Navigating the Commons

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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 investment in capacity 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 strategic firm dynamics with production externalities, 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. Using the estimated model, I quantify the shadow prices of externalities and propose a tractable framework for optimal policy design. The results show that per-unit Pigouvian taxes alone cannot achieve the long-run social optimum, as they correct stock externalities but leave persistent overcapacity and congestion unaddressed. Optimal regulation combines per-unit taxes with state-dependent lump-sum taxes that vary with vessel capacity and productivity to internalize firms' dynamic interactions. The welfare effects of these policies depend critically on technology, demand, and resource regeneration, underscoring the importance of adaptive policy design.

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

1. Introduction

This paper examines how entry, exit, and investment shape common-pool externalities through the case of 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 has analyzed harvest dynamics and policy responses, little is known about entry, exit, and capital accumulation—key drivers of long-run inefficiencies and resource misallocation.

Studying long-run commons problems presents three main challenges. First, it requires long panel data that link firms' entry, exit, and investment to resource dynamics over time, yet such datasets are rarely available in open-access environments. Second, firm behavior and externalities are connected through feedback loops: each firm's actions affect stock depletion and congestion, which in turn shape future decisions. This interdependence makes firm choices inherently strategic and dynamic, substantially increasing computational complexity. Third, externalities are endogenous to regulation. Firms' equilibrium behavior responds to policy interventions, altering the externalities that regulation seeks to internalize. Hence, effective regulation must account for these endogenous responses to achieve the social optimum.

To address these challenges, I first construct a firm-level panel of the 19th-century American whaling industry, 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 but do not observe other firms' detailed states or actions. Instead, each firm conditions its decisions on its own state and a set of aggregate moments that capture common-pool externalities (Ifrach and Weintraub 2017). This structure renders dynamic strategic interactions tractable in markets with many firms. To recover the primitives that rationalize observed behavior, I estimate the production function, the demand curve, and the costs of dynamic actions. Finally, for counterfactual analysis, I introduce a policy-design framework that quantifies the shadow prices of externalities. This framework sets policy instruments equal to these shadow prices using a fixed-point algorithm, aligning firms' incentives with the social optimum.

Three main findings emerge from the empirical estimates and counterfactuals. First, the production function estimates reveal a severe commons problem in the American whaling industry. A back-of-the-envelope calculation based on the estimated coefficients for whale stock and aggregate capacity indicates substantial efficiency losses during the industry's peak expansion (1820–1850). A 1 percent increase in whale stock raises an individual firm's production by 5.2 percent. Because whale stock declined by 14 percent over the same period, the implied reduction in production efficiency is 54.4 percent.

Likewise, a 1 percent increase in aggregate vessel capacity reduces an individual firm's production by 0.065 percent. Between 1820 and 1850, aggregate capacity expanded by 545 percent, implying an 11.4 percent decline in individual harvests due to congestion.

Second, implementing only per-unit Pigouvian taxes, often regarded as an efficient policy instrument, cannot achieve the long-run social optimum. While per-unit taxes correct stock externalities, they do not directly address persistent overcapacity and congestion externalities arising from firms' entry, exit, and investment decisions. The optimal policy combines time-varying per-unit taxes with lump-sum taxes, which vary by vessel capacity and productivity, to curb inefficient industry expansion, particularly before 1860. This two-part policy delivers welfare gains of 248% relative to the observed allocation, which is 17.5% higher than the gains achieved under a per-unit-tax-only policy.[1]

Third, long-run economic and environmental changes have important implications for policy design in the commons. Higher productivity growth, stronger demand, and faster stock regeneration intensify the commons problem and magnify welfare losses from externalities. These forces directly benefit the industry by raising efficiency and expanding market size, but they also trigger more aggressive entry and investment. When policy instruments effectively target these amplified externalities, the resulting welfare gains from regulation increase proportionally. Policies must therefore adapt to evolving economic and environmental conditions to sustain efficient resource use over time. These dynamics are directly relevant to modern industries such as fisheries, forestry, and energy, where innovation and demand growth are pervasive.

These findings draw on a combination of new data, a dynamic model of firm behavior, structural estimation of key parameters, and a tractable policy-design framework. First, I construct a firm–year panel using the expanded American Offshore Whaling Voyages Database (Mystic Seaport Museum, New Bedford Whaling Museum, and Nantucket Historical Association 2024b).[2] The sample covers U.S.-registered voyages between 1804 and 1909 and records vessel tonnage, output volumes, and crew size. I link these firm–year observations to annual whale-stock estimates and market prices for whale products. The resulting panel spans the industry's rise and decline, providing near-complete coverage of U.S. voyages. At its mid-century peak, when most externalities were generated, American fleets dominated global whaling. In the late 1840s, of roughly 900 whaling vessels worldwide, about 750 were American (Moment 1957). This historical context, combined

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

[2] In July 2020, the Whaling History Project (whalinghistory.org) expanded its coverage of whaling agents from about one-fifth to nearly two-thirds of the 15,000 recorded voyages. I further supplement missing agent information using *Ship Registers* (see Appendix B.2 for details). In this paper, I use "firms" and "whaling agents" interchangeably. Earlier studies lacked this breadth of coverage (e.g., Hilt 2006; Hilt 2007; Hilt 2008; Davis, Gallman, and Gleiter 2007).

with the data, offers a rare opportunity to study a large-scale common-pool resource in the absence of regulation.

Based on this context, I develop a dynamic model with *moment-based* externalities to address complex interactions among firms. Whaling firms make entry, exit, and capacity-adjustment decisions based on their current vessel capacity and productivity (Ericson and Pakes 1995).[3] Their actions generate externalities that they have no incentive to internalize: a stock externality when overexploitation reduces future resource availability (Gordon 1954), and a congestion externality when many vessels operate simultaneously (Smith 1969). To capture these forces, I specify production as a function of aggregate moments that govern congestion and stock effects, along with firms' own states. Firms' actions endogenously determine these aggregates, which in turn affect their decisions (Huang and Smith 2014). This structure motivates the use of the *moment-based* Markov equilibrium framework of Ifrach and Weintraub (2017), which makes the feedback mechanism computationally tractable.[4]

I estimate the model in two steps. First, I identify the harvest (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 outputs (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 lagged inputs as instruments. I estimate the demand curve using supply-side cost shifters as instruments to recover the price elasticity consistently. The instruments for price include the level of whale stocks five years earlier and long-term bond yields in New England, both of which affect whaling costs but not demand directly. Estimates from the production and demand equations yield period payoffs for each firm state and year. I then embed these payoffs in the dynamic optimization to recover firms' behavior and the evolution of industry structure.

In the second step, I estimate dynamic costs for entry, exit, and capacity adjustment using a full-solution maximum-likelihood approach.[5] Estimating these costs requires computing firms' best responses for both discrete (entry and exit) and continuous (capacity adjustment) decisions. Continuous decisions differ from discrete ones because they require discretizing the capacity space, which makes best responses highly sensitive to the chosen grid. To address this issue, I adopt the recent methodology of Gowrisankaran and Schmidt-Dengler (2025). This approach introduces random shocks to marginal adjustment

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

[4]Recent applications of the MME framework include Corbae and D'Erasmo (2021), Jeon (2022), Sears et al. (2022), Vreugdenhil (2023), Thurk (2023), and Chen (2024).

[5]See Appendix C for a detailed discussion of methodological considerations.

costs, ensuring stable solutions across different discretizations. I then use the resulting equilibrium choice probabilities for entry, exit, and capacity adjustment to estimate the dynamic cost parameters that best rationalize firms' observed decisions in the data.

To analyze counterfactuals, I compute the shadow prices of externalities and solve for a fixed point in which policy instruments are set equal to the shadow prices. This equality ensures that policies fully internalize externalities and steer firms toward the social optimum. Starting from the observed equilibrium, I solve the dynamic entry–exit–investment game and compute two shadow prices that quantify the marginal external costs of firms' actions: (i) a harvest shadow price—the marginal welfare effect of an additional unit of whale harvest in a given year; and (ii) a firm shadow price—the marginal welfare effect of an additional firm in a given state (vessel capacity and productivity) in that year. I then set per-unit taxes equal to the harvest shadow price and lump-sum taxes equal to the firm shadow price. Next, I re-solve the game under these policies, recompute the shadow prices, and update the policies, repeating until convergence. Proposition 1 in Section 5 establishes conditions under which the fixed point is unique. The resulting policies are time-varying per-unit taxes that adjust marginal costs and state-dependent lump-sum taxes that regulate fixed costs.

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 quantifying optimal policies.

My model builds on recent advances in the study of common-pool resources and the industry dynamics in industrial organization. A seminal contribution is Huang and Smith (2014), who examine dynamic strategic interactions in shrimp fisheries. The key challenge in their setting is that fishers' payoffs depend dynamically on others' actions through externalities, complicating empirical analysis. To address this issue, they assume that fishers' behavior affects others only through the total number of vessels, which in turn influences shrimp stocks. Their model features a fixed set of players, appropriate for a relatively short horizon. Over longer horizons, especially in open-access commons, firms enter, exit, and invest. A large literature on industry dynamics shows that these firm-level dynamics 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 due to over-capacity.

The policy question in this paper speaks 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 decisions, 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 controlling both the intensive margin (additional harvest) and the extensive margin (entry, exit, and investment).

A related literature examines how broader environmental and institutional changes shape commons outcomes. Copeland and Taylor (2009) develop a theory of how extraction technology, institutions, and prices affect the commons. Taylor (2011) provides supporting evidence from the 19th-century American buffalo slaughter, driven by technological progress, demand growth, and institutional failure. Noack and Costello (2024) show that credit-market expansion without secure property rights fuels overexploitation. In contrast, I focus on how firm-level responses to economic and environmental change shape production efficiency and resource allocation. I show that technological growth, demand shifts, and ecological improvements alter firms' entry, exit, and investment decisions, with corresponding welfare implications and changing needs for optimal regulation.

Beyond the commons, a growing recent literature has studied the design of regulation in environmental and energy markets under industry dynamics. Fowlie, Reguant, and Ryan (2016) examine the dynamic implications of market-based environmental regulation with market power and emissions leakage. Elliott (2024) investigates the tradeoffs between emissions from coal and gas and intermittency from wind and solar in designing carbon taxes and capacity subsidies. Aronoff and Rafey (2023) study the welfare gains and externalities from environmental offset trading. Gowrisankaran, Langer, and Zhang (2025) and Chen (2024) show that policy uncertainty affects dynamic market efficiency. Relative to this literature, I design policies that set instruments equal to the shadow prices at the efficient allocation, which is the key condition for achieving the social optimum. To implement this, I propose a fixed-point framework for policy design that is broadly applicable when externalities are the central distortion.

Finally, I contribute to the literature on long-run productivity in economic history. Drawing on unique historical settings and detailed data, this literature has identified several sources of productivity growth: management practices (Braguinsky et al. 2015; Giorcelli 2019; Bianchi and Giorcelli 2022; Rubens 2023a), technology adoption and innovation (Hanlon 2015; Braguinsky et al. 2021; Juhász, Squicciarini, and Voigtländer 2024; Hornbeck et al. 2025), and industrial policy (Juhász 2018; Lane 2025). I add to this literature by showing that the absence of resource management in an open-access industry led to a substantial decline in production efficiency. Counterfactual analysis further suggests that appropriate regulation could have mitigated these losses and increased long-run productivity.

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 and data patterns (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 used for illumination and as a lubricant for fast-moving machinery (e.g., spindles). Whale oil, extracted from baleen whales, served as a lubricant for heavy machinery and as an illuminant. Whalebone, taken from the mouths of baleen whales, had industrial uses in products such as corsets. Appendix Figure E1 shows trends in output quantities and prices. The product market featured homogeneous goods and was competitive. Individual whaling firms had no significant ability to affect whale-product prices (as there were many firms), nor could they effectively 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 drove a substantial increase in oil demand, expanding markets for whaling. The industry entered its "Golden Age" between 1830 and 1860, when American whalers produced over 90% of the world's sperm oil (Tillman and Donovan 1983).[6] During this period, the United States overtook Britain as the leading whaling nation, supported by strong domestic demand growth, technological and institutional advantages, and the use of higher-skilled crews (Davis, Gallman, and Hutchins 1987). Thereafter, the industry gradually declined,

[6] I treat non-American whaling operations as exogenous due to their relatively small size. If they responded endogenously to regulations on American whaling but were not themselves subject to regulation, the counterfactual policy effects in Section 5 would be smaller.

driven by factors such as 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 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 Appendix A.1 for an example). The plan was made before the vessel sailed but was frequently subject to change. Unforeseen success or challenges could necessitate altering the original schedule. For instance, exceptional success might prompt an early stop at a transshipment point; setbacks could extend the time at sea beyond the initial plan. While the captain made day-to-day sailing and hunting decisions, the agents held general authority, ensuring consistent communication between them as best as possible. Before the voyage commenced, the captain and agent agreed on dates and stations for exchanging letters. These exchanges occurred at predetermined rendezvous points, either between whaling vessels or between supply ships and whaling vessels (see Appendix A.2 for an example). For instance, Santa Maria, a small island in the Galapagos archipelago, became a mail hub because it was frequented by vessels hunting whales in the Pacific (Nicholas 2019).

In many cases, whaling agents 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 Appendix Figure B2 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 Appendix B 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 nineteenth 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 Appendix Figure B1 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 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 construct a firm–year panel from voyage records. This construction is 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 1,000 voyages (see Appendix B.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 Appendix B.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. Appendix Figure E2 reports the annual whale price.

[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).

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

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

Variable	Unit	Mean	SD	P10	Median	P90
Panel A. Outputs						
Whales harvested	Number	39.16	46.11	4.95	22.54	94.47
Sperm oil	Thousand barrels	0.50	0.69	0.01	0.28	1.28
Whale oil	Thousand barrels	0.76	1.26	0.00	0.22	2.31
Whale bone	Thousand pounds	5.79	12.48	0.00	0.00	18.85
Panel B. Firm characteristics						
Vessel capacity	Tonnage	756.04	801.15	143.00	392.00	1798.50
	Number	2.60	2.39	1.00	2.00	6.00
Crew size	Number	77.99	76.04	20.50	49.00	182.50
Firm age	Year	11.16	10.83	1.00	7.00	26.00
Panel C. Dynamic decisions						
Exit	Proportion	0.10	0.30	0.00	0.00	1.00
Investment	Proportion	0.15	0.36	0.00	0.00	1.00
	Tonnage	326.91	217.38	95.00	311.50	609.00
Divestment	Proportion	0.15	0.35	0.00	0.00	1.00
	Tonnage	-337.88	240.70	-646.00	-308.00	-98.00

Note: The dataset includes 10,450 firm-year observations and 1,060 firms, covering the years 1804 to 1909. Reported quantities of sperm oil, whale oil, and whalebone determine the number of harvested whales (see Appendix B.3 for details). Changes in vessel tonnage between the current year and the following year capture investment and divestment, excluding changes caused by wreckage.

To explore common-pool features, I capture two key externalities (Gordon 1954; Smith 1969). 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. population, U.S. GDP per capita, and petroleum prices. These data come from the Historical Statistics of the United States (Carter et al. 2006). Appendix Table B1 provides summary statistics.

2.4. Descriptive statistics

Table 1 reports firm-year level statistics and highlights substantial variability across observations. Panel A shows that some firms harvested only a few whales, while others caught nearly one hundred. In panel B, annual operations ranged from a single vessel to more than six, with corresponding variation in vessel tonnage and crew size. Panel C summarizes dynamic decisions. Changes in vessel tonnage between the current year and the following year capture investment and divestment, excluding changes caused by wreckage due to weather, accidents, war, or other causes. On average, 10% of firms exited, 15% invested, and 15% divested in a given year. Mean investment amount was about 327 tons, and mean divestment amount about 338 tons, with large dispersion in both—reflecting the lumpy nature of capacity adjustments.

Figure 1 presents the total whaling vessel capacity and whale stock. Panel A indicates the rise of American whaling to world dominance during the golden age period, followed by its collapse within a single century. In terms of capital stock, the industry employed an annual average of only eighteen thousand vessel-tons in the years 1816-20. Over the next three decades, tonnage increased more than fifteen-fold. However, in the 1900s, following a prolonged decline, the capital stock became smaller compared to its level in 1816-20. Panel B displays the projected population of whales as a sum of baleen and sperm whales, calculated using the method outlined in Sections 2.3. It shows that whale stock experienced substantial declines during the golden age period.

Figure 2 provides suggestive evidence of the presence of negative externalities. Panel A displays the number of whales harvested per vessel. Following a marked increase in the 1800s-1820s, it reached around 25 during the 1820s and reduced to 12 in the 1850s.[9] This decline is striking in light of technological growth over the period—about 1.4% 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 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 Appendix Figure E1). This suggests the presence of incentives for firms to continue operating despite cost increases.

3. A model of common-pool industry dynamics

This section develops a strategic industry dynamics model 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 concept (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:

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

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

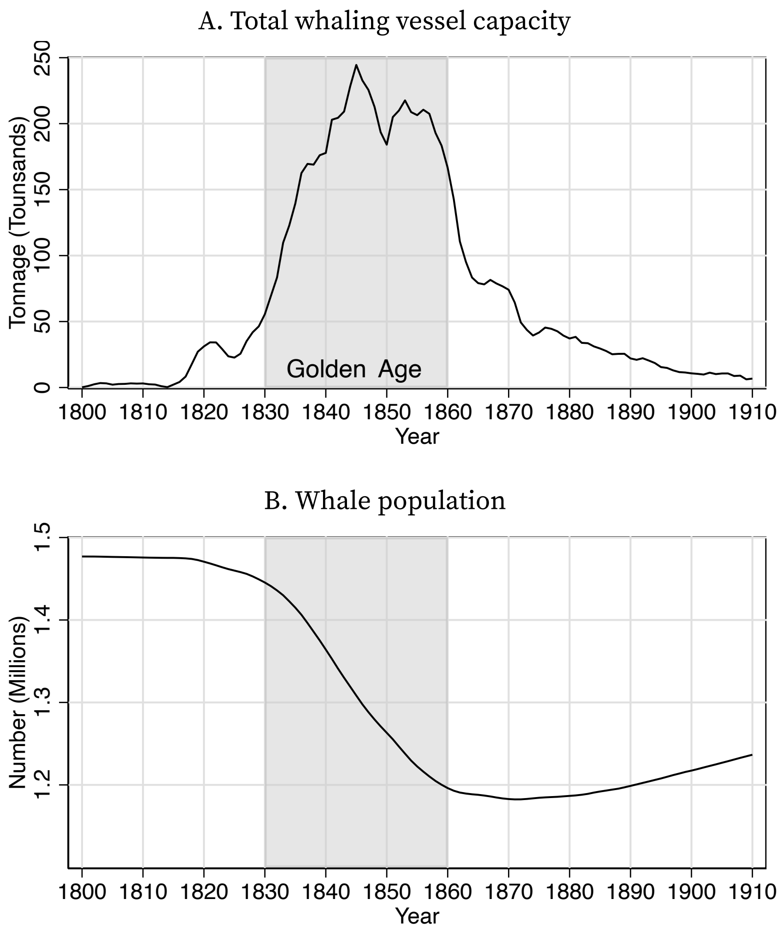

FIGURE 1. Aggregate whaling vessel capacity and whale stock

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).

it captures the industry's rise and fall and permits nonstationarity in equilibrium. By contrast, the standard infinite-horizon stationary framework in resource economics 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 $\mathcal{I}_t^{pe}$, with $|\mathcal{I}_t^{pe}| = N_t^{pe}$.

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

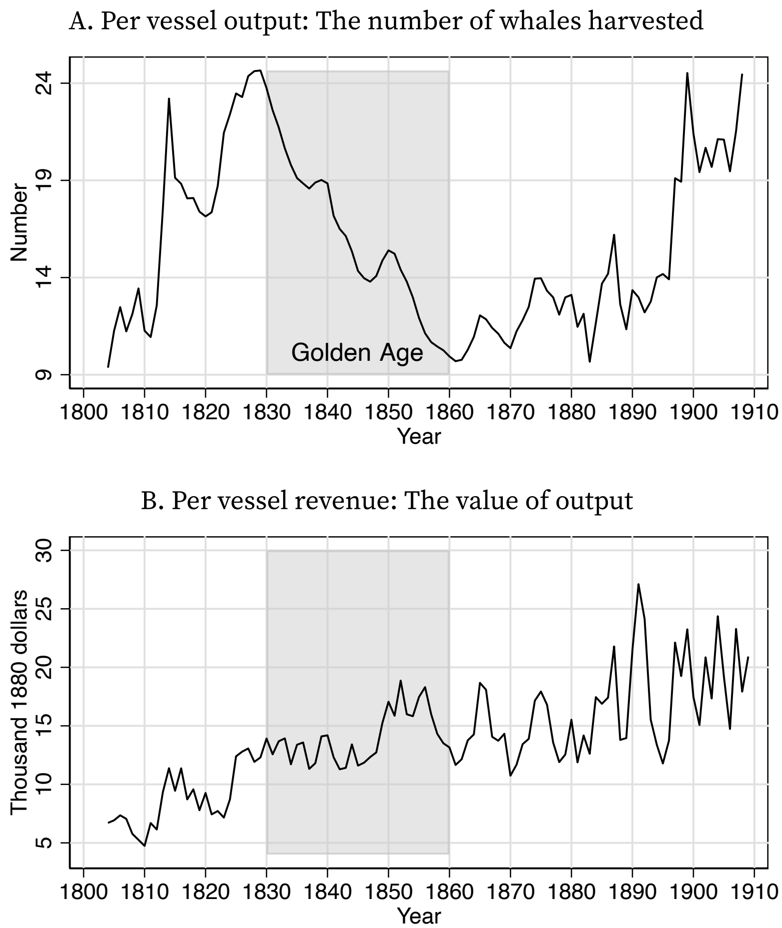

FIGURE 2. Suggestive evidence of negative externalities

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.

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. 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 $x_{it} \equiv (K_{it}, \Omega_{it}) \in \mathcal{X}$.[10] Vessel capacity changes through costly adjustment (investment or divestment) I_{it}:

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

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

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

where ξ_{it+1} is unexpected productivity innovation drawn from i.i.d standard Normal distribution. 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:

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

Harvesting combines vessel capacity and crew in fixed proportions, reflecting a Leontief technology. Empirical evidence shows a tight relationship between vessel tonnage and crew size. I therefore model crew size a $L(K_{it}) = cK_{it}$, where c denotes crew per tonnage. The harvesting function also 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

[10] 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).

consists of exogenous demand shifters—U.S. population, GDP per capita, and petroleum prices (since 1859)—which lie outside the model. 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 period payoff function Π at year t is the revenue minus labor costs:

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

where w_t 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.[11] 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 directly affect their payoffs and follow the *moment-based* strategies introduced by Ifrach and Weintraub (2017).

As shown in equation (6), the payoff-relevant moments include total vessel capacity

[11] 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). In particular, firms in identical states often make different decisions. To explain such micro-level behavior, each dynamic choice must include a relevant random noise.

and total whale harvest. Total vessel capacity equals the sum of all firms' capacities:

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

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:

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

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 known 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 $\psi_t(\cdot)$ highlights that strategies are non-stationary due to the evolution of the industry, embodied in whale stock transition, 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

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

Let $M_t(x' \mid x, \psi_t)$ 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:

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

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 payoffs. They discount future payoffs 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 κ and variance κ^2. This entry cost captures uncertainty in initial setup costs. An incumbent firm faces two shocks. First, it draws an exit scrap value ζ_{it} from an i.i.d. exponential distribution with mean ζ and variance ζ^2, reflecting uncertainty in asset liquidation and external opportunities. Second, it draws a marginal capacity adjustment cost ϵ_{it} from an i.i.d. normal distribution with standard deviation σ.[12] Capacity adjustments involve buying or selling ships, along with equipment and staffing changes. Variation in input prices, business networks, or other firm-specific factors drives uncertainty in these 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:

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

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), fully incorporating asymmetries between investment and divestment cost structure.

An active whaling 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:

$$
\begin{aligned}
V_t(s_{it}, \psi_t; \Theta) = {} & \Pi_t(s_{it}; \alpha, \beta) + \mathbb{E}_\zeta\Bigg[\max\Bigg\{\zeta_{it}, \\
& \mathbb{E}_\epsilon\left[\max_{K_{it+1}}\{-C(K_{it+1}, K_{it}; \gamma) - I_{it}\epsilon_{it} + \rho\,\mathbb{E}_t\left[V_{t+1}(s_{it+1}, \psi_{t+1}; \Theta)\,|\,s_{it}, \psi_t\right]\}\,\Bigg|\, s_{it}\right]\Bigg\}\,\Bigg|\, s_{it}\Bigg].
\end{aligned} \tag{12}
$$

where $\Theta = \{\alpha, \beta, \gamma, \zeta, \kappa\}$. The time subscript in the value function $V_t(\cdot)$ features the nonstationarity, as period payoffs $\Pi_t(\cdot)$ 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.

[12] 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.

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

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

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 about externalities using the moment-based states (7) and (8).

Existence of equilibrium follows from Ifrach and Weintraub (2017) and Benkard, Jeziorski, and Weintraub (2024). Uniqueness relies on four features of the environment (see Appendix D.1 for a formal proposition and proof). First, strictly convex adjustment costs make capacity choices single-valued. Second, continuous idiosyncratic shocks pin down unique entry and exit cutoffs. Third, firms interact only through aggregate moments and the common stock: higher aggregate capacity lowers individual payoffs through con-

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		
Entry costs	κ	NFXP-MLE (Section 4.2)
Exit scrap values	ζ	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)
Stochastic marginal adjustment costs	σ	NFXP-MLE (Section 4.2)
Panel C. Transitions		
Annual discount factor	$\rho = 0.925$	Calibrated
Vessel capacity destruction	$\delta = 0.05$	Calibrated
Whale population 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).

gestion, and higher aggregate harvest diminishes future harvest via the stock effect. These stabilizing forces eliminate the possibility of multiple consistent paths. Finally, given these conditions, backward induction from the terminal period ensures a unique sequence of equilibrium strategies—that is, a unique nonstationary MME.

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. In year t, whaling firm i's harvest Q_{it} depends on vessel capacity K_{it}, (Hicks-neutral) productivity Ω_{it}, aggregate capacity K_t, whale stock W_t, and technological progress. Optimal crew size L_{it} is determined by vessel capacity, which is omitted in the dynamic model under a Leontief technology assumption (Eq. 4).[13] For robustness, I also estimate specifications that include crew size explicitly. I parameterize equation (4) as a Cobb–Douglas production function in logarithmic form:

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

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 ex-post 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 a richer productivity transition in equation (3) and does not fully address selection bias from endogenous exit. However, working with an unbalanced panel already alleviates most concerns about selection (Olley and Pakes 1996; De Loecker et al. 2016; Rubens 2023b).[14]

Firms choose vessel capacity in year $t-1$ (Eq. 2) and crew size between $t-1$ and t, both prior to the year t productivity shock (Ackerberg, Caves, and Frazer 2015). 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

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

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)–(4) use the subsample with crew data, while column (5) employs the full sample and serves as the baseline for the dynamic analysis. Column (1) includes firm capacity, crew size, and aggregate capacity. Column (2) adds whale stock, and column (3) further incorporates a time trend. Column (4) drops crew size from the subsample to compare with the full-

[13] Firms face a common wage (Eq. 6).

[14] A common alternative is a control function approach that inverts intermediate-input demand to recover latent productivity (Levinsohn and Petrin 2003; Ackerberg, Caves, and Frazer 2015). This requires an intermediate input with demand monotonically increasing in productivity. Because the American whaling industry lacks such an input, the control function approach is infeasible.

TABLE 3. Estimates of the whale harvesting function

	(1)	(2)	(3)	(4)	(5)
Vessel capacity: β_k	1.134	0.874	0.904	1.059	1.049
	(0.050)	(0.030)	(0.027)	(0.009)	(0.007)
Crew size: β_l	-0.109	0.224	0.192		
	(0.061)	(0.033)	(0.030)		
Persistence: λ	0.651	0.297	0.261	0.345	0.150
	(0.106)	(0.114)	(0.112)	(0.114)	(0.100)
Aggregate vessel capacity: β^K	-0.231	-0.232	-0.046	-0.032	-0.065
	(0.017)	(0.011)	(0.013)	(0.014)	(0.008)
Whale stock: β^W		3.201	7.195	7.020	5.169
		(0.160)	(0.279)	(0.299)	(0.247)
Time trend: β^t			0.020	0.021	0.014
			(0.001)	(0.001)	(0.001)
Returns to scale: $\beta_k + \beta_l$	1.034	1.098	1.096	1.059	1.049
Number of firms	461	461	461	461	986
Observations	4,880	4,880	4,880	4,880	9,032

Notes: This table reports the estimated harvesting function. Columns (1)–(4) use the subsample with crew data; column (5) 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.

sample results in column (5).

The sum of capacity and crew size elasticities ($\beta_k + \beta_l$) ranges from 1.03 to 1.09, indicating modest increasing returns to scale. Columns (4) and (5) show that vessel capacity alone, without crew size, explains most production scale. This pattern is reasonable because nineteenth-century American whaling was capital-intensive, and crew size was roughly proportional to capacity.[15]

Based on the results of column (5), the back-of-the-envelope calculation suggests strong production externalities. First, the coefficient for whale stock (β^W) captures 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 0.065 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.

[15] 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.

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

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

where q_t represents the log of aggregate whale demand and p_t is the log of whale price. Pop_t denotes U.S. population, and GDP_t is U.S. real GDP per capita. 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 following petroleum discovery and the Civil War (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 marginal costs and hence prices (relevance) but are orthogonal to η_t conditional on controls (exclusion).

First, I use the level of whale stocks five years earlier. Because whales are slow-growing animals, past abundance strongly predicts current biomass and expected harvest cost. A five-year lag exceeds the typical voyage length of two to four years, breaking simultaneity with current harvest outcomes. Demand for whale products in the current year cannot influence whale abundance five years earlier. Any reverse channel would require persistent unobserved shocks linking past effort and current demand, but controls for U.S. population and GDP per capita absorb the main aggregate demand drivers. Remaining correlation would require long memory in unobserved demand shocks that simultaneously predicted past harvest effort and current U.S. demand—an implausible pathway.

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

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, Figure 1). Between 1859 and 1910, whale stocks remained 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

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

TABLE 4. Estimates of the whale demand curve

	OLS		IV	
	(1)	(2)	(3)	(4)
Whale price: α_p	-1.976	-0.148	-4.325	-4.325
	(0.906)	(0.068)	(0.748)	
US population: α^{pop}	5.758	-1.875	4.798	-3.958
	(1.131)	(0.224)	(0.844)	(0.863)
US real GDP per capita: α^{gdp}	-3.795	0.094	3.534	0.877
	(4.410)	(0.238)	(2.522)	(0.886)
Petroleum price: α^{pet}		0.046		-0.233
		(0.030)		(0.245)
Observations	55	51	51	51
Sample period	1804-1858	1859-1909	1804-1858	1859-1909
First-stage F-statistic			44.379	
Adjusted R-squared	0.844	0.963	0.788	0.711

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.

using the elasticity estimated from the pre-petroleum period.

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 −1.976 and −0.148, respectively. Column (3) shows IV estimates for the pre-petroleum sample; the elasticity rises in absolute magnitude to -4.325, consistent with Kaiser (2013). For the post-petroleum period, I fix the price coefficient α_p at -4.325 and estimate the remaining parameters via OLS. The results in columns (3) and (4) form the basis for all subsequent dynamic analyses.

4.2. Dynamic costs and values of whaling

This paper estimates the dynamic parameters using a full-solution approach (see Appendix C for methodological details). Two challenges arise. First, open access and rivalry in commons settings naturally involve many firms, creating a curse of dimensionality. The MME framework addresses this by allowing firms to condition strategies on their own states and a small set of aggregate moments rather than on the full distribution of competitors' states. This reduces the problem to a single-agent dynamic program while preserving strategic interactions through the endogenous evolution of aggregate moments. Second, computing best responses for continuous investment and divestment is difficult because firms face a wide range of choices that require discretizing the continuous state (and action) space. Previous approaches have been either unstable across discretizations or unable to match observed behavior. To resolve this, I adopt the method of Gowrisankaran and Schmidt-Dengler (2025), which introduces random shocks to marginal adjustment costs and delivers stable adjustment probabilities.

I discretize the continuous capacity space into 41 grid levels, spaced at 200-ton increments: $\mathcal{K} = \{K^1 < K^2 < \cdots < K^J\}$ where $K^1 = 200$, $K^J = 8200$, and $J = 41$. I also discretize the productivity space into 7 grid levels, with transition probabilities directly computed from data.

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

$$v_{it}^j = -C(K^j, K_{it}; \gamma) + \rho\, \mathbb{E}_t \left[V_{t+1}(s_{it+1}, \psi_{t+1}; \Theta) \,|\, s_{it}, \psi_t \right] \tag{17}$$

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 adjustment. 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

$$\Pr_t\left(a_{it} = K^j \,\middle|\, a_{it} > 0, s_{it}, \psi_t\right) = \Phi\left(\frac{\overline{\epsilon}_{it}^j}{\sigma}\right) - \Phi\left(\frac{\underline{\epsilon}_{it}^j}{\sigma}\right), \tag{18}$$

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, $\forall j = 1, \ldots, J$,

$$\mathbb{E}\left[\epsilon_{it} \mid a_{it} = K^j, s_{it}, \psi_t\right] = \frac{\phi\left(\underline{\epsilon}_{it}^j/\sigma\right) - \phi\left(\overline{\epsilon}_{it}^j/\sigma\right)}{\Phi\left(\overline{\epsilon}_{it}^j/\sigma\right) - \Phi\left(\underline{\epsilon}_{it}^j/\sigma\right)}, \tag{19}$$

where $\phi(\cdot)$ is the standard normal probability density function. By using (17), (18), and (19), I define the expected continuation value as

$$V_{it}^{\text{cont}} = \sum_{j>0} \Pr_t\left(a_{it} = K^j \,\middle|\, a_{it} > 0, s_{it}, \psi_t\right) \left\{v_{it}^j - I_{it}^j\, \mathbb{E}\left[\epsilon_{it} \mid a_{it} = K^j, s_{it}, \psi_t\right]\right\} \tag{20}$$

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

$$\Pr_t\left(a_{it} = 0 \,\middle|\, s_{it}, \psi_t\right) = \Pr\left(\zeta_{it} \geq V_{it}^{\text{cont}}\right) = \exp\left(-V_{it}^{\text{cont}}/\zeta\right). \tag{21}$$

Combining the period payoff (6), the exit probability (21), and the expected continuation value (20) 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

$$\Pr_t\left(a_{it} = K^j \,\middle|\, s_{it}, \psi_t\right) = \left(1 - \Pr_t\left\{a_{it} = 0 \,\middle|\, s_{it}, \psi_t\right\}\right) \Pr_t\left(a_{it} = K^j \,\middle|\, a_{it} > 0, s_{it}, \psi_t\right). \tag{22}$$

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

$$\begin{aligned} \Pr_t\left(a_{it}^{\text{pe}} = 1 \,\middle|\, s_{it}, \psi_t\right) &= \Pr\left(\kappa_{it} \leq \rho\, \mathbb{E}_t[V_{t+1}(s_{it+1}, \psi_{t+1}) | s_t, \psi_t]\right) \\ &= 1 - \exp\left(-\rho\, \mathbb{E}_t[V_{t+1}(s_{it+1}, \psi_{t+1}) | s_t, \psi_t]/\kappa\right). \end{aligned} \tag{23}$$

Using equations (21), (22), and (23), 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

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

The maximum likelihood estimator is then defined as

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

Some capacity adjustment choices can have zero probability when $\overline{\epsilon}_t^j \leq \underline{\epsilon}_t^j$ for $j = 1, \ldots, J$, making log-likelihood function undefined. But even studies with well-defined likelihoods, such as logit cost shocks, typically bound probabilities below by a small positive constant to avoid numerical precision issues. Following this practice, I impose a small lower bound on predicted probabilities. Estimation results are robust to alternative values.[17]

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 scrap values ζ increases the predicted probability of continuation and decreases the probability of exit. Accordingly, when few active firms exit in a given state and year, this pattern results in a smaller estimate for ζ. Likewise, a lower mean entry cost κ raises the probability of entry. Firms' observed investment and divestment frequencies, conditional on state and year, help identify the fixed adjustment costs γ_0^+, γ_0^-. Conditional on adjustment, the magnitude of capacity changes informs the linear and convex cost parameters $\gamma_1^+, \gamma_2^+, \gamma_1^-, \gamma_2^-$. 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 both demand and costs. The discovery of petroleum in 1859 sharply reduced demand for sperm and whale oil.[18] The Civil War (1861–1865) also disrupted shipping and global trade, making 1860 a natural break point. In the mid-1840s, additional shocks reshaped the industry: coal oil entered lighting markets around 1844, the California gold rush raised wages starting in 1848, and voyages shifted toward the Pacific. These events altered costs 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 reliable data, estimation begins in 1815.

[17] In the baseline, I set the lower bound to 10^{-20}. 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) reported:

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

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.

TABLE 5. Estimates of whaling industry dynamics

	Unit	1815-1829	1830-1844	1845-1859	1860-1874	1875-1889	1890-1905
Panel A. Maimum likelihood estimates							
Entry: κ	\$000	616.72	426.97	1173.69	2482.30	1093.95	2501.03
		(147.2)	(43.98)	(126.2)	(456.4)	(241.2)	(814.3)
Exit: ζ	\$000	157.07	109.75	213.87	352.37	278.95	364.42
		(39.69)	(10.48)	(18.88)	(56.12)	(54.35)	(102.4)
Investment fixed: γ_0^+	\$000	10.63	5.43	10.95	4.64	1.30	13.36
		(2.10)	(0.74)	(1.19)	(1.15)	(1.32)	(5.94)
Investment linear: γ_1^+	\$/ton	198.29	242.11	333.94	384.43	432.68	524.28
		(19.98)	(13.14)	(16.76)	(27.59)	(41.34)	(97.44)
Investment convex: γ_2^+	\$/ton^2	0.32	0.23	0.38	0.26	0.18	0.60
		(0.04)	(0.02)	(0.03)	(0.03)	(0.03)	(0.19)
Divestment fixed: γ_0^-	\$000	11.61	15.64	17.01	11.18	10.40	8.94
		(2.62)	(1.77)	(1.77)	(1.68)	(1.58)	(2.30)
Divestment linear: γ_1^-	\$/ton	0.01	49.58	135.08	237.60	265.88	215.60
		(33.50)	(16.53)	(16.53)	(15.16)	(16.58)	(26.97)
Divestment convex: γ_2^-	\$/ton^2	0.25	0.35	0.35	0.27	0.29	0.28
		(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
Marginal adjustment SD: σ	\$/ton	168.69	182.63	240.71	182.52	177.04	324.81
		(27.4)	(17.5)	(20.4)	(21.3)	(30.3)	(106.9)
Log likelihood		1278.0	4802.2	5297.1	2715.8	1176.2	583.0
Number of years		15	15	15	15	15	16
Numbser of observations		814	3,060	3,456	1,667	709	366
Panel B. Dispersion of estimates							
Entry fixed costs with κ_{it} draw							
P16	\$000	107.53	74.44	204.64	432.80	190.73	436.06
P84	\$000	1130.18	782.45	2150.89	4549.01	2004.76	4583.33
Exit scrap values with ζ_{it} draw							
P16	\$000	27.39	19.13	37.29	61.44	48.64	63.54
P84	\$000	287.85	201.12	391.93	645.76	511.19	667.84
Investment costs $I_{it} = 300$, with ϵ_{it} draws							
P16	\$000	48.03	43.66	73.53	88.37	94.55	127.20
Mean	\$000	98.63	98.45	145.75	143.12	147.67	224.65
P84	\$000	149.24	153.24	217.96	197.88	200.78	322.09
Divestment costs $I_{it} = -300$, with ϵ_{it} draws							
P16	\$000	85.10	86.62	80.40	18.77	9.43	67.32
Mean	\$000	34.50	31.83	8.19	-35.99	-43.68	-30.13
P84	\$000	-16.11	-22.96	-64.03	-90.74	-96.79	-127.57

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. In panel A, parameters are estimated by maximum likelihood estimation (MLE). 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 mean and median adjustment size in Table 1.

Table 5 reports the dynamic-parameter estimates. Panel A indicates that all estimates are of plausible magnitude and precisely estimated. Mean entry costs range from \$426,970 to \$2,501,030 across the nine decades, while mean exit scrap values are lower, between \$109,750 and \$364,420. Adjustment fixed costs indicate sizable setup costs for changing capacity: \$1,300–\$13,360 for investment and \$8,940–\$17,010 for divestment. Linear cost terms suggest that investment costs rise with scale, between \$198.29 and \$524.28 per ton, while divestment yields range from \$0.01 to \$265.88 per ton.[19] Convex cost parameters fall between \$0.18 and \$0.60 per ton squared for investment and \$0.25–\$0.35 for divestment. Finally, the standard deviation of the marginal adjustment cost shock indicates substantial variability in adjustment intensity, ranging from \$168.69 to \$324.81 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 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 \$0.70 million in 1830–1844 to more than \$4.1 million in 1860–1874, suggesting growing heterogeneity in financial barriers to entry. Exit value dispersion also increases, from \$0.18 million to \$0.46 million over the same period. For a 300-ton change, investment costs range from \$43,000 to \$300,000, while divestment costs range from -\$127,000 to \$9,000, implying that divestment can be profitable (negative costs). Overall, the inter-percentile range for adjustment costs is about \$100,000, indicating substantial variation even among observationally similar firms.

I evaluate model fit by comparing observed behavior with predictions from the estimated model. Because the counterfactual analysis in Section 5 relies on it, the model must replicate actual equilibrium behavior. Figure 3 compares actual data (solid line) with model-implied paths (dashed line) for total whale harvest (Panel A) and total whaling-vessel capacity (Panel B). Model paths are the average of 300 simulations under the estimated parameters, with shaded bands showing 95 percent confidence intervals. The figure indicates that the model reproduces the industry's rise and fall over nine decades, including the expansion from 1815 to 1845, the peak around 1845, and the long decline through 1905.

5. Counterfactuals

Whaling firms impose social costs through congestion and stock depletion, leading to inefficient resource allocation. I begin by defining the policy instruments, the long-run

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

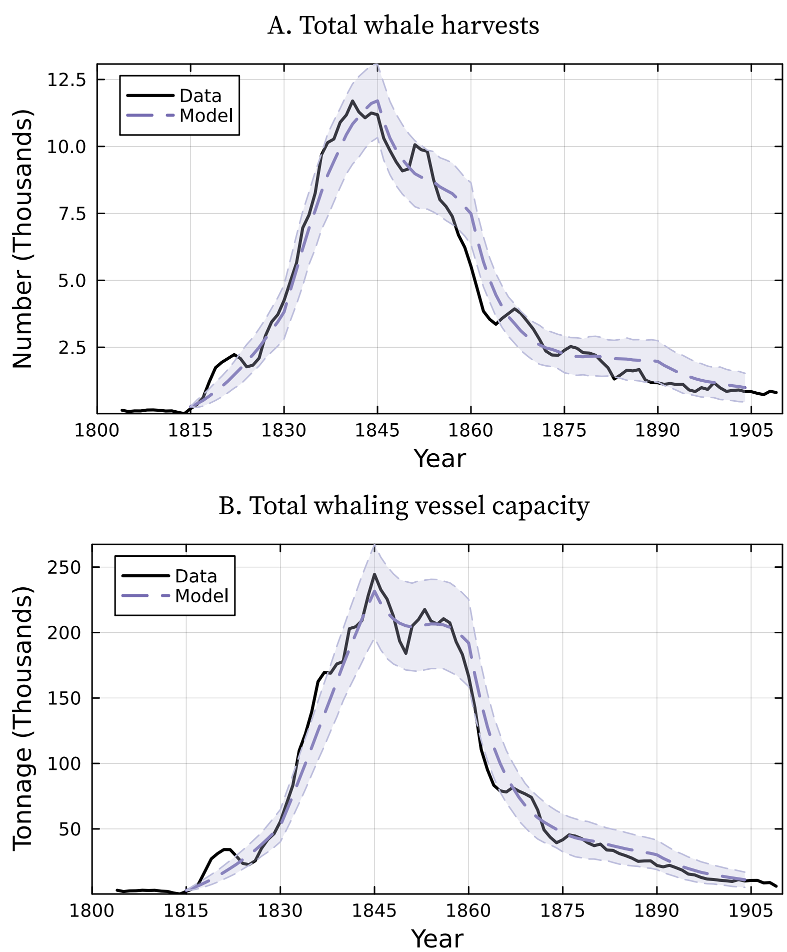

FIGURE 3. Fit of the estimated model

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.

social welfare function, and 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 policy responses vary across changing environments (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.

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 tax $\mathcal{F}_t(x)$ that adjusts operating fixed costs.

I define the complete schedules of policy paths as

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

and the admissible policy set as

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

For any policy path $c \in \mathcal{C}$, let ψ_t^c denote the strategy profile induced by 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 period-t payoff (6) extends to include policy instruments as follows:

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

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

$$\begin{aligned}
\text{(24)} \qquad \mathbb{W}_t(f_t, W_t, \tau_t, \mathcal{F}_t; \psi_t^c) = {} & \underbrace{\int_0^{Q_t} \mathcal{P}_t(\varphi)\mathrm{d}\varphi - \mathcal{P}_t(Q_t)Q_t}_{\text{consumer surplus}} \\
& \underbrace{+ \sum_{i \in \mathcal{I}_t} \left\{\Pi_t(s_{it}, \tau_t, \mathcal{F}_t(x_{it})) + \mathbf{1}_{\{a_{it}=0\}}\zeta_{it} - \mathbf{1}_{\{a_{it}>0\}}\left[C(I_{it}) + I_{it}\epsilon_{it}\right]\right\} - \sum_{i \in \mathcal{I}_t^{\mathrm{pe}}} \mathbf{1}_{\{a_{it}^{\mathrm{pe}}=1\}}\kappa_{it}}_{\text{producer surplus}} \\
& \underbrace{+ \sum_{i \in \mathcal{I}_t} \{\tau_t Q_{it} + \mathcal{F}_t(x_{it})\}}_{\text{government revenue}},
\end{aligned}$$

where the firm distribution $f_t \in \mathbb{N}^{|\mathcal{X}|}$ 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:

$$\mathbb{W}(c;\psi^c) = \mathbb{E}\left[\sum_{t\geq 1} \rho_s^{t-1} \mathbb{W}_t(f_t, W_t, \tau_t, \mathcal{F}_t;\psi_t^c) \,\middle|\, \psi^c\right] \tag{25}$$

where $\psi^c = \{\psi_t^c\}_{\forall t}$. Given the initial distribution f_1 and whale stock W_1, the prescribed strategy profile ψ^c determines the entire history 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 (see Appendix D.2 for detailed derivations). The *harvest* shadow price $\Lambda_t^h(c)$ measures the uninternalized marginal welfare change from an additional unit of whale harvest in year t:

$$\Lambda_t^h(c) = -\left[\frac{1}{\rho_s^{t-1}}\frac{\partial \mathbb{W}(c;\psi^c)}{\partial Q_t} - (\mathcal{P}_t(Q_t) - \tau_t) - \tau_t\right]. \tag{26}$$

The *firm* shadow price $\Lambda_t^f(x;c)$ measures the uninternalized marginal welfare change from an additional firm in state x in year t:

$$\begin{aligned}\Lambda_t^f(x;c) = -\Bigg[\frac{1}{\rho_s^{t-1}}\frac{\partial \mathbb{W}(c;\psi^c)}{\partial f_t(x)} &- \sum_{\ell=t}^{T}\rho_s^{\ell-t}\sum_y M_{t:\ell}(x,y)\Pi_\ell(y,K_\ell,W_\ell,\tau_\ell,\mathcal{F}_\ell(y)) \\ &- \sum_{\ell=t}^{T}\rho_s^{\ell-t}\sum_y M_{t:\ell}(x,y)\mathcal{F}_\ell(y)\Bigg].\end{aligned} \tag{27}$$

where

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

denotes the probability that a firm in state x at year t is in state y at year ℓ. 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.

Equations (26) and (27) net out both (a) the private component and (b) the portion already internalized by existing policies. The derivatives $\partial\mathbb{W}/\partial Q_t$ and $\partial\mathbb{W}/\partial f_t(x)$ already incorporate all equilibrium responses under the current policy. To price only the uninternalized part (the externality), the shadow prices subtract (a) the private payoff the decision-maker accounts for—$(\mathcal{P}_t(Q_t) - \tau_t)$ in (26) and the discounted expected stream of profits $\sum_{\ell=t}^{T}\rho_s^{\ell-t}\sum_y M_{t:\ell}(x,y)\Pi_\ell(y,\cdot)$ in (27)—and (b) the contribution of policies already in place—τ_t in (26) and $\sum_\ell \rho_s^{\ell-t}\sum_y M_{t:\ell}(x,y)\,\mathcal{F}_\ell(y)$ in (27). Item (a) avoids double counting relative to the firm's first-order condition; item (b) ensures Λ_t^h and Λ_t^f are incremental to the status quo policy—that is, the additional per-unit tax or lump-sum tax, on top of τ and $\mathcal{F}$, required to decentralize the planner's allocation.

Collectively, I write complete paths of shadow prices as:

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

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, rendering the planner's problem intractable.

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

$$c^* = \left(\Lambda^h(c^*), \Lambda^f(c^*)\right) \tag{28}$$

Proposition 1 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.

PROPOSITION 1. *For any $c = (\tau, \mathcal{F}) \in \mathcal{C}$, define the operator $\mathscr{T}: \ c \longmapsto \left(\Lambda^h(c), \Lambda^f(c)\right)$. Assume that there exist constants $L_P, L_{MC}, L_{HD}, L_{FD} > 0$, $m_{\min} > 0$ and $m_{\max} \geq 0$ such that for every t, x, Q_t and c:*

- (A1) *Inverse demand: $\mathcal{P}_t'(Q_t) < 0$ and $|\mathcal{P}_t'(Q_t)| \leq L_P$.*
- (A2) *Private marginal cost: $0 \leq PMC_t'(Q_t) \leq L_{MC}$.*
- (A3) *Slope dominance: $PMC_t'(Q_t) - \mathcal{P}_t'(Q_t) \geq m_{\min}$.*
- (A4) *Harvest shadow price: $\Lambda_t^h(c)$ is non-decreasing in Q_t and $\left|\partial\Lambda_t^h(c)/\partial Q_t\right| \leq L_{HD}$.*
- (A5) *Firm shadow price: $\Lambda_t^f(x; c)$ is continuous in $f_t(x)$ and $\left|\partial\Lambda_t^f(x; c)/\partial f_t(x)\right| \leq L_{FD}\left(1 + m_{\max}\right)$, where $m_{\max} := \sup_{t,x,c} \max\left\{|\partial Q_t/\partial f_t(x)|,\ |\partial Q_t/\partial \mathcal{F}_t(x)|\right\} < \infty$.*

Define $\Lambda := \max\left\{\frac{L_{HD}}{m_{\min}},\ L_{FD}\left(1 + m_{\max}\right)\right\} < 1$. Then, under Assumptions (A1)–(A5):

- (a) *$\mathscr{T}$ is a contraction on $(\mathcal{C}, \|\cdot\|_\infty)$ with modulus $\mathcal{M}$.*
- (b) *A unique fixed point $c^* = (\tau^*, \mathcal{F}^*) \in \mathcal{C}$ exists and satisfies $c^* = \left(\Lambda^h(c^*), \Lambda^f(c^*)\right)$.*
- (c) *For any initial $c^0 \in \mathcal{C}$ the iterates $c^{m+1} := \mathscr{T}(c^m)$ obey $\|c^m - c^*\|_\infty \leq \mathcal{M}^m \|c^0 - c^*\|_\infty$; convergence is geometric.*

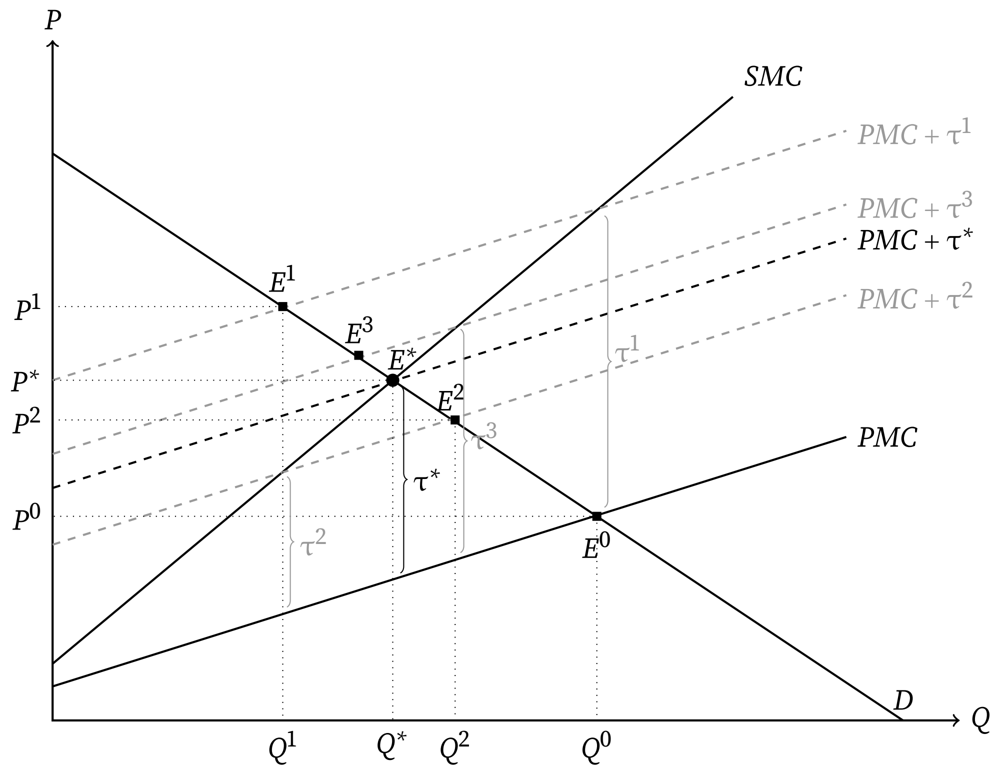

FIGURE 4. Static example of Pigouvian per-unit tax iterations

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.

PROOF. See Appendix D.3. □

Figure 4 provides a graphical companion to Proposition 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 $\tau^* = \Lambda^h(\tau^*, \mathbf{0}) = \Lambda^h(\tau^*)$.[20] The initial equilibrium begins at $E^0 = (Q^0, P^0)$. The first iteration shifts the equilibrium to E^1. 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. Assumptions (A1)–(A4) are visually represented in the figure: downward-sloping demand (A1), upward-sloping *PMC* (A2), strictly positive slope-gap (A3), and bounded harvest shadow price (A4), collectively ensuring the iterative process's convergence to a unique fixed point.

[20]In this short-run case, a Pigouvian tax alone can guarantee the social optimum (Carlton and Loury 1980).

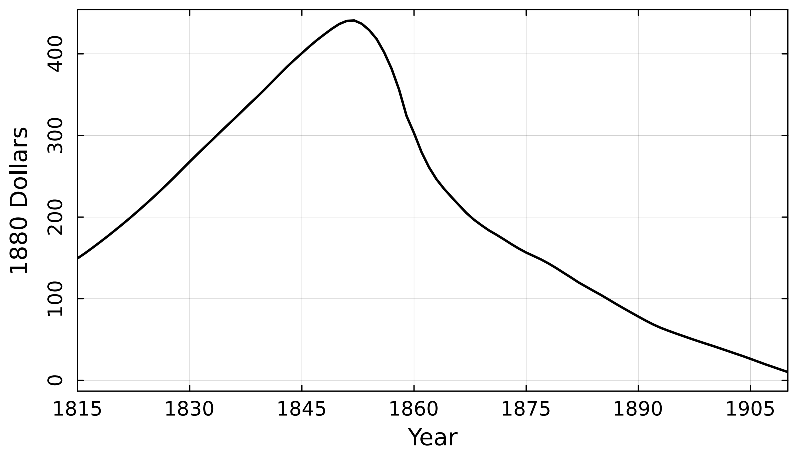

FIGURE 5. Fixed-point Pigouvian per-unit taxes

Note: Per-unit taxes τ^* are the fixed point of the iterative process $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$. The figure shows the average from 300 simulations.

Applying Proposition 1, I solve for the joint policy consisting of per-unit taxes and lump-sum taxes. Figure 5 plots the resulting time-varying 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. During the peak years between 1830 and 1860, whale stocks became increasingly depleted, and each additional harvest imposed substantial costs on other firms. Consequently, the optimal Pigouvian tax reached its maximum of around $440 per unit by 1850. After 1860, as the industry contracted, the shadow price of additional harvesting declined. Accordingly, the optimal tax fell gradually to roughly $40 by 1900.

Figure 6 plots the time-varying, state-dependent lump-sum taxes $\{\mathcal{F}_t^*(x)\}_{\forall t, x \in \mathcal{X}}$ for four representative years: 1815, 1850, 1870, and 1905. Darker shades indicate higher taxes, ranging from $2,000 (in 1880 dollars) to $500,000 over the course of a century. Lump-sum taxes are generally low in the early years but rise steadily by 1850 and remain high thereafter. Firms with greater capacity and higher productivity pay larger lump-sum taxes because they impose stronger congestion externalities. Firms operating more vessels directly expand aggregate capacity, intensifying congestion for all participants. Moreover, highly productive firms are more likely to invest rather than exit or divest, thereby exacerbating congestion over time. In 1815, firms pay an average lump-sum tax of about $3,000, reflecting weak congestion in the early industry (see Appendix Figure E3 for the firm size distribution under the joint policy). By 1850, as the industry expands, the average lump-sum tax rises sharply to $30,000. Taxes remain elevated in later years, consistent with persistent overcapacity that would prevail in the absence of regulation.

Figure 7 compares market outcomes under the observed allocation and alternative

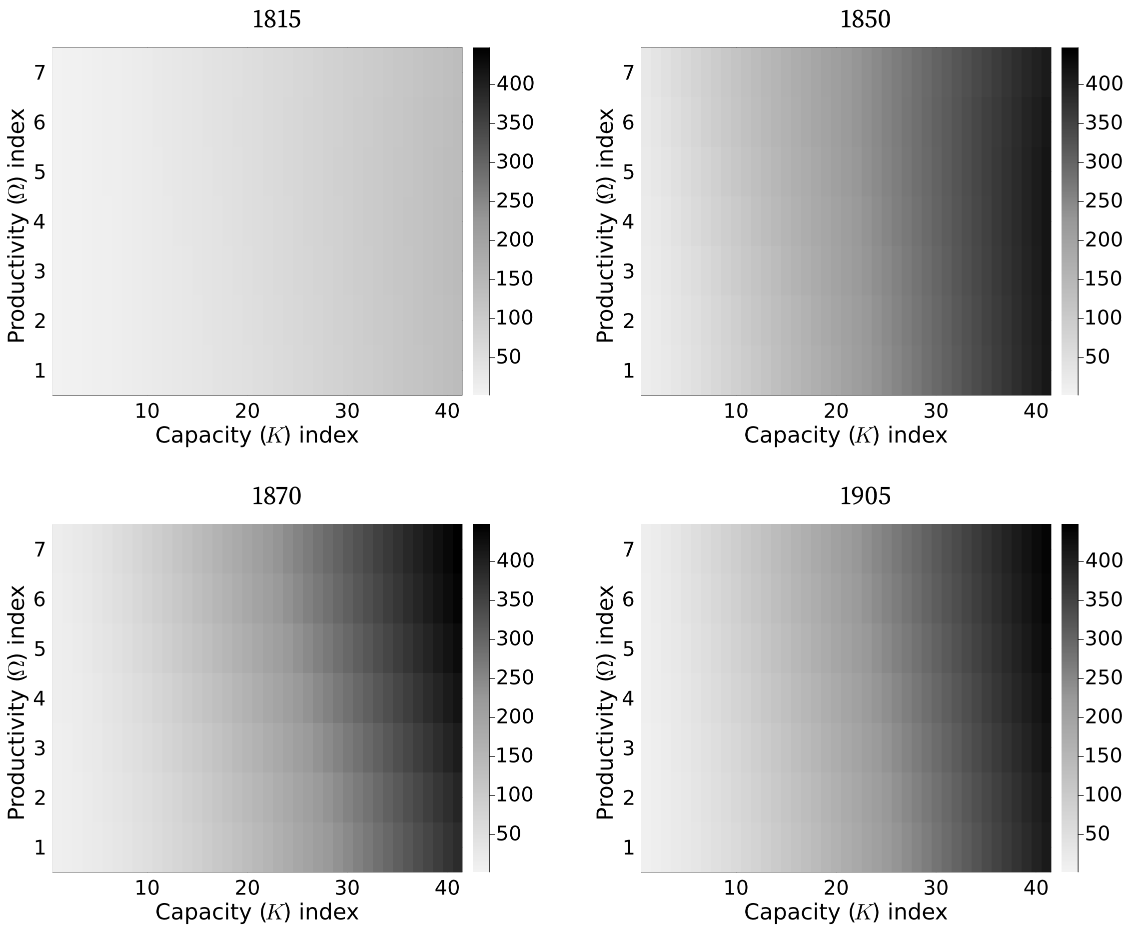

FIGURE 6. Fixed-point lump-sum taxes

Note: Lump-sum taxes $\mathcal{F}^*$ are the fixed point of the iterative process $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$. The color bar indicates values in thousands of 1880-adjusted dollars. Each panel displays four representative years: 1815, 1850, 1870, and 1905. Darker shades represent higher fees. The horizontal axis denotes capacity index K, and the vertical axis denotes productivity index Ω. Values are averaged over 300 simulations.

policy scenarios. Panel A shows total whale harvests, and Panel B shows whale stock levels. Policy interventions substantially slow harvest rates and stock depletion. Relative to the per-unit-tax-only policy, the joint policy further reduces total harvests in the early years by curbing firm entry and investment through the combined effects of per-unit and lump-sum taxes. This correction prevents the sharp stock decline during the golden-age period and yields a more balanced, efficient harvesting path in later years.

Table 6 summarizes welfare outcomes under the observed allocation and policy scenarios. In Panel A, total social welfare is approximately \$35.2 million, comprising a consumer surplus of \$42.8 million and a producer surplus of −\$-7.6 million. The negative producer surplus reflects the industry's excessive entry and investment before 1860, when firms incurred large fixed costs and generated substantial negative externalities. Panel B shows

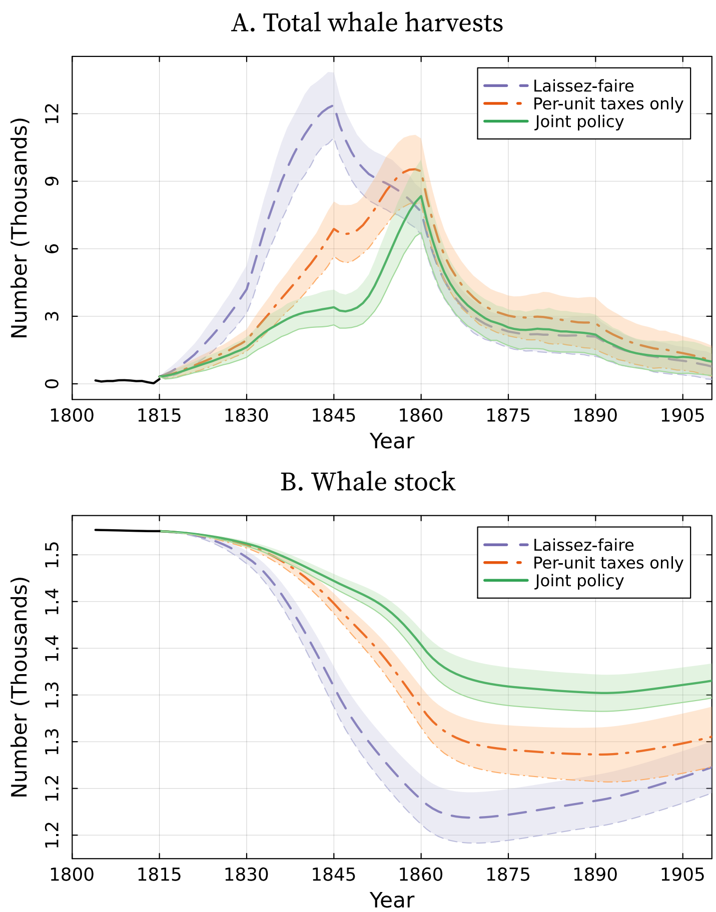

FIGURE 7. Market outcomes under observed allocation and alternative policy scenarios

Note: The lines show averages from 300 simulations, with 95 percent confidence intervals indicated by shaded areas. Each panel compares trends under the observed allocation (no policy) with 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. The observed allocation corresponds to the model outcomes in Figure 3. Panel A displays total whale harvests, while Panel B shows whale stock.

that introducing per-unit taxes substantially corrects these inefficiencies, raising total welfare to \$104.2 million—an increase of 196% relative to the observed allocation. Most of this improvement arises from the pre-1860 period, where welfare rises by 402.8%. In Panel C, I combine per-unit taxes with lump-sum taxes. Total social welfare increases even more, exceeding the observed allocation by 247.6% and the per-unit-tax-only case by 17.5%.

Discussion. The additional welfare gains from lump-sum taxes arise from addressing congestion externalities and overcapacity, which are not corrected by per-unit taxes. In Appendix D.2, equations (D.5) and (D.9) show that firm shadow prices retain congestion components even after conditioning on per-unit taxes that equal harvest shadow prices.

To verify this theoretical result, I examine an environment in which congestion ex-

TABLE 6. Welfare outcomes under observed allocation and alternative policy scenarios

	Pre–1860	Post–1860	Total
Panel A: Laissez-faire			
Consumer surplus	31.9	10.9	42.8
Producer surplus	–48.3	40.8	–7.6
Social welfare	–16.5	51.6	35.2
Panel B: Per-unit taxes only			
Consumer surplus	23.1	12.8	35.9
Producer surplus	–6.5	36.0	29.5
Government surplus	33.2	5.5	38.7
Social welfare	49.8	54.3	104.2
vs. Laissez-faire	[+402.8%]	[+5.2%]	[+195.9%]
Panel C: Joint policy			
Consumer surplus	16.8	11.5	28.3
Producer surplus	10.8	27.1	37.9
Government surplus	42.9	13.2	56.2
Social welfare	70.4	51.9	122.3
vs. Laissez-faire	[+528.2%]	[+0.5%]	[+247.6%]
vs. Per-unit taxes only	[+41.4%]	[–4.5%]	[+17.5%]

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 taxes, 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.

ternalities are absent. In this case, once Pigouvian per-unit taxes are correctly specified based on harvest shadow prices, the state-dependent lump-sum taxes should converge to zero according to equations (D.5) and (D.9). The computational results confirm this prediction: without congestion externalities, lump-sum taxes become negligible, and Pigouvian per-unit taxes alone achieve the long-run social optimum.

When congestion externalities are present, however, overcapacity emerges as a persistent problem, as shown in Appendix Figure E4. Under the observed allocation and the per-unit-tax-only policy, firms continue to enter and invest excessively. This inefficient expansion of the industry generates capital misallocation, as the marginal product of capital across firms deviates from its socially efficient level due to congestion externalities. Appendix Table E1 reports the dispersion of the marginal product of capital and shows that, under the joint policy, capital misallocation is substantially reduced.

5.3. Comparative statics

This subsection examines how welfare and policy respond to economic and environmental changes. I consider three scenarios: (a) higher whaling productivity growth, (b) stronger demand, and (c) faster whale regeneration. Although each scenario directly benefits the industry, the resulting equilibrium can intensify externalities, making the net welfare effect ambiguous. The optimal policy must therefore adjust depending on the magnitude of these externalities.

If productivity growth accelerates, firms can harvest more with the same capacity, pushing whale stocks toward depletion sooner. These efficiency gains encourage continued entry and investment even as stocks decline. Stronger demand, by raising equilibrium prices, stimulates expansion and intensifies externalities. Faster regeneration reduces scarcity-driven damages but can still lead to greater crowding as firms exploit the resource more aggressively. In all cases, the welfare impact depends on how these forces interact with the commons nature of the resource.

I vary one primitive at a time and recompute the policy fixed point $(\tau^*, \mathcal{F}^*)$. For higher TFP, I raise the annual productivity growth rate from 1.4% (Column 5, Table 3) to 2.4%. Stronger demand scales up the population shifter—$\alpha^{\text{pop}}_{\text{pre}}$ and $\alpha^{\text{pop}}_{\text{post}}$ (Columns 3 and 4, Table 4)—in the demand curve by 3%. Faster regeneration increases the reproduction rate in the stock-transition equation (1) from $r = 0.011$ (Table 2) to $r = 0.05$. All other primitives remain at their baseline. The exact magnitude of policy changes naturally depends on the size of these parameter shifts, so the emphasis here is on the *direction* of adjustment rather than the precise level.

Table 7 reports how the optimal two-part policy affects welfare relative to the laissez-faire allocation under different conditions. Panel A replicates the baseline results from Table 6, while Panels B–D show that the joint policy yields larger welfare gains than in the baseline case. Therefore, absent appropriate policy intervention, potential welfare losses (i.e., deadweight losses) would be greater in these environments. In addition, the extra welfare improvement from introducing lump-sum taxes, beyond that achieved by per-unit taxes alone, is significant across scenarios. These results underscore the importance of adapting policy to economic and environmental conditions to achieve the long-run social optimum.

6. Conclusion

This paper examines the long-run commons problem through the lens of strategic firm dynamics. Compared with standard common-pool resource models, I explicitly incorporate firms' entry, exit, and investment decisions. To capture these dynamic behaviors over the long run, I construct a firm-level panel from the 19th-century American whaling industry. This unique historical setting provides rich micro-level data in an unregulated environment, offering an ideal context for studying pure common-pool externalities.

The model and policy-design framework developed in this paper are broadly applicable to common-pool resource industries where many firms interact dynamically through exter-

TABLE 7. Welfare effects of the joint policy across alternative environments

	Pre–1860	Post–1860	Total
Panel A: Baseline			
vs. Laissez-faire	+528.2%	+0.5%	+247.6%
vs. Per-unit taxes only	+41.4%	–4.5%	+17.5%
Panel B: Higher whaling productivity growth			
vs. Laissez-faire	+505.2%	+15.8%	+358.0%
vs. Per-unit taxes only	+18.9%	–0.0%	+10.2%
Panel C: Stronger demand for whales			
vs. Laissez-faire	+390.7%	+12.1%	+395.7%
vs. Per-unit taxes only	+25.5%	–2.5%	+11.4%
Panel D: Faster whale regeneration			
vs. Laissez-faire	+273.9%	–10.7%	+340.2%
vs. Per-unit taxes only	+106.9%	–10.5%	+27.7%

Note: Welfare outcomes are averages from 300 simulations and expressed in millions of 1880 dollars. Values show the effect of the optimal two-part policy $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$ relative to the laissez-faire allocation. "Pre–1860" and "Post–1860" show contributions by period. "Total" is the sum of the two. Panel A is the baseline, which corresponds to the percent change between Panel C and Panel A in Table 6. Panels B–D change one primitive at a time. Higher TFP raises the annual productivity growth rate from 1.4% (Col. 5, Table 3) to 2.4%. Stronger demand increases the population shifter—$\alpha^{\text{pop}}_{\text{pre}}$ and $\alpha^{\text{pop}}_{\text{post}}$ (Cols. 3–4, Table 4)—in the demand curve by 3%. Faster regeneration increases the whale reproduction rate in equation (1) from $r = 0.011$ (Table 2) to $r = 0.05$. The social discount factor ρ_s is set to 0.97.

nalities. To solve for firms' equilibrium behavior, I embed externalities in a moment-based Markov equilibrium (Ifrach and Weintraub 2017), making the decentralized equilibrium tractable and enabling full-solution estimation. For counterfactual policy analysis, I quantify the shadow prices of externalities and introduce a fixed-point framework for policy design. This framework sets policy instruments equal to these shadow prices—the key condition that implements the social optimum.

My empirical findings have important policy implications. Conventional policies, especially in fisheries, primarily target total harvest levels. A prominent example is the system of tradable fishing permits (or individual transferable quotas), which, like per-unit taxes, internalizes the marginal externality from harvesting. Such policies can effectively regulate how much to harvest but are often insufficient to govern firms' long-run dynamic behavior. Entry, exit, and investment decisions depend on the long-run profitability of operating in the industry, whereas per-unit taxes only affect marginal production costs. To fully achieve the long-run social optimum, policy must also address externalities that operate through firms' fixed-cost margins. Therefore, optimal regulation requires complementary instruments such as state-dependent taxes or entry regulations.

Future work can extend the empirical framework developed in this paper 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 resource regeneration and technological change to study adaptive, state-contingent policy design. Together, these extensions would clarify when market-based instruments most effectively promote long-run industry efficiency.

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Appendix A. Agents' supervision

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

A.1. Planning by agent

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

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

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

> As you have now taken the responsible station of Master of a Ship and are a young man you will permit me to offer some advice. The greatest difficulty I have observed with young Masters, is either too great indulgence or too great severity towards their crew. Discipline must be effectual, be administered with a steady hand especially among Sailors, and there is no station which requires more guard over the temper, than that of a master of a Ship. And on your first voyage depends in a great measure your future success in life. Let me then beg of you to keep a strict watch over the moral conduct of your crew, never permit your authority to be abused or set at naught, but at the same time never to use undue severity yourself or permit it in your officers. I have a real confidence in you and I trust you will not feel hurt at my giving advice which I feel it my duty to offer you. (Morgan Collection)

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

A glimpse of the exchanges between the captain and agent can be obtained from the letter books of whaling agents. For instance, in February 1858, Matthew Howland wrote to one of his captains, Philip Howland, advising him over his recent performance:

Name of vessel.	Class.	Tonnage.	Captain.	Managing owner or agent.	Whaling-ground.	Date— Of sailing.	Date— Of arrival.	Result of voyage. Sperm-oil.	Result of voyage. Whale-oil.	Result of voyage. 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	36[illegible]	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 B1. Sample of Starbuck (1878)

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

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

Appendix B. Details of data

This section describes a detail of data sources and modifications.

B.1. *Voyage Database*

The American Whaling Voyage database includes information about all known US whaling voyages from the 1700s to the 1920s. Voyages have been defined based on customs house records, following Starbuck (1878), with each departure and subsequent return to the port of origin constituting a single voyage. Figure B1 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/).

B.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 B2. 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 B2 is an example of voyages by the vessel "Abigail" from *Ship Registers of New Bedford*. In the 1821 voyage, the owners were **Benjamin Rodman**, Andrew Robeson, David Coffin, and Elisha Dunbar. In the 1825 voyage, the ownership structure shows a subtle change to **Benjamin Rodman**, Charles W. Morgan, David Coffin, and Elisha Dunbar. In the 1835 voyage, we can see even clearer change in the ownership structure: **Charles W. Morgan**, William R. Rodman, David Coffin, Benjamin Clark, and Elisha Dunbar.

The first name of the owner list typically indicates principal owner or agent. Though principal owner and agent were not always the same, they played similar roles and in most of the cases they were the same. Indeed, Starbuck (1878) identified the whaling agent/owner of the vessel "Abigail" as Benjamin Rodman in 1825 and Charles W. Morgan in 1835 and later. However, the *Voyage Database* is missing agent/owner information for the 1821 voyage, so I have filled this gap with **Benjamin Rodman**, following the *Ship Registers*.

B.3. 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 whale oil, and Q_{it}^{woil} is the barrels of whale oil. From logbook database,[21] 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:

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

B.4. Aggregate demand variables

The online version is available at https://hsus.cambridge.org/. The annual measures of US population are derived from Series Ca14, and US GDP per capita is obtained from Series Ca9. Petroleum price is from Series Db56. Table B1 summarizes the demand-side statistics for the American whaling industry.

Appendix C. 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.

[21]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.

TABLE B1. Demand-side statistics for the American whaling industry

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

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

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.[22] 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).

[22] 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 D. Theoretical results

D.1. Equilibrium uniqueness

Proposition D.1 states conditions for uniqueness of the nonstationary moment-based Markov equilibrium (MME) in common-pool resource industries—defined in Section 3.4.

PROPOSITION D.1. *Fix primitives and an initial firm distribution f_1 and whale stock W_1. Suppose:*

- *(A1)* ***Finite horizon with stationary continuation.*** *There exists $\overline{T} \in \mathbb{N}$ such that for all $t > \overline{T}$ the industry follows a stationary moment-based Markov equilibrium.*[23]
- *(A2)* ***Feasible capacity and adjustment costs.*** *The feasible capacity set $\mathcal{K} \subset \mathbb{R}_+$ is nonempty and compact. For every $K \in \mathcal{K}$, the adjustment cost $C(K', K; \gamma)$ is continuous in (K', K) and strictly convex in K'.*
- *(A3)* ***Idiosyncratic shocks.*** *The entry cost κ_{it} and exit scrap value ζ_{it} have continuous densities with full support on $\mathbb{R}_+$, independent across i, t, and the state; the marginal adjustment shock ϵ_{it} has a continuous density with full support on $\mathbb{R}$, independent across i, t, and the state.*
- *(A4)* ***Moment structure and feedbacks.*** *Payoffs depend on competitors only through the payoff-relevant moments (K_t, Q_t) and the stock W_t. Higher aggregate capacity reduces each firm's payoff via congestion, and higher aggregate harvest reduces future stock and thus firms' payoffs. These feedbacks are monotone and stabilizing. The maps defining (K_t, Q_t) in* (7)–(8) *and the stock transition* (1) *are continuous in (f_t, W_t).*

Then there exists a unique sequence of strategy profiles $\{\psi_t\}_{t=1}^{\overline{T}}$ that constitutes a nonstationary moment-based Markov equilibrium.

PROOF. **Step 1 (Single-valued firm policies).** Fix $t \le \overline{T}$ and a state s_{it}. An incumbent that remains active chooses $K' \in \mathcal{K}$ to maximize the inner term of (12):

$$-C(K', K_{it}; \gamma) \; - \; I_{it}(K', K_{it})\,\epsilon_{it} \; + \; \rho\,\mathbb{E}_t\big[V_{t+1}(s_{it+1}, \psi_{t+1}; \Theta)\,\big|\, s_{it}, \psi_t\big].$$

By (A2), $-C(\cdot, K_{it}; \gamma)$ is strictly concave in K'. The only non-smooth part is the kink at $K' = K_{it}$ from $-I_{it}\epsilon_{it}$; conditional on a continuously distributed ϵ_{it} (A3), ties occur with probability zero. With compact $\mathcal{K}$ and continuity of the other terms, the argmax exists and is almost surely unique. The exit rule compares a unique continuation value with ζ_{it}; with continuous density on ζ_{it} (A3), the cutoff is unique almost surely. Potential entrants solve (13); with continuous density on κ_{it} (A3), the entry cutoff is also unique almost surely. Hence, each firm's policy (entry/exit/capacity adjustment) is single-valued with probability one.

[23]The terminal period and stationary continuation assumption is similar to Benkard, Jeziorski, and Weintraub 2024.

Step 2 (Unique aggregate transitions). Given single-valued policies, the law of motion for f_{t+1} is uniquely determined by (10). By (A4), (K_t, Q_t, W_{t+1}) depend continuously on (f_t, W_t), and the congestion and stock feedbacks ensure monotone responses. These stabilizing feedbacks eliminate the possibility of multiple consistent aggregate paths.

Step 3 (Backward induction). By (A1), for $t > \overline{T}$ the industry follows the stationary continuation equilibrium. At $t = \overline{T}$, firms solve a dynamic problem with that continuation; Step 1 ensures policies are single-valued, so $\psi_{\overline{T}}$ is unique. Inductively, if $\psi_{t+1}, \ldots, \psi_{\overline{T}}$ are unique, then the continuation value at t is uniquely defined; Step 1 gives a unique best response for each firm, so ψ_t is unique. Iterating back to $t = 1$ yields uniqueness of $\{\psi_t\}_{t=1}^{\overline{T}}$. □

D.2. Shadow prices

This section provides derivations of shadow prices, defined in Section 5.1. Here, I omit dynamic decision parts because they are not affected by derivatives. Then, I can rewrite the per-period social welfare function $\mathbb{W}_t(\cdot)$ defined in equation (24) as:

$$
\text{(D.1)} \quad \begin{aligned} \mathbb{W}_t(f_t, W_t, \tau_t, \mathcal{F}_t) &= \int_0^{Q_t} \mathcal{P}_t(\varphi)\mathrm{d}\varphi - \mathcal{P}_t(Q_t)Q_t \\ &+ \sum_z f_t(z)\left\{[\mathcal{P}_t(Q_t) - \tau_t]\,\mathcal{H}_t(z, K_t, W_t) - w_t L(K(z)) - \mathcal{F}_t(z)\right\} \\ &+ \sum_z f_t(z)\left\{\tau_t \mathcal{H}_t(z, K_t, W_t) + \mathcal{F}_t(z)\right\} \\ &= \int_0^{Q_t} \mathcal{P}_t(\varphi)\mathrm{d}\varphi - \mathcal{P}_t(Q_t)Q_t + \sum_z f_t(z)\left\{\mathcal{P}_t(Q_t)\mathcal{H}_t(z, K_t, W_t) - w_t L(K(z))\right\}, \end{aligned}
$$

where the last equality holds because the per-unit tax and lump-sum tax in producer surplus and government revenue cancel each other.

As shown in equation (26), the shadow price of an additional unit of whale harvest in year t is:

$$
\text{(26)} \qquad \Lambda_t^h(c) = -\left[\frac{1}{\rho_s^{t-1}} \frac{\partial \mathbb{W}(c;\psi^c)}{\partial Q_t} - (\mathcal{P}_t(Q_t) - \tau_t) - \tau_t\right].
$$

The derivative of the long-run social welfare with respect to Q_t is

$$
\text{(D.2)} \qquad \frac{\partial \mathbb{W}(c;\psi^c)}{\partial Q_t} = \rho_s^{t-1}\frac{\partial \mathbb{W}_t(\cdot)}{\partial Q_t} + \frac{\partial W_{t+1}}{\partial Q_t}\sum_{\ell=t+1}^{T} \rho_s^{\ell-1}\left(\prod_{m=t+1}^{\ell-1}\frac{\partial W_{m+1}}{\partial W_m}\right)\frac{\partial \mathbb{W}_\ell(\cdot)}{\partial W_\ell}.
$$

Here, I break down each derivative on the right hand side in equation (D.2). The first derivative $\frac{\partial \mathbb{W}_t(\cdot)}{\partial Q_t}$ reflects the immediate welfare change in year t due to harvesting one more whale in year t:

$$\frac{\partial \mathbb{W}_t(\cdot)}{\partial Q_t} = \underbrace{\mathcal{P}_t(Q_t) - \mathcal{P}'_t(Q_t)Q_t - \mathcal{P}_t(Q_t)}_{\Delta \mathrm{CS}_t} + \underbrace{\mathcal{P}'_t(Q_t)Q_t + \mathcal{P}_t(Q_t)}_{\Delta \mathrm{PS}_t} = \mathcal{P}_t(Q_t).$$

The next two derivatives $\frac{\partial W_{t+1}}{\partial Q_t}$ and $\frac{\partial W_{m+1}}{\partial W_m}$ of equation (D.2) describe how harvesting affects future whale stock, and come directly from the stock transition equation (1):

(D.3)

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

where $G(\cdot)$ describes how an additional unit of stock contributes to future stock through natural growth, and $\Upsilon_m^W(\cdot)$ measures the marginal increase in total harvest due to higher stock (which depends on the firm distribution f_m and the whale stock W_m). Note that $G(W_m) > 1$ for sufficiently low stocks ($W_m < W_1(1/(1+z))^{1/z}$) and falls below 1 as the stock approaches carrying capacity; under $\partial\mathcal{H}_m/\partial W_m > 0$, $\Upsilon_m^W(f_m, W_m) > 0$.

The last derivative $\frac{\partial \mathbb{W}_\ell(\cdot)}{\partial W_\ell}$ of equation (D.2) gives the welfare impact in year ℓ of having one more whale in that year:

$$\text{(D.4)}\qquad \frac{\partial \mathbb{W}_\ell(\cdot)}{\partial W_\ell} = \mathcal{P}_\ell(Q_\ell)\sum_{z\in\mathcal{X}} f_\ell(z)\frac{\partial \mathcal{H}_\ell(z, K_\ell, W_\ell)}{\partial W_\ell} = \mathcal{P}_\ell(Q_\ell)\Upsilon_\ell^W(f_\ell, W_\ell),$$

which shows that it depends on the total harvest, the distribution of firms, and the whale stock.

Putting these pieces together, equation (D.2) can be rewritten as:

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

As a result, the shadow price of an additional unit of whale harvest in year t (Eq. 26) is:

$$\text{(D.5)}\qquad \begin{aligned}\Lambda_t^h(c) &= \sum_{\ell=t+1}^{T}\rho_s^{\ell-t}\left(\prod_{m=t+1}^{\ell-1}\frac{\partial W_{m+1}}{\partial W_m}\right)\frac{\partial \mathbb{W}_\ell(\cdot)}{\partial W_\ell}\\ &= \sum_{\ell=t+1}^{T}\rho_s^{\ell-t}\left(\prod_{m=t+1}^{\ell-1}\frac{\partial W_{m+1}}{\partial W_m}\right)\mathcal{P}_\ell(Q_\ell)\Upsilon_\ell^W(f_\ell, W_\ell).\end{aligned}$$

Now I derive the shadow price of an additional firm in state x in year t, defined in equation (27):

$$\text{(27)} \qquad \Lambda_t^f(x; c) = -\left[\frac{1}{\rho_s^{t-1}}\frac{\partial \mathbb{W}(c;\psi^c)}{\partial f_t(x)} - \sum_{\ell=t}^{T}\rho_s^{\ell-t}\sum_y M_{t:\ell}(x,y)\Pi_\ell(y, K_\ell, W_\ell, \tau_\ell, \mathcal{F}_\ell(y)) \right. $$
$$\left. - \sum_{\ell=t}^{T}\rho_s^{\ell-t}\sum_y M_{t:\ell}(x,y)\mathcal{F}_\ell(y)\right].$$

where

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

denotes the probability that a firm in state x at year t is in state y at year ℓ. Here, M_m is the matrix representation of the transition kernel $[M_m]_{x,y} = M_m(y \mid x, \psi_m)$, 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.

Then, the derivative of the long-run social welfare with respect to $f_t(x)$ is

(D.6)

$$\begin{aligned}
\frac{\partial \mathbb{W}(c;\psi^c)}{\partial f_t(x)} &= \rho_s^{t-1}\frac{\partial \mathbb{W}_t(\cdot)}{\partial f_t(x)} + \rho_s^t\left[\sum_y M_{t:t+1}(x,y)\frac{\partial \mathbb{W}_{t+1}(\cdot)}{\partial f_{t+1}(y)} + \frac{\partial W_{t+1}}{\partial f_t(x)}\frac{\partial \mathbb{W}_{t+1}(\cdot)}{\partial W_{t+1}}\right] \\
&+ \rho_s^{t+1}\left[\sum_y M_{t:t+2}(x,y)\frac{\partial \mathbb{W}_{t+2}(\cdot)}{\partial f_{t+2}(y)} + \left(\frac{\partial W_{t+1}}{\partial f_t(x)}\frac{\partial W_{t+2}}{\partial W_{t+1}} + \sum_y M_{t:t+1}(x,y)\frac{\partial W_{t+2}}{\partial f_{t+1}(y)}\right)\frac{\partial \mathbb{W}_{t+2}(\cdot)}{\partial W_{t+2}}\right] \\
&+ \rho_s^{t+2}\left[\sum_y M_{t:t+3}(x,y)\frac{\partial \mathbb{W}_{t+3}(\cdot)}{\partial f_{t+3}(y)} + \left(\frac{\partial W_{t+1}}{\partial f_t(x)}\frac{\partial W_{t+2}}{\partial W_{t+1}}\frac{\partial W_{t+1}}{\partial W_{t+2}} + \sum_y M_{t:t+1}(x,y)\frac{\partial W_{t+2}}{\partial f_{t+1}(y)}\frac{\partial W_{t+3}}{\partial W_{t+2}} \right.\right. \\
&\qquad \left.\left. + \sum_y M_{t:t+1}(x,y)\frac{\partial W_{t+3}}{\partial f_{t+2}(y)}\right)\frac{\partial \mathbb{W}_{t+3}(\cdot)}{\partial W_{t+3}}\right] \\
&+ \cdots + \rho_s^{T-1}\left[\sum_y M_{t:T}(x,y)\frac{\partial \mathbb{W}_T(\cdot)}{\partial f_T(y)} + \left(\sum_{m=t}^{T-1}\Delta W_{m+1}^{(x)}\prod_{m=t+1}^{T-1}\frac{\partial W_{m+1}}{\partial W_m}\right)\frac{\partial \mathbb{W}_T(\cdot)}{\partial W_T}\right] \\
&= \rho_s^{t-1}\frac{\partial \mathbb{W}_t(\cdot)}{\partial f_t(x)} + \sum_{\ell=t+1}^{T}\rho_s^{\ell-1}\left[\sum_y M_{t:\ell}(x,y)\frac{\partial \mathbb{W}_\ell(\cdot)}{\partial f_\ell(y)} + \left(\sum_{m=t}^{\ell-1}\Delta W_{m+1}^{(x)}\prod_{k=m+1}^{\ell-1}\frac{\partial W_{k+1}}{\partial W_k}\right)\frac{\partial \mathbb{W}_\ell(\cdot)}{\partial W_\ell}\right],
\end{aligned}$$

where

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

represents the change in whale stock in year $m+1$ caused by adding one firm in state x at year t, with the effect propagated through the subsequent state transitions.

Below, I break down each derivative on the right hand side in equation (D.6). The first derivative $\frac{\partial \mathbb{W}_t(\cdot)}{\partial f_t(x)}$ reflects the immediate welfare change in year t due to adding one more firm in state x in year t:

$$\text{(D.7)}\quad \begin{aligned} \frac{\partial \mathbb{W}_t(\cdot)}{\partial f_t(x)} &= \left[\mathcal{P}_t(Q_t) - \mathcal{P}_t'(Q_t)Q_t - \mathcal{P}_t(Q_t)\right]\frac{\partial Q_t}{\partial f_t(x)} + \mathcal{P}_t(Q_t)\mathcal{H}_t(x, K_t, W_t) - w_t L(K(x)) \\ &\quad + \sum_z f_t(z)\mathcal{P}_t'(Q_t)\frac{\partial Q_t}{\partial f_t(x)}\mathcal{H}_t(z, K_t, W_t) + \sum_z f_t(z)\mathcal{P}_t(Q_t)\frac{\partial \mathcal{H}_t(z, K_t, W_t)}{\partial f_t(x)} \\ &= \underbrace{\mathcal{P}_t(Q_t)\mathcal{H}_t(x, K_t, W_t) - w_t L(K(x))}_{\text{private term}} + \underbrace{\mathcal{P}_t(Q_t)K(x)\Upsilon_t^K(f_t, W_t)}_{\substack{\text{impact on total harvest value} \\ \text{through capacity increase}}}, \end{aligned}$$

where $\Upsilon_t^K(f_t, W_t) := \sum_z f_t(z)\,\frac{\partial \mathcal{H}_t(z,K_t,W_t)}{\partial K_t}$ measures the marginal change in total harvest from an increase in total (aggregate) capacity. The derivative $\frac{\partial \mathbb{W}_t(\cdot)}{\partial f_t(x)}$ has two components of the immediate welfare change: (i) the direct effect through the new firm's private term and (ii) the indirect effect through the firm's impact on total harvest via total capacity (i.e., the congestion externality). The derivative $\frac{\partial \mathbb{W}_\ell(\cdot)}{\partial f_\ell(y)}$ is analogous.

Inside $\Delta W_{m+1}^{(x)}$, the derivative $\frac{\partial W_{t+1}}{\partial f_t(x)}$ describes how adding one more firm in state x in year t affects next period's whale stock. This expression follows directly from the stock transition equation (1):

$$\text{(D.8)}\qquad \frac{\partial W_{t+1}}{\partial f_t(x)} = \frac{\partial W_t}{\partial Q_t}\frac{\partial Q_t}{\partial f_t(x)} = -\left[\mathcal{H}_t(x, K_t, W_t) + K(x)\Upsilon_t^K(f_t, W_t)\right]$$

Combininig equations (D.3), (D.4), (D.7), and (D.8), equation (D.6) can be rewritten as:

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

Then, the shadow price of an additional firm in state x in year t (Eq. 27) is:

(D.9)

$$\begin{aligned} \Lambda_t^f(x;c) = -\Bigg[&\frac{1}{\rho_s^{t-1}}\frac{\partial \mathbb{W}(c;\psi^c)}{\partial f_t(x)} - \sum_{\ell=t}^{T}\rho_s^{\ell-t}\sum_y M_{t:\ell}(x,y)\Pi_\ell(y, K_\ell, W_\ell, \tau_\ell, \mathcal{F}_\ell(y)) \\ &- \sum_{\ell=t}^{T}\rho_s^{\ell-t}\sum_y M_{t:\ell}(x,y)\mathcal{F}_\ell(y)\Bigg] \end{aligned}$$

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

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

This section proves Proposition 1, which establishes the conditions for the uniqueness of a fixed point of shadow prices.

PROPOSITION 1. *For any $c = (\tau, \mathcal{F}) \in \mathcal{C}$, define the operator $\mathscr{T} : \ c \longmapsto \big(\Lambda^h(c), \Lambda^f(c)\big)$. Assume that there exist constants $L_P, L_{MC}, L_{HD}, L_{FD} > 0$, $m_{\min} > 0$ and $m_{\max} \geq 0$ such that for every t, x, Q_t and c:*

- (A1) *Inverse demand: $\mathcal{P}'_t(Q_t) < 0$ and $|\mathcal{P}'_t(Q_t)| \leq L_P$.*
- (A2) *Private marginal cost: $0 \leq PMC'_t(Q_t) \leq L_{MC}$.*
- (A3) *Slope dominance: $PMC'_t(Q_t) - \mathcal{P}'_t(Q_t) \geq m_{\min}$.*
- (A4) *Harvest shadow price: $\Lambda^h_t(c)$ is non-decreasing in Q_t and $\big|\partial\Lambda^h_t(c)/\partial Q_t\big| \leq L_{HD}$.*
- (A5) *Firm shadow price: $\Lambda^f_t(x; c)$ is continuous in $f_t(x)$ and $\big|\partial\Lambda^f_t(x;c)/\partial f_t(x)\big| \leq L_{FD}\big(1 + m_{\max}\big)$, where $m_{\max} := \sup_{t,x,c}\max\big\{|\partial Q_t/\partial f_t(x)|,\ |\partial Q_t/\partial \mathcal{F}_t(x)|\big\} < \infty$.*

Define $\Lambda := \max\Big\{\frac{L_{HD}}{m_{\min}},\ L_{FD}\big(1 + m_{\max}\big)\Big\} < 1$. Then, under Assumptions (A1)–(A5):

- (a) *$\mathscr{T}$ is a contraction on $(\mathcal{C}, \|\cdot\|_\infty)$ with modulus $\mathcal{M}$.*
- (b) *A unique fixed point $c^* = (\tau^*, \mathcal{F}^*) \in \mathcal{C}$ exists and satisfies $c^* = \big(\Lambda^h(c^*), \Lambda^f(c^*)\big)$.*
- (c) *For any initial $c^0 \in \mathcal{C}$ the iterates $c^{m+1} := \mathscr{T}(c^m)$ obey $\|c^m - c^*\|_\infty \leq \mathcal{M}^m\|c^0 - c^*\|_\infty$; convergence is geometric.*

PROOF. Fix two policies $c = (\tau, \mathcal{F})$ and $\tilde{c} = (\tilde{\tau}, \tilde{\mathcal{F}})$ in $\mathcal{C}$. Set $\Delta\tau := \tau - \tilde{\tau}$, $\Delta\mathcal{F} := \mathcal{F} - \tilde{\mathcal{F}}$ and denote $\|\cdot\| \equiv \|\cdot\|_\infty$.

Harvest shadow price. Assumption A4 implies

(P1) $$\big\|\Lambda^h(c) - \Lambda^h(\tilde{c})\big\| \ \leq\ L_{HD}\,\|Q - \tilde{Q}\|.$$

The market-level FOC $PMC_t(Q_t) + \tau_t = \mathcal{P}_t(Q_t)$ and the mean-value theorem give

$$|Q_t - \tilde{Q}_t| \;\le\; m_{\min}^{-1}\,|\tau_t - \tilde{\tau}_t|, \qquad m_{\min} := \inf_t\big(PMC_t' - \mathcal{P}_t'\big) > 0.$$

Because A1–A3 bound both slopes, $m_{\min} \in (0, \infty)$, hence

(P2)
$$\|Q - \tilde{Q}\| \;\le\; m_{\min}^{-1}\|\Delta\tau\|.$$

Combining (P1) and (P2) yields

(P3)
$$\big\|\Lambda^h(c) - \Lambda^h(\tilde{c})\big\| \;\le\; \frac{L_{HD}}{m_{\min}}\,\|\Delta\tau\|.$$

Firm shadow price. Apply the mean-value theorem to the map $\mathcal{F}_t(x) \mapsto \Lambda_t^f(x\,;c)$, keeping every other policy component fixed. For some intermediate policy $\bar{c}$,

(P4)
$$\big|\Lambda_t^f(x;c) - \Lambda_t^f(x;\tilde{c})\big| \;=\; \left|\frac{\partial\Lambda_t^f(x;\bar{c})}{\partial\mathcal{F}_t(x)}\right|\big|\mathcal{F}_t(x) - \tilde{\mathcal{F}}_t(x)\big|.$$

and write

$$\frac{\partial\Lambda_t^f(x;\bar{c})}{\partial\mathcal{F}_t(x)} = \underbrace{\frac{\partial\Lambda_t^f(x;\bar{c})}{\partial\mathcal{F}_t(x)}}_{\text{direct}} + \underbrace{\frac{\partial\Lambda_t^f(x;\bar{c})}{\partial Q_t}}_{\text{via } Q_t}\,\frac{\partial Q_t}{\partial\mathcal{F}_t(x)}.$$

- **Direct (government-surplus) channel.** Lump-sum taxes enter welfare linearly; therefore
$$\Big|\partial_{\mathcal{F}_t(x)}\Lambda_t^f(x;\bar{c})\Big| \le 1.$$
- **Indirect (congestion → harvest) channel.** Assumption A5 gives $|\partial_{f_t(x)}\Lambda_t^f| \le L_{FD}(1 + m_{\max})$ and since $\partial_{Q_t} f_t(x)$ is at most one in magnitude,
$$\Big|\partial_{Q_t}\Lambda_t^f(x;\bar{c})\Big| \le L_{FD}.$$

By definition of $m_{\max}$, $\big|\partial_{\mathcal{F}_t(x)}Q_t\big| \le m_{\max}$. Hence the cross term is bounded by $L_{FD}m_{\max}$. Adding the two channels yields

$$\Big|\partial_{\mathcal{F}_t(x)}\Lambda_t^f(x;\bar{c})\Big| \;\le\; L_{FD}(1 + m_{\max}).$$

Substituting this in (P4) and taking the supremum over (t, x) gives

(P5)
$$\big\|\Lambda^f(c) - \Lambda^f(\tilde{c})\big\| \;\le\; L_{FD}(1 + m_{\max})\,\|\Delta\mathcal{F}\|.$$

Contraction. Since $\|c - \tilde{c}\| = \max\{\|\Delta\tau\|, \|\Delta\mathcal{F}\|\}$, (P3) and (P5) imply

$$\|\mathscr{T}(c) - \mathscr{T}(\tilde{c})\| \leq \Lambda \|c - \tilde{c}\|, \quad \Lambda := \max\{L_{HD}/m_{\min}, L_{FD}(1 + m_{\max})\} < 1.$$

Fixed point and convergence. Because $\mathscr{T}$ is a strict contraction on $(\mathcal{C}, \|\cdot\|)$, Banach's fixed-point theorem furnishes a unique $c^* = (\tau^*, \mathcal{F}^*)$ with $c^* = \mathscr{T}(c^*)$ and

$$\|\mathscr{T}^m(c^0) - c^*\| \leq \mathcal{M}^m \|c^0 - c^*\|, \qquad m = 0, 1, 2, \dots,$$

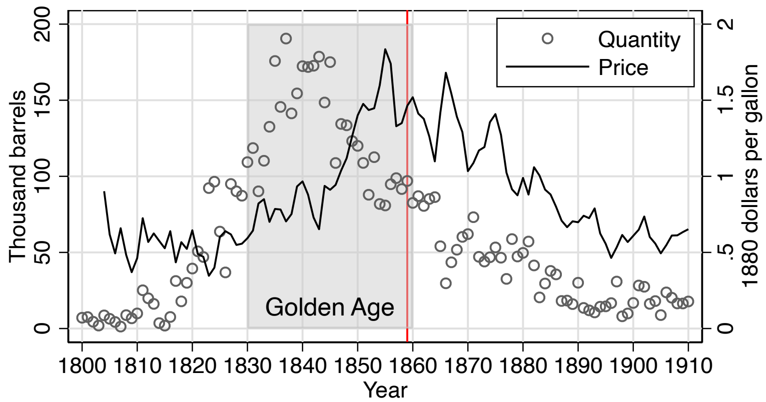
for every starting point $c^0 \in \mathcal{C}$. Finally, $(\tau^*, \mathcal{F}^*) = \big(\Lambda^h(c^*), \Lambda^f(c^*)\big)$, completing the proof. □

Appendix E. Additional figures and tables

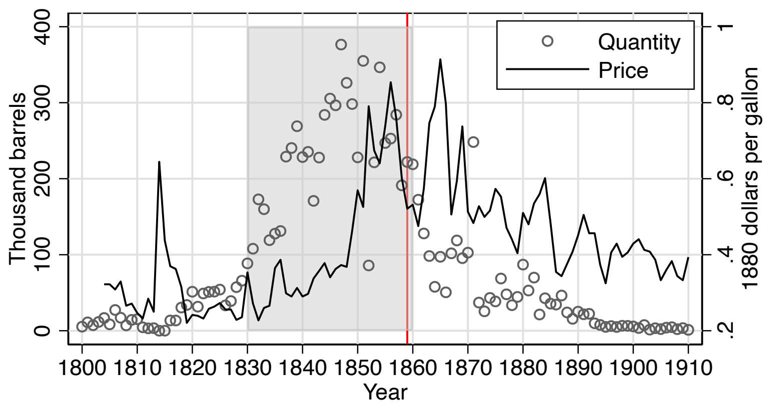
Figure E1 illustrates trends in output quantities and prices for whaling products. Panel A shows sperm oil output peaking around 1840, followed by a decline; as supply diminished, prices rose. The introduction of petroleum (red vertical line) gradually displaced sperm oil. Panel B, on whale oil, displays a similar trajectory but with a later production peak, suggesting that the more valuable sperm oil was exploited earlier. As sperm oil output became harder to sustain from the 1840s, American whalers shifted to whale oil, which peaked around 1850. Whalebone, shown in Panel C, was initially a by-product of whale oil during the golden age period. Its value surged from the 1870s, driven largely by the women's fashion industry—particularly corset demand. By then, the industry had already declined, leaving supplies scarce and prices high. This pattern indicates that even after petroleum replaced whale oils, distinct demand for whales persisted through whalebone.

Figure E2 shows the trend in price per whale. The price per whale significantly increased until the 1860s, driven by rising demand and decreasing supply. After the 1860s, the price stabilized and slightly declined, likely due to the introduction of petroleum as an alternative to sperm oil and whale oil.

A. Sperm oil



B. Whale oil



C. Whalebone

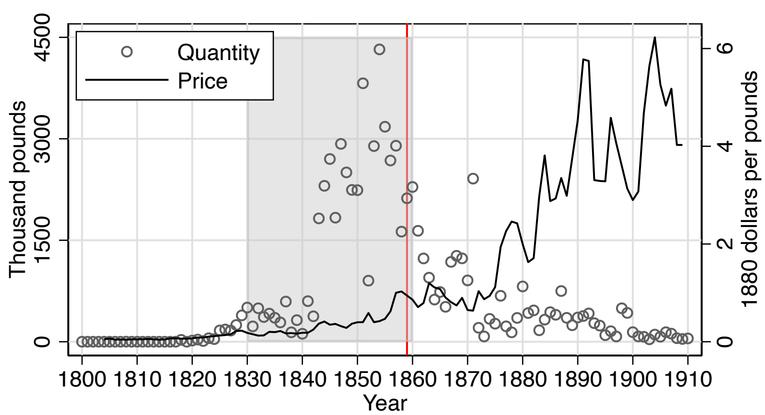


FIGURE E1. Quantities and prices for whaling products

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.

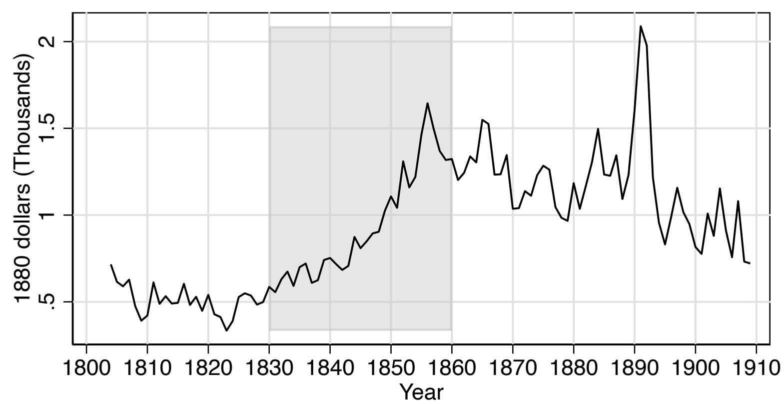


FIGURE E2. Whale price

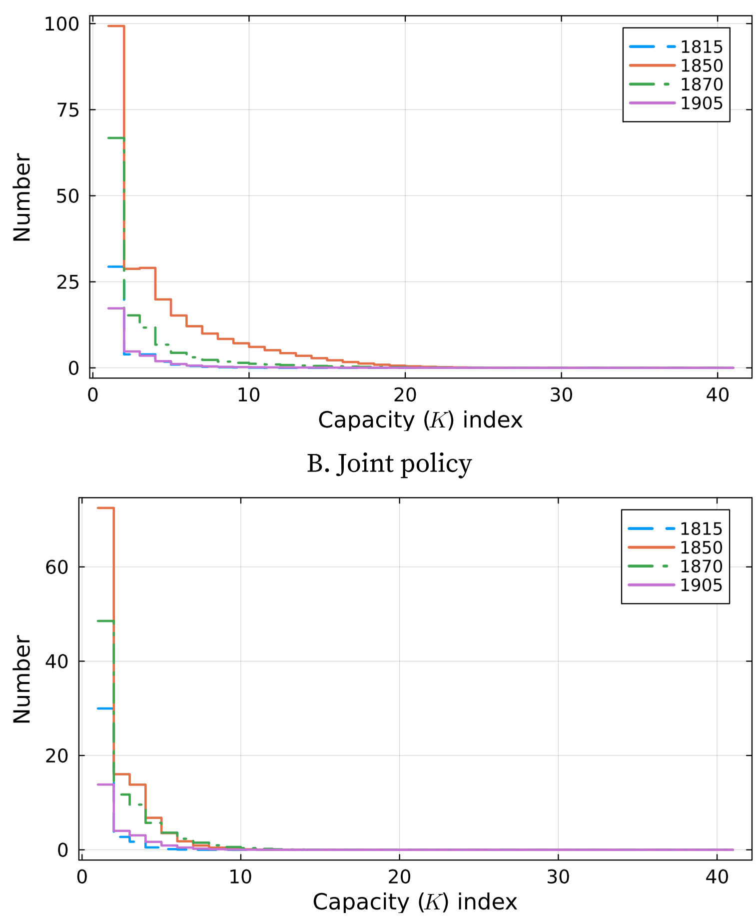
Note: The prices of whaling products come from Tower (1907) and Davis, Gallman, and Gleiter (2007). I calculate the price *per whale* as total output value divided by total whales harvested each year. The output value equals sperm oil quantity × price + whale oil quantity × price + whalebone quantity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

TABLE E1. Capital misallocation under observed allocation and alternative policy scenarios

	Pre–1860	Post–1860	Total
Panel A: Laissez-faire			
MPK Dispersion	1.005	0.979	0.991
Panel B: Per-unit taxes only			
MPK Dispersion	0.806	0.993	0.909
vs. Laissez-faire	[–19.8%]	[+1.4%]	[–8.3%]
Panel C: Joint policy			
MPK Dispersion	0.742	0.904	0.831
vs. Laissez-faire	[–26.2%]	[–7.6%]	[–16.1%]
vs. Per-unit taxes only	[–8.0%]	[–8.9%]	[–8.5%]

Note: MPK (marginal product of capital) dispersion is measured as the standard deviation of log MPK across firms in a given year. "Pre–1860" and "Post–1860" report the average MPK dispersion within each subperiod, while "Total" reports the average over the full sample period (1804–1909). Panel A presents the observed allocation outcomes from the estimated model. Panel B reports outcomes under Pigouvian per-unit taxes only, obtained from the fixed point $\tau^* = \Lambda^h(\tau^*, \mathbf{0})$. Panel C combines per-unit taxes with lump-sum taxes, determined by the joint fixed-point condition $(\tau^*, \mathcal{F}^*) = (\Lambda^h(\tau^*, \mathcal{F}^*), \Lambda^f(\tau^*, \mathcal{F}^*))$. Percent changes in MPK dispersion are shown in square brackets.

A. Laissz-faire



B. Joint policy

FIGURE E3. Firm size distribution under observed allocation and joint policy

Note: The lines show averages from 300 simulations. Each panel compares the distribution of firms by vessel capacity K in years 1820, 1850, 1870, and 1890. Panel A is for the observed allocation while panel B shows the joint policy allocation with $(\tau^*, \mathcal{F}^*)$.

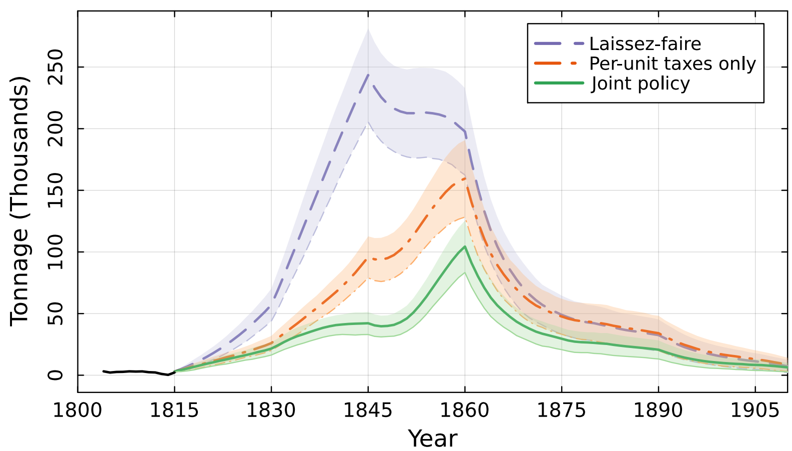


FIGURE E4. Total whaling vessel capacity

Note: The lines show averages from 300 simulations, with 95 percent confidence intervals indicated by shaded areas. Each panel compares trends under the observed allocation (no policy) with 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. The observed allocation corresponds to the model outcomes in Figure 3.