr>
<td></td>
<td>(1.60)</td>
<td>(2.32)</td>
<td>(0.74)</td>
</tr>
<tr>
<td>2009+</td>
<td>2.70</td>
<td>3.79</td>
<td>3.55**</td>
</tr>
<tr>
<td></td>
<td>(2.20)</td>
<td>(3.03)</td>
<td>(1.80)</td>
</tr>
<tr>
<td>$\bar{s}_{jt}$</td>
<td>0.74***</td>
<td>0.87***</td>
<td>1.44***</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.087)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Bulk price</td>
<td>2.05***</td>
<td>1.97***</td>
<td>1.34***</td>
</tr>
<tr>
<td></td>
<td>(0.46)</td>
<td>(0.57)</td>
<td>(0.30)</td>
</tr>
<tr>
<td>Tanker price</td>
<td>0.48</td>
<td>1.89*</td>
<td>0.81***</td>
</tr>
<tr>
<td></td>
<td>(0.93)</td>
<td>(1.14)</td>
<td>(0.13)</td>
</tr>
<tr>
<td>Container price</td>
<td>-1.25</td>
<td>-1.49</td>
<td>-0.55</td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td>(1.06)</td>
<td>(0.34)</td>
</tr>
<tr>
<td>Steel price</td>
<td>-2.49***</td>
<td>-4.44***</td>
<td>-4.38***</td>
</tr>
<tr>
<td></td>
<td>(0.53)</td>
<td>(0.61)</td>
<td>(0.19)</td>
</tr>
</tbody>
</table>

|                |        |           |           |
| N              | 4286   |           |           |
| $N(I > 0)$     | 3301   |           |           |
| $N(I = 0)$     | 985    |           |           |

In Column (1), we carry out an OLS regression of investment ($I$) on basis functions of the states, including both observations with $I > 0$ and $I = 0$. In (2), we estimate the policy function using a Tobit regression of $I$ on the basis functions. In (3), we estimate the investment policy function using a censored least absolute deviations estimator. $\bar{s}_{jt}$ is an index capturing the effect of backlog, age, ownership, region, and size on a firm’s per-period payoffs. Investment is measured in million RMBs in these regressions.
Table B2: Estimates of exit policy function

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th></th>
<th>(2)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.57 (0.97)</td>
<td>-0.56 (1.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>K</td>
<td>0.05 (0.35)</td>
<td>0.54 (0.43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$K^2$</td>
<td>-0.05 (0.12)</td>
<td>-0.16 (0.15)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006-2008</td>
<td>-0.57 (0.41)</td>
<td>-0.64 (0.43)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009+</td>
<td>-0.47 (0.41)</td>
<td>-0.72 (0.44)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\bar{s}_{jt}$</td>
<td>-0.01 (0.01)</td>
<td>-0.04 (0.02)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bulk price</td>
<td>0.36 (0.12)</td>
<td>0.36 (0.12)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tanker price</td>
<td>-0.18 (0.11)</td>
<td>-0.16 (0.11)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Container price</td>
<td>-0.22 (0.10)</td>
<td>-0.25 (0.11)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Steel price</td>
<td>-0.06 (0.07)</td>
<td>-0.10 (0.08)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Jiangsu</td>
<td></td>
<td>0.77 (0.24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Zhejiang</td>
<td></td>
<td>0.58 (0.19)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liaoning</td>
<td></td>
<td>1.04 (0.28)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| N(exit)           | 47         | 47       |
| N                 | 4605       | 4605     |

Residual deviance  478.59  459.47
Log-likelihood    -239.30  -229.74
Pseudo-R2          0.09     0.12

We carry out a probit regression of a binary indicator of exit on basis functions of the states. We restrict the estimation to 1999-2011, because firm exits in 2012 and 2013 are not reliably measured.
Table B3: AR(1) estimates for state transition processes

<table>
<thead>
<tr>
<th></th>
<th>Bulk</th>
<th>Tanker</th>
<th>Container</th>
<th>Steel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.88</td>
<td>0.70</td>
<td>1.25</td>
<td>-0.023</td>
</tr>
<tr>
<td></td>
<td>(0.87)</td>
<td>(0.94)</td>
<td>(1.11)</td>
<td>(0.37)</td>
</tr>
<tr>
<td>Post</td>
<td>3.44</td>
<td>3.63</td>
<td>1.80</td>
<td>2.32</td>
</tr>
<tr>
<td></td>
<td>(2.28)</td>
<td>(3.43)</td>
<td>(3.33)</td>
<td>(1.01)</td>
</tr>
<tr>
<td>Price (t-1)*Pre</td>
<td>0.86</td>
<td>0.92</td>
<td>0.88</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.086)</td>
<td>(0.090)</td>
<td>(0.19)</td>
</tr>
<tr>
<td>Price (t-1)*Post</td>
<td>0.86</td>
<td>0.86</td>
<td>0.88</td>
<td>0.69</td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.095)</td>
<td>(0.10)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Trend*Pre</td>
<td>0.042</td>
<td>0.038</td>
<td>0.029</td>
<td>0.024</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.028)</td>
<td>(0.024)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>Trend*Post</td>
<td>-0.058</td>
<td>-0.054</td>
<td>-0.040</td>
<td>-0.022</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.041)</td>
<td>(0.040)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>N</td>
<td>57</td>
<td>57</td>
<td>57</td>
<td>57</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.95</td>
<td>0.97</td>
<td>0.96</td>
<td>0.80</td>
</tr>
</tbody>
</table>

* The dependent variable is the price in quarter t, or $p(t)$. Standard errors in parenthesis. “Pre” refers to 2005Q4 or earlier. “Post” refers to 2006Q1 or later. The sample ranges from 1999 Q4 to 2013Q4.

1. Compute all objects that do not require knowledge of the value function:
   - Expected profits $\pi(s)$ at all states.

2. Start with an initial guess of the exit policy function $p^{0,*}(s)$ and investment policy function $i^0(s,v)$.

3. Update the policy functions. At each iteration $j$:
   - Solve for the value function coefficients $\gamma^{j+1}$ using the equation $V^{j+1}(s) = \pi(s) + p^{j,x}\sigma + CV^{j+1}(s)$. Note that this involves computing $EV^{j+1}(s'|s,i)$ for every possible $i$, using the investment policy function $i^{j}(s,v)$ from the previous iteration $j$.
   - Update the investment policy function to $i^{j+1}(s,v)$ by solving the investment FOC, using $V^{j+1}$ and $CV^{j+1}$. As the value function is approximated by cubic B-splines, the investment policy function has an analytic solution.
   - Update the exit policy function to $p^{j+1,x}$ using $V^{j+1}$ and $CV^{j+1}$.
   - Check whether $||p^{j+1,x}(s) - p^{j,x}(s)|| < tol$ and $||i^{j+1}(s,v) - i^{j}(s,v)|| < tol$, where $tol$ is a pre-assigned tolerance level.
D A Simple Model on Subsidies

This is a static model with one period and identical firms. Each firm has a starting capital stock of $K_0$. Price is equal to $P$. Marginal cost of production equals $MC(q_t) = \alpha - \beta K + \delta q_t$. Total cost of investment equals $C_I(I) = c_1I + (c_2/2)I^2$. The firm chooses $q$ and $I$ simultaneously to maximize profit:

$$V(K_0) = \max_{q,I} Pq - \left( (\alpha - \beta (K_0 + I))q - \frac{\delta}{2} q^2 \right) - \left( c_1I + \frac{c_2}{2}I^2 \right)$$

The optimal quantity and investment are denoted $q^*$ and $I^*$, respectively.

Now suppose that the government introduces production subsidies of $\tau_p$ per unit. For simplicity, we assume that the firm only adjusts its level of production not investment; thus investment remains fixed at $I^*$. The new level of production, $\hat{q}$, is:

$$\hat{q} = q^* + \frac{\tau_p}{\delta}$$

Return to Prod. Subsidies = $\left( q^* + \frac{\tau_p}{2\delta} \right) / \left( q^* + \frac{\tau_p}{\delta} \right)$

Alternatively suppose that the government introduces investment subsidies of $\tau_i$ per unit. Similarly, the new level of investment, $\hat{I}$, is:

$$\hat{I} = I^* + \frac{\tau_i}{c_2}$$

Return to Invest Subsidies = $\left( I^* + \frac{\tau_i}{2c_2} \right) / \left( I^* + \frac{\tau_i}{c_2} \right)$

$$\text{DWL from Invest Subsidies} = \frac{\tau_i^2}{2c_2}$$

$$\text{DWL from Prod. Subsidies} = \frac{\tau_p^2}{2\delta}$$

(1)

Holding the adjustment cost parameters $c_2$ and $\delta$ fixed, the return to subsidies is increasing in $I^*$ (for investment) and $q^*$ (for production). In other words, subsidizing "better" firms leads to higher returns.

Our derivation of the DWL showed that the magnitude of DWL is independent of whether a firm has low or high marginal costs: $\tau_p^2/\delta$. Essentially, all firms (large or small) increase their output by the same amount when they receive the same subsidy. However, the return to subsidies is higher for low-cost firms than high-cost ones. This is because low-cost firms receive a higher absolute amount of subsidies due to the fact that they produce a higher quantity. Thus the DWL loss is divided by a larger denominator which means the per-dollar return to subsidies is higher.