Navigating the Commons

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This paper develops a dynamic empirical model to evaluate markets for common-pool resources under open access. A novel feature of the model is that firms enter, exit, and invest while accounting for latent resource dynamics and industry evolution. Their actions influence one another through congestion and stock externalities, but individual firms lack incentives to internalize their own impacts. The model is applied to long-panel data from the 19th-century American whaling industry, an unregulated global commons for oil and bone production. The estimated model shows that high sunk costs of entry and investment delayed exit and divestment, leading to more firms and vessels than socially optimal. Counterfactual simulations indicate welfare losses of 40% over a century compared to a social planner's benchmark.

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1. Introduction

This paper investigates market failure in common-pool resources, a central concern in environmental challenges such as overfishing, deforestation, and groundwater depletion (Coman 1911; Hardin 1968; Ostrom 1990; Stavins 2011). Addressing negative externalities requires a policy that accounts for the social value of resources, shaped by producer responses, consumer demand, and evolving environmental conditions. This paper contributes to this understanding by developing a dynamic empirical framework and applies it to the 19th-century American whaling industry.[1]

The 19th-century U.S. whaling industry provides an ideal setting for studying commons problems for several reasons. First, the micro-level data reveals the lifecycles of whaling firms—from birth and growth to decline—along with detailed physical input-output of production spanning over a century. Such comprehensive long-panel data permits analyses of firms' behavioral responses to various environmental changes, like whale stock decline, demand shift, and technology improvements. Second, the industry was completely unregulated. Therefore, it is a nearly ideal laboratory for the study of firm behavior under pure open access. Without any regulatory constraints, one can apply stylized economic models based on profit maximization with minimal distortion of reality. Finally, the global scale of the whaling industry offers unique, large-scale implications for the commons dilemma. While small communities frequently provide collective self-governance (Ostrom 1990), as the scale of society has grown, commons problems have spread across communities and even across nations (Stavins 2011).

This paper's framework builds on the model of firm and industry dynamics in the tradition of Hopenhayn (1992) and Ericson and Pakes (1995). Importantly, firms' actions impact each other through common-pool externalities. First, a congestion externality arises from the large number of firms and vessels operating concurrently (Smith 1969; Weitzman 1974). Second, a stock externality emerges due to overexploitation, reducing the resource stock available for the future (Gordon 1954; Smith 1969). These externalities contribute to increasing costs over time. Escalating market prices, driven by rising costs, further reinforce these tendencies by incentivizing firms to operate in the commons.

A few key statistics—total vessel capacity and total whale harvest—effectively capture

[1] The novel *Moby-Dick* by Herman Melville (1851) provides an intriguing connection between the American whaling industry and the commons problem (Libecap 2024).

> But still another inquiry remains [...] Whether owing to the almost omniscient look-outs at the mast-heads of the whale-ships, now penetrating even through Behring's straits, and into the remotest secret drawers and lockers of the world; and the thousand harpoons and lances darted along all continental coasts [...] whether Leviathan can long endure so wide a chase, and so remorseless a havoc; whether he must not at last be exterminated from the waters, and the last whale, like the last man, smoke his last pipe, and then himself evaporate in the final puff.

these externalities, providing information of congestion, whale stock, and market prices. Dynamic strategic interactions arise because firms' actions collectively shape the evolution of these aggregates over time, while the aggregates, in turn, influence firm behavior. This motivates the application of *moment-based Markov equilibrium* (MME) framework of Ifrach and Weintraub (2017), along with its non-stationary extension inspired by Benkard, Jeziorski, and Weintraub (2024).[2] Thus, the non-stationary MME is an appealing behavioral modeling choice on its own for analyzing commons problem, with its computational tractability. In doing so, the model integrates the equilibrium framework of firm and industry dynamics into common-pool resource dynamic games (Levhari and Mirman 1980; Huang and Smith 2014).

The model is estimated in two steps. The first step involves estimating the production function and demand curve. For the production function, the dynamic panel approach addresses the endogeneity between firms' productivity and their input decisions (Blundell and Bond 2000). For the demand curve, supply-side cost shifters serve as instruments to consistently estimate the price elasticity of demand. Together, they provide period payoffs for every firm in each year. The next step estimates the dynamic cost parameters of entry, capital adjustment, and exit. It takes a full-solution approach, specifically the nested-fixed point with maximum likelihood estimation (Rust 1987). This method is particularly suited to analyze US whaling for two reasons: (1) it accommodates the non-stationarity in a single world market; (2) it facilitates the numerical solution of the model for counterfactual analyses. Alternative methods, such as conditional choice probability approaches, do not directly address these aspects.[3]

This study presents three main findings. First, the estimated model shows that the inefficiently large number of vessels and firms was driven by sunk costs of entry and investment. Firms exhibited hysteresis in exiting and divesting due to substantial, unrecoverable costs incurred during the entry and investment process (Dixit 1989). Second, the analysis highlights significant welfare losses in the industry compared to the social planner's first-best benchmark. Over-harvesting in the early years led to under-harvesting in later periods as rising harvesting costs created intertemporal misallocation. Furthermore, unproductive firms operated longer than socially optimal, due to sunk costs, resulting in misallocation across firms. Third, [*Note: this part will be potentially policy experiments*].

Contributions to the literature. This study makes three primary contributions. First, this paper introduces an empirical model for analyzing a market for shared resources un-

[2] Non-stationarity is particularly important in resource industries. For example, the American whaling industry experienced rapid growth and decline over a century due to changes in whale stocks, alternative resource availability, and technological advancements. Similar trends can be observed in modern energy sectors, such as cost reductions and increasing demand for solar panels, electric vehicles, and other renewables.

[3] See Appendix D for a detailed discussion.

der evolving industry structure and the resource stock. Extensive studies in industrial organization have explored how the dynamics of entry, exit, and capital accumulation interact to shape the long-run market structure and misallocation (see Aguirregabiria, Collard-Wexler, and Ryan 2021 for a survey). Environmental and energy markets, in particular, have drawn considerable interest in this endeavor (Ryan 2012; Fowlie, Reguant, and Ryan 2016; Aronoff and Rafey 2023; Elliott 2024; Gowrisankaran, Langer, and Zhang 2023). However, there has been a lack of empirical frameworks for exploring industry dynamics in the commons, despite common-pool resources constituting a significant part of environmental and energy concerns (Stavins 2011). The framework developed in this paper can be generally applicable to many industries with shared and partially renewable (or depletable) resources, such as fisheries, groundwater, and deforestation.

Second, using this framework, the paper quantifies equilibrium outcomes and welfare effects of managing the commons. A standard approach, relying on descriptive analysis, has provided robust empirical evidence on the differential effects of policies across resource stocks (Segerson and Squires 1993; Costello et al. 2012, 2016; Worm et al. 2009). However, these studies say little about the effects on overall welfare or other behavioral outcomes and cannot be used to study counterfactual policies. Thus, there has been limited evidence on how much welfare changes occur or how alternative policies in different times cause different equilibrium outcomes. This paper shows that policy effectiveness hinges on whether regulators account for firms' equilibrium behaviors and how to direct their behaviors to internalize externalities.

Third, this paper extends the vast literature on the economics of the commons by investigating the drivers of the "tragedy of the commons." Theoretical works have highlighted the inefficiencies that arise in the absence of property rights (Gordon 1954; Scott 1955; Smith 1969; Clark 1973). Empirical analyses have largely concentrated on the aggregate-level trends (e.g., Wilen 1976; Bjorndal and Conrad 1987; Huppert 1990; Amundsen, Bjorndal, and Conrad 1995; Allen and Keay 2004; Homans and Wilen 2005). More recent studies have begun addressing micro-level strategic dynamics (Huang and Smith 2014; Sears, Lin Lawell, and Walter 2022), influenced by game-theoretic models that account for how players' actions affect one another (Dawes 1973; Levhari and Mirman 1980; Sethi and Somanathan 1996; Baland and Platteau 2003). This paper demonstrates that firm entry, exit, and investment play a significant role in shaping competition dynamics and contribute to inefficiencies in the commons.

Outline. The rest of the paper is organized as follows. Section 2 provides a historical overview and descriptive analyses from data of the American whaling industry. Section 3 develops the model of common-pool industry dynamics. Section 4 describes the estimation strategies and presents the results. Section 5 implements counterfactual exercises. Section 6 concludes.

2. The American whaling industry

This section provides a historical overview and data of the industry. It offers a summary of the industry's major products and the shifts in market size (Section 2.1), the primary decision-makers (Section 2.2), data sources (Section 2.3), and descriptive statistics and data patterns (Section 2.4).

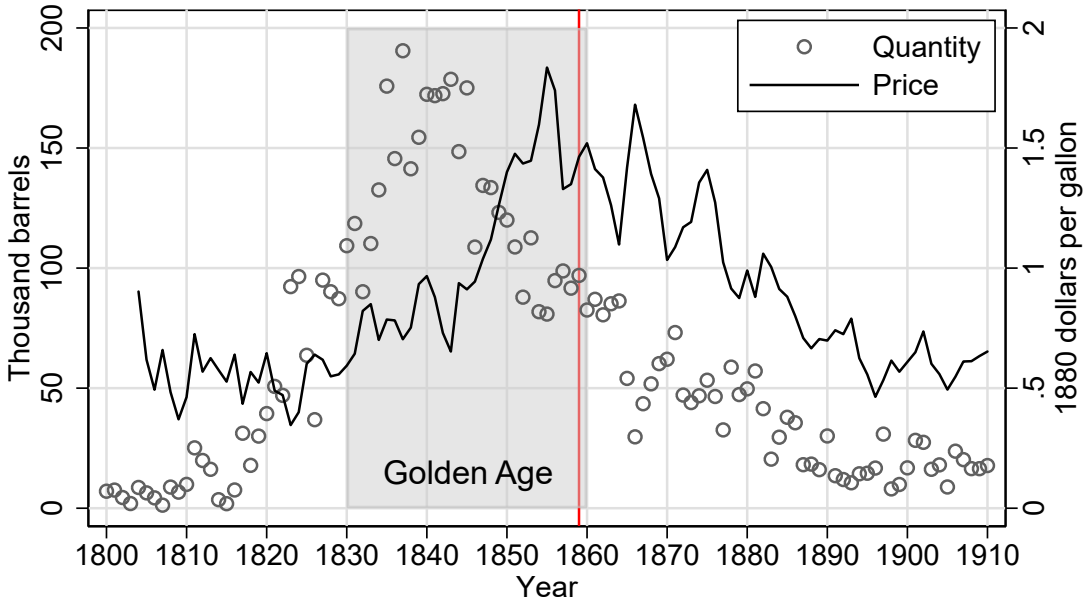
2.1. Products and markets

The industry primarily produced three commodities: sperm oil, whale oil, and whalebone. Sperm oil was obtained from the blubber of sperm whales through a boiling process and was highly valued for its clean and bright burning properties. It served as an illumination source and lubricant for fast-moving machinery (e.g., spindle). Whale oil, extracted from baleen whales, was used as a lubricant for heavy machinery (e.g., train) and provided illumination but was considered less valuable than sperm oil. Whalebone, obtained from the mouths of baleen whales, had industrial applications in products like corsets.

During the first half of the century, the process of industrialization in the United States led to a substantial increase in oil demand, creating larger markets for whaling. The industry experienced a period of global dominance during its "Golden Age" from 1830 to 1860, with American whalers accounting for over 90% of the world's sperm oil production (Tillman and Donovan 1983). During this time, the United States surpassed Britain as the leading whaling nation due to favorable domestic demand growth, institutional technology differences, and the use of higher-skilled crews (Davis, Gallman, and Hutchins 1987). Of the 900 vessels of all nations engaged in whaling in the late 1840s, over 700 were American (Moment 1957). After then, the industry gradually declined with various reasons such as the discovery of petroleum in 1859 and the Civil War from 1861 to 1865. By the late nineteenth century, output and value had fallen to levels similar to those of the early 1800s.

Figure 1 illustrates the trends of output quantities and prices for whaling products. Figure 1A, representing sperm oil, demonstrates a peak in output quantity around 1840, followed by a decline. As the supply diminished, prices rose. The introduction of petroleum (marked by the red vertical line) gradually replaced sperm oil. Figure 1B, focusing on whale oil, exhibits a similar trend to sperm oil, with a notable difference: the peak production occurred later than that of sperm oil. This suggests that the more valuable sperm oil was extensively exploited earlier. As sperm oil production declined from the 1840s, American whalers shifted their focus to whale oil, reaching its peak around 1850. Whalebone, in Figure 1C, initially served as a by-product of whale oil until the golden age period. Its value surged from the 1870s, primarily due to the expansion of the women's fashion industry, particularly the demand for corsets. However, by this time, the industry had

A. Sperm oil



B. Whale oil

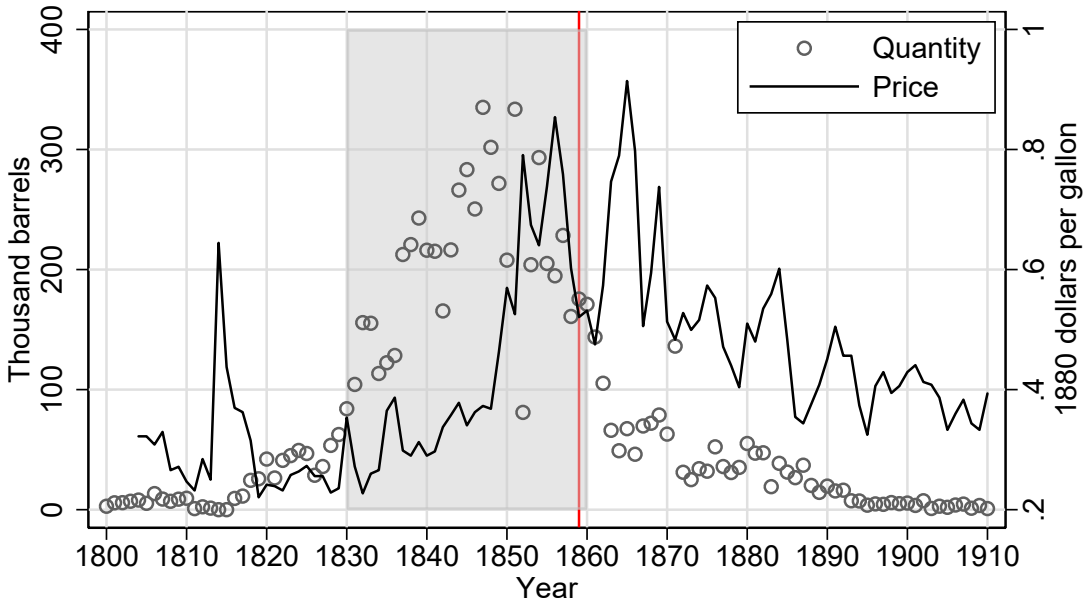


FIGURE 1. Quantities and prices for whaling products

Note: The term "Golden Age" refers to the period when the American whaling industry was at its peak, from the 1830s to the 1850s. The year of petroleum discovery in 1859 is indicated by the vertical red line.

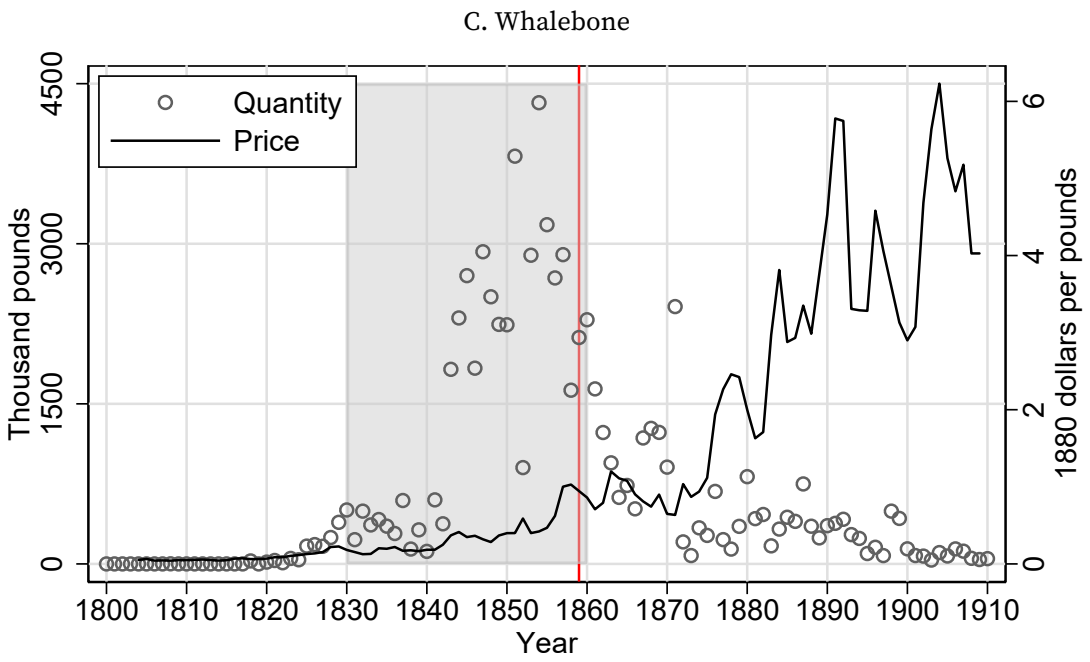


FIGURE 1 (Cont'd). Quantities and prices for whaling products

already declined significantly, leading to a shortage in supply and driving whalebone prices considerably high. This indicates that despite the substitution of sperm oil and whale oil by petroleum, there existed another form of demand for whales during this period.

2.2. Whaling agents

Whaling agents, interchangeably denoted to as "firms" in this paper, were the primary decision-makers (see Chapter 10 of Davis, Gallman, and Gleiter 2007 and Chapter 1 of Nicholas 2019 for a more in-depth discussion of whaling agents). As American whaling voyages typically spanned multiple seasons (averaging around 2.5–3 years), effective planning and management by agents were crucial in achieving success. They were responsible for acquiring vessels and hiring a captain, as well as determining the necessary equipment and crew. In the process of decision making, agents utilized logbooks from prior voyages. These contained daily notes made by captains and first mates, providing detailed information on whale sightings, weather, locations, and crew morale. At the end of a venture, the logbook became the property of the agent or owner, serving as a repository of accumulated knowledge (Nicholas 2019).

Plans by agents included voyage duration, hunting grounds, locations and dates for resupplying, and shipping oil or bone back home (see Appendix A.1 for an example). The

plan was made before the vessel sailed but was frequently subject to change. Unforeseen success or challenges could necessitate altering the original schedule. For instance, exceptional success might prompt an early stop at a transshipment point; setbacks could extend the time at sea beyond the initial plan. While the captain made day-to-day sailing and hunting decisions, the agents held general authority, ensuring consistent communication between them as best as possible. Before the voyage commenced, the captain and agent agreed on dates and stations for exchanging letters. These exchanges occurred at predetermined rendezvous points, either between whaling vessels or between supply ships and whaling vessels (see Appendix A.2 for an example). For instance, Santa Maria, a small island in the Galapagos archipelago, became a mail hub because it was frequented by vessels hunting whales in the Pacific (Nicholas 2019).

In many cases, whaling agents actually owned the vessel (as a principal owner), flying a "house flag" reflecting the ownership. But it does not mean that the agent himself financed the entire voyage. Multiple investors were involved, with variations from one voyage to another (see Appendix A2 for an example). This is due to the substantial capital investment required for the operation of whaling voyages. A typical New Bedford whaling venture in the 1850s called for $20,000 to $30,000 (evaluated at that time period). This was considerable, especially when compared to other sectors. For instance, American farms were valued at $2,258 in 1850 and $3,251 in 1860. The capital stock of the average manufacturing firm was valued at $4,335 in 1850 and $7,191 in 1860 (Davis, Gallman, and Gleiter 2007).

2.3. Data

This paper constructs datasets for examining the whaling market. This subsection describes the novel aspects of the data, emphasizing how they reveal (i) firm-level behaviors; (ii) price per whale; and (iii) common-pool features. See Appendix B for a detailed description.

The primary data source to track whaling firms is the *Voyage Database*, which covers almost all US whaling voyages operated in the 19th century. This database contains vessel characteristics such as name, unique ID, tonnage, and rigging type, as well as information on managing owner/agent, captains, out- and in-bound years, outputs (sperm oil, whale oil, and whalebone), ports, and other related data (see Figure A1 for an example). However, the *Voyage Database* lacks crew information, thus the *Crew List Database* is employed as a supplement source to obtain the number of crews for each voyage. It covers around half of the voyages in the *Voyage Database*.

To investigate firms' production, entry, exit, and capital accumulation, I construct a firm-year level panel data using the voyage-level information. Voyage level outputs are divided by the voyage duration using departure and return years. They are then aggregated at the firm-year level based on owner/agent record. As there are three outputs (sperm oil,

whale oil, and whale bone), I convert them into the *number of whales harvested* based on historical account (see Appendix B.4). Voyage level inputs, vessel tonnage and crew size, are also aggregated at the firm-year level, assuming to be constant over the journey.[4]

The prices of whaling products come from Tower (1907) and Davis, Gallman, and Gleiter (2007). The price *per whale* is calculated by the aggregate value of outputs, divided by the total number of whales harvested in each year. The aggregate output value is obtained by the sum of the product values: sperm oil quantity × sperm oil price + whale oil quantity × whale oil price + whalebone quantity × whalebone price. The total number of whales harvested is calculated by summing the whale catch numbers of all whaling voyages.

To explore common-pool features, two externalities should be taken into consideration. First, the congestion externality is reflected by total whaling vessel tonnage. This is calculated by summing the tonnage of all whaling vessels for each year from the *Voyage Database*. Second, the stock externality is represented by whale population. The whale stock is projected using a discrete time, generalized logistic model of whale population dynamics (see equation [4] in Section 3.1).

For the demand factors, three exogenous variables are gathered. Demand evolves in response to exogenous demand shifters: US population, US GDP per capita, and petroleum prices. These data come from the Historical Statistics of the United States (Carter et al. 2006).

2.4. Descriptive statistics

Table 1 presents the firm level statistics. Notably, there exists significant variability across firm-year observations. For example, 2% of observations indicate zero whales harvested, whereas others report hundreds of catches. Inputs also exhibit wide variation. Some firms operated only one vessel in a year, but others operated more up to 20. Variations in vessel tonnage and crew size reflect this heterogeneity. Panel C describes the statistics for dynamic decisions. Investment is measured by tonnage increase between current year and next year, excluding vessel wreckage due to factors such as bad weather, accidents, war, etc. Divestment is similarly calculated by tonnage decrease. On average, 10% opt to exit, 15% to invest, and 11% to divest. The mean investment level is approximately 345 tons, while that of divestment is about 333 tons. These levels vary from few tons to thousands of tons, illustrating the lumpy nature of capacity adjustments.

Figure 2 presents the total whaling vessel capacity and whale stock. Panel A indicates the rise of American whaling to world dominance during the golden age period, followed

[4]Though there is evidence that crew desertion and addition were frequent, the overall crew size is largely constrained by vessel tonnage as shown in Figure A3. Therefore, this assumption should not impact much for empirical results.

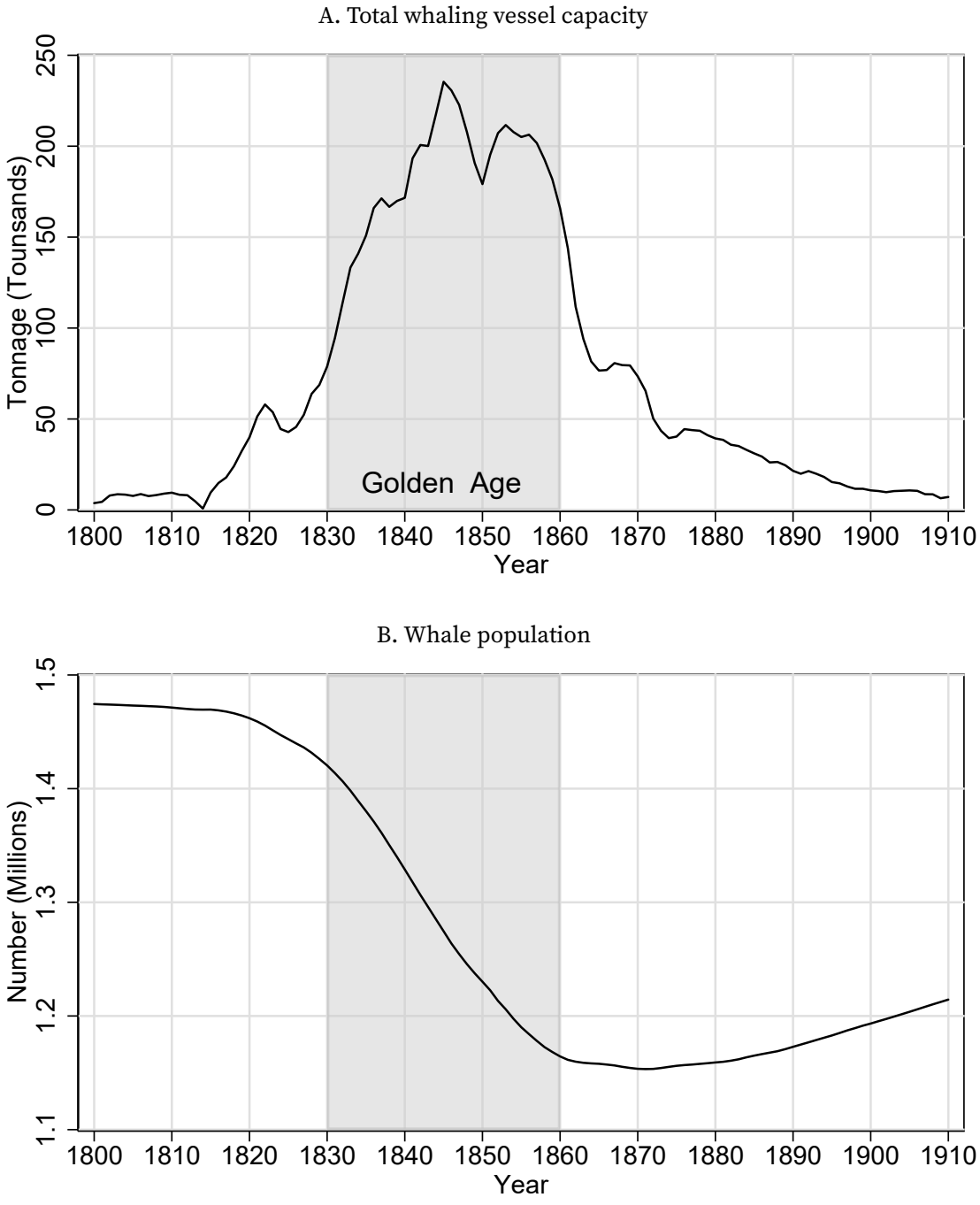


FIGURE 2. Aggregate whaling vessel capacity and whale stock

Note: The term "Golden Age" refers to the period when the American whaling industry was at its peak, from the 1830s to the 1850s. Total whaling vessel capacity is calculated by summing the tonnage of all whaling vessels for each year from the *Voyage Database*. Whale population is projected using a discrete time, generalized logistic model of whale population dynamics (see equation (4) in Section 3.1).

TABLE 1. Firm-year level statistics for the American whaling industry

Variable	Unit	Mean	SD	Min	Median	Max
Panel A. Outputs						
Whales harvested	Number	39.07	45.99	0.00	22.58	459.30
Sperm oil	Thousand barrels	0.50	0.68	0.00	0.28	8.58
Whale oil	Thousand barrels	0.76	1.26	0.00	0.22	12.40
Whale bone	Thousand pounds	5.81	12.49	0.00	0.00	193.54
Panel B. Inputs						
Vessel capacity	Tonnage	754.35	800.98	42.00	391.00	7533.00
	Number	2.59	2.39	1.00	2.00	20.00
Crew size	Number	41.20	67.62	0.00	17.00	549.00
Firm age	Year	11.13	10.80	1.00	7.00	74.00
Panel C. Dynamic decisions						
Exit	Proportion	0.10	0.30	0.00	0.00	1.00
Investment	Proportion	0.15	0.35	0.00	0.00	1.00
	Tonnage	345.68	231.48	1.67	321.00	2782.50
Divestment	Proportion	0.11	0.32	0.00	0.00	1.00
	Tonnage	-333.04	245.00	-3217.00	-306.00	-0.50

Note: The number of firm-year level observations is 10,450 and the number of firms is 1,060. The time period spans from 1804 to 1909. The number of harvested whales is calculated based on sperm oil, whale oil, and whale bone quantities (see Appendix B.4 for details). Investment and divestment are measured as the difference in tonnages between the current year and the next year, excluding any tonnage difference attributable to vessel wreckage.

by its collapse within a single century. In terms of capital stock, the industry employed an annual average of only eighteen thousand vessel-tons in the years 1816-20. Over the next three decades, tonnage increased more than fifteen-fold. However, in the 1890s, following a prolonged decline, the capital stock became smaller compared to its level in 1816-20. Panel B displays the projected population of whales as a sum of baleen and sperm whales, calculated using the method outlined in Sections 2.3. It shows that whale stock experienced substantial declines during the golden age period.

Figure 3 provides suggestive evidence of the presence of negative externalities. Panel A displays the number of whales harvested per vessel. Following a marked increase in the 1800s-1820s, it reached around 25 during the 1820s and reduced to 12 in the 1850s.[5] This decline is noteworthy, considering the overall technology growth during this period, estimated at approximately 1.4% per year in Section 4.1.1. On the other hand, panel B

[5]Anecdotal evidence suggests the increasing difficulty of hunting whales over time. For example, the following excerpt is from a logbook during the voyage of the vessel *Roman* (Agent Dunbar, Joseph & Co.) on August 16, 1838:

> these 24 hours brisk winds from E & some squals saw fin backs Jumpers & porpuses but No Sperm Whales. O dear whare are all the whales gone to are they all Killed of[f] or Not.

shows a non-decreasing revenue per vessel. It was $13,000 (in 1880 dollars) in the 1820s, and then increased to $17,000 in the 1850s. This increase is attributed to a significant rise in prices. For instance, the price of sperm oil was around $0.5 per gallon in the 1820s and tripled in the 1850s (see Figure 1). This suggests the presence of incentives for firms to continue operating despite cost increases. See Appendix C for a conceptual framework rationalizing this descriptive pattern.

3. A model of common-pool industry dynamics

This section builds a strategic industry dynamics model in the spirit of Hopenhayn (1992) and Ericson and Pakes (1995). This paper combines the *moment-based Markov* equilibrium framwork by Ifrach and Weintraub (2017) and the transitional market dynamics by Benkard, Jeziorski, and Weintraub (2024) with common-pool dynamic games by Levhari and Mirman (1980) and Huang and Smith (2014). The subsections cover the model setup (Section 3.1), strategies (Section 3.2), industry dynamics (Section 3.3), and the equilibrium concept (Section 3.4).

3.1. Setup

Time. Each period is indexed with $t \in \{1, 2, ..., T\} \subset \mathbb{N}$, where T denotes the terminal period.

Players. There are N_t incumbent whaling firms and N_t^{pe} potential entrants, indexed by $i \in \mathcal{I}_t$.[6]

Resource. The whale stock at period t is denoted by $W_t \in [0, W_0] \subset \mathbb{R}$, where W_0 is the natural carrying capacity without harvesting.

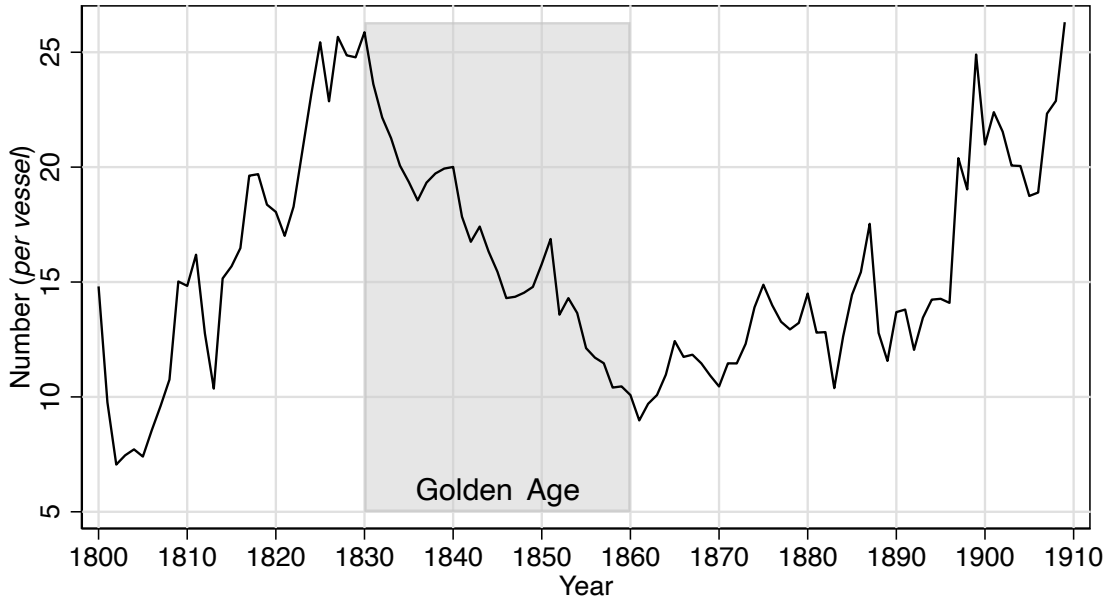
State space. Whaling firms exhibit heterogeneity across two dimensions. First, vessel capacity (K) measures the sum of vessel tonnage in operation. Second, productivity (Ω) captures the efficiency related to informational and managerial conditions, given the whale stock. Though firms do not directly observe whale stock, they learn about it from their experience. Thus, the *individual* state of firm i in period t is denoted by $x_{it} \equiv (K_{it}, \Omega_{it}) \in \mathcal{X}$.[7] With a slight abuse of notation, $K(x)$ is the vessel capacity and $\Omega(x)$ is productivity at

[6] [*Note: characterize the number of potential entrants*]

$$\text{potential entrants}(s) = 30 \; + \; \left(s - s_{\min}\right) \times \frac{(60 - 30)}{\left(s_{\max} - s_{\min}\right)}$$

[7] Incorporating firm-level time-varying productivity into the state space addresses the limitation that arises when independent private shocks are the only source of unobserved variation over time (Bajari, Benkard, and Levin 2007).

A. Per vessel output: The number of whales harvested



B. Per vessel revenue: The value of output

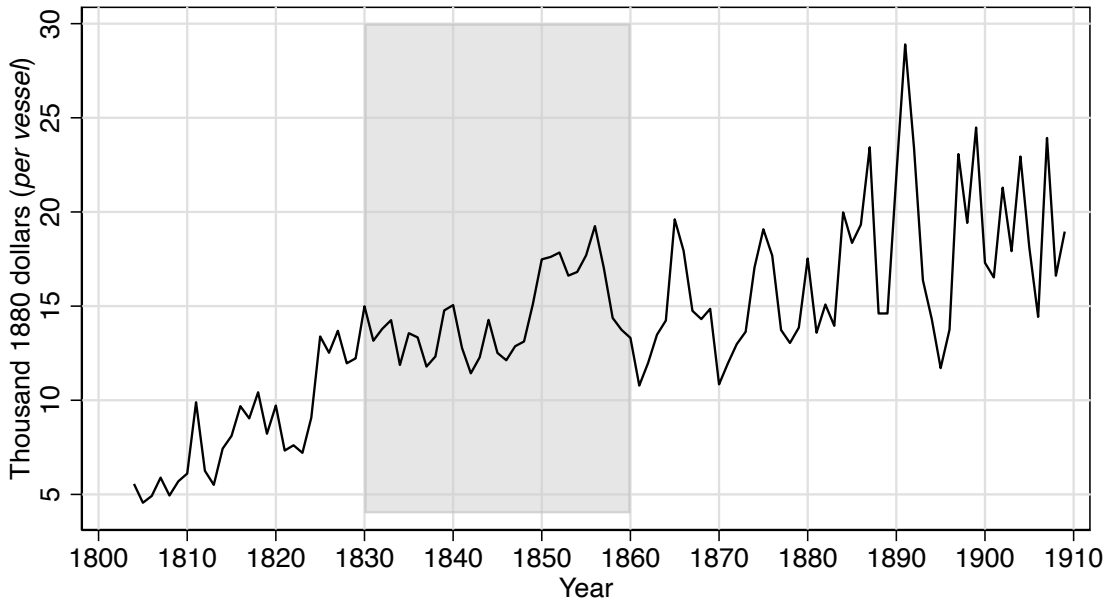


FIGURE 3. Suggestive evidence of negative externalities

Note: In panel A, the output is measured by the number of harvested whales. In panel B, the value of output is calculated as the sum of the product values: sperm oil quantity × sperm oil price + whale oil quantity × whale oil price + whalebone quantity × whalebone price. The term "Golden Age" refers to the period when the American whaling industry was at its peak, from the 1830s to the 1850s.

each individual state x. The distribution of firms is defined by $f_t \in \mathbb{N}^{|\mathcal{X}|}$ as a vector over individual states that characterizes the number or mass of firms, $f_t(x)$, at each possible value of $x \in \mathcal{X}$.

Decisions. At each time t, incumbent firm i chooses to exit or remain in the market. If it stays, the firm can adjust its vessel capacity. Potential entrants decide whether to enter the market. The decisions of incumbent whaling firms are denoted by a_{it}, while those of potential entrants are denoted by a_{it}^{pe}.

Production. The whale harvesting function $\mathcal{H}$ represents the number of whales harvested by firm i, given its state $x_{it} = (K_{it}, \Omega_{it})$, the total vessel capacity K_t, and the whale stock W_t:

$$Q_{it} = \mathcal{H}_t(x_{it}, K_t, W_t; \boldsymbol{\beta}). \tag{1}$$

It captures the effects of congestion externality through K_t and resource stock externality through W_t. The time subscript in $\mathcal{H}_t(\cdot)$ indicates the time dependence due to overall exogenous technological growth in the industry. $\boldsymbol{\beta}$ is a vector of parameters governing the harvesting function.

Demand. The inverse whale demand function $\mathcal{P}$ captures the relationship between price, aggregate whale harvest, and demand conditions:

$$P_t = \mathcal{P}(Q_t; Z_t^d, \boldsymbol{\alpha}) = \mathcal{P}_t(Q_t; \boldsymbol{\alpha}). \tag{2}$$

Here, P_t represents the common price charged by all firms. The vector Z_t^d includes exogenous demand shifters, including U.S. population, GDP per capita, and petroleum prices (available from 1859), which are determined outside of the model. To simplify notation, the exogenous demand shifters Z_t^d are embodied by a time subscript in $\mathcal{P}_t(\cdot)$. $\boldsymbol{\alpha}$ is the vector of parameters for the demand system.

Period payoff. Assuming the marginal costs to be zero,[8] firm i's period payoff function at time t is

$$\Pi_t(x_{it}, K_t, Q_t, W_t; \boldsymbol{\alpha}, \boldsymbol{\beta}) = \mathcal{P}_t(Q_t; \boldsymbol{\alpha})\mathcal{H}_t(x_{it}, K_t, W_t; \boldsymbol{\beta}) \tag{3}$$

The payoff depends on the past decisions of all competitors, as reflected in K_t, Q_t, and W_t.

[8] Including constant labor costs as marginal costs is possible, but the high correlation between crew size and vessel capacity offers little additional variation. See Appendix B.3.

3.2. Moment-based states and strategies

Common-pool resources, characterized by open access and rivalry, naturally involve many players in the industry. From a firm's behavioral perspective, gathering information on the states of numerous firms is costly. Consequently, firms refrain from monitoring detailed information about the states of competitors. Instead, they track key summary statistics that are relevant to their payoffs, following the *moment-based* strategies developed by Ifrach and Weintraub (2017).

As shown in equation (3), the payoff-relevant moments include total vessel capacity, whale harvest, and whale stock. Accordingly, the *moment-based industry state* is defined as $s_t = (K_t, Q_t, W_t)$. First, the *perceived* total vessel capacity is expressed as:

$$K_t = \sum_{x \in \mathcal{X}} f_t(x) K(x),$$

representing the sum of vessel capacities across the firm distribution as the first unnormalized moment. Then, the *perceived* total whale harvest function $\mathcal{Q}$ is defined as:

$$Q_t = \mathcal{Q}_t(K_t, W_t; \boldsymbol{\beta}) = \sum_{x \in \mathcal{X}} f_t(x)\, \mathcal{H}_t\left(x, K_t, W_t; \boldsymbol{\beta}\right),$$

which depends on the current total vessel capacity and whale stock. Finally, the transition of whale stock follows a discrete-time, generalized logistic model of population dynamics (Baker and Clapham 2004; Breiwick and York 2009):

$$W_{t+1} = W_t + r_{\max} W_t \left[1 - \left(\frac{W_t}{W_0}\right)^z\right] - Q_t, \tag{4}$$

where $r_{\max}$ is the maximum potential rate of increase of whale population and z is the exponent setting the maximum sustainable yield level.

Following Ifrach and Weintraub (2017), a *moment-based strategy* for firm i at time t can be defined as

$$\begin{aligned} \sigma_t(x_{it}, s_t, \nu_{it}) &= a_{it} \\ \sigma_t^{pe}(x_{it}^{pe}, s_t, \nu_{it}^{pe}) &= a_{it}^{pe}, \end{aligned}$$

where x_{it}^{pe} indicates the status of potential entrants and $\nu_t = (\nu_{it}, \nu_{it}^{\text{pe}})_{i \in \mathcal{I}_t}$ are private shocks that capture the idiosyncratic fortune experienced by each firm regarding dynamic actions. Hence, they take the form of independently and identically distributed (i.i.d.) private information. This study focuses on an anonymous, type-symmetric pure strategy that links states and private shocks to firms' decision-making.

3.3. Dynamic evolution of the whaling industry

Timing and state transitions.

- At the beginning of each period t, incumbent firms engage in whale hunting and earn period payoffs as described in equation (3). In the process of whaling, there can be vessel wreckage with a probability of δ due to factors such as bad weather, accidents, war, etc.
- Then, all firms draw private shocks $\nu_t = (\nu_{it}, \nu_{it}^{\text{pe}})_{i \in \mathbb{J}_t}$ for their dynamic actions. Observing these private shocks, they simultaneously make their decisions $\boldsymbol{\sigma}_t = (\sigma_{it}, \sigma_{it}^{\text{pe}})_{i \in \mathbb{J}_t}$. Incumbent firms decide whether to exit or not. If they exit, then they can scrap vessels and other related materials, getting a real-valued sell-off value ϕ^{ex}. If staying, they have the opportunity to adjust vessel capacity. They can increase or decrease their capacity through costly adjustment, denoted by I_{it}. The cost associated with these behaviors is denoted by

$$C(I_{it}; \boldsymbol{\Gamma}) = \gamma_2 I_{it}^2 + \gamma^{\text{inv}} \mathbb{1}\{I_{it} > 0\} I_{it} + \gamma^{\text{div}} \mathbb{1}\{I_{it} < 0\} I_{it} + \gamma_0 \mathbb{1}\{I_{it} \neq 0\} \tag{5}$$

  where $\boldsymbol{\Gamma} = \{\gamma_2, \gamma^{\text{inv}}, \gamma^{\text{inv}}, \gamma_0\}$. γ_2 captures the convex adjustment cost, γ^{inv} represents investment cost, γ^{div} denotes divestment value, and γ_0 stands for adjustment fixed cost. Potential entrants make decisions of entering the market or not. If they choose to quit, they abandon the prospect of entry and disappear from the potential entrants pool. If they enter, they become actual entrants by paying entry fixed costs ϕ^{en} that include initial investment setup costs.
- All these decisions are realized at the beginning of the next period. The vessel capacity accumulates

$$K_{it+1} = (1 - \delta) K_{it} + I_{it} \tag{6}$$

  where δ is the exogenous destruction (or depreciation) rate. The index of (log) productivity, $\omega_{it} = \log \Omega_{it}$, follows a first-order Markov process:

$$\omega_{it+1} = \mathbb{E}[\omega_{it+1} | \omega_{it}] + \xi_{it+1} \tag{7}$$

  where ξ_{it+1} is unexpected productivity innovation drawn from i.i.d standard Normal distribution. Industry state transitions from s_t to s_{t+1} based on all firms' decisions.

Dynamic problem of whaling firms. Firms make their dynamic choices of entry, exit, and capacity adjustment to maximize their expected discounted stream of payoffs, discounting future payoffs by a factor $\rho \in (0, 1)$.

The dynamic programming problem of an active whaling firm with state $x_{it} = (K_{it}, \Omega_{it})$

at time t is characterized by the following Bellman equation:

$$V_t(x_{it}, s_t; \boldsymbol{\sigma}_t) = \mathbb{E}_{\nu}\Bigg[\Pi_t(x_{it}, s_t) + \max\Bigg\{\underbrace{\phi^{\text{ex}} + \nu_{it}(0)}_{\text{exit}},\ \underbrace{\max_{I_{it}}\left[-C(I_{it}) + \rho\,\mathbb{E}_t\left[V_{t+1}(x_{it+1}, s_{t+1}; \boldsymbol{\sigma}_{t+1}) \mid x_{it}, s_t, \boldsymbol{\sigma}_t\right] + \nu_{it}(I_{it})\right]}_{\text{stay and capacity adjustment}}\Bigg\} \Bigg| x_{it}, s_t\Bigg]. \tag{8}$$

Here, the parameters $\theta = \{\phi^{\text{ex}}, \boldsymbol{\Gamma}\}$ are omitted for a simple exposition. The value function varies over time due to the evolution of the industry, embodied in the demand shifters and overall technology growth. Having earned the period payoffs, firms decide whether to exit or stay. An incumbent decides to exit at time t if and only if the sum of exit scrap value and exit private shock surpasses the continuation value. The continuation value represents the discounted expected value, net of capacity adjustment costs and private shock, while considering state transitions via the perceived transition kernel. The staying firm determines the adjustment level for the next period capacity that maximizes its continuation value.

For a potential entrant, the objective is to solve the following optimization problem:

$$V_t(x^{\text{pe}}_{it}, s_t; \boldsymbol{\sigma}_t) = \mathbb{E}_{\nu}\Bigg[\max\Bigg\{\underbrace{\nu^{\text{pe}}_{it}(0)}_{\text{not enter}},\ \underbrace{\rho\,\mathbb{E}_t\left[V_{t+1}(x_{it+1}, s_{t+1}; \boldsymbol{\sigma}_{t+1}) \mid x^{\text{pe}}_{it}, s_t, \boldsymbol{\sigma}_t\right] - \phi^{\text{en}} + \nu^{\text{pe}}_{it}(1)}_{\text{enter}}\Bigg\} \Bigg| x^{\text{pe}}_{it}, s_t\Bigg]. \tag{9}$$

A potential entrant decides to enter at time t if and only if the net entry value is greater than the private shock of not entering. Those who make entry decisions become actual entrants and begin their operation from the next period.

The equations (8) and (9) imply that the operation fixed cost is normalized to zero, as the entry fixed cost, exit scrap value, and operation fixed cost in a dynamic model cannot be jointly identified. With this normalization, the estimates of entry cost and exit scrap value incorporate the operation fixed cost. See Table 3 in Aguirregabiria and Suzuki (2014) for further discussion.

3.4. Equilibrium

To ensure computational feasibility, it is assumed that the industry's nonstationary evolution converges to its stationary counterpart in the sufficiently long time span (Benkard, Jeziorski, and Weintraub 2024). Let the period of interest be the time interval from $t = 1$

to $t = T$. Additionally, there exists a finite time horizon of length $\overline{T} > T$. Firms anticipate that the industry will transition to a stationary state for $t \geq \overline{T}$. Consequently, the industry exhibits nonstationary behavior between $t = 1$ and $t = \overline{T} - 1$, whereas it adheres to the stationary equilibrium from $t \geq \overline{T}$. This simplification should not significantly impact the industry's behavior during the time periods of interest spanning from $t = 1$ to $t = T$. This assumption enables us to solve the model by backward induction.

The terminal value associated with a firm's state $x_{i\overline{T}} = (K_{i\overline{T}}, \Omega_{i\overline{T}})$ is

$$V(x_{i\overline{T}}, s, \nu_{i\overline{T}}) = \Pi(x_{i\overline{T}}, s) + \max\Bigg\{\phi^{\text{ex}} + \nu_{i\overline{T}}(0), \max_{I_{i\overline{T}}}\left[-C(I_{i\overline{T}}) + \rho\,\mathbb{E}\left[V(x_{i\overline{T}+1}, s, \nu_{i\overline{T}+1})|x_{i\overline{T}}, s, \nu_{i\overline{T}}\right] + \nu_{i\overline{T}}(I_{i\overline{T}})\right]\Bigg\}.$$

Note that the value function, payoff function, and moment-based industry state do not have a time subscript. Hence, the corresponding policy functions associated with entry, exit, and capacity adjustment are also stationary, meaning they do not vary over time for $t \geq \overline{T}$. From the terminal period, the model is solved via backward induction all the way back to the initial period.

Now define the nonstationary moment-based equilibirum (NMME).

DEFINITION 1 (NMME). *A nonstationary moment-based strategy* $\boldsymbol{\sigma} = (\sigma, \sigma^{pe})$ *is a NMME if*

$$\max_{\sigma'} V_t(x, s; \sigma', \sigma, \sigma^{pe}) = V_t(x, s; \sigma, \sigma^{pe})$$
$$\max_{\sigma'^{pe}} V_t(x^{pe}, s; \sigma'^{pe}, \sigma, \sigma^{pe}) = V_t(x^{pe}, s; \sigma, \sigma^{pe})$$

for all firm state x, the moment-based industry state s, and time t.

[Note: need to discuss the dependence on f_0, equilibrium existence, and multiple equilibria.]

4. Estimation

This section outlines the estimation procedure and presents the results. The empirical approach consists of two steps. In the first step, it recovers parameters for period payoffs (Section 4.1). This involves estimating the whale harvesting function and the whale demand curve. These estimates allow the calculation of period payoffs for all possible firm states in each year. In the second step, these period payoffs are embedded into the dynamic problem to estimate the costs and values associated with entry, capacity adjustment, and exit (Section 4.2).

4.1. Period payoffs

4.1.1. Whale harvesting

Whaling firm i harvests Q_{it} number of whales per year t. The production requires vessels (capacity) K_{it} and labor (crew size) L_{it}. Productivity Ω_{it} affects harvesting amount for any given inputs and other conditions. I specify the Cobb-Douglas production function in logarithmic terms:

$$q_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \beta^K k_t + \beta^W w_t + \beta^t t + \underbrace{\mu_{it} + \varepsilon_{it}}_{\omega_{it}}, \tag{10}$$

where q_{it} represents the log of the number of harvested whales (sperm whales + baleen whales), k_{it} is the log of vessel capacity, l_{it} is the log of crew size, k_t is the log of aggregate vessel capacity, w_t is the log of whale stock, and t is the time trend. The firm-level total productivity, ω_{it}, is divided into persistent productivity μ_{it} and ex-post shock ε_{it}.

In order to identify the production function, I impose assumptions on the transition process of persistent productivity and the timing of firms' input choices, aligning with the model outlined in Section 3.1. Following the dynamic panel approach by Blundell and Bond (2000), let the transition of persistent productivity μ_{it} be given by an AR(1) process with serial correlation λ:

$$\mu_{it} = \lambda \mu_{it-1} + \chi_{it}, \tag{11}$$

where χ_{it} is an independent and identically distributed (i.i.d.) shock to persistent productivity. Though the dynamic panel approach does not address selection bias caused by endogenous exit, using an unbalanced panel generally mitigates most concerns of selection bias (Olley and Pakes 1996; De Loecker et al. 2016). An alternative approach in the literature involves inverting the intermediate input demand function to estimate the latent persistent productivity level (Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015). However, in the data from the American whaling industry, a credible intermediate input that satisfies the key assumptions of monotone increasing relationship with productivity is lacking.

The decision regarding vessel capacity, as described in equations (5) and (6), occurs at time $t-1$ through costly adjustment, before the productivity shock is realized. Given the close link between vessel capacity and crew size, crew size is likewise assumed to be set at time $t-1$. These timing assumptions, together with equation (11), lead to the following exclusion restriction to identify $\boldsymbol{\beta} = (\beta_0, \beta_l, \beta_k, \beta^K, \beta^W, \beta^t, \lambda)$. The productivity shock, χ_{it}, is orthogonal to current vessel capacity, crew size, aggregate vessel capacity, whale stock,

TABLE 2. Whale harvesting function estimates

	(1)	(2)	(3)	(4)	(5)
Vessel capacity: β_k	1.009	1.067	0.917	0.935	1.048
	(0.032)	(0.028)	(0.023)	(0.021)	(0.007)
Crew size: β_l	-0.001	-0.029	0.174	0.153	
	(0.026)	(0.024)	(0.025)	(0.023)	
Persistence: λ	0.692	0.673	0.350	0.304	0.258
	(0.117)	(0.096)	(0.118)	(0.116)	(0.097)
Aggregate vessel capacity: β^K		-0.233	-0.253	-0.012	-0.048
		(0.018)	(0.012)	(0.018)	(0.012)
Whale stock: β^W			3.314	7.148	5.119
			(0.140)	(0.296)	(0.277)
Time trend: β^t				0.021	0.014
				(0.001)	(0.001)
Returns to scale: $\beta_k + \beta_l$	1.009	1.047	1.091	1.088	1.048
Number of firms	462	462	462	462	983
Observations	4,891	4,891	4,891	4,891	9,043

Notes: The robust standard errors are reported in parentheses.

and time trend. Therefore, a set of seven moment conditions is

$$\mathbb{E}\left[\mathcal{M}_{it}(\boldsymbol{\beta}) \otimes \boldsymbol{\Delta}_{it}\right] = 0,$$

where $\mathcal{M}_{it}(\boldsymbol{\beta}) = \chi_{it} + (\varepsilon_{it} - \lambda\varepsilon_{it-1})$ and $\boldsymbol{\Delta}_{it} = (1,\ k_{it},\ k_{it-1},\ l_{it},\ k_t,\ w_t,\ t)'$. Finally, I obtain the estimates by minimizing the generalized method of moments (GMM) criterion function

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \left(\sum_i \sum_t \mathcal{M}_{it}(\boldsymbol{\beta}) \otimes \boldsymbol{\Delta}_{it} \right)' \mathcal{W} \left(\sum_i \sum_t \mathcal{M}_{it}(\boldsymbol{\beta}) \otimes \boldsymbol{\Delta}_{it} \right)$$

where $\mathcal{W}$ is a weight matrix.

Table 2 provides estimates for the whale harvesting function. Comparing the incremental addition of aggregate factors demonstrates their critical role in explaining production. The coefficients associated with aggregate vessel capacity provide evidence of congestion externality. As more vessels engage in whaling, each firm's output decreases. The coefficients for whale stock indicate a stock externality, suggesting that, all else being equal, it is more productive to engage in whaling if there is a higher whale population. The time trend reveals overall technological growth, estimated at around 1.4% to 2.1%.

Notably, the sum of the vessel capacity and crew size elasticities ($\beta_k + \beta_l$) consistently approximates one, indicating the constant returns to scale. Additionally, columns (4) and (5) show that vessel capacity alone (without crew size) explains most of the production scale, because crew size is generally proportional to capacity. Therefore, column (5) forms

the basis for the subsequent analysis. It offers a more parsimonious specification with full sample coverage and can be consistently mapped to the dynamic model, which abstracts from labor choice.

4.1.2. Demand

Firms face a demand curve in the form of (2), parameterized as:

$$Q_t = \alpha_0 + \alpha_p P_t + Z_t^{d\prime} H + \eta_t, \tag{12}$$

where Z_t^d includes aggregate demand factors, such as the US population, petroleum price, and time trend. The term η_t represents i.i.d. demand shocks.

There may be potential endogeneity of price with the demand shock η_t. In particular, an unobserved demand shock can shift the demand curve, which can confound the estimated price elasticity of demand. Therefore, one may need supply-side cost shifters as instruments for prices. This study employs the long-term bond yields in New England.[9] It is relevant to whaling costs because whaling required significant capital investment in ships, equipment, and infrastructure as discussed in Section 2.2. Changes in long-term bond yields can influence the cost of financing these investments. Higher yields result in higher borrowing costs, making it more expensive for whaling companies to fund their capital expenditures.

However, the instrument variable approach is only applied to the period before the petroleum discovery in 1859. As detailed in Section 2.1, San Francisco emerged as a new whaling center after the middle of the 19th century. Consequently, the bond yields in New England are less likely to have an impact on whaling activity during the post-petroleum period.

Table 3 summarizes the results of demand curve estimation. Columns (1) and (2) present OLS estimates before and after the petroleum discovery. The median of estimated price elasticities are -1.7 and -0.31, respectively. Column (3) reports instrumental variable estimates for the pre-petroleum period, yielding a median elasticity of -1.93, higher than the OLS estimate in column (1). The estimated results from colum (3) are used throughout the rest of the analysis for the pre-petroleum period. For the post-petroleum period, the estimated price coefficient, $\hat{\alpha}_p$ is taken from column (3), and then other parameters are recovered by matching predicted prices, via inverse demand, to their empirical counterparts. Column (4) displays these recovered parameters for the post-petroleum period. Standard errors for column (4) will be added in a future draft. [Note: add columns to Table 3 by fixing different price coefficients for the post-petroleum period.]

[9] The data is constructed by Homer and Sylla (1996).

TABLE 3. Demand curve estimates

	OLS		IV	
	(1)	(2)	(3)	(4)
Whale price: α_p	-14.567	-0.440	-16.518	-16.518
	(2.064)	(0.241)	(3.477)	
Aggregate demand shifters				
US population	0.644	-0.068	0.692	-0.300
	(0.160)	(0.013)	(0.184)	
US GDP	11.571	0.277	12.252	2.555
	(4.396)	(0.251)	(4.252)	
Petroleum price		7878.436		1198.892
		(1035.722)		
Observations	55	51	51	51
Sample period	1804-1858	1859-1909	1804-1858	1859-1909
First-stage *F*-statistic			23.50	
Adjusted R-squared	0.786	0.902	0.785	

Notes: The robust standard errors are reported in parentheses. Columns (1) and (2) are the results from OLS, while column (3) reports results from instrumental variable approach for the pre-petroleum period. Column (4) displays estimates for the post-petroleum period, holding the estimated price coefficient from column (3) fixed.

The estimated parameters for aggregate demand factors indicate expected shifts in whale demand. During the pre-petroleum period, U.S. population and economic growth drove substantial demand for whale oils. However, after petroleum became available, whale demand sensitivity to population and GDP growth became less pronounced. Notably, the estimated parameter on petroleum price highlights a strong substitution relationship between whales and petroleum.

4.2. Dynamic costs of entry, exit, and capacity adjustment

To simplify both the model's solution, this study makes the following two assumptions: (1) staying incumbent firms determine the capacity for the next period at the discretized grid level [Note: discuss how many grids with what grid width is used.]; (2) private shocks follow an independent and identically distributed (i.i.d.) type-1 extreme value distribution (EV1).

As initially observed by Rust (1987), the logic shock assumption allows the solution to the dynamic programming problem and the choice probability have closed forms. It eliminates the need for numerical integration, as required in the case of additive normal errors. The cdf of an extreme value random variable $\nu_{it}(\sigma_{it})$ is $\exp(-\exp(-\nu_{it}(\sigma_{it})/\psi))$ with a mean of $\psi\zeta$, where ζ is Euler's constant ($\simeq 0.57722$) and ψ is the logit scale parameter, and a variance of $\pi^2\psi^2/6$. This approach shares similarities with a static entry game introduced by Seim (2006) and a dynamic game that encompasses both entry and exit, as

examined by Igami (2017), Igami (2018), and Igami and Uetake (2020).

This characterization enables the derivation of a closed-form expression for the expected value:

$$\mathbb{E}\left[V_t(x_{it}, s_t; \boldsymbol{\sigma}_t)\right] = \Pi_t(x_{it}, s_t) + \psi\left\{\zeta + \ln\left[\exp\left(\frac{\phi^{\text{ex}}}{\psi}\right) + \sum_{j=1}^{J}\exp\left(\frac{-C\left(I_{it}^{j}\right) + \rho\,\mathbb{E}\left[V_{t+1}(x_{it+1}, s_{t+1}; \boldsymbol{\sigma}_{t+1}) \,|\, x_{it}, s_t, \boldsymbol{\sigma}_t\right]}{\psi}\right)\right]\right\}. \tag{13}$$

This computation is applied iteratively from year $\overline{T}$ down to year 1. During process of backward induction, the value function entails the conditional choice probabilities in the form of firms' equilibrium policy functions.

The conditional choice probability that an incumbent firm i takes strategy $\sigma_{it}^{\text{inc}} = j \in \{0, 1, ..., J\}$ in year t is

$$\begin{aligned}&\Pr_t(\sigma_{it}^{\text{inc}} = j \,|\, x_{it}, s_t) \\ &= \begin{cases} \exp\left(\frac{\phi^{\text{ex}}}{\psi}\right) \Big/ \Upsilon^{\text{inc}} & \text{if } j = 0 \\ \exp\left(\frac{-C\left(I_{it}^{j}\right) + \rho\,\mathbb{E}\left[V_{t+1}(x_{it+1}, s_{t+1}; \boldsymbol{\sigma}_{t+1}) \,|\, x_{it}, s_t, \boldsymbol{\sigma}_t\right]}{\psi}\right) \Big/ \Upsilon^{\text{inc}} & \text{if } j > 0, \end{cases}\end{aligned} \tag{14}$$

where $\Upsilon^{\text{inc}} \equiv \exp\left(\frac{\phi^{\text{ex}}}{\psi}\right) + \sum_{j=1}^{J}\exp\left(\frac{-C\left(I_{it}^{j}\right) + \rho\,\mathbb{E}\left[V_{t+1}(x_{it+1}, s_{t+1}; \boldsymbol{\sigma}_{t+1}) \,|\, x_{it}, s_t, \boldsymbol{\sigma}_t\right]}{\psi}\right)$. Similarly, the probability that a potential entrant i takes action $\sigma_{it}^{\text{pe}} = j \in \{0, 1\}$ in year t is

$$\begin{aligned}&\Pr_t(\sigma_{it}^{\text{pe}} = j \,|\, x_{it}^{\text{pe}}, s_t) \\ &= \begin{cases} \exp(0) / \Upsilon^{\text{pe}} & \text{if } j = 0 \\ \exp\left(\frac{\rho\,\mathbb{E}\left[V_{t+1}(x_{it+1}, s_{t+1}; \boldsymbol{\sigma}_{t+1}) \,|\, x_{it}^{\text{pe}}, s_t, \boldsymbol{\sigma}_t\right] - \phi^{\text{en}}}{\psi}\right) \Big/ \Upsilon^{\text{pe}} & \text{if } j = 1, \end{cases}\end{aligned} \tag{15}$$

where $\Upsilon^{\text{pe}} \equiv \exp(0) + \exp\left(\frac{\rho\,\mathbb{E}\left[V_{t+1}(x_{it+1}, s_{t+1}; \boldsymbol{\sigma}_{t+1}) \,|\, x_{it}^{\text{pe}}, s_t, \boldsymbol{\sigma}_t\right] - \phi^{\text{en}}}{\psi}\right)$.

Table 4 provides an overview of the model parameters and the empirical approach. Panel A presents the model primitives obtained in the previous steps, which yield period payoffs for each firm state in each year. Panel B outlines the objective of this subsection: estimating dynamic parameters denoted as $\Theta = \{\phi^{\text{ex}}, \phi^{\text{en}}, \boldsymbol{\Gamma}, \psi\}$, using maximum likelihood

TABLE 4. List of parameters and empirical approach

Parameters	Notation	Empirical approach
Panel A. Period competition		
Production	$\beta_0, \beta_l, \beta_k, \beta_a, \mathcal{B}, \lambda$	DP-GMM (Section 4.1.1)
Demand	α_0, α_p, H	OLS, IV (Section 4.1.2)
Panel B. Dynamic costs		
Entry, exit	$\phi^{\text{en}}, \phi^{\text{ex}}$	NFXP-MLE (Section 4.2)
Capacity adjustment	$\gamma_2, \gamma^+, \gamma^-, \gamma_0$	NFXP-MLE (Section 4.2)
Logit scale parameter	ψ	NFXP-MLE (Section 4.2)
Panel C. Transitions		
Annual discount factor	$\rho = 0.94$	Calibrated
Vessel capacity destruction	$\delta = 0.05$	Calibrated
Whale population dynamics	$z = 1.4$, $r_{max} = 0.02$	Calibrated

Note: The vessel destruction rate parameter δ is determined based on the data of yearly vessel destruction rate. Parameters related to whale population dynamics are calibrated from previous literature (Baker and Clapham 2004; Whitehead 2002).

estimation (MLE). Each possible combination of Θ leads to specific values for each firm state in each year, along with the conditional choice probabilities (CCPs) for entry, capacity adjustment, and exit. The maximum likelihood estimates represent the parameter vector that maximizes the likelihood of observing the actual choice probabilities in the data.

In Panel C, the annual discount factor is calibrated rather than being subject to estimation due to well-known identification challenges (Rust 1987). The vessel destrunction rate δ is calibrated from data. The parameters related to whale population transition are calibrated based on previous literature (Whitehead 2002; Baker and Clapham 2004).

The conditional choice probabilities of entry, capacity adjustment, and exit in equations (14) and (15) constitute the likelihood function. The contribution of an action profile $\boldsymbol{\sigma} \equiv \left\{ \left\{ \sigma_{it}, \sigma_{it}^{\text{pe}} \right\}_{\forall i} \right\}_{t=1}^{T-1}$ to the overall joint likelihood is

$$\mathcal{L}(\boldsymbol{\sigma}; \Theta) = \prod_{t=1}^{T} \prod_{i} \Pr_t(\sigma_{it} \,|\, x_{it}, s_t) \Pr_t(\sigma_{it}^{\text{pe}} \,|\, x_{it}^{\text{pe}}, s_t).$$

Thus the maximum likelihood estimator is

$$\hat{\Theta} = \arg\max_{\Theta} \ln\left[\mathcal{L}(\boldsymbol{\sigma}; \Theta)\right] \tag{16}$$

The entry, capacity adjustment, and exit choices observed in the panel data of whaling firms pin down the dynamic parameters. For example, a lower exit scrap value, ϕ^{ex}, increases the predicted probabilities of continuation (and consequently capacity adjustment) through Υ^{inc}. Then it decreases the predicted probability of choosing exit. Correspond-

ingly, when a small proportion of active firms selects the exit choice in the panel data, this pattern results in a smaller estimate for ϕ^{ex}. Likewise, a small entry cost, ϕ^{en}, raises the probability of entry, allowing the observed entry decisions in the data to determine the estimate for ϕ^{en}. Note that the payoffs are dollar-valued, which helps to identify the logit scale parameter. A larger ψ would make the model less responsive to these dollar-valued payoffs, whereas a smaller ψ would make the predicted CCPs highly sensitive to their changes (Igami and Uetake 2020).

The dynamic parameters are separately estimated before and after the petroleum discovery. The reasoning behind this choice is the structural change in whale demand, thereby shifting firms' perceived future values. Since the arrival of petroleum in 1859, whalers speculated that the whaling industry would gradually decline due to the substitution effect. This is clearly evidenced by the *Whalemen's Shipping List and Merchants' Transcript* (WSL) in 2 July 1861

> It is known that the discovery and extensive manufacture of coal oil has had a most ruinous effect upon the whaling interest. At New Bedford the business has declined about one-third during the past three years, and it is believed will decline fully a third more within the present year [1861] ... Oil, which costs 60 cents to produce, will now bring but 40 cents.

And Tower (1907) wrote

> The date of opening the first oil well in Pennsylvania may be regarded as the day when the fate of the whale fishery was decided.

Furthermore, the industry experienced severe disruption due to the War of 1812 (Jun 18, 1812 – Feb 18, 1815), making it challenging to obtain reliable estimates for the very early period preceding the war. Consequently, the dynamic parameters are estimated after the conclusion of the war.

Table 5 reports estimates for dynamic cost parameters. Each column presents the estimation results for the corresponding period. Entry fixed costs (ϕ^{en}), exit scrap values (ϕ^{ex}), and adjustment fixed costs (γ_0) are evaluated in thousand 1880 dollars. Convex adjustment costs (γ_2), investment coss (γ^{inv}), and divestment values (γ^{div}) are measured in 1880 dollars per ton. There are two interesting observations. First, the estimates are noticeably different depending on periods. [... interpret the differences]. Second, the estimates reveal significant sunk costs of entry and investment. [... interpret the sunk costs].

One can evaluate the fit of the model by comparing the observed behaviors in the data and predicted one by the estimated model. In Figure 4, solid line represents actual data patterns, while dashed line depicts model-driven paths. The model outcome displays the average from 10,000 simulations using the estimated model, and their 95 percent

TABLE 5. Estimates of dynamic parameters

	1804-1830	1831-1858	1859-1884	1885-1909
	(1)	(2)	(3)	(4)
Entry fixed cost:	246.51	167.73	340.73	744.43
ϕ^{en} ($000)	[155.48, 337.54]	[137.5, 197.9]	[268.5, 412.8]	[369.0, 1119.8]
Exit scrap value:	195.55	141.57	294.00	556.21
ϕ^{ex} ($000)	[125.4, 265.6]	[116.1, 166.9]	[233.2, 354.7]	[288.8, 823.5]
Convex adjustment cost:	0.010	0.035	0.000	0.000
γ_2 ($/ton^2)	[-0.06, 0.084]	[0.015, 0.055]	[-0.030, 0.030]	[-0.120, 0.120]
Investment cost:	213.83	97.21	269.66	447.81
γ^{inv} ($/ton)	[104.0, 323.6]	[68.34, 126.0]	[207.7, 331.6]	[222.5, 673.1]
Divestment value:	3.80	28.95	97.60	135.95
γ^{div} ($/ton)	[-118.0, 125.61]	[-0.95, 58.85]	[43.14, 152.04]	[-70.34, 342.23]
Fixed adjustment cost:	-0.16	17.52	23.85	74.11
γ_0 ($000)	[-28.0, 27.7]	[9.44, 25.6]	[5.77, 41.9]	[-12.3, 160.5]
Logit scale parameter:	0.18	0.13	0.24	0.53
ψ	[0.10, 0.24]	[0.10, 0.15]	[0.18, 0.30]	[0.23, 0.83]
Log likelihood	-1205.87	-6535.21	-2525.46	-688.26
Number of years	27	28	26	25
Numbser of observations	865	6,021	2,344	602
Sunk costs:				
Entry ($000)	50.96	26.17	46.72	188.22
Investment ($/ton)	210.03	68.27	172.06	311.86

Note: All values are adjusted to 1880 prices. The 95 percent confidence intervals are in brackets. Each column presents the estimation results for the corresponding period. The sunk cost of entry is defined as the difference between entry fixed cost (ϕ^{en}) and exit scarp value (ϕ^{ex}). The sunk cost of investment is defined as the difference between investment cost (γ^{inv}) and divestment cost (γ^{inv}). See Appendix XX for additional sensitivity analysis.

confidence intervals (shaded area). This illustrates that the estimated model generates a smoothed representation of the industry's evolutionary process in the data. Specifically, Figures 4 replicates key aspects of the industry's boom and bust in terms of aggregate catch. Overall, the estimated model provides a reasonable starting point for evaluating the welfare performance of counterfactual scenarios in Section 5.

5. Counterfactual analysis

This section presents counterfactual exercises to evaluate market performance across different scenarios. First, benchmark cases for the social planner and perfect collusion are simulated (Section 5.1). Second, [Note: this part will be policy experiments, shadow values, etc.] (Section 5.2).

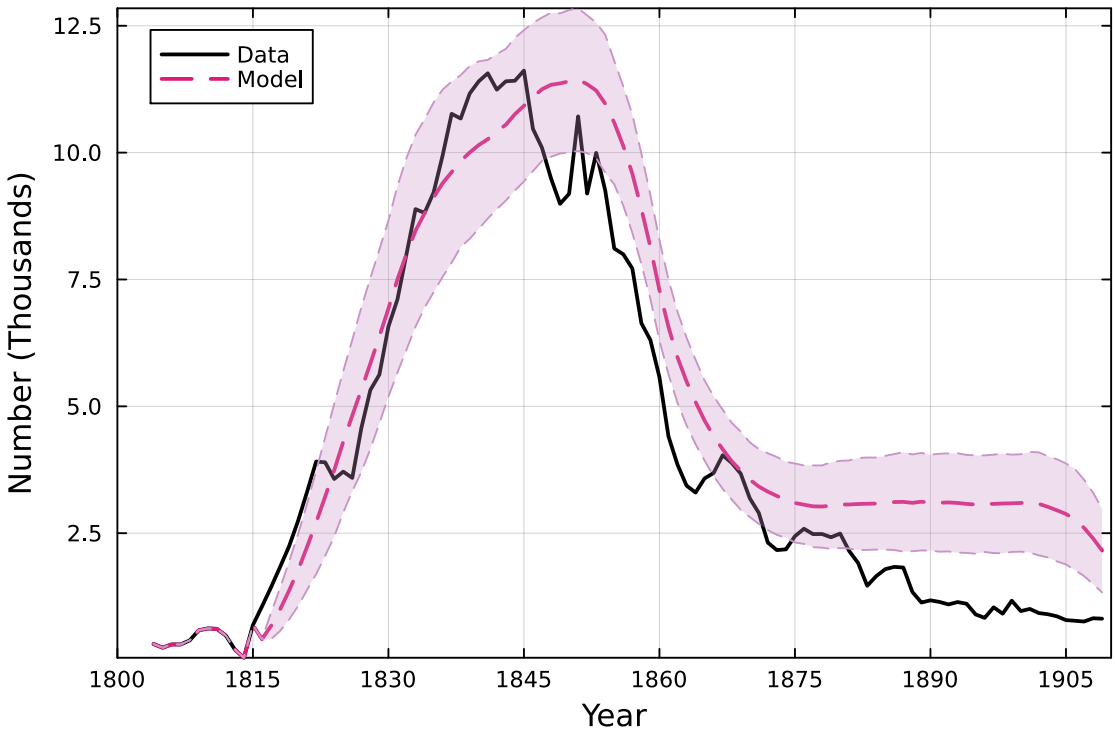


FIGURE 4. Model fit: Total whale catch

Note: The model outcome displays the average from 10,000 simulations using the estimated model, and their 95 percent confidence intervals (shaded area).

5.1. Benchmark

Whaling firms do not account social costs, generating negative externalities on other firms. This non-cooperative market outcome leads to suboptimal welfare as it does not maximize overall social welfare.

To this investigation, the equilibrium welfare per period is calculated as follows:

$$\text{CS}_t = \int_0^{Q_t} \mathcal{P}_t(\varphi)\mathrm{d}\varphi - \mathcal{P}_t(Q_t)Q_t \tag{17}$$

$$\begin{aligned}\text{PS}_t = \sum_i \Big[&\Pi_t(x_{it}, K_t, W_t) + \mathbb{1}\{\sigma_{it}^{\text{inc}} = 0\}(\hat{\phi}^{\text{ex}} + \nu_{it}^0) \\ &- \mathbb{1}(1)\{\sigma_{it}^{\text{inc}} > 0\}(C(I_{it}^j) + \nu_{it}^j) - \mathbb{1}\{\sigma_{it}^{\text{pe}} = 1\}(\hat{\phi}^{\text{en}} + \nu_{it}^1)\Big]\end{aligned} \tag{18}$$

$$\text{SW}_t = \text{CS}_t + \text{PS}_t \tag{19}$$

where CS_t is the consumer surplus, PS_t is the producer surplus, and SW_t is the social welfare in year t.

Social planner. The social planner chooses a sequence of entry, investment, divestment, and exit decisions for each firm $\boldsymbol{\sigma} \equiv \{\boldsymbol{\sigma}_t\}_{t=1}^{T-1} \equiv \left\{\left\{\sigma_{it}^{\text{inc}}, \sigma_{it}^{\text{pe}}\right\}_{i\in\mathcal{J}_t}\right\}_{t=1}^{T-1}$ to maximize the net present value (NPV) of social surpluses.

$$\max_{\boldsymbol{\sigma}} \mathbb{E}\left[\sum_{t=1}^{T} \text{SW}_t\right] \tag{20}$$

where the expectation is taken with respect to the sequence of firms' idiosyncratic shocks and productivity transition.

The social planner's problem poses computational challenges due to the large number of firms. To address this, rather than attempting to solve the planner's complete dynamic decision problem, the approach involves seeking the maximum value of the objective function (20) by directly dictating firms' decisions. This is carried out in two steps. First, I simulate a large number of sample paths for aggregate outputs and whale population.[10] Second, for a given path of output and whale population, the *Sorting* algorithm (outlined in Algorithm 1, Appendix E) dictates the entry, exit, and capacity adjustment decisions of firms, taking into account their marginal product of capital (MPK).

The social welfare (19) is computed for each period based on sorted market outcomes for any paths of output and whale population. The objective of the social planner (20) is to find the path that maximizes the NPV of social surpluses. In this manner, the social planner internalizes the social cost of whaling. To safeguard consumer welfare, the planner selects the aggregate output (and whale population) path to prevent excessively high whale prices. At the same time, the planner considers efficient production of the target output to enhance producer surplus. This minimizes the number of firms and capital within the industry, sustaining a suitable whale population.

Perfect collusion. All firms partake in perfect collusion resembling a monopoly cartel or trade association. Unlike the social planner's strategy, firms exclusively focus on maximizing producer surplus (18) each period. Consequently, the goal of establishing collusion is to maximize the NPV of producer surpluses by controlling a sequence of entry, capacity adjustment and exit decisions for each firm $\boldsymbol{\sigma}$ as below:

$$\max_{\boldsymbol{\sigma}} \mathbb{E}\left[\sum_{t=1}^{T} \text{PS}_t\right] \tag{21}$$

Applying the sorting algorithm, the producer surplus (18) is calculated for each period for any provided trajectories of aggregate output and whale population. Then, the objective

[10] Note that the trajectory of the whale population is determined based on (4) once the trajectory for total output is generated.

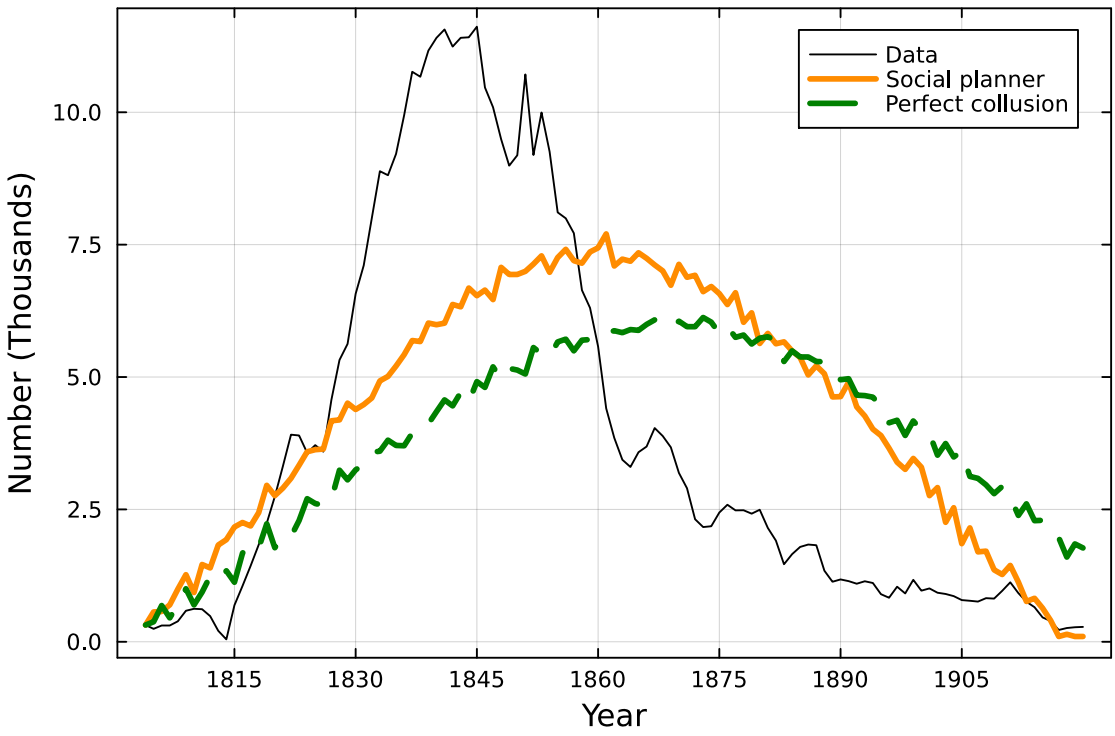


FIGURE 5. Benchmark cases: Total whale catch

Note: Benchmark allocations are simulated based on the *Sorting* algorithm (outlined in Algorithm 1, Appendix E).

(21) corresponds to choose the specific path of aggregate output and whale population that maximizes the NPV of producer surpluses. Therefore, the colluding cartel internalizes the future value of whale population, with firms (including potential entrants) coordinating to alleviate congestion and stock externalities for industry efficiency. It is important to note that the evident trade-off is a price increase stemming from the behavior of monopolist.

Figure 5 illustrates the total whale catch resulting from the two benchmark cases compared with actual data. Two findings stand out. First, in both cases, the total harvest is significantly lower during the pre-petroleum period and higher during the post-petroleum period. This suggests that the actual data pattern confirms over-harvesting of whales occurred in the early years, leading to inefficient production later on. Second, the social planner would allocate more resources than perfect collusion until the 1880s. This difference is largely driven by the distinction in objectives between the social planner and perfect collusion, specifically the consideration of consumer surplus. Perfect collusion would delay whale harvest slightly more compared to the social planner, solely to increase producer surplus.

Table 6 reports the welfare comparison between the market outcome and the benchmark cases. Perfect collusion can increase social welfare by 28% compared to the market

TABLE 6. Welfare comparison between market outcome and benchmark cases

	Market outcome	Perfect collusion	Social planner
Producer surplus	73.189	280.360	274.360
Consumer surplus	1083.893	1203.579	1353.579
Social welfare	1157.081	1483.939	1627.939

Note: All values are expressed in million dollars, adjusted to 1880 prices. The market outcome is simulated from the identified model. The welfare under perfect collusion and the social planner are simulated using the *Sorting* algorithm (outlined in Algorithm 1, Appendix E).

outcome simulated from the identified model. This improvement results from an approximately 280% increase in producer surplus and an 11% increase in consumer surplus. The social planner's allocation shows an even larger increase in social welfare, which is 40% higher than the market outcome. As expected, producer surplus is lower than under perfect collusion, but consumer surplus is higher, resulting in an overall larger improvement.

5.2. Policy experiments

[IN PROGRESS]

6. Conclusion

Common-pool resource exploitation has attracted considerable attention in economics. It has been well documented that rising competition can lead to resource depletion and congestion in the commons. However, the drivers of this inefficient and excessive competition remain poorly understood, even though it is essential for effective policy design. To fill this gap, this article builds a tractable empirical model of common-pool industry dynamics, identified using data from the historical American whaling industry.

The estimated model reveals the presence of substantial sunk costs associated with entry and investment. This asymmetry in costs reflects the competitive entry and investment but the delay in exit and divestment. As a result, there existed early over-harvesting of whales and inefficient production later on. A sole-ownership would have partially addressed these inefficiencies, albeit reducing output more than a social planner would deem optimal. Motivated by these benchmark results, in a future version of draft, I will investigate an optimal policy design to achieve a socially efficient allocation.

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Appendix A. Agents’ supervision

The following examples are borrowed from the Chapter 10 of Davis Davis, Gallman, and Gleiter (2007) and the Chapter 1 of Nicholas (2019).

A.1. Planning by agent

A formal statement of the main outlines of the plan was usually given to the captain, as seen in the following passage from a letter dated 1 November 1834 from *Agent* Charles W. Morgan to *Captain* Reuben Russell, 2d.

> The Bark being now ready for sea, as agent I have to advise you that she is bound on a whaling voyage to the Pacific Ocean-That she is fitted for thirty months-and that we wish you to cruise for sperm whales for 20 to 24 months and if not then full, fill up with whale Oil-we leave to your judgment the cruising ground on the Pacific though we would recommend the neighborhood of New Zealand, where both right & sperm whales are to be taken, and it would be well especially towards the end of the voyage to be where right whales could be taken. (Morgan Collection)

The following letter from agent Charles W. Morgan to a young captain George H. Dexter shows that agents also provided advice and encouragement.

> As you have now taken the responsible station of Master of a Ship and are a young man you will permit me to offer some advice. The greatest difficulty I have observed with young Masters, is either too great indulgence or too great severity towards their crew. Discipline must be effectual, be administered with a steady hand especially among Sailors, and there is no station which requires more guard over the temper, than that of a master of a Ship. And on your first voyage depends in a great measure your future success in life. Let me then beg of you to keep a strict watch over the moral conduct of your crew, never permit

> your authority to be abused or set at naught, but at the same time never to use undue severity yourself or permit it in your officers. I have a real confidence in you and I trust you will not feel hurt at my giving advice which I feel it my duty to offer you. (Morgan Collection)

A.2. Contact between agent and captain during the voyage

A glimpse of the exchanges between the captain and agent can be obtained from the letter books of whaling agents. For instance, on 21 November 1836, Charles W. Morgan wrote to George H. Dexter, a Morgan Captain, at Montevideo, stating:

> I wrote to you 15 Inst advising you that if you could get a price for your oil equal to 40 cts clear of every charge remitted home, you might sell it, but in consequence of news received of the failure of the Greenland Fishery, we think oil will be very high the next season. Therefore, we now advise that unless the oil will net 45 cts clear, we would wish you to bring it home. (Morgan Collection)

Similarly, in February 1858, Matthew Howland wrote to one of his captains, Philip Howland, advising him over his recent performance:

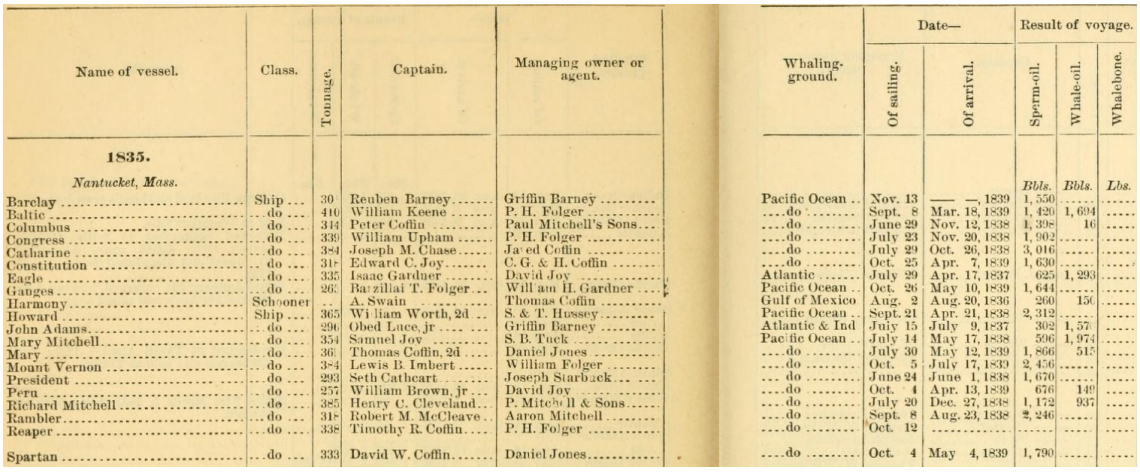
> 25 months out with 600 bbl sperm & 130 whale is rather low, but I am in hopes that you will come up now and be equal to any of them according to time out—I shall expect to hear of you into Talcuahana in March with from 800 to 1000 bbls of sperm oil on board. (Howland Collection)

Appendix B. Details of data

This section describes a detail of data sources and modifications.

B.1. *Voyage Database*

The American Whaling Voyage database includes information about all known US whaling voyages from the 1700s to the 1920s. Voyages have been defined based on customs house records, following Starbuck (1878), with each departure and subsequent return to the port of origin constituting a single voyage. Figure A1 provides an example page from Starbuck (1878). A basic suite of information is included for most voyages, along with additional information on the ship's capacity and rig, declared destination, and amount of whale products. The database is digitized and provided by Mystic Seaport Museum and New Bedford Whaling Museum (https://whalinghistory.org/). [Note: add cleaning process, including the number of observations excluded from each step.]



Name of vessel.	Class.	Tonnage.	Captain.	Managing owner or agent.	Whaling-ground.	Date— Of sailing.	Date— Of arrival.	Result of voyage. Sperm-oil.	Whale-oil.	Whalebone.
1835.										
Nantucket, Mass.								*Bbls.*	*Bbls.*	*Lbs.*
Barclay	Ship	30	Reuben Barney	Griffin Barney	Pacific Ocean	Nov. 13	—— —, 1839	1,550	.....	.....
Baltic	do	410	William Keene	P. H. Folger	do	Sept. 8	Mar. 18, 1839	1,420	1,694	.....
Columbus	do	344	Peter Coffin	Paul Mitchell's Sons	do	June 29	Nov. 12, 1838	1,398	10	.....
Congress	do	339	William Upham	P. H. Folger	do	July 23	Nov. 20, 1838	1,902	.....	.....
Catharine	do	384	Joseph M. Chase	Jared Coffin	do	July 29	Oct. 26, 1838	3,016	.....	.....
Constitution	do	318	Edward C. Joy	C. G. & H. Coffin	do	Oct. 25	Apr. 7, 1839	1,630	.....	.....
Eagle	do	335	Isaac Gardner	David Joy	Atlantic	July 29	Apr. 17, 1837	625	1,293	.....
Ganges	do	266	Barzillai T. Folger	William H. Gardner	Pacific Ocean	Oct. 26	May 10, 1839	1,644	.....	.....
Harmony	Schooner	...	A. Swain	Thomas Coffin	Gulf of Mexico	Aug. 2	Aug. 20, 1836	260	150	.....
Howard	Ship	365	William Worth, 2d	S. & T. Hussey	Pacific Ocean	Sept. 21	Apr. 21, 1838	2,312	.....	.....
John Adams	do	290	Obed Luce, jr	Griffin Barney	Atlantic & Ind	July 15	July 9, 1837	302	1,57	.....
Mary Mitchell	do	354	Samuel Joy	S. B. Tuck	Pacific Ocean	July 14	May 17, 1838	596	1,974	.....
Mary	do	361	Thomas Coffin, 2d	Daniel Jones	do	July 30	May 12, 1839	1,866	515	.....
Mount Vernon	do	384	Lewis B. Imbert	William Folger	do	Oct. 5	July 17, 1839	2,456	.....	.....
President	do	293	Seth Cathcart	Joseph Starbuck	do	June 24	June 1, 1838	1,670	.....	.....
Peru	do	257	William Brown, jr	David Joy	do	Oct. 4	Apr. 13, 1839	676	149	.....
Richard Mitchell	do	385	Henry C. Cleveland	P. Mitchell & Sons	do	July 20	Dec. 27, 1838	1,172	937	.....
Rambler	do	318	Robert M. McCleave	Aaron Mitchell	do	Sept. 8	Aug. 23, 1838	2,246	.....	.....
Reaper	do	338	Timothy R. Coffin	P. H. Folger	do	Oct. 12	.....	.....	.....	.....
Spartan	do	333	David W. Coffin	Daniel Jones	do	Oct. 4	May 4, 1839	1,790	.....	.....

FIGURE A1. Sample of Starbuck (1878)

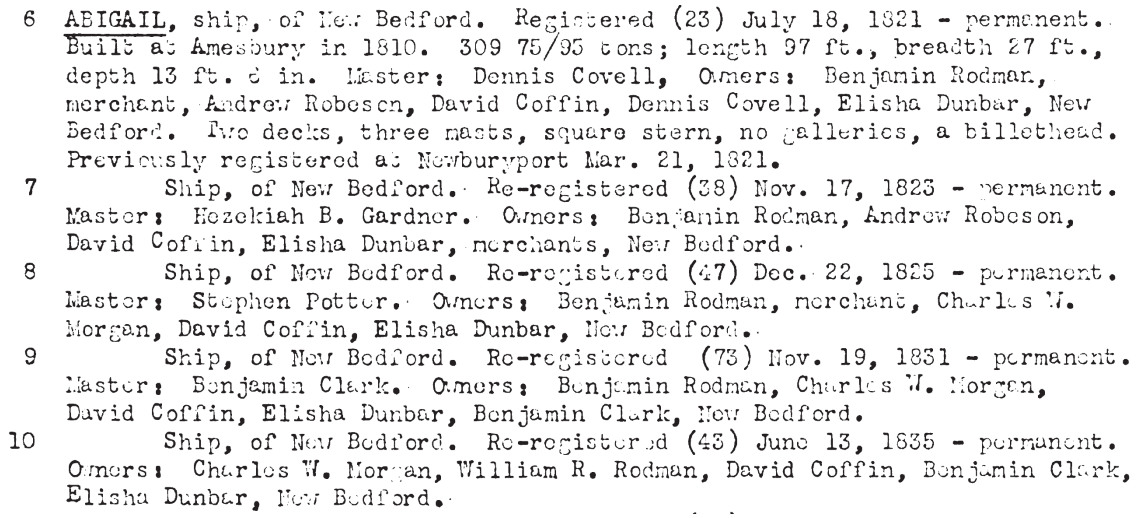
Source: Starbuck, A. 1878. *History of the American whale fishery from its earliest inception to the year 1876*.

B.2. Missing owner/agent record and *Ship Registers*

For some voyage observations, the *Voyage Database* is missing owner/agent information, especially before the 1930s. To address this issue, I rely on *Ship Registers* from each port, mainly New Bedford. For instance, the *Ship Registers of New Bedford* includes information of owners for vessels departed from ports nearby New Bedford, Massachusetts. Figure A2 is an example of voyages by the vessel "Abigail" from *Ship Registers of New Bedford*. In the 1821 voyage, the owners were **Benjamin Rodman**, Andrew Robeson, David Coffin, and Elisha Dunbar. In the 1825 voyage, the ownership structure shows a subtle change to **Benjamin Rodman**, Charles W. Morgan, David Coffin, and Elisha Dunbar. In the 1835 voyage, we can see even clearer change in the ownership structure: **Charles W. Morgan**, William R. Rodman, David Coffin, Benjamin Clark, and Elisha Dunbar. The first name of the owner list typically indicates principal owner or agent. Though principal owner and agent were not always the same, they played similar roles and in most of the cases they were the same. Indeed, Starbuck (1878) identified the whaling agent/owner of the vessel "Abigail" as Benjamin Rodman in 1825 and Charles W. Morgan in 1835 and later. However, the *Voyage Database* is missing agent/owner information for the 1821 voyage, so I have filled this gap with **Benjamin Rodman**, following the *Ship Registers*.

B.3. The relationship between vessel capacity and crew size

Figure A3 shows the comparison between the US whaling industry and Colombian manufacturing census, as an example of a general plant-level data. The left panel depicts the relationship between vessel tonnage and the number of crews in American whaling, and the right one is for capital and the number of workers in Colombian manufacturing.



6 ABIGAIL, ship, of New Bedford. Registered (23) July 18, 1821 - permanent. Built at Amesbury in 1810. 309 75/95 tons; length 97 ft., breadth 27 ft., depth 13 ft. 6 in. Master: Dennis Covell, Owners: Benjamin Rodman, merchant, Andrew Robeson, David Coffin, Dennis Covell, Elisha Dunbar, New Bedford. Two decks, three masts, square stern, no galleries, a billethead. Previously registered at Newburyport Mar. 21, 1821.

7 Ship, of New Bedford. Re-registered (38) Nov. 17, 1823 - permanent. Master: Hezekiah B. Gardner. Owners: Benjamin Rodman, Andrew Robeson, David Coffin, Elisha Dunbar, merchants, New Bedford.

8 Ship, of New Bedford. Re-registered (47) Dec. 22, 1825 - permanent. Master: Stephen Potter. Owners: Benjamin Rodman, merchant, Charles W. Morgan, David Coffin, Elisha Dunbar, New Bedford.

9 Ship, of New Bedford. Re-registered (73) Nov. 19, 1831 - permanent. Master: Benjamin Clark. Owners: Benjamin Rodman, Charles W. Morgan, David Coffin, Elisha Dunbar, Benjamin Clark, New Bedford.

10 Ship, of New Bedford. Re-registered (43) June 13, 1835 - permanent. Owners: Charles W. Morgan, William R. Rodman, David Coffin, Benjamin Clark, Elisha Dunbar, New Bedford.

FIGURE A2. A sample of ship registers of New Bedford: Vessel *Abigail*

Source: Ship registers of New Bedford from HathiTrust (https://www.hathitrust.org/).

Compared to manufacturing plants, whaling voyages show extremely high correlation between vessel size and labor size.

B.4. Modifications

For the purpose of empirical analysis, the output quantities (in barrels of sperm oil and whale oil, and pounds of whalebone) are converted into the number of whales harvested. Following Scammon (1874), this paper assumes that an average sperm whale taken yielded 25 barrels of sperm oil and an average baleen whales taken yielded 60 barrels of whale oil. Additionally, historical accounts document that around 10% of whales escaped, but subsequently died from their wounds. Therefore I relate the barrels of oils observed in the data to the number of whales harvested in the following way:

$$Q_{it}^{SW} = \frac{Q_{it}^{\text{s-oil}}}{25} + 0.1 \times \frac{Q_{it}^{\text{s-oil}}}{25}$$
$$Q_{it}^{BWO} = \frac{Q_{it}^{\text{w-oil}}}{60} + 0.1 \times \frac{Q_{it}^{\text{w-oil}}}{60}$$

where Q_{it}^{SW} is the number of sperm whales harvested by firm i in year t, $Q_{it}^{\text{s-oil}}$ is the barrels of sperm oil, Q_{it}^{BWO} is the number of baleen whales harvested to make whale oil, and $Q_{it}^{\text{w-oil}}$ is the barrels of whale oil. From logbook database,[11] I assume that an average baleen

[11]The American Offshore Whaling Log database comprises information from 1,381 logbooks documenting US whaling voyages spanning 1784 to 1920. This dataset was extracted from the original whaling logbooks during three distinct scientific research projects. The first initiative was led by Lt. Cmdr. Matthew Fontaine

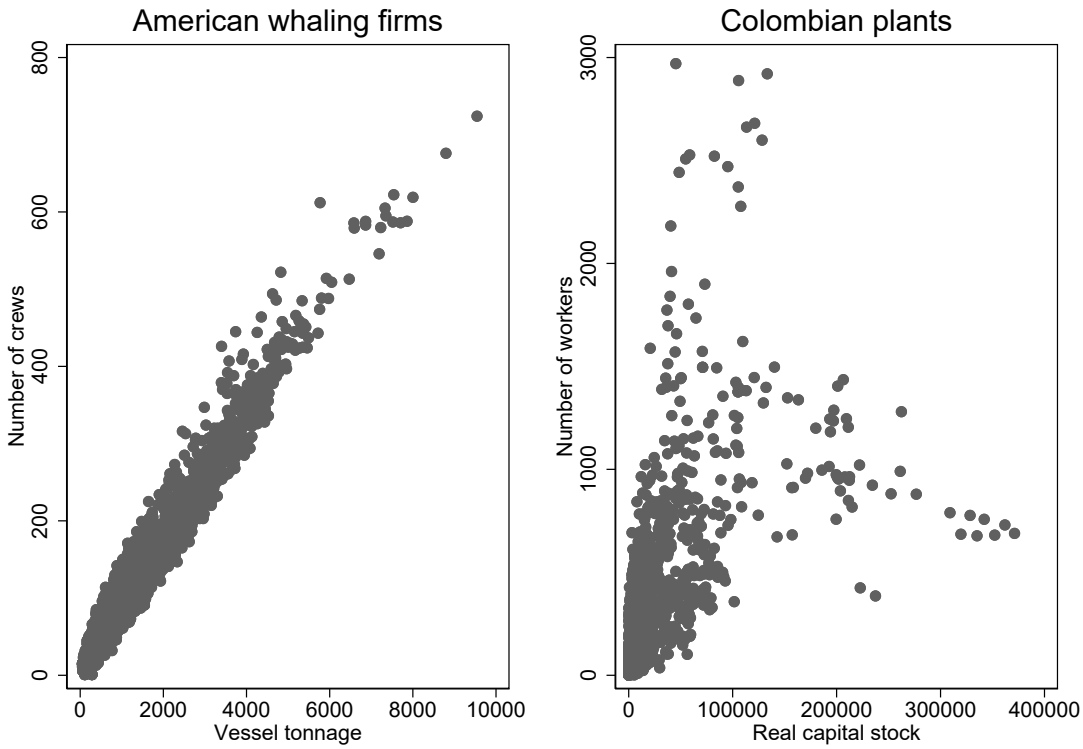


FIGURE A3. Comparison of labor-capital relationship

Note: [Add explanations and sources.]

whale taken yielded 500 pounds of whalebone.

$$Q_{it}^{BWB} = \frac{Q_{it}^{\text{bone}}}{500} + 0.1 \times \frac{Q_{it}^{\text{bone}}}{500}$$

where Q_{it}^{BWB} is the number of baleen whales harvested to make whalebone and Q_{it}^{bone} is the pounds of whalebone. Then, the number of baleen whales harvested, Q_{it}^{BW}, are determined as follow:

$$Q_{it}^{BW} = \max\left\{Q_{it}^{BWO}, Q_{it}^{BWB}\right\}$$

Maury in the 1850s, the second by Charles Haskins Townsend in the 1930s, and the third by a team from the Census of Marine Life project (CoML, www.coml.org), led by Tim Denis Smith from 2000 to 2010. The CoML team assembled the Maury and Townsend data from archival sources. The data file encompasses 466,134 records organized in a standardized format, including voyage ID, coordinates (latitude/longitude), date, whale encounter, species, harpooned, place, and so on.

TABLE A1. Demand-side statistics for the American whaling industry

Variable	Unit	Mean	SD	Min	Max
Whales demanded	Number	4184.44	3656.28	45.47	11624.38
Whale price	1880 dollars per whale	942.43	372.12	348.35	2093.87
US population	Thousand number	35171.98	25059.13	5991.00	90490.00
US GDP	Million 1996 dollars	2434.03	1103.68	1249.00	5357.00
Petroleum price	1880 dollars	0.05	0.06	0.01	0.41
Year		1856.50	30.74	1804.00	1909.00

Notes: The dataset comprises 106 observations. One exception is petroleum price data, which dates back to 1859, the year of petroleum discovery.

Finally, the whaling output by firm i in year t is defined as the total number of whales harvested:

$$Q_{it} = Q_{it}^{SW} + Q_{it}^{BW}$$

B.5. Aggregate demand variables

The online version is available at https://hsus.cambridge.org/. The annual measures of US population are derived from Series Ca14, and US GDP per capita is obtained from Series Ca9. Petroleum price is from Series Db56.

Appendix C. A two-stage framework for a competitive market in the commons

To build intuition for the basic economic forces at work, this section presents a simple, two-stage framework. The full strategic dynamic model for heterogeneous firms is developed in Section 3.

Figure A4 illustrates the behaviors of price-taking firms and the market. In stage one (panel A), the non-excludability and rivalry of the commons prompt firms to enter and invest until they reach the break-even point A. This can lead to resource overuse beyond the maximum sustainable yield.[12] In stage two (panel B), a typical firm's cost increases due to congestion and resource stock decline. Thus, the reduction of quantity produced from q_1 to q_2 could be an indication of the presence of negative externalities. This is consistent with the pattern observed in Figure 3A.

With the original market price p_1 and the new marginal cost curve MC_2, the firm is expected to exit because point B falls below the zero-profit point C. However, the market supply curve shifts to the left from S_1 to S_2, as all firms share the resource and

[12] In (partially) renewable resources, such as fisheries, the maximum sustainable yield refers to the highest annual harvesting level that can be maintained over time without harming resource stock.

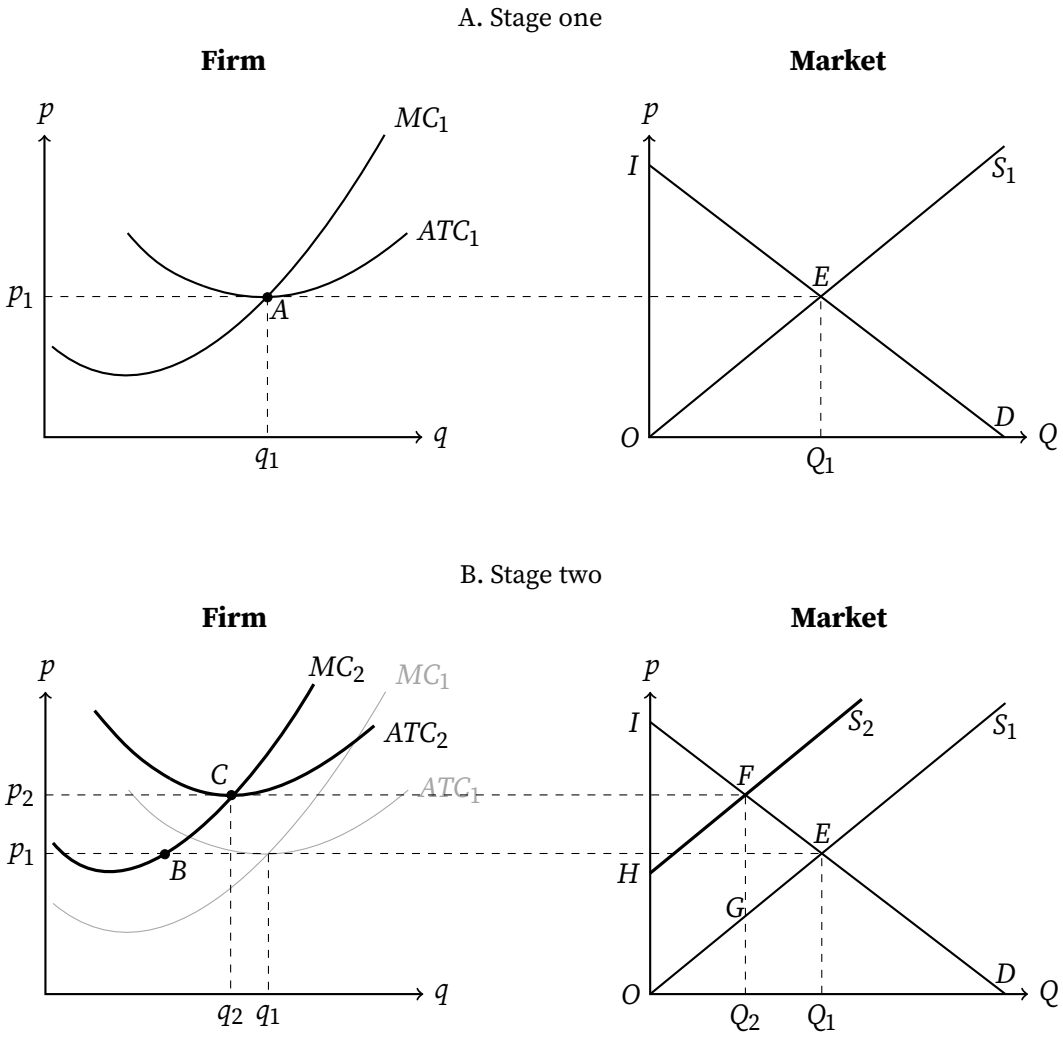


FIGURE A4. A competitive market in the commons

Note: A typical firm has a marginal cost curve of *MC*, and an average total cost curve of *ATC*. *D* represents market demand curve. Aggregate supply curve, *S*, is the accumulation of firms' production. Costs increase in stage two due to congestion and resource depletion, assuming Q_1 is beyond the maximum sustainable yield level.

face increased costs. Because a higher price p_2 incentivizes its operation, as evidenced by Figure 3B, the firm now produces at q_2 instead of exiting. This results in a market production of Q_2. The equilibrium yields social welfare represented by area *EIO* in the stage one and area *FHI* in the stage two.

Appendix D. Methodological considerations

This section discusses considerations behind the modeling and estimation approach choices. The subsections detail the empirical approach for a nontationary global market (Section D.1) and the implementation of the nested fixed point (NFXP) algorithm (Section D.2).

D.1. Empirical approach for a nonstationary global market

This paper takes a full-solution approach for empirical analyses. This subsection describes the two reasons behind this choice.

The first reason is for estimation. A global whaling industry fundamentally complicates an empirical approach, as economic funamentals evolved in a nonstationary manner. Figures 1, 2, and 3 show the dynamics of American whaling, in relation with demand shifts, whale population transitions, and the technological changes. Because the paper focuses on the whaling firms' entry, exit, and investment decisions in such a nonstationary environment, the firms' policy function should be allowed to change with time (i.e., time becomes as if another state variable, so that policy functions are time-dependent, as shown in Section 3.3).

These cross-sectional and time-series features of the data generating process reduce the effecdtive sample size. The application of two-step estimation (e.g., Aguirregabiria and Mira 2007; Bajari, Benkard, and Levin 2007; Pakes, Ostrovsky, and Berry 2007; Pesendorfer and Schmidt-Dengler 2008) becomes difficult because the first-step nonparametric estimates of conditional choice probabilities will be imprecise when only a handful of choices are observed (or no choice is observed) in each state. The model has to fill in these blanks, and hence this paper takes a full-solution approach instead, as in Benkard (2004), **?**, Igami (2017), Elliott (2024).

To this investigation, the main challenge is the large number of firms in the industry when solving the model numerically. The open-access and rivalry feature naturally involves many firms in the commons. This makes the empirical application of Ericson and Pakes (1995)-type model infeasible due to the curse of dimensionality. To address this issue, this study employs the *moment-based Markov equilibrium* (MME) proposed by Ifrach and Weintraub (2017). The model assumes that whaling firms' strategies depend on their own state and the evolution of few key aggregate statistics, based on their com-

petitors' optimal strategies. The statistics include total whaling vessel capacity (to capture congestion externality) and total whale harvest that determine future whale population (to capture stock externality). Each firm has a negligible impact on these moments, but their effects accumulate in aggregate. Moreover, to accommodate the rise and fall of the industry along with the evolution of demand and whale population, the equilibrium is nonstationary as developed by Benkard, Jeziorski, and Weintraub (2024), rather than stationary equilibrium.

The second reason is for counterfactuals. The aim of this paper is to evaluate firms' behavioral responses for exploiting shared resources with environmental and economic changes. It requires firms' counterfactual strategies for each scenario as a result of solving the model. Therefore, counterfactual analyses alone already demand numerical solution of the model and equilibrium outcomes. The full-solution approach has a major advantage because the model solving for counterfactuals is exactly same with that for estimation. This allows a consistent comparison between estimated model and counterfactual model outcomes.

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D.2. Implementation of the NFXP algorithm

TEXT

Appendix E. Benchmark simulation

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Algorithm 1 *Sorting*

Require: $\{Q_t\}_{t=1}^{T}$ and $\{W_t\}_{t=1}^{T}$

for $t = 1$ to T **do**
  Do sorting: Set the firm index i to order firms from the highest to the lowest MPK, such that a lower i corresponds to a higher MPK
  $i = 1$
  while $\sum_{j=1}^{i} Q_{jt} < q_t$ **do** ▷ $Q_{it} = \mathcal{H}_t(x_{it}, s_t)$ by (1)
    if $\exists j > i$ **then**
      $i = i + 1$
    else
      Introduce a new firm with an index $i = i + 1$
    end if
  end while
  Let the remaining firms ($j > i$) exit if any
  Allow the evolution of productivity ($\Omega_{it} \to \Omega_{it+1}\ \forall i \in \mathcal{I}_t$) for staying firms
  Do sorting
  $i = 1$
  while $\sum_{j=1}^{|\mathcal{J}_{t+1}|} Q'_{jt+1} < q_{t+1}$ and $i \leq |\mathcal{I}_{t+1}|$ **do**
    Let i increase its capacity one step
    $i = i + 1$
  end while
  $i = |\mathcal{I}_{t+1}|$
  while $\sum_{j=1}^{|\mathcal{I}_{t+1}|} Q'_{jt+1} > q_{t+1}$ and $i \geq 1$ **do**
    Let i decrease its capacity one step
    $i = i - 1$
  end while
end for