Industrial Policy Implementation: Empirical Evidence from China's Shipbuilding Industry *

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Abstract

Industrial policies are widely used across the world. In practice, designing and implementing these policies is a complicated task. In this paper, we assess the long-term performance of different industrial policy instruments, which include production subsidies, investment subsidies, entry subsidies, and consolidation policies. To do so, we examine a recent industrial policy in China aiming to propel the country's shipbuilding industry to become the largest globally. Using firm-level data and a dynamic model of firm entry, exit, investment, and production, we find that (i) the policy boosted China's domestic investment, entry, and international market share dramatically, but delivered low returns and led to fragmentation, idleness, as well as depressed world ship prices; (ii) the effectiveness of different policy instruments is mixed: production and investment subsidies can be justified by market share considerations, while entry subsidies are wasteful; (iii) counter-cyclical policies and firm-targeting can substantially reduce distortions. Our results highlight the critical role of firm heterogeneity, business cycles and firms' cost structure in policy design.

Keywords: Industrial policy, China, Investment, Dynamics, Shipbuilding

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1 Introduction

Industrial policy has been widely used in both developed and developing countries. Examples include the U.S. and Europe after World War II, Japan in the 1950s and 1960s (Johnson, 1982; Ito, 1992), South Korea and Taiwan in the 1960s and 1970s (Amsden, 1989; Lane, 2019), China, India, Brazil, and other developing countries more recently (Stiglitz and Lin, 2013; Peres, 2013). It is also back in the spotlight in developed countries, such as Europe and the US.[1] Designing and implementing industrial policies is a complicated task. Governments seeking to promote the growth of selected sectors have a wide range of policy tools at their disposal, including subsidies on output, provision of loans at below-market interest rates, preferential tax policies, tariff and non-tariff barriers, and so on. They must also choose the timing of policy interventions and whether to target selected firms within an industry. As Rodrik (2010) puts it, "The real question about industrial policy is not whether it should be practiced, but how." This paper tackles precisely this question.

We focus on China's shipbuilding industry which provides a clear illustration of the challenges associated with designing effective industrial policies. At the turn of the century, China's nascent shipbuilding industry accounted for less than 10% of the world production. During the 11th (2006-2010) and 12th (2011-2015) National Five-Year Plans, shipbuilding was dubbed a pillar industry in need of special oversight and consequently received numerous policy interventions. Within a few years, China overtook Japan and South Korea to become the world's leading ship producer in terms of output. However, this impressive output growth was achieved via a massive entry wave of new firms, which exacerbated industry fragmentation and low capacity utilization.[2] Plummeting ship prices during the aftermath of the financial crisis threatened the survival of many firms in the industry and prompted the government to place a moratorium on the entry of new firms. In addition, policy support was shifted towards selected firms on a "White List" in an effort to promote industry consolidation.[3]

The example of shipbuilding, which echoes patterns observed in other industries (steel, solar panels, auto, etc.), highlights the complexity of designing industrial policies and the difficulties associated with empirically evaluating past experiences. Not only do we need to identify policies that are implemented, which are often opaque, we also need to properly account for the role of industry

[1] See *The Economist* 2019: https://www.economist.com/europe/2019/02/21/how-china-has-pushed-germany-to-rethink-industrial-policy.

[2] This pattern is not unique to the shipbuilding industry. In many other industries that received government support in China in the 1990s and 2000s, such as steel, auto, and solar panels, sector growth was also characterized by the proliferation of small firms and an overall fragmented industry structure (Figure 1). This is in contrast to the experience of other countries. For example, South Korea's industrial policy of promoting heavy industries in the late 1970s mainly targeted large business conglomerates or the "chaebol" (Fukagawa, 1997).

[3] The "White List" consists of firms that "meet the industry standard" and thus receive priority in government support. See Section 2 for more details.

dynamics, business cycles and firm heterogeneity. As a result, relative to the large theoretical literature on industrial policy and its popularity in practice, the empirical analysis is much more limited (see Lane (2020) for an excellent review.)

In this paper, we use shipbuilding as a case study to address two questions of interest. First, how did China's industrial policy affect the evolution of both the domestic and global industry? Second, what is the relative performance of different policy instruments, which include production subsidies (e.g., subsidized material inputs, export credits, buyer financing), investment subsidies (e.g., low-interest long-term loans, expedited capital depreciation), entry subsidies (e.g., below-market-rate land prices), and consolidation policies (White Lists)?

A critical challenge in our analysis is the lack of information on the nature and magnitude of government subsidies. This is not specific to our analysis. As documented in a large literature (Bruce, 1990; Young, 2000; Anderson and Van Wincoop, 2004; Poncet, 2005; Kalouptsidi, 2018; Barwick et al., 2020; Bai and Liu, 2019), industrial subsidies are often purposefully covert and notoriously difficult to detect and measure. To overcome this challenge, we thus adopt the approach in the existing literature and recover the magnitude of subsidies by estimating the cost structure of the industry before and after the policies were implemented.

Specifically, we develop a structural model of the industry that incorporates dynamics and firm heterogeneity, both of which are essential for determining the long-term implications of industrial policy. In each period, firms engage in Cournot competition: they choose production output subject to convex production costs and charge a markup. Then they decide whether or not to exit and how much to invest conditional on staying. Investment increases firm capital, which in turn reduces future production costs. Potential entrants make entry decisions based on their expected lifetime profitability, as well as the cost of entry. China's industrial policy affects all of these decisions by lowering the relevant costs.

We next estimate the model using data on firm-level output, capital, and characteristics, as well as ship market prices. The main primitives of interest are production costs, investment costs, entry costs, exit scrap values, as well as the demand for ships. Estimates for industrial subsidies are obtained via changes in firm costs upon the introduction of different policies. Our empirical strategy departs from the literature on firm dynamic decisions in two ways. First, we estimate the fixed costs of production from accounting data to accommodate periods in the latter part of our sample when idling capacity and zero production plagued the industry. Second, we allow for continuous investment under unobserved cost shocks and adjustment costs, in light of heterogeneous investment across firms with similar attributes.[4] Once the key parameters are uncovered, we evaluate the long-term implications of China's industrial policy in counterfactual analysis, simulating

[4]Ryan (2012) is another example of continuous investment and heterogeneous shocks. Unlike our setting, he formulates investment as following an S-s rule.

the global shipbuilding industry over time and turning on and off different policy instruments as needed. Methodologically, our framework is quite general and can be adapted to the evaluation of other sector-specific industrial policies.

Our analysis delivers four sets of main findings. First, like many other policies unleashed by China's central government in the past few decades, the scale of the industrial policy in the shipbuilding industry is massive compared to the size of the industry. Our estimates suggest that the policy support from 2006 to 2013 boosted China's domestic investment and entry by 140% and 120%, respectively, and increased its world market share by over 40%. Importantly, 70% of this expansion occurred via business stealing from rival countries (Japan and South Korea). However, relative to its magnitude, the policy generated negligible profits to domestic producers and modest gains to worldwide consumer surplus. In the long run, the gross rate of return of the adopted policy mix, as measured by the lifetime profit gains of domestic firms divided by the magnitude of the policy, is only 18%. The policy attracted a large number of inefficient producers and exacerbated the extent of excess capacity. In addition, fixed costs contributed to the low returns due to the volatile nature of the industry.

Second, the effectiveness of different policy instruments is mixed. Production and investment subsidies can be justified on the grounds of revenue considerations, but entry subsidies are wasteful and lead to increased industry fragmentation and idleness. This is because entry subsidies attract small and inefficient firms; in contrast, production and investment subsidies favor large and efficient firms that benefit from economies of scale. As expected, production subsidies are more effective at achieving output targets, while investment subsidies facilitate higher capital formation over the long run. In addition, distortions are convex so that the rate of return deteriorates when multiple policies interact.

Third, our analysis suggests that the efficacy of industrial policy is significantly affected by the presence of boom and bust cycles, as well as by heterogeneity in firm efficiency, both of which are notable features of the shipbuilding industry. A counter-cyclical policy would have out-performed the pro-cyclical policy that was adopted by a large margin. Indeed, their effectiveness at raising long-term industry profit differs nearly twofold, which is primarily driven by two factors: a composition effect (more low-cost firms operate in a bust compared to a boom) and the much more costly expansion during booms (due to convex production and investment costs).

Fourth, we examine the consolidation policy adopted in the aftermath of the financial crisis, whereby the government implemented a moratorium on entry and issued a "White List" of firms that are prioritized for government support. This strategy was adopted in several industries to curb excess capacity and create national champions that can compete globally.[5] Consistent with the evidence discussed above, we find that targeting low-cost firms significantly reduces distortions.

[5]See https://www.wsj.com/articles/SB10001424127887324624404578257351843112188.

That said, the government's White List was suboptimal and favored state-owned enterprises (SOEs) at the expense of the most efficient firms.

Our results highlight potential mechanisms underlying industrial policies' diverging outcomes across countries. For instance, in East Asian countries, where industrial policy was considered successful, the policy support was often conditioned on performance. In contrast, in Latin America where industrial policy was viewed as ineffective, there were no mechanisms to weed out non-performing beneficiaries (Rodrik, 2009). Our analysis illustrates that similar mechanisms are at work in China's modern-day industrial policy in the shipbuilding industry. The policy's return was low in earlier years when output expansion was primarily fueled by the entry of inefficient firms, but increased considerably over time as the government used 'performance-based' criteria (the White List) to channel subsidies. This kind of targeted policy design is substantially more successful than open-ended policies that benefit all firms.

Finally, we examine possible rationales for adopting industrial policy in our context. As firms have market power which distorts market output, strategic trade considerations may provide an incentive for policymakers to intervene. Nonetheless, simulation results suggest that strategic trade benefits are small, as the extent of market power is limited. In addition, there is no evidence of industry-wide learning-by-doing (Marshallian externalities), another common rationale for industrial policy. In terms of spillovers to the rest of the economy, we find limited evidence that the shipbuilding industry generates significant spillovers to other domestic sectors (e.g., steel production, ship owning, or the labor market).

On the other hand, the substantial increase in the global fleet ensuing from China's increase in ship production did lower freight costs and increased China's imports and exports. Our (back of the envelope) calculations indicate that the policy (which averaged \$11.3bn annually between 2006 and 2013) lowered freight rates by 6% and boosted China's trade volume by 5%, or \$144 bn annually. That said, evaluating the welfare gains of the associated increase in trade volume requires a general equilibrium trade model and falls beyond the scope of this paper. Finally, non-economic arguments, such as national security, military considerations, and the desire to be the world number one (Grossman, 1990), could also be relevant in designing this policy. Regardless of the motivation, our analysis estimates the policy's costs and assesses the relative efficacy of different policy instruments.

Related Literature There is a large theoretical literature on industrial policy (Hirschman, 1958; Baldwin, 1969; Krueger, 1990; Krugman, 1991; Harrison and Rodriguez-Clare, 2010; Stiglitz et al., 2013; Itskhoki and Moll, 2019). The earlier empirical literature on industrial policy mostly focuses on describing what happens to the benefiting industries (or countries) with regards to output, revenue, and growth rates (Baldwin and Krugman, 1988; Head, 1994; Luzio and Greenstein, 1995;

Irwin, 2000; Hansen et al., 2003), while recent studies recognize the importance of measuring the impact on productivity and cross-sector spillovers (Aghion et al., 2015; Lane, 2019; Liu, 2019; Manelici and Pantea, 2021). Related literature analyzes trade policies, in particular export subsidies (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 (Kline and Moretti, 2014; Neumark and Simpson, 2015; Criscuolo et al., 2019), and environmental subsidies (Yi et al. 2015; Aldy et al. 2018).

Much of the existing literature focuses on whether an industrial policy should be implemented and which sectors should be targeted. Our analysis is complementary to the literature. We take a targeted sector as given and examine the design of industrial policy, a question that has received much less attention in prior work. To the best of our knowledge, our paper provides the first structural analysis of the design and performance of a large-scale industrial policy using firm-level data. The key features of our analysis are rich firm heterogeneity and market power, real business cycles and firm dynamics, and a variety of policy instruments in an important industry. We illustrate that how industrial policy is implemented can radically affect the dynamic evolution of an industry. At the same time, different policy instruments may entail very different returns.

Our paper also contributes to the growing literature studying how China's industrial development has been shaped by a variety of policy interventions, including consolidation policies (Rubens, 2021), R&D tax incentives (Chen et al., forthcoming), and value-added (VAT) tax reforms (Liu and Mao, 2019; Chen et al., 2019; Bai and Liu, 2019). In addition, our study builds on an emerging literature on the shipbuilding industry (Thompson, 2001, 2007; Hanlon, 2018). Kalouptsidi (2018) is closely related to our paper and detects evidence of production subsidies for a subset of bulk carriers (Handysize). In contrast, we examine the design, implementation, and efficacy of China's overall industrial policy and its impact on the global shipbuilding industry.

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). Complementing the macro literature that focuses on inaction (zero investment) and adjustment costs, our approach can rationalize different investments chosen by observably similar firms while at the same time accommodate inaction and adjustment costs. Our analysis of firm investment builds on Ackerberg et al. (2007) and provides one of the first empirical applications of this model with continuous investment. This approach can be used in a variety of settings where heterogeneity in investment is an important consideration. In addition, our framework is quite general and can be easily adapted to the evaluation of other sector-specific industrial policies.

The rest of the paper is organized as follows. Section 2 provides an overview of China's shipbuilding industry and discusses the relevant industrial policy and our datasets. Section 3 presents the model. Sections 4 and 5 describe the estimation strategy and empirical results. Section 6 quantifies the policy impact on industry evolution and evaluates the performance of different policy instruments. Section 7 evaluates traditional rationales for industrial policy. Section 8 concludes.

2 Industry Background and Data

2.1 Industry Background

Shipbuilding is a classic target of industrial policy, as it is often seen as a strategic industry for both commercial and military purposes. During the late 1800s and early 1900s, Europe was the dominant ship producer (especially the UK). After World War II, Japan subsidized shipbuilding along with several other 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 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 the 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 output) [...] 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 Hebei), the East Sea area (Shanghai, Jiangsu, and Zhejiang), and the South Sea area (Guangdong).

The most important initiative was the 11th National Five-Year Economic Plan (2006-2010) which 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. Jiangsu is the close second, and set up dedicated banks to provide shipyards 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 tons (DWT) to be achieved by 2010, and 22 million DWT by 2015. Both goals were met several years in advance. Table A1 in the Appendix documents major national policies issued during our sample period.

The government adopted interventions that affected firms along several dimensions. We group policies that supported the Chinese shipbuilding industry into three categories: production, investment, and entry subsidies. Production subsidies lower the cost of producing ships. For instance, the government-buttressed domestic steel industry provides cheap steel, which is an important input for shipbuilding. Besides subsidized input materials, export credits (Collins and Grubb, 2008) and buyer financing in the form of collateral loans provided by local banks constitute other important components of production subsidies.[6] To help attract buyers, shipyards have traditionally offered loans and various financial services to facilitate purchasing payment. 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.[7] Finally, shortened processing time and simplified licensing procedures, as well as heavily subsidized land prices along the coastal regions, greatly lower the cost of entry for potential shipyards.

In response to the 2008 economic crisis that led to a sharp decline in global ship prices and in an effort to curb excess capacity and industry fragmentation, the government unveiled the 2009 *Plan on Adjusting and Revitalizing the Shipbuilding Industry* that resulted in an immediate moratorium on entry with increased investment subsidies to existing firms. This marked an important shift in China's industrial policy in the shipbuilding sector, where government support moved toward facilitating consolidation and creating large successful firms that can compete against international conglomerates. 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 that "meet the industry standard" and thus receive priority in subsidies and bank financing.[8] The so called "White List" included sixty firms in 2014 upon announcement.

In this paper, we focus on the production of three ship types: dry bulk carriers, tankers, and containerships, which account for more than 90% of world orders in tons in our sample period. Dry bulk carriers transport homogeneous and unpacked goods, such as iron ore, grain, coal, steel, etc., for individual shippers on non-scheduled routes. Tankers carry chemicals, crude oil, and other oil products. Containerships carry containerized cargos from different shippers in regular port-to-port itineraries. As these types of ships carry entirely different commodities, they are not substitutable; we thus treat them as operating in separate markets.

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

[7]China implemented a value-added tax reform in 2009 that might have stimulated investment (Chen et al., 2019). This policy has limited impact on shipbuilding firms in our sample which are already exempt from value-added tax via exports subsidies.

[8]In practice, favorable financing terms and capital market access are often limited to firms on the White List post 2014.

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

2.2 Data

Our empirical analysis draws on a number of datasets. The first dataset comes from Clarksons and 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 Tons (CGT), for all major ship types, including bulk carriers, tankers, and containerships. CGT, 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 second data source is the annual database compiled by the National Bureau of Statistics (NBS) on Chinese manufacturing firms. 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).[9]

In addition to these firm-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.[10] The steel ship plate price is employed as a cost shifter, as steel is a major input in shipbuilding. We merge all datasets to obtain a quarterly panel of Chinese, South Korean, and Japanese shipyards ranging from 1998 to 2013.

2.3 Descriptive Evidence and Summary Statistics

Similar to many other manufacturing industries in China, the shipbuilding industry experienced exponential growth since the mid 2000s. China became the largest shipbuilding country in terms of deadweight tons in 2009, overtaking South Korea and Japan. Figure 2 plots China's rapid ascent into global influence from 1998 to 2013. At the same time, a massive entry wave of new shipyards

[9] One limitation of the NBS database is that data for 2010 are 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.

[10] We 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. Note that all monetary values reported in this paper are discounted and deflated to the 2006 RMB. The conversion rate for this period was 6.88 RMB for 1 U.S. dollar.

occurred along China's coastal area.[11] Figure 3 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 shipyards. In contrast, the number of new shipyards in China registered a historic record and exceeded 30 per year 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*.[12]

The rise in entry was accompanied by a large and unprecedented increase in capital expansion (Figure 4). 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 remaining 57% 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 policy 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 5 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 to 2013. China's production and investment, on the other hand, continued to expand well after the financial crisis.

Table 1 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 bulkers and less frequently for tankers 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 that rendered Chinese shipyards

[11]The entry year for a shipyard is defined as the first year it takes an order or the first year it delivers minus two years to account for the time it takes to build a ship, whichever is earlier. As an additional measure of firm entry, we extracted the registration information (date and business scope) for 90% of Chinese firms from the Trade and Industry Bureau database. The overall entry pattern is similar across these two measures: entry peaked in 2005-2007 and became minimal post 2009. We use the entry year from the Clarkson's database in our main analysis, as the registration data suffer from several limitations. First, it is difficult to identify firms whose core business is shipbuilding from the registration data alone, as firms often register with a wide business scope. In addition, some firms switch from ship repairs and marine equipment to shipbuilding years after their official registration.

[12]No 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) past 2009.

increasingly vulnerable to long periods of inaction during the recession, is a key feature of the industry that informs our modeling choices in Section 3.

Finally, 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 ship 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 engage in Cournot competition by choosing statically how much to produce. 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 $j = 1,...,J_t$ firms in the world that produce ships. There are $m = 1,...,M$ types of ships, such as dry bulk carriers, tankers, and containerships. Ships within a type are homogeneous.

Ship Demand The aggregate inverse demand for ship type m at time t is given by the function,

$$P_{mt} = P\left(Q_{mt}, d_{mt}\right) \tag{1}$$

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:

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

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 in later periods of our sample when the aggregate demand for new ships plummeted and many shipyards reported prolonged periods with zero production, fixed costs constitute a substantial fraction of overall costs and should thus not be omitted. They capture wages and compensation for managers, capital maintenance, land usage, etc.

The second term, $c_m(q_{jmt}, s_{jmt}, \omega_{jmt})$, is the variable production cost. We use s_{jmt} to denote firm characteristics (e.g. capital, backlog, age, location, ownership status), as well as aggregate cost shifters that affect all shipyards (e.g. government subsidies, steel prices). In addition, production costs depend on a shock ω_{jmt}: the larger ω_{jmt} is, the less productive the firm is.

Firms engage in Cournot competition. They choose how many tons of ship type m to produce in each period, q_{jmt}, to maximize their profits, taking as given the production decisions of rival firms. If the optimal production tonnage for type m, q^*_{jmt}, is positive, it satisfies the following first order condition:

$$P_{mt} + q_{jmt}\frac{\partial P\left(Q_{mt}, d_{mt}\right)}{\partial q_{jmt}} = MC_m\left(q^*_{jmt}, s_{jmt}, \omega_{jmt}\right) \tag{2}$$

where $MC_m\left(q_{jmt}, s_{jmt}, \omega_{jmt}\right)$ is the marginal cost of production of type m. Note that firms are able to charge a markup equal to $q_{jmt}\frac{\partial P(Q_{mt}, d_{mt})}{\partial q_{jmt}}$ (in absolute value), thus distorting the market output levels.

Firm Profit Let $s_{jt} = \{\{s_{i1t}, ..., s_{iMt}\}_{i=1,...,j,...,J}\}$ denote firm j's state variable at time t, which is the union of its own observed state variables across ship types, as well as the states of its rivals. Firm j's total expected profit from all types, before the cost shocks are realized, is given by:

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

where $\pi_m(s_{jt}, \omega_{jmt})$ is firm j's profit from producing ship type m,[13] and $\mathbb{E}$ integrates out uncertainties in firms' production cost shocks.

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 private scrap (sell-off) value, ϕ_{jt}, that is distributed i.i.d. with distribution F_ϕ 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, ν_{jt}, that is distributed i.i.d. with distribution F_ν, and chooses investment i_{jt} at cost $C^i(i_{jt}, \nu_{jt})$. The amount invested i_{jt} is added to the firm's capital stock next period, which in turn affects its future production costs.

The value function for incumbent firm j is:

$$\begin{aligned} V(s_{jt}, \phi_{jt}) &= \pi(s_{jt}) + \max\left\{\phi_{jt}, \mathbb{E}_{\nu_{jt}}\left(\max_i\left(-C^i(i, \nu_{jt}) + \beta\mathbb{E}\left[V(s_{jt+1})|s_{jt}, i\right]\right)\right)\right\} & (3)\\ &= \pi(s_{jt}) + \max\left\{\phi_{jt}, CV(s_{jt})\right\} \\ CV(s_{jt}) &\equiv \mathbb{E}_{\nu_{jt}}\left(-C^i(i^*, \nu_{jt}) + \beta\mathbb{E}\left[V(s_{jt+1})|s_{jt}, i^*\right]\right) & (4)\end{aligned}$$

[13]We take firms' product types as given and do not explicitly model firms' choices of which ship type to produce.

where $CV(s_{jt})$ denotes the continuation value, which includes the expected cost of optimal investment and the discounted future stream of profits. Note that, $\mathbb{E}_{\nu_{jt}}$ is the expectation with respect to the random investment cost shock ν_{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 ϕ_{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,

$$p^x(s_{jt}) \equiv \Pr\left(\phi_{jt} > CV(s_{jt})\right) = 1 - F_\phi\left(CV(s_{jt})\right) \tag{5}$$

where F_ϕ is the distribution of ϕ_{jt}.

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

$$\beta \frac{\partial \mathbb{E}\left[V(s_{jt+1})|s_{jt}, i^*\right]}{\partial i} \leq \frac{\partial C^i(i^*, \nu_{jt})}{\partial i} \tag{6}$$

with equality if and only if the optimal investment is strictly positive, $i^*(s_{jt}, \nu_{jt}) > 0$. When the investment costs are prohibitively high or the expected benefit too low, firms opt for no investment. Capital depreciates at rate δ that is common to all firms.

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

$$C^i(i_{jt}, \nu_{jt}) = c_1 i_{jt} + c_2 i_{jt}^2 + c_3 \nu_{jt} i_{jt} + c_4 T_t i_{jt} \tag{7}$$

This (quadratic) specification borrows from the macro literature on investment costs (e.g. Cooper and Haltiwanger 2006) with two important differences. First, investment costs depend on the unobserved marginal cost shock ν_{jt}. Much of the existing literature has focused on the lumpy nature of investment (inaction) and adjustment costs, but has not modeled heterogeneous investment decisions among observationally similar firms.[14] In practice, many factors affect firms' investment decisions. Some firms have political connections that grant them favorable access to the capital market (Magnolfi and Roncoroni, 2018). Others might be experienced at sourcing from equipment suppliers at low costs. We accommodate heterogeneous investment decisions among similar firms by introducing ν_{jt} that shifts the marginal cost of investment across firms. Note that ν_{jt} can also explain inaction: firms with unfavorably large ν_{jt} will choose not to invest. Once we control for ν_{jt}, additional adjustment costs, such as $\frac{i_{jt}^2}{k_{jt}}$ and/or a (random) fixed cost, contribute little to the model fit.[15] A second difference from the literature is that we allow government policies T_t to directly

[14]Notable exceptions include Ryan (2012) that models firm investment decisions as following an S-s rule and Collard-Wexler (2013) that analyzes discrete investment.

[15]The estimated fixed cost of investment, once included, is economically small. Fixed costs are associated with an

affect the marginal cost of investment.

Entry In each period t, $\bar{N}$ potential entrants observe the payoff relevant state variables and their private i.i.d. entry cost κ_{jt} before making a one-time entry decision. The entry cost is drawn from a distribution F_κ that is shifted by the government policy. If potential entrant j decides not to enter, it vanishes with a payoff of zero.[16] If j 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 the following period once the firm becomes an incumbent and begins operation.

Potential entrant j solves,

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

where κ_{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 κ_{jt} drawn is lower than the value of entering, i.e.

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

Since κ_{jt} is random, the potential entrant enters with probability, p^e_{jt}, defined by,

$$p^e_{jt} \equiv \Pr\left(\kappa_{jt} \leq VE(s_{jt})\right) = F_\kappa\left(VE(s_{jt})\right) \tag{8}$$

Equilibrium A Markov-Perfect Equilibrium of this model consists of policies, $\{q_{jmt}\}_{m=1}^M$, $i^*(s_{jt}, v_{jt})$, $p^x(s_{jt})$, p^e_{jt}, value function $V(s_{jt})$ and prices P_{mt}, such that the production quantity satisfies (2) and maximizes 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 aggregate supply. Moreover, the incumbent's value function satisfies (3) and firms employ the above policies to form expectations.[17]

Industrial Policy Industrial policies affect the costs of production, investment, and entry and are thus part of the payoff relevant state variables, s_{jt}. We assume that these policies are unexpected

inaction region where firms will not make investments smaller than a threshold. The larger the fixed cost, the larger the inaction region. Firms do make small investments in our data, which is inconsistent with a large fixed cost.

[16] Here we follow the bulk of the empirical literature on industry dynamics (Ericson and Pakes, 1995), where the entry decision involves a simple comparison between the value from entering the market and the random entry cost.

[17] Existence of equilibrium follows from Ericson and Pakes (1995) and Doraszelski and Satterthwaite (2010).

and perceived as permanent by all shipyards once they are in place. This is consistent with the empirical patterns documented in Section 2.3, where the spike in entry and investment coincides remarkably well with the timing of these policies. We assume that the equilibrium before and after the policy is stationary and that thus the value functions are not indexed by t.

Discussion We close this section with a brief discussion on our assumptions. We assume that ships are homogeneous within a type conditioning on size. To substantiate this assumption, we explore a sub-sample of new ship purchase contracts with detailed price information and ship attributes. Ship type, ship size in CGT, and quarter dummies explain most of the price variation: the R^2 of a hedonic price regression when these are the only regressors is 0.93 for bulkers, 0.94 for tankers, and 0.75 for containerships. Ship and shipyard characteristics (age, country, number of docks and berths, etc.) have limited explanatory power: including shipyard fixed effects in the hedonic regressions adds little to the fit except for containerships where the R^2 increases moderately. On the ship buyer side (shipowners), monopsony power is not a first-order issue as the concentration among shipowners is low.[18]

We assume away 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 interventions on firms' production costs. This is partly because the amount of drastic production expansion seen in practice cannot be explained by inter-temporal considerations that arise with dynamic production. We allow backlogs to affect the marginal cost of production, which proxies for dynamic considerations in a reduced-form manner.

We assume that cost shocks ω_{jmt} are i.i.d. There are several reasons for this choice. First, ω_{jmt} is estimated to be only moderately persistent, with a serial autocorrelation of 0.28 for bulkers, 0.27 for tankers, and 0.39 for containerships. Second, while it is straightforward to estimate the persistence of these shocks using observed quantity choices (see Section 4.1), 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 ν_{jt} are assumed i.i.d. Given that aggregate investment increased by more than four-fold within a year upon the announcement of the 11th National Five-Year Plan (Figure 4) 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.

[18]The containership segment may be concentrated among the operators, but they lease containerships from a large number of shipowning firms.

Last, we follow the literature standard (Ryan, 2012) and assume that government policies are perceived as permanent by all firms. Relaxing this assumption and estimating firms' expectations 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 lower 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 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 dynamic decisions (entry, exit, and investment) for Chinese shipyards. This is because aggregate data suggest that entry, exit, and capacity expansion are limited in Japan and South Korea (OECD, 2015, 2016), and because we do not have firm-level data on dynamic decisions for shipyards outside China.

This section is self-contained and the reader may omit it and proceed to the results section if desired. Section 4.1 discusses estimation of the static parameters (demand and production costs). Sections 4.2.1 and 4.2.2 present the first and second stage of estimating dynamic parameters respectively (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:

$$Q_{mt} = \alpha_{0m} + \alpha_{pm} P_{mt} + d'_{mt} \alpha_{dm} + \varepsilon^{d}_{mt} \tag{9}$$

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.[19] 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

[19]The 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.

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.

Prices are instrumented by steel prices and steel production.[20] 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 ε_{mt}^{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 ($\varepsilon_{mt}^{d} > 0$) is unlikely to have much impact on steel prices.[21] As there is a single global market for each ship type, the demand curves are estimated from time series variation.

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

$$MC_m(q_{jmt}, s_{jmt}, \omega_{jmt}) = \beta_{0m} + s_{jmt}\beta_{sm} + \beta_{qm}q_{jmt} + \omega_{jmt}$$

where q_{jmt} denotes tons of ship type m produced by firm j in period t. Because of time to build, there are differences between orders placed, deliveries and production in a given period. We use orders as a measure of q_{jmt}, because the number of tons ordered is the relevant quantity decision made by the firm and responds to observed ship prices. In addition, our data source reports orders and deliveries instead of production and it is not straightforward to infer production from orders.

Cost shifters s_{jmt} include firm j's capital and its backlog of all ship types. Capital stock accumulates through investment over time and reduces production costs via economies of scale. Backlogs capture learning by doing, economies of scale, and possibly capacity constraints. In addition, s_{jmt} contains shipyard j's age and ownership status, nationality and region (for Chinese firms), a dummy for large firms, the steel price, as well as polynomial terms of these state variables.[22] Lastly, s_{jmt} includes dummies for the policy intervention between 2006 and 2008 and then from 2009 onwards. The production cost shock ω_{jmt} is assumed to be normally distributed with mean zero and variance $\sigma_{\omega m}^{2}$. The parameters characterizing shipyards' production costs are

[20]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.

[21]Internationally traded steel accounts for less than 8%of the volume of goods transported by dry bulk carriers (UNCTAD, 2018). Thus, changes in the steel price that affect the amount of steel transported by sea are unlikely to directly affect demand for dry bulk carriers.

[22]Large firms are defined as firms that account for top 90% of aggregate industry revenue from ship production during our sample period. Fifty-five Chinese shipyards are large. 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 improves the fit of our model.

$\theta^q \equiv \{\beta_{0m}, \beta_{sm}, \beta_{qm}, \sigma_{\omega m}\}_{m=1}^{M}$. We estimate these parameters via a Tobit model:

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

Note that θ^q is consistently estimated even when ω_{jmt} is correlated over time, despite the fact that this likelihood function assumes (erroneously) that ω_{jmt} is i.i.d. (Robinson, 1982).[23] To obtain the standard errors allowing for autocorrelation in ω_{jmt}, we use 500 block bootstraps.

A firm's production decisions provide no information on the fixed cost c_0 (costs of land usage, capital maintenance, etc.), since the firm incurs this regardless of whether it produces. Unlike most empirical studies where fixed costs are assumed away, we take advantage of the accounting cost data to calibrate c_0, as firms report costs incurred even during periods when the production facility is idle. Details on this calibration procedure are reported in Appendix B.1. Restricting the fixed cost to zero may bias the counterfactual analyses (Aguirregabiria and Suzuki, 2014; Kalouptsidi et al., 2021); we discuss this issue further in Section 6.1.

4.2 Estimation of Dynamic Parameters

We use observed firm investment decisions, entry and exit to estimate dynamic parameters. An important complication is that firms' optimal choices depend on the value function (as well unobserved cost shocks for investment), which is unknown. To tackle this challenge, we follow the tradition of Hotz and Miller (1993) and Bajari et al. (2007) (henceforth BBL) and estimate the parameters 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. We approximate the value function by a set of B-spline basis functions of state variables, following Sweeting (2013) and Barwick and Pathak (2015). In the second stage, we formulate the likelihood of the observed investment and exit and recover the dynamic parameters of interest. Appendix B contains additional details.

4.2.1 First Stage

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 are robust across different specifications:

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

[23] Intuitively 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.

where χ_{jt} equals 1 if firm j exits in period t, $h(s_{jt})$ is a flexible polynomial of the states, and Φ 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 $i^*_{jt}(s_{jt}, \nu_{jt})$ is implicitly defined by the first order condition in equation (6). Our goal is to flexibly estimate $i^*_{jt}(s_{jt}, \nu_{jt})$. Under reasonable assumptions, one can show that the optimal investment is monotonically decreasing in ν_{jt}: firms with more favorable (smaller) cost shocks invest more, all else equal.[24] As a result, conditioning on s_{jt}, the jth quantile of ν_{jt} corresponds to the $(100 - j^{th})$ quantile of i_{jt} in the data. As shown in Bajari et al. (2007), we can recover the optimal investment policy function $i^*_{jt}(s_{jt}, \nu_{jt})$ as follows:

$$\begin{aligned} F(i|s_{jt}) &= Pr(i^*_{jt} \le i|s_{jt}) = Pr(\nu_{jt} \ge i^{*-1}(s_{jt}, i)|s_{jt}) = Pr(\nu_{jt} \ge \nu|s_{jt}) \\ &= 1 - F_\nu(\nu|s_{jt}) \\ \text{which implies} \qquad i^*|s_{jt} &= F^{-1}\big(1 - F_\nu(\nu|s_{jt})\big) \end{aligned} \tag{10}$$

where $F(i|s_{jt})$ denotes the empirical distribution of investment given the state variables and F_ν is the distribution of ν. The data requirement for estimating this conditional distribution non-parametrically increases dramatically with the number of state variables. We make the simplifying assumption that the investment cost shock ν_{jt} is independent of observed state variables s_{jt} and is additive:

$$i^*_{jt} = h_1(s_{jt}) + h_2(\nu_{jt})$$

where both $h_1(s_{jt})$ and $h_2(\nu_{jt})$ are unknown functions to be estimated. Moreover, since the distribution of ν_{jt} cannot be separately identified from $h_2(\nu_{jt})$ non-parametrically, we assume that ν_{jt} is distributed standard normal. We first flexibly regress observed investment on the state variables to obtain an estimate of $h_1(s_{jt})$. Then we treat $i^*_{jt} - \hat{h}_1\left(s_{jt}\right)$ as the relevant data and estimate function $h_2(\cdot)$ using equation (10).

We do not incorporate divestment in our analysis. Compared to the massive investment undertaken by Chinese shipyards, divestment is much less common and an order of magnitude smaller.[25] Modeling the level of divestment introduces a kink in the cost function and makes the value function non-differentiable, which raises considerable computational challenges.

[24] One sufficient condition for monotonicity is that the value function has increasing differences in investment and the negative of the investment shock.

[25] The aggregate divestment is about 12% of the aggregate positive investment in the industry. We also drop 5% outliers with investment exceeding RMB 250 million or capital stocks exceeding RMB 4 billion. In addition, we perform two robustness checks on estimates of the investment policy function that formally address non-negative investment: Tobit and the Censored Least Absolute Deviation estimator (CLAD). Appendix B.2 provides more details.

State Space The state variable s_{jt} is a high-dimensional object because of the large number of firms in the industry. To reduce the computational burden, we assume that firms do not keep track of the state variables of every rival. Instead, they use industry-level prices as sufficient statistics. As discussed in section 5.1, our estimates suggest that the extent of market power is limited. This approach is similar in spirit to the oblivious equilibrium concept by Weintraub et al. (2008) and Benkard et al. (2015) that approximates the Markov Perfect Equilibrium in industries with many firms, as well as Ifrach and Weintraub (2017). These techniques have been utilized in a series of empirical papers, including Huang et al. (2015), Sweeting (2015), Gerarden (2017), Jeon (2018) and Chen and Xu (2018).

In addition, we utilize the fact that a number of state variables enter the firm's marginal cost linearly and collapse them into a one-dimensional index, $\bar{s}_{jt} = -s_{jmt}\hat{\beta}_{sm}$, using the estimated production cost coefficients. This index measures firms' observed cost efficiency: a higher $\bar{s}_{jt}$ is associated with a lower marginal cost and a higher variable profit. Appendix B.3 provides more details.

State Transition Process Some state variables, such as the province and ownership status, are fixed over time. The transition process for age is deterministic. Capital (k_{jt}) depreciates at a common rate δ: $k_{jt+1} = (1-\delta)k_{jt} + i_{jt}$. We calibrate δ to 2.3% quarterly (Brandt et al., 2012), reflecting China's high interest rates over our sample period. 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: $b_{jm,t+1} = (1-\delta_{bm})b_{jmt} + q_{jmt}$, and calibrate δ_{bm} based on average deliveries.[26]

The equilibrium price for each ship type is a complicated object, determined by the aggregate demand and supply. Following other work in the literature (e.g. Aguirregabiria and Nevo 2013), we model ship prices as an AR(1) process. The introduction of government policies presents a permanent and unanticipated shock to the industry, which can potentially affect the evolution of 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. We assume that the scrap value ϕ_{jt} is distributed exponentially with parameter $1/\sigma_\phi$ and obtain the ex ante value function (i.e. prior to the realization of

[26]The backlog's quarterly depreciation rate , δ_{bm}, equals 6.8% for bulk carriers, 6.3% for tankers, and 6.2% for containerships.

ϕ_{jt}) as follows:

$$\begin{aligned} V(s_{jt}) &\equiv \mathbb{E}_{\phi} V\left(s_{jt}, \phi_{jt}\right) = \mathbb{E}_{\phi}\left[\pi(s_{jt}) + \max\left\{\phi_{jt}, CV(s_{jt})\right\}\right] \\ &= \pi(s_{jt}) + p^x(s_{jt})\mathbb{E}\left(\phi_{jt}|\phi_{jt} > CV\left(s_{jt}\right)\right) + \left(1 - p^x(s_{jt})\right)CV(s_{jt}) \\ &= \pi(s_{jt}) + p^x(s_{jt})\sigma_{\phi} + CV(s_{jt}) \end{aligned} \tag{11}$$

where we use the fact that $\mathbb{E}(\phi|\phi > CV) = \sigma_{\phi} + CV$, as shown in Pakes et al. (2007). $\pi_{jt}(s_{jt})$ and $p^x(s_{jt})$ 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 by B-spline basis functions of state variables, so that $V(s_{jt}) = \sum_{l=1}^{L} \gamma_l u_l(s_{jt})$, 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, it 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.[27] Third, the accuracy of the value function approximation can be controlled via appropriate choices of basis functions and is directly benchmarked by the violation of the Bellman equation (11). Appendix B.3 provides more details on the value function approximation and describes how we construct the state space and estimate $\{\gamma_l\}_{l=1}^{L}$.

4.2.2 Second Stage

Investment and Exit We estimate the dynamic parameters $\theta^i \equiv \left\{\sigma_{\phi}, c_1, c_2, c_3, c_4\right\}$ via MLE, where the sample likelihood includes both the likelihood for exit decisions and the likelihood for investment decisions. The log-likelihood for exit is:

$$\sum_{j,t} \log(f(\chi_{jt})) = \sum_{j,t}\left[(1-\chi_{jt})\log(1-e^{-\frac{CV(s_{jt};\gamma)}{\sigma_{\phi}}}) - \chi_{jt}\frac{CV(s_{jt};\gamma)}{\sigma_{\phi}}\right]$$

where $\chi_{jt} = 1$ if firm j exits in period t.

Optimal investment $i^*_{jt} = i^*(s_{jt}, \nu_{jt})$ is defined by the first order condition in (6). By construction, when $i^*(s_{jt}, \nu_{jt})$ is positive, it is strictly monotonic in ν_{jt}. Assuming it is also differentiable,

[27] 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.

the likelihood of investment can be written as follows:[28]

$$g(i_{jt}) = \begin{cases} \frac{f_v(\nu_{jt})}{|i'(\nu_{jt})|} & \text{if } i^*(s_{jt},\nu_{jt}) > 0 \\ Pr\Big(\big[\beta\frac{\partial \mathbb{E}(V(s_{jt+1};\gamma)|s_{jt},i)}{\partial i} - \frac{\partial C^i(i,\nu_{jt})}{\partial i}\big]_{i=0} \leq 0\Big) & \text{if } i^*(s_{jt},\nu_{jt}) \leq 0 \end{cases}$$

where in the first row, $f_v(\nu_{jt})$ is the density of cost shock ν_{jt} and $|i'(\nu_{jt})|$ is the absolute value of the derivative of $i^*(s_{jt},\nu_{jt})$ with respect to ν_{jt}.

Since the scrap value ϕ_{jt} and investment shock ν_{jt} are assumed independent, the joint log-likelihood for exit and investment decisions is the sum of the two respective log-likelihoods. We maximize the sample log likelihood subject to the constraint that the Bellman equation (11) is satisfied (see Appendix B.3 for details):

$$\max_{\theta^i} L = \sum_{j,t} log(f(\chi_{jt};\theta^i)) + \sum_{j,t} log(g(i_{jt};\theta^i)) \tag{12}$$
$$\text{s.t.} \quad V(s_{jt};\theta^i) = \pi(s_{jt}) + p^x(s_{jt})\sigma_\phi + CV(s_{jt};\theta^i)$$

Entry Cost 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 the random entry cost:

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

Upon entry, an entrant is endowed with a capital that is drawn from the observed distribution of initial capital stocks. The cost of the initial capital equals $C^i(k_{t+1}) = c_1k_{t+1} + c_4T_tk_{t+1}$, which is the same as the cost of investment, except that there are no adjustment costs. We first construct the value of entry $VE(s_{jt})$ plugging in dynamic parameter estimates and then estimate the mean entry costs using the observed entry decisions via MLE.

5 Results

This section follows closely the sequence in Section 4. Section 5.1 presents results on static parameters (demand and production costs). Section 5.2 discusses policy functions and state transition process. Section 5.3 reports dynamic parameter estimates (investment cost, scrap values, as well as entry costs). Section 5.4 evaluates robustness.

[28]The necessary condition for differentiability is that the value function is twice differentiable in investment, which holds since the value function is approximated by smooth spline basis functions.

5.1 Static Parameters

Demand Table C2 in the Appendix reports estimates of the demand curve (9). Demand becomes less elastic post 2006. According to our preferred specification (Column 2), the price elasticity prior to 2006 was 1.8 for bulk carriers and tankers, and 3.4 for containerships. It fell to 0.3 for bulk carriers, 0.6 for tankers, and 1.7 for containerships post 2006.[29] As expected, demand is also responsive to backlog (which affects the future competition that shipowners face): a 1% increase in the backlog leads to a 1% decrease in the quantity of new ships demanded. The remaining variables have the expected sign.

Production Costs Table 2 shows the estimated marginal cost parameters for Chinese yards for each ship type (standard errors are computed from 500 block bootstrap simulations). Marginal costs are measured in 1000 RMB per CGT. The key parameters that characterize the curvature of production cost is type specific (the coefficients on quantity, capital, backlog, and steel price), but coefficients on subsidy dummies and shipyard attributes are restricted to be the same across ship types, to reduce the number of parameters. There are intuitive reasons for these restrictions. For example, the benefit 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, the effect of subsidies on production costs is probably similar across types, as subsidies are not earmarked for a particular ship type and firms can produce different kinds of ships depending on prevailing market conditions.

As China's policies came into effect in 2006 and underwent major changes in 2009, we allow production subsidies to be different between 2006-2008 and from 2009 onwards. The production subsidy is estimated to be 2,100 RMB/CGT between 2006-2008, which is 14-18% of the average price. The subsidy from 2009 onwards is smaller, at 1,220 RMB/CGT. Though our estimation method, sample period, and industry coverage are different from those in Kalouptsidi (2018), the estimated production subsidy is of a similar magnitude (with ours being slightly smaller), which is reassuring.

The parameter β_q captures the increase in marginal cost (in 1000 RMB/CGT) from taking an additional order of 100,000 CGT. The larger β_q is, the more convex the cost function is, and the less responsive supply is to price changes. On average, a 10% price increase causes bulk carrier production to increase by 22%, tanker production by 27%, and containership production by 20%. 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 RMB 100 million for an

[29] Demand elasticity for new ships, which are durable goods, is driven by complicated dynamic considerations that include the composition of existing fleet, the expected number of new ships to be delivered in the near future, and beliefs about future freight rates and fuel costs. Hence, it could either increase or decrease post 2006.

average firm with a capital of RMB 400 million reduces marginal cost of production by 2.7% for bulkers, 2.2% for tankers, and 2.2% for containerships. To put these numbers into context, the average firm's per-period profits would decline by 19% if its capital stock were halved.

Moreover, we find evidence of economies of scale in production with respect to backlog: it is cheaper to produce multiple ships at the same time. The effect of backlog on marginal cost is sizable: increasing backlog by 100,000 CGT reduces marginal cost of production by 13% to 30% on average across ship types. As backlogs continue to increase, capacity constraints begin to bind and drive up marginal costs, as reflected in the positive coefficient (though much smaller in magnitude) on backlog squared.

Firms located in Jiangsu, Liaoning, and Zhejiang provinces (the major shipbuilding regions in China) have lower marginal costs, by 20-26% for Jiangsu, 14-18% for Liaoning, and 11-14% for Zhejiang. As shipyards age, their marginal cost increases by about 1% each year. The (additional) effect of ownership is limited and statistically insignificant. Increases in steel price raise marginal cost for all types, as expected.

Our results indicate that market power distortions are limited. For instance, the average markup for bulk carriers is 6.39% of new ship prices and even lower for tankers and containerships. As a result, firms' production decisions are not far from setting marginal cost equal to the market price, suggesting that the industry is close to competitive.

Finally, the fixed cost calibrated from accounting data equals RMB 15 million per quarter, equivalent to 12% of the industry profit on average. Hence, setting it to zero, as is commonly done in the literature, would significantly overestimate per-period profits accruing to firms.

5.2 Dynamic Parameters: First Stage

Investment Policy Function Table C7 in the Appendix reports estimates for the investment policy function using OLS, Tobit with $h_2(\nu)$ normally distributed, and the Censored Least Absolute Deviation estimator (CLAD) that does not impose a distributional assumption on the cost shock and estimates $h_2(\nu)$ non-parametrically. Our preferred specification is OLS, which delivers the highest model fit. Investment increases in ship prices and decreases in steel price. Firms with higher $\bar{s}_{jt}$ (i.e., more productive) invest more all else equal. As expected, 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 capital stock, reaches a peak when capital is between RMB 1-1.5 billion, and then falls.

Exit Policy Function We estimate the exit policy function via a probit regression. Table C8 in the Appendix presents two sets of estimates using linear terms of all states as well as 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 Dynamic Parameters: Second Stage

Investment and Exit Table 3 reports investment cost estimates. Following the empirical literature on investment (Cooper and Haltiwanger, 2006), we assume that the unit investment cost is equal to one ($c_1 = 1$).[30] Between 2006-2008, the subsidy was 0.27 RMB per RMB of investment, implying that 27% of the per-unit cost of investment (excluding adjustment costs) is subsidized. Post 2009, the subsidy jumps to 0.46 RMB per RMB of investment, which helps rationalize the elevated investment 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 RMB 50 million. The large estimate of c_3 reflects the importance of firm-level unobserved investment shocks. Finally, average scrap value is estimated to be RMB 0.98 billion. 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 C1 in the Appendix plots the distribution of the observed and simulated investment. These two distributions are reasonably similar, though actual investment has a longer tail of large investments and fewer medium-sized ones. Table C10 in the Appendix compares the actual number of exits with the model's estimates. Firm exits are low-probability events and in general difficult to predict (Goldfarb and Xiao, 2016). Our model roughly matches the sample mean but under-predicts the number of exits post 2006.

Entry Cost Estimates The number of entrants is quite different across provinces, with Zhejiang having the highest number of entrants during our sample period at 95, and the three provinces – Liaoning, Jiangsu, Zhejiang – collectively accounting for 70% of new shipyards. Hence, we estimate the entry cost separately for Liaoning, Jiangsu, Zhejiang, and the rest of China.[31] We also allow the entry cost to differ across policy periods. Table 4 reports estimates for κ_{jt}, the mean entry costs, for period before 2006, between 2006 and 2008, and post 2009 respectively. In light of 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 51% in Liaoning to

[30] Monte Carlo evidence indicates that it is difficult to identify all cost parameters in equation (7).

[31] 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. The observed entry peaked earlier in Zhejiang than the rest of the country.

64% in Jiangsu. Entry costs increased substantially in 2009 when the entry moratorium was put in place. Conditional on entering, the average entry cost paid is RMB 2.5 billion, close to a shipyard's accounting value.[32] Our estimated number of entrants is reasonably close to the actual number of entrants in each policy period (Table C11 in the Appendix).

5.4 Robustness

The baseline specification estimates production costs separately for each country. Table C4 in the Appendix displays parameter estimates pooling shipyards from all three countries, which amounts to a differences-in-differences estimator. As we do not observe capital for Japanese and South Korean shipyards, we set their capital stock to zero and add country dummies. Results are qualitatively similar to the baseline, though the 2006-08 subsidy is somewhat larger. We prefer the baseline specification, which allows more flexibility in capturing production differences across countries and delivers a more conservative estimate of the subsidy magnitude.[33]

Next, we explore whether there is evidence of learning-by-doing among Chinese shipyards (Benkard, 2004). We examine both within-firm and industry-wide learning-by-doing by allowing the marginal cost of production to depend on a firm's past production, as well as the industry cumulative past production. The results are illustrated in Table C5 in the Appendix. Despite the potential upward bias in the estimated spillover effects in the absence of suitable instruments, our estimates suggest no evidence of learning-by-doing: marginal costs tend to *increase* rather than decrease in past production. This is consistent with industry reports that the technology for producing ships, especially bulk carriers and tankers, has been around for decades and is mature. Incorporating a time trend or excluding new shipyards that entered after the policy announcement (which might have newer and better technologies) leads to similar results (see Table C6 in the Appendix). We have also estimated production subsidies separately for each region. They are higher in Jiangsu and Liaoning than in Zhejiang and the rest of China, although the differences are statistically insignificant.

While in principle the estimated production costs depend on demand elasticity for new ships, in our setting they are robust to demand elasticity largely because markups are modest. For example, assuming the pre-2006 demand elasticity to be the same as the post-2006 demand elasticity only moderately increases the average markup from 6.39% of the average price to 6.71% for bulk carriers and has little impact on cost estimates.

A common challenge in estimating entry costs is that the number of potential entrants $\bar{N}$ is

[32]The average entry cost conditional on entering is given by $\mathbb{E}(\kappa_{jt}|\kappa_{jt} \leq VE(s_{jt}))$. See http://www.jiemian.com/article/1483665.html and http://www.wuhu.com.cn/compay_mod_file/news_detail.php?cart=3&id=595 for news articles that report the book value of shipyards.

[33]Using cost estimates that pool data from all three countries leads to qualitatively similar counterfactual results.

inherently unobserved. Our baseline assumes that the number of potential entrants in a region in any quarter is twice the maximum number of observed entrants in that region, following the literature (Seim, 2006). We have estimated the entry cost under alternative assumptions (e.g. the maximum number of entrants ever observed, or a large number such as 20 and 40). While a higher number of potential entrants leads to a higher estimate κ_{jt}, the estimated entry cost paid upon entering and entry subsidies are remarkably robust as they are determined by the actual number of entrants and the value of entry (which is estimated using observed ship prices and firm production). Finally, our main specification assumes an annual discount rate of 0.08, reflecting the high interest rates in China (averaging 6% from 1996 to 2018). Results are reasonably robust to different discount factors and exhibit intuitive patterns.[34]

6 Evaluation of China's Industrial Policy in Shipbuilding

Like other countries that use industrial policies to promote specific sectors (Krugman et al., 1983; Lane, 2019), China adopted a variety of policy instruments to boost the shipbuilding industry's output, including production, entry and investment subsidies. Moreover, the policy implementation underwent significant changes over time. Early on, subsidies were widely accessible to all firms. In latter years, the government shifted support towards SOEs and established firms (the White List), while curbing entry of new firms.

In this section, we evaluate the long-term implications of China's industrial policy. Our goal is to assess the relative performance of different policy instruments, taking into account the critical role played by firm heterogeneity, dynamics and business cycles. Specifically, we address the following questions: (i) which policy instruments are the most effective among production, investment and entry subsidies; (ii) how should industrial policy be designed in the presence of industry fluctuations and business cycles; (iii) what are the consequences of targeting subsidies towards selected firms through consolidation policies such as the White List?

Evaluating the industrial policy's long-term impact necessitates simulating the world shipbuilding industry for a long period of time, as both entry and investment have dynamic consequences – the accumulated capital remains productive and new firms often continue operation long after the policy ends.[35] Our simulation begins in 2006, when the Chinese government started subsidizing its domestic industry, and ends in 2050, a period long enough to evaluate a policy's dynamic impacts, though results are similar if the simulation ends in 2099 or between 2050 and 2099. In each coun-

[34] For example, using a discount rate of 0.05, investment subsidy in 2006-2008 changes from 0.27 to 0.25 and subsidy post-2009 changes from 0.46 to 0.4. Intuitively, the higher the discount rate, the less firms value future profits, and the bigger investment subsidies are to rationalize observed jumps in investment.

[35] Production subsidies also have dynamic consequences through backlogs that affect future costs of production, though these effects disappear within a few years when backlogs are converted to deliveries.

terfactual scenario, we turn on and off the subsidies as needed, and report the industry average over 50 independent simulations (results are nearly identical with 100 simulations.) Chinese firms make production, investment, exit and entry decisions. Japanese and South Korean firms choose production. Equilibrium prices are determined by the intersection of the industry demand and supply curves. All monetary values reported in this paper are discounted and deflated to the 2006 RMB. Appendix D.1 contains more details on implementation.

Section 6.1 quantifies how the policy affected the actual evolution of the domestic and global industry between 2006 and 2013. Section 6.2 assesses the long-term performance of different policy instruments and discusses various aspects of policy design, such as the timing of subsidies and targeting. Section 6.3 evaluates the consolidation policy.

6.1 Impact on Industry Evolution

Perhaps not surprisingly, the Chinese government's subsidies had a significant impact on the evolution of every outcome of interest: China's market share, total ship production, ship prices, entry and exit, investment, profits, industry concentration and capital utilization.

Total (discounted) subsidies handed out to Chinese shipbuilders between 2006 and 2013 were close to RMB 624 billion ($91 billion), which can be broken down into entry subsidies (RMB 431 billion), production subsidies (RMB 156 billion) and investment subsidies (RMB 37 billion).[36] These subsidies are massive in comparison to the size of the domestic industry, whose revenue was around RMB 1360 billion during the same period.

Government support increased China's world market share during 2006-13 by 42%. The ascent in market share is most pronounced for bulk carriers, since a large fraction of new shipbuilders produce bulk carriers and the cost advantage enjoyed by Japanese and South Korean firms is narrower for such ships.

In absolute terms, only 30% of China's increased production translated into higher world industry output. The remaining 70% 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 world market share decreased from 48% to 39% and Japan's world market share from 23% to 20% during 2006-2013, with profits earned by shipyards in these two countries falling by RMB 144 billion. Despite Chinese shipyards' rising market share, their gross-profit gains during this period are a modest RMB 153 billion, as the output expansion was largely fueled by the entry of inefficient firms.[37]

[36]While entry subsidies are large in magnitude, they are consistent with a back-of-the-envelope calculation: entry subsidies induced the entry of 80 additional firms and each firm is worth a few billion RMB.

[37]Gross profit equals revenue minus production costs. Net profit equals gross profit plus the scrap value upon exiting, minus the costs of investment and entry. We discuss changes in long-term net profit in detail in Section 6.2.

The rising global supply induced by the subsidies led to a substantial reduction in global ship prices: the price of bulk carriers, oil tankers, and containerships fell by 9.9%, 10.1%, and 4.3% from 2006 to 2008, respectively (Table D12). The price effect is the most significant for bulk carriers, because Chinese shipyards account for a bigger market share and demand for bulk carriers is less elastic. As the impact of past subsidies accumulates over time through the slow increase in the world fleet, the price drop became more pronounced post 2009 and reached 16.8% for bulk carriers, 14.8% for tankers, and 4.2% for containerships. Lower ship prices benefited world shipowners by RMB 290 billion, though only a small proportion of these gains accrues to Chinese shipowners as they account for a small fraction of the world fleet.[38]

Figure 6 illustrates the striking effect of subsidies on investment, which skyrocketed post 2006. Total investment during 2006-2013 is RMB 80 billion with subsidies, compared to RMB 33 billion without subsidies. Figure 7 compares the number of Chinese firms by year with and without subsidies. Government support more than doubled the entry rate: 143 firms enter with subsidies vs. 64 without subsidies from 2006 to 2013. It also depressed exit (38 firms exit vs. 43).

Finally, the policy led to increased fragmentation. Entry subsidies induce entry of small inefficient firms. Production and investment subsidies boost firms' variable profit and retain unprofitable firms that should have exited. China's domestic Herfindahl-Hirschman index (HHI) plummeted from 1,200 in 2004 to less than 500 in 2013 with a significantly lower 4-firm concentration ratio (Figure D2 in the Appendix). Despite a sizable increase in China's overall production, capacity utilization was much lower, particularly when demand was low post 2009. If China had not subsidized the shipbuilding industry, the ratio of production to capital (which proxies for capacity utilization) would have been 19% higher during the 2009-2013 recession.

6.2 Long-term Performance of Policy Instruments

In this section, we turn to policy design. We assess the long-term performance of different policy instruments and search for general lessons that can be applied in other contexts. Since China's domestic consumer surplus is modest compared to the industry profit as discussed earlier, we focus on industry outcomes, such as output and profits, in our discussion below.[39]

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 noted otherwise. For example, in the sce-

[38] According to Clarkson World Shipyard Monitor, orders by Chinese shipowners have been growing but still account for under 10% of world orders in 2010-2013.

[39] Incorporating benefits in consumer surplus enjoyed by Chinese shipowners increases the gross rate of return from 18% to 24%.

nario with all subsidies, entry subsidies run from 2006 to 2008, whereas production and investment subsidies run from 2006 to the end.

The results are summarized in Table 5, which reports the discounted sums of long-term industry revenue and profit for Chinese shipyards, as well as the magnitude of different subsidies. The last two rows, "ΔRevenue/Subsidy" and "ΔNet Profit/Subsidy", constitute different measures of policy effectiveness. "ΔRevenue" is the revenue difference between the scenario with subsidies and the scenario without subsidies. The ratio between increased revenue and subsidy cost reflects a policy's effectiveness on promoting industry revenue. This is of interest, as China's official government documents explicitly state production targets for the domestic shipbuilding industry. "ΔNet Profit" is the difference in net profit which equals revenue plus the scrap value upon exiting, minus the costs of production, investment, and entry. "ΔNet Profit/Subsidy" measures the gross rate of return. A rate lower than 100% indicates that the cost of subsidies exceeds the net benefits to the domestic industry.[40]

Comparison of Different Policy Instruments When all subsidies are in place, the policy mix is highly ineffective, as reflected by the rate of return being merely 18%. When each policy is in place in isolation, the return is 50% for production subsidies, 74% for investment subsidies, and 32% for entry subsidies, respectively. We thus find that entry subsidies are substantially less effective than production and investment subsidies (more on that below). In addition, 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. Entry subsidies lower the entry threshold and thus attract inefficient entrants. With the introduction of production and investment subsidies, the number of firms in operation is further inflated due to subsidized revenue. This 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. 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: firms are willing to suffer temporary losses and stay idle in expectation of higher demand in the future (hysterisis). If fixed costs were zero, the rate of return on subsidies would increase from 18% to 25%.

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. A one RMB increase in either subsidy raises the industry's revenue by RMB 1.5. This might justify the popularity of these subsidies in China, since quantity and revenue targets are often linked to local officials' promotions (Jin et al., 2005). Investment subsidies appear less distortionary than production subsidies (74%

[40]The discussion below does not take into consideration the cost to finance these subsidies. Estimates from Ballard et al. (1985) suggest that collecting one dollar of government revenue costs 17 to 56 cents in the U.S. Including the cost to finance subsidies will further drive down the rates of return.

vs. 50%). Investment subsidies lead to a higher level of capital formation and facilitate long-term industry growth, while production subsidies have a more immediate impact on output.[41]

Entry subsidies are the least effective policy instrument among the three by a large margin. They predominantly attract small and high-cost firms that would not find it profitable to enter in the absence of subsidies. The large number of additional entrants contributes little to industry profits, while it exacerbates excess supply and reduces ship prices. In contrast, the take-up rate for production and investment subsidies is much higher among firms that are more efficient, receive more orders (higher backlogs), and are more likely to invest. For example, 82% of production subsidies and 68% of investment subsidies is allocated to firms that are more efficient than the median firm, whereas only 49% of entry subsidies goes to more efficient firms.[42] In addition, production and investment subsidies increase backlogs and capital stocks that lead to economies of scale and drive down both current and future production costs.

Business Cycles and Industrial Policy Like many other manufacturing industries, cycles of booms and busts are a fundamental feature of shipbuilding. The macro and public finance literature that explores optimal fiscal policies over the business cycle 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-term investment by lowering volatility (Aghion et al., 2014). It is less well-understood, however, how industrial policy should be designed in the presence of industry fluctuations.

To explore whether the effectiveness of subsidies varies over the business cycle, we carry out two counterfactual simulations. The first simulation subsidizes production and investment during the 2006-08 boom, while the second simulation subsidizes production and investment during the 2009-13 bust. All subsidies are discontinued afterwards. The subsidy rates are calibrated so that government spending is identical in both scenarios.

Strikingly, subsidizing firms during the boom leads to a net return of only 38%, whereas subsidizing firms during the downturn leads to a much higher return of 70%, as shown in Table 6. 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 optimal, incurring large adjust-

[41] We carry out a more systematic comparison of production and investment subsidies in the Appendix (Table D13).

[42] Appendix D.4 uses a simple static model to illustrate that the rate of return is higher when taken up by efficient firms. Firms in our empirical analysis make four decisions each period: entry, production, investment, and exit. Compared to efficient firms, inefficient firms are more likely to be distorted in all these four margins with subsidies. Efficient firms also enjoy considerable economies of scale as a result of larger backlogs and capital stocks relative to inefficient firms, which further widens the wedge in efficiency.

ment costs. During a bust, on the other hand, the industry operates well below capacity and many production facilities remain idle. Subsidies mobilize underutilized facilities, 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 8 plots the average marginal cost index over time for both scenarios. Marginal costs are higher when subsidies are distributed during the boom than during the bust, as expected.

Despite the benefits of a counter-cyclical policy, the actual policy mix was overwhelmingly pro-cyclical: 90% of total subsidies was handed out between 2006 and 2008 vs. 10% 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).

6.3 Consolidation Policies

To facilitate consolidation and create large firms that can compete against international conglomerates, China implemented *Shipbuilding Industry Standard and Conditions* in 2013 and periodically announces a list of firms that meet the industry standard, the so called "White List". This section evaluates whether and to what extent the consolidation policy improves the return of subsidies, as well as the government's choices of firms on the White List.

Gains from Targeting The first official White List consisted of 56 firms.[43] In our counterfactual exercise, we rank firms based on their expected variable profits ($E[\pi_{jt}]$) in 2013, select 56 firms with the highest profitability to form the "optimal White List," and simulate the industry from 2014 to 2050. 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 scenario with no subsidies.

As shown in Table D14 in the Appendix, directing subsidies towards the best set of firms (the optimal White List) generates *considerable* gains. The net rate of return for targeted production and investment subsidies is 71%, whereas the return is 37% when all firms are subsidized. This pattern holds across both measures of policy effectiveness (revenue and net profit), due to several reasons. First, subsidizing all firms encourages sub-optimal entry, while the White List policy only subsidizes existing firms and does not distort entry. Second, firms on the White List are more productive and less prone to sub-optimal decisions than the average firm, both of which lead to less distortion.

[43] Four out of sixty firms on the 2014 official White List cannot be matched to our datasets. Hence we focus on the remaining fifty-six firms.

China's White List While subsidies are less distortionary when targeted towards efficient firms, it is unclear a priori whether the government chose the right set of firms. Information asymmetries and regulatory capture might bias the process in favor of interest groups or "sunset sectors" (Lane, 2019).

To examine the performance of China's actual White List, we discontinue all subsidies post 2013 and examine post-2013 profit for firms on the actual White List and firms on our optimal White List as constructed above. Note that our selection criterion is short-run profitability. Thus this is a weak test: if the government chose firms with the highest long-term profitability, then their selection should do at least as well as the set of firms we choose.

As shown in Figure D3 in the Appendix, industry profits are lower with the actual White List (the dashed blue line) than our optimal White List (the solid red line). The difference in industry profits and revenue in the long run (the discounted sum from 2014 to 2050) is 12% and 8%. Out of the 56 firms chosen by the government, only 31 firms appear in our White List. 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.

Summary Our results shed light on the underlying mechanisms for diverging outcomes across countries that adopted different policy implementations, due to the timing of intervention, choice of policy instruments, and the discriminatory nature of the policy. For instance, in East Asian countries where industrial policy is often regarded as successful, policy support was conditioned on performance, with non-performing firms penalized by the withdrawal of support. In contrast, in Latin America where the import-substitution policies were less effective and abandoned in the 1980s, there were no effective mechanisms to weed out non-performing beneficiaries (Rodrik, 2009).[44] Our analysis highlights that similar mechanisms are at work in China's modern-day industrial policy in the shipbuilding industry. The policy's return was low in earlier years when output expansion was primarily fueled by the entry of inefficient firms, but increased over time as the government shifted support to more efficient firms and used 'performance-based' criteria (the White List) to channel subsidies.

A key insight from our analysis is that industrial policy is relatively more effective when it takes into consideration firm heterogeneity and the nature of business cycles, prioritizing support for efficient firms at times when economic expansion is not costly. Investment subsidies out-perform entry subsidies in part because they are mostly taken up by more efficient firms that dominate investment activity. Similarly, counter-cyclical policy mobilizes underutilized resources and indirectly targets low-cost firms, since these are the firms that are more likely to operate during a downturn. Finally, there are gains from consolidation and channeling resources to better-performing firms, though as

[44]Lack of policy evaluations in Latin American countries is a significant hindrance to this debate (Peres, 2013).

China's experience with the White List suggests, it can be difficult for the government to pick the most efficient firms.

7 Rationales for Industrial Policy

We now assess traditional arguments in favor of industrial policy and evaluate the extent to which the policy in the shipbuilding industry is effective in achieving these objectives. In the presence of market power, there are in principle strategic trade benefits from subsidizing industries that compete with foreign firms (Dixit, 1984; Krugman, 1986; Eaton and Grossman, 1986; Brander, 1995). For these considerations to be relevant, a necessary condition is the existence of substantial market power and thus 'rent on the table' that when shifted from foreign to domestic firms outweighs the cost of subsidies. To investigate this, we carry out a counterfactual simulation where firms are price takers in the product market, which eliminates any strategic trade motives behind industrial policy. As Table D15 in the Appendix illustrates, the overall return of subsidies with perfect competition is lower than our baseline estimates, but the gap is modest (14% vs. 18%). The difference is mainly driven by production subsidies becoming less effective when firms are price takers (their return drops from 50% to 38%). These results suggest that market power considerations in the shipbuilding industry cannot justify the strategic trade arguments, consistent with results in Section 5.1 that markups are low.

Another justification for subsidies is the presence of positive externalities (such as industry-wide learning-by-doing), in which case each firm produces less than socially optimal. As discussed in Section 5.1, there is no evidence of significant spillover effects in this industry, corroborating industry reports that much of the production by Chinese shipyards occurs in product sectors with mature technologies, where the scope for learning is limited.[45]

Industrial policies are often argued on the ground of labor market consequences: subsidies could have welfare benefits if they increase employment or offset distortions that lead to depressed employment. Even in the grand scheme of things, total employment in shipbuilding and related industries (ship repairs, marine equipment, etc.) accounts for less than 0.1% of national employment, suggesting that any potential labor market benefits would be modest.[46]

There are potential spillovers to upstream sectors, as intermediate inputs from other sectors

[45] There might be technological 'catching-up' and learning among Chinese shipyards for producing the latest generation ships (e.g. large containerships or LNG's), where most of the patents and 'know-how' are possessed by Japanese and South Korean firms. Unfortunately, there are few orders of these ships and we cannot directly test this.

[46] According to OECD (2016), it takes 8 worker-years in shipbuilding and 26 worker-years in upstream sectors to produce ships valued at $1 million in China. As 1 unit of production subsidy is associated with 1.5 units of revenue increase (Table 5), these numbers suggest that production subsidies of $1 million create 12 jobs in the shipbuilding sector and 39 jobs in upstream sectors for one year. Thus, subsidizing shipbuilding does not appear cost effective to create jobs given China's GDP per capita at $2,099 in 2006 and $7,051 in 2013.

account for 63% of the value of ships produced and steel alone contributes to 13%. One might argue that shipbuilding subsidies are partially designed to boost demand for steel, a strategic sector that has been subject to many policy interventions. However, steel used in shipbuilding accounts for less than 1.5% of total steel produced (China's 2012 Input-Output Table). Looking at downstream sectors, three-quarters of the output from this industry is used for final consumption. However, more than 80% of ships produced is exported, which limits the fraction of subsidy benefits that is captured domestically.

One rationale that might help justify China's shipbuilding subsidies relates to the role of ships in international trade: a larger worldwide fleet reduces transportation costs (freight rates). As China is the world's biggest exporter and the (close) second largest importer, transport cost reductions can lead to substantial increases in trade volume. If Chinese exporters and importers face trade barriers or other frictions, the associated welfare considerations could justify subsidizing the shipbuilding sector.

To evaluate this argument, we carry out a back-of-the-envelope calculation of the subsidies' impact on China's trade volume in Appendix D.3. To do so, we first assess changes in freight rates resulting from the increased global fleet. We find that subsidies reduced bulk carrier freight rates by 6.1% and containership freight rates by 2% between 2006 and 2013. Using trade elasticities with respect to transport prices from the literature (Brancaccio et al., 2020; Jeon, 2018), we estimate that the industrial policy raised China's annual trade volume by 4.9% ($144 bn) between 2006 and 2013. The effect is sizeable compared to other major trade-related policies in recent decades. For instance, Ianchovichina and Martin (2004) estimate that China's accession to WTO led to a 40% increase in its trade volume. The increase in trade volume was also large relative to the size of the subsidies (which averaged $11.3 bn annually between 2006 and 2013); however, calculating the welfare gains associated with the increased trade volume falls beyond the scope of this paper.[47]

Finally, other considerations, including national security and military implications, as well as the desire to be the world leader in heavy-manufacturing industries (as stated in various government documents), might also be relevant in motivating these policies. Regardless of the motivation, our analysis evaluates various policy design considerations and the relative efficacy of different instruments that can be used as guidance for future polices.

8 Conclusion

Industrial policy, which until recently was considered old-fashioned, has reemerged in many regions around the world, including the EU and the US. Despite the strong interest from policy makers and economists alike, few studies have used firm-level data to examine the relative efficacy

[47]To do so would require overlaying our framework within a general equilibrium trade model.

of different designs, as well as the long term implications of industrial policies.

We conduct such an analysis of China's industrial policy in the shipbuilding industry, using firm-level data and a dynamic model of firms' entry and exit, production and investment decisions. While subsidies significantly boosted China's world market share and buttressed China's ascent into global influence, they also exacerbated industry fragmentation and led to increased capacity idleness. The policy initially exhibited a low rate of return, though returns improved overtime as the government shifted away from subsidizing all firms and adopted policies that better targeted efficient firms. An important insight from the setup we study is that firm heterogeneity, the nature of business cycles, firms' cost structure, and the choice of policy instruments could all significantly alter policy efficacy and are important considerations for a more effective policy design.

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Table 1: Summary Statistics

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

Note: Summary statistics for shipyards in China, Japan, and South Korea from 1998 Q1 to 2014 Q1. CGT is compensated gross tons, a widely used size measure and comparable across types. Bulk carriers, tankers, and containerships account for more than 90% of world orders in tons in our sample period. Investment and capital are limited to Chinese yards. Source: Clarksons and China's National Bureau of Statistics.

Table 2: Cost Function Estimates

	Bulk carrier		Tanker		Containership	
Type-specific	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
β_q	7.29	7.59	14.13	5.10	10.58	5.01
σ_ω	9.58	8.93	16.27	6.91	13.77	5.14
Constant (1000 RMB/CGT)	20.37	14.05	39.71	8.78	34.92	7.27
Steel Price (1000 RMB/Ton)	1.68	6.85	1.14	2.83	0.66	1.50
Capital (Bill RMB)	-2.67	-2.85	-2.89	-1.74	-2.44	-1.93
Capital^2	0.20	0.80	0.07	0.24	0.06	0.28
Backlog	-1.80	-5.03	-5.02	-4.97	-3.30	-3.19
Backlog^2	0.08	3.94	0.26	3.44	0.20	1.94
Backlog of Other Types	0.13	0.86	0.38	1.57	0.53	2.61
Common						
2006-2008	-2.10	-3.01				
2009+	-1.22	-1.78				
Large firms	-4.32	-6.54				
Jiangsu	-2.96	-4.61				
Zhejiang	-1.62	-2.80				
Liaoning	-2.10	-2.01				
CSSC/CSIC	-0.86	-1.17				
Private	0.16	0.30				
Foreign JV	-0.86	-1.41				
Age	0.21	3.22				
N	4886		4977		2504	

Note: Standard errors bootstrapped using 500 bootstrap samples. Marginal costs are measured in 1000 RMB per CGT. For example, a coefficient of -2.10 on the policy dummy '2006-2008' implies that production subsidy during 2006-2008 is 2,100 RMB per CGT across ship types, or 14-18% of the average price.

Table 3: Estimates of Investment Cost and Scrap Value Parameters

	Coeff.	T-stat
σ_ϕ	0.98	12.32
c1	1.00	
c2	29.54	14.49
c3	2.07	9.67
$c4_{2006-08}$	-0.27	-1.70
$c4_{2009+}$	-0.46	-3.27
N	4286	

Note: Standard errors bootstrapped using 200 block bootstrap samples. Both investment and investment cost are measured in billion RMB. Between 2006-2008, the subsidy was 0.27 RMB per RMB of investment. Post 2009, the subsidy jumps to 0.46 RMB per RMB of investment, which helps rationalize the elevated investment with plummeting ship prices post the financial crisis.

Table 4: Entry Cost Distribution (Mean) by Province, Billion RMB

	κ_{pre}	$\kappa_{post,06}$	% of pre costs	$\kappa_{post,09+}$	% of pre costs
Jiangsu	86	31	36%	91	106%
Zhejiang	133	54	41%	264	199%
Liaoning	82	40	49%	-	-
Other	38	15	38%	61	160%

Note: κ_{pre}: mean of the entry cost distribution prior to 2004 for Zhejiang, and prior to 2006 for Jiangsu, Liaoning and Other regions. $\kappa_{post,06}$: mean of the entry cost distribution between 2004 and 2008 for Zhejiang, between 2006 and 2008 for Jiangsu, Liaoning and Other regions. $\kappa_{post,09+}$: mean of the entry cost distribution from 2009 onwards. The number of potential entrants, $\bar{N}$, is assumed to equal twice the maximum number of potential entrants ever observed in a region. Compared to κ_{pre}, entry costs are much lower when entry subsidies were in place ($\kappa_{post,06}$) and much higher with entry restrictions ($\kappa_{post,09+}$). Conditional on entering, the average entry cost paid is RMB 2.5 bill, close to a shipyard's accounting value.

Table 5: Comparison of Policy Instruments (in Bill RMB)

	All subsidies	Production subsidy	Investment subsidy	Entry subsidy	Remove all subsidies
Lifetime Revenue 2006-	2361	2154	1873	1961	1810
Lifetime Net Profit 2006-	1085	1061	981	1023	950
Production Subsidy	262	225	0	0	0
Investment Subsidy	77	0	42	0	0
Entry Subsidy	431	0	0	231	0
Δ Revenue/Subsidy	72%	153%	153%	66%	
Δ Net Profit/Subsidy	18%	50%	74%	32%	

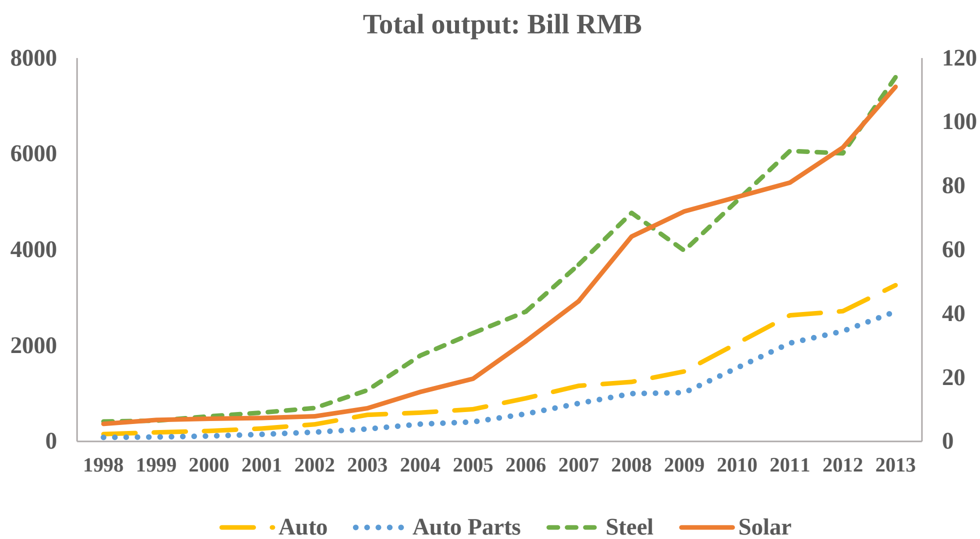
Note: Revenue, net profit, and subsidy are discounted sums for Chinese shipyards from 2006 to 2050, averaged across simulations and measured in billion RMB. For example, "Lifetime Revenue (Net Profit) 2006-" refers to the discounted sum of revenue (net profit) earned by Chinese firms from 2006 to 2050. "Net Profit": Revenue-Production Cost-Investment Cost+Scrap Value-Entry Cost. "ΔRevenue/Subsidy": the discounted sum of revenue in the column scenario minus the discounted sum of revenue with no subsidies, divided by the discounted sum of subsidies. "ΔNet Profit/Subsidy" equals the discounted sum of net profits in the column scenario minus the discounted sum of net profits with no subsidies, divided by the discounted sum of subsidies. Government policy in 2013 carries onward till the end of the simulation period (2050) in all columns. In Column "All subsidies", firms receive production and investment subsidy (as estimated in the baseline) in all periods, but entry subsidy terminates in 2009. In Column "Production subsidy", we maintain the same production subsidy as in the baseline, but shut down entry and investment subsidies. Columns "Investment subsidy" and "Entry subsidy" are similar.

Table 6: Pro-cyclical vs. Counter-cyclical Industrial Policy (in Bill RMB)

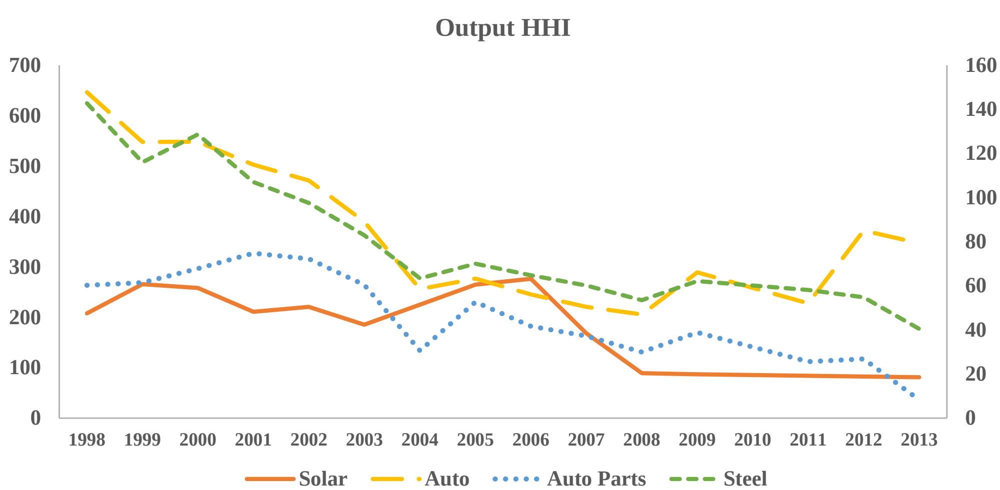
	Subsidize during boom	Subsidize during recession
Lifetime Revenue 2006-	1880	1872
Lifetime Profits 2006-	961	975
Production Subsidy	29	29
Investment Subsidy	13	14
Δ Revenue/Subsidy	189%	168%
Δ Net Profit/Subsidy	38%	70%

Note: In Column "Subsidize during boom," the government only subsidizes production and investment during the boom of 2006-08. In Column "Subsidize during recession," the government subsidizes during the recession of 2009-13, but offers no subsidy before 2009 or after 2013. The subsidy rates during the 2006-08 boom are adjusted downwards to match the amount handed out during the recession. No entry subsidy is offered in either scenario. All rows are defined as in Table 5.

Figure 1: Output and Industry Concentration in Selected Chinese Industries

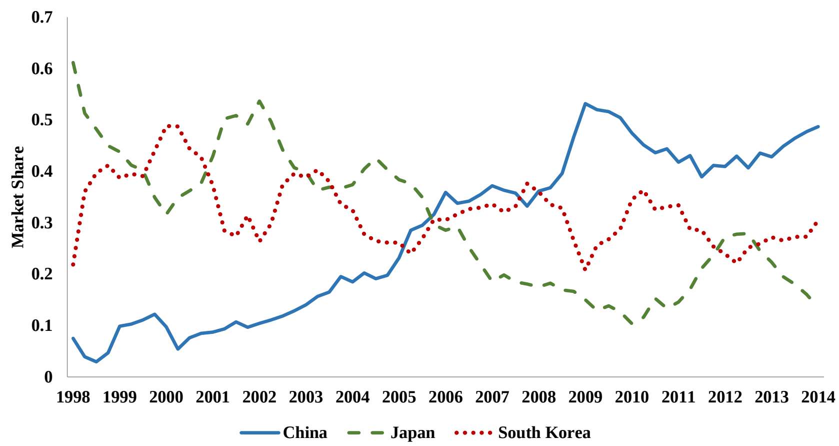


Source: China's National Bureau of Statistics. The output of the auto, auto parts and steel industries are plotted on the left vertical axis, while the output of the solar industry is plotted on the right vertical axis.



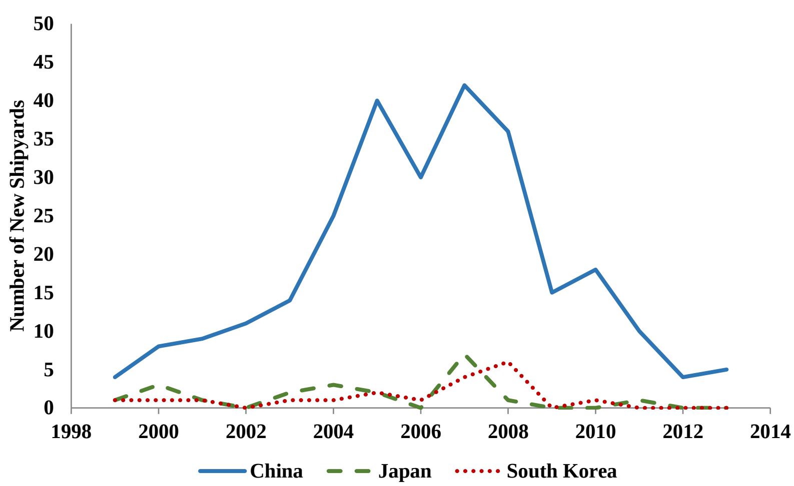
Source: China's National Bureau of Statistics. The HHI of the auto and solar industries are plotted on the left vertical axis, while the HHI of the auto parts and steel industries are plotted on the right vertical axis.

Figure 2: China's Market Share Expansion



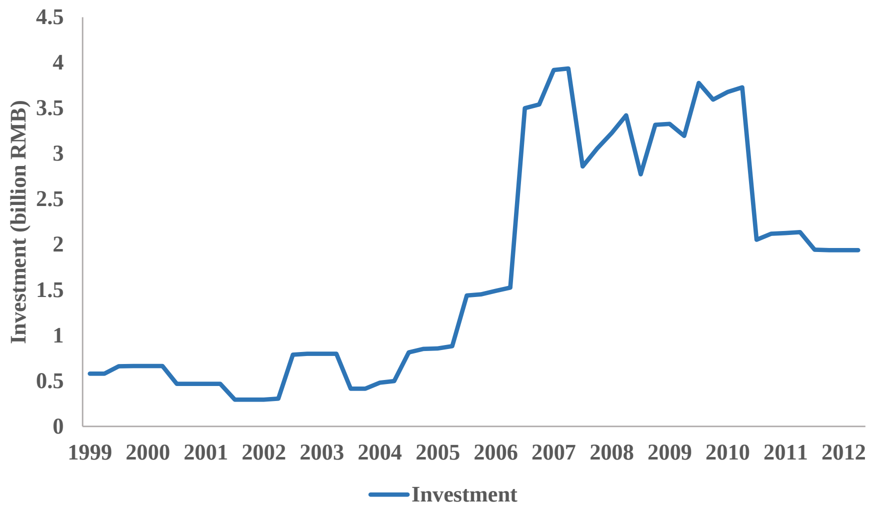
Source: Clarkson Research. Market shares by country computed from quarterly ship orders.

Figure 3: Entry of New Shipyards by Country



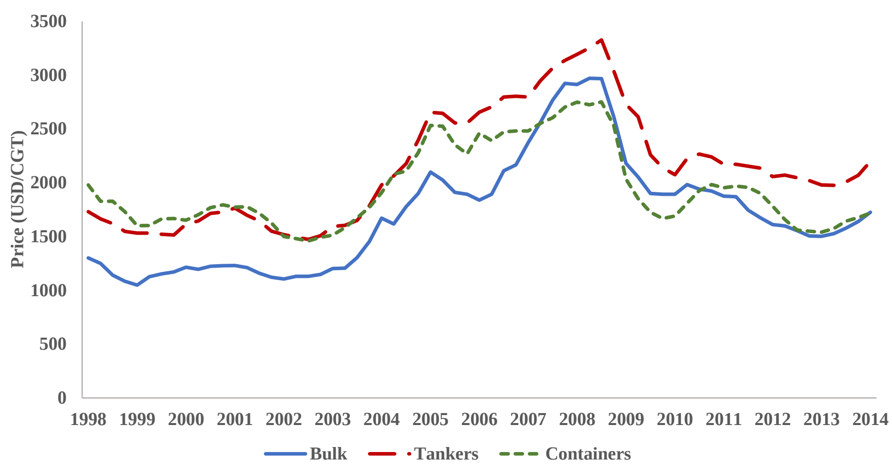
Source: Clarksons Research. Number of new shipyards each year by country.

Figure 4: Investment by Chinese Shipyards



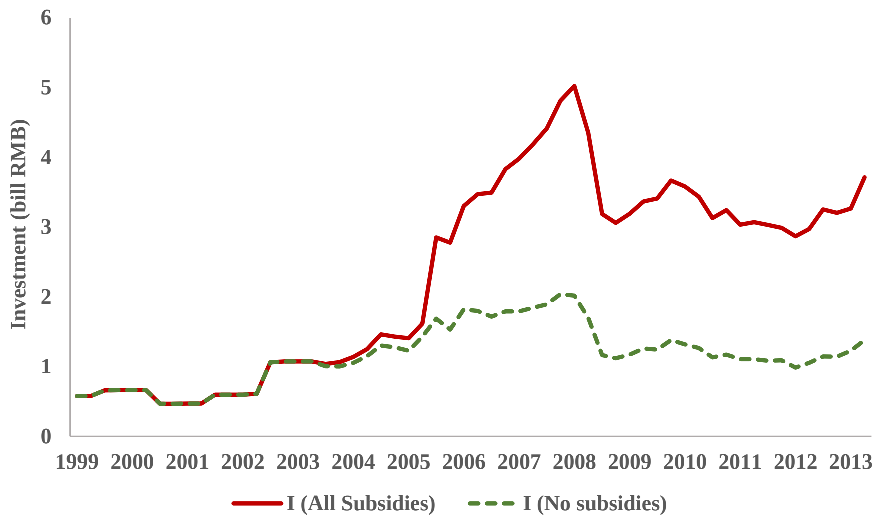
Source: China's National Bureau of Statistics. Industry aggregate quarterly investment by Chinese shipyards.

Figure 5: New Ship Prices



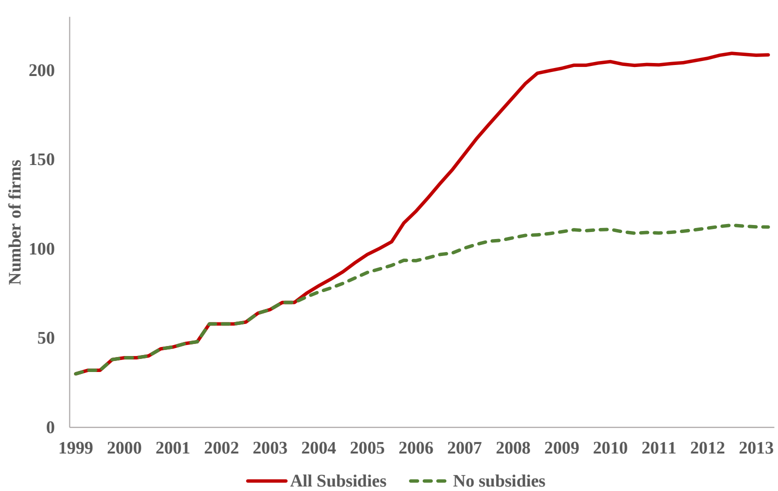
Source: Clarksons Research. Average new ship price in USD/CGT by ship type.

Figure 6: Investment, with and without Subsidies



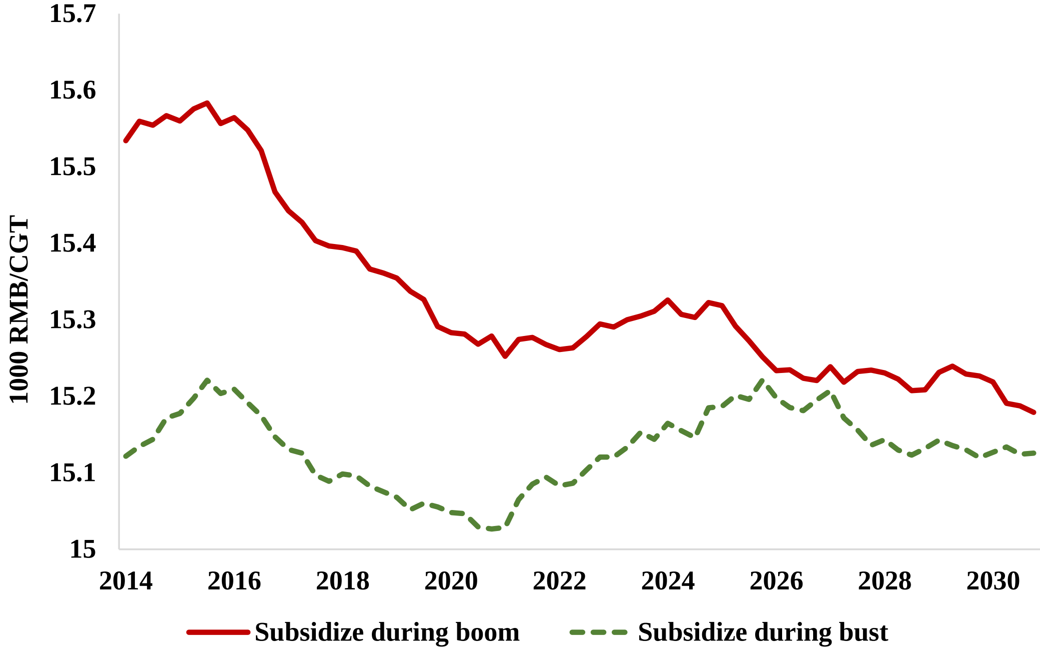
Note: Total quarterly investment by Chinese shipyards in the case of all subsidies as observed in the data (solid red line) and counterfactual investment with no subsidies (dashed green line).

Figure 7: Number of Firms, with and without Subsidies



Note: Total number of firms in the case of all subsidies as observed in the data (solid red line) and counterfactual number of firms with no subsidies (dashed green line).

Figure 8: Marginal Cost Index with Subsidies During the Boom vs. Subsidies During the Bust



Note: The marginal cost index is defined as the portion of marginal cost determined by the firm's capital stock, backlog and other firm-level characteristics (such as age, size and ownership status), in 1000 RMB per CGT. The graph plots the average marginal cost index when subsidies are distributed during the boom of 2006-2008 (solid red line) vs. during the bust of 2009-2013 (dashed green line).

Online Appendix for "China's Industrial Policy: an Empirical Evaluation"

Appendix A provides some additional background on China's industrial policy for the shipbuilding sector. Appendix B discusses additional steps of the estimation procedure, including the calibration of the fixed production cost, the estimation of investment policy functions and the value function approximation. Appendix C describes estimation results not included in the main text, including demand estimates, production cost estimates, robustness analysis, first-stage policy function estimates, estimates of the state transition process, and overall model fit. Finally, Appendix D describes how we implement the counterfactual analyses and presents some additional results relating to the counterfactual simulations.

A Additional Background on Industrial Policies in China

Table A1 documents major national policies issued that were relevant for the shipbuilding sector. The most important initiative was the 11th National Five-Year Economic Plan (2006-2010) which dubbed shipbuilding as a strategic industry. The central government also 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 the Shipbuilding Industry*, the government set an annual production goal of 15 million deadweight tons (DWT) to be achieved by 2010, and 22 million DWT by 2015.

In the aftermath of the 2008 economic crisis that led to a sharp decline 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 that "meet the industry standard" and thus receive priority in subsidies and bank financing.[48] The so called "White List" included sixty firms in 2014 upon announcement.

The 12th Five-Year Plan for the Development of Shipbuilding Industry (2011-2015) set a number of targets for achieving increased industrial concentration, including 70% of the country's shipbuilding to be carried out by the top ten domestic firms, and at least five Chinese firms to be included in the world's top ten largest firms.

[48] In practice, favorable financing terms and capital market access are often limited to firms on the White List post 2014.

Table A1: Shipbuilding National Industrial Policies

Year	Shipbuilding National Industrial Policies	Plan Period
2003	National Marine Economic Development Plan	2001-2010
2006	The 11th Five-Year Plan for National Economic and Social Development	2006-2010
2006	The Medium and Long Term Development Plan of Shipbuilding Industry	2006-2015
2007	The 11th Five-Year Plan for the Development of Shipbuilding Industry	2006-2010
2007	The 11th Five-Year Plan for the Development of Shipbuilding Technology	2006-2010
2007	11th Five-Year Plan for the Development of Ship Equipment Industry	2006-2010
2007	Guideline for Comprehensive Establishment of Modern Shipbuilding (2006-2010)	2006-2010
2007	Shipbuilding Operation Standards	2007-
2009	Plan on the Adjusting and Revitalizing the Shipbuilding Industry	2009-2011
2010	The 12th Five-Year Plan for National Economic and Social Development	2011-2015
2012	The 12th Five-Year Plan for the Development of the Shipbuilding Industry	2011-2015
2013	Plan on Accelerating Structural Adjustment and Promoting Transformation and Upgrading of the Shipbuilding Industry	2013-2015
2013	Shipbuilding Industry Standard and Conditions	2013-

B Estimation Details

B.1 Calibrating the Fixed Cost

The National Bureau of Statistics (NBS) data include information on operating 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_{it} orders that is estimated from the Clarkson data, as discussed in Section 4.1.

Some shipyards both produce ships and carry out repairs. 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 operating cost of ship production as:

$$\hat{C}_{jt} = C_{jt}^{NBS} * (R_j^{Clarkson} / R_j^{NBS})$$

where C_{jt}^{NBS} denotes the accounting operating costs, which include the costs of both ship production and ship repairs. $R_j^{Clarkson} = \sum_t R_j^{Clarkson}$ denotes shipyard j's lifetime revenue from building new ships that is reported in Clarkson, and $R_j^{NBS} = \sum_t R_{jt}^{NBS}$ 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 operating costs and the average estimated variable cost of production:

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

B.2 Estimating the Investment Policy Function

Our baseline estimator of the investment policy function does not account for the fact that investment is non-negative. To address this issue, we perform two robustness checks. The first is a Tobit model that assumes $h_2(\nu_{jt})$ is normally distributed. The second approach assumes that the median of $h_2(\nu_{jt})$ is zero and estimates $h_1(s_{jt})$ using the Censored Least Absolute Deviation estimator (CLAD) that was first proposed by Powell (1984) and later extended by Chernozhukov and Hong (2002). In this note, we describe how we implement the second approach based on the CLAD estimator.

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

$$\begin{aligned} I^*_{jt} &= h_1(s_{jt}) + h_2(\nu_{jt}) \\ I_{jt} &= max(I^*_{jt}, 0) \end{aligned}$$

where the second equation states explicitly 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 $h_2(\nu_{jt})$ to 0. Once we obtain the CLAD estimate $\hat{h}_1(s)$, we treat $I_{jt} - \hat{h}_1(s_{jt})$ as data with the goal of estimating $h_2(\nu_{jt})$ with the truncated data:

$$\begin{aligned} \tilde{i}_{jt} \equiv I_{jt} - \hat{h}_1(s_{jt}) &= max(h_2(\nu_{jt}), -\hat{h}_1(s_{jt})), \text{or} \\ \tilde{i}_{jt} &= max(h_2(\nu_{jt}), \bar{h}_{jt}) \end{aligned}$$

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

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

$$Pr(\tilde{i}_{jt} > \bar{h}_{jt}|\bar{h}_{jt}) = Pr(h_2(\nu_{jt}) > \bar{h}_{jt}) = Pr(\nu_{jt} < h_2^{-1}(\bar{h}_{jt})) = Pr(\nu_{jt} < \tilde{\nu}_{jt})$$
$$= \Phi(\bar{\nu}_{jt}), \text{or}$$
$$\bar{\nu}_{jt} = \Phi^{-1}\left(Pr(\tilde{i}_{jt} > \bar{h}_{jt}|\bar{h}_{jt})\right)$$

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

To estimate $h_2(\nu_{jt})$, we categorize all the uncensored observations (where $\tilde{i}_{jt} > \bar{h}_{jt}$) into distinct bins. Specifically, suppose the thresholds are $\{\bar{h}_1, \bar{h}_2, ...\bar{h}_{R+1}\}$. Then any uncensored observation $\tilde{i} \in (\bar{h}_r, \bar{h}_{r+1}]$ is placed in bin r. We carry out the BBL inversion separately for each bin. In particular, if $i^* = max(h_2(\nu^*), \bar{h}_{jt})$ for some arbitrary ν^*, where i^* lies in bin r, then the following expression must hold:

$$F(i^*|i^* \in (\bar{h}_r, \bar{h}_{r+1}]) = Pr(\tilde{i} \leq i^*|i^* \in (\bar{h}_r, \bar{h}_{r+1}))$$
$$= Pr(\nu \geq \nu^*|\bar{\nu}_{r+1} < \nu < \bar{\nu}_r)$$
$$= \frac{\Phi(\bar{\nu}_r) - \Phi(\nu^*)}{\Phi(\bar{\nu}_r) - \Phi(\bar{\nu}_{r+1})}$$

In other words,

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

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 (e.g. five) can lead to surprisingly well-behaved estimates with minimal bias in the estimated function $h_2(\nu)$.

As shown in Section C.3 of the Appendix, Tobit and CLAD deliver similar estimates of the investment policy function as OLS, though OLS outperforms both Tobit and CLAD in terms of the overall sample fitness.

B.3 Value Function Approximation

As discussed in the main text, we approximate the value function $V(s_{jt})$ via B-spline basis functions $V(s_{jt}) = \sum_{l=1}^{L} \gamma_l^0 u_l(s_{jt})$ and impose the Bellman equation as a constraint when estimating the parameters governing investment costs and scrap value.[49] We now discuss how we approximate the value functions.

[49] We refer interested readers to supplemental material in Barwick and Pathak (2015) and Kalouptsidi (2018) for Monte Carlo evidence on the performance of value function approximations.

Constructing Basis Functions In our model, firm value functions are in principle a function of a large number of state variables. However, several state variables enter the shipyard's payoff as a single index $s_{jmt}\beta_{sm}$ in the marginal cost of production (B1), including the shipyard's region, ownership, size, age, and backlog.

$$MC_m(q_{jmt}, s_{jmt}, \omega_{jmt}) = \beta_{0m} + s_{jmt}\beta_{sm} + \beta_{qm}q_{jmt} + \omega_{jmt} \tag{B1}$$

As such, instead of keeping track of each state separately, we collapse them into a single-dimensional state using the estimated coefficients:

$$\bar{s}_{jt} = -\sum_m s_{jmt}\beta_{sm}$$

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 profits. We further assume that $\bar{s}_{jt}$ 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 in the dynamic estimation are the capital stock, the price for each ship type, the steel price, and $\bar{s}_{jt}$ (which subsumes the remaining firm characteristics); as well as 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.

Estimating Approximating Coefficients We search for $\{\gamma_l\}_{l=1}^{L}$ that minimize the violation of the Bellman equation (11) given the dynamic parameters:

$$\{\gamma_l\}_{l=1}^{L} = \arg\min_{\gamma_l} \left\| V(s_{jt};\gamma) - \pi(s_{jt}) - \hat{p}^x(s_{jt})\sigma_\phi - CV(s_{jt};\gamma) \right\|_2 \tag{B2}$$

where $\hat{p}^x(s_{jt})$ and $\hat{i}^*(s_{jt}, \nu_{jt})$ are the estimated first-stage exit and investment policy functions, respectively, $CV(s_{jt};\gamma) = \mathbb{E}_{\nu_{jt}}\{-C^i(\hat{i}^*(s_{jt}, \nu_{jt})) + \beta\mathbb{E}[V(s_{jt+1};\gamma)|s_{jt}, \hat{i}^*_{jt}]\}$ is the continuation value evaluated at these estimated policy functions, and $\|.\|_2$ is the L^2 norm.

Equation (B2) is imposed as a constraint in the estimation of dynamic parameters. Specifically, for each guess of the dynamic parameters, we solve for $\{\gamma_l\}_{l=1}^{L}$ that satisfy equation (B2), and use the estimated $\{\hat{\gamma}_l\}_{l=1}^{L}$ to construct the sample log likelihood in equation (12).

Recovering the approximating coefficients γ 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_{add} additional states to span the full range of the state variables. The coefficients γ are recovered using these $N + N_{add}$ states.[50] 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 Additional Estimation Results

C.1 Demand Estimates

Table C2 reports estimates of the demand curve (9). Given the limited number of observations for each ship type, we restrict the price coefficient post-2006 and the coefficient on backlog to be the same across types in order to improve the precision of the estimates. We use GMM and estimate equation (9) jointly across the three types. 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 price coefficient before and after 2006 to capture changes in the slope of the demand curve after the introduction of Chinese subsidies. Adding demand shifters improves the fit, though time trends appear to matter little. As such we use Column (2) as our preferred specification.

C.2 Production Cost Estimates: Robustness

This section carries out a robustness analysis for production cost estimates.

First, we estimate production costs assuming the firms are price-takers rather than Cournot competitors. Table C3 shows that the estimated coefficients remain quantitatively similar. We then explore how our estimates of ship production costs change when we pool data from China, Japan and South Korea. As the capital stock is unobserved for firms in Japan and South Korea, we set these shipyards' capital to zero and add country dummies. The results are illustrated in Table C4. The key coefficients are generally similar to those in the baseline. The subsidy is estimated to be higher in the 2006-08 period but somewhat lower in the 2009+ period.

[50] In our empirical analysis, $N = 4,286$ and $N_{add} = 80,000$. Using larger values of N_{add} leads to very similar estimates of the approximating coefficients.

Table C2: Demand Estimates

Dependent variable:	(1) Orders	(2) Orders	(3) Orders	(4) Orders
Price (bulk carriers)	-2.34***	-1.67***	-2.07***	-2.12***
	(0.77)	(0.64)	(0.69)	(0.75)
Price (tankers)	-2.66***	-1.46*	-1.80**	-1.76**
	(0.60)	(0.88)	(0.78)	(0.89)
Price (containerships)	-4.85***	-2.44***	-3.39***	-3.39***
	(0.91)	(0.85)	(1.01)	(0.99)
Price*Post2006	1.34***	1.00***	1.15***	1.34**
	(0.18)	(0.14)	(0.15)	(0.55)
Backlog (log)	0.34	-1.00***	-0.78**	-0.81**
	(0.25)	(0.33)	(0.38)	(0.37)
Freight rate (bulk carriers)	2.84***	3.27***	3.35***	3.33***
	(0.45)	(0.56)	(0.57)	(0.56)
Freight rate (tankers)	4.04***	3.24***	2.94***	2.91***
	(0.70)	(0.68)	(0.65)	(0.65)
Freight rate (containerships)	6.45***	4.47***	4.69***	4.60***
	(0.87)	(0.73)	(0.77)	(0.75)
US Wheat price		-0.12	-0.10	-0.12
		(0.48)	(0.48)	(0.49)
Iron ore imports, China		2.62***	2.93***	3.01***
		(0.90)	(0.89)	(0.92)
Middle East refinery production		1.37	1.84*	1.66*
		(1.05)	(0.97)	(0.99)
World car trade		1.32***	2.08***	2.05***
		(0.44)	(0.49)	(0.49)
Trend			-0.026**	-0.020
			(0.011)	(0.019)
Trend*Post2006				-0.0026
				(0.0076)
R^2, bulk carriers	0.68	0.71	0.71	0.71
R^2, tankers	0.26	0.33	0.35	0.36
R^2, containerships	0.44	0.52	0.51	0.51

Note: the number of observations equals 64 for bulk carriers and containerships and 61 for tankers. The freight rate is the Baltic Exchange Freight Index for bulk carriers, 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 carriers, Middle East refinery production for tankers, and world car trade for containerships. We instrument ship prices using steel production and the steel ship plate price. Parameters are estimated using GMM.

Next, we examine evidence of learning-by-doing by shipyards. First, we evaluate within-firm learning-by-doing by allowing a firm's marginal cost to depend on its cumulative past production. As shown in Table C5, a larger past production leads to higher marginal costs, which is inconsistent with there being within-firm learning-by-doing. Second, we allow a firm's marginal cost to depend on the industry cumulative output, as a crude test of industry-wide learning-by-doing (where firms learn from each other). Without instrumenting for the industry cumulative output, this exercise is likely to over-estimate spillover effects: if there are common unobserved shocks that raise the output of all firms, the model will attribute it to positive spillover effects. Despite this, we find limited evidence for spillover effects, as shown in the third panel of Table C5. Marginal costs increase with the cumulative industry production for tankers and containerships and only modestly decrease for bulk carriers, though the latter coefficient is statistically insignificant and small in magnitude.

Table C6 reports results from additional robustness exercises. First, we allow for a time trend in the cost function. This captures changes in the production technology over time. The time trend is estimated to be very small in magnitude and has little effect on other estimated cost parameters. Second, we repeat the analysis on a sub-sample that excludes Chinese yards that entered after the policies were announced (which might have newer technology). The results are robust and broadly similar to other specifications.

Table C3: Cost Function Estimates under Perfect Competition vs. Cournot Competition

	Bulk carrier		Tanker		Containership	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Cournot						
Capital (bill RMB)	-2.67	-2.85	-2.89	-1.74	-2.44	-1.93
Backlog	-1.80	-5.03	-5.02	-4.97	-3.30	-3.19
2006-2008	-2.10	-3.01				
2009+	-1.22	-1.78				
Perfect competition						
Capital (bill RMB)	-2.43	-2.96	-2.61	-1.80	-2.19	-2.01
Backlog	-1.56	-5.29	-4.44	-5.04	-2.88	-3.34
2006-2008	-1.51	-2.62				
2009+	-1.38	-2.37				
N	4886		4977		2504	

Note: The first panel reports the baseline cost function estimates from Table 2, which assumes that firms compete in Cournot. The second panel reports the cost estimates assuming perfect competition. The table reports estimates for key coefficients. Full tables are available upon request. Marginal costs measured in 1000 RMB per CGT. Standard errors bootstrapped using 500 bootstrap samples.

Table C4: Cost Function Estimates when Pooling Data across China/Japan/South Korea

	Bulk carrier		Tanker		Containership	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Chinese yards						
Capital (bill RMB)	-2.67	-2.85	-2.89	-1.74	-2.44	-1.93
Backlog	-1.80	-5.03	-5.02	-4.97	-3.30	-3.19
2006-2008	-2.10	-3.01				
2009+	-1.22	-1.78				
N	4886		4977		2504	
Chinese/Japanese/Korean yards						
Capital (bill RMB)	-3.33	-2.98	-2.47	-1.53	-1.57	-1.28
Backlog	-2.45	-6.14	-5.45	-6.05	-3.58	-4.27
China 2006-2008	-3.60	-4.85				
China 2009+	-0.70	-1.02				
N	10013		10429		4661	

Note: The first panel reports the baseline cost function estimates from Table 2, which only uses data on Chinese yards. In the second panel, we pool together Chinese/Japanese/Korean yards. To account for missing capital stock for non-Chinese yards, we set the capital variable to zero for Japanese and Korean yards and add country dummies. Backlog coefficients differ by country. The table reports backlog coefficient for Chinese shipyards; backlog coefficients for Japan and Korea are not reported to save space. Full tables are available upon request. Standard errors bootstrapped using 500 bootstrap samples.

Table C5: Cost Function Estimates and Learning: All Shipyards

	Bulk carrier		Tanker		Containership	
Type-specific	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Baseline specification						
Capital (bill RMB)	-3.33	-2.98	-2.47	-1.53	-1.57	-1.28
Backlog	-2.45	-6.14	-5.45	-6.05	-3.58	-4.27
Allow for within-firm learning						
Capital (bill RMB)	-2.16	-1.85	-2.29	-1.43	-1.22	-1.12
Backlog	-1.67	-4.78	-5.30	-5.09	-1.13	-1.40
Cumulative Q	0.08	4.12	0.10	5.22	0.02	3.60
Allow for within-firm and industry-wide learning						
Capital (bill RMB)	-2.48	-2.14	-4.80	-1.66	-2.81	-1.26
Backlog	-1.60	-4.14	-9.24	-3.67	-2.47	-1.15
Cumulative Q	0.09	4.49	0.18	3.93	0.03	2.58
Cumulative Q, China	-0.02	-0.79	0.39	2.10	0.68	1.61

Note: All panels pool together Chinese/Japanese/Korean yards. The first panel repeats key coefficients from the second specification reported in Table C4. The second panel includes all regressors from the first panel, as well as each firm's cumulative past production. The third panel includes all regressors from the first panel, each firm's cumulative past production, and the country's cumulative past production. Backlog coefficients differ by country. The table reports backlog coefficient for Chinese shipyards; backlog coefficients for Japan and Korea are not reported to save space. Full tables are available upon request. Standard errors bootstrapped using 500 bootstrap samples.

Table C6: Cost Function Estimates: Additional Robustness Checks

	Bulk carrier		Tanker		Containership	
	Coefficient	T-stat	Coefficient	T-stat	Coefficient	T-stat
Baseline specification						
Capital (bill RMB)	-3.33	-2.98	-2.47	-1.53	-1.57	-1.28
Backlog	-2.45	-6.14	-5.45	-6.05	-3.58	-4.27
China 2006-2008	-3.60	-4.85				
China 2009+	-0.70	-1.02				
Add time trend						
Capital (bill RMB)	-3.40	-2.93	-2.51	-1.57	-1.60	-1.23
Backlog	-2.49	-6.06	-5.51	-5.90	-3.64	-3.99
China 2006-2008	-3.76	-4.48				
China 2009+	-0.87	-1.19				
Trend	0.03	0.50				
Existing yards						
Capital (bill RMB)	-3.98	-3.04	-3.26	-1.39	-0.48	-0.35
Backlog	-3.90	-5.71	-6.73	-5.77	-4.38	-3.94
China 2006-2008	-3.01	-3.03				
China 2009+	-0.92	-0.91				

Note: this table reports additional robustness pooling shipyards from all three countries. The first panel repeats key coefficients from the second specification reported in Table C4. The second panel includes all regressors from the first panel, as well as a quarterly time trend. The third panel repeats the regression from the first panel on a sub-sample of shipyards and excludes Chinese yards that entered after the policies were announced. Backlog coefficients differ by country. The table reports backlog coefficient for Chinese shipyards; backlog coefficients for Japan and Korea are not reported to save space. Full tables are available upon request. Standard errors bootstrapped using 500 bootstrap samples.

C.3 First-stage Policy Functions and State Transition Estimates

This section presents the first-stage estimates of investment and exit policy functions, as well as the state transition process. Table C7 reports the estimated investment policy function using OLS, Tobit, and CLAD. Table C8 reports the estimated exit policy function. Table C9 presents estimates of the transition process for the prices of bulk carriers, tankers, containerships, and steel.

Table C7: Estimates Of The Investment Policy Function

	(1) OLS	(2) Tobit	(3) CLAD
Constant	-0.066	-12.2	-31.9***
	(7.54)	(8.17)	(4.09)
B-spline 1 Capital	-69.7***	-63.8***	-69.6***
	(22.0)	(17.2)	(1.67)
B-spline 2 Capital	-74.7***	-71.7***	-68.2***
	(17.7)	(13.5)	(1.41)
2006-08	6.42***	4.59**	17.9***
	(1.60)	(2.32)	(0.74)
2009+	2.70	3.79	3.55**
	(2.20)	(3.03)	(1.80)
$\bar{s}_{jt}$	0.74***	0.87***	1.44***
	(0.11)	(0.087)	(0.040)
Bulk carrier price	2.05***	1.97***	1.34***
	(0.46)	(0.57)	(0.30)
Tanker price	0.48	1.89*	0.81***
	(0.93)	(1.14)	(0.13)
Containership price	-1.25	-1.49	-0.55
	(0.87)	(1.06)	(0.34)
Steel price	-2.49***	-4.44***	-4.38***
	(0.53)	(0.61)	(0.19)
N	4286		
$N(I>0)$	3301		
$N(I=0)$	985		

Note: In column (1), we carry out an OLS regression of investment (I) on basis functions of state variables, including both observations with $I>0$ and $I=0$. In column (2), we estimate the policy function using a Tobit regression of I on basis functions. In column (3), we estimate the investment policy function using a censored least absolute deviations estimator. $\bar{s}_{jt}$ is a production-efficiency index that captures the effect of backlog, age, ownership, region, and size on a firm's per-period payoffs. Investment is measured in million RMB.

Table C8: Estimates of the Exit Policy Function

	(1)		(2)	
	Coefficient	SE	Coefficient	SE
Constant	-0.57	(0.97)	-0.56	(1.02)
K	0.05	(0.35)	0.54	(0.43)
K^2	-0.05	(0.12)	-0.16	(0.15)
2006-2008	-0.57	(0.41)	-0.64	(0.43)
2009+	-0.47	(0.41)	-0.72	(0.44)
$\bar{s}_{jt}$	-0.01	(0.01)	-0.04	(0.02)
Bulk carrier price	0.36	(0.12)	0.36	(0.12)
Tanker price	-0.18	(0.11)	-0.16	(0.11)
Containership price	-0.22	(0.10)	-0.25	(0.11)
Steel price	-0.06	(0.07)	-0.10	(0.08)
Jiangsu			0.77	(0.24)
Zhejiang			0.58	(0.19)
Liaoning			1.04	(0.28)
N	4605		4605	
Log-likelihood	-239.30		-229.74	
Pseudo-R2	0.09		0.12	

Note: We carry out a probit regression of a binary indicator of exit on basis functions of state variables. We restrict the estimation to 1999-2011, because firm exits in 2012 and 2013 are not reliably measured as our sample of orders ends in Q1 2014.

Table C9: AR(1) Estimates for State Transition Processes

	Bulk carriers	Tankers	Containerships	Steel
Constant	0.88	0.70	1.25	-0.023
	(0.87)	(0.94)	(1.11)	(0.37)
Post	3.44	3.63	1.80	2.32
	(2.28)	(3.43)	(3.33)	(1.01)
Price (t-1)*Pre	0.86	0.92	0.88	0.89
	(0.12)	(0.086)	(0.090)	(0.19)
Price (t-1)*Post	0.86	0.86	0.88	0.69
	(0.072)	(0.095)	(0.10)	(0.11)
Trend*Pre	0.042	0.038	0.029	0.024
	(0.033)	(0.028)	(0.024)	(0.027)
Trend*Post	-0.058	-0.054	-0.040	-0.022
	(0.027)	(0.041)	(0.040)	(0.013)
N	57	57	57	57
R^2	0.95	0.97	0.96	0.80

Note: The dependent variable is the price in quarter 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.

C.4 Estimation of Dynamic Parameters: Model Fit

Table C10 compares the actual number of exits with model-predicted exits across 50 simulations. Firm exits are low-probability events and in general difficult to predict (Goldfarb and Xiao, 2016). Our model roughly matches the sample mean, though it under-predicts the number of exits post 2006. Table C11 compares the actual number of entrants with model-predicted number of entrants. Finally, Figure C1 plots both the distribution of actual investment as well as the distribution of model-predicted investment.These two distributions are reasonably similar, though actual investment has a long-tail of large investments and fewer medium-sized ones.

Table C10: Actual vs. Simulated Exit

	1999-2005	2006-2013	Total
Actual exits	5	43	48
Simulated exits	9	32	41

Note: We simulate the model 50 times from 1999 to 2013 under the baseline and report the average number of exits across these simulations.

Table C11: Actual vs. Simulated Entrants

	Pre	Post, Until 2008	Post, 2009+	Total
Actual entries	83	122	39	244
Simulated entries	65	132	28	225

Note: “Pre”refers to the period prior to 2004 for Zhejiang, and prior to 2006 for Jiangsu, Liaoning and Other regions. “Post, Until 2008” refers to the period between 2004 and 2008 for Zhejiang and between 2006 and 2008 for Jiangsu, Liaoning and Other regions. “Post, 2009+” refers to the period from 2009 onwards. We simulate the model 50 times from 1999 to 2013 under the baseline and report the average number of entries across these simulations.

D Counterfactual Exercises: Details

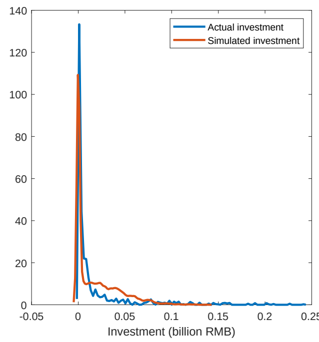
D.1 Implementation of Counterfactual Analyses

Each counterfactual analysis involves two steps: first, solving for the new Bellman equation and policy functions, and second, simulating the industry forward until 2050. Here we briefly explain how to implement the first step through a fixed point algorithm:

1. Compute expected profits $\pi(s)$ at all states.

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

Figure C1: Simulated vs. Actual Investment



Note: For the model-predicted investment, we use the estimated parameters and value function, randomly draw ν for every observation, and plot the distribution of optimal investment predicted by the model.

3. Update the policy functions. At each iteration j:

- Solve for the value function coefficients γ^{j+1} using the equation $V^{j+1}(s) = \pi(s) + p^{j,x}\sigma + CV^{j+1}(s)$.
- Update the investment policy function to $i^{j+1}(s,\nu)$ 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 $||i^{j+1}(s,\nu) - i^{j}(s,\nu)|| < tol$, where tol is a pre-assigned tolerance level.

D.2 Additional Counterfactual Results

Table D12 shows the effect of subsidies on ship prices. We show average prices for different ship types (bulk carriers, tankers and containerships), both for the 2006-08 period and the 2009-13 period.

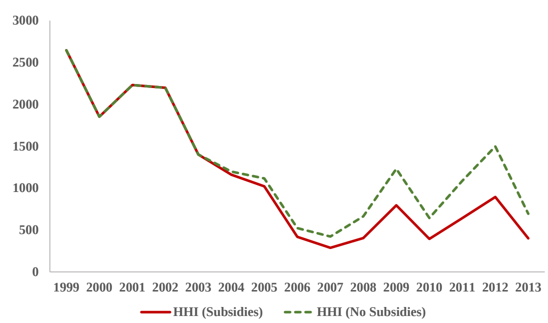
Table D12: Impact of Subsidies on Ship Prices

	Bulk	Tanker	Container
Subsidies, 2006-08	16.4	20.7	17.4
No subsidies, 2006-08	18.1	22.8	18.2
% difference	9.9%	10.1%	4.3%
Subsidies, 2009-13	8.8	6.4	9.0
No Subsidies, 2009-13	10.2	7.3	9.4
% difference	16.8%	14.8%	4.2%

Note: Prices in 1000 RMB/CGT for all ship types.

Figure D2 shows the HHI of the Chinese shipbuilding industry, both in the baseline scenario as well as in a scenario where firms do not receive any subsidies.

Figure D2: HHI For Chinese Shipbuilding, with and without Subsidies



Notes: The HHI reported in the above figure is calculated using all Chinese yards in a given year. It measures the concentration of the Chinese shipbuilding industry.

Table D13 presents the results from a counterfactual simulation comparing production and investment subsidies. The first column considers a scenario where firms receive only production subsidies at the baseline rate. In the third column, firms receive only investment subsidies. Investment subsidies appear less distortionary than production subsidies (74% vs. 50%).

However, this comparison is confounded by the larger magnitude of the production subsidies, as bigger subsidies are associated with more distortion. In the second column, we reduce the per-unit production subsidies by 75% to make the total amount of these two subsidies comparable. The return to investment subsidies remains higher, though the difference is smaller (74% vs 62%). Investment subsidies lead to a higher level of capital formation over the long run, which facilitates long-term industry growth, while production subsidies have a more immediate impact on output. Production subsidies are slightly more effective at increasing revenue: the increase in revenue per RMB of subsidy is 1.9 RMB for production subsidies, versus 1.5 RMB for investment subsidies. 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.

Table D13: Comparing Production and Investment Subsidies (in Bill RMB)

	100% Production Subsidy	25% Production Subsidy	Investment Subsidy
Lifetime Revenue 2006-	2154	1898	1873
Lifetime Net Profit 2006-	1061	978	981
Production Subsidy	225	47	0
Investment Subsidy	0	0	42
Δ Revenue /Subsidy	153%	190%	153%
Δ Net Profit/Subsidy	50%	62%	74%

Note: Revenue, net profit and subsidy are the discounted sum from 2006 to 2050 in billion RMB and averaged across simulations. ΔRevenue/Subsidy and ΔNet Profit/Subsidy are defined as in Table 5. In scenario "100% Production Subsidy", we keep the production subsidy at the baseline estimate, but shut down entry and investment subsidies. In scenario "25% Production Subsidy", we set the per unit production subsidy to 25% of the baseline estimate to make the aggregate subsidy amount in the last two columns similar. In scenario "Investment Subsidy", we keep investment subsidy but shut down entry and production subsidies. In all scenarios, the 2013 government policy carries onward till the end of the simulation period (2050).

Table D14 shows the differential policy impact if the government were to only subsidize White List firms (2nd column), as opposed to subsidizing all firms in the industry after 2013 (1st column). We include the top 56 firms with highest profitability to form the White List. As a benchmark we also show industry revenues and profits if the government were to discontinue subsidies entirely after 2013.

Figure D3 compares the performance of two groups of firms: those on the actual White List and those on the optimal White List. To ease comparison, all other firms are forced to exit in 2013. We also discontinue subsidies post 2013. The solid red line plots profit for firms on the "optimal White List", while the dashed blue line plots profit for firms on the "actual White List." The difference in the long-term industry profits and revenue (the discounted sum from 2014 to 2050) between the optimal and the actual White List is 12% and 8%, respectively.

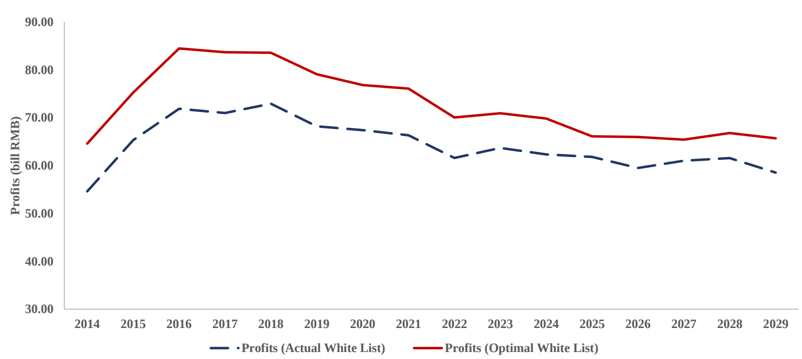
Finally, we analyze how the performance of policy instruments depends on the nature of competition. Table D15 illustrates counterfactual simulation results where we assume that firms take prices as given (perfect competition), instead of competing in quantities. Eliminating market-power considerations helps us evaluate the importance of the strategic trade argument in this setting. Relative to the benchmark results in Table 5, the overall return on subsidies is indeed lower under perfect competition, though the gap is modest. This is mainly driven by the fact that production subsidies are less effective when firms are price-takers (38% vs. 50%).

Table D14: Targeting Subsidies to White List Firms (in Bill RMB)

	Subsidize all firms after 2013	Subsidize White List firms after 2013	No subsidies after 2013
Lifetime Revenue 2014-	922	882	793
Lifetime Net Profit 2014-	712	716	656
Production Subsidy	106	70	0
Investment Subsidy	40	13	0
Entry Subsidy	0	0	0
Δ Revenue/Subsidy	85%	105%	
Δ Net Profit/Subsidy	37%	71%	

Note: this table reports discounted sum of revenue, net profit and subsidy from 2014 to 2050 in billion RMB, averaged across simulations. In column 1, all firms receive production and investment subsidies from 2014 to 2050; in column 2, only (optimal) White List firms receive subsidies; in column 3, no firms receive any subsidies. The (optimal) White List includes 56 firms with the highest profitability in 2013.

Figure D3: Industry Profits Under Different White Lists



Note: from 2013 onward, we keep firms on the White List, force all other firms to exit, and discontinue all subsidies. The solid red line plots profit in bill RMB for firms on the "optimal White List" from 2014 to 2029, while the dashed blue line plots profit in bill RMB for firms on the "actual White List" for the same period.

Table D15: Performance of Different Policy Instruments with Perfect Competition (in Bill RMB)

	All Subsidies	Production subsidies	Investment subsidies	Entry subsidies	Remove all subsidies
Lifetime Revenue 2006-	2253	2055	1786	1867	1716
Lifetime Net Profits 2006-	963	943	888	937	856
Production subsidies	267	227	0	0	0
Investment subsidies	78	0	42	0	0
Entry subsidies	412	0	0	217	0
Δ Revenue/Subsidy	71%	150%	166%	70%	
Δ Net Profit/Subsidy	14%	38%	74%	37%	

Note: in this set of simulations, firms are assumed to be price-takers and optimally choose production, investment, entry and exit. Revenue, net profit and subsidy refer to the discounted sum from 2006 to 2050 in bill RMB and averaged across simulations. ΔRevenue/Subsidy and ΔNet Profit/Subsidy are defined as in Table 5.

D.3 Impact of Industrial Policy on Freight Rate and Trade

China is the world's biggest exporter and the close second largest importer behind the USA in 2019. Given its fast growth in trade volume over the past couple of decades and its prominent role in global trade today, another reason to subsidize shipbuilding during the 2000s may have been to boost its imports and exports. Indeed, a larger worldwide fleet reduces transportation costs (or freight rates) and thus increases trade; if Chinese exporters and importers face entry barriers or other frictions, these subsidies may be justifiable.

To evaluate this argument, we first assess the extent to which industrial policy reduced freight rates. We then examine how changes in freight rates induced by the industrial policy have affected China's export and imports.

Effect of Industrial Policy on Freight Rates As ships' lifetime discounted stream of profits depends on freight rates, and prices of new ships reflect their discounted future profits (the shipping industry is competitive), we use observed ship prices to invert freight rates. A ship's lifetime profit is equal to:

$$\Pi_t = \sum_t \beta^t (P_t^f Q_t^f - C(Q_t^f)) = \sum_t \beta^t (\bar{P}^f Q_t^f - C(Q_t^f)) \tag{D3}$$

where P_t^f is the freight rate in period t, $\bar{P}^f$ is the average freight rate, Q_t^f denotes the total number of voyages undertaken by the ship in period t, and $C(Q_t^f)$ is the operating cost. We obtain estimates of operating costs from UNCTAD (2012). We use the price of a ship to approximate its lifetime expected profit, invert equation (D3) and average over our sample period to obtain the long-term steady-state freight rate as a function of ship prices and operating costs. Since our counterfactuals have calculated changes in ship prices, we can use this to evaluate changes in freight rates.

We estimate that industrial policy caused the price of bulk carriers to fall by 13.2%, leading to a corresponding decline in bulk carrier freight rates of 6.1% (Table D16). Similarly, China's subsidies reduced containership prices by 4.3%, resulting in a 2% decrease in containership freight rates.

Effect of Freight Rates on China's Exports and Imports Next, we evaluate how this reduction in freight rates affected China's exports and imports. The key determining factor is the trade elasticity with respect to shipping costs. Brancaccio et al. (2020) estimate a trade elasticity of -1 for bulk shipping, while Jeon (2018) estimates the elasticity to be -3.9 for container shipping. As there is no available data on the breakdown of China's trade volume by transport type, we assume that 70% of China's overall trade is seaborne, following UNCTAD (2012). Since China primarily imports raw materials and commodities that are typically transported in bulk carriers, while it exports manufactured goods that are usually transported in containerships, we assume that China's imports use bulk carriers and that its exports use containerships. We ignore tankers due to the lack of the appropriate trade elasticity estimate, as well as the considerably smaller associated trade volume.

Table D16 presents the estimated impact on China's trade volume. Subsidies had led to an annual increase in the amount of US$ 57 bn for China's imports and US$87 bn for China's exports between 2006 and 2013. The total effect of the subsidies on China's trade volume was therefore $144 bn annually. In contrast, the subsidies amounted to $11.3 bn annually during the same period. Whether or not the welfare gains associated with the increased trade volume could justify the cost of subsidies is an important question; however, answering this question requires a general equilibrium trade model and thus falls beyond the scope of this paper.

Table D16: Impact of Industrial Policy on Freight Rates and China's Trade Volume

Imports	2006-13
% decrease in bulk carrier prices	13.2%
% decrease in bulk carrier freight rate	6.1%
Bulk trade elasticity	1
% change in seaborne imports	6.1%
% change in imports	4.3%
Impact on annual imports (US$ bn)	57
Exports	2006-13
% decrease in containership prices	4.3%
% decrease in containership freight rate	2.0%
Container trade elasticity	3.89
% change in seaborne exports	7.9%
% change in exports	5.5%
Impact on annual exports (US$ bn)	87

Note: We obtain operating cost estimates for bulk carriers and containerships from UNCTAD (2012) and use them to calculate the effect of industrial policy on freight rates. China's total export and import value comes from the UNSD Commodity Trade database. We assume 70% of China's trade (in value) is searborne, following UNCTAD (2012).

D.4 A Simple Model of Subsidies

To illustrate the welfare effect of subsidies, we use a simple static model with homogeneous 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 $C_I(I) = c_1 I + (c_2/2)I^2$. The firm chooses q and I simultaneously to maximize profits:

$$V(K_0) = max_{q,I} Pq - \left((\alpha - \beta(K_0 + I))q - \frac{\delta}{2}q^2\right) - \left(c_1 I + \frac{c_2}{2}I^2\right)$$

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

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

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

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

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

Below we provide expressions for the return to subsidies, which is the change in industry profits from the subsidies divided by the cost of providing the subsidies. We also provide expressions for the deadweight loss from subsidies:

$$\begin{aligned}
\text{DWL from Prod. Subsidies} &= \tau_p^2/2\delta \\
\text{DWL from Invest Subsidies} &= \tau_i^2/2c_2 \\
\text{Return to Prod. Subsidies} &= (q^* + \frac{\tau_p}{2\delta})/(q^* + \frac{\tau_p}{\delta}) \\
\text{Return to Invest Subsidies} &= (I^* + \frac{\tau_i}{2c_2})/(I^* + \frac{\tau_i}{c_2})
\end{aligned}$$

Holding the adjustment cost parameters c_2 and δ 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 shows that the magnitude of DWL is independent of whether a firm has low or high marginal costs: τ_p^2/δ. 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.