# Essays on Empirical Industrial Organization and Environmental Economics

Sean Ewen

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2024

Reading Committee:

Yuya Takahashi, Chair

Fahad Khalil

Yael Jacobs

Program Authorized to Offer Degree:
Economics

University of Washington

**Abstract**

Essays on Empirical Industrial Organization and Environmental Economics

Sean Ewen

Chair of the Supervisory Committee:
Yuya Takahashi
Department of Economics

This dissertation contributes to two major research areas: the analysis of endogenous product characteristics in structural models of demand and dynamic models of invasive species management.

In the first chapter, I analyze claims of falling business travel demand in the US following the COVID-19 pandemic. I focus on the US domestic airline market in between 2019 and 2022 and construct a structural model of air travel demand that assumes heterogeneity in consumers takes two forms: business travellers and leisure travellers. I endogenize the number of daily departures on a given route to account for changes in fuel cost that may affect carriers' flight frequency decisions. I find that both consumer "types" became less price-sensitive and average price elasticity increased. There was a large shift in the share of passengers from "leisure"-type to "business"-type. I interpret this as evidence that many leisure travellers behaved as business travellers during 2022 – forgoing their usual concerns about price to partake in revenge travel..

In the second chapter, I examine common ownership, or the phenomenon of several diversified, institutional investors owning overlapping shares in competing firms. Existing research has thus far highlighted the common ownership effects on pricing and entry, but the effects on non-price product characteristics has not drawn significant attention. I aim to fill this gap by analyzing deposit market competition. I build a structural

model of bank branching decisions in the United States and estimate the cost of a bank branch implied by two different modes of conduct: own-profit maximization and common ownership. I find that if banks internalize the competitive effect of their branch networks on commonly-owned firms' profits, the difference in implied branch cost is small. Indeed, a Vuong-type model selection test does not find a statistically significant difference between the two models' ability to explain the observed data.

In the third chapter, we study invasive aquatic plants (IAP) and their harmful effects on river ecosystems. Managing invasive aquatic plant species is complicated by their inherent downstream dispersal patterns, and likely recurrence in already-treated invaded patches. Furthermore, as climate change alters riparian environments, the cost and spatial dispersion of species management will likely change as both growing conditions and control efficacy shift. To address how costs and optimal management strategies change with a changing climate, we develop a model of IAP management that incorporates spatial heterogeneity and downstream dispersal and can be calibrated to habitat suitability data at a coarse scale. We utilize parametric dynamic programming techniques to quickly and efficiently compute an approximation to the optimal policy. As a case study, we calibrate the model to simulate the management of water-primrose (*Ludwigia spp.*) in the Willamette River basin, Oregon, USA using data from a climate-sensitive habitat suitability model trained on occurrence data for water-primrose. We find the climate change model implies differential changes across different segments of the river system. Accounting for spread in the management model leads to an optimal management policy that differs from the naive one that allocates management in proportion to the climate change-induced differences.

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

## ACKNOWLEDGEMENTS

I would like to express my sincere thanks to my advisor and chair, Yuya Takahashi, for his expert guidance and advice. I would also like to thank my committee members, Fahad Khalil, Yael Jacobs, and David Layton, for their feedback and attention. Thank you to Braeden Van Deynze for his constant support and guidance, as well as my other co-authors, Sunny Jardine, Emily Smoot, Rebecca Flitcroft, and Samuel Chan, for being great collaborators. Thank you to my internship manager, Pavel Kapinos, for excellent research advice and mentorship.

I would also like to thank my friends and family who grounded and supported me throughout the process. Thank you to my partner, Lily, for her love and patience, and for always believing in me. Thank you to my parents for their love and support. Thank you to Jorge Rivero and the rest of the UW Econ Family for being great friends and fellow researchers.

Thank you to Arlo for being a good boy.

To Mom, Dad, and Lily.

Chapter 1

# ZOOM CALLS AND REVENGE TRAVEL: PANDEMIC-INDUCED CHANGES TO DEMAND FOR US DOMESTIC AIR TRAVEL

August 13, 2024

The market for air travel was among the industries most affected by the COVID-19 pandemic. Business and media commentators have speculated about numerous changes to the industry including the decline of business travel and the rise of pandemic-induced "revenge travel." Empirical investigation of these claims is complicated by carriers' rising fuel and labor costs and the endogeneity of flight frequency decisions. I analyze these claims in US domestic air travel in 2022 relative to 2019 using a structural model of air travel demand that assumes heterogeneity in consumers takes two forms: business travellers and leisure travellers. I endogenize the number of daily departures on a given route to account for changes in fuel cost that may affect carriers' flight frequency decisions. I find that both consumer "types" became less price-sensitive and average price elasticity increased. There was a large shift in the share of passengers from "leisure"-type to "business"-type. I interpret this as evidence that many leisure travellers behaved as business travellers during 2022 – forgoing their usual concerns about price to partake in revenge travel.

## *1.1 Introduction*

The market for air travel was among the industries most affected by the COVID-19 pandemic. Global travel decreased drastically as many practiced social distancing to limit their exposure to the virus. Additionally, governments worldwide imposed travel restrictions into and out of their countries. The result was a 50% decrease in available airplane seats and 2.7 billion less passengers flown in the year 2020 than in 2019.[1] In the US, domestic enplanements decreased 28% between 2019 and 2020[2], provoking Congress to pass several pieces of legislation aimed at supporting the struggling industry. Over the course of 2020 and 2021, Congress authorized the Treasury to issue over $50 billion in loans to US airlines.[3] Figure 1.1 plots US domestic enplanements over the years 2019-

[1]Source: International Civil Aviation Organization

[2]Source: Bureau of Transportation Statistics

[3]Source: US Department of the Treasury

2023. By 2022, enplanements had not yet fully recovered. In the last three quarters of the year, the number of enplaned domestic passengers was still 5.8% lower than the corresponding quarters in 2019 and major airlines such as American, United, and Southwest reported negative net income.[4]

On its face, this appears to be an, as yet, incomplete recovery. However, many attribute the continued weak demand and poor financial performance not only to lingering effects of pandemic restrictions, but also to a permanent change in the behavior and preferences of business travellers. These travellers are now said to substitute "Zoom" or other videoconferencing calls for meetings where travel may have once been prominent. Since the pandemic induced mass adoption of videoconferencing technology, many believe this has permanently altered the nature of business travel demand.

Decreased business travel demand is a problem for airlines, as business travellers are observed to have lower price-sensitivity than leisure travellers. On the other hand, easing of pandemic restrictions and widespread vaccination status has precipitated discussions of so-called "revenge travel."[5] This describes a phenomenon where consumers, prevented from vacationing over a long period, suddenly increase their consumption of travel to "make up for" lost vacation experiences. This suggests there may be two countervailing effects of the post-lockdown environment on air travel demand: one of decreasing price-insensitive business travel, and one of increasing price-sensitive leisure travel.

Disentangling these effects is further complicated by the fact that airlines faced significantly higher operating costs during and after the pandemic. Fuel costs rose due to geopolitical instability and carriers experienced labor shortages. The labor shortages were due in part to a pre-existing pilot shortage and in part to layoffs during the pandemic. These costs are likely to significantly effect carriers' decisions of how much to

[4]Source: Bureau of Transportation Statistics

[5]See, for example, "'Revenge travel' is surging. Here's what you need to know" by Manuela López Restrepo, from *NPR.org* (2022)

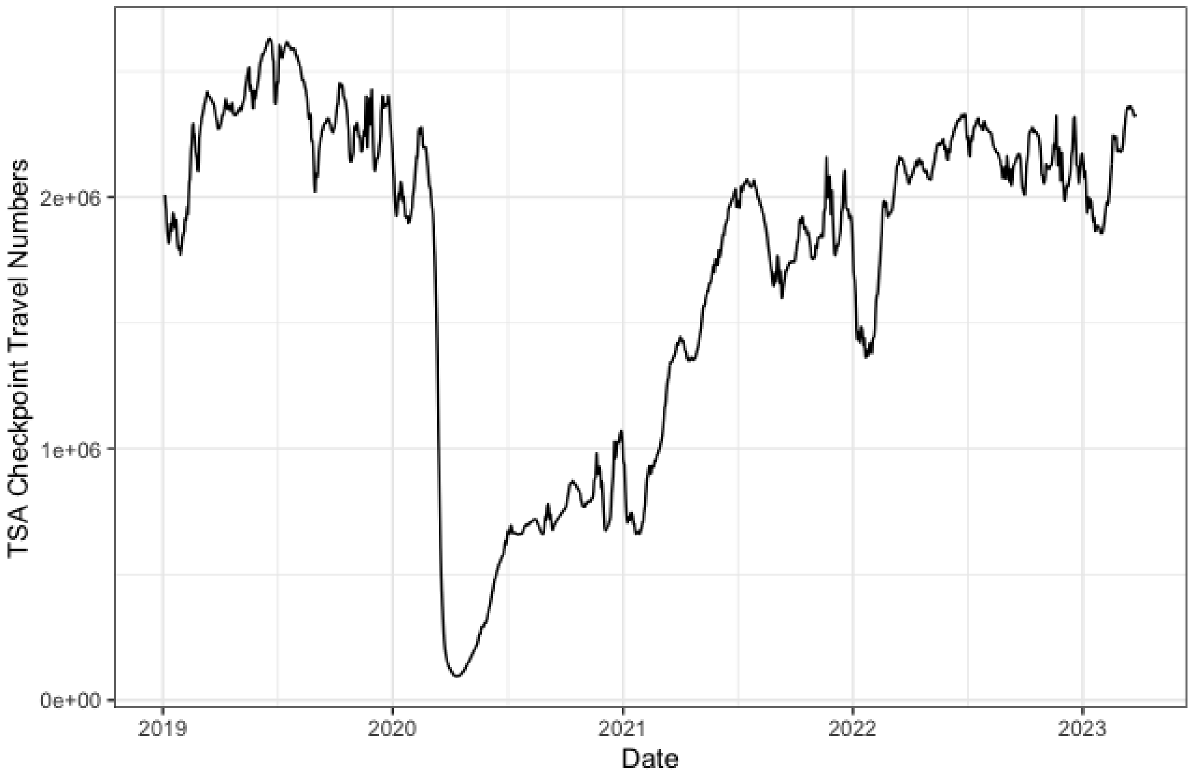



Figure 1.1: TSA Checkpoint Travel Numbers (7-day moving average), 2019-2023
Source: Transportation Security Administration

fly on a given route (their flight frequency), all else equal, so any empirical investigation needs to account for this.

In this paper, I investigate the substantial differences in the market for US domestic air travel in 2022 relative to 2019 using a structural model of air travel demand that assumes heterogeneity in consumers takes two forms: business travellers and leisure travellers. I endogenize the number of daily departures on a given route to account for changes in fuel and labor costs that may affect carriers' flight frequency decisions. I use this model to analyze claims of decreasing business travel and "revenge travel" in the wake of the COVID-19 pandemic, and their effect on airline profits. I find that both consumer "types" became less price-sensitive and average price elasticity decreased in absolute value. There was a large shift in the share of passengers from "leisure"-type to "business"-type. I interpret this as evidence that many leisure travellers behaved as business travellers during 2022 – forgoing their usual concerns about price to partake in revenge travel. I also conduct counterfactual analyses to examine the effects of these changes on airlines' profits. I show that the change in demand was relatively more important than the change in cost to for airline profits in 2022.

The paper is organized as follows: Section 1.2 reviews the literature, Section 1.3 develops the model, Section 1.4 describes the data, Section 1.5 reports results and counterfactual estimates, and Section 1.6 concludes.

## *1.2 Related Literature*

My work contributes to two distinct strands of literature: structural models of demand and competition in air travel markets and studies concerning the impacts of the COVID-19 pandemic on economic activity. I consider each of these in turn.

Several papers have investigated demand for air travel using structural estimation methods. Most studies in this field rely on a key insight due to Berry [1990] that a carrier's presence at an airport (measured by the number of markets they serve out of that airport) is an important determinant of demand for their flights in that market. This allows researchers to use airport presence as a measure of product differentiation, facilitating the use of structural demand models. One of the seminal works in this vein is Berry et al. [2006] (BCS) who applied a random coefficients logit model in the style of Berry et al. [1995] (BLP) to aggregate US ticket data. Using this model, they find an airline can charge a premium for flights out of their hubs because of price-insensitive business travellers who value the airline's airport presence. They also find evidence of considerable economies of density from airlines' hub-and-spoke networks.

BCS employed two techniques that would become widely used in air travel demand estimation. The first was their decision to model consumer heterogeneity as coming from differences between two discrete types of consumers, which they interpret as business and leisure travellers. This interpretation comes from the widely documented observation that business travellers are relatively less price-sensitive and relatively more connection-averse than leisure travellers. Business travellers do not generally pay for tickets themselves, instead they may book a flight and bill their company, hence their lower responsiveness to price. The second technique used by BCS was to allow for correlation between price and unobserved ticket characteristics like advance-purchase requirements and Saturday night stayover rules (more common in the 1990's than today) by incorporating an unobserved product characteristic term into the consumer's utility function. In estimation, this is treated as a product-specific econometric error (see Berry [1994]).

My paper closely resembles work by Berry and Jia [2010]. These authors estimate demand for US domestic air travel in two years, 1999 and 2006, and compare the estimates in between the two. They seek to explain the causes of legacy carriers' low profits in the first decade of the 21st century. They find that consumers became more price sensitive and more connection averse and that this accounts for most of the decrease in airlines' profits. The entry and expansion of several low-cost carriers such as Southwest and JetBlue was another contributing factor.

Ciliberto and Williams [2014] use a similar structural demand model to estimate the competition softening effects of multi-market contact. They relax the Bertrand-Nash pricing assumption common in BLP-style models and instead allow the markup to depend on an estimated "conduct parameter." This parameter summarizes the extent to which firms internalize the effects of their own pricing decisions on rivals' products. They find that this conduct parameter is positively correlated with the number of markets in which two firms compete and conclude that multi-market contact facilitates tacit collusion.

Several papers find that fixed costs and entry decisions are important aspects of competition and price setting in airline markets. This literature has roots in Berry [1992] but several developments have been made since then. For instance, Ciliberto and Tamer

[2009] develop a model of entry where firms with unique identities make simultaneous entry decisions in travel markets. They estimate the payoff functions of carriers and find that legacy carriers have different "competitive effects" on rivals' profits than low-cost carriers. Ciliberto et al. [2021] extend this model to one of simultaneous entry and price setting. They show that if there exists correlation between firms' fixed cost and demand unobservables, traditional demand estimation will be biased. Li et al. [2022] estimate a model of sequential product choice and price competition in airline markets. They allow firms to first choose whether to offer nonstop or connecting service, then decide on prices. They use the estimated parameters to conduct merger simulations that closely match results of observed mergers. Finally, Aguirregabiria and Ho [2012] use a dynamic model of oligopolistic competition to show that the sunk entry cost in an airline market declines with the number of flights offered out of the endpoint airports.

My model does not estimate fixed costs but rather the slope of fixed cost with respect to product characteristics. I use the method described in Fan [2013], who endogenizes product characteristic decisions in the US newspaper industry. To my knowledge, this is the first study to incorporate endogenous product characteristics to a static demand model in the airline industry. For a more general treatment of endogenous product characteristics in static demand models, see Petrin et al. [2022].

My research also relates to work on the COVID-19 pandemic and its impact on economic activity. Recent years have produced an especially large amount of work on this topic and I do not attempt a complete review here. Instead, I highlight work related to consumption during and after the lockdown phases of the pandemic. For an extensive literature review, refer to Brodeur et al. [2021].

Much pandemic-related literature has focused on the effects of the virus on consumption. Chetty et al. [2020] analyze the heterogeneity of changes in consumption at the onset of the pandemic and find that high-income individuals reduced their consumption sharply in 2020. This led to revenue and job losses for many businesses. High-wage employment experienced a sharp decline, followed by a relatively quick recovery, whereas low-wage job losses persisted into 2022.

Kapetanios et al. [2022] study policy interventions intended to encourage social distance during the pandemic and their effect on consumption. They find that, for Dutch citizens, the spread of the virus caused a drop in consumption early in the pandemic, but this effect disappears as the pandemic went on. Coibion et al. [2020] find that differential lockdown policies across US counties explain differences in expected employment, inflation, and mortgage rates. Bounie et al. [2020] use transaction and bank data from France to document virus-induced changes in consumption in the country. They find a sharp reduction in consumption in the early stages of the pandemic but a strong recovery over the following year.

Several papers from travel and marketing disciplines have also considered the specific phenomenon of "revenge spending" after social distancing phases of the pandemic. For instance, Zaman et al. [2021] survey a sample of international travellers and find a positive association between pandemic fatigue and "revenge travel" motivations. These are motivations for travel that include "escape from the psychological pressure, daily routines, and rules that resulted from the pandemic." Additionally, Gupta and Mukherjee [2022] survey a sample of Indian consumers and find that revenge buying was associated with feelings of autonomy need frustration in consumers during the pandemic.

## *1.3 Model*

I consider a structural model of oligopolistic competition between airlines in the style of Berry et al. [1995]. My model follows other demand analyses of air travel, namely BCS (2006), Berry and Jia (2010), and Ciliberto and Williams (2014). Airlines compete for travellers in markets composed of an origin and destination pair. Flight products are differentiated by fare, nonstop status, and frequency. Other variables that affect demand such as time of departure and number of days until departure at the time of purchase are unobserved and are thus modelled as a product-level unobservable. The specifics of the model are outlined below.

### *1.3.1 Demand*

In what follows, consumers are indexed by $i$, products by $j$, markets by $m$, and time periods by $t$. Let $J_{mt}$ denote the number of products in market $m$ in time period $t$. There are two discrete types of consumers, with types indexed by $r$. For consumer $i$ of type $r$ in market $m$, at time $t$, utility for product $j$ is given by

$$u_{ijmt} = x_{jmt}\beta_r - \alpha_r p_{jmt} + \xi_{jmt} + \nu_{jmt}(\lambda) + \lambda\varepsilon_{ijmt},$$

where $x_{jmt}$ is a vector of product characteristics for product $j$, $p_{jmt}$ is product fare, $\beta_r$ and $\alpha_r$ are consumer type $r$'s taste parameters for nonprice characteristics and price, respectively, $\xi_{jm}$ is an unobserved (to the researcher) product characteristic, and $\nu_{jmt}(\lambda) + \lambda\varepsilon_{ijmt}$ is an error term that generates nested-logit preferences. The nesting parameter $\lambda \in [0, 1]$ governs substitution between product nests. There are two nests: one that comprises all products in a market and another that consists only of the outside good of not purchasing a flight. The deterministic portion of utility for the outside good is normalized to zero. Hence, utility from not purchasing a flight is given by

$$u_{i0mt} = \varepsilon_{i0mt},$$

where $\varepsilon_{i0mt}$ is a logit error.

Conditional on flying, the share of type $r$ consumers who purchase product $j$ is

$$\frac{e^{(x_{jmt}\beta_r - \alpha_r p_{jmt} + \xi_{jmt})/\lambda}}{D_{rmt}}, \tag{1.1}$$

where

$$D_{rmt} = \sum_{k=1}^{J_{mt}} e^{(x_{kmt}\beta_r - \alpha_r p_{kmt} + \xi_{kmt})/\lambda}.$$

The share of type $r$ consumers who purchase a flight is

$$\frac{D_{rmt}^{\lambda}}{1 + D_{rmt}^{\lambda}}. \tag{1.2}$$

Putting together equations (1.1) and (1.2) and aggregating across consumer types, the market share of product $j$ in market $m$ is given by

$$s_{jmt}(\mathbf{x}_{mt}, \mathbf{p}_{mt}, \xi_{jmt}, \theta_d) \equiv \sum_{r=1}^{2} \gamma_r \frac{e^{(x_{jmt}\beta_r - \alpha_r p_{jmt} + \xi_{jmt})/\lambda}}{D_{rmt}} \frac{D_{rmt}^{\lambda}}{1 + D_{rmt}^{\lambda}},$$

where $\gamma_r$ is the proportion of consumers of type $r$ in market $m$ and $\theta_d \equiv (\beta, \alpha, \lambda, \gamma)$ is the vector of demand parameters. Following BCS (2006) and Berry and Jia (2010), $\gamma_r$ is assumed to be constant across all markets.

I add carrier and time fixed effects to control for correlation in consumers' preferences within the same carrier and across time. Thus the unobserved component of mean utility for product $j$ can be represented as

$$\Delta\xi_{jmt} = \xi_{jmt} - d_{jmt}\phi,$$

where $d_{jmt}$ is a vector of carrier and time period dummy variables.

I can then invert the market share equation to obtain the vector of demand unobservables, $\Delta\xi_{jmt}$. Because preferences are specified as a random coefficients nested logit model, I use a modification of the BLP contraction mapping (see Grigolon and Verboven [2014] for details). Specifically, each step $T+1$ of the iteration is "dampened" by the nesting parameter, $\lambda$. For example, the $T+1$ step is calculated as

$$\Delta\xi_{jmt}^{T+1} = \Delta\xi_{jmt}^{T} + \lambda[\ln s_{jmt} - \ln s_{jmt}(\mathbf{x}_{jmt}, \mathbf{p}_{jmt}, \xi_{jmt}^{T}, \theta_d)].$$

Let $z_{jmt}$ denote a vector of instruments. The model satisfies the moment condition

$$\mathbb{E}[\Delta\xi_{jmt}|z_{jmt}] = 0,$$

which, in turn, implies

$$\mathbb{E}[h(z_{jmt})\Delta\xi_{jmt}] = 0, \tag{1.3}$$

for some function $h(\cdot)$ of the instruments. Ticket fare, $p_{jm}$, is endogenous in this model and hence left out of the instrument vector, $z_{jm}$.

### *1.3.2 Supply*

Airlines are assumed to compete in a static Bertrand-Nash price game. This implies that prices are set at a markup above marginal costs:

$$\mathbf{p}_{mt} = \mathbf{mc}_{mt} + \Delta^{-1}\mathbf{s}_{mt}, \tag{1.4}$$

where $\Delta$ is a matrix whose $(j,k)$-th element corresponds to

$$\Delta_{j,k} = -\frac{\partial s_j}{\partial p_k} \cdot \mathbf{1}\{\text{product } j \text{ and } k \text{ are produced by the same firm}\}.$$

Thus I can recover the market-level vector of marginal costs from the equation

$$\mathbf{mc}_{mt} = \mathbf{p}_{mt} - \Delta^{-1}\mathbf{s}_{mt}.$$

Marginal costs are then parameterized as

$$mc_{jmt} = [w_{jmt}, d_{jmt}]'\psi + \omega_{jmt},$$

where $w_{jmt}$ is a vector of observable cost-shifters, $\psi$ is a vector of parameters, and $\omega_{jmt}$ is a product-level structural error term.

The model implies the following moment conditions:

$$\mathbb{E}[\omega_{jmt}|z_{jmt}] = 0,$$

which, as in the demand side, are used to construct

$$\mathbb{E}[h(z_{jmt})\omega_{jmt}] = 0. \tag{1.5}$$

Finally, carriers' flight frequency decisions are endogenous. Let $x^f_{jmt}$ be flight frequency for carrier $j$ in market-quarter $mt$. I assume that they choose their flight frequency for each market before choosing prices, thus their first order condition for frequency sets the derivative of the profit function equal to 0. I further assume that fixed costs, $FC$, are a quadratic function of frequency. The optimality condition is given by

$$\frac{d\pi_{jmt}}{dx^f_{jmt}} = \sum_{k\in\mathcal{J}_|} \left[ \left( \frac{\partial p_{kmt}}{\partial x^f_{jmt}} - \frac{\partial mc_{jmt}}{\partial x^f_{jmt}} \right) M_{mt} s_{kmt} + (p_{kmt} - mc_{kmt})\, M_{mt} \frac{\partial s_{kmt}}{\partial x^f_{jmt}} \right] - \frac{\partial FC_{jmt}}{\partial x^f_{jmt}} \tag{1.6}$$

$$= \sum_{k\in\mathcal{J}_|} \left[ \left( \frac{\partial p_{kmt}}{\partial x^f_{jmt}} - \frac{\partial mc_{jmt}}{\partial x^f_{jmt}} \right) M_{mt} s_{kmt} + (p_{kmt} - mc_{kmt})\, M_{mt} \frac{\partial s_{kmt}}{\partial x^f_{jmt}} \right] - \tau_0 - \tau_1 x^f_{jmt} - v_{jmt} \tag{1.7}$$

$$= 0, \tag{1.8}$$

where $M_{mt}$ is market size in market-quarter $mt$, $\tau_0$ and $\tau_1$ are fixed cost parameters to be estimated, and $v_{jmt}$ is a structural error. These first-order conditions imply the third and final moment condition

$$\mathbb{E}[v_{jmt}|z_{jmt}] = 0,$$

which can be taken to data with the following unconditional moment:

$$\mathbb{E}[h(z_{jmt})v_{jmt}] = 0. \tag{1.9}$$

Calculating the gradient $\frac{\partial p_{kmt}}{\partial x^f_{jmt}}$ in (1.6) is not straightforward. To do this, I follow Fan (2013) and assume the pricing function is smooth in response to changes in characteristics. I then take the derivative of (1.4) with respect to frequency. Since (1.6) is the first-order condition for the observed product characteristics, the derivative only needs to be calculated at the values of these observed characteristics.

### *1.3.3 Consumer Type Interpretation*

Consumer heterogeneity is modelled by assuming each consumer is one of two types. In the air travel demand literature (BCS (2006), Berry and Jia (2010), Ciliberto and Williams (2014)), these types are interpreted as leisure and business travellers. This assumption derives from a desire to fit a documented difference in preferences between the two consumers in a parsimonious way. Leisure travellers are generally considered to be more price sensitive than business travellers and business travellers more connection averse. Thus I allow coefficients on three variables to vary with type: fare, nonstop status, and a constant.

Note that while this interpretation is convenient for my purposes, I do not have data on the actual share of business and leisure travellers. More generally, the types can be considered price sensitive and non-price sensitive types, respectively.

## *1.4 Data*

The data I use comes from three sources. The first is the DB1B Origin and Destination Survey, a 10% sample of all domestic airline tickets in the US for a given quarter published by the Bureau of Transportation Statistics (BTS). The DB1B contains data on individual tickets including the fare, connection, and ticketing and operating carriers. The second source is the Airline On-Time Performance Data, also published by the BTS, from which I derive a measure of flight frequency. Finally, demographic data comes from US Census Bureau.

### 1.4.1 Sample Selection

I use data from the second, third, and fourth quarters of 2019 and 2022. This allows me to compare demand from before the pandemic, with demand after leisure travel is said to have mostly recovered.[6] Using data from multiple quarters allows for more heterogeneity in choice sets, which aids in identifying the type parameter, $\gamma_r$.

I drop tickets with unrealistic fares such as those below $30 or above $3000 or whose credibility has been questioned by the BTS. I also drop itineraries with more than one ticketing carrier, more than 2 connections on a leg, or those that include ground transportation. Finally, I drop carriers from markets that do not represent a competitive presence in that market. In practice, this means I drop carriers that transport less than 100 passengers in a market-quarter.

I define a market as a directional trip between two airports. Thus SEA-JFK is a different market than JFK-SEA. I restrict attention to airports in metropolitan areas with populations greater than 1 million. I also focus on markets whose endpoints are at least 150 miles apart. On-Time Performance Data contains carriers with at least 0.5% of all domestic service scheduled passenger revenue. The only carrier that does not meet this threshold but has a significant market share in the data is Sun Country, which has a hub at the Minneapolis-St. Paul airport. Thus I drop markets that involve Minneapolis-St.Paul as one of the endpoints. Finally, if a metropolitan area has more than one airport, I treat each as part of a separate market.

[6] See Belaich and Pisani-Ferry (2022) for evidence of this claim

### 1.4.2 Product Definition

A product is a unique combination of carrier, fare, and nonstop status. A carrier can offer at most two products in a market, a nonstop flight and a connecting flight. Unlike Berry and Jia (2010), products are not differentiated by connecting airport. Also unlike Berry and Jia (2010), who account for product heterogeneity by creating separate products for different fare values, I follow Ciliberto and Williams (2014) and define a product's fare to be the mean fare over all tickets sold by the carrier in the market for a given nonstop status. I use this definition because the Berry and Jia (2010) definition is prone to a selection problem where demand shocks induce entry for certain products. Thus, due to Ciliberto, Murry, and Tamer (2021), estimation will be biased under this product definition.

### 1.4.3 Exogenous Variables

Nonprice variables are flight frequency, the size of a carrier's network, market distance, hub status of the endpoint airports, whether either of the endpoint airports is slot-controlled, and the number of nonstop markets served out of the endpoint airports. Flight frequency is measured as the number of daily departures in a quarter, as reported in the BTS Airline On-Time Performance data. For connecting flights, I measure frequency as follows: for an observed itinerary leg between airports A and C, connecting through airport B, if a flight departs B for C at least 45 minutes and no more than 4 hours after a flight arrives at B from A, I count it as one connecting departure from A to C. I then sum over all such combinations to find a measure of connecting frequency. If there are multiple possible connections after the flight from A to B, I only count one.

As is well documented in the air travel literature (see e.g. Berry (1992)), the size of a carrier's network at a particular airport is an important determinant of demand for that carrier. This is due to the value of frequent flyer miles for that carrier operating out of that airport. Thus I incorporate network size into consumers' utility. In constructing the network size variable for a particular carrier-airport pair, I follow Aguirregabiria and Ho (2012) and sum over the populations of the endpoints of every market served by the carrier out of that airport. Defining network size in this way serves two purposes: 1) higher population areas are likely to be visited more frequently and thus matter more as a destination to consumers who may be deciding which frequent flyer program to join, and 2) it is less correlated with the number of nonstop destinations served out of an airport than is the number of total markets served. This second point allows me to use the number of nonstop destinations served out of the endpoint airports in a market as supply side cost shifters.

I include both distance and its square. It is widely recognized in air travel demand estimation that air travel demand's response to distance is hump-shaped (see e.g. Berry and Jia (2010)). At short distances, air travel competes more heavily with other forms of transportation, such as bus and rail, than at long distances. In addition, when the length of travel is too long, travel itself becomes less desirable.

Hub status and slot-controlled status are dummy variables equal to one if either endpoint is a hub or slot-controlled, respectively. Flying through a hub airport could plausibly impact the marginal cost of a product either positively or negatively. If hubs are very congested, flying through a hub may increase marginal cost. If hubs lead to economies of density (as estimated in BCS (2006)), flying through one could decrease marginal cost. If an airport is slot-controlled, this means the Federal Aviation Administration assigns carriers certain time slots to take off and land. Slot-controlled airports have high traffic and are capacity-constrained, thus flying through one should increase marginal cost.

I use the number of nonstop destinations served out of the endpoint airports as determinants of supply. The justification for this is that the more destinations offered at a certain airport, the more the carrier must pay in personnel costs and gates. I also include a dummy variable in the cost equation that is equal to one when a market is less than 1,500 miles. This is because carriers use different planes and perhaps regional codeshare partners for short distance flights (Forbes and Lederman [2007]).

Finally, I follow standard practice in transportation demand studies and define the market size as the geometric mean of the metropolitan populations at the endpoints in the market.[7]

I take all nonprice variables as exogenous.[8] This assumption is true when equilibrium is a result of a game where carriers first decide on product characteristics and then decide on price. This also assumes that carriers take the network structure as given. This assumption seems reasonable given the large fixed costs that go into creating and maintaining a hub. A carrier is unlikely to substantially change its network in response to a competitor's price change in a single market.

Tables 1.1 and 1.2 report summary statistics by year for products and markets, respectively. Means and standard deviations are broadly similar between both years. The exceptions are the daily departures and passengers variables, which decreased significantly from 2019 to 2022. There are 55,150 total products in 13,129 market-quarters in 2019 and 58,152 products in 13,580 market-quarters in 2022.

Table 1.3 reports summary statistics by carrier. Most carriers increased their fares slightly from 2019 to 2022 with small increases in dispersion. Carriers entered about the same number of markets, except for Southwest, which enters considerably more markets in 2022.

### *1.4.4 Instruments*

Price is an endogenous variable in my model and must be instrumented for. As instruments, I use BLP-style "markup shifters" that serve as measures of a product's isolation in the characteristics space. These are:

- The exogenous product characteristics, $x_j$

[7]For an alternative measure of market size, see Li et al. (2022)

[8]Berry and Jia (2010) model flight frequency as an endogenous variable. I find this assumption does not make a significant difference in my parameter estimates

| | 2019 | | 2022 | |
|---|---|---|---|---|
| Statistic | Mean | SD | Mean | SD |
| Fare (2022 $100) | 2.83 | 0.92 | 2.82 | 1.02 |
| Market share | 0.001 | 0.002 | 0.001 | 0.002 |
| Daily departures | 7.66 | 7.80 | 5.98 | 6.25 |
| Origin network size (10 million people) | 27.82 | 7.93 | 27.79 | 7.49 |
| Dest. network size (10 million people) | 27.84 | 7.90 | 27.79 | 7.48 |
| Nonstop | 0.23 | 0.42 | 0.23 | 0.42 |
| Distance (thousands of miles) | 1.26 | 0.66 | 1.26 | 0.65 |
| Hub | 0.24 | 0.42 | 0.23 | 0.42 |
| Slot | 0.08 | 0.27 | 0.08 | 0.27 |
| Obs. | 65,016 | | 65,610 | |

Table 1.1: Product characteristics means and standard deviations.
Notes: Network size is the sum of populations at the endpoints of each market the carrier serves out of that airport. Hub = 1 if either endpoint is a hub for the carrier that owns the product. Slot = 1 if either endpoint is a slot-controlled airport.

- The exogenous cost shifters, $w_j$
- The sums of rival network size, nonstop frequency, and connecting frequency
- Route-level variables such as the number of carriers in a market, the number of low-cost carriers in a market, the number of nonstop products in a market, and the market size

These are correlated with price through their competitive impact on a product's markup, but are uncorrelated with the unobserved component of utility, thus valid instruments.

### *1.4.5 Model Limitations*

The model has several limitations. One, pointed out by Berry and Jia (2010), is it cannot account for differences in price due to airlines' revenue management pricing strategies. In short, revenue management implies that airlines intertemporally price discriminate –

| | 2019 | | 2022 | |
|---|---|---|---|---|
| Statistic | Mean | SD | Mean | SD |
| Products | 3.85 | 2.14 | 3.99 | 2.23 |
| Carriers | 3.29 | 1.59 | 3.41 | 1.66 |
| Passengers (thousands) | 16.59 | 28.92 | 15.79 | 26.70 |
| Nonstop passengers (thousands) | 13.99 | 28.31 | 13.28 | 26.13 |
| Market size (millions) | 3.54 | 2.45 | 3.60 | 2.48 |
| Market-Quarters | 16,866 | | 16,445 | |

Table 1.2: Market characteristics means and standard deviations

they sell a fixed number of seats for a low price, then raise the price as more seats are sold.[9]. This, along with other ticket characteristics that certainly affect demand, such as time and day of the week of the flight, are not observed in my dataset. Thus, I assume that any impact this has on mean fares is captured by the unobserved product characteristic term, $\xi_j$.

Second, I do not observe the consumer's choice set. It is probable that all products observed in a market will not be available to a consumer at the time of purchase. Furthermore, the prices in a consumer's choice set likely differ from the mean fares I calculate in my dataset. Unobserved product availability will likely bias my coefficient estimates. I follow Berry and Jia (2010) and assume that product availability is also captured by the unobserved product characterisitics term. Those authors show that the bias due to this assumption is likely to be small when the share of the outside good is large, as is the case here.

Finally, my model does not allow me to estimate fixed costs. Only the slope of the fixed cost equation with respect to frequency is estimable. This is problematic for two reasons. The first is that estimates of profit can only be interpreted as variable profits. The second and more substantial concern is that if fixed costs are correlated with the

[9] For an empirical investigation of the welfare effects of these strategies, see Lazarev [2013]

| Carrier | 2019 # of Markets | 2019 Mean Fare | 2019 SD Fare | 2022 # of Markets | 2022 Mean Fare | 2022 SD Fare |
|---|---|---|---|---|---|---|
| American | 13,824 | 2.79 | 0.74 | 13,125 | 2.81 | 0.79 |
| Alaska | 1,301 | 2.22 | 0.70 | 1,293 | 2.49 | 0.76 |
| JetBlue | 1,480 | 2.35 | 0.78 | 1,663 | 2.29 | 0.90 |
| Delta | 12,551 | 2.75 | 0.81 | 12,112 | 2.85 | 0.93 |
| Frontier | 2,850 | 0.98 | 0.24 | 2,992 | 1.06 | 0.32 |
| Allegiant | 660 | 0.95 | 0.22 | 747 | 0.95 | 0.24 |
| Spirit | 2,059 | 0.93 | 0.23 | 2,700 | 1.18 | 0.38 |
| United | 10,713 | 2.85 | 0.76 | 10,078 | 2.80 | 0.88 |
| Southwest | 10,096 | 2.13 | 0.51 | 11,393 | 1.95 | 0.61 |

Table 1.3: Carrier summary statistics
Note: Mean and standard deviation of fare is weighted by passenger

demand shock, $\xi_j$, parameter estimates will be biased. This is due to a selection problem where firms with both low fixed costs and high demand shocks enter the market. Assuming $\xi_j$ is conditionally mean zero is hence violated. Although this is a concern in airline markets,[10] I have roughly the same number of products per market in 2019 and 2022 with about the same amount of dispersion. This suggests that entry rates are not significantly different between the two years and that parameter estimates should still be broadly comparable.

## 1.5 Results

In this section, I present estimates of the parameters of the model in Section 1.3, along with elasticities and profits, followed by counterfactual analyses. I estimate the model by first forming the sample analogues of the moments in (1.3) and (1.9). I then stack the moments and perform two-step GMM to recover the parameter estimates. I allow for arbitrary correlation between the demand and supply unobservables within markets. In

[10]See Ciliberto et al. (2021) for a discussion on this point.

practice, this affects the construction of the second step weight matrix and calculation of the standard errors. In what follows, I interpret the first consumer type as the "leisure" or price-sensitive type.

### *1.5.1 Demand Parameters*

Corresponding with the conventional wisdom that business travel demand has weakened since the pandemic, I expect the coefficient on fare for the business type to be larger in absolute value in 2022. I also expect the type parameter, $\gamma$, which is interpreted as the share of leisure travellers, to be larger in 2022. This is associated with a scenario where business-type consumers drop out of the market and leisure-types enter the market.

I also expect results to be similar to previous demand estimation studies in finding that utility for all consumers increases with a nonstop flight, network size, and the number of daily departures. Utility is expected to respond to distance following an upside-down parabola, as air travel competes with ground travel at short distances, and travel becomes undesirable at long distances.

Finally, note that coefficient estimates are, in general, not comparable across logit models estimated on different data. This is because the parameters indicate the importance of a variable to a consumer's decision *relative to the unexplained variance in their decision*. Since I estimate two models in broadly the same markets for different time periods, I expect the magnitudes of the coefficients to be similar. However, comparisons should be interpreted as rough approximations to the actual differences. I report more rigorous comparisons below using elasticity estimates.

Columns 2 and 3 of Table 1.4 report demand parameter estimates for 2019 and 2022, respectively. For both consumer types, the fare coefficient decreased. Leisure-type consumers saw a drop from $-4.48$ to $-5.38$ and business-type from $-0.51$ to $-0.34$. This suggests that consumers across the board became more price sensitive. The coefficient on nonstop is positive for both types in both years but decreases significantly between the years for the leisure type.

Estimates of the type parameter, $\gamma$, differ significantly from my expectations. While the values of the coefficients of the share equation are not particularly informative, they imply that 31% of passengers were leisure travellers in 2019 and only 8% were leisure travellers in 2022. The Bureau of Transportation Statistics reports that roughly 20% of domestic air travellers are traveling for business so this result casts doubt on the interpretation of the two types as leisure and business travellers. Instead, this can be rationalized with a situation where both business and leisure types were relatively price insensitive in the strong macroeconomic environment of 2019. After the pandemic shock, a small group of travellers became much more price sensitive, whereas another group of travellers undertook "revenge spending," which is described by Nguyen and Chao [2021] as a "situation in which the demand for specific goods and services suddenly skyrockets and remains high for an extended period of time." This is commonly attributed to demand for goods and services after the pandemic as consumers who saved during the lockdown phases of the pandemic increase their consumption heavily after the lockdown phases end. In this scenario, the consumer types lose their interpretation as leisure and business travellers and are more appropriately described as price-sensitive and price-insensitive types, respectively.

The nesting parameter changed significantly, as well. In 2019, it was 0.72 while in 2022 it was 0.84, suggesting that flight products became less close substitutes for each other in 2022. This, along with a decrease in the magnitude of the coefficient on flight frequency, may be because of carriers offering less flights in 2022. Consumers may have a particular flight schedule in mind and only purchase flights on that schedule.

Other demand parameters – network size, distance, and its square – all had the expected sign. Marginal utility from distance became negative at around 5,400 miles in 2019 and around 2,100 miles in 2022, suggesting consumers valued shorter trips in 2022.

### 1.5.2 Cost Parameters

Marginal cost is specified as a linear function of eight variables: distance, nonstop status, the number of daily departures, the number of nonstop destinations the carrier flies to out of both endpoints and short-distance, hub, and slot-controlled dummy variables. I have strong expectations for the signs of three cost-side parameters: distance, slot-controlled dummy variable, and short dummy variable. I expect marginal cost to increase with distance and slot-controlled airports as the amount of fuel required is higher for longer distance flights and slot-controlled airports are more highly congested so there are probably higher landing fees.

Fixed costs are assumed to be quadratic in the number of daily departures. I estimate the slope of the fixed cost function at the observed characteristics, which is expected to be positive. Carriers are expected to have higher costs of maintaining airport gates, higher payroll, and higher opportunity cost of the use of planes when they have higher flight frequency on a given route.

Marginal costs may either increase or decrease with hub, daily departures, destinations, and nonstop status. Carriers may be able to capture higher economies of density with hubs and other airports where they have large operations but they may also have higher personnel and/or gate costs at these airports. Similarly, economies of density may also be captured from connecting flights or increased flight frequency but a large fraction fuel is consumed during takeoff and landing. So increased flights – whether by the scale of operation or through more connections – may increase marginal costs.

Cost-side parameter estimates are reported in columns 2 and 3 of Table 1.5. Signs are largely as expected, save for short, which one would expect to decrease marginal costs. Coefficients on distance, nonstop, daily departures, and extra miles increased from 2019 to 2022. This is expected if fuel costs are higher in 2022 than 2019. Interestingly, signs change the constant and slot-controlled airports between 2019 and 2022. The coefficient on hub is also not significant in 2022. Together, these tell a story of flights out of large, connected airports becoming less costly in 2022. Finally, the coefficients for the slope of fixed costs are small but significant. In addition, increasing daily departures increases fixed costs over the relevant range for both years. The effect is small, most likely due to the fact that most of the cost of daily departures is conceptualized as marginal cost.

### *1.5.3 Elasticities and Marginal Costs*

Elasticity estimates are given in the first three rows of Table 1.6. Two price elasticities are reported: the aggregate price elasticity, which is the percent change in demand for all products if the price of all products rise by 1%, and the median product price elasticity. These largely confirm the findings discussed over the demand parameters. Aggregate price elasticity rose from $-2.87$ to $-1.17$. Type 1 elasticity increased from $-6.48$ to $-5.24$ and the corresponding values for the type 2 consumer are $-1.32$ and $-0.81$. Median price elasticities are much smaller, as we would expect due to the effect of competition. My overall price elasticities are within the range of those found in Berry and Jia (2010) and Ciliberto and Williams (2014).

Nonstop semielasticity is defined as the percentage change in demand when the nonstop variable of a flight product is changed from 0 to 1 and estimates are reported in rows 4-6 of Table 1.6. An increase in overall nonstop semielasticity from 2.32 in 2019 to 5.25 in 2022 indicates that consumers cared relatively more about taking nonstop flights in 2022 than they did in 2019. This could perhaps be explained by consumers being more averse to spending time in airports in 2022. Consumers may perceive airports as places with a large risk of COVID-19 transmission and so wish to avoid exposure by taking more nonstop flights. Broken down by type, the more price sensitive consumer was relatively less likely to value nonstop flights than the price-insensitive consumer (semielasticities of 0.20 and 13.26 in 2019 and 0.79 and 10.57 in 2022). It is apparent that the increase in willingness-to-pay for nonstop flights in 2022 is driven primarily by the shift from price-sensitive to price-insensitive consumers.

Estimates of marginal costs are reported in the last three rows of Table 1.6. Average marginal costs decreased from 2019 to 2022 from 181 to 53. Marginal costs are higher for connecting flights than for nonstop flights. The decrease in marginal costs as well as the presence of a large number of negative marginal costs in 2022 raises the concern of misspecification of the markup equation for that year. It's plausible that in the high fuel cost, labor-constrained environment of 2022, costs are not well fit by the supply side of the model. More research is needed to investigate this finding.

### *1.5.4 Profits*

Estimated average variable profits per market for both years are reported by carrier in Table 1.7. Despite large changes to demand and supply during the period, average profits increased 118% across all carriers between 2019 and 2022. Most of the legacy carriers[11] and Southwest experienced increases in average profit between the two years. Low-cost carriers saw only small changes in average profits. Note, however, that profits cannot be interpreted as total profits, as I do not observe fixed costs. If higher fuel and labor costs can be interpreted as fixed over this time period, it is likely that carriers' true profits were much lower in 2022.

## 1.6 Conclusion

This study employs a differentiated products discrete choice model to estimate demand for air travel between 2019 and 2022. To account for the endogenous nature of flight frequency, I allow for carriers to choose flight frequency before making price decisions. This is incorporated via the method described in Fan (2013).

I find that consumers became less price sensitive in 2022 relative to 2019, before the

[11] Legacy carriers are those that were in operation before airline deregulation and are composed of American, Alaska, Delta, and United. They are defined in contrast to low-cost carriers who entered the air travel industry since deregulation and are generally associated with cheaper fares and lower quality service.

COVID-19 pandemic. Moreover, changes in demand are explained by large changes in the types of consumers traveling. In 2019, 31% of consumers were relatively price sensitive (elasticity of $-6.48$) compared to 69% who were less so (elasticity of $-1.32$). In 2022, both consumers became less price-sensitive (elasticities of $-5.24$ and $-0.81$, respectively) and the share of the most price sensitive consumers dropped to 8%. I attribute this change to one in which many leisure travellers partake in "revenge travel" after staying home for long periods during the pandemic, thus decreasing their price-sensitivity. In addition, consumers value nonstop flights more in 2022 than in 2019, which I attribute to decreased willingness to be in crowded airports. Despite these changes, carrier variable profits grew 118% between the two years, although counterfactuals show profits would have been much higher in 2022 under 2019 demand. I also raise concerns about the ability of the BLP-style model I use to capture the cost dynamics of airlines in 2022. Negative marginal costs in 2022 – a year marked by high fuel costs and capacity constraints for airline – cast doubt on the pricing equation of my model. More research is needed to investigate how to appropriately model these costs.

| Nonlinear Variables | 2019 | 2022 | Linear Variables | 2019 | 2022 |
|---|---|---|---|---|---|
| Fare 1 | −4.478*** | −5.381*** | Origin Network size | 0.086*** | 0.090*** |
| | (0.008) | (0.040) | | (0.001) | (0.001) |
| Nonstop 1 | 1.394*** | 0.508*** | Destination Network size | 0.086*** | 0.089*** |
| | (0.015) | (0.040) | | (0.001) | (0.001) |
| Constant 1 | −2.458*** | −4.880*** | Daily departures | 0.021*** | 0.010*** |
| | (0.043) | (0.106) | | (0.000) | (0.000) |
| Fare 2 | −0.513*** | −0.341*** | Distance | 0.941*** | 0.758*** |
| | (0.003) | (0.005) | | (0.018) | (0.016) |
| Nonstop 2 | 2.018*** | 2.112*** | Distance$^2$ | −0.087*** | −0.179*** |
| | (0.014) | (0.013) | | (0.006) | (0.006) |
| Constant 2 | −9.755*** | −11.081*** | Extra Miles | −0.416*** | −0.683*** |
| | (0.001) | (0.072) | | (0.013) | (0.010) |
| Nest param. ($\lambda$) | 0.720*** | 0.835*** | Tour | −0.019 | 0.030*** |
| | (0.001) | (0.003) | | (0.010) | (0.009) |
| | | | Hub | −0.141*** | −0.317*** |
| | | | | (0.007) | (0.007) |
| Type function ($\gamma$) | | | | | |
| Constant | 0.630*** | −1.078*** | | | |
| | (0.044) | (0.188) | | | |
| Personal Income | 0.157*** | 0.171*** | | | |
| | (0.004) | (0.010) | | | |
| Type 1 share | 0.308 | 0.084 | | | |
| Function value | 6173 | 7894 | | | |

Table 1.4: Demand parameter estimates for 2019 and 2022
Notes: Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Carrier and Quarter dummy variables are included in both regressions. Their coefficient estimates are omitted here.

| Cost Variables | 2019 | 2022 |
| --- | --- | --- |
| Constant | 1.245*** | −0.522*** |
| | (0.017) | (0.026) |
| Short | 0.203*** | 0.055*** |
| | (0.015) | (0.024) |
| Distance | 0.341*** | 0.613*** |
| | (0.008) | (0.014) |
| Nonstop | −0.468*** | −0.227*** |
| | (0.004) | (0.006) |
| Short×Distance | −0.139*** | −0.163*** |
| | (0.008) | (0.013) |
| Daily departures | 0.001*** | 0.008*** |
| | (0.001) | (0.001) |
| Extra Miles | 0.143*** | 0.201*** |
| | (0.005) | (0.009) |
| Hub | 0.033*** | 0.016 |
| | (0.005) | (0.008) |
| Slot-control airports | 0.060*** | −0.086*** |
| | (0.005) | (0.008) |
| Origin destinations | −0.000*** | −0.002*** |
| | (0.000) | (0.000) |
| Dest. destinations | −0.000*** | −0.002*** |
| | (0.000) | (0.000) |
| Slope of Fixed Cost | | |
| Constant | 0.000*** | −0.000*** |
| | (0.000) | (0.000) |
| Daily departures | 0.000*** | 0.000*** |
| | (0.000) | (0.000) |

Table 1.5: Cost parameter estimates for 2019 and 2022
Notes: Standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$
Carrier and Quarter dummy variables are included in both regressions. Their coefficient estimates are omitted here.

| Elasticity | 2019 | 2022 |
|---|---|---|
| Price (Aggregate) | −2.87 | −1.17 |
| Type 1 | −6.48 | −5.24 |
| Type 2 | −1.32 | −0.81 |
| Price (Product Median) | −14.01 | −9.53 |
| Type 1 | −16.52 | −17.26 |
| Type 2 | −1.87 | −1.08 |
| Nonstop semielasticity | 2.32 | 5.25 |
| Type 1 | 0.20 | 0.79 |
| Type 2 | 13.26 | 10.57 |
| Marginal Costs | 182 | 58 |
| Nonstop | 126 | 7 |
| Connecting | 199 | 73 |

Table 1.6: Median elasticities and average marginal costs
Notes: Nonstop semielasticity is the percent change in demand when a product's non-stop status changes from 0 to 1

| | Profit ($100k) | |
|---|---|---|
| Carrier | 2019 | 2022 |
| American | 4.11 | 7.84 |
| Alaska | 0.76 | 2.11 |
| JetBlue | 0.80 | 2.05 |
| Delta | 3.39 | 7.12 |
| Frontier | 0.12 | 0.46 |
| Allegiant | 0.05 | 0.10 |
| Spirit | 0.18 | 0.76 |
| United | 3.15 | 6.28 |
| Southwest | 3.13 | 8.15 |
| Total | 1.06 | 2.31 |

Table 1.7: Carrier average variable profit per market

| | Observed | | Counterfactual | |
|---|---|---|---|---|
| Carrier | 2019 | 2022 | 1 | 2 |
| American | 3.96 | 5.06 | 28.28 | 4.26 |
| Delta | 3.24 | 4.46 | 22.64 | 4.14 |
| United | 3.03 | 3.89 | 18.70 | 3.69 |
| Southwest | 2.83 | 3.67 | 29.80 | 3.16 |

Table 1.8: Counterfactual profits under 2 different scenarios
Notes: Scenario 1: 2022 product characteristics and marginal costs, 2019 demand parameters.
Scenario 2: 2022 product characteristics and demand, 2019 cost parameters.

# Chapter 2

# COMMON OWNERSHIP AND ENDOGENOUS PRODUCT CHARACTERISTICS: EVIDENCE FROM BANK BRANCHING DECISIONS

Common ownership, or the phenomenon of several diversified, institutional investors owning overlapping shares in competing firms, has recently drawn increased attention from researchers and policymakers. Research thus far has highlighted the common ownership effects on pricing and entry, but the effects on non-price product characteristics has not drawn significant attention. I aim to fill this gap by analyzing deposit market competition. I build a structural model of bank branching decisions in the United States and estimate the cost of a bank branch implied by two different modes of conduct: own-profit maximization and common ownership. I find that if banks internalize the competitive effect of their branch networks on commonly-owned firms' profits, the difference in implied branch cost is large. In addition, a Vuong-type model selection test rejects the null that both own-profit maximization and common ownership explain the data equally well in favor of the common ownership model.

## *2.1 Introduction*

Common ownership, or the phenomenon of several diversified, institutional investors owning overlapping shares in competing firms, has recently drawn increased attention from researchers and policymakers. Central to this interest is whether and how much firms soften competition due to common ownership incentives. Authors such as Azar et al. [2018], Azar et al. [2022], and Backus et al. [2021] empirically investigate this question in the context of price competition, finding mixed results. Less well studied is common ownership's effect on non-price dimensions of competition. I analyze the implications of common ownership on the market for retail deposits, specifically in regard to bank branching decisions. I employ a revealed-preference approach similar to Pakes et al. [2015]. I first estimate demand for retail deposits and use the resulting estimates to generate profit differences for deviations from the observed number of branches. I use these profit differences to construct bounds on the cost of a bank branch. I perform this analysis under two models of conduct: own-profit maximization and common ownership. I find that if banks internalize the competitive effect of their branch networks on commonly-owned firms' profits, the difference in implied branch cost is large. In addition, a Vuong-type model selection test rejects the null that both own-profit maximization and common ownership explain the data equally well in favor of the common ownership model.

My finding complements Azar et al. [2022], who find that deposit rate competition is softened by common ownership. The approach taken by these authors differs from mine in that they assume banks tailor their deposit rates to local markets, whereas my analysis assumes banks set uniform deposit rates across markets. I argue that this assumption is justified based on the work of d'Avernas et al. [2023] and Begenau and Stafford [2023].

This paper contributes to the literature on structural estimation of common ownership models.[1] This line of research involves estimating structural models of firm competition under differing conduct assumptions and applying a model selection test to determine which conduct assumption fits the model better. Backus et al. [2021] note that this method is preferred to reduced-form methods where the analyst regresses a market outcome variable (typically price) on the so-called modified Herfindahl-Hirschman Index (MHHI). These types of models suffer from problems common to the structure-conduct-performance literature generally, notably that they rely on an assumption of Cournot competition – a restrictive assumption when the actual data-generating process

[1] For a thorough review of the common ownership literature in general, see Schmalz [2021].

is characterized by product differentiation. Examples in this literature include Backus et al. [2021] and Park and Seo [2019] for models of price competition and Ruiz-Pérez [2019] for entry. To my knowledge, mine is the first paper to consider non-price product characteristics as a strategic variable in a common ownership setting. This paper is also the first to use a conduct test based on moment inequalities, leveraging a contribution made by Shi [2015] and Hsu and Shi [2017].

This paper is also related to the large literature on retail deposit competition. I use a structural demand model similar to the seminal paper by Dick [2008] and used by authors such as Egan et al. [2017], Xiao [2020], and Egan et al. [2022]. I also consider a revealed preference approach to estimating the costs of branches, an approach previously considered by Aguirregabiria et al. [2016]. Their application studies how banks manage their branch network to mitigate geographic risk. In contrast to their model, I abstract from situations where banks may face economies of scale or density in their branch network and I emphasize tractability so as to feasibly perform the conduct test.

The paper is organized as follows. Section 2.2 provides background on common ownership and institutional characteristics of deposit markets. Section 3.2 builds the model. Section 2.4 presents my data. Section 2.5 discusses the results. Section 2.6 concludes.

## 2.2 *Background*

### *2.2.1 Common Ownership*

I first set up the model of firm decision making under common ownership. I assume that in a given market $m$, there are $L$ shareholders that own $J$ different firms. Profit to shareholder $l$ is

$$\pi^l = \sum_{j=1}^{J} \phi_{lj} \pi_j(x_j)$$

where $\phi_{lj}$ denotes the ownership share of firm $j$ accruing to shareholder $l$ and $x_j$ denotes a strategic variable for firm $j$. The variable $x_j$ most often denotes price, but in the empirical analysis in section 2.5.3, $x_j$ will denote a bank's number of branches in a market. Firms seek to maximize shareholder profit. Because shareholders are diversified in different ways, shareholders will disagree on a firm's optimal strategy. If shareholder $l$ has control share $\zeta_{lj}$ of firm $j$, firm $j$'s objective function can be written as

$$\max_{x_j} \sum_{l=1}^{L} \zeta_{lj} \pi^l .$$

Thus firm $j$ maximizes a linear combination of its profits and its competitors' profits,

$$\sum_{l}^{L} \left[ \zeta_{lj} \phi_{lj} \pi_j + \sum_{k \neq j} \zeta_{lk} \phi_{lk} \pi_k \right] .$$

This is proportional to

$$\pi_j + \sum_{k \neq j} \frac{\sum_l \zeta_{lj} \phi_{lk}}{\sum_l \zeta_{lj} \phi_{lj}} \pi_k .$$

The quantity

$$\kappa_{jk} \equiv \frac{\sum_l \zeta_{lj} \phi_{lk}}{\sum_l \zeta_{lj} \phi_{lj}}$$

is the weight firm $j$ puts on firm $k$'s profits due to the the returns its shareholders earn from firm $k$'s profits. Following Backus et al. [2021], I assume shareholders exercise proportional control, so $\zeta_{lj} = \phi_{lj}$. This gives the version of profit weights I use,

$$\kappa_{jk} = \frac{\sum_l \phi_{lj} \phi_{lk}}{\sum_l \phi_{lj}^2} . \tag{2.1}$$

There are two main ways common ownership has been measured in the literature. The first, the modified Herfindahl-Hirschman Index (MHHI), is used by Azar et al. [2018]

and Azar et al. [2022]. The MHHI is defined by

$$MHHI = \sum_j \sum_k s_j s_k \kappa_{jk}.$$

Decomposing this sum, we get

$$\sum_j s_j^2 + \sum_j \sum_{k \neq j} s_j s_k \kappa_{jk}. \tag{2.2}$$

The second term in (2.2) is called the MHHI delta. These authors employ models regressing prices on the MHHI delta for the market and interpret the coefficient as the causal effect of institutional investor concentration on prices. This is problematic as it relies on an assumption of symmetric Cournot competition, as pointed out in Backus et al. [2021].[2] Because of this shortcoming, I use a structural framework where firms take into account competitors' profits directly, weighted by the profit weights, $\kappa$. This is the approach used by Backus et al. [2021] and Ruiz-Pérez [2019].

### 2.2.2 *Uniform Rate Setting*

Studies of deposit rate competition often assume uniform rate setting by banks. Recent work by d'Avernas et al. [2023] and Begenau and Stafford [2023] validate this assumption. For example, d'Avernas et al. [2023] find that bank-time fixed effects explain 98.8% of variation in 12-month certificate of deposit rates and 94.9% of variation in 2.5K Savings rates. In light of these findings, it seems unlikely that common ownership incentivizes banks to soften rate competition at the market level. However, there are other strategic variables that banks control at a market level that could be influenced by common ownership. Namely, Ho and Ishii [2011] and Wang et al. [2021] show that consumers heavily value the convenience of bank branch locations relative to interest rates. Given such an important competitive variable, it seems likely that if banks do soften competition

[2] This problem is common to models that use HHI, generically.

through common ownership, their choices of branch locations would reflect this.

## 2.3 Model

In what follows market-years are indexed by $m$ and products are indexed by $j$. For brevity, I refer to market-years as simply markets.

Following the literature on uniform rates, I assume each bank sets a uniform rate for all markets each period. Specifically, I assume that deposit competition takes place in a two-stage game each period. In the first stage, regional branch managers decide how many branches to operate in their local market. In the second stage, national banks observe their network and set uniform rates. Finally, banks' unobserved product characteristics are revealed and consumers choose where to deposit their money. I describe the details of the model below, starting with the demand model and working backwards.

### 2.3.1 Demand

I assume that each consumer $i$ is endowed with $D_i$ dollars they can choose to deposit in $j \in \{0, \ldots, J_m, J_m + 1\}$ products, where 0 denotes bonds and $J_m + 1$ denotes cash. Consumer $i$'s utility from product $j$ is given by

$$u_{ijm} = x'_{jm}\beta - \alpha p_{jm} + \xi_{jm} + \varepsilon_{ijm},$$

where $x_{jm}$ is a vector of product characteristics, $p_{jm}$ is the interest rate spread between product $j$ and the rate earned by bonds (the Federal Funds rate), $\xi_{jm}$ is an unobservable product characteristic, $\varepsilon_{ijm}$ is the logit error, $\alpha$ is the coefficient that governs deposit rate sensitivity, and $\beta$ is a vector of coefficients on non-price characteristics. The non-interest-rate characteristics in $x_{jm}$ are the natural log of a bank's number of branches in a market and the natural log of the bank's employees per branch.[3] The non-price characteristics

[3]The choice of simple multinomial logit vs. a model with random coefficients is worth mentioning. Random coefficients are appealing in my case as they do not restrict substitution patterns to exhibit

are included to capture the value of convenience and customer service to a consumer when choosing between deposit services. The unobservable product characteristic, $\xi_{jm}$, is composed of bank and market-year fixed effects,

$$\xi_{jm} = \xi_j + \xi_m + \Delta\xi_{jm}.$$

I normalize the utility of investing in bonds to 0 and assume cash earns 0 interest, so $p_{J_m+1}$ is equal to minus the Federal Funds rate in all markets. The probability that consumer $i$ in market $m$ chooses to deposit \$1 in product $j$ is

$$\mathbb{P}(u_{ijm} > u_{ikm}, k \neq j) = \frac{\exp\left(x'_{jm}\beta - \alpha p_{jm} + \xi_{jm}\right)}{1 + \sum_{k=1}^{J_m} \exp\left(x'_{km}\beta - \alpha p_{km} + \xi_{km}\right)}.$$

Thus, the market share of product $j$ in market $m$ is given by

$$s_{jm} = \frac{\exp\left(x'_{jm}\beta - \alpha p_{jm} + \xi_{jm}\right)}{1 + \sum_{k=1}^{J_m} \exp\left(x'_{km}\beta - \alpha p_{km} + \xi_{km}\right)}. \tag{2.3}$$

Interest rate spreads are endogenous and must be instrumented for. I use two sets of instruments to identify price sensitivity: cost-shifters and quadratic differentiation IVs. Following the literature (Dick [2008], Ho and Ishii [2011], Egan et al. [2022]), I use several variables as cost-shifters: four-quarter moving averages of premises and equipment expense, salary expense, and other noninterest expense. These variables reflect the cost of a bank's operations and thus should be correlated with price. Moreover, they are valid instruments as customers are unlikely to pay attention to these variables into account when selecting a bank. I also use a bank's contemporaneous interest income weighted by interest bearing assets. This instrument will be correlated with the deposit rate as banks that can earn a higher return on their depostis will have higher willingness-to-pay

the well-known Independence of Irrelevant Alternatives (IIA) property. However, a test of instrument relevance, introduced by Gandhi and Houde [2019], did not reject the null hypothesis of IIA preferences.

for deposits. For the other cost-shifters, I take the ratio of the instrument to the bank's total assets. Differentiation IVs for a characteristic, $x_{jm}$, are defined as

$$z_{jm}^{\text{Diff}} = \sum_{k \in \mathcal{J}_m \setminus j} \left( x_{jm} - x_{km} \right)^2 .$$

I create these differentiation IVs for the exogenous characteristics log (# branches) and log (employees per branch). I then take the market-size-weighted average of these variables for each bank-year, similar to Egan et al. [2022]. These instruments measure a product's isolation in the product space and thus serve as markup-shifters that allow me to identify $\alpha$, the sensitivity of of demand to interest rates.

Let $Z_{jm} \equiv \left[ Z_{jm}^{\text{Cost}}, Z_{jm}^{\text{Diff}} \right]$ be the matrix of instruments for bank $j$ in market $m$. The model implies the conditional moment restrictions

$$\mathbb{E} \left[ \Delta \xi_{jm} | Z_{jm} \right] = 0.$$

These conditional moments can be transformed into the unconditional ones

$$\mathbb{E} \left[ \Delta \xi_{jm} A(Z_{jm}) \right] = 0,$$

for an arbitrary function of the instruments $A(\cdot)$. I construct the sample moments

$$\frac{1}{M} \sum_{m=1}^{M} \frac{1}{J_m + 1} \sum_{j=1}^{J_m+1} \Delta \xi_{jm} Z_{jm} = 0$$

and estimate the model using the algorithm described in Berry et al. [1995] and Conlon and Gortmaker [2020]. This procedure involves first estimating the parameters $(\beta, \alpha)$ via 2-step GMM, then, using these estimates, constructing feasible approximations to the optimal instruments, $\hat{A}(Z_{jm})$, and estimating the model again.

### 2.3.2 Branching Decisions

In the first stage, banks simultaneously choose their branch network, $n_{jmt}$, in each market to maximize their present value of expected profits, $\pi^s_{jmt}(n_{jmt}, \mathbf{n}_{-jmt})$, for a certain mode of conduct, $s$. Bayesian-Nash equilibrium implies

$$\pi^s_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) \geq \pi^s_{jmt}(n', \mathbf{n}_{-jmt}), \tag{2.4}$$

for any $n' \neq n_{jmt}$.

Note that the branch decision is inherently a dynamic one, as there may be differences between a bank's sunk and fixed costs of a bank branch. However, modelling the problem as a dynamic one is very difficult due to the large dimension of states and actors. Hence, I follow the approach used in Aguirregabiria et al. [2016] and assume bank managers make a static decision each period.

Let $\pi_{jmt}(n_{jmt}, \mathbf{n}_{-jmt})$ and $\pi^{CO}_{jmt}(n_{jmt}, \mathbf{n}_{-jmt})$ denote profit for firm $j$ in market $m$ under own-profit maximization and common ownership, respectively, and note that

$$\pi^{CO}_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) = \pi_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) + \sum_{k \in J_m \backslash j} \kappa_{jk} \pi_{km}(n_{km}, n_{-km}).$$

I parameterize the profit function in a manner similar to Aguirregabiria et al. [2016]. I decompose $\pi_{jmt}(n_{jmt}, \mathbf{n}_{-jmt})$ into variable profits, $VP_{jmt}(n_{jmt}, \mathbf{n}_{-jmt})$, fixed costs of bank branches, $FC_{jmt}(n_{jmt})$, and sunk costs of bank branches, $SC_{jmt}(n_{jmt})$, so

$$\pi_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) = \frac{1}{1-\rho}\left[VP_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) - FC_{jmt}(n_{jmt})\right] - SC_{jmt}(n_{jmt}), \tag{2.5}$$

where $\rho = 0.95$ is the discount factor. I make the following parameterizations:

$$\begin{aligned} VP_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) &= r_{jt} M_{mt} s_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) \\ FC_{jmt}(n_{jmt}) &= \left(\theta_j^{(1)} + \nu_{jmt}^{(1)}\right) n_{jmt} \\ SC_{jmt}(n_{jmt}) &= \left(\theta_j^{(2)} + \nu_{jmt}^{(2)}\right) n_{jmt}, \end{aligned} \tag{2.6}$$

where $r_{jt}$ is the net return bank $j$ receives from a dollar of deposits,[4] $M_{mt}$, is the market size (total deposits) of market $m$, $s_{jmt}(n_{jmt}, \mathbf{n}_{-jmt})$ is bank $j$'s market share in market $m$ is defined by (2.3), is a function of the bank's number of branches in that market, $\theta_j^{(1)}$ is the mean fixed cost of a branch location for bank $j$, $\theta_j^{(2)}$ is the mean sunk cost of a branch location for bank $j$, and $\nu_{jmt} = \left(\nu_{jmt}^{(1)}, \nu_{jmt}^{(2)}\right)'$ is a market-bank-specific component of branch cost unobservable to the econometrician but observable to banks at the start of the game. Note that both $FC_{jmt}(n_{jmt})$ and $SC_{jmt}(n_{jmt})$ are linear in $n_{jmt}$ and thus I can write

$$\pi_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) = \frac{1}{1-\rho} VP_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) - \left(\tilde{\theta}_j + \tilde{\nu}_{jmt}\right) n_{jmt} \tag{2.7}$$

where $\tilde{\theta}_j \equiv \frac{1}{1-\rho}\theta_j^{(1)} + \theta_j^{(2)}$ and $\tilde{\nu}_j \equiv \frac{1}{1-\rho}\nu_{jmt}^{(1)} + \nu_{jmt}^{(2)}$.

Denote the difference in variable profits due to one branch deviations as

$$\begin{aligned} &\Delta^+ VP_{jmt}^s(n_{jmt}, \mathbf{n}_{-jmt}) \equiv VP_{jmt}^s(n_{jmt}, \mathbf{n}_{-jmt}) - VP_{jmt}^s(n_{jmt}+1, \mathbf{n}_{-jmt}), \quad \text{and} \\ &\Delta^- VP_{jmt}^s(n_{jmt}, \mathbf{n}_{-jmt}) \equiv VP_{jmt}^s(n_{jmt}, \mathbf{n}_{-jmt}) - VP_{jmt}^s(n_{jmt}-1, \mathbf{n}_{-jmt}). \end{aligned}$$

Define $\Delta^+\pi_{jmt}^s(n_{jmt}, \mathbf{n}_{-jmt})$ and $\Delta^-\pi_{jmt}^s(n_{jmt}, \mathbf{n}_{-jmt})$ similarly and note that (2.4) and re-

[4] I use a 4-quarter moving average to mitigate the effect of seasonality.

vealed preference implies

$$\begin{aligned}
\Delta^{+}\pi^{s}_{jmt}(n_{jmt},\mathbf{n}_{-jmt}) &= \frac{1}{1-\rho}\Delta^{+}VP^{s}_{jmt}(n_{jmt},\mathbf{n}_{-jmt}) + \tilde{\theta}_j + \tilde{v}_{jmt} \\
&\geq 0, \quad \text{and} \\
\Delta^{-}\pi^{s}_{jmt}(n_{jmt},\mathbf{n}_{-jmt}) &= \frac{1}{1-\rho}\Delta^{-}VP^{s}_{jmt}(n_{jmt},\mathbf{n}_{-jmt}) - \tilde{\theta}_j - \tilde{v}_{jmt} \\
&\geq 0.
\end{aligned}$$

Note that, even for the common ownership model, these equations only depend on other banks' branch network through the first term, $\Delta VP^{s}_{jmt}(n_{jmt},\mathbf{n}_{-jmt})$. Assuming $\mathbb{E}\left[\tilde{v}_{jmt}\right] = 0$, upper and lower bounds on a bank's mean branch cost under conduct assumption $s$ can be written as

$$\begin{aligned}
\overline{\theta}^{s}_{j} &\equiv \frac{1}{1-\rho}\mathbb{E}\left[\Delta^{-}VP^{s}_{jmt}(n_{jmt},\mathbf{n}_{-jmt})\right] \\
\underline{\theta}^{s}_{j} &\equiv -\frac{1}{1-\rho}\mathbb{E}\left[\Delta^{+}VP^{s}_{jmt}(n_{jmt},\mathbf{n}_{-jmt})\right].
\end{aligned} \tag{2.8}$$

I estimate $\overline{\theta}^{s}_{j}$ and $\underline{\theta}^{s}_{j}$ by first computing variable profit from (2.6) and the demand model in Section 2.3.1. I then find $\Delta VP$ by computing counterfactual market shares for one branch deviations in a bank-market, holding all other variables fixed. To allow for clustered dependence of the error term $\tilde{v}$ within bank-markets, I first take the average of $\Delta VP_{jmt}$ over $t$ and treat each bank-market average as an observation. Denote this bank-market average as $\Delta\overline{VP}^{s}_{jm}$. Then the estimators of (2.8) are

$$\begin{aligned}
\widehat{\overline{\theta}}^{s}_{j} &= \frac{1}{N_{JM}}\sum_{j,m}\Delta^{-}\overline{VP}^{s}_{jm} \\
\widehat{\underline{\theta}}^{s}_{j} &= \frac{1}{N_{JM}}\sum_{j,m}-\Delta^{+}\overline{VP}^{s}_{jm},
\end{aligned}$$

where $N_{JM}$ is the number of bank-market combinations. These equations provide estimated bounds on the cost of a bank branch.

### *2.3.3 Test of Conduct*

To test whether banks expand their branch networks less aggressively in markets with more overlapping ownership, I employ a Vuong-type model selection test introduced by Shi [2015] and Hsu and Shi [2017]. The test allows selection between two models described by moment inequalities by comparing their Kullback-Leibler distances to the true data distribution. Note that the model described in 2.3.2 implies the following moment inequality conditions:

$$\begin{aligned} \mathbb{E}\left[\Delta^{-} VP^{s}_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) - \theta_j\right] &\geq 0 \\ \mathbb{E}\left[\Delta^{+} VP^{s}_{jmt}(n_{jmt}, \mathbf{n}_{-jmt}) + \theta_j\right] &\geq 0. \end{aligned} \tag{2.9}$$

Let $m_s(\Delta VP, \theta), s \in \{P, CO\}$ denote the moment conditions in (2.9) for own-profit maximization and common ownership, respectively. Define the sample criterion function for model $s$ as

$$T_s(\lambda, \theta) = \frac{1}{N}\sum_{i=1}^{N} \exp\left(\lambda' m_s(\Delta VP_i, \theta)\right).$$

Then the quasi-likelihood ratio test statistic is defined as

$$\widehat{QLR} \equiv \max_{\theta}\min_{\lambda} T_P(\lambda, \theta) - \max_{\theta}\min_{\lambda} T_{CO}(\lambda, \theta).$$

Under the null hypothesis that both models explain the data equally well, $T_P = T_{CO}$ and $\sqrt{N}\widehat{QLR} \sim \mathcal{N}(0, \omega^2)$, where $\omega^2$ is the variance of the test statistic. Positive values of this statistic provide evidence against the null in favor of model $P$. Negative values provide evidence in favor of model $CO$.

## 2.4 Data

My primary data comes from several sources. First, I gather information on bank characteristics from the FDIC's Statistics on Depository Institutions (SDI). The SDI contains data on every US commercial and is available on a quarterly basis. Variables include banks' assets, deposits, deposit expenses, income from fees, and other cost variables. The second source is the FDIC's Summary of Deposits, which provides detailed information on the amount of deposits held by individual bank branches. To measure common ownership incentives, I use the dataset used by Backus et al. [2021] and made available on Michael Sinkinson's website. This dataset contains institutional investor holdings scraped from SEC 13(f) filings from 1999 through 2017. By matching CUSIP numbers in this dataset with Federal Reserve bank identifiers, I can create the profit weights for each bank pair defined in (2.1). I gather demographic variables on county income and population from the Bureau of Economic Analysis. Data on monetary aggregates – cash, treasury bonds, and money market accounts held by households – are from FRED. The market definition is a Bureau of Labor Statistics Labor Market Area (LMA). These are composed of one or more economically integrated contiguous counties. LMAs are exhaustive and non-overlapping and are defined so that a person can reside and find employment within a reasonable distance. I use this definition as research shows that convenience is a major factor is a consumer's choice of bank, with consumers heavily valuing banks with branches close to both their home and places of work Wang et al. [2021].

Tables 2.1 and 2.2 present selected summary statistics for banks and markets. Figure 2.1 plots the quarterly time series of mean profit weight, $\kappa$, for banks in the S&P 500 index for at least one quarter. The mean $\kappa$ generally trends up, with a stark drop in 2007 due to the financial crisis.

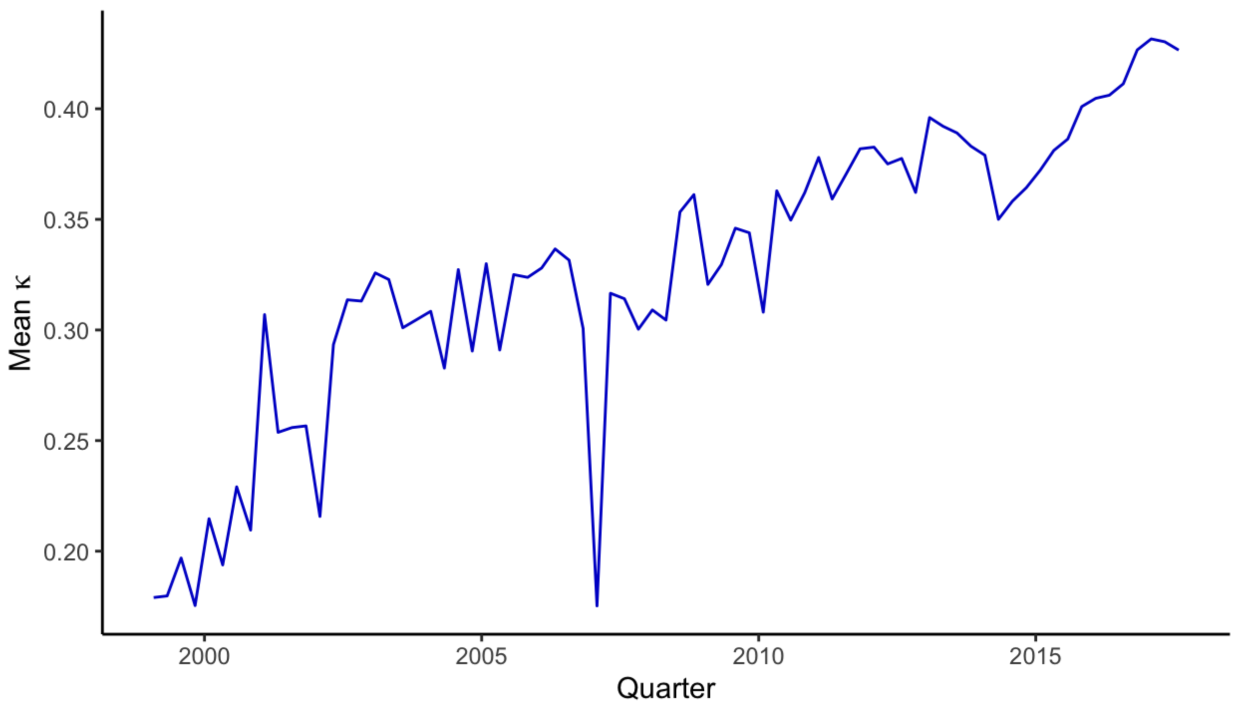



Figure 2.1: Mean profit weight for banks in S&P 500 index for at least one quarter.

| Variable | Mean | SD |
|---|---|---|
| Shares (%) | 7.41 | 9.82 |
| Interest rate spread | 1.43 | 1.87 |
| # of branches | 4.34 | 14.26 |
| Employees per branch | 20.44 | 202.23 |
| Net return on deposits (% of assets, MA) | 2.31 | 0.87 |
| Interest income (% of assets) | 2.74 | 0.87 |
| Premises and equipment expense (% of assets) | 0.27 | 0.26 |
| Salary and benefits expense (% of assets) | 1.04 | 0.88 |
| Other expense (% of assets) | 0.73 | 3.06 |
| Observations | | 358102 |

Table 2.1: Summary statistics for bank-market-years. Sample covers the years 1999-2017.

| Variable | Mean | SD |
|---|---|---|
| Banks | 9.04 | 13.37 |
| Population (10,000s) | 14.50 | 71.53 |
| Market size ($1M) | 4.82 | 35.83 |
| Market-years | | 39616 |
| Profit-weights (MA) | 0.55 | 9.39 |
| Publicly-owned banks | | 817 |

Table 2.2: Summary statistics for market-years. Sample covers the years 1999-2017.

## 2.5 *Results*

This section discusses results from the model estimation. I first discuss demand estimates and then estimates of the cost of a bank branch.

### 2.5.1 Demand

Table 2.3 presents the results of the demand estimation. The estimated coefficient on the interest rate spread is $-15.5$, which is comparable to estimates from other authors such as Dick [2008], Egan et al. [2017], and d'Avernas et al. [2023]. This coefficient corresponds to a median own-interest-rate elasticity of $-0.10$, implying market shares are relatively insensitive to deposit rates, a finding corroborated by the previous literature. Figure 2.2 plots a histogram of estimated own-interest-rate elasticities. There is a large mass around 0, as well as a significant minority of elasticities estimated to be positive. Positive price elasticities are possible under logit demand if some prices are positive, which is true with my data, as some banks have higher service fee rates that deposit interest rates.

In contrast, the coefficients on log branches and log employees per branch are positive and precisely estimated. This result confirms the finding in d'Avernas et al. [2023] that for many consumers, convenience and customer service are much more important to their choice of bank than deposit rates. Figure 2.3 plots log branches against the log odds ratio, $\log(s_{jm}/s_{0m})$, for each product with fixed effects removed. It also shows a polynomial spline fit, which is approximately linearly. This fit implies the relationship between the number of branches and market share is captured well by my specification.

### 2.5.2 Cost of Bank Branch

Table 2.4 presents results for the estimates of the mean sunk cost of a bank branch. Mean costs are estimated separately for each of the "Big Four" banks and regional banks. Since the cost parameters are set identified, I report estimates as 95% confidence intervals. I present estimates from several different potential models of competition: own-profit maximization, common ownership, and collusion. Note that these conduct models are only with respect to banks' branching decisions – price competition is assumed to still be own-profit maximizing at the bank-year level. Since common ownership competition depends on a time series of profit weights, I use 3 different specifications of common

| Variable | Value | Std. Err. |
|---|---|---|
| Interest-rate spread | −15.505 | 6.973 |
| Log(# of branches) | 1.267 | 0.003 |
| Log(Employees per branch) | 0.623 | 0.011 |
| Bank Fixed Effects | | Yes |
| Market-Year Fixed Effects | | Yes |
| Obs. | | 358102 |
| Adj. $R^2$ | | 0.88 |
| Within $R^2$ | | 0.57 |
| $F$-stat (1st stage) | | 1320 |

Table 2.3: Results of demand estimation parameters. Standard errors are clustered at the market level.

ownership. The baseline (column "CO" in Table 2.4) represents the scenario where banks weight competitors profits according to contemporaneous common ownership profit weights. I also estimate specifications using the one-quarter lag of profit weights and a 4 quarter moving average of profit weights. The collusion specification assumes all profit weights between the relevant banks (i.e. publicy listed banks) are equal to 1.

For all banks, estimated costs are largest under own-profit maximization and smallest under collusion. This result is expected as common ownership and collusion dampen the potential increase in profits from adding one more branch, making the cost that rationalizes observed branching decisions lower. Citibank has the largest estimated costs across all specifications, likely reflecting Citibank's propensity to primarily locate in large city centers where the market size is large and counterfactual branching decisions have large effects on profits. Citibank's rather centralized branching decisions also contribute to their presence in relatively few markets (53) and relative imprecision of cost estimates.

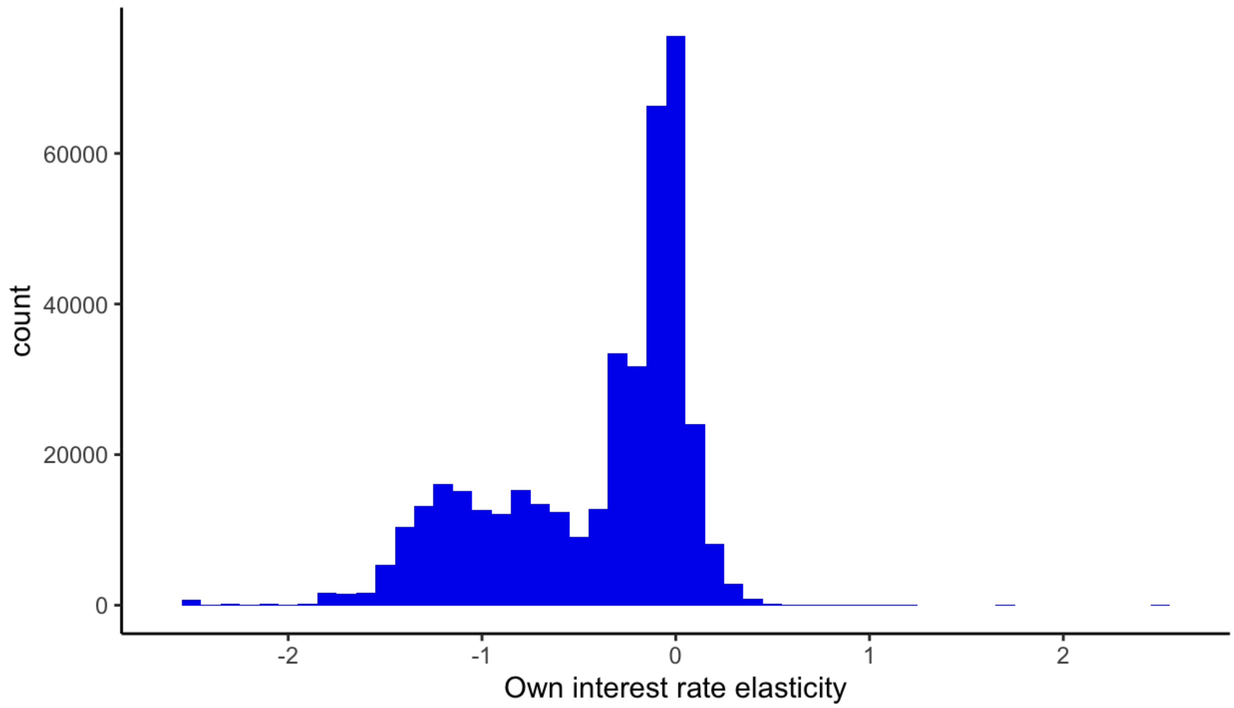



Figure 2.2: Histogram of own-interest-rate elasticities, winsorized at ±2.5.

The confidence interval for cost under own-profit maximization has a range of \$ 413.3 million relative to a range of only \$ 7.8 million regional banks. The three common ownership specifications produce very similar cost estimates across all five bank groups.

At first glance, cost estimates under all models seem high relative to prior estimates. For example, Aguirregabiria et al. [2016] estimate that average sunk cost of *de novo* branching to be \$ 1.3 million if the new branch is located in the same state as the bank's headquarters and \$ 2.1 million for a different state. This is in line with reports from industry publications, such as **?**, which reports the mean cost of a new branch as \$ 1.3 million in a 2013 survey. However, recall that my measure of cost is sunk costs plus total discounted future fixed operating costs. If a branch's sunk cost is \$1.3 million and incurs \$ 1 million in yearly fixed costs discounted by $\rho = 0.95$, this corresponds to \$ 21.3 million in my measure of costs, well within the estimated costs for some of the banks


Figure 2.3: Polynomial spline regression of log market share on log number of branches after removing fixed effects.

and models.

| Bank | 95% Confidence Interval | | | | | Obs. |
|---|---|---|---|---|---|---|
| | Own-profit max. | CO | CO (Lag) | CO (MA) | Collusion | |
| Bank of America | [ 30.9, 31.8] | [ 21.6, 22.3] | [ 19.7, 20.4] | [ 20.4, 21.2] | [ 9.1, 9.8] | 329 |
| Citibank | [369.3, 782.6] | [154.8, 274.7] | [142.1, 257.7] | [150.7, 267.6] | [ 85.1, 153.9] | 53 |
| JP Morgan-Chase | [ 33.6, 41.2] | [ 17.3, 20.0] | [ 16.9, 19.2] | [ 13.3, 13.4] | [ 7.0, 9.6] | 212 |
| Wells Fargo | [ 35.9, 38.7] | [ 29.2, 30.5] | [ 26.3, 27.6] | [ 29.6, 29.6] | [ 13.7, 14.5] | 415 |
| Regional | [ 24.3, 32.1] | [ 8.5, 21.3] | [ 10.0, 22.2] | [ 7.8, 20.1] | [ 8.6, 14.9] | 7531 |

Table 2.4: 95% confidence intervals for the cost of a bank branch, by model. Estimates are in millions of 2010 US dollars.

### 2.5.3 Conduct Test

Table 2.5 reports the results of conduct tests of the null hypothesis that own-profit maximization explains the observed data as well as the alternative models against the two-sided alternative that one model better explains the data.

The test rejects own-profit maximization in favor of common ownership and lagged common ownership at the 95% level. In addition, own-profit maximization is rejected against a four-quarter moving average of common ownership and the collusive model at the 90% level. I was not able to detect a significant difference between the costs implied by the common ownership model and the collusive model.

Thus the results find significant evidence of common ownership incentives in banks' branching decisions. However, collusion between publicly-listed banks explains the data at least as well as common ownership. More research is needed to differentiate between these two models.

| Own-profit maximization vs. | QLR test statistic |
|---|---|
| Common Ownership | $-2.63$ |
| Common Ownership (Lag) | $-2.06$ |
| Common Ownership (MA) | $-1.87$ |
| Collusion | $-1.87$ |
| Common Ownership vs. Collusion | 0.79 |

Table 2.5: Test statistics for pairwise conduct tests between own-profit maximization and other models. Large positive values indicate evidence against the null in favor of the own-profit maximization model.

## 2.6 *Conclusion*

This paper studies the effect of common ownership incentives on bank branching decisions. Using a structural, partially-identified model of branch investment, I find that common ownership implies a large difference in cost of a bank branch relative to own-profit maximization and a model selection test rejects own-profit maximization in favor of a common ownership model. The model has some limitations, namely it eschews any impact of or synergies from banks' loan business and it does not consider the dynamic implications of common ownership. Further research should seek to illuminate whether considering these aspects is important when discussing common ownership and retail deposit competition.

# Chapter 3

# DYNAMIC MODEL OF AQUATIC INVASIVE SPECIES MANAGEMENT

Invasive aquatic plants (IAP) present threats to river ecosystems by altering chemical and thermal characteristics of water bodies, displacing native plants, and compromising the habitats that native vertebrates and invertebrates rely upon. Managing invasive aquatic plant species is complicated by their inherent downstream dispersal patterns, and likely recurrence in already-treated invaded patches. Furthermore, as climate change alters riparian environments, the cost and spatial dispersion of species management will likely change as both growing conditions and control efficacy shift. To address how costs and optimal management strategies change with a changing climate, we develop a model of IAP management that incorporates spatial heterogeneity and downstream dispersal and can be calibrated to habitat suitability data at a coarse scale. We utilize parametric dynamic programming techniques to quickly and efficiently compute an approximation to the optimal policy. As a case study, we calibrate the model to simulate the management of water-primrose (*Ludwigia spp.*) in the Willamette River basin, Oregon, USA using data from a climate-sensitive habitat suitability model trained on occurrence data for water-primrose. We find the climate change model implies differential changes across different segments of the river system. Accounting for spread in the management model leads to an optimal management policy that differs from the naive one that allocates management in proportion to the climate change-induced differences.

This is a work-in-progress and represents my contribution to a joint work with Samuel Chan, Rebecca Flitcroft, Sunny Jardine, Emily Smoot, and Braeden Van Deynze. I thank Sunny for funding me as her research assistant and Braeden for the excellent guidance.

## 3.1 Introduction

Invasive aquatic plants (IAP) present threats to river ecosystems by altering chemical and thermal characteristics of water bodies, displacing native plants, and compromising the habitats that native vertebrates and invertebrates rely upon. For example, water primrose (*Ludwigia spp.*), an emergent aquatic plant, changes water shading dynamics and sedimentation processes, thus affecting water quality (Grewell et al. [2016], Khanna et al. [2018], Bunch et al. [2010], Ebersole et al. [2001], Ecology [2017]). This compares with the riparian invasive plant, knotweed (*Reynoutria spp.*), that displaces native vegetation, reducing local biodiversity by compromising habitats for native species [Urgenson, 2006]. The changes wrought by either of these species have adverse effects on local wildlife and hinder commercial and recreational activities like fishing, boating, and hydropower generation (Colleran et al. [2020], Pelella et al. [2023], Thouvenot et al. [2013]).

Managing invasive aquatic plant species is complicated by their inherent downstream dispersal patterns, and likely recurrence in already-treated invaded patches. Furthermore, as climate change alters riparian environments, the cost and spatial dispersion of species management will likely change as both growing conditions and control efficacy shift. As these changes occur, river managers and policymakers will seek solutions to adapt their management strategies to new cost and spread conditions. This provides a natural opportunity for bioeconomic models to inform public policy.

Previous literature has examined dynamic models of optimal invasive species management in connected river systems (Albers et al. [2018]; Hall et al. [2018]) and the role of spatial heterogeneity in the allocation of invasive species management efforts (e.g., Epanchin-Niell and Wilen [2012]). However, these models incorporate spatial heterogeneity in a limited way, considering only a handful of invasion sites at once. This limitation is due to the inherently intractable nature of dynamic programming models with large state spaces: the state and action spaces increase exponentially in the number of invasion sites. This feature makes applications involving rich spatial heterogeneity difficult to model. In particular, the effect of climate change on IAP management can be diverse across many interdependent geographies. In addition, data on invasions or spread is typically limited. Predictions of how spread will change with climate change is often not granular enough to incorporate into models at the site level. To our knowledge no bioeconomic models of riparian invasive species management in the peer-reviewed literature account for spatial heterogeneity in ways that can capture potential large-scale heterogeneous impacts of changing climate conditions.

To address this gap, we develop a model of IAP management that incorporates spatial heterogeneity and downstream dispersal and can be calibrated to habitat suitability data at a coarse scale. We segment a river into distinct reaches that may each hold many potential invasion sites. We accommodate the size of these reaches by allowing states to be characterized by an arbitrary and continuous amount of IAP. We represent the manager's decision as a Markov Decision Problem and solve for the manager's optimal policy. We assume the manager has a constant budget each period that they can allocate to treating a stochastically growing IAP invasion in a river system. The river system is split into distinct reaches, each of which may have a different cost of management. This management cost may depend on reach characteristics such as access and water flow rate, and growth rates may depend on the level of invasions in upstream reaches. Thus, the manager's decision to allocate part of their budget to a given reach depends on their knowledge of the cost, growth rates, and invasions of each reach in the system. We compare the manager's optimal policy under suitable habitat probabilities associated with the current climate regime and multiple future climate change scenarios. Obtaining these policies allows us to compare the level of control achievable across representative budgets through optimal invasive species management under current and simulated future climates.

Our approach is not without costs. Solving a dynamic decision problem with a multi-dimensional continuous state and action space is prohibitively complex using traditional dynamic programming techniques. Thus we utilize parametric dynamic programming techniques similar to, for example, Daniel [1976], to quickly and efficiently compute an approximation to the optimal policy. This technique allows relatively quick solutions for problems with large amounts of spatial heterogeneity, which allows a more granular representation of how climate impacts are distributed over space. Although the computed policy is only an approximation, we show that it behaves intuitively for our formulation of the problem.

As a case study, we calibrate the model to simulate the management of water-primrose (*Ludwigia spp.*) in the Willamette River basin, Oregon, USA using data from a climate-sensitive habitat suitability model trained on occurrence data for water-primrose. This model provides estimates of growth and spread parameters and we assume that growth and spread rates are proportional to a reach's percent of suitable habitat. We document that climate change is likely to change the habitat suitability of water-primrose across different sections of the river and this has effects on optimal management strategy that differ from a naive response. Future work will incorporate cost data from a survey of invasive species management practitioners.

### *3.1.1 Related Literature*

Of the rich literature on the economics of invasive species management,[1] our work is most similar to that of Albers et al. [2018] and Hall et al. [2018]. These authors also model manager decisions in a river system with stochastic downstream dispersal. However, our model differs from theirs in that we examine relatively coarse segments of river and allow for continuous representations of the state and action variables. We do this by approximating the value function and solving for an approximate optimal policy.

Our model is also related to other papers in the economics of invasive species management. Examples of papers that consider optimal management of the spatial spread of the invasive species include Epanchin-Niell and Wilen [2012], Epanchin-Niell et al.

[1] For a thorough review of this literature, see Marbuah et al. [2014].

[2012], and Sanchirico et al. [2010]. These papers often have discrete state and/or action spaces and focus on non-riparian environments. For an example of a model with a continuous state and action space, see Olson and Roy [2002]. These authors model invasive species control as an optimal control problem but do not consider spatial heterogeneity or spread.

We also contribute to the literature on invasive species and climate change. Hellmann et al. [2008] list 5 consequences of climate change on invasive species:

> (1) altered transport and introduction mechanisms, (2) establishment of new invasive species, (3) altered impact of existing invasive species, (4) altered distribution of existing invasive species, and (5) altered effectiveness of control strategies.

Our analysis of the spread and management of water primrose in the Willamette Basin is related to the fourth and fifth consequences put forth by those authors. Our model of habitat suitability captures changes in the environmental constraints that allow water-primrose to establish and thrive in various parts of the Willamette. Indeed, different climate change scenarios lead to different distributions of the suitability of water primrose in the Willamette Basin. In addition, our economic model captures changes in the interaction between the distribution of the invasive species and the optimal management strategy. Due to recurrence and downstream dispersal, altered habitat suitability can cause management strategies to be more or less effective depending on the climate change scenario.

Other authors consider how climate change interacts with invasive species generally [Wallingford et al., 2020], and with specific regard to invasive plant's effect on river geomorphology [O'Briain et al., 2023]. However, to our knowledge, ours is the first to consider how the economics of invasive species management changes with climate change.

The paper proceeds as follows. Section 3.2 sets up the model. Section **??** presents model performance on simulations. Section 3.3 discusses the effect of climate change. Section 2.6 concludes.

## 3.2 Model

In this section, we introduce the theoretical model. In what follows, time is indexed by $t$ and reaches are indexed by $k$. Let $x_{k,t}$ be the area of IAP cover in reach $k$ at time period $t$.[2] A time period is assumed to be a year (or growing season) as this most closely matches the frequency of separate treatment actions made by managers, as reported to us by our conversations with various practitioners. Reaches are numbered in order of upstream to downstream, hence $l < k$ implies reach $l$ is further upstream than reach $k$.

### 3.2.1 Ecological Model

Absent treatment, we assume the law of motion for the invasion area in each reach depends on both the patches' deterministic growth and random introductions. Deterministic growth of an invasion in reach $k$ of size $x_k$ is characterized by a function $x'_k = f(x_k, C_k)$ , where $C_k$ is carrying capacity in reach $k$. We parameterize $f$ as a logistic growth function with growth rate $\rho$. Thus,

$$x' = \left(1 + \rho\left(1 - \frac{x}{C}\right)\right)x.$$

Using a logistic growth function (instead of, say, an exponential one) is important to our application as the invasion will not diverge under the carrying-capacity-constrained logistic growth and we can guarantee a solution to the dynamic programming problem. In addition, the scenario in which the IAP grows without bound in a given reach is not attractive as a model of real world population growth as resource and environmental constraints are most often relevant in biological systems. Note also that the carrying

[2] We use area instead of biomass to better fit our application, where managers have a much better idea of the size of an IAP patch than the amount of biomass.

capacity parameter, $C$, does not reflect a hard limit on the size of the invasion in a given reach. Rather, when the invasion size grows beyond the level of the carrying capacity, the environment cannot support all of the IAP in the reach and the size tends to shrink back.

We assume reaches experience random introductions of IAPs, $u_t$, each period. We further assume $u_{k,t}$ is distributed as a vector of exponential random variables with heterogeneous scale parameter $\phi_k + \zeta_k x_{k-1}$. This specification implies that the random introductions depend on reach-specific characteristics (summarized by $\phi_k$, $\zeta_k$) and upstream invasion magnitude ($x_{k-1,t}$).The stochastic introductions are assumed to depend on the magnitude of invasive area in upstream reaches ($x_{k-1,t}$) because a larger amount of IAP upstream increases the probability of dispersal downstream. In addition, these upstream invasions are scaled by a reach-specific parameter, $\zeta_k$, to reflect the fact that the relative success of establishment from upstream dispersal depends on reach specific characteristics. For example, *Ludwigia* is known to establish well in sloughs and other low-flow sections of river. Reaches that contain many sloughs may have higher *Ludwigia* growth rates than other river sections. Finally, the parameter $\phi_k$ captures the mean-level establishment probability in reach $k$. The value of this parameter depends on the probability of establishment from exogenous sources of dispersal such as boats or animals. This parameter can vary by reach for similar reasons to $\rho_k$ and $\zeta_k$, as well as the relative presence of exogenous sources of dispersal in reach $k$. Capturing this reach-level heterogeneity is an important contribution of our model.

### *3.2.2 Economic Model*

We now put forth a model of optimal management decisions, taking as given the IAP growth pattern described above. The agent of interest is a river manager, who we assume makes decisions regarding IAP treatment in the river section. The section is composed of $K$ reaches connected linearly, each of which can be described by the vector of parameters

$(\rho_k, \zeta_k, \phi_k, C_k)$ introduced in 3.2.1. Each period $t$, the state of the river section is described by a vector, $x_t \in \mathbb{R}_+^K$ and the manager is endowed with a budget of $B$ labor field days they can allocate between the reaches to reduce the invasion area present.[3] In the practice, this budget depends on many things: sources of state funding, state and federal grants, volunteer pool, etc. In the model, we abstract from how management actions may affect the size of the budget and instead assume the manager takes the budget as given.

Let $l_{k,t}$ represent the amount of labor used to treat reach $k$ at time $t$ and $l_t = (l_{1,t}, \ldots, l_{K,t})$. We assume a production function $h(l_{k,t}; c_k) = \gamma_k l_{k,t}^{\alpha}$, $\alpha \in (0,1)$ that governs the amount of IAP removable by one unit of labor in a time period. The function $h(\cdot)$ exhibits decreasing returns to scale as a manager cannot eliminate an invasion completely from an individual reach in a single time period. Instead the typical management strategy is to treat a patch with an herbicide, wait for the plants to die, observe which plants survive, and then treat again next season. Most of the time, invasions are not completely eradicated with a single treatment. In addition, the parameter $\gamma_k$ determines the efficacy of a unit of labor. This may vary by reach as some reaches may require more labor-hours to treat than others. For example, reaches that have a high proportion of private land may require a significant amount of field days to meet with landowners and acquire permission to treat on their land. This source of heterogeneity is important to treating IAP in many river systems.

Treatment allocation decisions are complicated by the dynamics of the IAP growth: if the manager wants to minimize total invasion area, she faces an intertemporal tradeoff between prioritizing the reduction of the largest current invasions or prioritizing treatment of upstream invasions that will disperse and create larger invasions downstream in later time periods. To formalize this tradeoff, we model the river manager's decision problem as a dynamic programming problem. The river manager seeks to choose

[3] In our conversations with river managers, most noted that labor hours were their primary constraint in treating invasion patches. Other potential costs are the costs of herbicide and equipment. We assume the cost of herbicide is proportional to the cost of labor and equipment is most appropriately considered a fixed cost. Thus we can use labor as the only decision variable without loss of generality.

the optimal management strategy, $\{l_t\}_{t=0}^{\infty}$, that minimizes the infinite sum of discounted cost from invasive species in a river system. The total amount of labor allocated per period must satisfy $\sum_{k=1}^{K} l_{kt} \leq B$. Let $w \in \mathbb{R}^K$ be a vector of weights the manager assigns to each reach when making her management decisions. Weights may be different if reaches have different recreational value or habitat value for native, endangered or other important species. Assuming the manager is risk-neutral, her per period cost given state $x$ is $w'x$. The timing of the model is as follows: at the start of period $t$, the manager observes $x_t$ and incurs cost $w'x_t$. She then makes the decision $l_t$ and the state transitions to $x_{t+1} = f(x_t - \gamma l_t^{\alpha}) + u_{t+1}$.

Formally, the manager's decision problem can be written as

$$\begin{aligned}
\min_{\{l_t\}_{t=0}^{\infty}} \quad & \sum_{t=0}^{\infty} \beta^t w' x_t \\
\text{s.t.} \quad & x_{t+1} = f(x_t - l_t^{\alpha}, C) + u_{t+1} \\
& f\left(x_{k,t}, C_k\right) = \left(1 + \rho\left(1 - \frac{x_{k,t}}{C_k}\right)\right) x_{k,t} \\
& u_{k,t+1} \sim \text{Exp}\left(\phi_k + \zeta_k x_{k-1,t}\right) \\
& \sum_{k=1}^{K} l_{kt} \leq B, \quad \forall t \\
& l_{kt}^{\alpha} \leq x_{kt}, \quad \forall k, t.
\end{aligned}$$

where $\beta$ is the manager's rate of time preference (discount factor). Rewriting this as a Bellman equation, we have

$$\begin{aligned}
\min_{l_t} \quad & w' x_t + \beta \mathbb{E}\left[V\left(x_{t+1}\right) | x_t, l_t\right] \\
\text{s.t.} \quad & x_{t+1} = f(x_t - l_t^{\alpha}, C) + u_{t+1} \\
& f\left(x_{k,t}, C_k\right) = \left(1 + \rho\left(1 - \frac{x_{k,t}}{C_k}\right)\right) x_{k,t} \\
& u_{k,t+1} \sim \text{Exp}\left(\phi_k + \zeta_k x_{k-1,t}\right) \\
& \sum_{k=1}^{K} l_{kt} \leq B \\
& l_{kt}^{\alpha} \leq x_{kt}, \quad \forall k, t.
\end{aligned}$$

for each $t$, where the expectation in the first line is taken with respect to $u_{t+1}$.

Table 3.1 summarizes the definitions of variables and parameters introduced thus far.

| Variable/Parameter | Definition |
|---|---|
| $x$ | Invasion area |
| $l$ | Units of labor used |
| $u$ | Stochastic IAP introduction |
| $w$ | Manager's reach weights |
| $C$ | Carrying capacity |
| $B$ | Manager's labor budget |
| $f(\cdot)$ | Transition function |
| $h(\cdot)$ | Production function |
| $\alpha$ | Elasticity of labor |
| $\gamma$ | Productivity of labor |
| $\beta$ | Manager rate of time preference (discount factor) |
| $\rho$ | Logistic growth rate |
| $\phi$ | Mean external introduction rate |
| $\zeta$ | Mean dispersal rate |

Table 3.1: Table of variable and parameter definitions.

### *3.2.3 Growth Rate Parameters: Suitable Habitat Probability*

We do not have data on growth or dispersal rates for our invasive species of interest. Hence, we need a method of calibrating our growth and dispersal parameters, $\rho_k$, $\zeta_k$, and $\phi_k$. To approximate the growth parameters, we use a model of suitable habitat probability (SHP) of the IAP in the individual reaches. The suitable habitat probability model is a predictive model of species establishment in an environment, conditional on certain environmental characteristics such as temperature and humidity. To predict establishment of an invasive species in a non-native environment, the model is trained on data from its native environment.[4] We model the growth and dispersal parameters in reach $k$ as being proportional to the SHP of the IAP in reach $k$. The justification for this assumption lies in the fact that invasive species tend to grow faster and more easily in environments that are suitable habitats. If a reach has a higher percentage of suitable habitat, we expect an IAP to grow faster in that reach.

Figure 3.1a plots a map of average SHP by reach for water-primrose in the Willamette Basin using data on hindcasted 1970-2000 climate conditions. It is clear that the main stem and tributary reaches closest to the main stem have the highest habitat suitability while the reaches furthest upstream the tributaries have the lowest. Figure 3.1b plots the change in SHP relative to the hindcast under two climate models. These models represent different global climate model assumptions and correspond to a “warm-dry” and “warm-wet” environment in the Willamette river, respectively. There are heterogeneous effects across the river system: the largest changes happen in the middle reaches of the tributaries while the ends are less affected. Note that the direction of the change depends on the specific climate model we use. We see an increase in SHP among these reaches under the ″warm-dry″ scenario and a decrease under the ″warm-wet″ scenario.

[4]For details of the Habitat Suitability model, refer to Smoot et al. [2024].

### 3.2.4 Solution Method

This problem involves a multidimensional continuous state variable which poses significant computational challenges to finding a solution. Traditional value or policy function iteration by discretization of the state space is infeasible due to the size of the state space and the complexity of the transition function (making it hard to "stay on the grid"). Therefore, we approximate the value function using a linear combination of basis functions, $\psi_j(x)$, $j = \{1, 2, \ldots\}$. Let $\Psi(x)$ be a vector of the evaluation of these basis functions at a state, $x$. Then the value function approximation at is given by

$$V(x) \approx \widehat{V}(x, \theta) = \Psi(x)'\theta,$$

where $\theta$ is a vector of coefficients. The parameters $\theta$ are estimated through value or policy function iteration on the approximate Bellman equation

$$\widehat{V}(x_t, \theta_m) = \min_l w' x_t + \beta \mathbb{E}\left[\widehat{V}\left(x_{t+1}, \theta_{m-1}\right) | x_t, l\right].$$

This method is useful for two reasons: 1) it provides an approximation to a function without a closed form, and 2) given a state, it allows for relatively fast computation of the optimal policy, provided the basis functions are differentiable. The second point reduces the time complexity of the problem considerably, especially in a problem with such a large state space.

This method is not without costs, however, and significant care is needed when choosing the function approximation. First, the approximation $\widehat{V}$ does not necessarily inherit the contraction properties of the Bellman operator, $V$. Thus there is no guarantee that the iteration actually converges. To ameliorate this issue, one may try to pick the most flexible function approximation method they can, but this can cause further problems. Traditional flexible function approximations such as polynomials or splines may perform poorly when used as a value function approximation because of well-known "oscillation" properties of these functions. In short, the approximation may overfit the value function leading to many local optima. This distorts the computation of the optimal policy and thus causes the algorithm to converge to a value that may not be close to the truth. To avoid these problems, and to keep the problem tractable, we use relatively simple approximations to the value function. These approximations include a linear specification, quadratic specification, and quadratic specification with interactions between the states.

## 3.3 Climate Change

This section discusses the implications of climate change on water-primrose management. For simplicity, we first focus on changes in one tributary of the Willamette, the Calapooia River. Then we consider basin-wide comparisons between the optimal management strategy and a naive approach.

### 3.3.1 Calapooia River

Figure 3.2 highlights the Calapooia River within the broader Willamette Basin.

To analyze the impact of climate change on management outcomes, we simulate trajectories of IAP spread under different parameter values for the three different climate scenarios discussed in Section 3.2.3. The baseline parameter values are listed in Table 3.2.

The results for various budget values are plotted in 3.3. The mean invasion size decreases as the budget gets larger for each climate scenario. Furthermore, the warm-dry scenario predicts similar invasions to the hindcast model, while the warm-wet scenario predicts up to 29% less mean invasion area when the budget is 0.6. Referring to Figures 3.1a and 3.1b, this appears to be because the habitat suitability model predicts a decrease in average SHP in the warm-wet scenario, making invasions spread more slowly and being easier to manage. Interestingly, we do not observe the converse for the warm-

| Parameter | Definition | Value |
|---|---|---|
| $w$ | Manager's reach weights | $\mathbf{1}$ |
| $C$ | Carrying capacity | 10 |
| $B$ | Manager's labor budget | 1 |
| $\alpha$ | Elasticity of labor | 0.5 |
| $\gamma$ | Productivity of labor | $\mathbf{1}$ |
| $\beta$ | Manager rate of time preference (discount factor) | 0.97 |
| $\rho$ | Logistic growth rate | $0.1SHP_k$ |
| $\phi$ | Mean external introduction rate | $0.5SHP_k$ |
| $\zeta$ | Mean dispersal rate | $0.1SHP_k$ |

Table 3.2: Table of baseline parameter values.

dry scenario even though average SHP increases relative to the hindcast. This result is presumably because the optimal strategy is able to shift enough to control for the increased spread probability under this scenario.

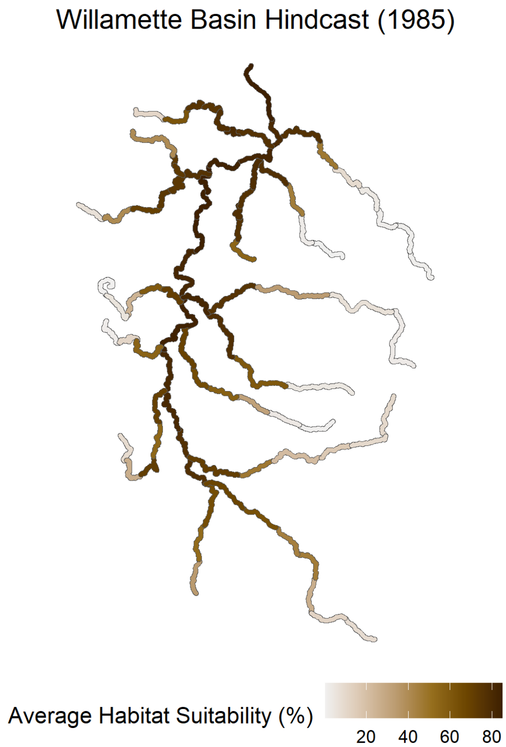
In Figure 3.4, we plot the standard deviation of labor allocation, $l_k$, over reaches $k$ for each climate projection. This quantity represents the distribution of management action as the budget changes. As the budget increases, the standard deviation first increases and then trends down. For low budgets, the manager focuses attention most on reaches that accumulate a large amount of invasive biomass from other reaches as she is unable to fully eradicate problematic upstream invasions. As the budget increases, she shifts her attention to first both upstream and downstream reaches, and then only downstream reaches again. This reflects the manager focusing more treatment attention on the few reaches with the highest exogenous invasion probability, $\phi_k$. Since the manager treats these invasions before they get large, the invasions do not spread to other reaches as readily.

### *3.3.2 Willamette River System*

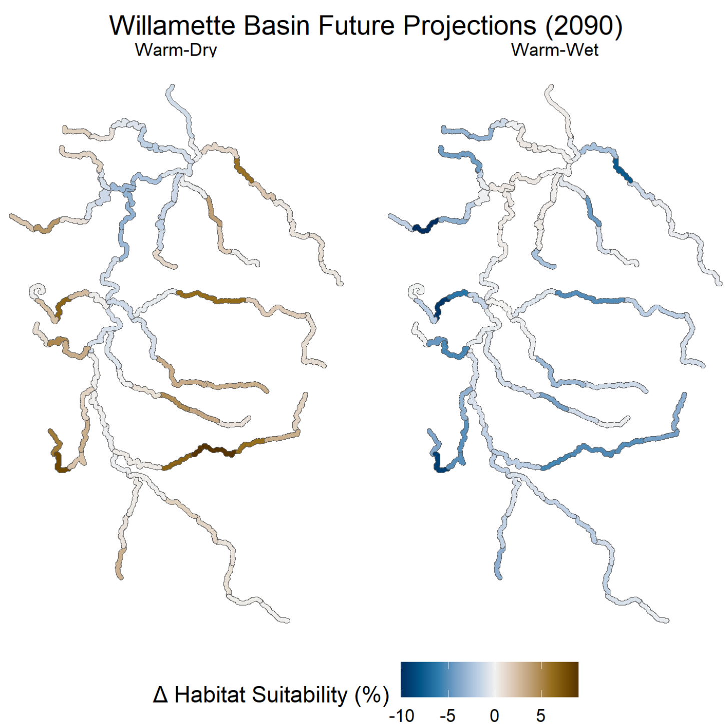
We now shift focus to the entire watershed. Our aim is to characterize how the distribution of management changes with the projected changes in climate. To accomplish this, we simulate management trajectories under each of the Warm-Wet and Warm-Dry climate scenarios using (1) the optimal management policy given a specific climate scenario and (2) the optimal management policy for the hindcast scenario. The trajectories are simulated for each section of river, where the sections correspond to either a tributary or main stem. We then take the difference between the mean labor allocation under (1) and (2). Formally, let $\bar{l}_k^{(1)}$ and $\bar{l}_k^{(2)}$ correspond to mean labor allocation in reach $k$ for policies (1) and (2), respectively. In 3.5, we plot $\bar{l}_k^{(1)} - \bar{l}_k^{(2)}$ for each reach.

We see that using the optimal management strategy implies a significant difference in labor allocation than under a naive management strategy where the manager's value function does not update to the new habitat suitability probabilities. Furthermore, there is no apparent pattern between which reaches show increased labor allocation under the optimal management policy and which reaches show decreased labor allocation. This is true under both climate scenarios and there is no systematic difference between the climate scenarios.

Our model implies that relying on a policy that is only optimal under past climate conditions will be significantly different from the optimal policy under climate change. Moreover, where and how management changes appears to be unpredictable. Hence, river managers will need to take downstream dispersal and changes in habitat suitability into account when adapting their management policies to climate change.




(a) Map of average percent habitat suitability for each reach of the Willamette using data on 1970-2000 climate conditions.




(b) Map of the change in average percent habitat suitability relative to the 1970-2000 hindcast for each reach of the Willamette. Data are from two 2090 emissions scenario projections: one that predicts a "Warm-Dry" climate for the Willamette and one that predicts a "Warm-Wet" climate.

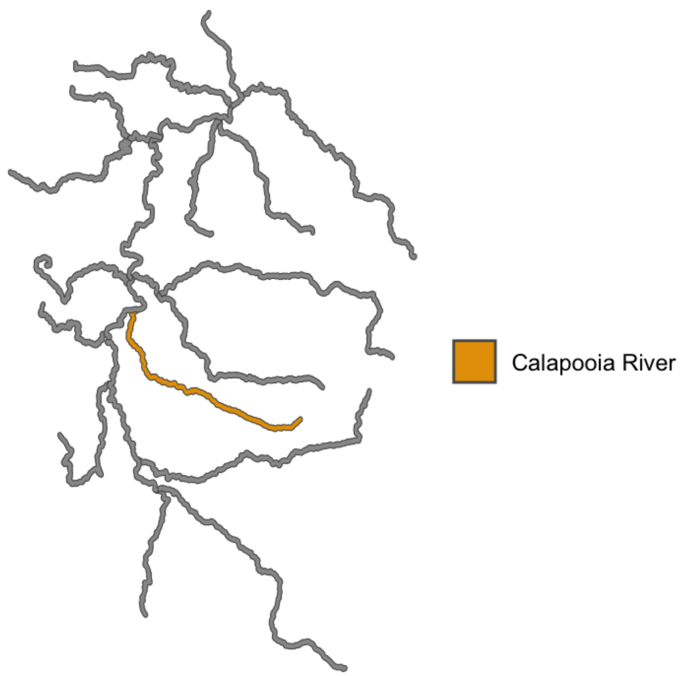



Figure 3.2: Map of the Willamette Basin with the Calapooia River Highlighted

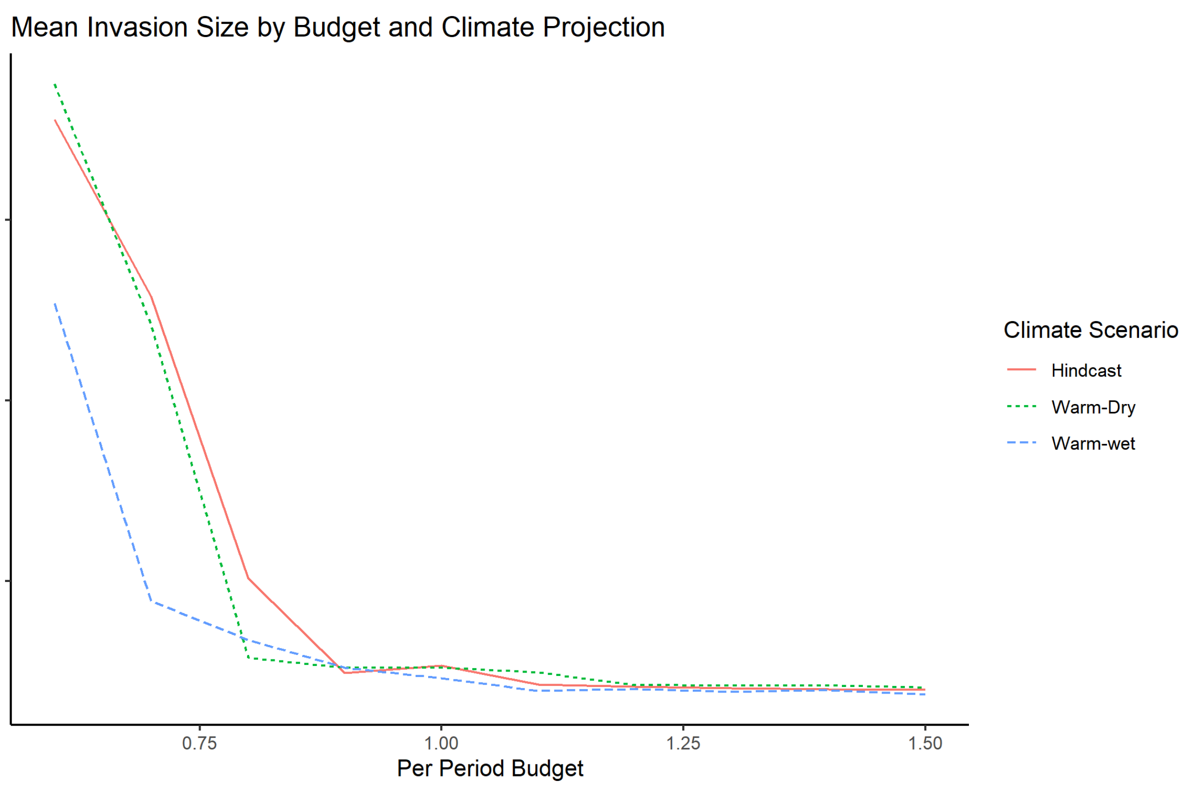



Figure 3.3: Mean Invasion Size by Budget and Climate Scenario for the Calapooia River. Means are taken over simulated trajectories of 1000 time periods.

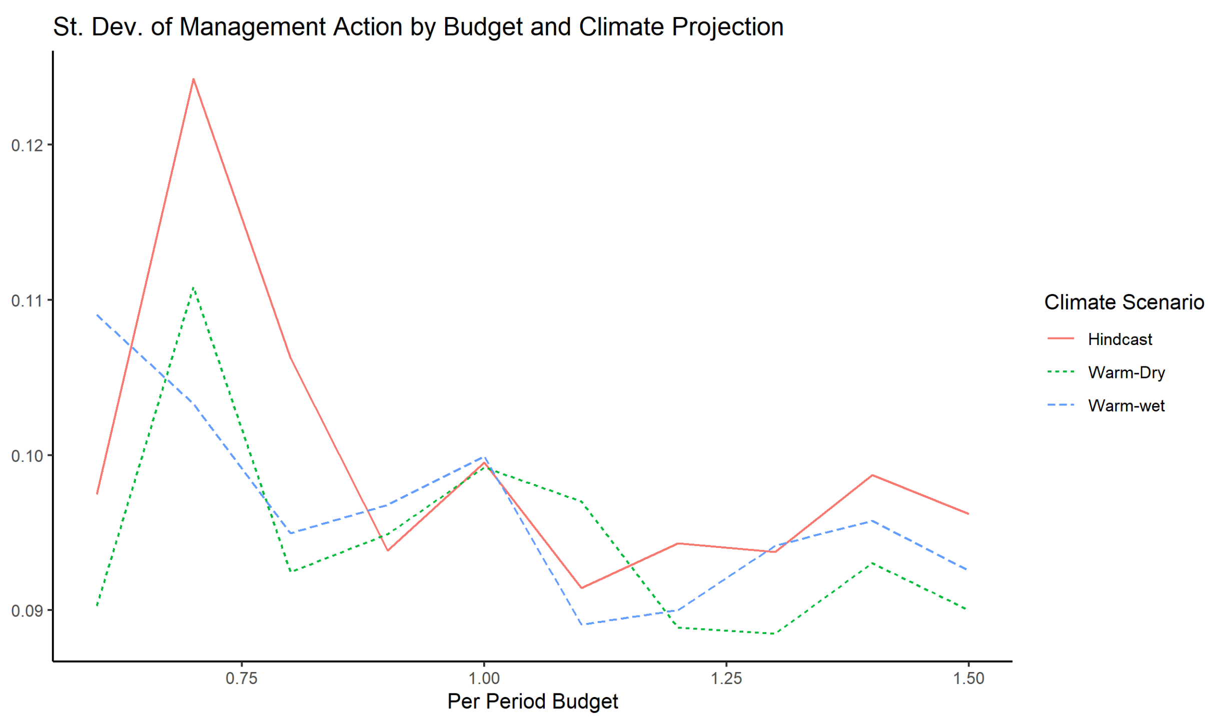



Figure 3.4: Standard Deviation of Management Action by Budget and Climate Scenario for the Calapooia River. Standard Deviations are taken over simulated trajectories of 1000 time periods.

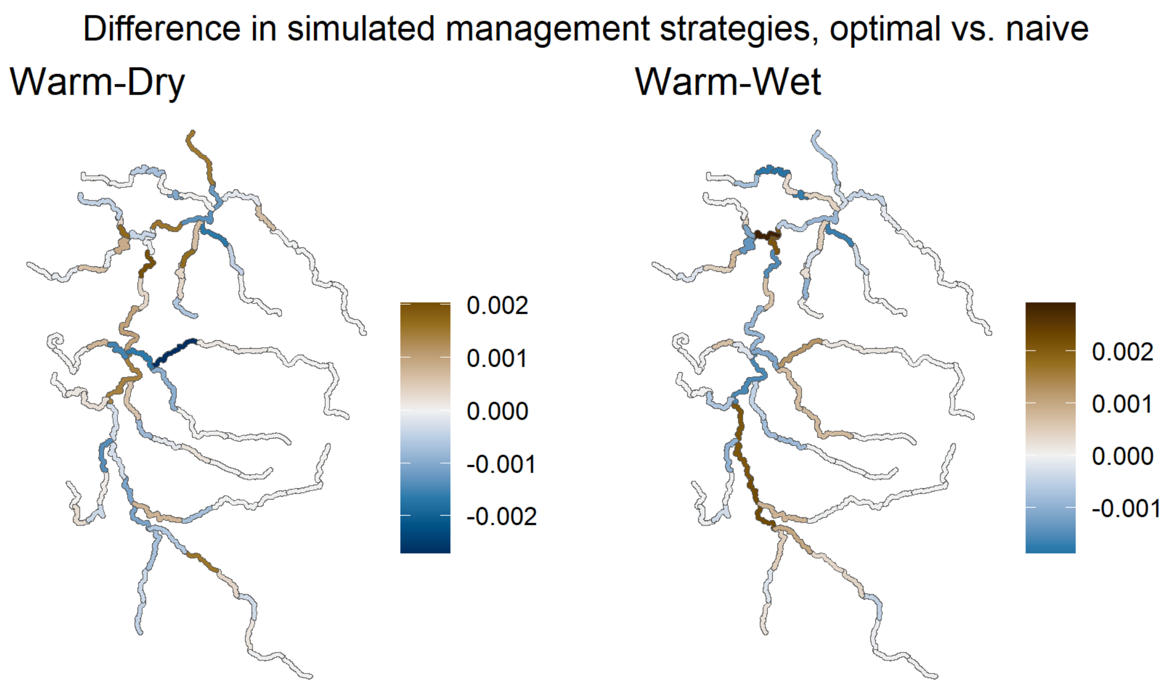



Figure 3.5: Difference in simulated mean labor allocation for each reach under the optimal management policy given a specific climate scenario and the optimal management policy for the hindcast scenario. Management trajectories are simulated at the section level, where each tributary corresponds to a section.

# BIBLIOGRAPHY

V. Aguirregabiria and C.-Y. Ho. A dynamic oligopoly game of the US airline industry: Estimation and policy experiments. *Journal of Econometrics*, 168(1):156–173, May 2012. ISSN 0304-4076. doi: 10.1016/j.jeconom.2011.09.013. URL https://www.sciencedirect.com/science/article/pii/S030440761100176X.

V. Aguirregabiria, R. Clark, and H. Wang. Diversification of geographic risk in retail bank networks: evidence from bank expansion after the Riegle-Neal Act. *The RAND Journal of Economics*, 47(3):529–572, 2016. ISSN 1756-2171. doi: 10.1111/1756-2171.12136. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12136. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12136.

H. J. Albers, K. M. Hall, K. D. Lee, M. A. Taleghan, and T. G. Dietterich. The Role of Restoration and Key Ecological Invasion Mechanisms in Optimal Spatial-Dynamic Management of Invasive Species. *Ecological Economics*, 151:44–54, Sept. 2018. ISSN 0921-8009. doi: 10.1016/j.ecolecon.2018.03.031. URL https://www.sciencedirect.com/science/article/pii/S0921800917310455.

J. Azar, M. C. Schmalz, and I. Tecu. Anticompetitive Effects of Common Ownership. *The Journal of Finance*, 73(4):1513–1565, 2018. ISSN 1540-6261. doi: 10.1111/jofi.12698. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.12698. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12698.

J. Azar, S. Raina, and M. Schmalz. Ultimate ownership and bank competition. *Financial Management*, 51(1):227–269, 2022. ISSN 1755-053X. doi: 10.1111/fima.12368. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/fima.12368. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/fima.12368.

M. Backus, C. Conlon, and M. Sinkinson. Common Ownership and Competition in the Ready-to-Eat Cereal Industry, Jan. 2021. URL https://www.nber.org/papers/w28350.

J. Begenau and E. Stafford. Uniform Rate Setting and the Deposit Channel, Dec. 2023. URL https://papers.ssrn.com/abstract=4136858.

S. Berry and P. Jia. Tracing the Woes: An Empirical Analysis of the Airline Industry. *American Economic Journal: Microeconomics*, 2(3):1–43, Aug. 2010. ISSN 1945-7669, 1945-7685. doi: 10.1257/mic.2.3.1. URL https://pubs.aeaweb.org/doi/10.1257/mic.2.3.1.

S. Berry, J. Levinsohn, and A. Pakes. Automobile Prices in Market Equilibrium. *Econometrica*, 63(4):841–890, 1995. ISSN 00129682, 14680262. doi: 10.2307/2171802. URL http://www.jstor.org/stable/2171802. Publisher: [Wiley, Econometric Society].

S. Berry, M. Carnall, and P. T. Spiller. Airline hubs : costs, markups and the implications of customer heterogeneity. *Competition policy and antitrust*, 2006. URL https://trid.trb.org/view/815368.

S. T. Berry. Airport Presence as Product Differentiation. *The American Economic Review*, 80(2):394–399, 1990. ISSN 0002-8282. URL https://www.jstor.org/stable/2006607. Publisher: American Economic Association.

S. T. Berry. Estimation of a Model of Entry in the Airline Industry. *Econometrica*, 60(4): 889, July 1992. ISSN 00129682. doi: 10.2307/2951571. URL https://www.jstor.org/stable/2951571?origin=crossref.

S. T. Berry. Estimating Discrete-Choice Models of Product Differentiation. *The RAND Journal of Economics*, 25(2):242–262, 1994. ISSN 0741-6261. doi: 10.2307/2555829. URL https://www.jstor.org/stable/2555829. Publisher: [RAND Corporation, Wiley].

D. Bounie, Y. Camara, E. Fize, J. Galbraith, C. Landais, C. Lavest, T. Pazem, B. Savatier, and others. Consumption dynamics in the covid crisis: real time insights from French transaction bank data. *Covid Economics*, 59:1–39, 2020.

A. Brodeur, D. Gray, A. Islam, and S. Bhuiyan. A literature review of the economics of COVID-19. *Journal of Economic Surveys*, 35(4):1007–1044, 2021. ISSN 1467-6419. doi: 10.1111/joes.12423. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/joes.12423. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/joes.12423.

A. J. Bunch, M. S. Allen, and D. C. Gwinn. Spatial and Temporal Hypoxia Dynamics in Dense Emergent Macrophytes in a Florida Lake. *Wetlands*, 30(3):429–435, June 2010. ISSN 1943-6246. doi: 10.1007/s13157-010-0051-9. URL https://doi.org/10.1007/s13157-010-0051-9.

R. Chetty, J. N. Friedman, N. Hendren, M. Stepner, and T. O. I. Team. The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data. Working Paper 27431, National Bureau of Economic Research, June 2020. URL http://www.nber.org/papers/w27431. Series: Working Paper Series.

F. Ciliberto and E. Tamer. Market Structure and Multiple Equilibria in Airline Markets. *Econometrica*, 77(6):1791–1828, 2009. ISSN 0012-9682. doi: 10.3982/ECTA5368. URL http://doi.wiley.com/10.3982/ECTA5368.

F. Ciliberto and J. W. Williams. Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry. *The RAND Journal of Economics*, 45(4):764–791, 2014. ISSN 1756-2171. doi: 10.1111/1756-2171.12070. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12070. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12070.

F. Ciliberto, C. Murry, and E. Tamer. Market Structure and Competition in Airline Markets. *Journal of Political Economy*, 129(11):2995–3038, Nov. 2021. ISSN 0022-3808. doi: 10.

1086/715848. URL https://www.journals.uchicago.edu/doi/full/10.1086/715848. Publisher: The University of Chicago Press.

O. Coibion, Y. Gorodnichenko, and M. Weber. The Cost of the Covid-19 Crisis: Lockdowns, Macroeconomic Expectations, and Consumer Spending. Working Paper 27141, National Bureau of Economic Research, May 2020. URL http://www.nber.org/papers/w27141. Series: Working Paper Series.

B. Colleran, S. N. Lacy, and M. R. Retamal. Invasive Japanese knotweed (Reynoutria japonica Houtt.) and related knotweeds as catalysts for streambank erosion. *River Research and Applications*, 36(9):1962–1969, 2020. ISSN 1535-1467. doi: 10.1002/rra.3725. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/rra.3725. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/rra.3725.

C. Conlon and J. Gortmaker. Best practices for differentiated products demand estimation with PyBLP. *The RAND Journal of Economics*, 51(4):1108–1161, 2020. ISSN 1756-2171. doi: 10.1111/1756-2171.12352. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12352. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12352.

J. W. Daniel. Splines and efficiency in dynamic programming. *Journal of Mathematical Analysis and Applications*, 54(2):402–407, May 1976. ISSN 0022-247X. doi: 10.1016/0022-247X(76)90209-2. URL https://www.sciencedirect.com/science/article/pii/0022247X76902092.

A. d'Avernas, A. L. Eisfeldt, C. Huang, R. Stanton, and N. Wallace. The Deposit Business at Large vs. Small Banks, Nov. 2023. URL https://www.nber.org/papers/w31865.

A. A. Dick. Demand estimation and consumer welfare in the banking industry. *Journal of Banking & Finance*, 32(8):1661–1676, Aug. 2008. ISSN 0378-4266. doi: 10.1016/j.

jbankfin.2007.12.005. URL https://www.sciencedirect.com/science/article/pii/S0378426607003937.

J. L. Ebersole, W. J. Liss, and C. A. Frissell. Relationship between stream temperature, thermal refugia and rainbow trout Oncorhynchus mykiss abundance in arid-land streams in the northwestern United States. *Ecology of Freshwater Fish*, 10(1):1–10, 2001. ISSN 1600-0633. doi: 10.1034/j.1600-0633.2001.100101.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1034/j.1600-0633.2001.100101.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1034/j.1600-0633.2001.100101.x.

M. Ecology. 2016 Water Quality and Ludwigia Monitoring Report for Stewart Slough, Collins Bay, and Scatter Bar Pond. Technical report, May 2017.

M. Egan, A. Hortaçsu, and G. Matvos. Deposit Competition and Financial Fragility: Evidence from the US Banking Sector. *American Economic Review*, 107(1):169–216, Jan. 2017. ISSN 0002-8282. doi: 10.1257/aer.20150342. URL https://www.aeaweb.org/articles?id=10.1257/aer.20150342.

M. Egan, S. Lewellen, and A. Sunderam. The Cross-Section of Bank Value. *The Review of Financial Studies*, 35(5):2101–2143, May 2022. ISSN 0893-9454. doi: 10.1093/rfs/hhab089. URL https://doi.org/10.1093/rfs/hhab089.

R. S. Epanchin-Niell and J. E. Wilen. Optimal spatial control of biological invasions. *Journal of Environmental Economics and Management*, 63(2):260–270, Mar. 2012. ISSN 0095-0696. doi: 10.1016/j.jeem.2011.10.003. URL https://www.sciencedirect.com/science/article/pii/S0095069611001392.

R. S. Epanchin-Niell, R. G. Haight, L. Berec, J. M. Kean, and A. M. Liebhold. Optimal surveillance and eradication of invasive species in heterogeneous landscapes. *Ecology Letters*, 15(8):803–812, 2012. ISSN 1461-0248. doi: 10.1111/j.1461-0248.2012.01800.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1461-0248.

2012.01800.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1461-0248.2012.01800.x.

Y. Fan. Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market. *American Economic Review*, 103(5):1598–1628, Aug. 2013. ISSN 0002-8282. doi: 10.1257/aer.103.5.1598. URL https://www.aeaweb.org/articles?id=10.1257/aer.103.5.1598.

S. Forbes and M. Lederman. The Role of Regional Airlines in the U.S. Airline Industry. *Advances in Airline Economics*, 2, Jan. 2007.

A. Gandhi and J.-F. Houde. Measuring Substitution Patterns in Differentiated-Products Industries, Oct. 2019. URL https://www.nber.org/papers/w26375.

B. J. Grewell, M. D. Netherland, and M. J. Skaer Thomason. Establishing Research and Management Priorities for Invasive Water Primroses (Ludwigia spp.). ERDC. Technical report, EL TR-162 Technical Report, Feb. 2016.

L. Grigolon and F. Verboven. Nested Logit or Random Coefficients Logit? A Comparison of Alternative Discrete Choice Models of Product Differentiation. *The Review of Economics and Statistics*, 96(5):916–935, Dec. 2014. ISSN 0034-6535. doi: 10.1162/REST_a_00420. URL https://doi.org/10.1162/REST_a_00420.

A. S. Gupta and J. Mukherjee. Decoding revenge buying in retail: role of psychological reactance and perceived stress. *International Journal of Retail & Distribution Management*, 50(11):1378–1394, Jan. 2022. ISSN 0959-0552. doi: 10.1108/IJRDM-01-2022-0022. URL https://doi.org/10.1108/IJRDM-01-2022-0022. Publisher: Emerald Publishing Limited.

K. M. Hall, H. J. Albers, M. Alkaee Taleghan, and T. G. Dietterich. Optimal Spatial-Dynamic Management of Stochastic Species Invasions. *Environmental and Resource Eco-*

*nomics*, 70(2):403–427, June 2018. ISSN 1573-1502. doi: 10.1007/s10640-017-0127-6. URL https://doi.org/10.1007/s10640-017-0127-6.

J. J. Hellmann, J. E. Byers, B. G. Bierwagen, and J. S. Dukes. Five Potential Consequences of Climate Change for Invasive Species. *Conservation Biology*, 22(3):534–543, 2008. ISSN 1523-1739. doi: 10.1111/j.1523-1739.2008.00951.x. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1523-1739.2008.00951.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1523-1739.2008.00951.x.

K. Ho and J. Ishii. Location and competition in retail banking. *International Journal of Industrial Organization*, 29(5):537–546, Sept. 2011. ISSN 0167-7187. doi: 10.1016/j.ijindorg.2010.11.004. URL https://www.sciencedirect.com/science/article/pii/S0167718710001372.

Y. Hsu and X. Shi. Model-selection tests for conditional moment restriction models. *The Econometrics Journal*, 20(1):52–85, Feb. 2017. ISSN 1368-4221. doi: 10.1111/ectj.12081. URL https://doi.org/10.1111/ectj.12081.

G. Kapetanios, N. Neuteboom, F. Ritsema, and A. Ventouri. How did consumers react to the COVID-19 pandemic over time? *Oxford Bulletin of Economics and Statistics*, 84(5):961–993, 2022. ISSN 1468-0084. doi: 10.1111/obes.12507. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/obes.12507. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/obes.12507.

S. Khanna, M. J. Santos, J. D. Boyer, K. D. Shapiro, J. Bellvert, and S. L. Ustin. Water primrose invasion changes successional pathways in an estuarine ecosystem. *Ecosphere*, 9(9):e02418, 2018. ISSN 2150-8925. doi: 10.1002/ecs2.2418. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/ecs2.2418. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/ecs2.2418.

J. Lazarev. The Welfare Effects of Intertemporal Price Discrimination:. *Working Paper*, 2013.

S. Li, J. Mazur, Y. Park, J. Roberts, A. Sweeting, and J. Zhang. Repositioning and market power after airline mergers. *The RAND Journal of Economics*, 53(1):166–199, 2022. ISSN 1756-2171. doi: 10.1111/1756-2171.12404. URL `https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12404`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12404.

G. Marbuah, I.-M. Gren, and B. McKie. Economics of Harmful Invasive Species: A Review. *Diversity*, 6(3):500–523, Sept. 2014. ISSN 1424-2818. doi: 10.3390/d6030500. URL `https://www.mdpi.com/1424-2818/6/3/500`. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

X. Nguyen and C.-C. Chao. Revenge consumption, product quality, and welfare. *International Review of Economics & Finance*, 76:495–501, Nov. 2021. ISSN 1059-0560. doi: 10.1016/j.iref.2021.05.007. URL `https://www.sciencedirect.com/science/article/pii/S1059056021001155`.

R. O'Briain, D. Corenblit, and A. Gurnell. Interacting effects of climate change and invasions by alien plant species on the morphodynamics of temperate rivers. *WIREs Water*, 10(5):e1649, 2023. ISSN 2049-1948. doi: 10.1002/wat2.1649. URL `https://onlinelibrary.wiley.com/doi/abs/10.1002/wat2.1649`. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/wat2.1649.

L. J. Olson and S. Roy. The Economics of Controlling a Stochastic Biological Invasion. *American Journal of Agricultural Economics*, 84(5):1311–1316, 2002. ISSN 0002-9092. URL `https://www.jstor.org/stable/1245064`. Publisher: [Agricultural & Applied Economics Association, Oxford University Press].

A. Pakes, J. Porter, K. Ho, and J. Ishii. Moment Inequalities and Their Application. *Econo-*

*metrica*, 83(1):315–334, 2015. ISSN 0012-9682. URL https://www.jstor.org/stable/43616929. Publisher: [Wiley, The Econometric Society].

A. H. Park and K. Seo. Common Ownership and Product Market Competition: Evidence from the U.S. Airline Industry. *Korean Journal of Financial Studies*, 48(5):617–640, Oct. 2019. ISSN 2005-8187. doi: 10.26845/KJFS.2019.10.48.5.617. URL http://www.e-kjfs.org/journal/view.php?doi=10.26845/KJFS.2019.10.48.5.617. Publisher: Korean Securities Association.

E. Pelella, B. Questino, B. Luzi, F. Mariani, and S. Ceschin. Impact of the Invasive Alien Macrophyte Ludwigia hexapetala on Freshwater Ecosystems: Evidence from Field Data. *Biology*, 12(6), 2023. ISSN 2079-7737. doi: 10.3390/biology12060794.

A. Petrin, M. Ponder, and B. Seo. Identification and Estimation of Discrete Choice Demand Models when Observed and Unobserved Characteristics are Correlated. *National Bureau of Economic Research Working Paper Series*, No. 30778, Dec. 2022. doi: 10.3386/w30778.

A. Ruiz-Pérez. Market Structure and Common Ownership: Evidence from the US Airline Industry. Nov. 2019.

J. N. Sanchirico, H. J. Albers, C. Fischer, and C. Coleman. Spatial Management of Invasive Species: Pathways and Policy Options. *Environmental and Resource Economics*, 45(4): 517–535, Apr. 2010. ISSN 1573-1502. doi: 10.1007/s10640-009-9326-0. URL https://doi.org/10.1007/s10640-009-9326-0.

M. C. Schmalz. Recent Studies on Common Ownership, Firm Behavior, and Market Outcomes. *The Antitrust Bulletin*, 66(1):12–38, Mar. 2021. ISSN 0003-603X. doi: 10.1177/0003603X20985804. URL https://doi.org/10.1177/0003603X20985804. Publisher: SAGE Publications Inc.

X. Shi. Model selection tests for moment inequality models. *Journal of Econometrics*, 187 (1):1–17, July 2015. ISSN 0304-4076. doi: 10.1016/j.jeconom.2015.01.004. URL https://www.sciencedirect.com/science/article/pii/S0304407615000135.

E. E. Smoot, R. L. Flitcroft, S. S. Chan, B. Van Deynze, S. Ewen, and S. L. Jardine. Climate change alters the invasion potential and distribution of established invasive aquatic plants Ludwigia spp., and Reynoutria spp., at watershed scales in the Pacific Northwest, USA. 2024.

L. Thouvenot, J. Haury, and G. Thiebaut. A success story: Water primroses, aquatic plant pests. *Aquatic Conservation: Marine and Freshwater Ecosystems*, 23, Aug. 2013. doi: 10.1002/aqc.2387.

L. S. Urgenson. *The Ecological Consequences of Knotweed Invasion into Riparian Forests*. PhD thesis, University of Washington, 2006.

P. D. Wallingford, T. L. Morelli, J. M. Allen, E. M. Beaury, D. M. Blumenthal, B. A. Bradley, J. S. Dukes, R. Early, E. J. Fusco, D. E. Goldberg, I. Ibáñez, B. B. Laginhas, M. Vilà, and C. J. B. Sorte. Adjusting the lens of invasion biology to focus on the impacts of climate-driven range shifts. *Nature Climate Change*, 10(5):398–405, May 2020. ISSN 1758-6798. doi: 10.1038/s41558-020-0768-2. URL https://doi.org/10.1038/s41558-020-0768-2.

H. Wang, A. T. Ching, and X. Zhao. Consumer Valuation of Network Convenience: Evidence from the Banking Industry, Nov. 2021. URL https://papers.ssrn.com/abstract=1738084.

K. Xiao. Monetary Transmission through Shadow Banks. *The Review of Financial Studies*, 33(6):2379–2420, June 2020. ISSN 0893-9454. doi: 10.1093/rfs/hhz112. URL https://doi.org/10.1093/rfs/hhz112.

U. Zaman, S. H. Raza, S. Abbasi, M. Aktan, and P. Farías. Sustainable or a Butterfly Effect in Global Tourism? Nexus of Pandemic Fatigue, COVID-19-Branded Destination

Safety, Travel Stimulus Incentives, and Post-Pandemic Revenge Travel. *Sustainability*, 13(22):12834, Jan. 2021. ISSN 2071-1050. doi: 10.3390/su132212834. URL https://www.mdpi.com/2071-1050/13/22/12834. Number: 22 Publisher: Multidisciplinary Digital Publishing Institute.