Navigating the Commons

Yangkeun Yun

February 19, 2026

[Link to the latest version]

The overuse of open-access resources is a classic example of externalities. Inefficiencies arise not only from resource use by existing participants but also from their capacity investment and the entry of new firms. Standard models of externalities, however, typically abstract from firms' entry, exit, and capital accumulation. This paper develops a model of firm dynamics in which firms interact through stock depletion and congestion. I estimate the model using firm-level panel data from the American whaling industry (1804–1909), an unregulated global commons. I then introduce a novel, tractable framework for optimal policy design by quantifying the shadow prices of externalities. Standard per-unit Pigouvian taxes substantially improve welfare but fall short of the first best: they correct stock externalities but leave congestion unpriced, leading to persistent overcapacity. Optimal regulation combines per-unit taxes with lump-sum fees to discipline entry, exit, and investment.

Keywords: externalities, common-pool resources, industry dynamics, optimal policy design

---

UCLA, Anderson School of Management (email: yangkeun.yun.phd@anderson.ucla.edu). I am indebted to my advisors John Asker, Will Rafey, Nico Voigtländer, and Romain Wacziarg for their invaluable advice and support throughout this project. I thank Dora Costa, David de la Croix, Meredith Fowlie, Takeshi Fukasawa, Michela Giorcelli, Martin Hackmann, Hugo Hopenhayn, Chieh-Hsuan Hu, Taylor Jaworski, Bryan Leonard, Zhijian Li, Geumbi Park, Jonathan Williams, David Qihang Wu as well as participants at seminars and conferences for their comments. I am also grateful to David Caldwell, Michael Dyer, Judith Lund, Paul J. O'Pecko, and Robert Rocha for their insightful discussions on the historical background of the American offshore whaling industry. I appreciate financial assistance from the Center for Global Management and the Center for Impact.

"...whether Leviathan can long endure so wide a chase, and so remorseless a havoc." — Herman Melville, *Moby-Dick*

1. Introduction

This paper investigates how firm entry, exit, and investment drive the tragedy of the commons by analyzing a canonical open-access setting: the 19th-century American whaling industry. Commons problems arise when one agent's use of a shared resource reduces others' returns, as in overfishing, deforestation, or groundwater overdraft (Hardin 1968; Ostrom 1990; Stavins 2011; Libecap 2024). While much research focuses on resource use by existing firms, little is known about their investment in capacity and the entry of new firms. Excess entry and capacity expansion not only accelerate future resource depletion but also intensify congestion immediately, lowering overall production efficiency. Ignoring these dynamics therefore misses key channels through which rents are dissipated in the long run.

Studying firm dynamics in the commons presents three main challenges. First, it requires long panel data that link firms' entry, exit, and investment to resource dynamics, yet such datasets are rarely available in open-access settings. Second, firm behavior and externalities are connected through complex feedback loops. Each firm's actions affect stock depletion and congestion, and these effects in turn shape future decisions. This interdependence makes firms' choices strategic and forward-looking, which expands the state space of the dynamic game and increases computational complexity. Third, policy design requires measuring external costs that reflect both contemporaneous impacts and future effects across all affected agents. Doing so is especially demanding as industry structure evolves, continually changing how externalities propagate over time.

To address these challenges, I first construct a firm-level panel of American whaling, tracing its evolution over a century under open access. I then develop a dynamic model in which firms enter, exit, and invest in vessels. Firms are heterogeneous in vessel capacity and productivity, making decisions on their own state and a few aggregate moments that summarize externalities. This structure renders dynamic strategic interactions tractable and enables estimation of the model by identifying the production function, demand curve, and dynamic cost parameters. Finally, I introduce a tractable policy-design framework that quantifies the shadow prices of externalities. Using a novel fixed-point algorithm, this framework sets policy instruments equal to these shadow prices, a key condition for achieving social efficiency.

Three main findings emerge from the empirical estimates and counterfactuals. First, the production function estimates indicate a severe commons problem in American whaling. A 1% increase in whale stock raises a firm's output by 5.2%, and a 1% increase in aggregate vessel capacity lowers it by 0.065%. Over 1820–1850, whale stock fell by 14%, implying a 54.4% decline in production efficiency, and aggregate capacity rose by 545%, implying an 11.4% decline in firm-level harvests due to congestion.

Second, per-unit Pigouvian taxes substantially improve welfare yet fall short of the first best. While they internalize the stock externality from harvest, they do not discipline congestion and the persistent overcapacity generated by firms' entry and capacity investment. The optimal policy therefore combines a per-unit tax with lump-sum license fees that depend on vessel capacity and productivity to curb inefficient industry expansion. Intuitively, the per-unit tax targets the intensive margin of extraction, while the license fee targets the extensive margins of entry and investment. Together, the two instruments align private and social incentives on both margins and raise welfare by 25.7% relative to the per-unit-tax-only policy.[1]

Third, long-run economic changes fundamentally reshape the commons problem and its regulation. Higher productivity growth and stronger demand intensify both stock depletion and congestion, leading to lower social welfare under open access despite improved fundamentals. Although these forces raise firms' private returns and expand market size, they also induce more aggressive entry and investment, accelerating rent dissipation. In contrast, when policy instruments internalize these amplified externalities, the welfare gains from regulation increase substantially. Economic growth therefore magnifies both the cost of laissez-faire and the value of well-designed policy. Effective commons regulation must adapt to evolving economic conditions to sustain efficient resource use over time.

These findings draw on new data, a model of firm dynamics with externalities, structural estimation of key parameters, and a tractable policy-design framework. I construct a firm–year panel from the expanded American Offshore Whaling

[1]This result relates to two theoretical insights. Carlton and Loury (1980) show that when social damages depend on both the number of firms and each firm's output, a Pigouvian tax should be supplemented with a lump-sum fee. Mankiw and Whinston (1986) show that free entry in homogeneous-product markets can be excessive, implying that entry regulation can improve welfare.

Voyages Database (Mystic Seaport Museum, New Bedford Whaling Museum, and Nantucket Historical Association 2024b), supplemented with *Ship Registers* to fill in missing firm information.[2] The sample covers U.S.-registered voyages from 1804 to 1909 and records vessel tonnage, output volumes, and crew size. I link these firm–year observations to annual whale-stock estimates and product prices, yielding a panel that spans the industry's rise and decline with near-complete coverage of U.S. voyages. At its mid-century peak, when externalities were most severe, American fleets dominated global whaling, accounting for roughly 750 of 900 vessels worldwide (Moment 1957). This setting provides a rare opportunity to study a large-scale common-pool resource in the absence of regulation.

Based on this context, I develop a model that combines common-pool externalities and firm dynamics. Whaling firms make entry, exit, and investment decisions based on their vessel capacity and productivity (Ericson and Pakes 1995).[3] Their actions generate externalities they do not internalize: a stock externality, as overexploitation reduces future resource availability (Gordon 1954), and a congestion externality, as contemporaneous activity crowds the hunting grounds (Smith 1969). I model production as a function of firms' own states and aggregate moments that summarize stock and congestion externalities. Firms' actions jointly determine these aggregates, which in turn feed back into individual incentives (Huang and Smith 2014). This structure motivates the *moment-based* Markov equilibrium framework of Ifrach and Weintraub (2017), which makes equilibrium computation tractable.

I estimate the model in two steps. First, I identify the production function and the demand curve. I estimate the production function using firm-level panel data on physical inputs (vessel hull capacity and crew size) and output (whales harvested). To address endogeneity between productivity and input choices, I employ a standard dynamic-panel approach that models productivity as an AR(1) process and uses

[2] In July 2020, the Whaling History Project (whalinghistory.org) expanded coverage of whaling agents from roughly one-fifth to nearly two-thirds of the 15,000 recorded voyages. See Online Appendix C.2 for details. I use "firms" and "whaling agents" interchangeably. Earlier studies relied on substantially more limited coverage (e.g., Hilt 2006; Hilt 2007; Hilt 2008; Davis, Gallman, and Gleiter 2007).

[3] Productivity is a key source of heterogeneity in whaling. Firm-level panel data show wide dispersion in output: some firms harvest only a few whales in a year, while others catch more than a hundred (Table 1). Observable characteristics such as vessel capacity and crew size cannot fully explain this persistent, systematic variation.

lagged inputs as instruments. I estimate the demand curve using supply-side cost shifters as instruments to recover the price elasticity consistently. Instruments for price include whale stocks five years earlier and long-term bond yields in New England, both of which affect whaling costs but not demand directly.

In the second step, I estimate dynamic costs for entry, exit, and capacity adjustment using a full-solution maximum-likelihood approach. Estimating these costs requires computing firms' best responses for both discrete (entry and exit) and continuous (capacity adjustment) decisions, which can be sensitive to the discretization of the continuous state and action spaces. To address this issue, I adopt the recent methodology of Gowrisankaran and Schmidt-Dengler (2025). This approach introduces random shocks to marginal adjustment costs, ensuring stable solutions across different discretizations. I then use the implied equilibrium choice probabilities to estimate the dynamic cost parameters that best rationalize firms' observed decisions in the data.

To analyze counterfactuals, I compute shadow prices of externalities and solve for a fixed point in which policy instruments are set equal to these shadow prices. Starting from the observed equilibrium, I solve the dynamic game and compute two shadow prices: (i) a harvest shadow price, the marginal welfare effect of an additional unit of harvest in a given year; and (ii) a firm shadow price, the marginal welfare effect of additional mass in a given firm state (capacity and productivity) in that year. I set the per-unit tax equal to the harvest shadow price and the lump-sum license fee equal to the firm shadow price, then re-solve the game, recompute the shadow prices, and update policies until convergence. The resulting regulation consists of time-varying per-unit taxes and state-dependent lump-sum fees. This procedure yields implementable, state-contingent policies that decentralize the social optimum while remaining computationally feasible in high-dimensional industries.

Relationship to the literature. The main contribution of this paper is to show how firm dynamics shape the long-run allocation of common-pool resources and to develop a framework for optimal policy design.

My model builds on recent advances in the study of common-pool resources and industry dynamics. A seminal contribution is Huang and Smith (2014), who examine dynamic strategic interactions in shrimp fisheries. The central challenge in their setting is that agents' payoffs depend on others' actions through dynamic externalities, complicating empirical analysis. To address this issue, they assume that fishers affect others only through the aggregate number of vessels, which in turn governs shrimp stocks. Their model features a fixed set of players, which is appropriate over relatively short horizons. Over longer horizons, especially under open access, firms enter, exit, and invest. A large literature on industry dynamics shows that these firm-level margins shape industry structure and resource allocation (see Aguirregabiria, Collard-Wexler, and Ryan 2021 for a review). I connect these strands by embedding entry, exit, and capacity adjustment into a common-pool resource game. This perspective highlights how entry and investment can outpace exit and divestment, generating persistent inefficiency through overcapacity.

The policy question in this paper relates to a growing literature on corrective policies for common-pool resources. Costello, Gaines, and Lynham (2008) show that catch shares sustain global fish stocks, and Costello et al. (2016) compare overfishing outcomes across management regimes. More recently, researchers have examined policy effects beyond stock levels. Ho (2023) studies productivity gains from individual transferable quotas. Englander (2023) identifies temporal and spatial spillovers from temporary closures. Aspelund (2025) analyzes redistribution and efficiency effects of trade restrictions in fishing-permit markets. A key difference is that these studies do not directly model firms' dynamic decisions as determinants of long-run efficiency in commons regulation. Segerson and Squires (1993) highlight capacity choices, showing that output quotas can induce divestment. However, direct evidence on the welfare effects of regulating firm dynamics remains scarce. I show that achieving the social optimum requires policies that target both the intensive margin (additional harvest) and the extensive margin (entry, exit, and investment).

Beyond the commons, a growing literature studies regulation design in environmental and energy markets with industry dynamics. Fowlie, Reguant, and Ryan (2016) examine the dynamic implications of market-based regulation in the presence of market power and emissions leakage. Elliott (2024) investigates carbon taxes and capacity subsidies when emissions trade off against intermittency from wind and solar. Aronoff and Rafey (2023) study welfare gains and externalities from environmental offsets. Butters, Dorsey, and Gowrisankaran (2025) analyze the equilibrium effects of large-scale battery storage. Gowrisankaran, Langer, and Zhang (2025) and Chen (2024) show that policy uncertainty shapes dynamic market efficiency. Relative to this literature, I design policies by setting instruments equal to the shadow prices at the efficient allocation, which is the key condition for decentralizing the social optimum. To implement this idea, I propose a fixed-point framework for policy design that is broadly applicable when externalities are the central distortion.

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 US whaling 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 (Section 2.4).

2.1. Products and markets

The American whaling industry primarily produced three commodities: sperm oil, whale oil, and whalebone (baleen). Sperm oil, rendered by boiling the blubber of sperm whales, was prized for its clean, bright flame and was used for illumination and as a lubricant for fast-moving machinery (e.g., spindles). Whale oil, extracted from baleen whales, was used as a lubricant for heavy machinery and as an illuminant. Whalebone, taken from the mouths of baleen whales, was used in products such as corsets.[4] The product market consisted of homogeneous goods and was competitive. Individual whaling firms had little ability to affect prices or differentiate their outputs from those of other firms (Davis, Gallman, and Gleiter 2007).

During the first half of the nineteenth century, industrialization in the United States substantially increased demand for oil, expanding markets for whaling. The industry entered its "Golden Age" between 1830 and 1860, when American whalers

[4] Online Appendix Figure E1 shows trends in output quantities and prices.

produced over 90% of the world's sperm oil (Tillman and Donovan 1983).[5] During this period, the United States overtook Britain as the leading whaling nation, supported by strong domestic demand growth, technological and institutional advantages, and higher-skilled crews (Davis, Gallman, and Hutchins 1987). Thereafter, the industry gradually declined, driven by the discovery of petroleum in 1859 and the disruption of the Civil War (1861–1865). By the late nineteenth century, output and value had fallen back to levels comparable to those of the early 1800s.

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, 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 Online Appendix B.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

[5] I treat non-American whaling operations as exogenous given their relatively small scale. If they responded endogenously to counterfactual regulations on American whaling but were not themselves regulated, the effects of the policy experiments in Section 5 would be smaller.

and stations for exchanging letters. These exchanges occurred at predetermined rendezvous points, either between whaling vessels or between supply ships and whaling vessels (see Online Appendix B.2 for an example).[6]

In many cases, whaling agents owned vessels as principal owners, flying a "house flag" that signaled ownership. But this did not mean the agent alone financed the voyage. Multiple investors typically contributed, with arrangements varying from one voyage to another (see Online Appendix Figure C2 for an example). The reliance on multiple investors reflected the substantial capital required to outfit a whaling expedition. A typical New Bedford voyage in the 1850s cost between \$20,000 and \$30,000 (equivalent to roughly \$831,000–\$1,200,000 today). The cost was considerable, especially when compared to other sectors: the value of the average manufacturing firm's capital stock was about \$4,335 in 1850 (≈\$180,000 today) and \$7,191 in 1860 (≈\$285,000 today) (Davis, Gallman, and Gleiter 2007).

2.3. Data

I construct several 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; (iii) common-pool features; and (iv) demand shifters. See Online Appendix C for a detailed description.

The primary source is the American Offshore Whaling Voyages Database (*Voyage Database*), which covers nearly all U.S. whaling voyages undertaken in the 19th-century (Mystic Seaport Museum, New Bedford Whaling Museum, and Nantucket Historical Association 2024b).[7] The database records vessel characteristics (name, unique ID, tonnage, rigging), the managing owner/agent, captains, outbound and inbound years, outputs (sperm oil, whale oil, whalebone), ports of departure and return, and other related information (see Online Appendix Figure C1 for an example).

However, the *Voyage Database* does not include crew information, so I supplement it with the American Offshore Whaling Crew Lists Database (*Crew Lists*

[6] 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).

[7] Prior studies in economics use related data sets to study risk sharing in financial markets, firm formation and corporate organization, productivity, and labor diversity (Hilt 2006, 2007, 2008; Davis, Gallman, and Gleiter 2007; Baggio and Cosgel 2024).

Database) to obtain crew size for each voyage (Mystic Seaport Museum, New Bedford Whaling Museum, and Nantucket Historical Association 2024a). The *Crew Lists Database* covers roughly half of the voyages in the *Voyage Database*.

To study firms' production, entry, exit, and capital accumulation, I build a firm-year panel from voyage records. This construction becomes possible because the *Voyage Database* recently expanded whaling agent coverage from about one-fifth to nearly two-thirds of the fifteen thousand voyages. I further supplement the data using *Ship Registers*, manually digitizing agents' names and adding information for roughly 500 voyages (see Online Appendix C.2 for an example). Based on this expanded dataset, I divide each voyage's output by its duration (measured from departure to return) and aggregate to the firm–year level by whaling agent. I convert the three outputs—sperm oil, whale oil, and whalebone—into the *number of whales harvested* using historical benchmarks (see Online Appendix C.3). I also aggregate inputs (vessel tonnage and crew size) to the firm–year level, assuming they remain constant throughout each voyage.[8]

The prices of whaling products come from Tower (1907) and Davis, Gallman, and Gleiter (2007). I calculate the price *per whale* as the aggregate value of outputs divided by the total number of whales harvested each year. The aggregate output value equals sperm oil quantity × sperm oil price + whale oil quantity × whale oil price + whalebone quantity × whalebone price. I compute the total number of whales harvested by summing catch records across all voyages. Online Appendix Figure E2 reports the annual whale price.

To explore common-pool features, I capture two key externalities. First, total vessel tonnage proxies for the congestion externality, computed by summing the tonnage of all whaling vessels in each year from the *Voyage Database*. Second, whale abundance reflects the stock externality, with dynamics projected using a discrete-time generalized logistic model of population and catch data (see Eq. 1 in Section 3.1).

I use three exogenous variables to capture demand shifters: U.S. GDP per capita, a linear time trend, and petroleum prices. These data come from the Historical Statistics of the United States (Carter et al. 2006).[9]

[8]Although crew desertion and recruitment occurred, vessel tonnage largely constrained crew size.

[9]The online version is available at https://hsus.cambridge.org/. Annual U.S. GDP per capita is

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

Variable	Unit	Mean	SD	P5	Median	P95
Panel A. Outputs						
Whales harvested	Number	39.306	46.156	2.42	22.79	133.10
Sperm oil	Thousand barrels	0.506	0.687	0.00	0.28	1.82
Whale oil	Thousand barrels	0.761	1.264	0.00	0.22	3.43
Whale bone	Thousand pounds	5.809	12.496	0.00	0.00	30.27
Panel B. Inputs						
Vessel capacity	Tonnage	758.307	801.833	110	395	2,486
	Number	2.605	2.392	1	2	8
Crew size	Number	78.108	76.069	16	49	242
Firm age	Year	11.198	10.830	1	7	33
Panel C. Dynamic decisions						
Entry	Rate	0.110	0.094	0.000	0.097	0.244
Exit	Rate	0.107	0.058	0.000	0.103	0.214
Investment	Rate	0.155	0.113	0.032	0.139	0.286
	Tonnage	327.192	217.379	70.5	311.5	747.0
Divestment	Rate	0.148	0.086	0.000	0.143	0.311
	Tonnage	-337.756	240.369	-813.5	-308.0	-71.5

Note: The dataset includes 10,394 firm-year observations and 1,044 firms, covering the years 1804 to 1909. Reported quantities of sperm oil, whale oil, and whalebone determine the number of harvested whales (see Online Appendix C.3 for details). Crew size is observed for 4,880 firm-year observations because the *Crew Lists Database* is a subsample of the *Voyage Database*. Entry and exit rates are defined as the fraction of firms that enter or exit in a given year; investment and divestment rates are defined analogously. Changes in vessel tonnage between the current year and the following year capture investment and divestment, excluding changes due to wreckage.

2.4. Descriptive statistics

Table 1 reports firm-year statistics and highlights substantial variation across observations. Panel A shows that some firms harvested only a few whales, while others harvested more than one hundred. Panel B shows wide dispersion in operational scale. Annual operations ranged from a single vessel to more than eight, with corresponding variation in vessel tonnage and crew size. Firm lifetimes also varied substantially. Some firms operated only briefly, while others remained in the industry for more than 30 years. Panel C summarizes dynamic decisions. Entry and exit

from Series Ca9, and petroleum prices are from Series Db56. Online Appendix Table C1 reports summary statistics.

rates are defined as the fraction of firms that enter or exit in a given year, and investment and divestment rates are defined analogously. Investment and divestment are measured as changes in vessel tonnage from year t to year $t + 1$, excluding changes due to wreckage from weather, accidents, war, or other causes. On average, relative to the number of firms active in each year, 11% of firms entered, 10.7% exited, 15.5% invested, and 14.8% divested. Median investment was about 311 tons and median divestment about 308 tons, with substantial dispersion in both—reflecting the lumpy and uncertain nature of capacity adjustment.

Figure 1 presents the evolution of total whaling vessel capacity and whale stock. Panel A shows the rise of American whaling to global dominance during the industry's golden age, followed 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 1816–1820. Over the subsequent three decades, total tonnage increased more than fifteen-fold. American whaling voyages typically clustered in a small number of major whaling grounds—such as the Sea of Okhotsk, the Bering Sea, and the North Pacific—depending on the period. As vessel capacity expanded rapidly, many ships hunted simultaneously in the same grounds, giving rise to substantial congestion.[10] Panel B displays the projected population of whales as a sum of baleen and sperm whales, calculated using a discrete-time generalized logistic model of stock dynamics and catch data (see Eq. 1 in Section 3.1). Whale stocks experienced sharp declines during the golden age, coinciding with the rapid expansion of vessel capacity.

Figure 2 provides suggestive evidence 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. This decline is striking in light of technological growth over the period—about 1.3% per year from the production function estimates (see Section 4.1). On the other hand, panel B shows a non-decreasing revenue per vessel. It was $13,000 (in 1880

[10]Contemporaneous logbooks provide direct evidence of such congestion. The log of the bark *Isabella* records that on July 28, 1854,

> Saw a few whales. Chased them to no effect. 94 Ships in sight from the deck. Most of them at anchor. Only 5 of them boiling.

Nearby entries also describe intense competition. For example, on July 29, 1854: "the boats all chasing whales. Saw considerable many more boats than whales."

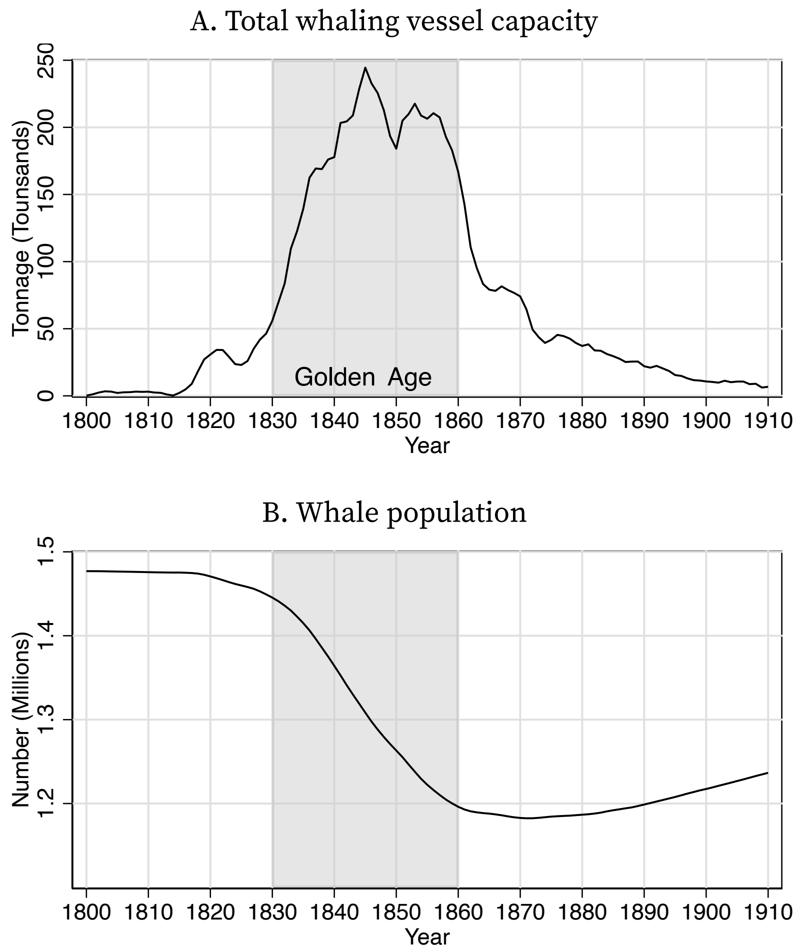

FIGURE 1. Aggregate whaling vessel capacity and whale stock

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 Eq. 1 in Section 3.1).

dollars) in the 1820s, and then increased to $17,000 in the 1850s. A significant rise in prices resulted in this increase. For instance, the price of sperm oil was around $0.5 per gallon in the 1820s and tripled in the 1850s (see Online Appendix Figure E1). These price increases sustain firms’ incentives to continue operating despite rising costs, reinforcing the equilibrium effect of continued entry and investment amid worsening common-pool conditions.

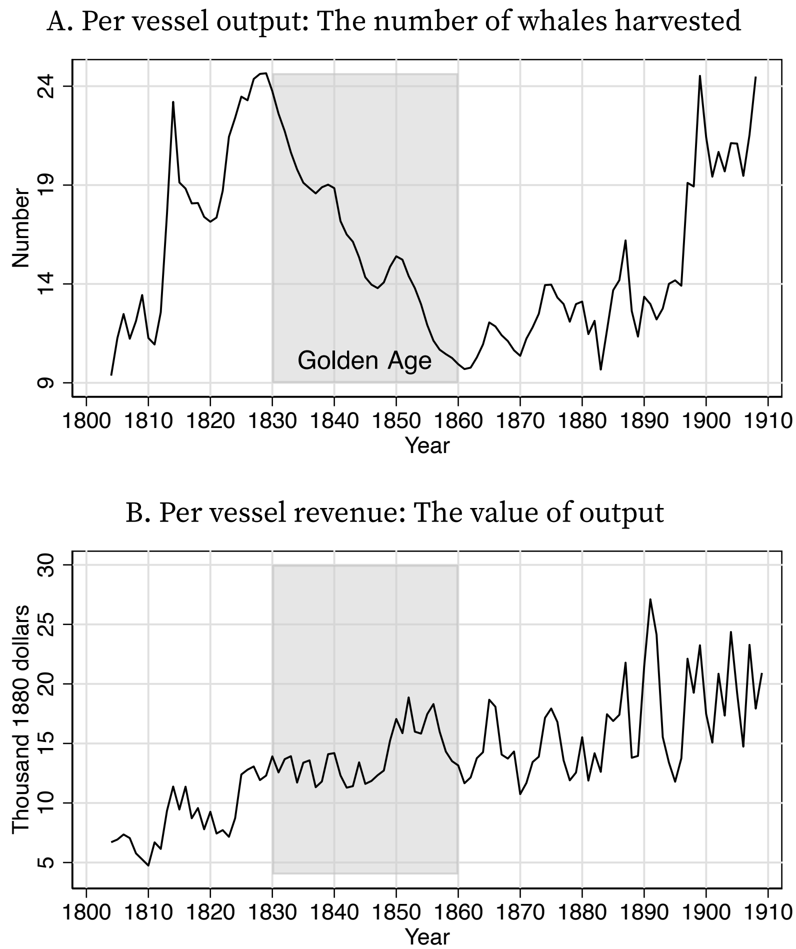

FIGURE 2. Suggestive evidence of negative externalities

Note: In panel A, the output is measured by the number of whales harvested. 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.

3. A model of common-pool industry dynamics

This section develops a model of strategic industry dynamics in the spirit of Ericson and Pakes (1995) and Ifrach and Weintraub (2017), with the key extension being an endogenous, evolving production externality that affects all firms. The subsections present the model setup (Section 3.1), firms' beliefs and strategies (Section 3.2), dynamic optimization (Section 3.3), and the equilibrium (Section 3.4).

3.1. Setup

Time. Each period corresponds to one year and is indexed by $t \in \{1, 2, \ldots, T\} \subset \mathbb{N}$, where T denotes the terminal period. A finite horizon is crucial for the empirical analysis: it captures the industry's rise and fall and permits nonstationarity in equilibrium. By contrast, the infinite-horizon stationary framework does not naturally accommodate this historical pattern.

Players. Firms are indexed by i. In year t, the set of incumbents is $\mathcal{I}_t$, with $|\mathcal{I}_t| = N_t$, and the set of potential entrants is $\mathcal{I}_t^{\text{pe}}$, with $|\mathcal{I}_t^{\text{pe}}| = N_t^{\text{pe}}$.

Resource. The whale stock in year t is denoted by $W_t \in [0, W_1] \subset \mathbb{R}$, where W_1 is the natural stock level without harvesting. The stock evolves according to a discrete-time generalized logistic model of population dynamics (Baker and Clapham 2004; Breiwick and York 2009):

$$W_{t+1} = W_t + rW_t\left[1 - \left(\frac{W_t}{W_1}\right)^z\right] - Q_t, \tag{1}$$

where r is the whale-stock regeneration rate, z is the exponent setting the maximum sustainable yield level, and Q_t is the total whale harvest in year t. Equation (1) implies that next year's stock depends on the current stock and its regeneration, net of the total harvest.

Firm state. Active whaling firms are heterogeneous along two dimensions. First, capacity (K) captures the total tonnage of operating vessels. Second, productivity (Ω) reflects managerial efficiency, modeled as Hicks-neutral technology.[11] I define productivity conditional on whale stock, so it does not directly depend on stock levels. The *individual* state of firm i in year t is denoted by $x_{it} \equiv (K_{it}, \Omega_{it}) \in \mathcal{X}$. Vessel capacity changes through costly adjustment (investment or divestment) I_{it}:

$$K_{it+1} = (1 - \delta)K_{it} + I_{it} \tag{2}$$

[11]Incorporating firm-level, time-varying productivity into the state space addresses the limitation of relying solely on i.i.d. random shocks as the source of unobserved variation over time (Bajari, Benkard, and Levin 2007). It is also crucial for capturing dispersion in output even after accounting for observed firm characteristics such as capacity and crew size (see Table 1).

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

$$\omega_{it+1} = \mathbb{E}\left[\omega_{it+1} | \omega_{it}\right] + \nu_{it+1} \tag{3}$$

where ν_{it+1} is unexpected productivity innovation, with $\mathbb{E}\left[\nu_{it+1} | \omega_{it}\right] = 0$. With a slight abuse of notation, $K(x)$ and $\Omega(x)$ denote vessel capacity and productivity at each individual state x. Potential entrants are ex ante identical prior to entry.

Production. The whale-harvesting function $\mathcal{H}$ gives the number of whales harvested by firm i with $x_{it} = (K_{it}, \Omega_{it})$ in year t:

$$Q_{it} = \mathcal{H}_t(x_{it}, W_t, K_t; \beta). \tag{4}$$

The harvesting function incorporates stock externalities through W_t and congestion externalities through K_t. Thus, firm i's harvest depends not only on its own state but also on these external factors. The time subscript in $\mathcal{H}_t(\cdot)$ reflects time dependence arising from exogenous technological growth in the industry. The vector β contains the parameters governing the harvesting function.

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

$$P_t = \mathcal{P}(Q_t; Z_t^d, \alpha) = \mathcal{P}_t(Q_t; \alpha). \tag{5}$$

Here, P_t denotes the market price in year t, common to all firms because the American whaling industry was competitive (Davis, Gallman, and Gleiter 2007). The vector Z_t^d consists of exogenous demand shifters—U.S. GDP per capita, time trend, and petroleum prices (since 1859). For notational simplicity, these shifters are absorbed into the time subscript of $\mathcal{P}_t(\cdot)$. The vector α contains the parameters of the demand system.

Period payoff. Firm i's profit Π at year t is the revenue minus labor costs:

$$\Pi_t(x_{it}, K_t, Q_t, W_t; \alpha, \beta) = \mathcal{P}_t(Q_t; \alpha)\mathcal{H}_t(x_{it}, K_t, W_t; \beta) - w_t^L L_{it}, \tag{6}$$

where L_{it} denotes crew size and w_t^L is common wage index for crew. Importantly, the payoff depends on the decisions of all firms, as reflected in K_t, Q_t, and W_t.

Dynamic actions. At each year t, incumbent firm i chooses either to exit or remain active. If it stays, the firm may adjust its vessel capacity for the next period. Incumbent decisions are denoted $a_{it} \in \mathcal{A} = \{0\} \cup \mathcal{K}$, where 0 represents exit and $\mathcal{K}$ is the set of feasible capacity levels. Potential entrants decide whether to enter the market, with actions denoted $a_{it}^{\text{pe}} \in \mathcal{A}^{\text{pe}} = \{0, 1\}$, where 0 indicates no entry and 1 indicates entry.

Timing. The industry evolves according to the following sequence. At the start of year t, incumbent firms hunt whales and earn period payoffs as defined in equation (6). After receiving payoffs, each firm draws i.i.d. random shocks $(\kappa_{it}, \zeta_{it}, \epsilon_{it})$ for entry, exit, and capacity adjustment (detailed in Section 3.3) and then makes its decisions.[12] At the end of the year, these decisions are implemented and states transition accordingly.

3.2. Moment-based states and strategies

Common-pool resources naturally attract many firms because of open access and rivalry. With many firms, the industry is competitive, yet firms still affect one another through common-pool externalities. For any individual firm, monitoring detailed information on numerous competitors is costly and impractical. Instead, firms track key summary statistics that affect their payoffs and follow the *moment-based* strategies (Ifrach and Weintraub 2017).

As shown in equation (6), the payoff-relevant moments include total vessel capacity and total whale harvest. Total vessel capacity equals the sum of all firms' capacities:

$$K_t = \sum_{x \in \mathcal{X}} f_t(x) K(x), \tag{7}$$

[12] Random shocks are essential in dynamic games for two reasons. First, they ensure the existence of pure strategy equilibria (Doraszelski and Satterthwaite 2010). Without shocks, ex-ante choice probabilities for continuous decisions, such as investment, become discontinuous in their corresponding value functions. This discontinuity prevents the application of Brouwer's fixed-point theorem, which is required to prove equilibrium existence. Second, random draws introduce ex-ante uncertainty into firms' decisions. They help capture variability in the data that would otherwise be hard to match empirically (Rust 1987).

where $f_t(x)$ denotes the number (or mass) of firms at each $x \in \mathcal{X}$ in year t. Total whale harvest equals the sum of all firms' harvests:

$$(8) \qquad Q_t = \mathcal{Q}_t(K_t, W_t; \beta) = \sum_{x \in \mathcal{X}} f_t(x)\, \mathcal{H}_t\,(x, K_t, W_t; \beta)\,,$$

which depends on current total vessel capacity and whale stock. Each firm can infer whale stock from equations (1), (7), and (8) in every year, given the natural carrying stock W_1. For notational convenience, I combine the firm state, industry moments, and resource stock into a payoff-relevant state $s_{it} = (x_{it}, K_t, Q_t, W_t) \in \mathcal{S}$.

With i.i.d. random shocks to dynamic actions, incumbents follow the decision rule $\psi_t(s_{it}, \zeta_{it}, \epsilon_{it}) = a_{it}$, while potential entrants use $\psi_t(s_{it}, \kappa_{it}) = a_{it}^{\mathrm{pe}}$. Here, the time subscript in $\psi_t(\cdot)$ indicates that strategies are non-stationary due to the evolution of the industry, embodied in exogenous demand shifters and overall technology growth. Throughout, this study focuses on anonymous, type-symmetric pure strategies that map states and choice-specific shocks into actions. The year-t strategy profile as the collection of all individual decision rules is

$$(9) \qquad \psi_t = \{\,\psi_t(s_{it}, \zeta_{it}, \epsilon_{it})\}_{i \in \mathcal{J}_t} \,\cup\, \{\,\psi_t(s_{it}, \kappa_{it})\}_{i \in \mathcal{J}_t^{\mathrm{pe}}}.$$

Let $M_t(x' \,|\, x, \psi_t)$ denote the transition kernel—the probability that a firm currently in state x in year t moves to state x' in year $t+1$ when all firms follow the strategy profile ψ_t. The distribution of firms evolves according to:

$$(10) \qquad f_{t+1}(x') = \begin{cases} \sum_{x \in \mathcal{X}} M_t(x' \,|\, x, \psi_t) f_t(x) + \sum_{i \in \mathcal{J}_t^{\mathrm{pe}}} \psi_t(s_{it}, \kappa_{it}) & \text{if} \quad x' = x^{\mathrm{e}} \\ \sum_{x \in \mathcal{X}} M_t(x' \,|\, x, \psi_t) f_t(x) & \text{otherwise,} \end{cases}$$

where x^{e} is the state of a new entrant. The evolution of the firm distribution depends on the initial distribution f_1 and the initial resource stock W_1. For notational simplicity, I suppress the year-1 dependence in the remainder of the analysis.

3.3. Dynamic optimization

Firms make their dynamic choices of entry, exit, and capacity adjustment to maximize their expected discounted stream of profits. They discount future profits by a factor $\rho \in (0, 1)$.

A potential entrant draws an entry cost κ_{it} from an i.i.d exponential distribution with mean $\bar{\kappa}$. This entry cost represents a barrier to profitable entry, capturing heterogeneity in firms' ability to successfully enter and operate in the industry.

An incumbent firm faces two shocks. First, it draws an exit scrap value ζ_{it} from an i.i.d. exponential distribution with mean $\bar{\zeta}$, which reflects the opportunity cost of remaining in the whaling industry, including outside opportunities. Second, it draws a marginal capacity adjustment cost ϵ_{it} from an i.i.d. normal distribution with standard deviation σ.[13] Capacity adjustments involve expanding or contracting fleet size and related operations. Variation in organizational frictions, financing conditions, and firm-specific constraints generates heterogeneity in adjustment costs.

In addition to random shocks, incumbent firms incur deterministic adjustment costs. These costs depend on current capacity, the magnitude of the adjustment, and whether the firm invests or divests:

$$C(K_{it+1}, K_{it}; \gamma) = \mathbb{1}\{K_{it+1} > K_{it}\} \left(\gamma_0^+ + \gamma_1^+ I_{it} + \gamma_2^+ I_{it}^2\right) + \mathbb{1}\{K_{it+1} < K_{it}\} \left(\gamma_0^- + \gamma_1^- I_{it} + \gamma_2^- I_{it}^2\right), \tag{11}$$

where $\gamma = \{\gamma_0^+, \gamma_1^+, \gamma_2^+, \gamma_0^-, \gamma_1^-, \gamma_2^-\}$ and I_{it} is defined by equation (2). The first part, indicated by $\mathbb{1}\{K_{it+1} > K_{it}\}$, captures investment costs, whereas the second part, indicated by $\mathbb{1}\{K_{it+1} < K_{it}\}$, represents divestment costs. Each part comprises three elements: a fixed cost (γ_0), a linear cost (γ_1), and a convex cost (γ_2).

An active firm with state $s_{it} = (K_{it}, \Omega_{it}, K_t, Q_t, W_t)$ at year t, given that all firms follow the strategy profile ψ_t, solves the following dynamic programming problem:

(12)

$$V_t(s_{it}, \psi_t; \Theta) = \Pi_t(s_{it}; \alpha, \beta) + \mathbb{E}_\zeta \Bigg[\max \Bigg\{ \zeta_{it},$$

[13]Introducing stochasticity into marginal adjustment costs follows Kalouptsidi (2018), Caoui (2023), Gowrisankaran, Langer, and Reguant (2024), and Gowrisankaran and Schmidt-Dengler (2025). In contrast, Ryan (2012) and Fowlie, Reguant, and Ryan (2016) apply stochastic shocks to fixed adjustment costs.

$$\mathbb{E}_{\epsilon}\left[\max_{K_{it+1}}\left\{-C(K_{it+1},K_{it};\gamma)-I_{it}\epsilon_{it}+\rho\,\mathbb{E}_t\left[V_{t+1}(s_{it+1},\psi_{t+1};\Theta)\,|\,s_{it},\psi_t\right]\right\}\middle|\, s_{it}\right]\Bigg\}\,\middle|\, s_{it}\Bigg].$$

where $\Theta = \{\alpha, \beta, \bar{\zeta}, \bar{\kappa}, \gamma\}$. The time subscript in the value function $V_t(\cdot)$ features the nonstationarity, as period profits $\Pi_t(\cdot)$ vary over year due to whale stock dynamics, demand shifts, and technological progress. A firm exits at year t if and only if its exit scrap value (ζ_{it}) exceeds the expected continuation value. If it stays, the firm selects the next period's capacity level K_{it+1} to maximize its discounted expected future value net of adjustment costs.

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

$$\mathbb{E}_{\kappa}\left[\max\left\{0,\ \rho\,\mathbb{E}_t\left[V_{t+1}(s_{it+1},\psi_{t+1};\Theta)\,|\,s_{it},\psi_t\right]-\kappa_{it}\right\}\middle|\, s_{it}\right]. \tag{13}$$

A potential entrant decides to enter at year t if and only if the discounted expected value net of the entry cost is greater than zero.

Equations (12) and (13) normalize the operating fixed cost to zero. This normalization is necessary because, in a dynamic setting, the entry cost, exit scrap value, and operating fixed cost cannot be jointly identified (Aguirregabiria and Suzuki 2014). As a result, estimates of entry cost and exit value incorporate the operating fixed cost.

3.4. Equilibrium

The model captures the rise and fall of the American whaling industry, together with shifts in technology, demand, and whale stocks over time. Because of this nonstationary nature, I solve for equilibrium via backward induction, assuming that the nonstationary equilibrium converges to a stationary equilibrium in the long run (Benkard, Jeziorski, and Weintraub 2024). This assumption is necessary because backward induction requires a terminal period value function.

Formally, firms anticipate that the industry will converge to a stationary equilibrium in the distant future. Let the period of interest be the time interval from $t = 1$ to T. There exists a sufficiently large $\overline{T} > T$ such that for $t > \overline{T}$, the industry follows a stationary equilibrium, while for $1 \leq t \leq \overline{T}$, it exhibits nonstationary behavior.

Now define the nonstationary *moment-based* Markov equilibirum (MME) of common-pool resource competition. Given an initial firm distribution f_1 and resource stock W_1, a nonstationary MME is a sequence of strategy profiles $\{\psi_t\}_{\forall t}$ that satisfies the following conditions:

1. Incumbent firms solve (12).
2. Potential entrants solve (13).
3. The resource stock W_t evolves according to (1).
4. The distribution of firms f_t evolves according to (10).
5. Firms form beliefs using the moment-based states (7) and (8).

Existence of equilibrium follows from Ifrach and Weintraub (2017) and Benkard, Jeziorski, and Weintraub (2024). The equilibrium is unique in the empirically relevant region. Strictly convex adjustment costs and continuous idiosyncratic shocks imply a unique mapping from the state to entry, exit, and capacity adjustment probabilities. Numerically, I test the equilibrium computation starting from a wide range of initial policy function (choice probability) guesses, and in all cases it converges to the same fixed point.

4. Estimation

The estimation proceeds in two stages. In the first stage, I estimate the whale harvesting (production) function and the whale demand curve (Section 4.1). These estimates provide period payoffs for all possible firm states and years. In the second stage, I embed these payoffs into the dynamic model and estimate the dynamic parameters (Section 4.2). Table 2 summarizes the structural parameters that are estimated and calibrated. Panel A reports the primitives from the harvesting function and demand curve. Panel B lists the dynamic parameters. Panel C includes calibrated values.

4.1. Period payoffs

Whale harvesting function. I parameterize equation (4) as a Cobb–Douglas production function in logarithmic form:

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta^K k_t + \beta^W w_t + \beta^t t + \underbrace{\mu_{it} + \varepsilon_{it}}_{\omega_{it}}, \tag{14}$$

TABLE 2. List of parameters and empirical approach

Parameters	Notation	Empirical approach
Panel A. Period payoffs		
Harvesting function	$\beta_0, \beta_l, \beta_k, \beta_a, \beta^K, \beta^W, \lambda$	DP-GMM (Section 4.1)
Demand curve	$\alpha_0, \alpha_p, \alpha^{\text{pop}}, \alpha^{\text{gdp}}, \alpha^{\text{pet}}$	OLS, IV (Section 4.1)
Panel B. Dynamic costs and values		
Mean of entry costs	$\bar{\kappa}$	NFXP-MLE (Section 4.2)
Mean of exit values	$\bar{\zeta}$	NFXP-MLE (Section 4.2)
SD of stochastic marginal adjustment costs	σ	NFXP-MLE (Section 4.2)
Deterministic adjustment costs	$\gamma_0^+, \gamma_1^+, \gamma_2^+, \gamma_0^-, \gamma_1^-, \gamma_2^-$	NFXP-MLE (Section 4.2)
Panel C. Transitions		
Private annual discount factor	$\rho = 0.925$	Calibrated
Vessel capacity destruction rate	$\delta = 0.05$	Calibrated
Whale stock dynamics	$z = 1.4, r = 0.011$	Calibrated

Note: This table summarizes key parameters of the model. Parameters in panels A and B are estimated, whereas those in Panel C are calibrated. In panel A, DP-GMM refers to dynamic panel estimation using the generalized method of moments. In panel B, NFXP-MLE denotes nested fixed-point maximum likelihood estimation. Parameters related to whale population dynamics are drawn from previous literature (Baker and Clapham 2004; Whitehead 2002).

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 (log) productivity, ω_{it}, is divided into persistent productivity μ_{it} and transitory shock ε_{it}.

Following the dynamic panel approach by Blundell and Bond (2000), persistent productivity μ_{it} evolves as an AR(1) with serial correlation λ:

$$\mu_{it} = \lambda\mu_{it-1} + \xi_{it}, \tag{15}$$

where ξ_{it} is an independent and identically distributed (i.i.d.) shock. Imposing this AR(1) structure rules out the richer productivity transition in equation (3) and may not fully address selection bias from endogenous exit. Nevertheless, using an unbalanced panel alleviates many concerns about selection (De Loecker et al. 2016; Rubens 2023).[14]

[14] As a robustness check, I also implement the Olley and Pakes (1996) approach, which uses

Firms choose vessel capacity in year $t-1$ (as in Eq. 2) and crew size between $t-1$ and t (as in Ackerberg, Caves, and Frazer 2015), both prior to the year t productivity shock ξ_{it}. Combined with the AR(1) process (Eq. 15), this timing yields the exclusion restriction identifying $\beta = (\beta_0, \beta_l, \beta_k, \beta^K, \beta^W, \beta^t, \lambda)$. Specifically, the year-t productivity shock ξ_{it} is orthogonal to $z_{it} = (1, l_{it-1}, k_{it}, k_{it-1}, k_t, w_t, t)$. The corresponding moment conditions are

$$\mathbb{E}\left[\widehat{\xi_{it} + (\varepsilon_{it} - \lambda\varepsilon_{it-1})}(\beta) \otimes z'_{it}\right] = 0.$$

I estimate the parameters using a standard two-step generalized method of moments (GMM) estimator.

Table 3 reports estimates of the whale harvesting function. Columns (1)–(3) use the subsample that contains crew data, while column (4) uses the full sample and serves as the baseline for the dynamic analysis. Column (1) only includes vessel capacity and crew size; column (2) adds aggregate time series variables, which absorb much of the serial correlation and reduce the estimated persistence parameter. Column (3) excludes crew size from the same subsample to compare with the full-sample specification in column (4).

The estimated results show that vessel capacity alone, without crew size, explains most of the variation in production scale. This pattern is intuitive because nineteenth-century American whaling was capital-intensive, and crew size was roughly proportional to vessel capacity. Accordingly, in the analyses that follow, I assume that harvesting combines vessel capacity and crew in fixed proportions, reflecting a Leontief technology.[15]

Based on the results of column (4), the back-of-the-envelope calculation suggests strong production externalities. First, the coefficient for whale stock (β^W) captures

investment as a proxy for productivity and corrects for endogenous exit. The results are qualitatively similar, although the sample size falls from 4,875 to 948 (in the same specification as column 2 of Table 3) because the method requires positive investment. A common alternative is an approach that inverts intermediate-input demand to recover latent productivity (Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015). This approach requires an intermediate input whose demand is monotonically increasing in productivity. Because the data for the American whaling industry lack such an input, this approach is not feasible here.

[15] I therefore model crew size a $L(K_{it}) = cK_{it}$, where c denotes crew per tonnage. The data support this assumption: vessel tonnage and crew size are tightly linked. The correlation coefficient between capacity K_{it} and crew size L_{it} is 0.92; between their logs k_{it} and l_{it} it is 0.9.

TABLE 3. Estimates of the whale harvesting function

	(1)	(2)	(3)	(4)
Vessel capacity: β_k	1.010	0.904	1.059	1.049
	(0.030)	(0.027)	(0.009)	(0.007)
Crew size: β_l	-0.003	0.192		
	(0.025)	(0.030)		
Persistence: λ	0.674	0.272	0.356	0.158
	(0.115)	(0.112)	(0.113)	(0.100)
Whale stock: β^W		7.199	7.023	5.162
		(0.282)	(0.302)	(0.248)
Aggregate vessel capacity: β^K		-0.046	-0.032	-0.067
		(0.013)	(0.014)	(0.008)
Time trend: β^t		0.020	0.021	0.013
		(0.001)	(0.001)	(0.001)
Returns to scale: $\beta_k + \beta_l$	1.01	1.096	1.059	1.049
Number of firms	459	459	459	971
Observations	4,875	4,875	4,875	9,025

Notes: This table reports the estimated harvesting function. Columns (1)–(3) use the subsample with crew data; column (4) employs the full sample. Identification relies on the following instruments: contemporaneous and lagged vessel capacity, lagged crew size, contemporaneous aggregate fleet capacity, whale–stock abundance, and a linear time trend. Parameters are estimated by two–step generalised method of moments (GMM). Robust GMM standard errors, based on the estimator's asymptotic variance–covariance matrix, appear in parentheses.

the stock externality. Holding other factors constant, a 1 percent increase in whale stock raises an individual firm's harvest by about 5.2 percent. Because whale stock fell by 14.1 percent between 1820 and 1850, the implied harvest reduction is 54.4 percent. Second, the coefficient for aggregate capacity (β^K) captures the congestion externality. A 1 percent increase in aggregate capacity reduces an individual firm's harvest by 0.067 percent. Between 1820 and 1850, aggregate capacity rose from 31,000 to 200,000 tons (an increase of 545.2 percent). Applying the elasticity estimate implies an 11.4 percent decline in an individual firm's harvest due to congestion.

Demand for whales. Whaling market features a demand curve in the form of equation (5), inverted and parameterized as:

$$q_t = \alpha_0 + \alpha_p p_t + \alpha^{\mathrm{gdp}} \ln \mathrm{GDP}_t + \alpha^t t + \alpha^{\mathrm{pet}} \ln \mathrm{Pet}_t + \eta_t, \tag{16}$$

where q_t represents the log of aggregate whale demand and p_t is the log of whale price. GDP_t denotes U.S. real GDP per capita, t is a time trend, and Pet_t, included for $t \geq 1859$, represents the price of petroleum. η_t is an i.i.d. demand shock. I estimate this specification separately before and after 1859, as demand likely shifted after the discovery of petroleum (see Section 2.1 for details).

The whale price may be endogenous because it can co-move with the demand shock η_t. Such shocks shift the demand curve and the equilibrium price, biasing the estimated price elasticity. I address this concern with two supply-side cost shifters as instruments for price. They move supply costs and hence prices (relevance) but are orthogonal to η_t conditional on controls (exclusion).

First, I use whale stocks lagged five years. Because whales are slow-growing, past abundance strongly predicts current stock levels, which affect harvest costs. A five-year lag also exceeds the typical voyage length of two to four years, reducing simultaneity with current harvest outcomes. Current demand for whale products cannot affect whale abundance five years earlier. Any reverse channel would require persistent unobserved shocks that link past harvesting effort to current demand. Macroeconomic controls (GDP per capita and a time trend) absorb the main aggregate demand drivers, so the remaining correlation would have to come from unobserved demand shocks with unusually long persistence that both influenced harvest effort five years earlier and predict current U.S. demand, which seems implausible.

Second, I exploit variation in long-term bond yields in New England.[16] Whaling was highly capital-intensive; firms relied on external finance to purchase ships, outfit crews, and finance long voyages (see Section 2.2). Higher bond yields increase borrowing costs and therefore raise the cost of supply. After controlling for aggregate U.S. demand conditions (GDP per capita and a time trend), regional long-term borrowing costs should be orthogonal to shocks in whale-product demand. Local credit conditions largely reflected banking cycles and regional capital scarcity rather than demand for whale products.

I restrict the IV strategy to the pre-petroleum era (before 1859) for two reasons. First, whale stock exhibits little variation after 1859, undermining its validity as an instrument (Panel B of Figure 1). Between 1859 and 1910, whale stocks remained

[16] The data are constructed by Homer and Sylla (1996).

TABLE 4. Estimates of the whale demand curve

	OLS		IV	
	(1)	(2)	(3)	(4)
Whale price: α_p	-1.875	-0.195	-4.170	-4.170
	(0.880)	(0.078)	(0.733)	
US GDP per capita	-3.771	0.095	3.331	2.138
	(4.220)	(0.249)	(2.458)	(1.378)
Time trend	0.168	-0.040	0.141	-0.118
	(0.031)	(0.005)	(0.023)	(0.027)
Petroleum price		0.072		-0.267
		(0.031)		(0.286)
Observations	55	51	51	51
Sample period	1804-1858	1859-1909	1804-1858	1859-1909
First-stage F-statistic			44.598	
Adjusted R-squared	0.853	0.956	0.800	0.661

Notes: This table reports estimates of the whale demand curve. Columns (1) and (2) present OLS results for the pre- and post-petroleum periods, respectively. Column (3) shows instrumental-variables estimates for the pre-petroleum sample. Column (4) presents post-petroleum estimates, fixing the price coefficient, $\hat{\alpha}_p$, at the elasticity from column (3). Throughout, Newey–West heteroskedasticity- and autocorrelation-consistent standard errors are reported in parentheses.

nearly constant (1.16–1.2 million), in contrast to the sharp decline from 1.48 to 1.2 million before 1858. Second, by the mid-century the whaling center shifted from New Bedford—and New England more broadly—to San Francisco, making New England bond yields no longer a credible cost shifter. Accordingly, for the post-petroleum period, I calibrate the price coefficient α_p using the elasticity estimated from the pre-petroleum period. I also consider a reasonable range of alternative price elasticities, re-estimate the dynamic model, and recompute the counterfactuals. The main welfare and policy implications are not sensitive to these assumptions; results are reported in Online Appendix Tables E5–E6.

Table 4 reports estimates of the whale demand curve. Columns (1) and (2) present OLS estimates for the pre- and post-petroleum eras, with price elasticities of −1.875 and −0.195, respectively. Column (3) shows IV estimates for the pre-petroleum sample; the elasticity rises in absolute magnitude to −4.17, consistent with Kaiser (2013). For the post-petroleum period, I fix the price coefficient α_p at −4.17 and estimate the remaining parameters via OLS. The results in columns (3) and (4) form the basis for subsequent dynamic analyses.

4.2. Dynamic costs and values of whaling

I estimate the dynamic parameters using a full-solution maximum likelihood (see Online Appendix D for methodological discussion). The main computational challenge comes from continuous capacity adjustment: computing best responses for dynamic actions can be highly sensitive to how the continuous state (and action) space is discretized. To address this issue, I adopt the approach of Gowrisankaran and Schmidt-Dengler (2025), which introduces random shocks to marginal adjustment costs and yields stable choice probabilities.[17] Online Appendix A.1 details the derivation of the dynamic choice probabilities and the likelihood function.

Identification of dynamic parameters relies on firms' observed decisions to enter, adjust capacity, and exit, given expected future profits across states and years. For example, a lower mean exit values $\bar{\zeta}$ decreases the predicted probability of exit. Accordingly, when few active firms exit in a given state and year, this pattern results in a smaller estimate for $\bar{\zeta}$. Likewise, a lower mean entry cost $\bar{\kappa}$ raises the probability of entry. Firms' observed investment and divestment frequencies, conditional on state and year, help identify the fixed adjustment costs γ_0^+ and γ_0^-. Conditional on adjustment, the magnitude of capacity changes informs the linear and convex cost parameters γ_1^+, γ_2^+, γ_1^-, and γ_2^-. In particular, higher γ_2^+ and γ_2^- imply larger one-time adjustments are more costly. Variation in adjustment choices across firms, given similar expected values, identifies the standard deviation of the marginal adjustment cost shock σ.

I estimate the model in six phases: 1815–1829, 1830–1844, 1845–1859, 1860–1874, 1875–1889, and 1890–1905. I divide the sample this way because the industry faced structural breaks that shifted firms' beliefs. The discovery of petroleum in 1859 sharply reduced demand for sperm and whale oil.[18] The Civil War (1861–1865) also

[17]With this approach, some capacity adjustment choices can have zero probability, making the log-likelihood function undefined. I address this issue by imposing a small lower bound on predicted choice probabilities, which keeps the objective function well defined. Estimation results are robust to a range of alternative values. In the baseline, I set the lower bound to 10^{-30}. Using alternative values of 10^{-10}, 10^{-20}, 10^{-40}, and 10^{-50} produces almost identical results (Online Appendix Tables E1–E4). On the other hand, Gowrisankaran, Langer, and Reguant (2024), who also apply the Gowrisankaran and Schmidt-Dengler (2025) algorithm, use GMM to handle zero-probability issues. In my setting, however, I find GMM estimates highly sensitive to moment selection and substantially less efficient than MLE.

[18]Since the arrival of petroleum in 1859, whalers speculated that the industry would gradually decline due to substitution. The *Whalemen's Shipping List and Merchants' Transcript* (WSL, July 2, 1861)

TABLE 5. Estimates of whaling industry dynamics

	Unit	1815-29	1830-44	1845-59	1860-74	1875-89	1890-1905
Panel A. Maximum likelihood estimates							
Mean of entry costs: $\bar{\kappa}$	\$000	536.95	370.15	976.68	1898.94	1115.89	2035.29
		(115.37)	(39.43)	(108.33)	(343.31)	(252.19)	(749.73)
Mean of exit scrap values: $\bar{\zeta}$	\$000	130.30	98.32	185.41	275.71	278.22	298.99
		(27.85)	(9.53)	(16.71)	(41.17)	(52.94)	(97.28)
SD of marginal adj. costs: σ	\$/ton	184.65	173.26	237.67	194.73	221.35	549.62
		(32.23)	(16.60)	(20.65)	(22.49)	(40.94)	(257.31)
Investment fixed: γ_0^+	\$000	8.45	5.47	11.18	1.67	0.00	0.00
		(3.65)	(1.14)	(1.87)	(2.20)	(3.05)	(15.77)
Investment linear: γ_1^+	\$/ton	262.09	267.32	377.74	461.23	528.92	916.42
		(29.85)	(14.99)	(20.97)	(35.33)	(53.36)	(308.69)
Investment convex: γ_2^+	\$/ton^2	0.31	0.20	0.34	0.22	0.21	0.70
		(0.06)	(0.02)	(0.03)	(0.03)	(0.04)	(0.34)
Divestment fixed: γ_0^-	\$000	8.70	18.02	20.78	14.87	14.55	43.15
		(4.34)	(2.34)	(2.38)	(2.44)	(4.10)	(22.69)
Divestment linear: γ_1^-	\$/ton^2	0.00	68.88	127.23	243.37	289.71	95.93
		(50.65)	(18.51)	(17.67)	(19.45)	(36.03)	(150.63)
Divestment convex: γ_2^-	\$/ton	0.22	0.27	0.30	0.24	0.30	0.43
		(0.06)	(0.03)	(0.03)	(0.03)	(0.06)	(0.20)
Log likelihood		1186.6	4281.2	4750.5	2390.3	1052.9	488.2
Number of observations		805	3053	3455	1663	705	366
Panel B. Dispersion of estimates							
Entry fixed costs: $\kappa_{it} \sim \text{Exp}(\bar{\kappa})$							
P16	\$000	93.62	64.54	170.29	331.09	194.56	354.86
P84	\$000	984.00	678.33	1789.84	3479.96	2044.97	3729.83
Exit scrap values: $\zeta_{it} \sim \text{Exp}(\bar{\zeta})$							
P16	\$000	22.72	17.14	32.33	48.07	48.51	52.13
P84	\$000	238.79	180.18	339.77	505.26	509.86	547.93
Investment costs $I_{it} = 300$*, with* $\epsilon_{it} \sim \mathcal{N}(0, \sigma^2)$							
P16	\$000	59.94	51.96	83.38	101.23	111.06	172.64
Mean	\$000	115.33	103.94	154.68	159.65	177.47	337.53
P84	\$000	170.73	155.92	225.99	218.07	243.87	502.41
Divestment costs $I_{it} = -300$*, with* $\epsilon_{it} \sim \mathcal{N}(0, \sigma^2)$							
P16	\$000	83.62	73.92	80.80	22.25	21.27	218.07
Mean	\$000	28.23	21.94	9.50	-36.17	-45.14	53.18
P84	\$000	-27.17	-30.03	-61.80	-94.59	-111.54	-111.70

Note: This table reports estimates of dynamic parameters for entry, exit, and capacity adjustment. All dollar values are adjusted to 1880 prices. Each column presents results for the corresponding period. Panel A summarizes maximum likelihood estimates. Standard errors, shown in parentheses, are computed as the square roots of the diagonal elements of the inverse observed information matrix, using numerically evaluated Hessians. Panel B presents dispersion of estimates. The 16th and 84th percentiles (P16 and P84) span approximately one standard deviation around the mean. Entry and exit percentiles are based on exponential draws, so their means match the estimates in Panel A. Investment and divestment percentiles are based on a normal shock evaluated at ±300 tons, close to the median adjustment sizes in Table 1.

disrupted shipping and global trade, making 1860 a natural breakpoint. In the mid-1840s, a series of shocks reshaped the industry: coal oil emerged as a credible future substitute, the California gold rush increased crew desertion, and voyages increasingly shifted toward the Pacific. These events altered the underlying cost structure and firm behavior, motivating a separate phase beginning in 1845. I divide the remaining phases into 15-year intervals for consistency. Finally, because the War of 1812 (1812–1815) severely disrupted the industry and left little firm-level data, the estimation sample begins in 1815.

Table 5 reports the dynamic-parameter estimates. Panel A shows that the estimates are economically plausible and precisely estimated. Mean entry costs range from $203,600 to $370,150 across the nine decades. For example, an entry cost of $537,000 in 1815–1829 is roughly eight years of profits for a typical whaling firm. Mean exit scrap values are lower, ranging from $98,320 to $299,070. Adjustment fixed costs indicate sizable frictions in changing capacity. The linear cost terms imply that investment costs rise with scale, ranging from $262.09 to $916.70 per ton, while divestment values range from $0.00 to $289.66 per ton.[19] Convex cost parameters range from $0.20 to $0.70 per ton squared for investment and from $0.22 to $0.43 for divestment. Finally, the standard deviation of marginal adjustment-cost shocks indicates substantial heterogeneity in adjustment intensity, ranging from $173.26 to $549.85 per ton.

Panel B of Table 5 reports the distribution of costs across phases. The 16th and 84th percentiles (P16 and P84) span roughly one standard deviation around the mean. For entry and exit, percentiles are based on exponential draws, so their means match the estimates in Panel A. For investment and divestment, percentiles are computed using a normal shock evaluated at an adjustment of ±300 tons, which

---

reported:

> 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.

Likewise, 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.

[19]When firms divest, a positive γ_1^- implies a positive linear "value." Total adjustment costs should be assessed jointly with fixed and convex costs; see Panel B of Table 5.

is close to the mean and median adjustment size in Table 1.

Entry cost dispersion widens notably after 1845: the inter-percentile range rises from \$0.6 million in 1830–1844 to \$3.0 million in 1860–1874, suggesting growing heterogeneity in barriers to entry. Exit value dispersion also increases, from \$0.16 million to \$0.3 million over the same period. For a 300-ton change, investment costs range from \$51,960 to \$500,000, while divestment costs range from $-\$111,000$ to \$218,000, implying that divestment can be profitable when adjustment costs are negative. Overall, the interpercentile ranges in adjustment costs indicate substantial heterogeneity even among observationally similar firms.

I evaluate model fit by comparing observed behavior in the data with predictions from the estimated model. Because the counterfactual analysis in Section 5 relies on model-implied behavior, the model must replicate key features of the observed equilibrium. Figure 3 compares the data (solid line) with model-implied paths (dashed line) for total whale harvest (Panel A) and total whaling-vessel capacity (Panel B). The model paths are averages across 300 simulations under the estimated parameters, with shaded bands indicating 95 percent confidence intervals. The figure shows that the model reproduces the industry's rise and fall over nine decades, including the expansion through the mid-1840s and the subsequent long decline.

5. Counterfactuals

Whaling firms impose social costs through stock depletion and congestion, leading to inefficient resource allocation. I begin by defining the policy instruments, the long-run social welfare function, and the shadow prices of externalities (Section 5.1). I then introduce a framework for optimal policy design and quantify welfare and market outcomes under alternative policies (Section 5.2). Finally, I examine how welfare and optimal policies vary with economic conditions (Section 5.3).

5.1. Policy, welfare, and shadow prices

The counterfactual analysis relies on three elements: (i) policy instruments; (ii) a social welfare function that aggregates consumer surplus, producer surplus, and government revenue; and (iii) shadow prices that measure the marginal external costs each firm imposes on the industry.

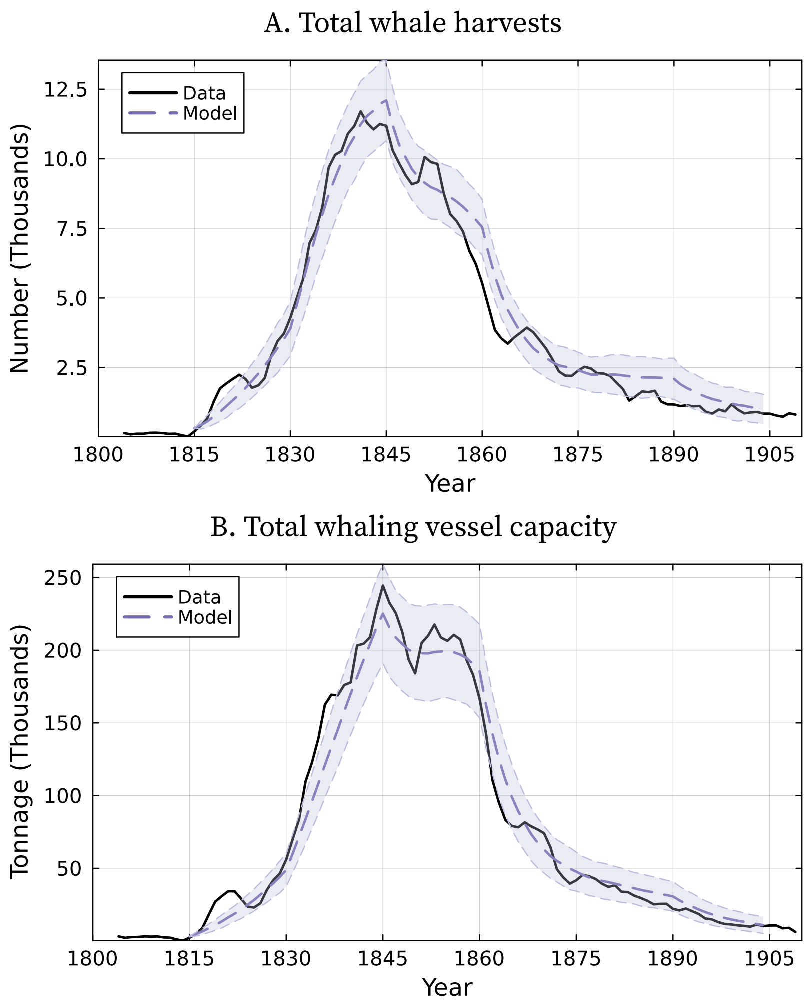

FIGURE 3. Fit of the estimated model

Note: Panel A shows total whale harvest; Panel B shows total whaling-vessel capacity. The black solid line indicates the actual data, and the purple dashed line shows the model-predicted paths. Model outcomes are averaged over 300 simulations of the estimated model, with shaded bands denoting 95 percent confidence intervals.

Policy. I consider two policy instruments: a time-varying per-unit harvest tax τ_t that targets marginal costs; and a time-varying, state-dependent (vessel capacity and productivity) lump-sum license fee $\mathcal{F}_t(x)$ that adjusts operating fixed costs.

I define the complete schedules of policy paths as

$$\tau = \{\tau_t\}_{\forall t}, \quad \mathcal{F} = \{\mathcal{F}_t(x)\}_{\forall t, \forall x \in \mathcal{X}}.$$

and the admissible policy set as

$$\mathcal{C} = \left\{(\tau, \mathcal{F}) \in \mathbb{R}^T \times \mathbb{R}^{T\times|\mathcal{X}|}\right\}.$$

Let ψ_t^c denote the strategy profile induced by a policy path $c \in \mathcal{C}$, reflecting that firms' equilibrium strategies depend on policy. In the observed market equilibrium, ψ_t^c reduces to ψ_t (Eq. 9) because no policies were in place throughout the history of the American whaling industry.

Welfare. With the presence of policies, the year-t profit (6) becomes:

$$\Pi_t\left(s_{it}, \tau_t, \mathcal{F}_t(x_{it})\right) = \left[\mathcal{P}_t(Q_t) - \tau_t\right]\mathcal{H}_t(x_{it}, K_t, W_t) - w_t^L L_{it} - \mathcal{F}_t(x_{it}).$$

The per-period social welfare function $\mathbb{W}_t(\cdot)$ is then:

(17)

$$\mathbb{W}_t(f_t, W_t, \tau_t, \mathcal{F}_t; \psi_t^c) = \underbrace{\int_0^{Q_t} \mathcal{P}_t(\varphi)\mathrm{d}\varphi - \mathcal{P}_t(Q_t)Q_t}_{\text{consumer surplus}}$$
$$+ \underbrace{\sum_{i\in\mathcal{I}_t}\left\{\Pi_t(s_{it}, \tau_t, \mathcal{F}_t(x_{it})) + \mathbf{1}_{\{a_{it}=0\}}\zeta_{it} - \mathbf{1}_{\{a_{it}>0\}}\left[C(I_{it}) + I_{it}\epsilon_{it}\right]\right\} - \sum_{i\in\mathcal{I}_t^{\mathrm{pe}}}\mathbf{1}_{\{a_{it}^{\mathrm{pe}}=1\}}\kappa_{it}}_{\text{producer surplus}}$$
$$+ \underbrace{\sum_{i\in\mathcal{I}_t}\left\{\tau_t Q_{it} + \mathcal{F}_t(x_{it})\right\}}_{\text{government revenue}},$$

where the firm distribution $f_t \in \mathbb{R}^{|\mathcal{X}|}$ is a vector over the individual state space $\mathcal{X}$. This distribution fully characterizes the set of incumbents $\mathcal{I}_t$ and the two aggregate moments (K_t, Q_t) according to equations (7)–(8), given W_t. Welfare also depends on the number of potential entrants, but I omit this for brevity since the sequence $\{\mathcal{I}_t^{\mathrm{pe}}\}_{\forall t}$ is exogenously given.

Long-run social welfare is the sum of the per-period welfare across all future years:

$$\mathbb{W}(c; \psi^c) = \mathbb{E}\left[\sum_{t\geq 1}\rho_s^{t-1}\mathbb{W}_t(f_t, W_t, \tau_t, \mathcal{F}_t; \psi_t^c)\,\middle|\,\psi^c\right] \tag{18}$$

where $\psi^c = \{\psi_t^c\}_{\forall t}$. Given the initial distribution f_1 and whale stock W_1, the strategy profile ψ^c determines the entire industry dynamics and, in turn, period welfares for all years. Expectation $\mathbb{E}[\cdot]$ is taken with respect to the transition of firm productivity (Ω_{it}) and the random shocks $(\kappa_{it}, \zeta_{it}, \epsilon_{it})$. The baseline analysis sets the social discount factor at $\rho_s = 0.97$.

Shadow prices. I define two sets of shadow prices that measure the wedge between social and private incentives (see Online Appendix A.2 for detailed derivations). The *harvest* shadow price $\Lambda_t^h(c)$ measures the uninternalized social cost from an additional unit of whale harvest in year t:[20]

$$\text{(19)} \qquad \Lambda_t^h(c) = -\left[\frac{1}{\rho_s^{t-1}}\frac{\partial \mathbb{W}(c;\psi^c)}{\partial Q_t} - \underbrace{(\mathcal{P}_t(Q_t) - \tau_t)}_{\text{private gain}} - \underbrace{\tau_t}_{\substack{\text{contribution by} \\ \text{the existing policy}}}\right]$$

$$= \sum_{\ell=t+1}^{T} \rho_s^{\ell-t} \left(\prod_{m=t+1}^{\ell-1} \frac{\partial W_{m+1}}{\partial W_m}\right) \mathcal{P}_\ell(Q_\ell) \Upsilon_\ell^W(f_\ell, W_\ell),$$

where $\Upsilon_m^W(f_m, W_m) := \sum_z f_m(z) \frac{\partial \mathcal{H}_m(z, K_m, W_m)}{\partial W_m}$ captures the stock externality. Thus, the harvest shadow price captures all future stock externalities that individual firms do not internalize. The *firm* shadow price $\Lambda_t^f(x;c)$ measures the uninternalized social cost from an additional mass of firms in state x in year t:

$$\text{(20)} \quad \Lambda_t^f(x;c) = -\left[\frac{1}{\rho_s^{t-1}}\frac{\partial \mathbb{W}(c;\psi^c)}{\partial f_t(x)} - \underbrace{\sum_{\ell=t}^{T} \rho_s^{\ell-t} \sum_y M_{t:\ell}(x,y) \Pi_\ell(y, K_\ell, W_\ell, \tau_\ell, \mathcal{F}_\ell(y))}_{\text{private gain}} - \underbrace{\sum_{\ell=t}^{T} \rho_s^{\ell-t} \sum_y M_{t:\ell}(x,y) \mathcal{F}_\ell(y)}_{\substack{\text{contribution by} \\ \text{the existing policy}}}\right]$$

[20] The derivative $\partial\mathbb{W}/\partial Q_t$ already incorporates all equilibrium responses under the already imposed policy. To price only the uninternalized part (i.e., the externality), the shadow prices must subtract (a) the private payoff the decision-maker internalizes and (b) the contribution of policies already in place. Part (a) avoids double counting relative to the firm's first-order condition; part (b) ensures Λ_t^h is incremental to the status quo policy—that is, the additional per-unit tax, on top of τ, required to decentralize the planner's allocation. The firm shadow price follows the same logic.

$$
\begin{aligned}
&= -\mathcal{P}_t(Q_t)K(x)\Upsilon_t^K(f_t, W_t) - \sum_{\ell=t+1}^{T} \rho_s^{\ell-t}\Bigg[\sum_y M_{t:\ell}(x,y)\mathcal{P}_\ell(Q_\ell)K(y)\Upsilon_\ell^K(f_\ell, W_\ell) \\
&\qquad + \left(\sum_{m=t}^{\ell-1} \Delta W_{m+1}^{(x)} \prod_{k=m+1}^{\ell-1} \frac{\partial W_{k+1}}{\partial W_k}\right)\mathcal{P}_\ell(Q_\ell)\Upsilon_\ell^W(f_\ell, W_\ell)\Bigg] \\
&\quad - \sum_{\ell=t}^{T} \rho_s^{\ell-t}\tau_\ell \sum_y M_{t:\ell}(x,y)\mathcal{H}_\ell(y, K_\ell, W_\ell)
\end{aligned}
$$

where $\Upsilon_t^K(f_t, W_t) := \sum_z f_t(z)\,\frac{\partial \mathcal{H}_t(z,K_t,W_t)}{\partial K_t}$ captures the congestion externality. The object $M_{t:\ell}(x, y)$ denotes the probability that a firm in state x at year t transitions to state y at year ℓ. Formally,

$$
M_{t:\ell}(x,y) := \begin{cases} \mathbf{1}\{x = y\}, & \ell = t, \\ M_t \cdots M_{\ell-1}(x,y), & \ell > t \end{cases}
$$

Here, M_m is the matrix representation of the transition kernel $[M_m]_{x,y} = M_m(y \mid x, \psi_m^c)$, that is, the probability that a firm in state x at year m moves to state y at year $m+1$ when all firms follow the strategy profile ψ_m^c. The object $\Delta W_{m+1}^{(x)}$ captures how an additional mass of firms at year t affects the whale stock in year $m+1$. Formally,

$$
\Delta W_{m+1}^{(x)} := \begin{cases} \dfrac{\partial W_{t+1}}{\partial f_t(x)}, & \text{if } m = t, \\ \sum_y M_{t:m}(x,y)\dfrac{\partial W_{m+1}}{\partial f_m(y)}, & \text{if } m > t. \end{cases}
$$

Therefore, the firm shadow price captures the contemporaneous congestion externality, all future congestion and stock externalities, and the extent to which these externalities are already internalized by the existing per-unit taxes.[21]

Collectively, I write complete paths of shadow prices as:

$$
\Lambda^h(c) = \left\{\Lambda_t^h(c)\right\}_{\forall t} \quad \text{and} \quad \Lambda^f(c) = \left\{\Lambda_t^f(x; c)\right\}_{\forall x \in \mathcal{X}, \forall t},
$$

implying that the harvest shadow price is time-varying, while the firm shadow price varies across both time and firm states (vessel capacity and productivity).

[21]This result is reminiscent of Carlton and Loury (1980)'s equation (8), in the sense that their lump-sum tax includes a subtraction term corresponding to the Pigouvian tax.

5.2. Optimal policy design

A regulator seeks policies that internalize the social costs of whaling. Prior studies typically solve the social planner's optimal-control problem to directly characterize the Pareto-efficient allocation. However, this approach becomes infeasible in the presence of many heterogeneous, forward-looking firms. The industry's state space is high-dimensional, making the planner's problem intractable.

An alternative, drawing on theoretical insights, is to use shadow prices to design a policy that decentralizes the planner's desired allocation. Yet shadow prices depend on the prevailing policy because firms' equilibrium behavior responds endogenously to it. Thus, a necessary condition for optimal policy design is a fixed point in which the policy induces behavior that generates shadow prices consistent with that same policy.

To achieve this, I propose an iterative fixed-point framework that relies solely on decentralized equilibrium solutions. Policies are updated repeatedly until they equal the shadow prices implied by firms' equilibrium behavior. The fixed point determines the optimal policies $c^* = (\tau^*, \mathcal{F}^*)$ and satisfies the following condition:

$$c^* = \left(\Lambda^h(c^*), \Lambda^f(c^*)\right) \tag{21}$$

Proposition A.1 in Online Appendix A establishes conditions under which the fixed point exists and is unique. The proof relies on the contraction mapping theorem, demonstrating that the iterative process is a contraction and converges geometrically to a unique fixed point.

Figure 4 provides a graphical companion to Proposition A.1, illustrating a single-period example with only a per-unit tax. The figure shows the private marginal cost (*PMC*), social marginal cost (*SMC*), and the demand curve (*D*). This simplified scenario reduces the fixed-point condition to $\tau^* = \Lambda^h(\tau^*, \mathbf{0}) = \Lambda^h(\tau^*)$. The initial equilibrium begins at $E^0 = (Q^0, P^0)$. The first iteration shifts the equilibrium to E^1 with the policy $\tau_1 = \Lambda^h(\mathbf{0})$. Subsequent iterations continue updating the tax $(\tau^2, \tau^3, \ldots)$ and equilibrium $(E^2, E^3, \ldots)$ until the fixed-point condition $\tau^* = \Lambda^h(\tau^*)$ holds. Proposition A.1 generalizes this logic to the joint policy with per-unit taxes and lump-sum fees and establishes that the induced mapping is a contraction.

Applying the proposition, I solve for the joint policy consisting of per-unit harvest taxes and lump-sum license fees. Panel A of Figure 5 plots the resulting time-varying

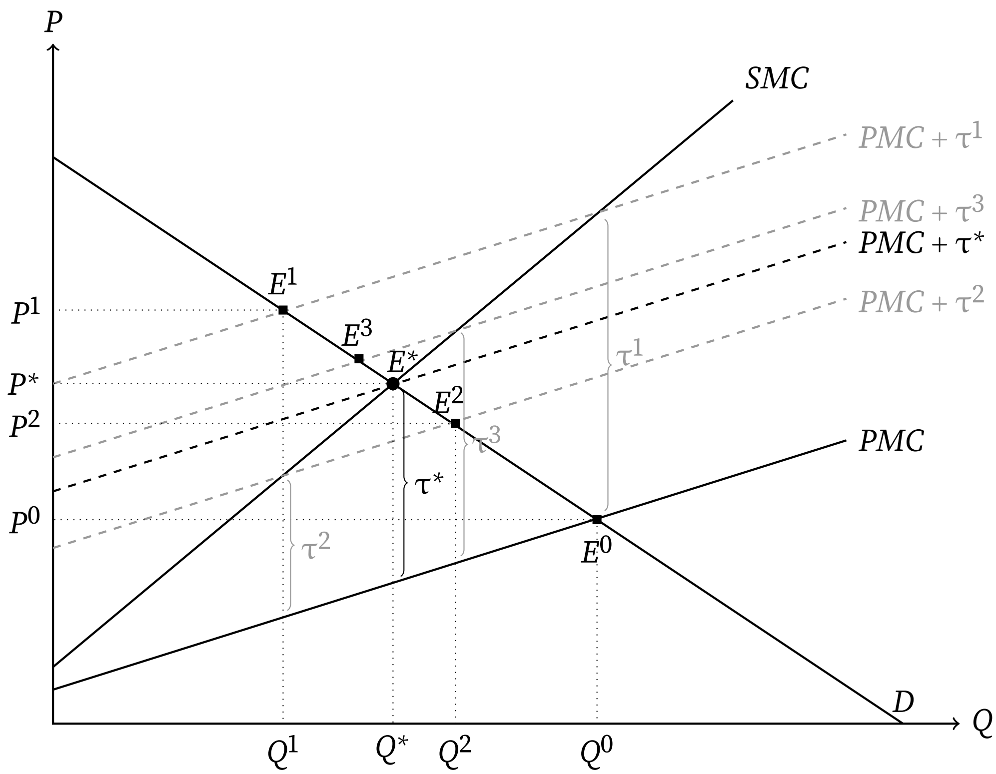

FIGURE 4. Static example of Pigouvian per-unit tax iterations

Note: The curve *PMC* denotes private marginal cost, and *SMC* represents social marginal cost; *D* is the market demand curve. The pre-policy equilibrium is at $E^0 = (Q^0, P^0)$. The socially optimal allocation is given by $E^* = (Q^*, P^*)$. The first iteration computes the harvest shadow price at E^0 and $\tau^1 = \Lambda^h(\tau^0) = \Lambda^h(\tau^0, \mathbf{0})$, where $\tau^0 = \mathbf{0}$. This tax shifts the equilibrium to E^1. The second iteration updates the tax to $\tau^2 = \Lambda^h(\tau^1)$, yielding equilibrium E^2. The third iteration gives $\tau^3 = \Lambda^h(\tau^2)$. The process continues until convergence at E^*, where the fixed point condition $\tau^* = \Lambda^h(\tau^*)$ holds.

optimal per-unit tax $\{\tau_t^*\}_{\forall t}$. The tax rises steadily from about $150 (in 1880 dollars) per unit in 1820 to over $400 by the mid-1840s, reflecting the growing severity of stock externalities as the industry expands. Whale stocks became increasingly depleted, and each additional harvest imposed larger costs on an increasing number of firms and vessels. After 1860, as the industry contracted, the shadow price of additional harvesting declined. Accordingly, the optimal tax fell gradually to roughly $40 by 1900.

Panel B of Figure 5 plots the average lump-sum license fees by year. Because license fees are time-varying and state dependent, I summarize them for visualization by computing annual averages using the equilibrium firm distribution f_t.

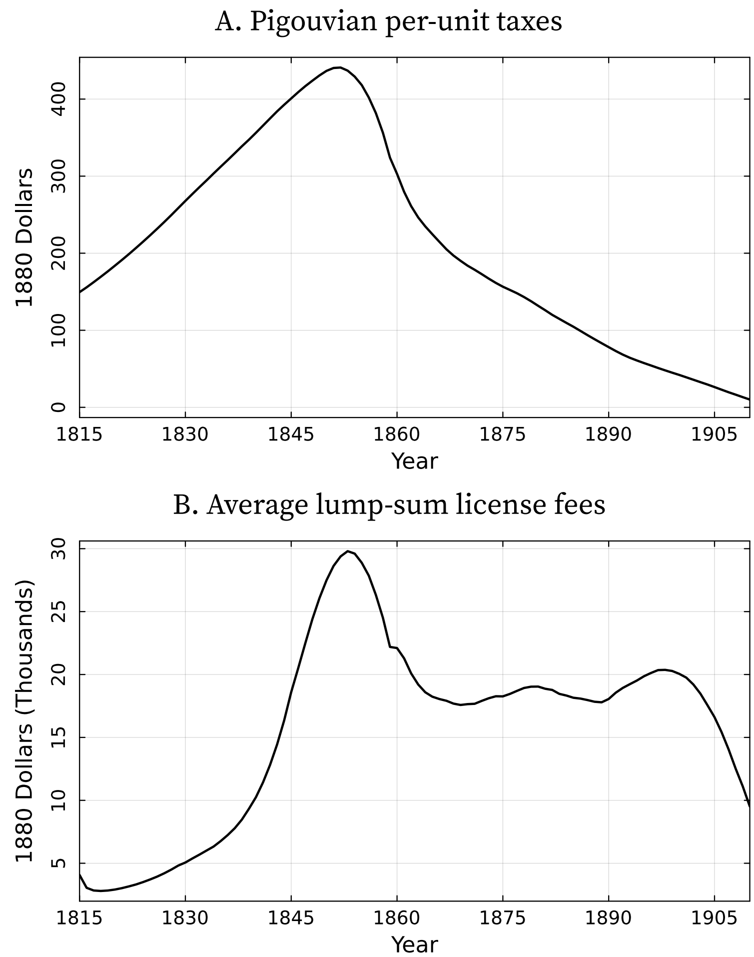

FIGURE 5. Fixed-point optimal policy

Note: Per-unit taxes τ^* and lump-sum license fees $\mathcal{F}^*$ are the fixed point of the iterative process $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$. The figure reports averages from 300 simulations. Panel A shows per-unit taxes. Panel B shows average lump-sum fees computed using the equilibrium firm distribution f_t: $\bar{\mathcal{F}}_t^* = \sum_x [f_t(x)/\sum_x f_t(x)]\mathcal{F}_t^*(x)$.

The fees are generally low in the early years, rise steadily through about 1850, and decline thereafter. Firms with greater capacity and higher productivity pay larger fees because they impose stronger congestion externalities. Operating more vessels directly expands aggregate capacity, intensifying congestion for all participants. Highly productive firms are more likely to invest rather than exit or divest, thereby exacerbating congestion over time. The magnitude of the average license fees—for example, about $30,000 in 1850—reflects substantial congestion externalities that are not fully addressed by per-unit taxes alone.

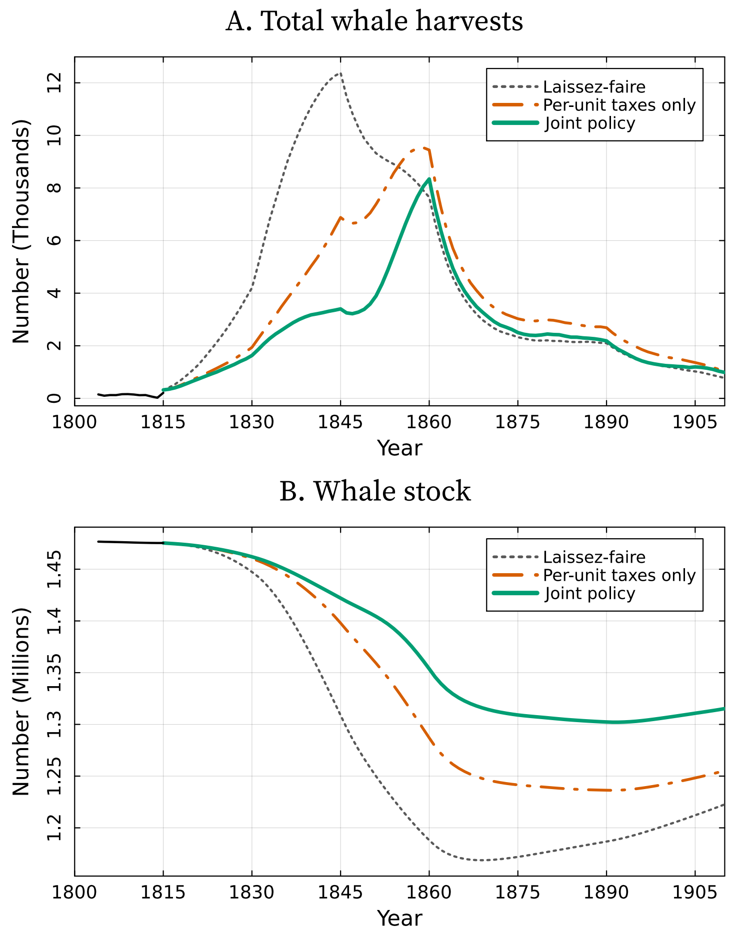

FIGURE 6. Market outcomes under observed allocation and policy scenarios

Note: The lines show averages from 300 simulations. Each panel compares trends under the observed allocation (laissez-faire; dashed line), per-unit taxes only $\tau^* = \Lambda^h(\tau^*, \mathbf{0})$ with dash-dotted line, and the joint policy $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$ with solid line. Laissez-faire corresponds to the model outcomes in Figure 3. Panel A displays total whale harvests, while Panel B shows whale stock.

Figure 6 compares market outcomes under the observed allocation with those under alternative policy scenarios. Panel A reports total whale harvests, and Panel B reports whale stock levels. Policy interventions substantially slow both harvest rates and stock depletion. A per-unit tax markedly reduces overharvesting; for example, it lowers catches in 1845 from roughly 12,000 to 7,000 whales. Relative to the per-unit-tax-only policy, the joint policy further reduces early harvests by curbing firm entry and investment through the combined effects of per-unit and lump-sum fees. In 1845, for instance, catches fall from 7,000 to 3,600 whales. This correction prevents the sharp stock decline during the golden-age period and yields

TABLE 6. Welfare outcomes under observed allocation and policy scenarios

	Pre–1860	Post–1860	Total
Panel A: Laissez-faire			
Consumer surplus	32.8	7.6	40.4
Producer surplus	–53.9	28.5	–25.5
Social welfare	–21.1	36.1	14.9
Panel B: Per-unit taxes only			
Consumer surplus	24.1	9.0	33.2
Producer surplus	–9.6	24.0	14.4
Government surplus	32.9	5.5	38.4
Social welfare	47.4	38.6	86.0
vs. Laissez-faire	[+324.3%]	[+7.1%]	[+476.2%]
Panel C: Joint policy			
Consumer surplus	17.9	7.9	25.8
Producer surplus	7.9	19.1	27.1
Government surplus	42.1	13.1	55.2
Social welfare	67.9	40.2	108.1
vs. Laissez-faire	[+421.4%]	[+11.5%]	[+624.2%]
vs. Per-unit taxes only	[+43.3%]	[+4.1%]	[+25.7%]

Note: Welfare outcomes are averaged over 300 simulations and expressed in millions of 1880 prices. "Pre–1860" and "Post–1860" report period contributions; "Total" is their sum. Panel A is the observed allocation outcomes from the estimated model. Panel B shows outcomes under Pigouvian per-unit taxes only, solving the fixed-point $\tau^* = \Lambda^h(\tau^*, \mathbf{0})$. Panel C combines both per-unit taxes and lump-sum fees, where the fixed-point condition is $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$. Percent changes in social welfare are shown in square brackets. The social discount factor ρ_s is set to 0.97.

a more balanced, efficient harvesting path in later years.

Table 6 summarizes welfare outcomes under the observed allocation and alternative policy scenarios. In Panel A, total social welfare is approximately $14.9 million, comprising consumer surplus of $40.4 million and producer surplus of -$25.5 million. The negative producer surplus reflects excessive entry and investment before 1860, when firms incurred large fixed costs and generated substantial negative externalities. Panel B shows that introducing per-unit taxes substantially corrects these inefficiencies, raising social welfare to $86 million, an increase of $71.1 million (476.2%) relative to laissez-faire. Most of this improvement arises in the pre-1860 period, when welfare increases by $68.5 million (324.3%). Panel C combines per-unit taxes with lump-sum fees. Total social welfare rises further to $108.1 million, exceeding laissez-fair by $93.2 million (624.2%) and the per-unit-tax-only case by \$22.1 million (25.7%).

Discussion. The additional welfare gains from lump-sum fees arise from addressing congestion externalities and overcapacity, which per-unit taxes do not correct. Equations (19) and (20) show that firm shadow prices retain congestion components even after conditioning on per-unit taxes set equal to harvest shadow prices. In (20), the last component exactly cancels the future stock-externality term (the third block) when per-unit taxes $\{\tau_t\}_{\forall t}$ are set based on the harvest shadow prices. This implies that, absent congestion externalities, correctly specified per-unit taxes would internalize the full dynamic externality. To verify this result, I examine an environment without congestion externalities. In that case, once Pigouvian per-unit taxes are specified based on harvest shadow prices, the state-dependent lump-sum fees should converge to zero by (19) and (20). The computational results confirm this prediction: without congestion externalities, lump-sum fees become negligible, and per-unit Pigouvian taxes alone achieve the long-run social optimum.

5.3. Comparative statics

This subsection examines how welfare and optimal policy respond to changes in economic fundamentals. I consider two scenarios: (a) higher productivity growth and (b) stronger demand. These forces are pervasive in modern industries, driven by technological progress and expanding markets. Although each scenario directly benefits the industry, it can also intensify externalities in common-pool resources, making the net welfare effect ambiguous.

If productivity growth accelerates, firms can harvest more with a given capacity, pushing whale stocks toward depletion more rapidly. Higher productivity sustains profitability even as stocks decline, encouraging continued entry and investment. Similarly, stronger demand raises equilibrium prices, stimulates industry expansion, and magnifies externalities. In both cases, the ultimate welfare effect depends on how these forces interact with the common-pool nature of the resource.

I vary one primitive at a time and recompute the policy counterfactuals. Under higher TFP growth, I raise the annual productivity growth rate from 1.3% (Column 4 of Table 3) to 2.3%. Under stronger demand, I scale up the GDP-driven demand shifter (Columns 3 and 4 of Table 4) by 3%. All other primitives remain at their baseline values. Because the magnitude of the resulting policy changes depends on

TABLE 7. Social welfare under policy scenarios across alternative environments

	Pre–1860	Post–1860	Total
Panel A: Baseline			
Laissez-faire	–21.1	36.1	14.9
Per-unit taxes only	47.4	38.6	86.0
Joint policy	67.9	40.2	108.1
vs. Laissez-faire	[+421.4%]	[+11.5%]	[+624.2%]
Panel B: Higher whaling productivity growth rate			
Laissez-faire	–30.9	37.0	6.2
Per-unit taxes only	74.0	47.4	121.5
Joint policy	88.9	52.0	140.9
vs. Laissez-faire	[+387.9%]	[+40.5%]	[+2188.0%]
Panel C: Stronger demand for whales			
Laissez-faire	–33.0	39.2	6.2
Per-unit taxes only	54.2	43.7	97.9
Joint policy	75.6	45.8	121.4
vs. Laissez-faire	[+329.3%]	[+16.8%]	[+1844.8%]

Note: Welfare outcomes are averaged over 300 simulations and reproted in millions of 1880 prices. "Pre–1860" and "Post–1860" report period contributions; "Total" is their sum. Panel A is the baseline, which corresponds to Table 6. Panel B raises the annual productivity growth rate from 1.3% (Col. 5, Table 3) to 2.3%. Panel C scales up the GDP-driven demand shifter (Columns 3 and 4 of Table 4) by 3%. Percent changes in social welfare for the joint policy (relative to laissez-faire) are shown in square brackets. The social discount factor ρ_S is set to 0.97.

the size of these shifts, I emphasize the direction of adjustment rather than precise levels.

Table 7 reports how changes in economic fundamentals affect welfare outcomes and the effectiveness of policy. Panel A replicates the baseline results from Table 6, while Panels B and C consider the higher-productivity and stronger-demand environments.

A striking pattern emerges. Under laissez-faire, social welfare declines when productivity growth is higher or demand is stronger. Compared to $14.9 million in Panel A, social welfare falls to $6.2 million in Panels B and C. Although stronger fundamentals raise firms' private returns, they also intensify entry and investment while delaying exit and divestment, thereby amplifying externalities. The resulting industry expansion accelerates rent dissipation, so the deadweight losses from amplified externalities outweigh the gains from improved economic fundamentals.

By contrast, when appropriate policy instruments are in place, welfare rises substantially in these more favorable environments. Under the joint policy, total welfare increases to $140.9 million in Panel B and $121.4 million in Panel C, exceeding even the baseline policy outcome. Thus, long-run growth in productivity and demand acts as an amplifier of inefficiency under open access but as a multiplier of welfare gains under optimal regulation. Economic progress translates into higher social surplus rather than faster rent dissipation only when policy internalizes externalities.

6. Conclusion

This paper studies the long-run commons problem through the lens of strategic firm dynamics. Using a newly constructed firm-level panel from the 19th-century American whaling industry, I develop and estimate a dynamic model in which firms enter, exit, and invest while generating stock depletion and congestion. For counterfactual policy analysis, I quantify the shadow prices of externalities and propose a fixed-point framework that sets policy instruments equal to these shadow prices. This approach overcomes computational challenges in designing optimal policy in dynamic games with externalities.

The results have direct implications for modern common-pool resource regulation. Policies that operate only on the intensive margin, such as per-unit taxes or tradable harvest permits, can reduce overharvesting but need not discipline excess entry and capital accumulation. Achieving the long-run social optimum generally requires complementary instruments that target fixed-cost margins, such as entry regulation or state-dependent license fees. While such restrictions are common in practice, they are often shaped by historical participation or political constraints rather than efficiency considerations. My framework provides a design principle by mapping equilibrium behavior into implementable shadow-price-based policies.

Future work can extend the empirical framework along several dimensions. One is to allow for spatially differentiated stocks and congestion. Another is to compare alternative institutions, such as cap-and-trade under different initial allocations, with the two-part policy analyzed here. A third is to introduce uncertainty in regeneration and technological change to study adaptive policy design. Together, these extensions would clarify when market-based instruments most effectively promote long-run efficiency.

References

Ackerberg, Daniel A, Kevin Caves, and Garth Frazer. 2015. "Identification properties of recent production function estimators." *Econometrica* 83 (6): 2411–2451.

Aguirregabiria, Victor, Allan Collard-Wexler, and Stephen P Ryan. 2021. "Dynamic games in empirical industrial organization." In *Handbook of Industrial Organization*, vol. 4, 225–343: Elsevier.

Aguirregabiria, Victor, and Junichi Suzuki. 2014. "Identification and counterfactuals in dynamic models of market entry and exit." *Quantitative Marketing and Economics* 12: 267–304.

Aronoff, Daniel, and Will Rafey. 2023. "Conservation priorities and environmental offsets: Markets for Florida wetlands.", National Bureau of Economic Research.

Aspelund, Karl M. 2025. "Redistribution in Environmental Permit Markets: Transfers and Efficiency Costs with Trade Restrictions." Working paper.

Baggio, Michele, and Metin M. Cosgel. 2024. "Racial diversity and team performance: Evidence from the American offshore whaling industry." Working paper.

Bajari, Patrick, C Lanier Benkard, and Jonathan Levin. 2007. "Estimating dynamic models of imperfect competition." *Econometrica* 75 (5): 1331–1370.

Baker, C Scott, and Phillip J Clapham. 2004. "Modelling the past and future of whales and whaling." *Trends in Ecology & Evolution* 19 (7): 365–371.

Benkard, C Lanier, Przemyslaw Jeziorski, and Gabriel Weintraub. 2024. "Transitional Market Dynamics in Complex Environments.", National Bureau of Economic Research.

Blundell, Richard, and Stephen Bond. 2000. "GMM estimation with persistent panel data: an application to production functions." *Econometric Reviews* 19 (3): 321–340.

Breiwick, Jeffrey M, and Anne E York. 2009. "Stock assessment." In *Encyclopedia of Marine Mammals*, 1110–1115: Elsevier.

Butters, R. Andrew, Jackson Dorsey, and Gautam Gowrisankaran. 2025. "Soaking Up the Sun: Battery Investment, Renewable Energy, and Market Equilibrium." *Econometrica* 93 (3): 891–927.

Caoui, El Hadi. 2023. "Estimating the costs of standardization: Evidence from the movie industry." *Review of Economic Studies* 90 (2): 597–633.

Carlton, Dennis W, and Glenn C Loury. 1980. "The limitations of Pigouvian taxes as a long-run remedy for externalities." *Quarterly Journal of Economics* 95 (3): 559–566.

Carter, Susan B, Scott Sigmund Gartner, Michael R Haines, Alan L Olmstead, Richard Sutch, Gavin Wright et al. 2006. *Historical statistics of the United States: millennial edition*. vol. 3: Cambridge University Press New York.

Chen, Luming. 2024. "The Dynamic Efficiency of Policy Uncertainty: Evidence from the Wind Industry." Working paper.

Costello, Christopher, Steven D Gaines, and John Lynham. 2008. "Can catch shares prevent fisheries collapse?" *Science* 321 (5896): 1678–1681.

Costello, Christopher, Daniel Ovando, Tyler Clavelle, C Kent Strauss, Ray Hilborn, Michael C Melnychuk, Trevor A Branch, Steven D Gaines, Cody S Szuwalski, Reniel B Cabral et al. 2016. "Global fishery prospects under contrasting management regimes." *Proceedings of the National Academy of Sciences* 113 (18): 5125–5129.

Davis, Lance E, Robert E Gallman, and Karin Gleiter. 2007. *In Pursuit of Leviathan: Technology, Institutions, Productivity, and Profits in American Whaling, 1816-1906*.: University of Chicago Press.

Davis, Lance E, Robert E Gallman, and Teresa D Hutchins. 1987. "Technology, productivity, and profits: British-American whaling competition in the North Atlantic, 1816–1842." *Oxford Economic Papers* 39 (4): 738–759.

De Loecker, Jan, Pinelopi K Goldberg, Amit K Khandelwal, and Nina Pavcnik. 2016. "Prices, markups, and trade reform." *Econometrica* 84 (2): 445–510.

Doraszelski, Ulrich, and Mark Satterthwaite. 2010. "Computable Markov-perfect industry dynamics." *The RAND Journal of Economics* 41 (2): 215–243.

Elliott, Jonathan T. 2024. "Investment, emissions, and reliability in electricity markets." Working paper.

Englander, Gabriel. 2023. "Information and spillovers from targeting policy in peru's anchoveta fishery." *American Economic Journal: Economic Policy* 15 (4): 390–427.

Ericson, Richard, and Ariel Pakes. 1995. "Markov-perfect industry dynamics: A framework for empirical work." *Review of Economic Studies* 62 (1): 53–82.

Fowlie, Meredith, Mar Reguant, and Stephen P Ryan. 2016. "Market-based emissions regulation and industry dynamics." *Journal of Political Economy* 124 (1): 249–302.

Gordon, H Scott. 1954. "The economic theory of a common-property resource: the fishery." *Journal of Political Economy* 62 (2): 124–142.

Gowrisankaran, Gautam, Ashley Langer, and Mar Reguant. 2024. "Energy transitions in regulated markets.", National Bureau of Economic Research.

Gowrisankaran, Gautam, Ashley Langer, and Wendan Zhang. 2025. "Policy uncertainty in the market for coal electricity: The case of air toxics standards." *Journal of Political Economy* 133 (6): 1757–1795.

Gowrisankaran, Gautam, and Philipp Schmidt-Dengler. 2025. "A computable dynamic oligopoly model of capacity investment." Working paper.

Hardin, Garrett. 1968. "The tragedy of the commons." *Science* 162 (3859): 1243–1248.

Hilt, Eric. 2006. “Incentives in corporations: Evidence from the American whaling industry.” *Journal of Law and Economics* 49 (1): 197–227.

Hilt, Eric. 2007. “Investment and diversification in the American whaling industry.” *Journal of Economic History* 67 (2): 292–314.

Hilt, Eric. 2008. “The negative trade-off between risk and incentives: Evidence from the American whaling industry.” *Explorations in Economic History* 45 (4): 424–444.

Ho, Phuong. 2023. “Why Is Trading So Important in Cap and Trade? The Role of Economies of Scale and Productivity.” *Working paper*.

Homer, Sidney, and Richard Eugene Sylla. 1996. *A history of interest rates.*: Rutgers University Press.

Huang, Ling, and Martin D Smith. 2014. “The dynamic efficiency costs of common-pool resource exploitation.” *American Economic Review* 104 (12): 4071–4103.

Ifrach, Bar, and Gabriel Y Weintraub. 2017. “A framework for dynamic oligopoly in concentrated industries.” *Review of Economic Studies* 84 (3): 1106–1150.

Kaiser, Brooks A. 2013. “Bioeconomic factors of natural resource transitions: The US sperm whale fishery of the 19th century.” Working paper.

Kalouptsidi, Myrto. 2018. “Detection and impact of industrial subsidies: The case of Chinese shipbuilding.” *Review of Economic Studies* 85 (2): 1111–1158.

Levinsohn, James, and Amil Petrin. 2003. “Estimating production functions using inputs to control for unobservables.” *Review of Economic Studies* 70 (2): 317–341.

Libecap, Gary D. 2024. “Variation in State Response to Open Access: Constituent Characteristics.” *NBER Working Paper* (No. 32021).

Mankiw, N Gregory, and Michael D Whinston. 1986. “Free entry and social inefficiency.” *The RAND Journal of Economics*: 48–58.

Moment, David. 1957. “The Business of Whaling in America in the 1850’s.” *Business History Review* 31 (3): 261–291.

Mystic Seaport Museum, New Bedford Whaling Museum, and Nantucket Historical Association. 2024a. “American Offshore Whaling Crew Lists.”. https://whalinghistory.org/av/crew/about/. Database, accessed 2025-09-23.

Mystic Seaport Museum, New Bedford Whaling Museum, and Nantucket Historical Association. 2024b. “American Offshore Whaling Voyages: A Database.”. https://whalinghistory.org/av/. Database, accessed 2025-09-23.

Nicholas, Tom. 2019. *VC: an american history*.: Harvard University Press.

Olley, Steven, and Ariel Pakes. 1996. “The dynamics of productivity in the telecommunications equipment industry.” *Econometrica* 64 (6): 1263–1297.

Ostrom, Elinor. 1990. *Governing the commons: The evolution of institutions for collective action.*:

Cambridge university press.

Rubens, Michael. 2023. “Market structure, oligopsony power, and productivity.” *American Economic Review* 113 (9): 2382–2410.

Rust, John. 1987. “Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher.” *Econometrica*: 999–1033.

Ryan, Stephen P. 2012. “The costs of environmental regulation in a concentrated industry.” *Econometrica* 80 (3): 1019–1061.

Segerson, Kathleen, and Dale Squires. 1993. “Capacity utilization under regulatory constraints.” *Review of Economics and Statistics*: 76–85.

Smith, Vernon L. 1969. “On models of commercial fishing.” *Journal of Political Economy* 77 (2): 181–198.

Stavins, Robert N. 2011. “The problem of the commons: Still unsettled after 100 years.” *American Economic Review* 101 (1): 81–108.

Tillman, Michael F, and Gregory P Donovan. 1983. “Historical whaling records.” In *International Workshop on Historical Whaling Records (1977: Sharon, Mass.),* International Whaling Commission.

Tower, Walter Sheldon. 1907. *A history of the American whale fishery*.: Pub. for the University.

Whitehead, Hal. 2002. “Estimates of the current global population size and historical trajectory for sperm whales.” *Marine Ecology Progress Series* 242: 295–304.

Navigating the Commons: Online Appendices

Yangkeun Yun

February 19, 2026

Appendix A. Technical appendix

A.1. Details of dynamic choice probabilties and likelihood function

Following Hotz and Miller (1993) and Gowrisankaran and Schmidt-Dengler (2025), I define the choice–specific value for selecting capacity K^j as

$$v_{it}^{j} = -C(K^{j}, K_{it}; \gamma) + \rho\, \mathbb{E}_t \left[V_{t+1}(s_{it+1}, \psi_{t+1}; \Theta) \,|\, s_{it}, \psi_t \right] \tag{A.1}$$

where j indexes the j-th grid of capacity space $\mathcal{K}$.

From the incumbent's Bellman equation (12), the firm chooses K^j if and only if $v_{it}^{j} - I_{it}^{j}\epsilon_{it} \;\geq\; v_{it}^{k} - I_{it}^{k}\epsilon_{it},\ \forall k \neq j$, where $I_{it}^{j} = K^j - (1-\delta)K_{it}$. Monotonicity of $I(\cdot, K_{it})$ implies that for $1 \leq j < k \leq J$, the firm prefers K^j to K^k if and only if

$$\epsilon_{it} \geq \frac{v_{it}^{k} - v_{it}^{j}}{I_{it}^{k} - I_{it}^{j}} = \epsilon_{it}(j, k)$$

where the last equality defines "ϵ-cutoff" following Gowrisankaran and Schmidt-Dengler (2025). Intuitively, if the firm draws a higher (less favorable) cost shock than the cutoff, it chooses a smaller capacity. The firm chooses K^j if and only if $\underline{\epsilon}_{it}^{j} \leq \epsilon_{it} < \overline{\epsilon}_{it}^{j}$, where

$$\underline{\epsilon}_{it}^{j} = \begin{cases} \epsilon_{it}\big(j,\, j+1\big), & j < J, \\ -\infty, & j = J, \end{cases} \qquad \overline{\epsilon}_{it}^{j} = \begin{cases} +\infty, & j = 1, \\ \epsilon_{it}\big(j-1,\, j\big), & j > 1. \end{cases}$$

Then the probability of choosing capacity K^j, conditional on survival ($a_{it} > 0$), is given by

$$\Pr_t \left(a_{it} = K^j \,\middle|\, a_{it} > 0, s_{it}, \psi_t \right) = \Phi\left(\frac{\overline{\epsilon}_{it}^{j}}{\sigma} \right) - \Phi\left(\frac{\underline{\epsilon}_{it}^{j}}{\sigma} \right), \tag{A.2}$$

where $\Phi(\cdot)$ denotes the standard normal cumulative distribution function.

Another contribution of Gowrisankaran and Schmidt-Dengler (2025) is the computation of the conditional mean of the ϵ-shock without requiring numerical integration. Using the properties of the truncated normal distribution, the conditional mean of the ϵ-shock is, $\forall j = 1, \ldots, J$,

$$\text{(A.3)} \qquad \mathbb{E}\left[\epsilon_{it} \mid a_{it} = K^j, s_{it}, \psi_t\right] = \frac{\phi\left(\underline{\epsilon}_{it}^j/\sigma\right) - \phi\left(\overline{\epsilon}_{it}^j/\sigma\right)}{\Phi\left(\overline{\epsilon}_{it}^j/\sigma\right) - \Phi\left(\underline{\epsilon}_{it}^j/\sigma\right)},$$

where $\phi(\cdot)$ is the standard normal probability density function. By using (A.1), (A.2), and (A.3), I define the expected continuation value as

$$\text{(A.4)} \qquad V_{it}^{\text{cont}} = \sum_{j>0} \Pr_t\left(a_{it} = K^j \,\middle|\, a_{it} > 0, s_{it}, \psi_t\right)\left\{v_{it}^j - I_{it}^j\, \mathbb{E}\left[\epsilon_{it} \mid a_{it} = K^j, s_{it}, \psi_t\right]\right\}$$

From the expected continuation value and the exponential exit scrap draw $\zeta_{it} \sim \text{Exp}(\zeta)$, the probability of exit is

$$\text{(A.5)} \qquad \Pr_t\left(a_{it} = 0 \,\middle|\, s_{it}, \psi_t\right) = \Pr\left(\zeta_{it} \geq V_{it}^{\text{cont}}\right) = \exp\left(-V_{it}^{\text{cont}}/\zeta\right).$$

Combining the period payoff (6), the exit probability (A.5), and the expected continuation value (A.4) yields a closed-form solution to the incumbent's Bellman equation:

$$V_t(s_{it}, \psi_t) = \Pi_t(s_{it}) + \Pr_t\left(a_{it} = 0 \,\middle|\, s_{it}, \psi_t\right)\left(\zeta + V_{it}^{\text{cont}}\right) + \left[1 - \Pr_t\left(a_{it} = 0 \,\middle|\, s_{it}, \psi_t\right)\right] V_{it}^{\text{cont}}.$$

The joint probability of survival and choosing capacity level K^j is given by

$$\text{(A.6)} \quad \Pr_t\left(a_{it} = K^j \,\middle|\, s_{it}, \psi_t\right) = \left(1 - \Pr_t\left\{a_{it} = 0 \,\middle|\, s_{it}, \psi_t\right\}\right) \Pr_t\left(a_{it} = K^j \,\middle|\, a_{it} > 0, s_{it}, \psi_t\right).$$

Finally, given the exponential entry cost draw $\kappa_{it} \sim \text{Exp}(\kappa)$, the probability of entry is

$$\text{(A.7)} \qquad \begin{aligned} \Pr_t\left(a_{it}^{\text{pe}} = 1 \,\middle|\, s_{it}, \psi_t\right) &= \Pr\left(\kappa_{it} \leq \rho\, \mathbb{E}_t[V_{t+1}(s_{it+1}, \psi_{t+1})|s_t, \psi_t]\right) \\ &= 1 - \exp\left(-\rho\, \mathbb{E}_t[V_{t+1}(s_{it+1}, \psi_{t+1})|s_t, \psi_t]/\kappa\right). \end{aligned}$$

Using equations (A.5), (A.6), and (A.7), the conditional choice probabilities for exit, capacity adjustment, and entry define the likelihood function. The contribution of an action profile $a = \left\{ \left\{ a_{it} \right\}_{\forall i \in \mathcal{I}_t}, \left\{ a_{it}^{\text{pe}} \right\}_{i \in \mathcal{I}_t^{\text{pe}}} \right\}_{t=1}^{T}$ to the joint likelihood is

$$\mathcal{L}(a; \Theta) = \prod_{t=1}^{T} \left[\prod_{i \in \mathcal{I}_t} \Pr_t(a_{it} \,|\, s_{it}, \psi_t, \Theta) \prod_{i \in \mathcal{I}_t^{\text{pe}}} \Pr_t(a_{it}^{\text{pe}} \,|\, s_{it}, \psi_t, \Theta) \right].$$

The maximum likelihood estimator is then defined as

$$\widehat{\Theta} = \arg\max_{\Theta} \ \ln\left[\mathcal{L}(a; \Theta)\right]$$

A.2. Shadow prices

This section derives the shadow prices defined in Section 5.1. I suppress the dynamic decision components, which do not enter the derivatives below. Using equation (17), per-period social welfare can be written as

$$\text{(A.8)} \qquad \mathbb{W}_t(f_t, W_t, \tau_t, \mathcal{F}_t) = \int_0^{Q_t} \mathcal{P}_t(\varphi)\, \mathrm{d}\varphi - \mathcal{P}_t(Q_t) Q_t + \sum_z f_t(z) \left\{ \mathcal{P}_t(Q_t) \mathcal{H}_t(z, K_t, W_t) - w_t^L L(K(z)) \right\},$$

where the simplification follows because producer payments $(\tau_t, \mathcal{F}_t)$ cancel with government revenue.

Harvest shadow price. The derivative of long-run social welfare with respect to Q_t is

$$\text{(A.9)} \qquad \frac{\partial \mathbb{W}(c; \psi^c)}{\partial Q_t} = \rho_s^{t-1} \frac{\partial \mathbb{W}_t(\cdot)}{\partial Q_t} + \frac{\partial W_{t+1}}{\partial Q_t} \sum_{\ell=t+1}^{T} \rho_s^{\ell-1} \left(\prod_{m=t+1}^{\ell-1} \frac{\partial W_{m+1}}{\partial W_m} \right) \frac{\partial \mathbb{W}_\ell(\cdot)}{\partial W_\ell}.$$

By the envelope argument, $\frac{\partial \mathbb{W}_t(\cdot)}{\partial Q_t} = \mathcal{P}_t(Q_t)$. Moreover, the stock transition equation (1) implies

(A.10)

$$\frac{\partial W_{t+1}}{\partial Q_t} = -1,$$

$$\frac{\partial W_{m+1}}{\partial W_m} = 1 + r\left[1 - \left(\frac{W_m}{W_1}\right)^z\right] + rW_m\left[-z\left(\frac{W_m}{W_1}\right)^{z-1}\frac{1}{W_1}\right] - \sum_{z\in\mathcal{X}} f_m(z)\frac{\partial\mathcal{H}_m(z,K_m,W_m)}{\partial W_m},$$

where $\Upsilon_m^W(f_m, W_m) := \sum_z f_m(z)\frac{\partial\mathcal{H}_m(z,K_m,W_m)}{\partial W_m}$. Finally,

$$\frac{\partial\mathbb{W}_\ell(\cdot)}{\partial W_\ell} = \mathcal{P}_\ell(Q_\ell)\Upsilon_\ell^W(f_\ell, W_\ell). \tag{A.11}$$

Substituting these expressions into (A.9) yields

$$\frac{\partial\mathbb{W}(c;\psi^c)}{\partial Q_t} = \rho_s^{t-1}\mathcal{P}_t(Q_t) - \sum_{\ell=t+1}^{T}\rho_s^{\ell-1}\mathcal{P}_\ell(Q_\ell)\left(\prod_{m=t+1}^{\ell-1}\frac{\partial W_{m+1}}{\partial W_m}\right)\Upsilon_\ell^W(f_\ell, W_\ell).$$

Therefore, equation (19) implies

(A.12)

$$\Lambda_t^h(c) = \sum_{\ell=t+1}^{T}\rho_s^{\ell-t}\left(\prod_{m=t+1}^{\ell-1}\frac{\partial W_{m+1}}{\partial W_m}\right)\frac{\partial\mathbb{W}_\ell(\cdot)}{\partial W_\ell} = \sum_{\ell=t+1}^{T}\rho_s^{\ell-t}\left(\prod_{m=t+1}^{\ell-1}\frac{\partial W_{m+1}}{\partial W_m}\right)\mathcal{P}_\ell(Q_\ell)\Upsilon_\ell^W(f_\ell, W_\ell).$$

Firm shadow price. The derivative of long-run welfare with respect to $f_t(x)$ satisfies the forward decomposition

(A.13)

$$\frac{\partial\mathbb{W}(c;\psi^c)}{\partial f_t(x)} = \rho_s^{t-1}\frac{\partial\mathbb{W}_t(\cdot)}{\partial f_t(x)} + \sum_{\ell=t+1}^{T}\rho_s^{\ell-1}\left[\sum_y M_{t:\ell}(x,y)\frac{\partial\mathbb{W}_\ell(\cdot)}{\partial f_\ell(y)} + \left(\sum_{m=t}^{\ell-1}\Delta W_{m+1}^{(x)}\prod_{k=m+1}^{\ell-1}\frac{\partial W_{k+1}}{\partial W_k}\right)\frac{\partial\mathbb{W}_\ell(\cdot)}{\partial W_\ell}\right],$$

where

$$\Delta W_{m+1}^{(x)} := \begin{cases}\dfrac{\partial W_{t+1}}{\partial f_t(x)}, & \text{if } m = t,\\ \sum_y M_{t:m}(x,y)\dfrac{\partial W_{m+1}}{\partial f_m(y)}, & \text{if } m > t.\end{cases}$$

The period-t derivative is

$$\frac{\partial\mathbb{W}_t(\cdot)}{\partial f_t(x)} = \mathcal{P}_t(Q_t)\mathcal{H}_t(x,K_t,W_t) - w_t^L L(K(x)) + \mathcal{P}_t(Q_t)K(x)\Upsilon_t^K(f_t,W_t), \tag{A.14}$$

where $\Upsilon_t^K(f_t, W_t) := \sum_z f_t(z)\,\frac{\partial\mathcal{H}_t(z,K_t,W_t)}{\partial K_t}$. Finally, from the stock transition equation (1),

$$\text{(A.15)} \qquad \frac{\partial W_{t+1}}{\partial f_t(x)} = \frac{\partial W_t}{\partial Q_t}\frac{\partial Q_t}{\partial f_t(x)} = -\left[\mathcal{H}_t(x, K_t, W_t) + K(x)\Upsilon_t^K(f_t, W_t)\right].$$

Combining (A.10), (A.11), (A.14), and (A.15) in (A.13) gives the expression for $\frac{\partial \mathbb{W}(c;\psi^c)}{\partial f_t(x)}$. Substituting this derivative into (**??**) yields equation (A.16).

(A.16)

$$\Lambda_t^f(x;\, c) = -\mathcal{P}_t(Q_t)K(x)\Upsilon_t^K(f_t, W_t) - \sum_{\ell=t+1}^{T}\rho_s^{\ell-t}\Bigg[\sum_y M_{t:\ell}(x,y)\mathcal{P}_\ell(Q_\ell)K(y)\Upsilon_\ell^K(f_\ell, W_\ell)$$
$$+\left(\sum_{m=t}^{\ell-1}\Delta W_{m+1}^{(x)}\prod_{k=m+1}^{\ell-1}\frac{\partial W_{k+1}}{\partial W_k}\right)\mathcal{P}_\ell(Q_\ell)\Upsilon_\ell^W(f_\ell, W_\ell)\Bigg] - \sum_{\ell=t}^{T}\rho_s^{\ell-t}\tau_\ell\sum_y M_{t:\ell}(x,y)\mathcal{H}_\ell(y, K_\ell, W_\ell).$$

A.3. Fixed-point framework for optimal policy design

PROPOSITION A.1. *For any $c = (\tau, \mathcal{F}) \in \mathcal{C}$, define the operator $\mathscr{T} : c \mapsto (\Lambda^h(c), \Lambda^f(c))$, and equip $\mathcal{C}$ with the sup norm $\|\cdot\|_\infty$. Let $PMC_t(\cdot)$ denote the market-level marginal private harvesting cost. Assume there exist constants $L_{HD}, L_{FQ}, L_{Ff} > 0$, $m_{\min} > 0$, and $m_f < \infty$ such that for every t, x, Q_t, and c:*

(A1) *Slope dominance:*

$$PMC_t'(Q_t) - \mathcal{P}_t'(Q_t) \geq m_{\min}.$$

(A2) *Harvest shadow price: $\Lambda_t^h(c)$ is differentiable in Q_t and*

$$\left|\frac{\partial \Lambda_t^h(c)}{\partial Q_t}\right| \leq L_{HD}.$$

(A3) *Firm shadow price: $\Lambda_t^f(x;c)$ is differentiable in $(Q_t, f_t(x))$ and*

$$\left|\frac{\partial \Lambda_t^f(x;c)}{\partial Q_t}\right| \leq L_{FQ}, \qquad \left|\frac{\partial \Lambda_t^f(x;c)}{\partial f_t(x)}\right| \leq L_{Ff}.$$

Moreover, for any $c, \tilde{c} \in \mathcal{C}$,

$$\sup_{t,x}|f_t(x) - \tilde{f}_t(x)| \leq m_f\,\|\mathcal{F} - \tilde{\mathcal{F}}\|_\infty.$$

Define

$$M := \max\left\{\frac{L_{HD}}{m_{\min}}, \frac{L_{FQ}}{m_{\min}}, L_{Ff}m_f\right\} < 1.$$

Then:

(a) $\mathscr{T}$ *is a contraction on* $(\mathcal{C}, \|\cdot\|_\infty)$ *with contraction constant* M.

(b) *There exists a unique fixed point* $c^* \in \mathcal{C}$ *satisfying* $c^* = \mathscr{T}(c^*)$.

(c) *For any initial* $c^0 \in \mathcal{C}$, *the iterates* $c^{m+1} := \mathscr{T}(c^m)$ *satisfy*

$$\|c^m - c^*\|_\infty \le M^m \|c^0 - c^*\|_\infty.$$

PROOF. Fix $c = (\tau, \mathcal{F})$ and $\tilde{c} = (\tilde{\tau}, \tilde{\mathcal{F}})$. Let $\Delta\tau := \tau - \tilde{\tau}$ and $\Delta\mathcal{F} := \mathcal{F} - \tilde{\mathcal{F}}$, and write $\|\cdot\| \equiv \|\cdot\|_\infty$. For each t, let Q_t and $\tilde{Q}_t$ denote the corresponding equilibrium market quantities satisfying

$$PMC_t(Q_t) + \tau_t = \mathcal{P}_t(Q_t), \qquad PMC_t(\tilde{Q}_t) + \tilde{\tau}_t = \mathcal{P}_t(\tilde{Q}_t).$$

Step 1: bounding $Q - \tilde{Q}$. Define $\mathscr{B}_t(q) := PMC_t(q) - \mathcal{P}_t(q)$. Then $\mathscr{B}_t(Q_t) = -\tau_t$ and $\mathscr{B}_t(\tilde{Q}_t) = -\tilde{\tau}_t$. By Assumption A1, $\mathscr{B}_t'(q) \ge m_{\min}$. By the mean-value theorem,

$$|Q_t - \tilde{Q}_t| \le \frac{1}{m_{\min}} |\tau_t - \tilde{\tau}_t|.$$

Taking the supremum over t,

$$\|Q - \tilde{Q}\| \le \frac{1}{m_{\min}} \|\Delta\tau\|. \tag{P1}$$

Step 2: bounding harvest shadow price. By Assumption A2 and the mean-value theorem,

$$|\Lambda_t^h(c) - \Lambda_t^h(\tilde{c})| \le L_{HD}|Q_t - \tilde{Q}_t|.$$

Hence

$$\|\Lambda^h(c) - \Lambda^h(\tilde{c})\| \le \frac{L_{HD}}{m_{\min}} \|\Delta\tau\|. \tag{P2}$$

Step 3: bounding firm shadow price. Fix (t, x). Consider the two equilibrium points $(Q_t, f_t(x))$ and $(\tilde{Q}_t, \tilde{f}_t(x))$. Using the triangle inequality,

$$|\Lambda_t^f(x;c) - \Lambda_t^f(x;\tilde{c})| \le \left|\Lambda_t^f(x)\big|_{Q_t, f_t(x)} - \Lambda_t^f(x)\big|_{\tilde{Q}_t, f_t(x)}\right| + \left|\Lambda_t^f(x)\big|_{\tilde{Q}_t, f_t(x)} - \Lambda_t^f(x)\big|_{\tilde{Q}_t, \tilde{f}_t(x)}\right|.$$

Applying the mean-value theorem and Assumption A3,

$$|\Lambda_t^f(x;c) - \Lambda_t^f(x;\tilde{c})| \le L_{FQ}|Q_t - \tilde{Q}_t| + L_{Ff}|f_t(x) - \tilde{f}_t(x)|.$$

Taking suprema and using (P1),

$$\|\Lambda^f(c) - \Lambda^f(\tilde{c})\| \le \frac{L_{FQ}}{m_{\min}}\|\Delta\tau\| + L_{Ff}m_f\|\Delta\mathcal{F}\|. \tag{P3}$$

Step 4: contraction. By definition,

$$\|\mathscr{T}(c) - \mathscr{T}(\tilde{c})\| = \max\{\|\Lambda^h(c) - \Lambda^h(\tilde{c})\|, \|\Lambda^f(c) - \Lambda^f(\tilde{c})\|\}.$$

Using (P2) and (P3),

$$\|\mathscr{T}(c) - \mathscr{T}(\tilde{c})\| \le M\|c - \tilde{c}\|.$$

Since $M < 1$, $\mathscr{T}$ is a contraction. Then, Banach's fixed-point theorem implies existence and uniqueness of c^* and geometric convergence of iterates:

$$\|c^m - c^*\| \le M^m\|c^0 - c^*\|.$$

□

Appendix B. 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).

B.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)

B.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, 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 C. Details of data

This section describes a detail of data sources and modifications.

C.1. *Voyage Database*

Name of vessel.	Class.	Tonnage.	Captain.	Managing owner or agent.	Whaling-ground.	Date—		Result of voyage.		
						Of sailing.	Of arrival.	Sperm-oil.	Whale-oil.	Whalebone.
1835.										
Nantucket, Mass.								*Bbls.*	*Bbls.*	*Lbs.*
Barclay	Ship	30[illegible]	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	314	Peter Coffin	Paul Mitchell's Sons	do	June 29	Nov. 12, 1838	1,398	16	......
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	265	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	296	Obed Luce, jr	Griffin Barney	Atlantic & Ind	July 15	July 9, 1837	302	1,570	......
Mary Mitchell	do	354	Samuel Joy	S. B. Tuck	Pacific Ocean	July 14	May 17, 1838	596	1,974	......
Mary	do	369	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 C1. Sample of Starbuck (1878)

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

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 C1 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/).

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

For some voyage observations, the *Voyage Database* is missing owner/agent information, especially before the 1830s. To address this issue, I rely on *Ship Registers* from each port, mainly New Bedford.

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 C2. A sample of ship registers of New Bedford: Vessel *Abigail*

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

For instance, the *Ship Registers of New Bedford* includes information of owners for vessels departed from ports nearby New Bedford, Massachusetts. Figure C2 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*.

C.3. 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:

$$Q_{it}^{SW} = \frac{Q_{it}^{\text{soil}}}{25} + 0.1 \times \frac{Q_{it}^{\text{soil}}}{25}$$
$$Q_{it}^{BWO} = \frac{Q_{it}^{\text{woil}}}{60} + 0.1 \times \frac{Q_{it}^{\text{woil}}}{60}$$

where Q_{it}^{SW} is the number of sperm whales harvested by firm i in year t, Q_{it}^{soil} is the barrels of sperm oil, Q_{it}^{BWO} is the number of baleen whales harvested to make

TABLE C1. 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 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.

whale oil, and Q_{it}^{woil} is the barrels of whale oil. From logbook database,[1] I assume that an average baleen 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:

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

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

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

C.4. Aggregate demand variables

Table C1 summarizes the demand-side statistics for the American whaling industry.

[1]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 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.

Appendix D. Estimation strategy for a nonstationary global whaling market

This section discusses considerations behind the modeling and estimation approaches, a full-solution method instead of conditional choice probability approaches.

The first reason relates to counterfactual analysis. This paper evaluates firms' behavioral responses to regulatory, environmental, and economic changes in exploiting shared resources. Such analysis requires counterfactual equilibrium strategies obtained by resolving the model under alternative conditions. For example, imposing a tax on whaling output raises costs and alters firms' equilibrium behavior. To assess these changes, the model must be solved again. A full-solution approach ensures consistency between estimation and counterfactual exercises, enabling direct and reliable comparisons of model outcomes.

The second reason relates to estimation. The global whaling industry presents significant empirical challenges due to the nonstationary evolution of economic fundamentals.[2] Figures E1, 1, and 2 illustrate the dynamics of American whaling, including demand shifts, whale stock transition, and technological advancements. Since this paper examines whaling firms' entry, exit, and investment decisions in such a nonstationary environment, the firms' policy functions must adapt over time. In essence, time becomes an additional state variable, making policy functions explicitly time-dependent, as detailed in Section 3.3.

The cross-sectional and time-series characteristics of the data reduce the effective sample size for every year, complicating the application of two-step estimation methods (e.g., Aguirregabiria and Mira 2007; Bajari, Benkard, and Levin 2007; Pakes, Ostrovsky, and Berry 2007; Pesendorfer and Schmidt-Dengler 2008). First-step nonparametric estimates of conditional choice probabilities become imprecise when only a few or no choices are observed in certain states. The model has to fill in these blanks, and hence this paper takes a full-solution approach instead, as in Benkard (2004), Goettler and Gordon (2011), Igami (2017), Elliott (2024).

[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.

Appendix E. Additional tables and figures

TABLE E1. Dynamic estimates with a lower bound on choice probabilities of 10^{-10}

	Unit	1815-29	1830-44	1845-59	1860-74	1875-89	1890-1905
Mean of entry costs: $\bar{\kappa}$	\$000	536.87	370.15	976.67	1898.93	1116.21	2035.09
		(115.33)	(39.43)	(108.32)	(343.31)	(252.33)	(749.65)
Mean of exit scrap values: $\bar{\zeta}$	\$000	130.29	98.32	185.40	275.71	278.26	298.98
		(27.84)	(9.53)	(16.71)	(41.17)	(52.96)	(97.28)
SD of marginal adj. costs: σ	\$/ton	184.67	173.26	237.67	194.73	221.27	549.62
		(32.24)	(16.60)	(20.65)	(22.49)	(40.89)	(257.31)
Investment fixed: γ_0^+	\$000	8.45	5.47	11.18	1.67	0.00	0.00
		(3.65)	(1.14)	(1.87)	(2.20)	(3.04)	(15.77)
Investment linear: γ_1^+	\$/ton	262.13	267.32	377.74	461.23	528.87	916.41
		(29.86)	(14.99)	(20.97)	(35.33)	(53.33)	(308.70)
Investment convex: γ_2^+	\$/ton^2	0.31	0.20	0.34	0.22	0.21	0.70
		(0.06)	(0.02)	(0.03)	(0.03)	(0.04)	(0.34)
Divestment fixed: γ_0^-	\$000	8.71	18.02	20.78	14.87	14.54	43.15
		(4.35)	(2.34)	(2.38)	(2.44)	(4.10)	(22.69)
Divestment linear: γ_1^-	\$/ton^2	0.00	68.88	127.23	243.37	289.76	95.84
		(50.66)	(18.51)	(17.67)	(19.45)	(36.02)	(150.69)
Divestment convex: γ_2^-	\$/ton	0.22	0.27	0.30	0.24	0.30	0.43
		(0.06)	(0.03)	(0.03)	(0.03)	(0.06)	(0.20)
Log likelihood		1186.6	4281.2	4750.5	2390.3	1052.9	488.2
Number of observations		805	3053	3455	1663	705	366

Note: This table reports estimates of the dynamic parameters governing entry, exit, and capacity adjustment, with the probability lower bound set at 10^{-10}. All dollar values are adjusted to 1880 prices. Baseline results are reported in Table 5.

TABLE E2. Dynamic estimates with a lower bound on choice probabilities of 10^{-20}

	Unit	1815-29	1830-44	1845-59	1860-74	1875-89	1890-1905
Mean of entry costs: $\bar{\kappa}$	\$000	536.95	370.15	976.68	1898.94	1117.53	2037.60
		(115.37)	(39.43)	(108.33)	(343.31)	(252.85)	(751.33)
Mean of exit scrap values: $\bar{\zeta}$	\$000	130.30	98.32	185.41	275.71	278.55	299.27
		(27.85)	(9.53)	(16.71)	(41.17)	(53.07)	(97.46)
SD of marginal adj. costs: σ	\$/ton	184.65	173.26	237.67	194.73	221.32	550.11
		(32.23)	(16.60)	(20.65)	(22.49)	(40.92)	(257.95)
Investment fixed: γ_0^+	\$000	8.45	5.47	11.18	1.67	0.00	0.00
		(3.65)	(1.14)	(1.87)	(2.20)	(3.04)	(15.78)
Investment linear: γ_1^+	\$/ton	262.09	267.32	377.74	461.23	528.87	916.94
		(29.85)	(14.99)	(20.97)	(35.33)	(53.35)	(309.36)
Investment convex: γ_2^+	\$/ton^2	0.31	0.20	0.34	0.22	0.21	0.70
		(0.06)	(0.02)	(0.03)	(0.03)	(0.04)	(0.34)
Divestment fixed: γ_0^-	\$000	8.70	18.02	20.78	14.87	14.53	43.19
		(4.34)	(2.34)	(2.38)	(2.44)	(4.10)	(22.74)
Divestment linear: γ_1^-	\$/ton^2	0.00	68.88	127.23	243.37	289.59	95.73
		(50.65)	(18.51)	(17.67)	(19.45)	(36.02)	(150.87)
Divestment convex: γ_2^-	\$/ton	0.22	0.27	0.30	0.24	0.30	0.43
		(0.06)	(0.03)	(0.03)	(0.03)	(0.06)	(0.20)
Log likelihood		1186.6	4281.2	4750.5	2390.3	1052.9	488.2
Number of observations		805	3053	3455	1663	705	366

Note: This table reports estimates of the dynamic parameters governing entry, exit, and capacity adjustment, with the probability lower bound set at 10^{-20}. All dollar values are adjusted to 1880 prices. Baseline results are reported in Table 5.

TABLE E3. Dynamic estimates with a lower bound on choice probabilities of 10^{-40}

	Unit	1815-29	1830-44	1845-59	1860-74	1875-89	1890-1905
Mean of entry costs: $\bar{\kappa}$	\$000	536.95	370.15	976.68	1898.94	1116.33	2038.46
		(115.37)	(39.43)	(108.33)	(343.31)	(252.37)	(751.93)
Mean of exit scrap values: $\bar{\zeta}$	\$000	130.30	98.32	185.41	275.71	278.30	299.34
		(27.85)	(9.53)	(16.71)	(41.17)	(52.97)	(97.51)
SD of marginal adj. costs: σ	\$/ton	184.65	173.26	237.67	194.73	221.27	550.09
		(32.23)	(16.60)	(20.65)	(22.49)	(40.89)	(257.93)
Investment fixed: γ_0^+	\$000	8.45	5.47	11.18	1.67	0.00	0.00
		(3.65)	(1.14)	(1.87)	(2.20)	(3.04)	(15.78)
Investment linear: γ_1^+	\$/ton	262.09	267.32	377.74	461.23	528.83	916.93
		(29.85)	(14.99)	(20.97)	(35.33)	(53.32)	(309.35)
Investment convex: γ_2^+	\$/ton^2	0.31	0.20	0.34	0.22	0.21	0.70
		(0.06)	(0.02)	(0.03)	(0.03)	(0.04)	(0.34)
Divestment fixed: γ_0^-	\$000	8.70	18.02	20.78	14.87	14.53	43.19
		(4.34)	(2.34)	(2.38)	(2.44)	(4.10)	(22.74)
Divestment linear: γ_1^-	\$/ton^2	0.00	68.88	127.23	243.37	289.68	95.79
		(50.65)	(18.51)	(17.67)	(19.45)	(36.02)	(150.84)
Divestment convex: γ_2^-	\$/ton	0.22	0.27	0.30	0.24	0.30	0.43
		(0.06)	(0.03)	(0.03)	(0.03)	(0.06)	(0.20)
Log likelihood		1186.6	4281.2	4750.5	2390.3	1052.9	488.2
Number of observations		805	3053	3455	1663	705	366

Note: This table reports estimates of the dynamic parameters governing entry, exit, and capacity adjustment, with the probability lower bound set at 10^{-40}. All dollar values are adjusted to 1880 prices. Baseline results are reported in Table 5.

TABLE E4. Dynamic estimates with a lower bound on choice probabilities of 10^{-50}

	Unit	1815-29	1830-44	1845-59	1860-74	1875-89	1890-1905
Mean of entry costs: $\bar{\kappa}$	\$000	536.95	370.15	976.68	1898.94	1117.27	2038.67
		(115.37)	(39.43)	(108.33)	(343.31)	(252.74)	(752.08)
Mean of exit scrap values: $\bar{\zeta}$	\$000	130.30	98.32	185.41	275.71	278.51	299.36
		(27.85)	(9.53)	(16.71)	(41.17)	(53.05)	(97.52)
SD of marginal adj. costs: σ	\$/ton	184.65	173.26	237.67	194.73	221.23	550.13
		(32.23)	(16.60)	(20.65)	(22.49)	(40.87)	(257.98)
Investment fixed: γ_0^+	\$000	8.45	5.47	11.18	1.67	0.00	0.00
		(3.65)	(1.14)	(1.87)	(2.20)	(3.04)	(15.78)
Investment linear: γ_1^+	\$/ton	262.09	267.32	377.74	461.23	528.76	916.98
		(29.85)	(14.99)	(20.97)	(35.33)	(53.30)	(309.40)
Investment convex: γ_2^+	\$/ton^2	0.31	0.20	0.34	0.22	0.21	0.70
		(0.06)	(0.02)	(0.03)	(0.03)	(0.04)	(0.34)
Divestment fixed: γ_0^-	\$000	8.70	18.02	20.78	14.87	14.53	43.19
		(4.34)	(2.34)	(2.38)	(2.44)	(4.09)	(22.74)
Divestment linear: γ_1^-	\$/ton^2	0.00	68.88	127.23	243.37	289.61	95.78
		(50.65)	(18.51)	(17.67)	(19.45)	(36.01)	(150.86)
Divestment convex: γ_2^-	\$/ton	0.22	0.27	0.30	0.24	0.30	0.43
		(0.06)	(0.03)	(0.03)	(0.03)	(0.06)	(0.20)
Log likelihood		1186.6	4281.2	4750.5	2390.3	1052.9	488.2
Number of observations		805	3053	3455	1663	705	366

Note: This table reports estimates of the dynamic parameters governing entry, exit, and capacity adjustment, with the probability lower bound set at 10^{-50}. All dollar values are adjusted to 1880 prices. Baseline results are reported in Table 5.

TABLE E5. Welfare implications of policies with a lower bound on post-petroleum demand elasticity

	Pre–1860	Post–1860	Total
Panel A: Laissez-faire			
Consumer surplus	32.8	21.3	54.1
Producer surplus	–53.9	29.0	–24.9
Social welfare	–21.1	50.3	29.2
Panel B: Per-unit taxes only			
Consumer surplus	24.5	23.6	48.2
Producer surplus	–12.7	25.7	13.0
Government surplus	32.6	4.6	37.3
Social welfare	44.5	54.0	98.5
vs. Laissez-faire	[+310.5%]	[+7.3%]	[+237.2%]
Panel C: Joint policy			
Consumer surplus	17.8	21.9	39.7
Producer surplus	8.1	19.5	27.6
Government surplus	42.0	12.5	54.5
Social welfare	68.0	53.9	121.9
vs. Laissez-faire	[+421.8%]	[+7.1%]	[+317.4%]
vs. Per-unit taxes only	[+52.9%]	[–0.2%]	[+23.8%]

Note: Welfare outcomes are averaged over 300 simulations and reported in millions of 1880 dollars. "Pre–1860" and "Post–1860" report period contributions; "Total" is their sum. Panel A reports outcomes under the observed allocation in the estimated model. Panel B reports outcomes under Pigouvian per-unit taxes only, solving the fixed point $\tau^* = \Lambda^h(\tau^*, \mathbf{0})$. Panel C reports outcomes under the joint policy with per-unit taxes and lump-sum fees, where the fixed-point condition is $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$. Percent changes in total social welfare relative to Panel A are shown in square brackets. The social discount factor ρ_s is set to 0.97. Post-petroleum demand elasticity is set to −0.2. Table 6 reports results under the baseline elasticity.

TABLE E6. Welfare implications of policies with a upper bound on post-petroleum demand elasticity

	Pre–1860	Post–1860	Total
Panel A: Laissez-faire			
Consumer surplus	32.8	6.1	38.9
Producer surplus	–53.9	28.6	–25.4
Social welfare	–21.1	34.7	13.6
Panel B: Per-unit taxes only			
Consumer surplus	24.1	7.4	31.5
Producer surplus	–9.6	23.8	14.2
Government surplus	32.9	5.7	38.6
Social welfare	47.4	36.9	84.3
vs. Laissez-faire	[+324.3%]	[+6.4%]	[+520.7%]
Panel C: Joint policy			
Consumer surplus	17.8	6.4	24.2
Producer surplus	8.0	18.9	26.9
Government surplus	42.1	13.3	55.3
Social welfare	67.9	38.6	106.5
vs. Laissez-faire	[+421.4%]	[+11.2%]	[+684.1%]
vs. Per-unit taxes only	[+43.2%]	[+4.6%]	[+26.3%]

Note: Welfare outcomes are averaged over 300 simulations and reported in millions of 1880 dollars. "Pre–1860" and "Post–1860" report period contributions; "Total" is their sum. Panel A reports outcomes under the observed allocation in the estimated model. Panel B reports outcomes under Pigouvian per-unit taxes only, solving the fixed point $\tau^* = \Lambda^h(\tau^*, \mathbf{0})$. Panel C reports outcomes under the joint policy with per-unit taxes and lump-sum fees, where the fixed-point condition is $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$. Percent changes in total social welfare relative to Panel A are shown in square brackets. The social discount factor ρ_s is set to 0.97. Post-petroleum demand elasticity is set to −0.5. Table 6 reports results under the baseline elasticity.

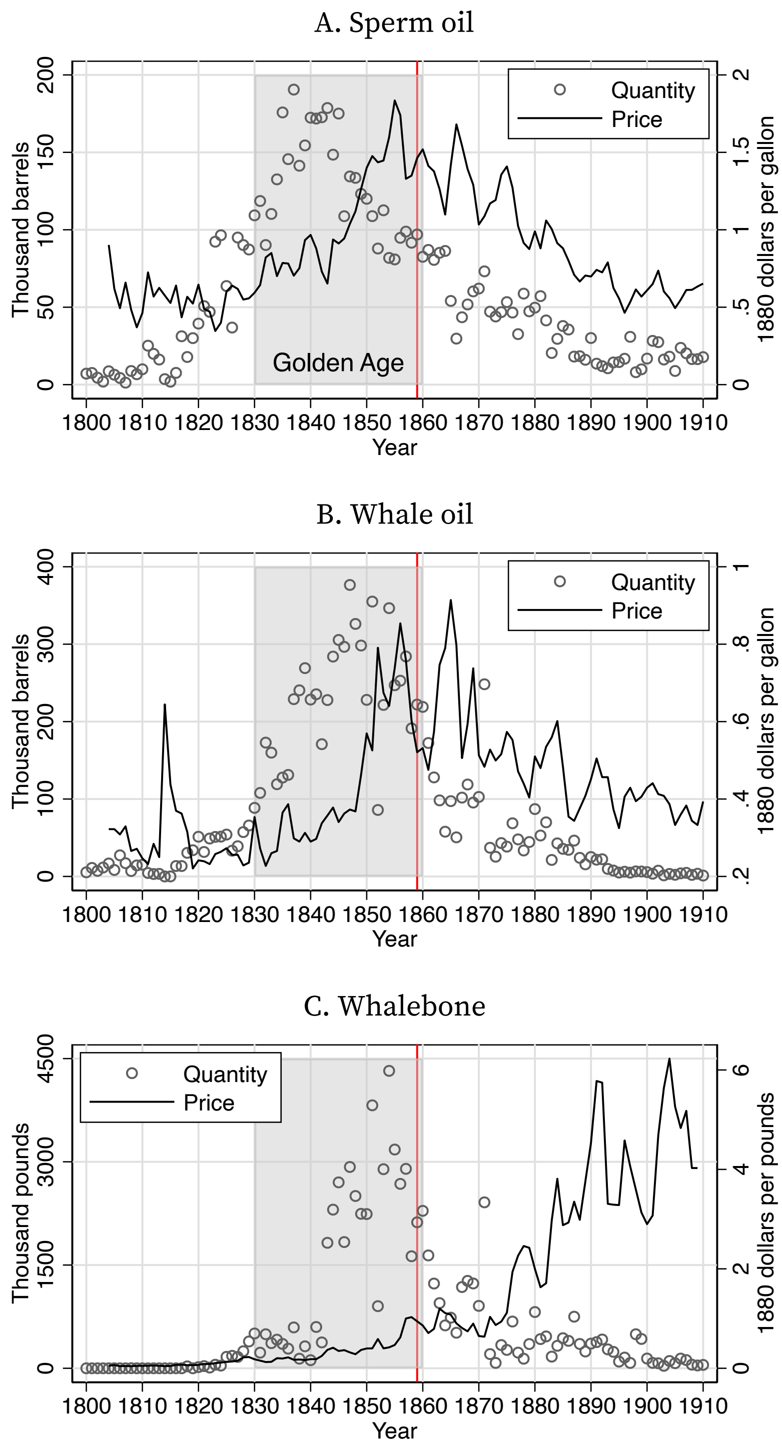

FIGURE E1. Quantities and prices for whaling products

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.

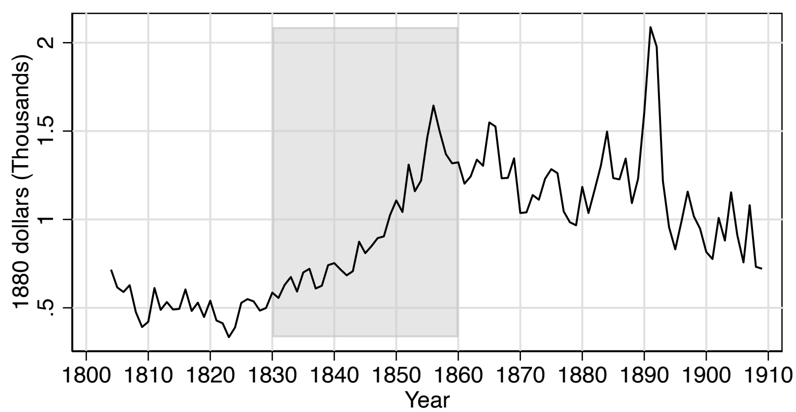

FIGURE E2. Whale price

Note: The prices of whaling products come from Tower (1907) and Davis, Gallman, and Gleiter (2007). I calculate the price *per whale* as total output value divided by total whales harvested each year. The output value equals sperm oil quantity × price + whale oil quantity × price + whalebone quantity × price. I compute total whales harvested by summing catches across all voyages.

References

Aguirregabiria, Victor, and Pedro Mira. 2007. "Sequential estimation of dynamic discrete games." *Econometrica* 75 (1): 1–53.

Bajari, Patrick, C Lanier Benkard, and Jonathan Levin. 2007. "Estimating dynamic models of imperfect competition." *Econometrica* 75 (5): 1331–1370.

Benkard, C Lanier. 2004. "A dynamic analysis of the market for wide-bodied commercial aircraft." *Review of Economic Studies* 71 (3): 581–611.

Davis, Lance E, Robert E Gallman, and Karin Gleiter. 2007. *In Pursuit of Leviathan: Technology, Institutions, Productivity, and Profits in American Whaling, 1816-1906*.: University of Chicago Press.

Elliott, Jonathan T. 2024. "Investment, emissions, and reliability in electricity markets." Working paper.

Goettler, Ronald L, and Brett R Gordon. 2011. "Does AMD spur Intel to innovate more?" *Journal of Political Economy* 119 (6): 1141–1200.

Gowrisankaran, Gautam, and Philipp Schmidt-Dengler. 2025. "A computable dynamic oligopoly model of capacity investment." Working paper.

Hotz, V Joseph, and Robert A Miller. 1993. "Conditional choice probabilities and the estimation of dynamic models." *Review of Economic Studies* 60 (3): 497–529.

Igami, Mitsuru. 2017. "Estimating the innovator's dilemma: Structural analysis of creative destruction in the hard disk drive industry, 1981–1998." *Journal of Political Economy* 125 (3): 798–847.

Nicholas, Tom. 2019. *VC: an american history*.: Harvard University Press.

Pakes, Ariel, Michael Ostrovsky, and Steven Berry. 2007. "Simple estimators for the parameters of discrete dynamic games (with entry/exit examples)." *The RAND Journal of Economics* 38 (2): 373–399.

Pesendorfer, Martin, and Philipp Schmidt-Dengler. 2008. "Asymptotic least squares estimators for dynamic games." *Review of Economic Studies* 75 (3): 901–928.

Scammon, Charles M. 1874. *The Marine Mammals of the North-western Coast of North America: Described and Illustrated Together with an Account of the American Whole-fishery*.: (Carmany),(Putnam).

Starbuck, Alexander. 1878. *History of the American whale fishery from its earliest inception to the year 1876*.: Commission of Fish and Fisheries.

Tower, Walter Sheldon. 1907. *A history of the American whale fishery*.: Pub. for the University.