# Learning and Investment under Demand Uncertainty in Container Shipping*

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**Abstract**

This paper investigates how firms invest under demand uncertainty focusing on the role of information. I develop a dynamic oligopoly model that allows uncertainty about the demand process: firms do not know the true parameters in the demand process, but form and revise expectations about demand based on information available at each decision-making moment. I estimate the model using firm-level data from the container shipping industry. The analysis shows that learning amplifies investment cycles and raises the correlation between investment and demand, which helps us explain the boom-bust investment patterns. I examine how learning interacts with firms' strategic incentives through counterfactual analysis. The results indicate that strategic incentives increase both the level and the volatility of investment and that learning intensifies these forces. I show that the regulator's modeling choice for firms' expectations has important policy implications, namely in merger evaluation.

KEYWORDS: Demand uncertainty, learning, dynamic games, investment, shipping

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# 1 Introduction

In many capital-incentive industries such as the oil, shipping, and chemical industries, firms invest in long-lived capital while facing highly volatile demand conditions. Thus, firms' expectations about demand often play an important role. When world trade was booming in the mid-2000's, container shipping companies ordered a large volume of new ships. Due to time-to-build a lot of these ships were delivered during the times of weak trade demand following the 2008 financial crisis.[1] As a result, firms faced an oversupply of ships, and in turn fierce price competition and low profitability.

Many industry experts attribute industry excess capacity to the firms' inability to forecast demand correctly.

> The container-shipping industry has been highly unprofitable over the past five years. ... Some of the pain is self-inflicted: as in past cycles, the industry extrapolated the good times and foresaw an unsustainable rise in demand (Mckinsey Insights, 2014).[2]

The problem is not limited to the 2008 crisis, as suggested by the CEO of one of the largest shipping companies:

> It's pretty clear that when we look back to the early part of 2011 when these ships were ordered, ours and everybody else's view on growth was somewhat different than what it turned out to be (The Wall Street Journal, 2013).[3]

This paper studies the role of information in investment cycles and overcapacity in the presence of market power and strategic considerations. I develop a dynamic oligopoly model of firm investment that allows uncertainty about the demand process in addition to uncertainty about demand realizations. Since agents do not know the parameters governing the evolution of demand, they form and revise their expectations based on information available at each decision-making moment. My estimation strategy involves employing commonly-unavailable data on investment costs and scrap values to pin down firms' learning process. I conduct counterfactual experiments with respect to competition, demand volatility, and scrapping subsidies. These counterfactuals serve three purposes: first, to understand how strategic incentives, demand volatility, and the irreversibility of investment affect investment cycles and industry outcomes and how these forces interact with learning; second, to evaluate

[1] Shipping firms face a lag between the order and the delivery of a new ship. This lag is often called time-to-build and ranges from 2 to 4 years in this industry.

[2] "The hidden opportunity in container shipping", accessed on January 11, 2016. http://www.mckinsey.com/insights/corporate_finance/the_hidden_opportunity_in_container_shipping

[3] "Maersk Line CEO: We Misjudged Container-Shipping Demand", accessed on January 11, 2016. http://www.wsj.com/articles/SB10001424052702303342104579098680549111434.

the welfare implications of relevant policy interventions; third, to understand the extent to which the modeling choice for firms' information matters in policy evaluation.

This paper has three main contributions. First, it provides a dynamic oligopoly framework that incorporates firms' changing beliefs about the aggregate demand process through learning. This framework is used to show that learning can help explain firm behavior in a setting subject to structural changes. Second, this paper sheds light on how learning and its interaction with firms' strategic incentives can lead to industry overcapacity and amplify boom-and-bust cycles of investment. Lastly, the paper shows that the modeling choice of firms' expectations has policy implications. In particular, I show that policy based on a full-information model is more likely to block welfare-enhancing mergers.

This paper relaxes the standard full-information assumption of rational expectations in a dynamic oligopoly model. Under the full-information assumption, firms may be uncertain about demand realizations due to the variance in the process, but know the true stochastic process of demand.[4] Although appropriate for many of the settings that we study, this assumption may be too restrictive in others. For example, agents may be relatively new to the industry or the environment may be subject to structural changes due to policy changes or exogenous shocks.

Motivated by these considerations and the example of container shipping, I allow firms to be uncertain not just about demand but also about the demand evolution process.[5] Firms learn the process from observing realizations of demand. In particular, they re-estimate parameters of the demand process using real-time data in each period under *adaptive learning*. Because firms may believe that the process itself can change over time, they are allowed to assign heavier weights to more recent realizations in forming their beliefs about the process.[6] I also compare the predictions of my model to those of alternative learning and knowledge structures.

One of the challenges in selecting appropriate informational assumptions and estimating a learning model is that the researcher does not directly observe agents' beliefs. And as Manski (1993) points out, it is hard to identify information and model parameters simultaneously. This paper's approach is to use data to investigate which model of firm beliefs can rationalize observed data patterns. Empirical papers on industry dynamics typically focus on recovering objects such as investment costs, entry costs, and exit values that can rationalize observe firm behavior while imposing a full-information structure (e.g. Collard-

[4] Note that this is different from perfect foresight where firms know future demand realizations exactly.

[5] The learning model builds on a fast-growing macroeconomic literature on learning (e.g.Cogley & Sargent (2005) and Orlik & Veldkamp (2014)).

[6] This is often called *constant-gain learning* in the literature. It is a natural way to model firms beliefs if firms believed that the underlying process changes over time (Evans & Honkapohja (2012)).

Wexler (2013)). For the container shipping industry, however, detailed data are available on investment costs and scrap values. Hence, I rely on these data to estimate these objects and instead focus on recovering the model of firm beliefs.[7]

Incorporating learning intensifies the computational burden of solving a dynamic model with many firms. Firms' beliefs change over time, which means that equilibrium needs to be solved separately for each period in time. This paper addresses this challenge by adopting an equilibrium concept in which firms keep track of some summary statistics of rivals' states instead of rivals' detailed states based on the moment-based Markov equilibrium (MME) notion proposed by Ifrach & Weintraub (2016) and the experience-based equilibrium (EBE) notion by Fershtman & Pakes (2012).[8] This approach vastly reduces the state space size, while still capturing strategic interaction among firms.

The estimation results show that an adaptive learning model that places 45% weight on a 10-year-old observation relative to the most current one can explain firm behavior better compared to alternative weighting schemes under adaptive learning or other learning and full-information models considered in this paper.[9] The full-information model offers predictions that are different from observed data both qualitatively and quantitatively: it predicts that firms withhold investment during demand boom years and suffer less from overcapacity when faced with downturns in demand. The total investment is lower by 17%, and the volatility of investment lower by 22%, compared to the data or the predictions of the learning model. In terms of welfare, this implies that producer surplus is greater by 85%, and consumer surplus lower by 3% under full information.

I use my estimated model to perform a series of counterfactual experiments that address various firm-strategy and public-policy issues. The first set of counterfactuals pertain to industry consolidation. Its goal is to highlight the effects of competition and how these effects interact with learning. This is important given theoretical predictions that strategic

[7]The underlying logic of this approach is similar to that of Hortacsu & Puller (2008). In their paper, the authors use commonly unavailable marginal cost data to quantify how much firms' actual bidding deviates from the optimal bidding predicted by their theoretical benchmark for the Texas electricity spot market. This paper similarly compares firms' optimal investment behavior given the investment cost data under full information with observed behavior in the data and further asks which informational structure can rationalized observed behavior.

[8]MME can be viewed as a special case of EBE. One interpretation of these two equilibrium concepts is that firms may have limited capacity to monitor or strategize over the relevant information of all rival firms, which justifies limiting agents' information sets. An alternative interpretation of MME is that it is an approximation to Markov-perfect equilibrium (MPE).

[9]This estimate is very close to the estimates in the previous studies that estimate a constant-gain learning model based on aggregate survey data such as the Survey of Professional Forecasts or micro data on expectations (e.g. Malmendier & Nagel (2016), Milani (2007), and Orphanides & Williams (2005)). Doraszelski *et al.* (2016) also find that firms weight recent play disproportionately when forming expectations about competitors' play.

incentives such as business stealing and preemption can lead to overinvestment as well as the industry's trend toward consolidation.[10] I perform a counterfactual experiment whereby the industry becomes monopolized. The total investment over the period of 2006 to 2014 drops by 34%, and the volatility of aggregate investment decreases by 22%. Producer surplus increases by $92 billion both from reduced shipbuilding costs and from higher prices, whereas consumer surplus drops by $42 billion in the Asia-Europe market. An alternative counterfactual of a merger between the top two firms decreases investment by 7.5%, increases producer surplus by $14 billion, and decreases consumer surplus by $1 billion. These results suggest that strategic incentives raise investment rates and amplify boom-and-bust investment cycles. The results also have policy implications as coordinated investment decisions lead to a consumer surplus loss but a total welfare gain.[11]

More importantly, I show that learning intensifies strategic motives. That is, when learning is allowed, reducing strategic interaction through a merger or monopolization leads to a larger decrease in investment and and a larger welfare gain. This is because during high demand periods in which firms have greater strategic incentives to increase investment, learning also leads firms to collectively become more optimistic. Consequently, policy that is based on a full-information model is more likely to block welfare-enhancing mergers.

The second counterfactual simulation examines the effect of demand volatility in the presence of learning. I find that an increase in demand volatility reduces investment, which is consistent with findings in previous empirical studies (e.g. Bloom (2009), Collard-Wexler (2013)). Furthermore, I show that introducing learning opens an additional channel through which demand volatility affects investment: large fluctuations in demand lead firms to revise their beliefs more frequently and more drastically, which in turn amplifies boom-bust investment cycles.

The third counterfactual simulates a ship-scrapping subsidy program. China initiated such a program in 2013, in an effort to support firms struggling with excess capacity. It grants 1500 yuan (approximately $US 240) per gross ton of scrapped old vessels. Scrapping programs have several effects: they encourage firms to scrap when demand conditions become unfavorable, thus alleviating the oversupply problem; however, investment decisions become more reversible, which in turn encourages investment. The net effect is unclear. Counterfactual results show that a subsidy program that makes a cash transfer for scrap-

[10]For example, see Mankiw & Whinston (1986) and Spence (1977). The top two firms in the industry formed a vessel-sharing agreement (the "2M Alliance") in 2014. China's two biggest shipping lines have also proposed to merge.

[11]US antitrust policy prohibits firms in the same business from colluding on investment decisions, while Japan allows cooperation among rivals along this dimension. O'brien (1987) argues that Japan's support for coordinated decision-making in investment is partially responsible for the country's success in the steel industry.

ping leads to more scrapping, especially in the post-crisis period from 2009, but also leads to a slight increase in investment. Overall, this policy proves to be ineffective in the social welfare sense, as a small increase in producer surplus is offset by a loss in consumer welfare from reduced supply.

### Related Literature

This paper builds on an emerging field that studies uncertainty and agents' beliefs in a learning framework. At the 2000 Ely Lecture, Hansen (2007) argued that the rational expectations approach endows agents with too much information and advocated putting econometricians and economic agents on comparable footing. Cogley & Sargent (2005) use a Bayesian learning model to study the role of the Federal Reserve's changing beliefs in the monetary policy. Orlik & Veldkamp (2014)) study uncertainty shocks in the Bayesian learning framework. This paper investigates how expectations formed through learning explain firm-level decisions and within-industry cycles of investment.

In the area of learning, the empirical literature in industrial organization has predominantly explored learning about firms' private information (e.g. Jovanovic (1982)), learning about a new technology (e.g. Covert (2014)), or consumers' learning about values of experience goods through experimentation (e.g. Dickstein (2011)). Doraszelski *et al.* (2016) examine learning about competitors' play and demand elasticity parameters in the context of the UK electricity market.

This paper is complementary to empirical studies on investment cycles, especially two papers on the bulk shipping industry: Kalouptsidi (2014) and Greenwood & Hanson (2015).[12] The paper's contribution is to introduce a new informational structure and strategic interaction. Kalouptsidi (2014) employs a fully rational model and uses second-hand ship prices to identify values of owning a ship non-parametrically. As the second-hand prices already reflect sellers' and buyers' beliefs about future demand, Kalouptsidi is indirectly incorporating firms' beliefs in the estimation of values of owning ships. By contrast, this study models firms' forecasting process explicitly. This approach will be useful in cases where the industry does not have active second-hand market or the second-hand market suffers from significant selection problems.[13] Understanding how firms form expectations is interesting in its own

[12]Although the two shipping industries share many similar characteristics, there is stark difference in terms of market power with much higher concentration in the container shipping industry. Kalouptsidi (2014) assumes that each firm owns one ship only and develops a competitive model of the bulk-shipping industry. Also, container shippers operate according to fixed schedules, while bulk shippers operate on-demand services much like taxis.

[13]Adverse selection may arise in the second-hand market if sellers privately observe the quality of the goods. If there is selection, the quality of goods traded in the second-hand market may be different from the quality of goods currently owned by firms. In this case, estimating the value of owning the goods from

right as well. Greenwood & Hanson (2015) introduce behavioral biases in persistence in earnings and long-run endogenous supply responses by rivals to explain bulk shippers' investment behavior. In contrast, this study does not require biases in firm beliefs. In particular, firms' beliefs about rivals' actions are consistent with the rivals' equilibrium strategies.

This paper makes a methodological contribution to the literature on the structural analysis of industry dynamics. Doraszelski & Pakes (2007)) provide an overview of this literature. Recent empirical papers include Ryan (2012), Collard-Wexler (2013), and Igami (2017). This paper adopts learning as the belief-formation process in a dynamic oligopoly framework. It shows that introducing an extra dimension of uncertainty (about the demand process) can be useful in analyzing firm behavior in an environment subject to structural changes. Incorporating this type of uncertainty also helps us understand the informational channel through which demand fluctuations can affect investment, which contributes to the body of empirical studies that quantify the effect of demand uncertainty on investment (e.g. Bloom (2009), Collard-Wexler (2013), and Kellogg (2014)).

The remainder of the paper is organized as follows. Section 2 describes the industry and the data. Section 3 presents the dynamic model of investment with learning for the shipping industry. Section 4 discusses the empirical implementation of the learning model. Section 5 describes the estimation procedure and and presents estimation results. Section 6 presents alternative models of firm beliefs and compares results under these models. It also diagnoses the models of firm beliefs using GDP forecast data. Section 7 discusses counterfactual experiments and section 8 concludes.

# 2 Industry and Data

This section describes key features of the container shipping industry and gives an overview of the data.

## 2.1 Container Shipping Industry

The container shipping industry's core activity is the transportation of containerized goods over sea according to fixed schedules between named ports. The containers come in two standard dimension (the twenty-foot dry-cargo container (TEU) or the forty-foot dry-cargo container (FEU)), which makes it easier to load, unload, and stack the cargo. The container ships transport a wide range of consumer goods and intermediate goods such as electronics,

second-hand prices will lead to biased estimates.

machinery, textiles, and chemicals. Container trade accounts for over 15% of global seaborne trade by volume and over 60% in value (Stopford (2009)).

Container shipping is a capital-intensive industry. Companies can invest in capital by purchasing new vessels. The price of building a ship fluctuates depending on the conditions of the shipbuilding and shipping markets at the time of the order, including freight rates, the strength of trade demand, the size of the order book, and expectations.[14] Container carriers also rely on chartered vessels, which are leased out by third parties. Chartered vessels account for approximately 50 percent of the total container ship capacity operated by the largest 20 firms. The majority of charter contracts for container ships are time charters which involve the hiring of a vessel for a specific period of time. The average contract length is 7-10 months (Reinhardt *et al.* (2012)). The charterer has operational control of the ships, while the ownership and management of the vessel are left in the hands of the shipowner. Firms can also scrap old ships which cannot be operated profitably. The demolition prices depend on the demand for scrap metal and the availability of ships for scrap.

The industry is vulnerable to sharp swings in global trade demand, but it is hard for firms to respond quickly to supply-demand imbalances in the short run. There is a gap between the time of placing a new order and the time of receiving the ordered ships due to time-to-build ranging from 2 to 4 years. Moreover, whereas bulk shippers can easily move their idle ships into lay-up, container shippers are limited to do so due to their pre-announced schedules (Stopford (2009)). When firms cannot fill their ships due to the oversupply of ships, they engage in fierce price competition in order to attract more customers.[15] Hence, the ability to make correct forecasts about future demand and invest accordingly is important in this industry.

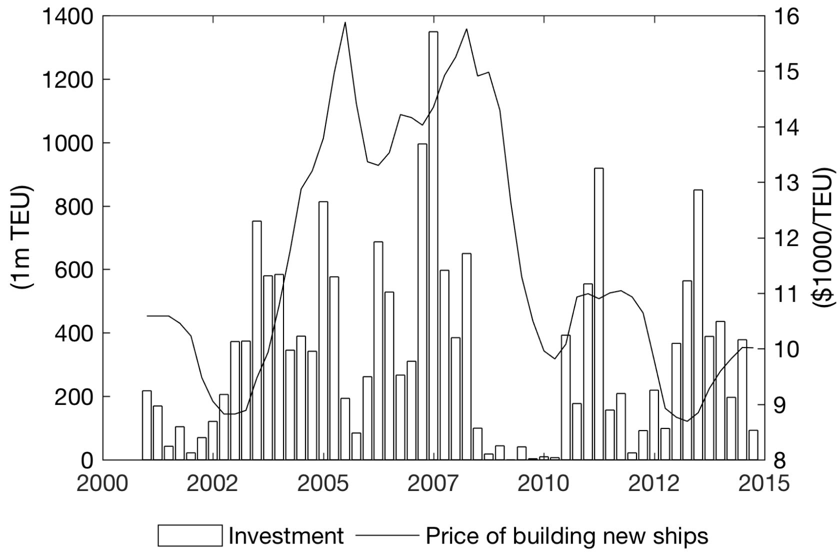
Figure 1 shows the industry-level quarterly quantity of ship orders and the price of those orders for 2001 to 2014.[16] Investment is concentrated in the times of high shipbuilding prices. Although the price is on average 42% higher compared to the 2009-2014 period, the quarterly investment is higher by more than 60% in the 2006-2008 period.

[14]The construction of new ships happens at shipyards. There are approximately 300 major shipyards and many smaller ones globally.

[15]The freight cost is the most important criterion for customers, although other factors such as transit time, schedule reliability, and frequency of departure matter as well (Reinhardt *et al.* (2012)).

[16]The prices of building a new ship and the number of ships in the industry order book are available by size category (2500 TEU, 3700 TEU, 6700 TEU, 8800 TEU, 10000 TEU, and 13500 TEU). I first obtain per TEU shipbuilding prices for each size category and construct the weighted average of these prices. The average scrap value is constructed in a similar way.

Figure 1: Total investment and investment costs




*Notes:* This figure shows the volume of new orders and the average price of building new ships from 2001:Q1 to 2014:Q4.

## 2.2 Data

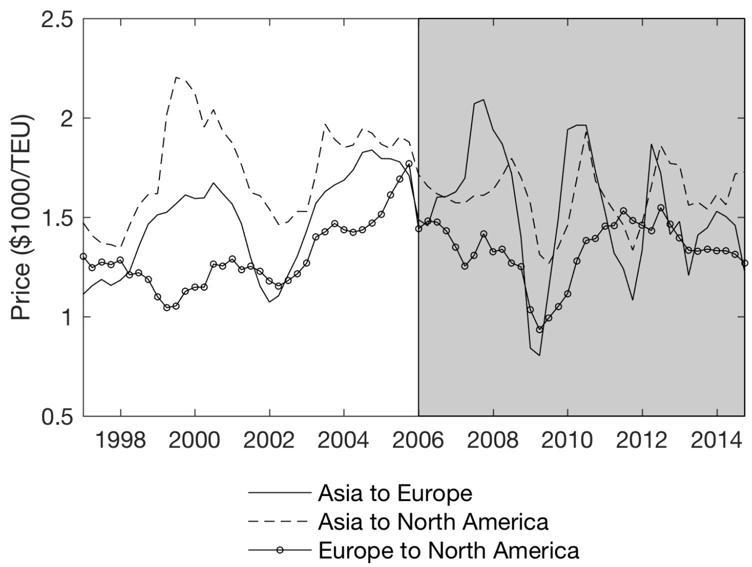
This project uses two main datasets on the container shipping industry. The first dataset combines data collected from two sources: MDS Transmodal, a U.K.-based research company, and Clarksons Research, a U.K.-based ship-brokering and research company. This dataset covers quarterly information from 2006 to 2014. The key information includes: (1) quantities and prices of container trade by trade route; (2) firm-level information on the number and the capacity of ships that each firm owns, charters, and has in its order book as well as the capacity deployed in each of the routes the firm operates on; and (3) industry-level charter rates, scrap prices, and shipbuilding prices.

Estimating firms' beliefs for the sample period from 2006 to 2014 requires historical price and quantity data that go further back than 2006, ideally from the inception of the industry. The first dataset on firm-level investment and capital is therefore supplemented with the historical price and quantity data compiled from the Review of Maritime Transport published by the United Nations that goes back to 1997.[17] It contains information on the

[17] Although this is roughly the start date of the official public data on the aggregate price and quantity of container trade, firms may have longer historical data and use them in forming expectations. Section 4 discusses my empirical strategy in estimating firms' beliefs given the truncated nature of the price and quantity data.

average freight rates and cargo flows on major routes. The volume of trade is available at the yearly level in this dataset, although the price level is available at the quarterly level. The quarterly quantity of container trade are imputed based on the data on the value of trade by origin-destination pair from the IMF Direction of Trade Statistics database.[18]

Figure 2: Prices on major trade routes




*Notes:* This figure shows quarterly average prices of shipping an unit of trade goods (TEU) on major container trade routes from 1997 to 2014. The shaded area covers the period on which this paper's main analysis lies from 2006 to 2014.

The analysis in this paper focuses on the Asia-Europe (A-E) market, but also accounts for demand conditions in other markets. In addition, the model allows learning with respect to demand in both the A-E and other markets. In practice, firms have to choose which route to operate on and how much capacity to deploy on each of the routes they operate on. However, it is computationally infeasible to endogenize capacity deployment decisions in every market in this model since there are a large number of firms and the markets are not independent of one another. To make the model tractable, firms are allowed to choose how much capacity to deploy in the Asia-Europe market and the "outside market" which includes all other main markets. The demand conditions in the outside market are estimated from the data from the Asia-North America (A-NA) and Europe-North America (E-NA) markets.[19]

[18]The imputation assumes that the quarterly container trade volume is proportional to the value of trade in each year.

[19]These two are two biggest markets besides the A-E market and also have the price and quantity data going back to 1997.

These two markets along with the A-E market account over 50 % of all interregional trade by volume and 67% by deployed ship capacity.

The reasons the analysis gives more attention on the Asia-Europe market are the following. First, it is the largest market in the container shipping industry accounting for over 23% of the total interregional container trade by volume and close to 40% in terms of the deployed ship capacity. Second, it was most heavily impacted by the downturns in 2008, so the effect of learning is likely to be more pronounced in this market. Figure 2 shows the average prices on the five major trade routes by trade volume from 1997 to 2014. The shaded area covers the 2006-2014 period on which the main analysis lies. The price fell by over 50 percent from the peak in 2007 to the trough in 2009 on the Asia to Europe route while it fell by less than 30 percent on the Asia to North America route, which is the second largest route.

Table 1: Descriptive statistics

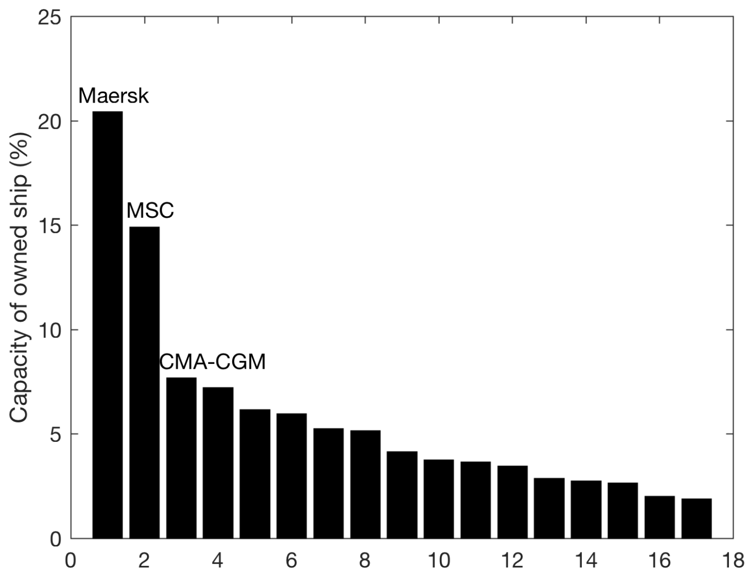
| | | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Industry-level data (2006-2014)** | | | | | |
| Shipbuilding price ($1000/TEU) | | 11.62 | 2.22 | 8.69 | 15.76 |
| Scrap price ($1000/TEU) | | 2.62 | 0.55 | 1.50 | 3.81 |
| **Market-level data (1997-2014)** | | | | | |
| Asia to Europe | Quantity (1 mil. TEU) | 2.37 | 1.10 | 0.70 | 3.98 |
| | Price ($1000/TEU) | 1.51 | 0.28 | 0.80 | 2.09 |
| Europe to Asia | Quantity (1 mil. TEU) | 1.08 | 0.39 | 0.51 | 1.76 |
| | Price ($1000/TEU) | 0.78 | 0.10 | 0.57 | 1.07 |
| Other routes | Quantity (1 mil. TEU) | 5.11 | 1.41 | 2.80 | 7.72 |
| | Price ($1000/TEU) | 1.36 | 0.12 | 1.06 | 1.60 |
| **Firm-level data (2006-2014)** | | | | | |
| Capacity of owned ships (1m TEU) | | 0.30 | 0.25 | 0.04 | 1.47 |
| Capacity of ships in order book (1m TEU) | | 0.18 | 0.13 | 0.00 | 0.64 |
| Capacity of chartered ships (1m TEU) | | 0.31 | 0.29 | 0.01 | 1.55 |
| Capacity of ships deployed in Asia-Europe market (1m TEU) | | 0.22 | 0.19 | 0.04 | 0.99 |

*Notes:* There are 36 industry-level, 216 market-level, and 612 firm-level observations. Other routes include Asia to North America, North America to Asia, North America to Europe, and Europe to North America routes.

The analysis is further restricted to firms that deployed over 80,000 TEU of ships in the Asia-Europe market on average in the 2006 to 2014 period. These firms account for more than 95 percent of the total capacity of ships deployed in the Asia-Europe market. This results in a quarterly panel of 17 firms from 2006 to 2014. There is no entry into or exit from the Asia-Europe market by these firms in this period. Table 1 provides summary statistics of this dataset. On average, firms in the sample own 300,000 TEU in capacity, charter 310,000

TEU and have an order book of 180,000 TEU.

Figure 3: The distribution of firm size




*Notes:* This figure shows the capacity owned by each firm as a percentage of total industry capacity, where the capacity is averaged over the period of 2006:Q1 to 2014:Q4.

Figure 3 shows the distribution of firm size based on the average owned capacity over the period from 2006 to 2014. The market structure is quite concentrated with more than 40% of the total capacity concentrated on the top three firms in contrast to the bulk shipping industry which consists of a large number of small ship-owning firms (Kalouptsidi (2014)).[20] While there is considerable size variation among the top two firms, the rest of the firms are similar in size.[21]

Before describing the model, I look for preliminary evidence of changes in firms' investment policy. It is inherently difficult to test whether firms are adjusting their beliefs about demand as they get new information since the beliefs are not directly observed. Instead, I search for suggestive evidence based on the difference in the predictions that a full-information model and a learning model make. A learning model generally predicts that even after controlling for the state (which includes all payoff-relevant variables), firms' beliefs, hence firms' actions will be different before and after experiencing large demand shocks.[22]

[20] Kalouptsidi (2014) shows that the largest fleet share is 3% for Handysize bulk carriers.

[21] The Herfindahl index for the industry is 970 when these 17 firms are accounted for.

[22] The payoff-relevant variables are defined to be those variables that are not current controls and affect the current profits of at least one of the firms as in Ericson & Pakes (1995) and Maskin & Tirole (2001).

By contrast, under full information firms' perceived probabilities of transitioning to different demand states from a given state stay fixed over time as new demand realizations do not contain any new information. Hence, I examine whether firm behavior changes significantly after firms experience large demand shocks. In particular, I test for a structural break in the firm's investment policy function and find evidence for such a break. The details of the test and the results are provided in appendix B.

# 3 Model

This section presents the model for the container shipping industry. The model builds on the dynamic oligopoly framework developed by Ericson & Pakes (1995) and the learning literature in macroeconomics. Firms' beliefs about demand change over time as firms re-estimate the parameters of the demand process using up-to-date information available to them. In each period a firm decides whether to invest in new ships and whether to scrap existing ships based on its own capital and order book levels, and rivals' aggregate capital and order book levels as well as its beliefs about future demand. In the product market competition stage, firms decide on how much capacity to charter (lease from a third-party chartering company) and how much capacity to station in each market. I start by describing the model of firm beliefs in section 3.1. Section 3.2 presents firms' dynamic problem, and section 3.3 demand for container shipping services and product market competition. Section 3.4 provides a definition of equilibrium.

## 3.1 A Model of Firms' Beliefs about Demand

This section proposes an adaptive learning model of firms' expectations about demand. Section 6.1 presents details of all alternative models considered in this paper including a full-information model, a Bayesian learning model, and a full-information model with time-varying demand volatility. Under adaptive learning agents form expectations about demand based on information available to them in each period. They operate like econometricians who estimate the parameters of the model based on best information at their disposal and make forecasts using their estimates.

Agents contemplate a first-order autoregressive model for demand in the Asia to Europe market, denoted by $z_t$, as the following:

$$\begin{aligned} z_t &= \rho^0 + \rho^1 z_{t-1} + \omega_t \\ &= \rho' x_t + \omega_t \end{aligned} \tag{1}$$

where $\omega_t \sim N(0, \sigma_t^2), \rho = [\rho^0, \rho^1]'$, and $x_t = [1, z_{t-1}]'$. Similarly, the model for the demand in the outside market ($\tilde{z}_t$) is given as:

$$\begin{aligned} \tilde{z}_t &= \tilde{\rho}^0 + \tilde{\rho}^1 \tilde{z}_{t-1} + \tilde{\omega}_t \\ &= \tilde{\rho}' \tilde{x}_t + \tilde{\omega}_t \end{aligned} \tag{2}$$

where $\tilde{\omega}_t \sim N(0, \tilde{\sigma}_t^2), \tilde{\rho} = [\tilde{\rho}^0, \tilde{\rho}^1]'$, and $\tilde{x}_t = [1, \tilde{z}_{t-1}]'$. In the full-information model, the parameters in the demand model, $\{\rho^0, \rho^1, \sigma, \tilde{\rho}^0, \tilde{\rho}^1, \tilde{\sigma}\}$ are known to the agents. By contrast, under adaptive learning agents revise expectations by re-estimating these parameters in each period based demand realizations up to time $t$, $\{z_\tau, \tilde{z}_\tau\}_{\tau=0}^t$. At each $t$, firms' beliefs about demand can be described by the estimates of the $AR(1)$ parameters, denoted as $\eta_t = (\rho_t^0, \rho_t^1, \sigma_t, \tilde{\rho}_t^0, \tilde{\rho}_t^1, \tilde{\sigma}_t)$.

Firms are assumed to have homogenous beliefs about the aggregate demand and they recognize this. The prices and quantities of container trade are public information periodically published in trade journals and other publications. Moreover, swings in global trade demand common to all firms are the main source of demand shocks in this industry.[23] The model also assumes that agents do not internalize the possibility of learning in the future.[24] In other words, firms use their current beliefs in forecasting demand. This assumption has two behavioral interpretations. The first interpretation is that agents believe current beliefs to be the correct forecasts for future demand. The alternative interpretation is that agents use current beliefs in forecasting as these approximate future beliefs.

Let $X_t = [x_0, x_1, ..., x_t]'$ and $R_t = \frac{X_t' X_t}{t}$. The expectations at time $t$ regarding the Asia-Europe market demand under adaptive learning can be written recursively as

$$\rho_t = \rho_{t-1} + \lambda_t (R_t)^{-1} x_t \left( z_t - \rho_{t-1}' x_t \right) \tag{3}$$

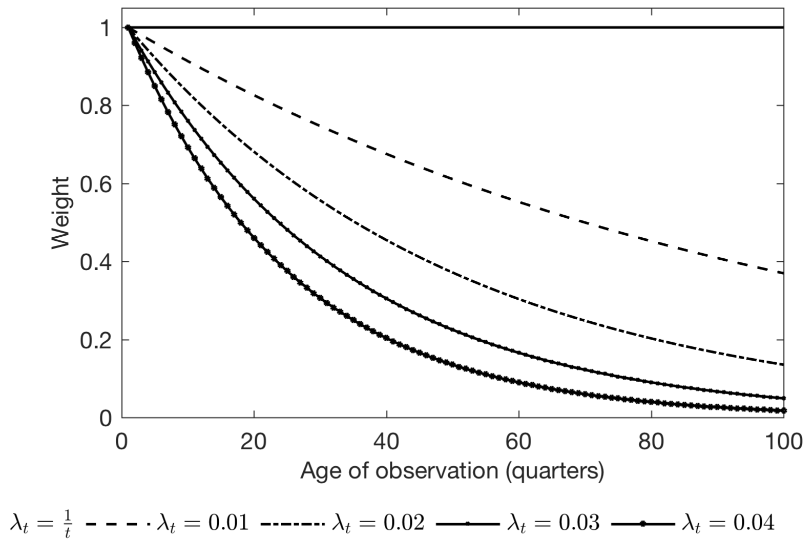
$$R_t = R_{t-1} + \lambda_t (x_t x_t' - R_{t-1}) \tag{4}$$

where $\lambda_t$ is the weight parameter that governs how responsive the estimate revisions are to new data. Figure 4 plots relative weights placed on observations for different values of $\lambda_t$.

[23] On a practical level there are no publicly available data that provide information on firm-level demand to my knowledge, which are necessary to allow heterogenous firm beliefs. Nevertheless, heterogeneity in firms' beliefs would arise if firms experienced different demand shocks, for example, through different customer pools. How firms form heterogeneous beliefs and how they affect firm decisions and industry dynamics are interesting topics of study for future work.

[24] This is often referred to as *myopic learning* in the literature. Suppose information is endogenous to agents' decisions, for example, because agents are making consumption decisions for experience goods for which quality is difficult to observe in advance. In this case, the assumption of myopic learning rules out experimentation, while allowing agents to internalize learning in the future may encourage experimentation. In this paper's setting, since information about the aggregate trade demand is exogenous to agents' actions, there is no room for experimentation regardless of the assumption on learning.

Figure 4: Weights on observations under adaptive learning




Nots: This figure plots weights that are applied to observations for different values of $\lambda_t$ in the adaptive learning model where $\lambda_t$ is the weight parameter that governs how responsive estimate revisions are to new data (see equation (3)).

For example, if $\lambda_t = \frac{1}{t}$, agents put equal weight on all observations in their information set. If $\lambda_t$ is some constant between 0 and 1, weights geometrically decline with the age of the observation such that agents assign heavier weights to more recent observations. This would be a natural way to form expectations if agents were concerned about the possibility of structural changes (Evans & Honkapohja (2012)). A larger value of $\lambda_t$ leads to heavier discounting of older observations. For example, when $\lambda_t = 0.03$, agents put a 30% weight on a 10-year-old observation relative to the most current observation, while when $\lambda_t = 0.02$, agents put a 45% weight on a 10-year-old observation.

## 3.2 Firms' Dynamic Problem

Time is discrete with an infinite horizon and is denoted by $t \in \{0, 1, 2, ...\}$. There are $n$ incumbent firms and the set of incumbent firms is denoted by $N = \{1, 2, ..., n\}$. Firms are heterogeneous with respect to their firm-specific state, $x_{it} = (k_{it}, b_{it})$, where $k_{it}$ is the capacity of ships owned by firm $i$ and $b_{it}$ is the backlog, or the capacity of firm $i$'s order book.[25] The

[25]The owned capacity space denoted by $\mathcal{K}$ is discretized into 19 points such that $\mathcal{K} = \{k_0, k_1, k_2, ..., k_{18}\}$ and the order book capacity space denoted by $\mathcal{B}$ into 7 points such that $\mathcal{B} = \{b_0, b_1, ..., b_6\}$. $\mathcal{K}$ and $\mathcal{B}$ are both discretized in 100,000 TEU increments such that $k_0 = 0$ TEU, $k_1 = 100,000$ TEU, and so on, and

underlying industry state is $s_t = ((x_{it})_i, d_t)$ where $(x_{it})_i$ is the list of all incumbents' firm-specific states and $d_t = (z_t, \tilde{z}_t)$ includes the demand states of the Asia-Europe market and the outside market.

The timing of events is as follows: (1) Firms observe their current state as well as their private cost shocks associated with investing and scrapping. They update their beliefs about demand. (2) Firms make investment and scrapping decisions. (3) Firms choose how much capacity to charter and how much capacity to deploy in the Asia-Europe market and the outside market. They engage in period competition and receive period profits. (4) The dynamic decisions are implemented and the delivery and depreciation outcomes are realized. The industry evolves to a new state.

Computing a Markov perfect equilibrium (in which each incumbent firm follows a Markov strategy that is optimal when all competitors firms follow the same strategy) is subject to the curse of dimensionality. As the number of incumbent firms grows, the number of states grows more than exponentially.[26] To address this challenge, I consider an alternative equilibrium concept which can be viewed in the context of the moment-based Markov Equilibrium (MME) of Ifrach & Weintraub (2016), or more broadly the experience-based equilibrium (EBE) of Fershtman & Pakes (2012).

In MME, firms keep track of and condition their strategies on the detailed state of strategically important firms (dominant firms) and a few moments of the distribution describing non-dominant firms' states, instead of the detailed state of all incumbents. This reduces the size of the state space thereby alleviating the computational burden. My application allows firms to keep track of their own firm-specific states, the sum of all incumbents' states, and the aggregate demand states. Firms' strategies thus depend on the firm-specific state, $x_{it} = (k_{it}, b_{it})$, and the moment-based industry state defined as $\hat{s}_t = (\sum_i x_{it}, d_t)$. MME strategies are not necessarily optimal, however; there may be a profitable unilateral deviation to a strategy that depends on the detailed state of all firms. This is because the moment-based state may not be sufficient statistics to predict the future evolution of the industry. In appendix D.1, I consider a version that allows richer information by adding a dominant firm's state into the moment-based industry state and show that the model predictions are robust to this change.

Firms make an investment decision ($\iota_{it} \in \{0, 1\}$) and a scrapping decision ($\delta_{it} \in \{0, 1\}$) in order to maximize expected discounted profits.[27] I denote the strategy profile as $\mu_{it} =$

$b_0 = 0$ TEU, $b_1 = 100,000$ TEU, and so on.

[26] There are 17 active firms in my application. Even a simple specification with a single state variable that can take up to 5 different values would result in over a billion of states.

[27] Firms are restricted to invest and/or scrap up to only one unit (100,000 TEU) per period. In the data there are no observations of a capital reduction by more than one unit and there are only three instances

$(\iota_{it}, \delta_{it})$. Each investing firm pays an investment cost. The investment cost consists of a part common to all firms which is a function of the aggregate state, $\kappa(\hat{s}_t)$, and a privately observed part of the cost, $\varepsilon^{\iota}_{it} \sim N(0, (\sigma^{\iota})^2)$. If a firm decides to scrap its ships or if there is depreciation, the firm receives a scrap value. The scrap value is the sum of the value common to all firms, $\phi(\hat{s}_t)$, and an iid private value distributed as $\varepsilon^{\delta}_{it} \sim N(0, (\sigma^{\delta})^2)$. Deprecation occurs with a probability proportional to the firm's current capital amount, given as $\zeta k_{it}$ for some constant $\zeta$.[28] I denote as $\nu(\delta_{it}, x_{it})$ the expected amount of capital reduction from depreciation or scrapping before the realization of the depreciation outcome such that $\nu(\delta_{it}, x_{it})$ is one if $\delta_{it} = 1$ and $\zeta k_{it}$ otherwise. The value function of a firm after observing its private shocks and before making investment and scrapping decisions can be written as

$$\begin{aligned} V^{\eta_t}(x_{it}, \hat{s}_t) = \max_{\iota_{it}, \delta_{it}} \pi(x_{it}, \hat{s}_t) - \iota_{it}\left(\kappa(\hat{s}_t) + \varepsilon^{\iota}_{it}\right) + \nu(\delta_{it}, x_{it}) \quad \phi(\hat{s}_t) + \varepsilon^{\delta}_{it} \\ + \beta E\left[V^{\eta_t}(x_{it+1}, \hat{s}_{t+1} | x_{it}, \hat{s}_t)\right] \end{aligned}$$

where $\eta_t$ is the vector of parameters summarizing firms' beliefs in period $t$ about future demand. The value function is a function of $\eta_t$ as it depends on how firms perceive the demand state to evolve.

The current model does not allow for persistent heterogeneity in the investment costs and scrap values across firms. The analysis of transaction-level pricing data on investment and demolition confirms that there is no significant firm heterogeneity at least in the observed transaction prices of investment and scrapping. The model incorporates firm heterogeneity in other areas, however, since it may be important given the persistent concentration of market power. First, the cost of chartering ships from a third party is allowed to depend on firm size, since larger firms may have greater bargaining power over charterers. Second, the marginal cost of production dethe capacity of firm's deployed ships. The detailed specification of these cost functions is given in section 3.3.

of an investment of more than one unit. Capping the maximum investment level to one unit for each firm reduces the action space thus alleviating the computational burden.

[28]If a firm scraps its vessels, there is no depreciation in the same period such that the maximum reduction in $k_{it}$ is one unit. This assumption is made since the data do not provide any observations of a capital reduction by more than one unit. The interpretation of this assumption can be that when a firm decides to scrap its vessels, it chooses the oldest vessels that are about to deprecate on their own. This assumption can be easily relaxed.

### State Transitions

When a firm invests, the order book capacity increases by one unit when there is no delivery at $t$ and stays constant if there is delivery.[29] A firm's own capacity is determined by scrapping decision, and depreciation and delivery outcomes. The transition of the firm-specific state is described as:

$$\begin{aligned} k_{it+1} &= k_{it} + \tau_{it} - \min(\delta_{it} + \psi_{it}, 1) \\ b_{it+1} &= b_{it} + \mu_{it} - \tau_{it} \end{aligned}$$

where $\tau_{it}$ is delivery and $\psi_{it}$ is depreciation. The probability of delivery is a linear function of the firm's order book capacity such that the delivery happens with the probability of $\xi b_{it}$ for some constant $\xi$. Similarly, the probability of depreciation is $\zeta k_{it}$ such that it linearly increases in the capital stock. The perceived evolutions at time $t$ of the aggregate demand states for the Asia-Europe market and the outside market follow first-order autoregressive processes as the following:

$$\begin{aligned} z_t &= \rho_t^0 + \rho_t^1 z_{t-1} + \omega_t \\ \tilde{z}_t &= \tilde{\rho}_t^0 + \tilde{\rho}_t^1 \tilde{z}_{t-1} + \tilde{\omega}_t \end{aligned}$$

where $\omega_t \sim N(0, \sigma_t^2)$ and $\tilde{\omega}_t \sim N(0, \tilde{\sigma}_t^2)$.[30] This process is described in more detail in section 3.1. The parameters in the $AR(1)$ model, $\eta_t = (\rho_t^0, \rho_t^1, \sigma_t, \tilde{\rho}_t^0, \tilde{\rho}_t^1, \tilde{\sigma}_t)$, summarize the beliefs about the evolution of future demand at time $t$. How firms update these beliefs as they get new information is described in section 3.1.

Note that even though the evolution of the underlying state $s_t$ is a Markov process under Markov strategies, the evolution of the moment-based industry state $\hat{s}_t$ may not be. This is because information is lost in the process of aggregating information through moments.[31]

[29] This paper does not take into account the fact that ships are becoming larger and thus more efficient. I investigate whether the improving efficiency of ships is the driving force in the investment boom and bust observed in the data. I regress firm investment on the current size of the ships and other firm characteristics and find that the current size is not a strong predictor of investment. It is possible to allow the efficiency of ships to be an endogenous state variable. This would increase the sizes of the state space and the action space dramatically, however.

[30] I explore alternative specifications including a case in which the errors in the AR(1) processes follow heavier-tailed t-distributions and a case in which correlation between demand in the Asia-Europe market and demand in the outside market is allowed. Main results are robust to these alternative specifications.

[31] To understand this, suppose that there are three firms. Each of these firms keeps track of its own firm-specific state, $x_{it}$ and the sum of all three firms' states as the moment-based industry state such that $\hat{s}_t = \quad {}_i x_{it}$. The underlying industry state is $s_t = (x_{it})_i$. In one case, suppose that the underlying state is $(10, 10, 10)$, while in another case the underlying state $(30, 0, 0)$. In both cases, the moment-based industry state is $\hat{s}_t = 30$. However, starting from these two different underlying states may not yield the same

Hence, I approximate the Markov process for the moments using empirical transitions following Ifrach & Weintraub (2016) and Fershtman & Pakes (2012).

Let $\mu$ denote the investment strategy and let $P_{\mu',\mu}$ denote the transition kernel of the underlying state $(x_{it}, s_t)$, when firm $i$ uses strategy $\mu'$ and its competitors use strategy $\mu$. Then, we can define an operator $\Phi$ such that $\hat{P}_{\mu',\mu} = \Phi P_{\mu',\mu}$ where a Markov process $\hat{P}_{\mu',\mu}$ approximates the non-Markov process of the moment-based state, $P_{\mu',\mu}$. In practice, the moment-based industry state's evolution is defined to be the long-run average of observed transitions from the moment-based state in the current period to the moment in the next period under strategy $\mu$ as follows:

$$\hat{P}_\mu[m'|\hat{s}] = (\Phi P_\mu)[m'|\hat{s}] = \lim_{T\to\infty} \frac{\mathbb{I}\{\hat{s}_t = \hat{s}, m_{t+1} = m'\}}{\sum_{t=1}^{T} \mathbb{I}\{\hat{s}_t = \hat{s}\}}$$

where $m_t = (\sum_i x_{it})$ includes the moments in the moment-based state.

## 3.3 Demand for Container Shipping and Product Market Competition

In each period, firms choose (a) how much capacity to charter $(h_{it})$, and (b) how much capacity to allocate to the Asia-Europe market $(\bar{q}_{it})$ and the outside market $(\tilde{q}_{it})$ given the state they are in. In other words, a firm chooses how much of its total capacity to allocate to the Asia-Europe market or the outside market where the total capacity is determined as the sum of its chartered and owned capacity. The capacity firms allocate to the Asia-Europe market determines the supply in the market, which along with demand determines the market-clearing price and quantity. Demand for each route in the Asia-Europe market is assumed to have constant elasticity as follows:

$$\log Q_{jt} = z_{jt} + \alpha_1 \log P_{jt} \tag{5}$$

where $z_{jt}$ denotes the demand state, $P_{jt}$ the price, and $Q_{jt}$ the quantity of route $j$ at time $t$.

The marginal cost of providing services on a route is linearly increasing in quantity up to the firms' capacity constraint as follows:[32]

$$mc(q_{ijt}, \bar{q}_{it}) = \begin{cases} a + \frac{bq_{ijt}}{\bar{q}_{it}} & \text{if } q_{ijt} \leq \bar{q}_{it} \\ \infty & \text{otherwise.} \end{cases} \tag{6}$$

distribution for the moment-based state in the next period $(\hat{s}_{t+1})$.

[32]This functional form assumption is based on the fact that it becomes increasingly hard to schedule loading and unloading as the ship reaches its full capacity.

Then, the supply curve for route $j$ is given as the horizontal sum of all firms' supply curves as follows:

$$P_{jt} = a + \frac{bQ_{jt}}{\bar{Q}_t} \quad \text{if } Q_{jt} \leq \bar{Q}_t \tag{7}$$

where $\bar{Q}_t = \quad {}_i\, \bar{q}_{it}$. The price in the Asia-Europe market is determined by the intersection of the demand curve given in equation (5) and the supply curve given in equation (7).

The period profit is the sum of profits from providing shipping services on the Asia to Europe route and the Europe to Asia route plus the profit from the outside market minus the charter cost and the fixed cost of capital:

$$\pi(x_{it}, \hat{s}_t) = \max_{\bar{q}_{it}, h_{it}} \left\{ \Big( \sum_{j \in \{1,2\}} P_{jt} q_{ijt} - c(q_{ijt}, \bar{q}_{it}) \Big) + R(\tilde{q}_{it}, \tilde{Q}_t, \hat{s}_t) - CC(h_{it}, x_{it}, \hat{s}_t) - FC \cdot k_{it} \right\} \tag{8}$$

where $FC$ is the fixed cost of holding one unit of capital, $R$ is the profit from the outside market, $CC$ is the charter cost, and $\tilde{q}_{it}$ is the capacity deployed in the outside market. The fixed cost of holding ships includes all costs that do not vary with the output level (or how full the ships are) such as docking fees, maintenance costs, canal dues, and port charges. I do not explicitly model the chartering market and the product market competition in the outside market but account for them in a reduced form way. The detailed specification of the reduced-form functions for the charter cost and the outside-market profit is given in section 5.2.

## 3.4 Equilibrium

The value function can be re-written as the perceived value of a firm using moment-based strategy $\mu'$ in response to all other firms following strategy $\mu$:

$$\hat{V}^{\eta}_{\mu',\mu}(x, \hat{s}) = \pi(x, \hat{s}) - \iota\left(\kappa(\hat{s}) + \varepsilon^{\iota}\right) + \nu(\delta, x) \quad \phi(\hat{s}) + \varepsilon^{\delta} \quad + \beta E_{\mu',\mu} \hat{V}^{\eta}(x', \hat{s}' | x, \hat{s}).$$

The definition of an equilibrium is then given as follows.

**Definition** Equilibrium comprises of an investment and scrapping strategy $\mu$ that satisfies the following conditions:

(a) Firm strategies satisfy the optimality condition:

$$\sup_{\mu' \in \mathcal{M}} \hat{V}^{\eta}_{\mu',\mu}(x, \hat{s}) = \hat{V}^{\eta}_{\mu}(x, \hat{s}) \quad \forall (x, \hat{s}) \in \mathcal{X} \times \hat{\mathcal{S}}.$$

(b) The perceived transition kernel is given by:

$$\hat{P}_\mu = \Phi P_\mu$$

Equilibrium is computed using an algorithm based on value-function iteration. Appendix C describes the algorithm in detail.

# 4 Empirical Implementation of the Learning Model

This section discusses the implementation of the learning model described in section 3.1 and presents expectations about demand implied by the model (see section 6.1 for the implementation of all alternative models of firm beliefs). The truncated nature of the price and quantity data for container trade poses a challenge in implementing the learning model. An agent's information set in each period includes all observations from the past. However, although firms may have access to observations from the inception of the industry, the researcher may not. This problem arises in most empirical settings when dealing with a learning model. In my particular setting, data on prices and quantities for major trade routes are available starting from 1997, although the first international voyage dates back to 1966. Given this challenge, I explore two alternative methods of empirically implementing an adaptive learning model: the truncation approach and the imputation approach.

The truncation approach entails setting the initial period of the information set as the start date of the data. This method is straightforward to implement and is appropriate if firms also do not have access to information beyond the data available to the researcher. However, bias can arise if agents' information set includes observations going further back than the start date of the data. The bias would be mitigated as agents discount older observations more heavily when forming expectations.

This approach is implemented as follows. The set of weight parameters ($\lambda_t$) that I consider is $\{\frac{1}{t}, 0.01, 0.02, 0.03, 0.04\}$.[33] If $\lambda_t = \frac{1}{t}$, equal weights are applied to all past observations. In practice, the estimation procedure under this parameter value amounts to applying least squares to estimate equation (1) for each period separately. The regression at period $t$ uses demand state data covering from the start date of the data to the current period $t$, or $\{z_\tau, \tilde{z}_\tau\}_{\tau=0}^{t}$ where the steps of recovering these data are provided in section 5.1. If $\lambda_t$ is a constant, weights on observations geometrically decline with the age. In this case, weighted leasts squares are applied where the weight on an observation from the period $\tau$ is

[33] Orphanides & Williams (2005) suggest that the constant gain parameter in the range between 0.01 and 0.04 match the data on expectations well.

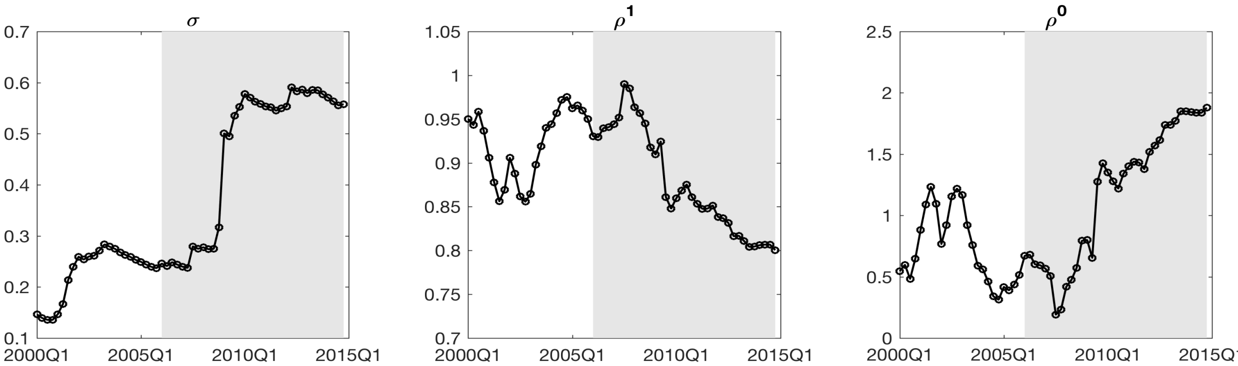
given by $(1-\lambda_t)^{t-\tau}$.

The imputation approach employs external data that provide information about the missing data. This approach is appealing if agents indeed use longer historical data in forming expectations than observed and the researcher has access to the external data that provide a good approximation to that data. Bias can arise, however, from the imputation process depending on the quality and scope of the external data. For this paper's setting, one could consider using international trade data to proxy demand for container shipping.

The imputation approach is implemented as follows. I set the start date for firms' information as the second quarter of 1966, which is the date of the first international container voyage. Then, I employ quarterly data on the value of trade by origin-destination pair from the IMF Direction of Trade Statistics database to impute the missing data on demand states from 1966:Q2-1996:Q4.[34] Finally, I estimate the beliefs using the imputed longer time-series data in the same way as the truncation approach.

The truncation approach is adopted in the end because it provides a better data fit. Moreover, it can be more universally applied since the imputation method requires some external data which are not always available. Figure 15 in appendix D.2 compares beliefs under the two approaches.

Figure 5: Beliefs under Learning for the Asia-Europe Market




*Notes:* This figure shows firms' beliefs about demand in the Asia-Europe market for 2000:Q1 to 2014:Q4 under adaptive learning with $\lambda_t = 0.02$. The beliefs are summarized by the three parameters, $\{\sigma_t, \rho_t^0, \rho_t^1\}$, in the AR(1) process as given in equation (1). Beliefs for 2006-2014 in the shaded area are used in the main analysis.

Figure 5 shows firms' demand parameter estimates from 2000 to 2014 under adaptive

[34]To translate the value of trade to the quantity of container trade, the demand state for the 1997-2014 period was regressed on the de-trended value of trade. Then, the demand states for periods with missing data are constructed as predicted values from the regression. For the 1997-2014 period, actual demand states are used.

learning with $\lambda_t = 0.02$ for the Asia-Europe market (see figure 11 in appendix A.1 for the outside market). The estimates in the shaded area are for 2006 to 2014, which will used in the estimation of the dynamic model. The estimate of the persistent parameter $\rho_t^1$ rises from 2006 to 2007 and shows a general downward trend thereafter. The variance parameter $\sigma_t$ hikes in early 2009 and stays high throughout the end of the sample period.

Under adaptive learning, the degree to which the parameter estimates react to recent events grows as agents put more weights on recent observations (as shown in figure 12 in appendix A.1). For example, the degree to which $\sigma_t$ jumps around 2009 is the smallest in the case where agents weigh all past demand realizations equally ($\lambda_t = 1/t$). When $\lambda_t$ is a constant, the larger $\lambda_t$, the larger the jump in $\sigma_t$ around 2009. Similarly, the larger the fall in the persistence parameter $\rho^1$ in the post-2008 period, the larger $\lambda_t$ becomes. It is this variation in beliefs and the variation in the data in investment and scrapping around demand shocks that identify the model of firm beliefs.

# 5 Estimation and Empirical Results

The estimation of the dynamic model of investment with learning proceeds as follows. First, I estimate demand for shipping services to recover the elasticity of demand and demand states. Second, I estimate parameters governing static competition including the marginal cost of production, the charter cost, and the outside market profit, which are used to compute period profits. Third, I estimate the investment cost and the scrap value based on the pricing data of shipbuilding and demolition as well as other model primitives such as the delivery and depreciation processes. Lastly, I estimate the dynamic model including the model of firm beliefs through the method of simulated moments.

## 5.1 Estimating Demand for Shipping Services

The goal of this section is to estimate the price elasticity of demand and to construct demand states for the Asia-Europe market and the outside market.[35] The empirical analogue of the constant elasticity demand model in equation (5) is:

$$\log Q_{jt} = \alpha_0 + \alpha_1 \log P_{jt} + \alpha_2 W_{jt} + \varepsilon_{jt} \tag{9}$$

where $j$ is an indicator for trade routes, $Q_{jt}$ is the amount of container shipping services in terms of TEU, $P_{jt}$ is the average price per TEU, and $W_{jt}$ is a demand shifter. I estimate

[35] This section follows the demand estimation of Kalouptsidi (2014) closely.

equation (9) using instrumental variables regression in order to correct for the endogeneity of prices. The price is instrumented with the average size and age of ships and the fraction of ships that are over 20 years old. The size of ships is one of the key determinants of cost efficiency as larger ships require less fuel per TEU on average. The age of ships matters as well, since older ships tend to require higher maintenance costs. Log GDP for the destination area is used as a demand shifter.

The estimation uses data from six major trade routes from 2001:Q2 to 2014:Q4.[36] The demand parameters are identified by the time-series variation as well as the cross-sectional variation across six different routes in the data along with the constant elasticity functional form assumption. In particular, since ships have to go back and forth the two routes in each market they serve, two routes in the same market (e.g. Asia to Europe and Europe to Asia) have the same level of supply while facing different demand shocks, which helps the identification of the demand parameters.

The price elasticity of demand is estimated to be -3.89 (see table 8 in Appendix A.1 for detailed results). This implies that a change in price from \$1510 per TEU to \$1360 per TEU would result in a change in quarterly quantity demanded of approximately 0.92 million $TEU$ on the Asia to Europe route.[37]

Given the elasticity of demand estimates, I construct the demand state for each trade route ($z_{jt}$) as the intercept of the demand curve:

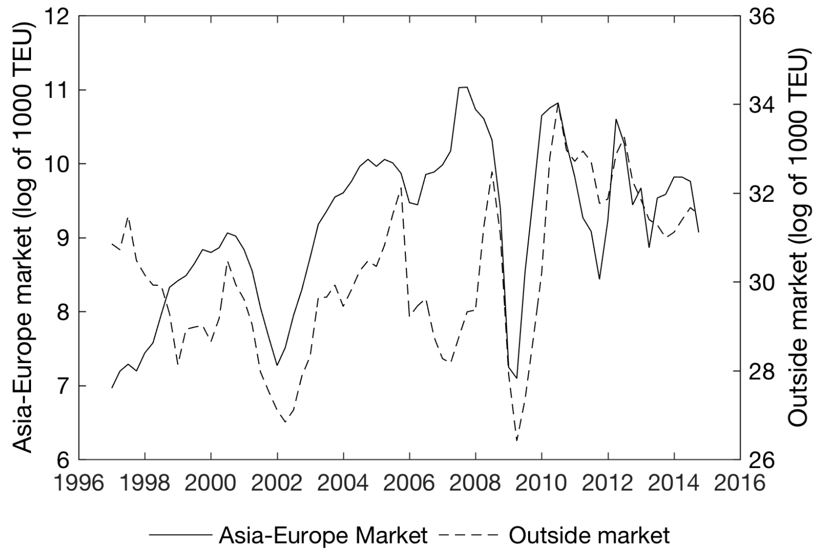
$$z_{jt} = \hat{\alpha}_0 + \hat{\alpha}_2 W_{jt} + \hat{\varepsilon}_{jt} \tag{10}$$

where $\{\hat{\alpha}_0, \hat{\alpha}_2\}$ are parameters estimated from the regression and $\hat{\varepsilon}_{jt}$ is the residual. Finally, I construct aggregate demand states for the Asia-Europe market and the outside market from the route-level demand. For the Asia-Europe market, I take the demand state for the Asia to Europe direction. Since the container trade volume is less than half on the Europe to Asia direction, firms' investment and capacity deployment decisions in the market are mostly dictated by the trade demand on the Asia to Europe direction. For the outside market, I take the sum of the demand states in the non-Asia-Europe routes. Figure 6 plots the demand states for 1997 to 2014 for the Asia-Europe and the outside markets. There is a large drop in demand in both markets in late 2008 to 2009. In the Asia-Europe market, the boom and

[36] Although the price, quantity, and GDP data available from 1997, the instruments are available starting from 2001:Q2. The included trade routes are Asia to Europe, Europe to Asia, Asia to North America, North America to Asia, Europe to North America, and North America to Europe.

[37] Stopford (2009) explains that container trade is price elastic because lowering prices encourages the subsitution of cheap foreign substitues for local products. Moreover, other transportation modes are available such as road and rail transportation and air freight. Kalouptsidi (2014) estimates the price elasticity of demand for bulk shipping to be -6.17 under a constant elasticity specification.

Figure 6: Demand states




bust cycles in demand are shorter in length after 2008.

## 5.2 Estimating the Profit Function

The second step of the estimation is to construct period profits by estimating the marginal cost, charter cost, and outside market profit functions. Firms' capacity deployment decisions yield a supply curve which along with the demand curve determines the equilibrium prices and quantities for the Asia-Europe market. The marginal cost of providing container shipping services is specified in equation (6), which serves as the basis for the maximum likelihood estimation of the cost parameters $(a, b)$.

The outside market profit and the charter cost functions are specified in a reduced-form way as:

$$R(\tilde{q}_{it}, x_{it}, \hat{s}_t) = \tilde{q}_{it} \quad r_0 + r_1 \tilde{z}_t + r_2 \tilde{Q}_t$$

$$CC(h_{it}, x_{it}, \hat{s}_t) = h_{it}(\gamma_0 + \gamma_1 z_t + \gamma_2 k_{it} + \gamma_3 K_t).$$

The profit from each unit of capacity deployed in the outside market is allowed to depend on the total deployed capacity in the outside market $(\tilde{Q}_t)$ since higher supply may lead to fiercer price competition and lower profit. The charter cost depends on the firm-level own capacity $(k_{it})$ since larger firms may get discounts on charter rates. The charter cost is also allowed to depend on the total capacity owned by operator $(K_t)$ as it is likely to affect demand for chartering.

The estimation of the charter cost and outside market profit functions is based on firms' static profit maximization problem. Given the demand estimates and the first-order conditions with respect to the capacity deployed on Asia-Europe route ($\bar{q}_{ijt}$) and the chartering decisions ($h_{it}$), I estimate the charter cost and the outside-market profit functions via maximum likelihood. The variations in capacity deployment and charter decisions across different firm types and across time along with the first-order conditions and the functional form assumptions provide identification for these parameters.

Table 9 in Appendix A.1 reports the estimates of the profit function parameters. The coefficients on the Asia-Europe market demand state in the outside market profit and charter cost functions ($r_1$ and $\gamma_1$) are positive. This implies that stronger demand leads to higher outside market profits as well as higher charter costs. The estimates also show that when there is more aggregate deployed capacity in the outside market, firms earn less from that market on average. In addition, larger firms tend to face lower charter costs, and an increase in total industry capacity owned by ship operators lowers charter costs.

## 5.3 Estimating Other Model Primitives

This study recovers the investment cost and scrap value directly from the data on shipbuilding prices and scrap prices. The first reason for doing so is that detailed data are available unlike in many other settings.[38] Moreover, this approach allows me to focus on identifying the model firm beliefs instead.

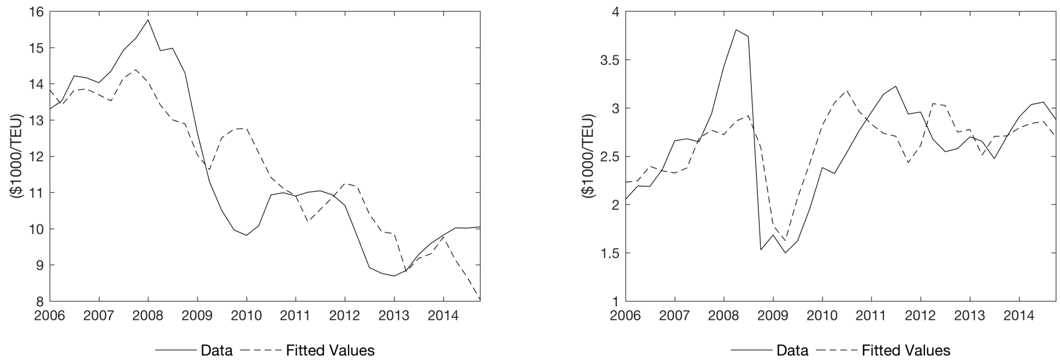
I use industry-level price data to estimate the investment cost and the scrap value as functions of the industry state variables (industry owned ship and order book capacities, and demand states for the Asia-Europe and outside markets) via least squares. Figure 7 compares investment costs and scrap values observed in the data to predicted values obtained from the regression (see table 10 in Appendix A.1 for the detailed estimates).

The delivery process of newly ordered ships and the depreciation process of existing ships are also estimated separately from the estimation of dynamic parameters. The mean delivery rate is estimated based on a simple regression of delivery on the firm's order book size with no constant.[39] For the depreciation process, I set an exogenous rate. This is because the data do not differentiate between depreciation and the scrapping of ships that can still be operated physically. Thus, the depreciation rate and the distribution of the private shocks

[38]Clarkson Research publishes monthly reports on average shipbuilding prices and scrap prices as well as a sample of transaction-level data.

[39]The current formulation assumes that the delivery rate depends solely on the firm's own order book size, since the industry order book size does not have a statistically significant effect on the delivery rate.

Figure 7: Predicted Investment Costs and Scrap Values




(a) Investment Costs

(b) Scrap Values

*Notes:* The left panel shows the average shipbuilding price observed in the data and the predicted shipbuilding price from the regression of the shipbuilding price on the industry state variables. The right panel shows the average scrap value and the predicted scrap value.

to the scrap value can not be separately identified. The depreciation rate, $\zeta$, is set such that the average age at which ships naturally depreciate is 20 years.[40]

## 5.4 Estimating the Dynamic Model of Investment with Learning

The last and most computationally intense step of the estimation entails estimating the model of firm beliefs and the dynamic parameters. The typical empirical strategy of estimating a dynamic game of investment is to recover objects like investment costs, entry costs, and exit values by searching for parameters that minimize the distance between actions observed in the data and the ones that the parameters imply (e.g. Ryan (2012) and Collard-Wexler (2013)). This paper instead employs data on shipbuilding and demolition prices to estimate investment costs and scrap values as described in section 5.3, which opens up the possibility to identify the model of firms beliefs. Although the application is different, the underlying logic of this approach is similar to that of Hortacsu & Puller (2008) in which the authors use marginal cost data to quantify how much firms' bidding deviates from the optimal bidding benchmark.

I employ the method of simulated moments (MSM) to estimate the dynamic model, which minimizes a distance criterion between key moments from the actual data and the

[40]Although historically the lifespan of container ships was 25 to 30 years, it has fallen in recent years especially for larger ships. *Vesselvalues* reports that the the average age of all sizes of container ships sold for scrap was around 22 years old and the average age at which Post-Panamax container ship was sold for scrap was around 19.5 years.

simulated data. Let $\theta$ denote the vector of dynamic and belief parameters such that $\theta = (\sigma^\iota, \sigma^\delta, FC, \lambda_t)$. I solve for an equilibrium of the dynamic investment model and obtain the optimal investment policy function for each candidate parameter vector.[41] Using equilibrium strategies obtained in the previous step, I simulate the equilibrium path for the 2006 to 2014 period $S = 1000$ times. And from these paths, I obtain the simulated moments as follows:

$$\Gamma(\theta) = \frac{1}{S} \sum_{s=1}^{S} \Gamma_s(\theta).$$

I search for the parameter vector that minimizes the weighted distance between the data and simulated moments given as:

$$f(\theta) = \left(\Gamma^d - \Gamma(\theta)\right)' W \left(\Gamma^d - \Gamma(\theta)\right). \tag{11}$$

where $\Gamma^d$ is the set of data moments.[42]

The identification relies on a revealed-preference argument. I have recovered the values of benefits and costs of each of the options that the firm faces–investment, scrapping, and staying for each state in the state space as described in section 5.3. As a result, given these values, firms' choices in various states observed in the data reveal their expectations about future demand. More concretely, the estimation relies the variation in firms' beliefs across different learning parameter values and the variation in firm behavior across time and firms observed in the data. As firms discount older observations more heavily, their beliefs become more responsive to recent shocks. This leads to different predictions about, for example, the effect of recent demand shocks on investment and the duration of the impact of demand shocks. In principle, the parameters are identified by both time-series and cross-sectional variations. Nevertheless, the main source of identification is time-series variation in investment and scrapping as well as investment costs and scrap values. And it is essential to observe a boom and a bust in my sample period. The shipping industry provides a great setting in that it is exposed to large exogenous fluctuations in demand coming from cycles

[41] Recently, empirical techniques have been proposed to estimate the dynamic industry equilibrium without having to solve for an equilibrium (e.g. Aguirregabiria & Mira (2007), Bajari *et al.* (2007), Pakes *et al.* (2007)). The first stage of this approach entails recovering firms' policy functions by regression observed actions on observed state variables. The second stage involves estimating structure parameters which make these policies optimal. This approach relies on flexible functional forms in the first step, so the data requirement is too high given the global nature of my data set. I use a full solution method instead, which involves solving the model at every guess of the parameter but is more efficient.

[42] The search is done over grids of $(\sigma^\iota, \sigma^\delta, FC, \lambda_t)$. The grids for $\sigma^\iota$ and $\sigma^\delta$ are in increments of 0.005 and the grid for $FC$ is in increments of \$50/TEU. The set of candidate belief parameter values is $\lambda_t \in \{\frac{1}{t}, 0.01, 0.02, 0.03, 0.04\}$. I use the inverse of the variance-covariance matrix of the simulated moments as the weighting matrix ($W$).

in world trade.

The moments used in the estimation include the average investment before and after 2008, the volatility of investment, the correlation in demand and investment, and the aggregate capacity of owned and backlogged ships. Table 2 lists these moments and compares the data moments and simulated moments under the parameter estimates.

Table 2: Data and Simulated Moments

| | Data moments | Simulated moments |
|---|---|---|
| Average investment in 2006-2008 (1 mil. TEU) | 0.23 | 0.23 |
| | | (0.03) |
| Average investment in 2009-2014 (1 mil. TEU) | 0.14 | 0.15 |
| | | (0.02) |
| Total capacity of owned ships (1 mil. TEU) | 5.09 | 5.15 |
| | | (0.27) |
| Total capacity in the order book (1 mil. TEU) | 3.07 | 2.98 |
| | | (0.14) |
| Correlation between demand and investment | 0.19 | 0.22 |
| | | (0.12) |
| Volatility of investment (1 mil. TEU) | 0.17 | 0.17 |
| | | (0.03) |

*Notes:* This table compares moments observed in the data and moments simulated under the estimated parameters. The simulated moments are computed based on 1000 series of equilibrium paths. Standard deviations are in parentheses.

Table 3: Dynamic Parameter Estimates

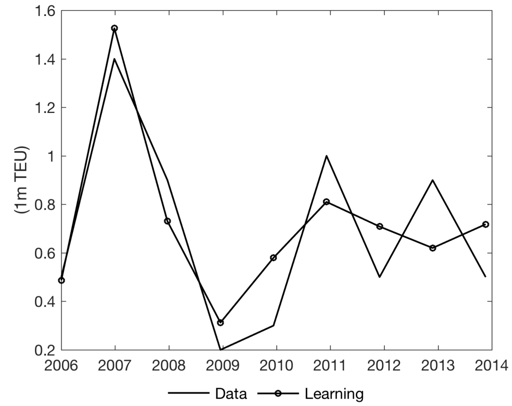
| | |
|---|---|
| $\lambda_t$ | 0.02 (0.005) |
| $\sigma^{\iota}$ (1 bil. US dollars) | 0.275 (0.055) |
| $\sigma^{\delta}$ (1 bil. US dollars) | 0.43 (0.092) |
| $FC$ (1 bil. US dollars) | 0.025 (0.0051) |

*Notes:* This table shows estimates of dynamic parameters. $\lambda_t$ is the weighting parameter in the adaptive learning model which governs how heavily agents discount older observations when forming expectations about demand. $\sigma^{\iota}$ is the standard deviation of the i.i.d. shock around the investment cost of building 100,000 TEU and $\sigma^{\delta}$ around the scrap value. $FC$ is the fixed cost of holding capacity of 100,000 TEU. Standard errors are in parentheses.

My estimates, reported in table 3, indicate that the adaptive learning model with $\lambda_t = 0.02$ provides the best fit to the observed data moments, which I will refer to as the *baseline learning model* in the rest of the paper. This implies that agents put approximately 45% weights on a 10-year-old observation compared to the most recent observation. This estimate is very close to the values that previous studies in macroeconomics have estimated based

Figure 8: Model Fit of the Learning Model


(a) Capacity of Owned Ships and Order book




(b) Yearly Investment

*Notes:* The left panel shows the industry evolution simulated under the baseline learning model (adaptive learning with $\lambda_t = 0.02$) and the industry evolution in the data. The right panel shows yearly investment simulated under the baseline learning model and observed in the data, respectively. The simulated moments are based on 1000 equilibrium paths.

on aggregate survey data such as the Survey of Professional Forecasts or micro data on expectations. For example, Malmendier & Nagel (2016), Milani (2007), and Orphanides & Williams (2005) estimate the constant-gain parameter ($\lambda_t$) to be 0.0175, 0.0183, and 0.02, respectively, with respect to expectations about macroeconomic conditions and monetary policy. Figure 8 shows that the baseline learning model does well at predicting the investment boom in 2007 and the plunge in investment in 2009.

The fixed cost of holding one unit of capital (100,000 TEU) in one quarter is estimated to be 25 million dollars, which is approximately 36% of the period's profit from one unit of capital (where the period profit is the sum of profits from the Asia-Europe market and the outside market minus the charter cost and does not include the investment cost and scrap value). This fixed cost includes all costs that owning and operating ships impose regardless of the production level such as maintenance costs, canal dues, and port charges. It also includes the cost of labor needed in the operation of the ships regardless of how full the ships are.

# 6 Alternative Models of Firm Beliefs and Model Diagnosis

So far this paper has considered an adaptive learning model. In section 6.1, I consider various alternative models for firms' belief-formation process. This serves as a robustness check for the baseline model. Moreover, the comparison of the estimation results under learning and full information will shed light on the role of learning. Comparing model fits across different models of firm beliefs, however, hinges on the assumptions made in various parts of the model and the structural estimation. In section 6.2, I discuss a way of diagnosing these models based on GDP forecast data which relies less heavily on modeling assumptions

## 6.1 Alternative Models of Firm Beliefs

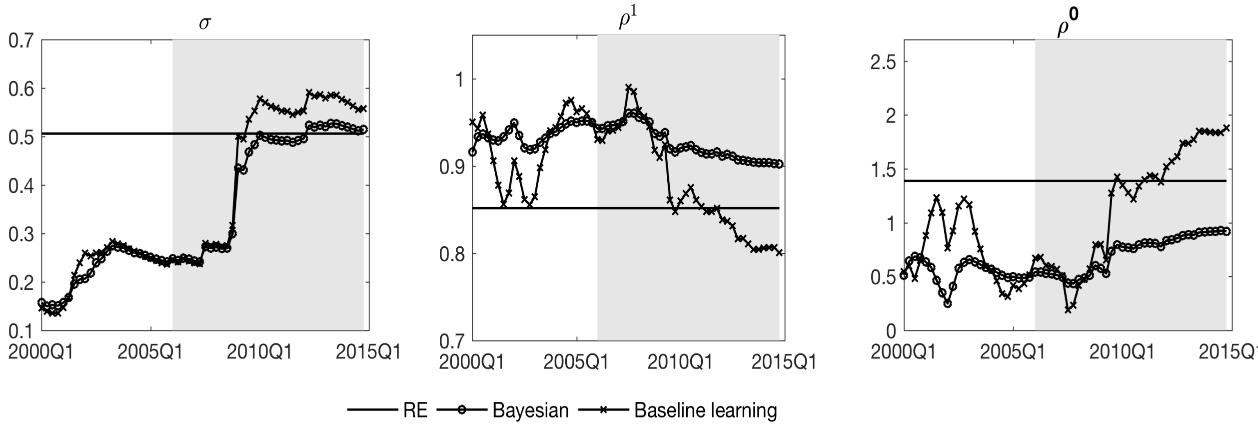
The models of firm beliefs considered in this section include: a full-information model with constant volatility; a Bayesian learning model; and a full-information model with time-varying volatility. This section presents model specifications, firm beliefs implied by each model, and estimation results.

### Full Information

Agents contemplate a first-order autoregressive model for demand in the Asia to Europe market and the outside market given by equations (1) and (2) as in the adaptive learning model. In the full-information model, however, the parameters in the demand model, $\{\rho^0, \rho^1, \sigma, \tilde{\rho}^0, \tilde{\rho}^1, \tilde{\sigma}\}$, are known to the agents. Then, estimating beliefs under the full-information model involves estimating the demand process using the full sample of data or as much data as available to the researcher. I apply least squares to estimate the $AR(1)$ processes using data from 1997:Q1 to 2014:Q4. Beliefs implied by the full information model as well as beliefs under the Bayesian learning model discussed later in this section and the baseline learning model are presented in figure 9. The parameter estimates stay constant under full information by construction. Compared to the baseline learning model, the volatility estimate ($\sigma$) is higher and the persistent parameter ($\rho^1$) lower in the pre-2008 period.

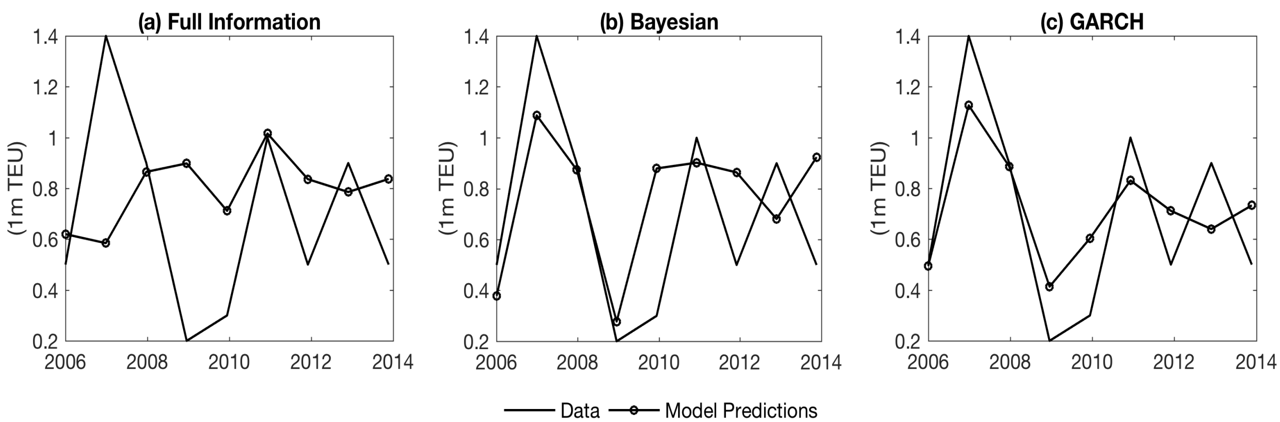
Figure 10(a) shows the annual investment levels predicted by the full-information model in comparison with those observed in the data. This model fails to predict the correct quantity and timing of investment. Specifically, it predicts that firms restrain from investing in the high demand period of 2006-2007 and invest more heavily in the post-2008 period. This happens for the following reason. A demand increase for shipping has two opposing forces on investment. On one hand, investment becomes more costly as increased demand for new

Figure 9: Beliefs under Alternative Models of Beliefs for the Asia-Europe Market




*Notes:* This figure shows firms' beliefs about demand in the Asia-Europe market for 2000:Q1 to 2014:Q4 under the full-information, Bayesian learning, and baseline learning (adaptive learning with $\lambda_t = 0.02$) models. The beliefs are summarized by the three parameters, $\{\sigma_t, \rho_t^0, \rho_t^1\}$, in the AR(1) process as given in equation (1). Beliefs for 2006-2014 in the shaded area are used in the main analysis.

Figure 10: Model Fits under Alternative Models of Firm Beliefs




*Notes:* This figure shows yearly investment observed in the data and predicted by each of the alternative models of firm beliefs. The simulated moments are based on 1000 equilibrium paths.

ships leads to a higher volume of backlogs. On the other hand, high demand raises returns to investment, raising demand for new ships. The positive demand-side effect is dominated by the negative supply-side effect resulting in firms investing more under weak demand conditions in this particular case. The positive effect is weaker under full information, because while high demand shocks make firms revise their expectations upward under learning, this is not the case under full information. As shown in figure 9, in 2006-2007 firms are more pessimistic and perceive the volatility of demand to be higher under full information compared to in the learning model.

### Bayesian Learning

Under Bayesian learning, each firm starts with prior beliefs about the parameters of the model. Then, based on its information set, $\{z_\tau, \tilde{z}_\tau\}_{\tau=0}^{t}$, the firm updates its beliefs about the parameters in the demand process, $(\rho_t^0, \rho_t^1, \sigma_t, \tilde{\rho}_t^0, \tilde{\rho}_t^1, \tilde{\sigma}_t)$. The $AR(1)$ coefficients for the Asia-Europe market, $\rho = [\rho^0, \rho^1]$, have normal priors given by $\rho_0 \sim N(\mu_0, \Sigma_0)$. The prior of $\sigma^2$ follows an inverse Gamma distribution. Then, the posterior distribution $\rho_t \sim N(\mu_t, \Sigma_t)$ has the mean and the variance given by

$$\begin{aligned} \mu_t &= \Sigma_t \;\; \Sigma_0^{-1}\mu_0 + \sigma^{-2}(X_t' Z_t) \\ \Sigma_t &= \;\; \Sigma_0^{-1} + \sigma^{-2}(X_t' X_t) \;\; ^{-1}. \end{aligned}$$

The beliefs are defined similarly for the outside market.

The first three years of the price and quantity data (1997:Q1-1999Q4) are used in the estimation of the prior beliefs.[43] I start from diffuse priors and apply the Gibbs sampling methods (see table 11 in appendix A.2 for the estimates). In the first quarter of 2000, firms start with the prior beliefs about the parameters and revise their beliefs using Bayesian updating in each period based on newly realized data. I apply the Gibbs sampling techniques to estimate the posterior beliefs.

Figure 9 shows beliefs under Bayesian learning. Compared to the baseline model of adaptive learning, the degree to which firms' beliefs react to new data is smaller under Bayesian learning. This is because there are less weights placed on new data under Bayesian learning as agents place positive weights on their prior beliefs. Consequently, although the Bayesian learning model correctly predicts the timing of the investment boom and bust, the magnitudes of the rise and the fall in investment are smaller as shown in figure 10(b).

### Full Information with Time-Varying Volatility

This paper has considered only homoskedastic models so far. However, changes in demand volatility may also be able to explain firms' investment behavior without the need to introduce parameter learning in the model. Therefore, I consider a full-information model with

[43] I also explore using the full sample from 1997 to 2014 for estimating the priors.

a more flexible specification of the variance of the model: the GARCH model.[44] Demand is assumed to follow the same $AR(1)$ process as in other models. But volatility is assumed to follow a GARCH(1,1) process such that the current period's variance depends on the last period's realized error and variance:

$$\sigma_t^2 = a_0 + a_1\omega_{t-1}^2 + b_1\sigma_{t-1}^2$$

where $\omega_{t-1}$ is the realized error in period $t-1$.

The GARCH model is estimated using the full sample of data (1997:Q1-2014:Q4). The estimates are presented in table 12 and the inferred conditional variance in figure 13 in appendix A.2. Compared to the volatility estimate in the learning model, the increase in the variance around 2009 is larger. But the increase is more temporary unlike in the learning model where the variance remains high through the end of the sample period.

The dynamic model presented in section 3.2 is modified to accommodate time-varying volatility. Since firms need the current period's variances and errors and the GARCH model parameters as well to predict the next period's variance, these parameters are included as state variables. As shown in figure 10, the time-varying volatility model predicts the investment patterns in the data better than the full-information model with constant volatility, in particular the timing of the investment boom and bust. Nevertheless, the magnitude of the investment cycles is smaller compared to observed in the data or predicted by the adaptive learning model. This finding provides some insights into firms' beliefs about demand. It shows that the low volatility in demand in the pre-2008 period and a sharp increase in volatility in 2009 help us explain the high level of investment in the pre-2008 period and the subsequent fall in investment. Nonetheless, the finding also suggests that changes in the level of demand forecasts in addition to the changes in the variance may be necessary to correctly predict firms' investment behavior.

## 6.2 Diagnosing Models of Firm Beliefs using GDP Data

In this section, I employ an alternative strategy to diagnose different models of firm beliefs. In particular, based on the fact that GDP and trade demand are highly correlated, I examine which model of firm beliefs generates beliefs that are most consistent with GDP forecasts. The ECB publishes the Survey of Professional Forecasters (SPF) for the euro area quarterly and reports the mean forecast of one-year-head and two-year-ahead GDP growth rates as

[44] As an alternative model of stochastic volatility, I consider a regime-switch mode where the variance is no longer a constant but can take on one of two values $\sigma_t \in \{\sigma_l, \sigma_h\}$ and state changes are governed by a Markov transition matrix. I omit details of this model as it produces similar results as the GARCH model.

well as a measure of how uncertain each forecaster is about his or her forecast. For the uncertainty measure, each forecaster is asked to allocate subjective probabilities to ranges of possible outcomes with a width of 0.5 percentage point.[45]

I take the forecast for the 2-year ahead GDP growth to construct the mean and the variance of the forecasts in each quarter from 2006 to 2014.[46] Then, I construct the mean and the variance of 2-year ahead demand growth that each model of beliefs implies. Finally, I compute correlation between the mean and the variance of GDP forecasts and the mean and the variance of demand forecasts implied by each model of beliefs. The correlation coefficients are reported in table 4.

Table 4: Correlation between GDP Forecasts and Demand Forecasts

| Correlation coefficient | Full info | Full info GARCH | Bayesian learning | Adaptive learning $\lambda_t = \frac{1}{t}$ | $\lambda_t = .01$ | $\lambda_t = .02$ | $\lambda_t = .03$ |
|---|---|---|---|---|---|---|---|
| Between means of GDP | -0.23 | -0.23 | 0.14 | 0.19 | 0.20 | 0.21 | 0.22 |
| & demand growth | (0.17) | (0.17) | (0.17) | (0.17) | (0.17) | (0.17) | (0.17) |
| Between variances of GDP | . | 0.37 | 0.83 | 0.86 | 0.86 | 0.85 | 0.83 |
| & demand growth | | (0.16) | (0.09) | (0.09) | (0.09) | (0.09) | (0.10) |

*Notes:* The mean and variance of GDP growth forecasts are based on two-year ahead forecasts published by the ECB.

The results confirm that the adaptive learning model produces beliefs that are most highly correlated with beliefs implied by GDP forecasts (although the exercise does not reveal which value of $\lambda_t$ produces the most favorable outcome). The correlation coefficient for the mean growth is approximately 0.20 for adaptive learning and 0.14 for Bayesian learning. The correlation for the variance ranges from 0.83 to 0.86 for the learning models. By contrast, the correlation for the mean is negative for the full-information models as they predict that the growth rate is higher during periods of weak demand.[47] In addition, under full information with constant volatility the correlation for the variance is zero since the variance is constant by construction. The correlation coefficient is 0.37 under the GARCH model, which is still significantly lower than under learning models.

[45] For example, forecasters are asked to assign a probability to real GDP rising between 0.0% and 0.4%, 0.5% and 0.9%, and so on.

[46] Only two-year ahead forecasts are used in the analysis because there is substantial bunching in the forecasters' probabilities in end bins for one-year forecasts. The bunching makes it difficult to construct variance estimates.

[47] This is because the AR(1) process has the mean-reversion property. So with the constant parameter estimates as in the full-information model, the expected growth rate is larger when current demand is lower.

# 7 Counterfactual Analysis

In this section, I address various firm-strategy and public-policy issues and assess the role of learning through counterfactual experiments. In the first set of counterfactuals, I consider policies that lessen competition and allow coordination among firms by simulating the industry under a multi-plant monopolist and the merger of top two firms. By doing so, I investigate how competition and strategic incentives affect investment and whether increased coordination among firms could have curtailed industry oversupply. Furthermore, I compare results from conducting these experiments under learning and full information to understand how the competitive forces interact with learning. In the second set of counterfactuals, I address the long-standing question on the effect of demand volatility on investment. By applying the learning framework I shed light on the new informational channel through which demand fluctuations affect investment. Lastly, I simulate a scrapping subsidy policy. This policy makes investment more reversible as it helps firms to scrap ships at a higher rate when demand conditions worsen. This policy may therefore help firms deal with excess capacity. It may also encourage investment, however, as it raises the value of owning ships.

## 7.1 Coordination among Firms

In this section, I study the effects of strategic incentives and consolidation as well as how the effects interact with agent beliefs arising from learning. To deal with the recent excess capacity in the industry, container shipping firms have increasingly moved towards consolidation. Maersk Line and MSC–the world's two biggest container-shipping companies-formed an alliance named 2M, which akin to a code-sharing deal between airlines, was meant to help firms cut costs by using each other's ships and port facilities and reduce competition. More firms are planning mergers and acquisitions as well. Cosco and CSCL, the sixth and seventh largest carriers by operated fleet capacity, have proposed a merger. CMA-CGM has proposed an acquisition of APL.

On one hand, increased consolidation may hurt consumers through reduced competition. On the other hand, there are potential sources of efficiency gains on the producers' side, which makes the final direction of the welfare change ambiguous. In particular, consolidation may reduce the business stealing effect and preemption motives that can lead to the capital level that is higher than the socially optimal level.[48]

[48]Mankiw & Whinston (1986) show that the business stealing effect can result in socially inefficient levels of entry when there are fixed costs of entry. Also, many theoretical studies predict that strategic incentives can lead to excess capacity, since firms may use investment as a commitment to deter entry or expansion of rivals (e.g. Spence (1977)).

My model incorporates several sources of strategic incentives. First, there is a business-stealing effect. A firm's deployment of an extra unit of capacity has a negative effect on the market price and the competitors' profitability. The business-stealing effect arises because this negative effect of increasing one's own capital is internalize by all incumbents in the market. Second, as the volume of the industry order book grows and shipyards get closer to their full capacity, the price of building a new ship increases. This generates dynamic incentives for firms to preemptively commit to investment before others do when they expect strong demand.

I first consider a monopolist who operates and makes joint decisions of investment, scrapping, chartering, and deployment for all firms in order to maximize the aggregate profits. I assume that the monopolist operates multiple plants while maintaining the same firm size distribution as observed in the data instead of assuming that the monopolist operates all ships under one entity. This helps disentangle the effect of strategic incentives from the effect arising from a change in the firm size distribution, for example, through cost savings, changes in bargaining power, etc. The monopolist is endowed with beliefs from the baseline learning model. Similarly, in a merger counterfactual, I allow the joint profit maximization of the top two firms.

Removing competition externalities through the monopoly case has a substantial effect on investment: during the period of 2006 to 2014, investment drops by 34% as shown in the second column of Table 5 Panel A. Under the merger case, investment drops by 7.5%. Investment falls heavily for the merging firms by 40%, but also falls for non-top-two firms by 2.5%. Under monopoly, producer surplus increases by 91 billion dollars, while consumer surplus in the Asia-Europe market falls by 42 billion dollars. This amounts to a 51% increase in total surplus, which is computed as the sum of consumer surplus in the Asia-Europe market and producer surplus. In the merger case, producer surplus almost doubles while consumer surplus drops only slightly by 1%.

I compare model predictions under full information and learning in panel B of table 5. It shows that, compared to the learning model, the full-information model underestimates changes in investment resulting from monopolization or a merger, thus underestimates welfare changes, especially the producer surplus gain. Hence, if a regulator used the full-information model, he is likely to underestimate gains from a merger or other forms of consolidation among firms. The fact that the effect of strategic incentives is greater under learning also sheds light on the relationship between the competitive forces and firm beliefs. Strong demand for shipping raises firms' strategic incentives (, for example, to preemptively commit to investment and to still business from others). But under learning strong demand also makes agents more optimistic, which amplifies these strategic incentives.

Table 5: Monopoly and Merger Counterfactuals

| Panel A: Industry Outcomes and Welfare | | |
|---|---|---|
| | Monopoly (%Δ) | Merger(%Δ) |
| Owned capacity (1 mil. TEU) | 3.95 (-23.18) | 5.02 (-2.53) |
| Orderbook (1 mil. TEU) | 2.35 (-21.33) | 2.78 (-6.80) |
| Investment (1 mil. TEU) | 0.12 (-33.92) | 0.17 (-7.50) |
| Volatility of investment (1 mil. TEU) | 0.13 (-21.51) | 0.15 (-14.66) |
| Consumer surplus (1 bil. US dollars) | 40.85 (-50.56) | 81.69 (-1.13) |
| Producer surplus (1 bil. US dollars) | 106.62 (616.14) | 28.85 (93.80) |
| Total surplus (1 bil. US dollars) | 147.47 (51.23) | 110.54 (13.36) |
| Investment by top two firms (1 mil. TEU) | . | 0.01 (-40.12) |
| Investment by other firms (1 mil. TEU) | . | 0.15 (-2.47) |
| Owned capacity of top two firms (1 mil. TEU) | . | 1.43 (-5.59) |
| Owned capacity of other firms (1 mil. TEU) | . | 3.59 (-1.25) |
| Producer surplus of top two firms (1 bil. US dollars) | . | 25.88 (105.15) |
| Producer surplus of other firms (1 bil. US dollars) | . | 2.97 (20.85) |

| Panel B: Welfare Changes under Learning and Full-Information Models | | | | |
|---|---|---|---|---|
| | Monopoly | | Merger | |
| | Learning | RE | Learning | RE |
| Δ in investment (1 mil. TEU) | -0.061 | -0.039 | -0.014 | -0.009 |
| Δ in investment volatility (1 mil. TEU) | -0.037 | -0.020 | -0.025 | -0.004 |
| Δ in consumer surplus (1 bil. US dollars) | -41.78 | -39.35 | -0.94 | -0.46 |
| Δ in producer surplus (1 bil. US dollars) | 91.73 | 83.27 | 13.96 | 10.04 |
| Δ in total surplus (1 bil. US dollars) | 49.95 | 43.92 | 13.03 | 9.58 |

*Notes:* Panel A shows results form the monopoly and the merger simulations over the sample period (2006:Q1-2014Q4) with the percent changes from the case of no monopolization or merger in parentheses. The owned capacity, order book, and investment are reported as the average over time, and the welfare measures as the sum over the entire period. Panel B compares changes predicted by the learning model and the full-information model. Consumer surplus is calculated with respect to the Asia-Europe market only.

## 7.2 Demand Volatility

Demand volatility can affect investment in several different ways. First, as real options theory predicts, an increase in demand volatility raises the cost of investment, since once a firm makes an investment it cannot disinvest should market conditions change adversely. Second, an increase in demand volatility may also increase the volatility of investment costs. Finally, the presence of learning opens up an additional channel through which demand fluctuations affect investment, since increased demand volatility makes agents revise their expectations more often and more drastically.

To quantify the effect of demand volatility, I conduct the following counterfactual simulations. I simulate two sets of demand series for 2006 to 2014–one with high volatility and the other with low volatility. In the high volatility case, the variances in the demand processes for the Asia-Europe and outside markets are doubled from the estimates based on the full sample of data. In the low volatility case, the variances are halved from the estimates. The remaining parameters are set to the estimates based on the full sample of data. For 1995 to 2005, I use demand state realizations recovered from the data.

Table 6: Demand VolatilityCounterfactuals

| Model | Learning | | RE | |
|---|---|---|---|---|
| Volatility | High | Low | High | Low |
| Investment (1 mil. TEU) | 0.15 | 0.16 | 0.14 | 0.16 |
| Volatility of investment (1 mil. TEU) | 0.08 | 0.04 | 0.05 | 0.03 |
| Corr. between demand and investment | 0.10 | -0.03 | -0.05 | -0.16 |
| Consumer surplus (1 bil. US dollars) | 112.60 | 85.30 | 113.27 | 84.11 |
| Producer surplus (1 bil. US dollars) | 24.59 | 33.28 | 26.84 | 35.08 |
| Total surplus (1 bil. US dollars) | 137.19 | 118.58 | 140.12 | 119.18 |

*Notes:* This table shows results form demand volatility counterfactuals. The owned capacity, order book, and investment are reported as the average over time, and the welfare measures as the sum over the entire period. Consumer surplus is calculated with respect to the Asia-Europe market only.

Table 6 shows simulation results for the high and low volatility cases under learning and full information, respectively. The results reveal that an increase in demand volatility has a negative effect on investment, which is consistent with findings in previous studies such as Bloom (2009) and Collard-Wexler (2013). Going from low to high volatility reduces investment by 6% under learning. This suggests that the value function is concave with respect to demand. If the value function is concave, lower volatility in demand raises the expected value of owning a ship. An increase in demand volatility also increases the volatility of investment as higher demand volatility leads to more volatile shipbuilding prices. In the learning model, higher demand volatility also leads to larger changes in firms' expectations about future demand, which further increases the volatility of investment.

The modeling choice for firms' expectations potentially matters for policy design as the learning model and the full-information model yield different predictions about investment patterns. When there is high demand volatility, the learning model predicts large investment boom and bust cycles that move in the same direction as the demand cycles, as revealed by the high investment volatility and the positive correlation between demand and investment. This is because when learning is present, higher demand volatility generates agents' beliefs that are more highly correlated with demand.

## 7.3 Scrapping Subsidies

In the container shipping industry, part of the irreversibility in investment stems from the fact that when demand conditions are not favorable, the scrap price is also low. This is because the scrap market is driven by demand for steel which is highly correlated with demand for trade. Therefore, firms often do not find it profitable to scrap existing ships even though there is excess capacity. China implemented a subsidy program in 2013 to help Chinese firms that are struggling with overcapacity and also to help its shipyards. The program grants 1500 yuan (around 220 US dollars) per gross ton to replace old ships registered in the country with new vessels.[49]

In this counterfactual, I apply a similar subsidy program to all firms which grants 150,000 dollars for scrapping 1000 TEU.[50] This amounts to be roughly 13% of the average new building price or 57% of the average scrap price. The program applies to all scrapped ships regardless of their age.[51]

Table 7: Scrapping Subsidy Counterfactuals

| | Subsidy (%Δ) |
|---|---|
| Owned capacity (1 mil. TEU) | 5.04 (-2.11) |
| Orderbook (1 mil. TEU) | 3.10 (4.07) |
| Investment (1 mil. TEU) | 0.19 (6.45) |
| Scrapping (1 mil. TEU) | 0.06 (45.87) |
| Consumer surplus (1 bil. US dollars) | 81.78 (-1.02) |
| Producer surplus (1 bil. US dollars) | 15.74 (5.70) |
| Subsidy (1 bil. US dollars) | 3.35 (.) |
| Total surplus (1 bil. US dollars) | 97.52 (0.00) |
| Total surplus accounting for subsidy (1 bil. US dollars) | 94.17 (-3.43) |

*Notes:* This table shows results form the scrapping subsidy counterfactual over the sample period (2006:Q1-2014Q4) with the percent changes from the case of no subsidy in parentheses. The owned capacity, order book, and investment are reported as the average over time, and the welfare measures as the sum over the entire period.

As table 7 shows, scrapped capacity increases by 46% under the subsidy program. The effect is particularly dramatic in 2009 where the total scrapped capacity more than doubles under the subsidy program. The subsidy also results in a 6.5% increase in investment as it

[49] There is a restriction that ships must be within 10 years before their mandatory retirement age to be eligible. Also, ship owners get half the subsidy when they finish scrapping an old ship and receive the remainder if a new ship is built.

[50] This corresponds to 1500 yuan per gross ton based on the conversion rate of 1 gross ton to 1 dwt suggested by Stopford (2009) and the conventional conversion rate of 1 dwt to 14 TEU.

[51] This choice is made since the current model abstracts away from efficiency gains from replacing old ships with new ships.

raises the value of owing ships. In terms of welfare, the policy leads to a 5.7 % increase in producer surplus, while it leads to a decrease in supply resulting in a consumer surplus loss. The net effect on total surplus not accounting for the subsidy would be zero, but the effect would be negative if the subsidy was factored into welfare.

The findings from this policy experiment confirm the theoretical prediction that the irreversibility of investment reduces investment in an environment with demand uncertainty. From a policy maker's point of view the scrapping subsidy may not be an effective way to address the excess capacity problem since it also encourages investment. A careful choice of timing might make the policy more effective, for example, through targeting periods in which the policy is less likely to encourage new investment. Such targeting may be difficult to implement ex-ante, however.

# 8 Conclusion

This paper evaluates learning as agents' expectation-formation process capable of endogenously generating investment boom and bust cycles. The paper develops a dynamic oligopoly model of investment which incorporates uncertainty and learning about the aggregate demand process. The model departs from the standard practice under the full-information assumption of rational expectations that firms know the true demand model and its parameters. Instead, it allows agents to form expectations about demand using best information available to them in each period. Agents use their changing forecasts about demand in making their investment and scrapping decisions.

I analyze the framework through data from the container shipping industry in which firms invest in long-lived capital while facing large fluctuations in demand. A key empirical strategy is to adopt the data on shipbuilding prices and demolition prices, which allows me to identify the model of firm beliefs. The analysis shows that learning amplifies investment cycles and raises the correlation between investment and demand, which helps us explain the boom-bust investment patterns. By contrast, the full-information model underestimates the volatility of investment and fails to predict the correct timing of investment. In particular, it predicts that firms withhold investment in high demand periods during which the price of investment is also higher.

This paper uses the framework to understand the effects of strategic incentives and their interaction with learning. Counterfactuals show that a policy that reduces competition among firms would result in a substantial reduction investment and an improvement in overall welfare. This finding has potential implications for antitrust regulations on coordinated investment. Moreover, I find that learning amplifies strategic incentives and thus the modeling choice for firms' expectations about demand matters in evaluating competition policy.

This paper also sheds light on the informational channel through which demand fluctuations affect investment. Under learning, high demand volatility leads to more frequent and larger revisions of expectations about demand, thereby amplifying the magnitude of investment cycles. Finally, I show that a scrapping subsidy policy that makes lump-sum transfers to firms for scrapping might be an ineffective way to deal with excess capacity as it increases investment along with increasing scrapping. It would benefit producers, but would reduce overall industry capacity, thus hurting consumers.

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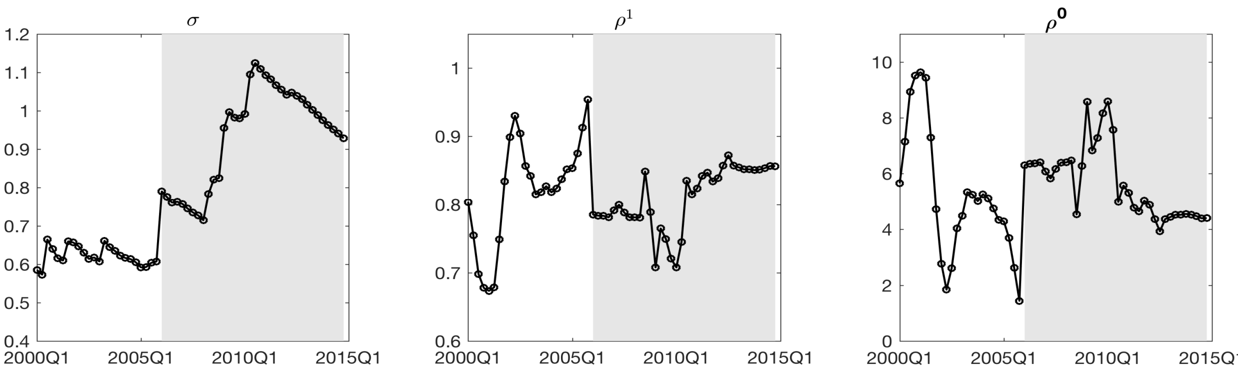
# A Detailed Estimation Results

## A.1 Demand, Profits, and Firm Beliefs

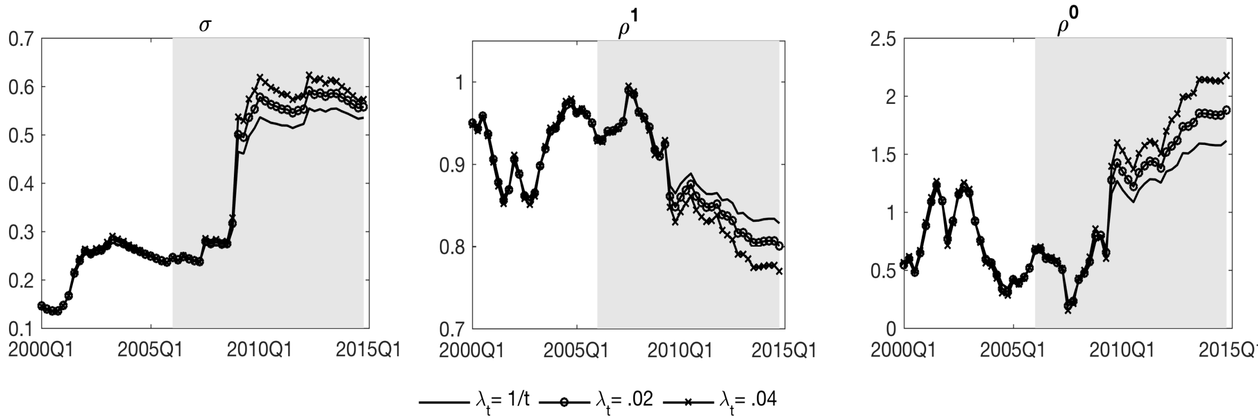
This section presents detailed results from the empirical implementation of the learning model in section 4 and the first three steps of the estimation described in sections 5.1 to 5.3.

Figure 11: Beliefs under Learning for the Outside Market




*Notes:* This figure shows firms' beliefs about demand in the outside market for 2000:Q1 to 2014:Q4 under adaptive learning with $\lambda_t = 0.02$. The beliefs are summarized by the three parameters, $\{\tilde{\sigma}_t, \tilde{\rho}_t^0, \tilde{\rho}_t^1\}$, in the AR(1) process as given in equation (2). Beliefs for 2006-2014 in the shaded area are used in the main analysis.

Figure 12: Beliefs under Learning with Different Weighting Parameters for the Asia-Europe Market




*Notes:* This figure shows firms' beliefs about demand in the Asia-Europe market for 2000:Q1 to 2014:Q4 under adaptive learning for different values of $\lambda_t$. The beliefs are summarized by the three parameters, $\{\sigma_t, \rho_t^0, \rho_t^1\}$, in the AR(1) process as given in equation (1). Beliefs for 2006-2014 in the shaded area are used in the main analysis.

Table 8: IV Regression Results for Demand for Container Shipping

| | First stage | Second stage |
|---|---|---|
| Dependent Variable | Log price | Log quantity |
| Size of owned ships (1000 TEU) | -0.13** | |
| | (0.06) | |
| Age of owned ships (year) | 0.03 | |
| | (0.03) | |
| Fraction of 20+ y.o. ships | -0.02* | |
| | (0.01) | |
| Log GDP | 0.44*** | 2.73*** |
| | (0.12) | (0.53) |
| Log price | | -3.89** |
| | | (1.87) |
| Route FE | Yes | Yes |
| Constant | -6.27*** | -32.66*** |
| | (1.79) | (7.48) |
| $R^2$ | 0.83 | 0.11 |

*Notes:* Standard errors are in parentheses. $^*$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.001$.

Table 9: Estimates of the Profit Function Parameters

| | | |
|---|---|---|
| **Marginal cost** | | |
| $a$ | 0.265 | (0.011) |
| b | 1.750 | (0.024) |
| **Outside market profit (R)** | | |
| $r_0$ | -1.238 | (0.177) |
| $r_1$ | 0.089 | (0.006) |
| $r_2$ | -0.117 | (0.008) |
| **Charter Cost (CC)** | | |
| $\gamma_0$ | 0.206 | (0.096) |
| $\gamma_1$ | 0.087 | (0.007) |
| $\gamma_2$ | -0.084 | (0.021) |
| $\gamma_3$ | -0.064 | (0.009) |

*Notes:* This table reports estimates of the parameters in the marginal cost, outside market profit, and charter cost functions. The unit of the marginal cost is $ per TEU. The unit of the aggregate deployed capacity ($\tilde{Q}_t$) in the outside market profit function; and the firm-level owned capacity ($k_{it}$) and the aggregate owned capacity ($K_{it}$) in the charter cost function is 1 million TEU. Standard errors for the estimates are in parentheses.

Table 10: Estimates of the Investment Cost and Scrap Value

| | Investment cost ($1000/TEU) | Scrap value ($1000/TEU) |
|---|---|---|
| Total capacity of owned ships | $-1.35^{***}$ | 0.11 |
| (1 mil. TEU) | (0.35) | (0.12) |
| Total capacity in order book | $1.12^{**}$ | 0.06 |
| (1 mil. TEU) | (0.54) | (0.19) |
| Demand state: A-E market | 0.50 | $0.25^{**}$ |
| | (0.31) | (0.11) |
| Demand state: outside market | -0.16 | 0.08 |
| | (0.17) | (0.06) |
| Constant | $15.09^{**}$ | $-3.17^{*}$ |
| | (4.81) | (1.68) |
| $R^2$ | 0.69 | 0.38 |

*Notes:* This table reports coefficient estimates in the investment cost and scrap value functions. Standard errors are in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.001$.

## A.2 Alternative Models of Firm Beliefs

This section presents detailed estimation results under various alternative models of firm beliefs including the full-information model, Bayesian learning model, and full-information model with time-varying volatility. The specification and implementation of these models are described in section 6.1.

Table 11: Moments of the Prior Distributions under Bayesian Learning

| | | |
|---|---|---|
| **Asia-Europe market** | | |
| $\rho^0$ | $\rho^1$ | $\sigma$ |
| 0.51 | 0.95 | 0.17 |
| (0.63) | (0.08) | (0.02) |
| **Outside market** | | |
| $\tilde{\rho}^0$ | $\tilde{\rho}^1$ | $\tilde{\sigma}$ |
| 8.11 | 0.72 | 0.68 |
| (5.19) | (0.17) | (0.27) |

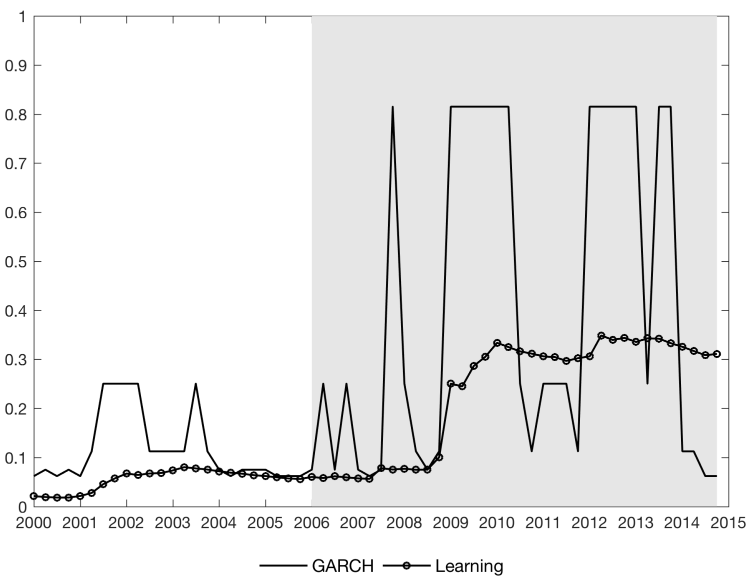
*Notes:* This table shows the estimated means and standard deviations (in parentheses) of the prior distributions of $AR(1)$ parameters. The estimation is based on data from 1997:Q1 to 1999:Q4.

Table 12: Estimates of the Time-Varying Volatility Models

| | | |
|---|---|---|
| Asia-Europe Market | | |
| $a_0$ | $a_1$ | $b_1$ |
| 0.05 | 0.83 | 0.17 |
| (0.01) | (0.28) | (0.16) |
| Outside Market | | |
| $\tilde{a}_0$ | $\tilde{a}_1$ | |
| 0.34 | 0.73 | |
| (0.11) | (0.25) | |

*Notes:* Standard errors are in parentheses.

Figure 13: Conditional Variances under Time-Varying Volatility Model




*Notes:* These figures plot the conditional variance for the Asia-Europe market under the GARCH model as well as the variance under the baseline adaptive learning model.

# B Preliminary Evidence of Investment Policy Changes

Learning and full-information models make different predictions about firm behavior. A learning model generally predicts that even after controlling for the state (which includes all payoff-relevant variables), firms' beliefs, hence firms' actions will be different before and after experiencing large demand shocks. By contrast, under full information firms' perceived probabilities of transitioning to different demand states from a given state stay fixed over time as new demand realizations do not contain any new information. Therefore, I examine whether firms' investment behavior changes significantly after they experience large demand shocks in order to search for indirect evidence of learning. In particular, I test for a structural break in the firm's investment policy function with an unknown break date following the approach proposed by Andrews (1993) closely.

The structural break equation is given by

$$y_{it} = \beta_1' x_{it} \mathbb{I}(t < \bar{t}) + \beta_2' x_{it} \mathbb{I}(t \geq \bar{t}) + e_{it}$$

where $\bar{t}$ is the break date, $y_{it}$ is new investment, and $x_{it}$ includes state variables. The state variables include the demand states for the Asia-Europe market and the outside market; firm-specific state variables including the owned capacity and the order book capacity; and the industry state including the aggregate capacity of operator-owned ships and the aggregate order book capacity.[52]

Instead of imposing an exogenous break date, I first pin down the break date by estimating a structural break equation with different break dates and searching for the one that maximizes the fit of the equation. A break date minimizes the sum of squared residuals function defined as the following:

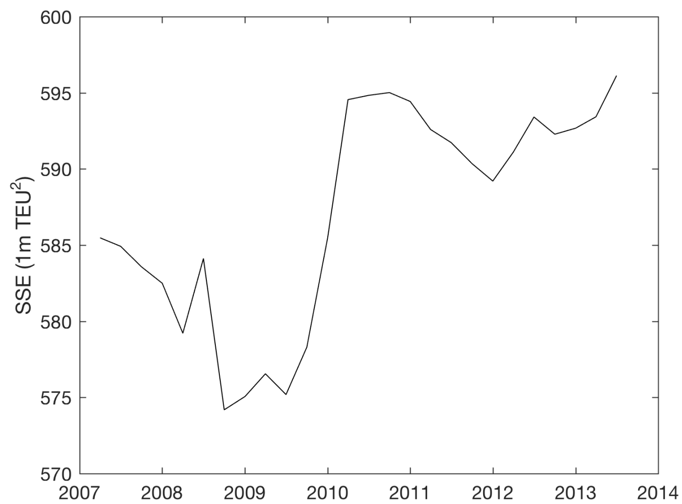
$$S(\beta, \bar{t}) = \sum_t \sum_i \left( y_{it} - \beta_1' x_{it} \mathbb{I}(t < \bar{t}) - \beta_2' x_{it} \mathbb{I}(t \geq \bar{t}) \right)^2 . \tag{12}$$

The periods from 2007:Q2 to 2013:Q3 are considered as a break date because I need sufficient observations before and after to estimate the equation. Figure 14 plots the sum of squared residuals function for different break dates. The break date that minimizes the SSE is the last quarter 2008, which coincides with the downturns in international trade.

Table 13 reports results for the estimation of the policy function with the last quarter of 2008 as the break point as well as results from the structural break test. Based on the test, I reject the null that the investment policy is the same before and after the last quarter

[52] The demand states are recovered through demand estimation as given in section 5.1.

Figure 14: Estimation of the Break Date in Investment Policy




*Notes:* This figure plots the sum of squared residuals as defined in equation (12) for each break date from 2007:Q3 to 2013:Q2.

of 2008.[53] The regression results suggest that in the post-2008 period firms' investment decisions are more responsive to the industry total capacity. That is, firms hold back from investment when there is a greater amount of total fleets available in the industry in the post-2008 periods. On the other hand, the industry capacity does not have a significant effect on investment in the pre-2008 period.

[53]This results could also arise if I failed to control for some pay-off relevant variable that is causing this change in firm investment. The most obvious candidate is the changes in credit market conditions. Appendix D.3 investigates whether credit market conditions played an important role in firms' investment decisions in this period.

Table 13: Investment Policy Estimation and a Test of a Structural Break

| | | |
|---|---|---|
| **Panel A: Regression** | | |
| Dependent variable: New investment (1000 TEU) | | |
| $t < 2008Q4$ | | |
| Constant | -324** | (151) |
| Demand state (Asia to Europe) | 22** | (11) |
| Demand state (Outside market) | 6.7 | (4.1) |
| Owned ship capacity (1000 TEU) | .037** | (.014) |
| Order book capacity (1000 TEU) | -.029 | (.022) |
| Aggregate owned ship capacity (1000 TEU) | .02 | (.015) |
| Aggregate order book capacity (1000 TEU) | -.055** | (.017) |
| $t \geq 2008Q4$ | | |
| Constant | 138** | (66) |
| Demand state (Asia to Europe) | -4.4* | (2.4) |
| Demand state (outside market) | .77 | (1.3) |
| Owned ship capacity (1000 TEU) | .01 | (.0075) |
| Order book capacity (1000 TEU) | -.0026 | (.015) |
| Aggregate owned ship capacity (1000 TEU) | -.0097** | (.0048) |
| Aggregate order book capacity (1000 TEU) | -.02** | (.0069) |
| Observations | 612 | |
| $R^2$ | 0.177 | |
| **Panel B: Test of a Structural Break** | | |
| $H_0 : \beta_1 = \beta_2$ | | |
| Test statistics | 4.38 | |
| p-value | ( 0.0001) | |

*Notes:* Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.

# C Computation

To compute strategies under MME for the model described in 3.2, I adopt a computational algorithm that is analogous to the standard value function iteration algorithm except for an extra simulation step. Because the transition of the moment-based industry state $\hat{s}$ may not be Markov, a simulation step is used to generate the Markov approximation of the transition of this state. The algorithm starts with a choice-specific value function that maps from the set of state-action pairs to values denoted as $W^{\eta}(\mu, x, \hat{s})$. It contains expected values of different actions prior to drawing random costs of investing and scrapping given beliefs about demand $\eta$. Then, based on a simulation run in which firms play optimal strategies implied by these choice-specific values, the algorithm constructs the perceived transition kernel $\hat{P}_{\mu}[m'|\hat{s}]$. The next step updates the values and strategies using the best response against the current strategy and the perceived transitions kernel. Finally, equilibrium conditions are checked based on the norm of the distance between the values in the memory and the updated values. A more detailed description of the algorithm is provided as follows:

1. Initialize $W^{\eta}(\mu, x, \hat{s})$ for all $(\mu, x, \hat{s}) \in \mathcal{M} \times \mathcal{X} \times \hat{\mathcal{S}}$, and optimal strategies, $\mu^*$, that $W^{\eta}$ implies.

2. Simulate a sample path of $\{\hat{s}_t\}_{t=1}^{T}$ for large $T$ based on $\mu^*$. Calculate the empirical frequencies of industry state $h(\hat{s}) = \frac{1}{T} I\{\hat{s}_t = \hat{s}\}$ for all $\hat{s} \in \hat{\mathcal{S}}$. Calculate the empirical transition kernel as

$$\hat{P}_{\mu}[m'|\hat{s}] = \frac{{}_{t=1}^{T} I\{\hat{s}_t = \hat{s}, m_{t+1} = m'\}}{{}_{t=1}^{T} I\{\hat{s}_t = \hat{s}\}}.$$

3. Calculate the new values for each state-action pair $(\mu, x, \hat{s})$ as:

$$\tilde{W}^{\eta}(\mu, x, \hat{s}) = \pi(x, \hat{s}) - \iota\kappa(\hat{s}) + \nu(\delta, x)\phi(\hat{s}) + \beta E_{a,\mu}\left[V^{\eta}(x', \hat{s}'|x, \hat{s})\right]$$

   and obtain the new best response $\tilde{\mu}^* = \arg\max_{\mu} W(\mu, x, \hat{s}|\mu, \mu^*)$ for all $(x, \hat{s}) \in \mathcal{X} \times \hat{\mathcal{S}}$.

4. Calculate the following norm: $\max_{x,\mu} \;{}_{\hat{s}\in\hat{\mathcal{S}}} |\tilde{W}^{\eta}(\mu, x, \hat{s}) - W^{\eta}(\mu, x, \hat{s})| h(\hat{s})$.

5. If the norm is greater than $\varepsilon$, update the values and the strategy profile with $\tilde{W}$ and $\tilde{\mu}^*$ and repeat steps 2-5.

# D Robustness

## D.1 Adding a Dominant Firm's State in the Moment-Based State

The moment-based Markov equilibrium as proposed by Ifrach & Weintraub (2016) allows firms to keep track of the detailed state of dominant firms (strategically important firms) as well as moments describing the state of fringe firms as their moment-based industry state. In my application, firms' industry states are further reduced to the the sum of states of all firms However, MME strategies may not be optimal (i.e. there may be a profitable unilateral deviation to a strategy that depends on more detailed information), if moments do not summarize all payoff-relevant information. In order to investigate how robust equilibrium strategies are to changes in the moment-based industry state, I consider a version in which richer information is allowed in the industry state and compare model predictions and values to the baseline case.

In particular, firms condition their strategy on the firm-specific state of the largest firm (the dominant firm) in addition to the states in the baseline case including their own firm-specific state, the sum of all firms' states, and demand states. In one version, the dominant firm's capital, denoted as $k_1$ is included in the information set and in the other version, the dominant firm's order book, $b_1$. Let $\hat{s}'$ denote the new industry state and let $\mu'$ and $\hat{V}'$ denote the optimal strategy and the value of the new game based on $\hat{s}'$ as the industry state. The difference in the values of the baseline model and the model that includes the dominant firm's state for each underlying state $s$ is defined as:

$$\Delta_{\mu'}(x, s) = \frac{V'^{\eta}_{\mu',\mu}(x, \hat{s}') - \hat{V}^{\eta}_{\mu}(x, \hat{s})}{\hat{V}^{\eta}_{\mu}(x, \hat{s})}.$$

The expected value of this deviation is computed as the weighted average through a simulation where the weights come from simulations based on the baseline model, or $\hat{V}$. Table 14 shows that model predictions stay robust when either of the dominant firm states is added. The average difference in the values is not significantly different from zero for both cases.

## D.2 Robustness Checks for the Adaptive Learning Model

As described in section 4, the adaptive learning model was implemented under the truncation approach. This section presents results from the imputation approach in which imputed data from 1966 to 1996 are used in the belief estimation. Figure 15 show the beliefs for the Asia-Europe market for the adaptive learning model with $\lambda_t = 0.02$. The beliefs under the

Table 14: Adding a Dominant Firm's State in the Moment-Based State

| **Panel A: Simulated moments** | Baseline | | Model with dominant firm's capital state | | Model with dominant firm's order book state | |
|---|---|---|---|---|---|---|
| Average investment in 2006-2008 (1 mil. TEU) | 0.23 | (0.03) | 0.23 | (0.03) | 0.23 | (0.03) |
| Average investment in 2009-2014 (1 mil. TEU) | 0.15 | (0.02) | 0.15 | (0.02) | 0.15 | (0.02) |
| Total capacity of owned ships (1 mil. TEU) | 5.15 | (0.27) | 5.13 | (0.28) | 5.14 | (0.28) |
| Total capacity in the order book (1 mil. TEU) | 2.98 | (0.14) | 2.98 | (0.14) | 2.99 | (0.14) |
| Correlation between demand and investment | 0.22 | (0.12) | 0.21 | (0.12) | 0.22 | (0.12) |
| Std. dev. in investment (1 mil. TEU) | 0.17 | (0.03) | 0.17 | (0.03) | 0.17 | (0.03) |
| **Panel B: Average difference in values** | | | | | | |
| All firms (%) | | | -0.35 | (0.46) | -0.42 | (0.54) |
| Dominant firm (%) | | | -0.18 | ( 0.22) | -0.21 | (0.26) |
| Fringe firms (%) | | | -0.36 | (0.48) | -0.43 | (0.56) |

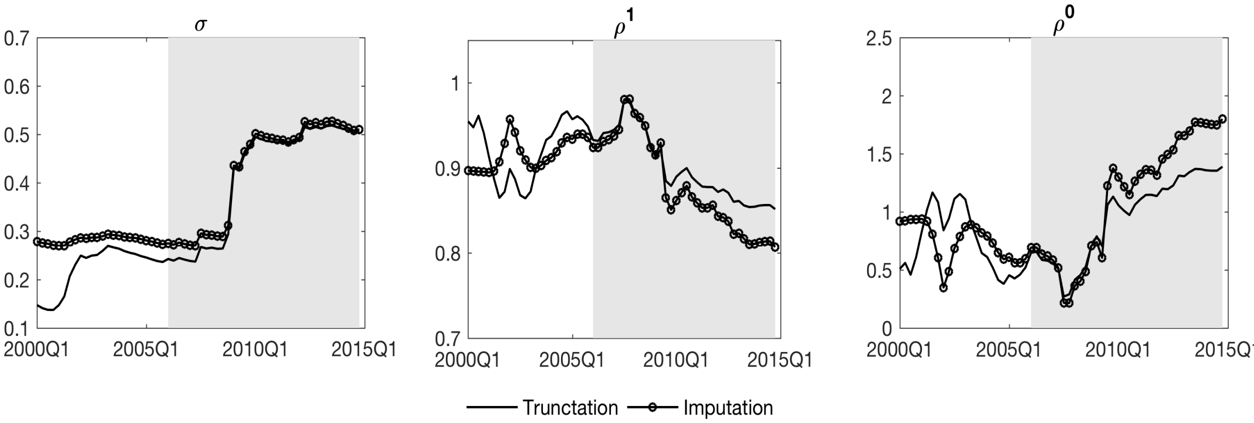
truncation and the imputation approaches are closer to one another especially for the period where the main analysis lies from 2006 to 2014. The model fits under the two approaches are also close to one another, although they are better under the truncation approach especially for the correlation between demand and investment as shown in table 15.

Table 15: Data Moments and Simulated Moments under the Truncation and Imputation Approaches

| | Data | Truncation | Imputation |
|---|---|---|---|
| Average investment in 2006-2008 (1 mil. TEU) | 0.23 | 0.23 | 0.22 |
| Average investment in 2009-2014 (1 mil. TEU) | 0.14 | 0.15 | 0.16 |
| Total capacity of owned ships (1 mil. TEU) | 5.09 | 5.15 | 5.17 |
| Total capacity in the order book (1 mil. TEU) | 3.07 | 2.98 | 2.98 |
| Correlation between demand and investment | 0.19 | 0.22 | 0.26 |
| Std. dev. in investment (1 mil. TEU) | 0.17 | 0.17 | 0.18 |

*Notes:* This table compares moments observed in the data and moments simulated under the truncation and imputation approaches of the baseline learning model.

Figure 15: Beliefs under Adaptive Learning Based on Two Alternative Approaches




*Notes:* This figure shows firms' beliefs about future demand under adaptive learning estimated with the truncation approach and the imputation approach, respectively, for the case of $\lambda_t = 0.02$. Beliefs for 2006-2014 in the shaded area are used in the main analysis.

## D.3 Credit Market Conditions

In the sample period that this study focuses from 2006 to 2014, there were sharp swings in credit market conditions along with swings in demand for international shipping. Therefore, one might worry that omitting information about credit market conditions might bias main results of the paper. This section therefore examines whether credit market conditions played an important role in firms' investment decisions. I use data from Compustat on company financials information, in particular the firm's debts and liabilities.[54]

Using these data I regress investment levels on state variables and variables relating to the firm's credit constraints including long-term debt and debt in current liabilities. If financial constraints were the main determinants of investment, we expect that firms that hold a higher amount of debt thus facing harsher credit constraints will withhold investment more. The regression results presented in table 16, nonetheless, suggest that debt levels do not have statistically significant effects on firms' investment.

Table 16: Regression of investment on debt-related variables

| Dependent variable: Investment (1000 TEU) | | |
|---|---|---|
| Owned ship capacity (1000 TEU) | -.037 | (.027) |
| Order book capacity (1000 TEU) | -.024 | (.017) |
| Aggregate owned ship capacity (1000 TEU) | .012 | (.01) |
| Aggregate order book capacity (1000 TEU) | -.015** | (.0064) |
| Demand state (Asia to Europe) | 1.1 | (2.3) |
| Demand state (Outside market) | .06 | (1.3) |
| Chartered ship capacity (1000 TEU) | -.025 | (.024) |
| Aggregate chartered ship capacity(1000 TEU) | -.019* | (.011) |
| Deployment in Asia-Europe market (1000 TEU) | .087** | (.043) |
| Aggregate deployment in Asia-Europe market (1000 TEU) | .019** | (.0078) |
| Long-term debt (1 bil. US dollars) | .00079 | (.002) |
| Debt in current liabilities (1 bil. US dollars) | -.0019 | (.0029) |
| Constant | -11 | (38) |
| Observations | 281 | |
| $R^2$ | 0.076 | |

*Notes:* Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.

[54] 281 company-quarter-level observations on company financials are available out of 612 observations used in the main analysis. There is, however, substantial variation on the magnitude of debts across firms in the data. The average firm-level long-term debt over the sample period varies from 0.06 million dollars for UASC to 4.3 billion dollars for Hyundai.