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Essays on Consumer Behavior and the Environment

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Essays on Consumer Behavior and the Environment

A dissertation

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by

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University of California - Santa Barbara September 2010 - June 2015
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PUBLICATIONS

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Steigerwald, Douglas G., Gonzalo Vazquez-Bare, and **Jason Maier**. “Measuring Heterogeneous Effects of Environmental Policies using Panel Data.” Journal of the Association of Environmental and Resource Economists 8.2 (2021): 277-313.

Maier, Jason, Roland Geyer, and Trevor Zink. “Circular economy rebound.” *Handbook of the Circular Economy.* Edward Elgar Publishing, 2020.

Costello, Christopher, et al. “The future of food from the sea.” Nature 588.7836 (2020): 95-100.

Cottrell*, Richard S., **Jason Maier***, et al. ”The overlooked importance of food disadoption for the environmental sustainability of new foods.” Environmental Research Letters (2021).

Maier, Jason, et al. ”How much potable water is saved by wastewater recycling? Quasi-experimental evidence from California.” Resources, Conservation and Recycling 176 (2022): 105948.

Submitted Papers:

[submitted: Environmental Research Letters] **Maier, J.**, and Geyer, R. 2021. “The Role of Prices in Determining the Environmental Impacts of Product Choice”

[submitted: Nature Sustainability] **Maier, J.**, 2021. “The effects of curbside recycling on household consumption”

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Abstract

Essays on Consumer Behavior and the Environment

by Jason Maier

There is increasing awareness of the key role that consumers play in creating a more sustainable future. While both regulations and eco-efficiency improvements have been proposed as levers to solve environmental challenges, a significant focus of recent research has been on understanding the environmental impacts of consumption and identifying the opportunities to reduce environmental impacts through changes in consumption patterns. This research agenda, covered by the field of *sustainable consumption*, has applied the tools and techniques of industrial ecology, in particular attributional life cycle assessment, to the quantification of individual and household environmental impacts (often called footprints) and the identification of sustainable consumption patterns. However, in practice, reducing environmental impacts through changes in consumption requires demand-side interventions - actions taken by individuals, companies, governments, or organizations that shift consumer demand. These interventions may be such things as a consumer deciding to adopt greener products, a company labeling their product with environmental information, a restaurant nudging consumer's towards meatless options, or the development and marketing of a novel product alternative. Understanding the potential of demand-side interventions to achieve desirable environmental outcomes requires a detailed understanding of how

interventions affect consumer behavior and, as a result, the environment.

The scope of this dissertation is captured by a simple question: what role does consumer behavior play in determining the environmental consequences of demand-side interventions? Such a question might seem simple on its face, or perhaps not wholly important. However, how consumers respond to interventions is critical in understanding a solution's environmental merit. Economic activities are linked together into an interdependent system by consumers. As such, interventions that affect consumers ripple throughout the economy in unexpected ways, determining the environmental consequences of the interventions along the way. While this is true broadly, these effects are particularly salient when the proposed environmental benefits are *demand mediated* - that is, the anticipated environmental benefit is solely a function of a change towards more sustainable consumption patterns. Such interventions are rampant, and their environmental consequences relatively unexplored. The extent to which information that affects consumer choices, interventions that affect the costs and benefits of particular household behaviors, or even new product introductions *cause* environmental benefits or damages is a result of how consumer demand responds to the particular intervention. What follows is a set of three essays that illuminates the importance of considering consumer behavior in the context of environmental sustainability and provides key contributions to both the theoretical and empirical understanding of the relationship between consumer behavior and the environment.

The first chapter of this dissertation, *The Role of Prices in Determining the Environmental Impacts of Product Choice*, explores how a consumer's choice between product alternatives affects his aggregate carbon footprint. The extent to which any product choice reduces environmental impacts is, at least in part, determined by the alternative streams of consumption that the consumer faces in his decision. His preferences, constraints, and beliefs, as well as the decision-making context determine these paths. Here we focus specifically on the role that prices and the consumer's budget constraint play in determining the environmental impacts of product choice. We present five case studies where commonly proposed environmental behaviors are found to cause additional environmental impacts as a result of price differences across salient choices.

The second chapter, *Curbside Recycling Increases Household Consumption*, uses econometric methods of causal inference to better understand how consumers respond to curbside recycling programs. Historically, recycling has been justified on environmental grounds by the comparing the environmental impacts of recycled product to the impacts of similar products made from primary materials; Since, in general, recycling products is less environmentally intensive than producing them from virgin sources, recycling interventions have been proposed as an environmental solution. In practice, the extent to which recycling interventions affect the composition and level of consumption is important in understanding the resulting the environmental consequences. We leverage variation in the regional adoption of curbside recycling programs in North Carolina (from 1999-2019) to compare similar communities with and without recycling programs, finding that household solid waste generation (and, thus, material consumption) increases by 7-10% in the presence of curbside recycling. This increase in consumption likely reduces the environmental benefits of recycling programs.

The third chapter, *Demand-driven Conservation*, takes a broader perspective on demand-side interventions. We focus on understanding to what extent demand-side interventions can lead to conservation outcomes. We concern ourselves with the general case of demand-driven conservation by developing a new statistic called the *demand elasticity of conservation*, which represents the percentage change in a desired conservation outcome that results from a percentage shift in demand. We build a theoretical bio-economic model of a fishery to analyze the potential for demand-driven conservation in the context of marine fisheries, then parameterize the model for 4,713 fish stocks to estimate the demand elasticity of conservation for 27 fish product classes. We then perform a case study to investigate the extent to which cell-based seafood, a novel food product in development, may lead to conservation benefits for wild bluefin tuna stocks.

Together, these chapters provide the basis for a deeper understanding of sustainable consumption, expand and solidify the methodology for evaluating the environmental merits of demand-side interventions and develop key insights about when and where consumer behavior can be leveraged for environmental gain. In all, this work is just the beginning of a larger conversation. It is my hope that it spurs additional research on consumer behavior and the environment, that it inspires readers to think deeply and think differently about how to make environmental choices, and that it opens the door just a fraction more to the possibility of an ecologically sound future.

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Chapter 1

The Role of Prices in Determining the Environmental Impacts of Product Choice

Authors: Jason Maier, Roland Geyer

1.1 Abstract

The general practice used to identify the product choice with the least environmental impact is to compare product alternatives based on their environmental footprint. However, such a framework overlooks the effects of purchasing decisions on household consumption as a whole. This paper outlines a general framework for considering the effects of product choice on a consumer's subsequent stream of consumption, with a specific focus on the effect of a price difference between alternatives on the net environmental impacts of the choice. We present five case studies that exemplify the need to consider the environmental impacts of product choice from the broader

perspective of household consumption: consumer goods purchases, convenience item purchases, the use of reusable vs. single use products, product lifetime extensions, and commercial air travel seat selection. Each case study suggests that simple product-to-product comparisons are insufficient to identify the product choice with the least environmental impact, calling for broader reforms in our understanding of 'green' goods, pro-environmental behaviors, and demand-side interventions for sustainable consumption.

1.2 Introduction

Households are responsible for a significant portion of global environmental impacts, and these impacts are expected to increase [1, 2]. Significant research has investigated the potential for voluntary changes in household purchasing decisions to reduce the environmental impacts of consumption, whether the changes are motivated by environmental concern or otherwise [3–9]. The dominant analytical framework used to understand the relative environmental impacts of goods (or bundles of goods) is to compare and contrast the goods' environmental profiles, or footprints, often called comparative life cycle assessment [10–12]. The framework of product-to-product comparisons results in a common decision-making rule proposed by research, environmental organizations, and the media: the choice with the least environmental impact is the product with the smallest environmental footprint. Such intuition is used to derive stoplight labels, carbon certifications, and recommendations for effective environmental actions [13–15]. However, simply comparing product environmental profiles does not provide sufficient information on which to determine whether a particular consumer choice reduces the total environmental impact of the decision-maker.

Attempts have been made to modify the framework of comparative life cycle assessment to address factors that affect the environment outside of the product systems in question - typically framed around the idea of accounting for rebound effects [16–18]. In the case of product choice, where a product with a smaller environmental impact is chosen, the direct environmental benefit is a function of the reduction in impact per unit of service [19]. In response to such a change, rebound effects may occur along several dimensions, including price rebounds, time rebounds, other spillovers, or macro-scale effects [17, 18, 20, 21]. Several notable studies have attempted to extend the framework of life cycle assessment to include such rebounds. Weidema (2003a) outlines the need for market information in life cycle assessment. Theisen et al. (2008) assesses a price rebound in comparative life cycle assessment using the case study of cheese. Girod et al. (2011) proposes a general framework for including direct and indirect rebound effects in life cycle assessment, arguing that the implicit constant demand assumption in the ISO standards for LCA should be replaced with a “consumption-as-usual” assumption. Our paper here builds upon the logic of Girod (2011), Weidema (2003a, 2003b, 2019), Thiesen (2008) and applies such thinking to the case of individual product choices and the effects of such choices on household consumption broadly. Here we focus on the importance of considering the impacts of product choice from the broader perspective of the household as a whole. We first present a general treatment of the environmental impacts of product choice for a household. Then, we present five case studies where comparative life cycle assessment is insufficient to determine the choice most likely to reduce household environmental impact. The results show the need for a broader perspective regarding the impacts of product choice and illustrate how much of our environmental intuition relies on the simple comparison of alternatives on environmental grounds. We suggest that commonly proposed ‘environmental’ behaviors can lead to increased environmental impacts - for instance product reuse and product lifetime extension considered in case study 3 (Section 1.5.3) and case study 4 (Section 1.5.4), respectively. Our goal is not to strictly prove which choice leads to the least environmental impact, but rather to use case studies as a medium to investigate the environmental impacts of product choice.

1.3 Understanding the environmental impacts of product choice

When consumers consider a purchase, the choice is between two alternative streams of consumption, the stream of goods and services consumed given the choice of good A as compared to the stream of goods and services consumed when good A is not purchased. In the most general sense, these alternative streams of consumption are not limited to the consumption of the decision maker, but are the future pathways of all consumption, though here we focus solely on the environmental footprint of the decision-maker. A consumer may face a salient choice between two alternatives (or alternative bundles), say a choice between two iPhone models (see case study 1 - Section 1.5.1). Alternatively, the consumer may consider whether or not to purchase a single product (such as a new pair of shoes), with no particular alternative in mind (see case study 4 - Section 1.5.4).

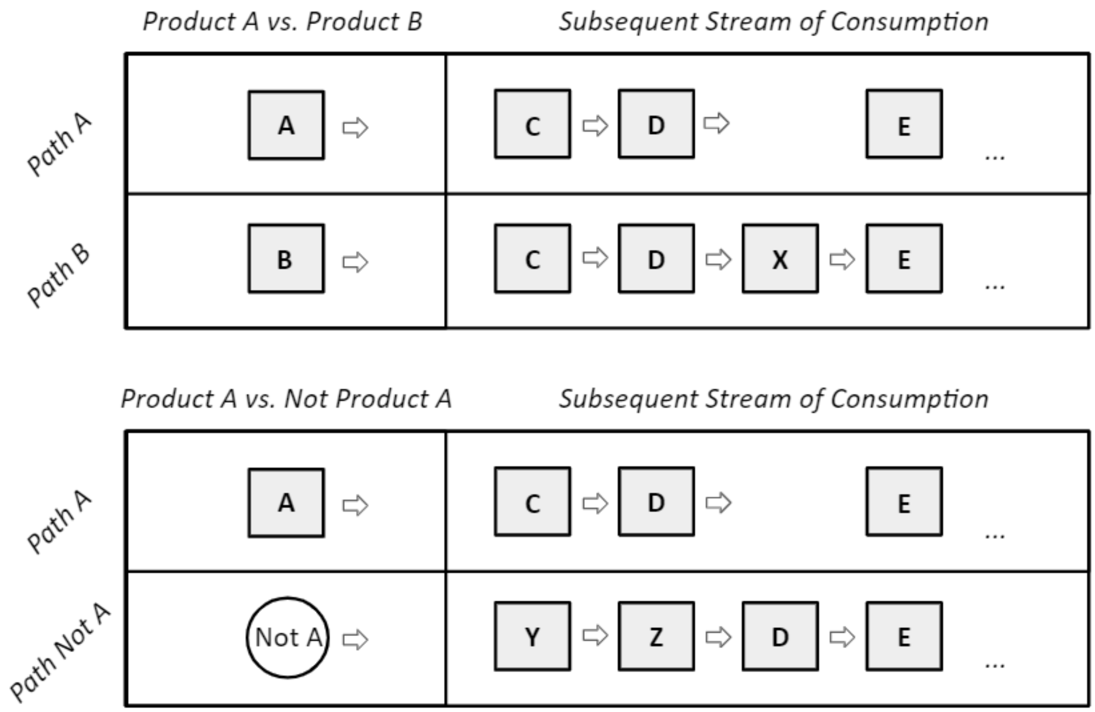

Figure 1.1: outlines two choice decisions a consumer may face. The top panel illustrates a choice between two salient alternatives; the bottom panel illustrates a choice to purchase or not to purchase a single good.

Figure 1.1 presents two hypothetical streams of goods and services. In both cases the decision to purchase product A or not (or B) affects the subsequent stream of consumption. While the consumption stream goes on further, we assume Figure 1.1 captures all differences between the compared product streams in question, and include product D and E (and C in the top panel) in the comparison for clarity. Why would the choice affect the subsequent stream of consumption? In the case of A vs. B, the services provided by product A relative to product B matters in understanding the subsequent stream of consumption. For instance, if product A is a smartphone with a camera and product B does not have a satisfactory camera, then the consumer may want to buy a camera in path B. Such an effect is a result of the difference in product characteristics between alternatives. Additionally, path A and path B will differ if the prices of good A and good B differ, since this affects the potential for future consumption. The question of whether or not the choice of product A has a lower environmental impact requires, to the best of our ability, comparing the alternative streams of consumption and assessing their environmental impacts. In our illustrative example the net environmental impacts of choosing path A are as follows, with E_i being the environmental impact in product system i that results from the decision maker's choice to purchase that product:

product A vs. product B

$$\Delta E = (E_A + E_C + E_D + E_E) - (E_B + E_C + E_X + E_D + E_E) = E_A - (E_B + E_X) \quad (1.1)$$

product A vs. not product A

$$\Delta E = (E_A + E_C + E_D + E_E) - (E_Z + E_C + E_D + E_E) =)(E_A + E_C) - (E_Y + E_Z) \quad (1.2)$$

In both instances, the choice of product A has a lower environmental impact if $\Delta E < 0$. The equations above can be re-written as:

$$\Delta E_{subseq} = \sum_i E_i^A - \sum_i E_i^B \quad (1.3)$$

$$\Delta E = (E_A - E_B) + \Delta E_{subseq} \quad (1.4)$$

where $\sum_i E_i^A$ is the sum of the impacts of goods consumed in the subsequent stream of consumption given the choice of product A and $\sum_i E_i^B$ is the sum of the impacts of goods consumed in the subsequent stream of consumption given the choice of product B. Here, ΔE_{subseq} can be used to directly evaluate the environmental impacts of product choice. Such equations point to the general possibility that accounting for the impacts associated with product system A and product system B is insufficient to determine the net environmental impacts of the choice. Notably, for $E_A < E_B$, if $-(E_A - E_B) < \Delta E_{subseq}$ the choice of product A increases environmental impacts compared to the choice of product B even though product A has a smaller environmental impact than B. However, how might we uncover ΔE_{subseq}? While many factors may affect ΔE_{subseq} (such as individual preferences, decision-making context, salient information, network effects, etc), here we focus on one particular effect, the effect of a price difference between goods, which is sufficient to prove the need to consider the subsequent stream of consumption in assessing the environmental impacts of product choice. Here we estimate this impact as the impact per dollar of spent savings times the price difference. Let's assume we know the environmental impact per dollar of spent savings, $e_{savings}$:

$$e_{savings} = \textit{environmental impact per dollar of spent savings} \tag{1.5}$$

When product A is cheaper than product B, choosing A will incur an additional environmental impact of $e_{savings}(p_B - p_A)$, where $e_{savings}(p_B - p_A) = \Delta E_{price}$, and we assume that $\Delta E_{price} = \Delta E_{subseq}$. In the case of product A vs. not product A, then $p_B = 0$. Notably, savings may be spent on additional units of either A or B, as long as that is appropriately accounted for in $e_{savings}$. We can write the environmental comparison, including prices, as follows:

$$\mathbf{E_A + e_{savings}(p_A - p_B) \lesseqgtr E_B} \tag{1.6}$$

In this sense, the choice is articulated as a choice about how to spend a fixed sum of money, p_B, since $p_A + (p_B - p_A) = p_B$. Such a comparison is equivalent to comparing the entire household consumption bundle given the assumption that $\Delta E_{price} = \Delta E_{subseq}$, since products consumed in both subsequent streams do not influence ΔE_{subseq}. The results can be summarized in the following table:

	$E_A > E_B$	$E_A < E_B$
$p_A > p_B$	B only better if: $E_A - E_B > e_{savings}(p_A - p_B)$	A is always better
$p_A < p_B$	B is always better	A only better if: $E_B - E_A > e_{savings}(p_B - p_A)$

Table 1.1: outlines the framework for identifying the choice with the least environmental impact between two alternatives, given environmental impacts of the products, prices of the products, and the environmental impact of spent savings.

As outlined in Table 1.1, the choice of an alternative always has lower net impacts when it is less impactful and more expensive. However, when the less impactful alternative is also cheaper, then the net environmental outcome depends on whether or not the impact of the spent savings is greater or less than the difference between the impact of the alternatives.

1.4 The GHG per dollar of spent savings, $e_{savings}$

To exemplify this framework, we focus on greenhouse gas emissions of spent savings, though this framework applies to other impacts as well. When consumers save money from a particular decision, they may spend that savings on a variety of goods or services directly or indirectly related to the outcome of the choice. How consumers spend savings may differ, so rather than being opinionated about this spending we estimate the greenhouse gas emissions per dollar of spending in a broad range of consumption categories, including the category of marginal expenditure (the bundle of goods consumed as a result of marginal increases in income). Estimates of environmental impacts per dollar are constructed using Exiobase 3's 2011 environmentally extended input-output tables and are presented in 2020 US purchaser dollars, inclusive of trade and transportation margins (Figure 1.2). Details of the environmentally extended input-output methodology and the estimation of the average impact of marginal expenditure are presented in the supplemental information (Section 1.7.1).

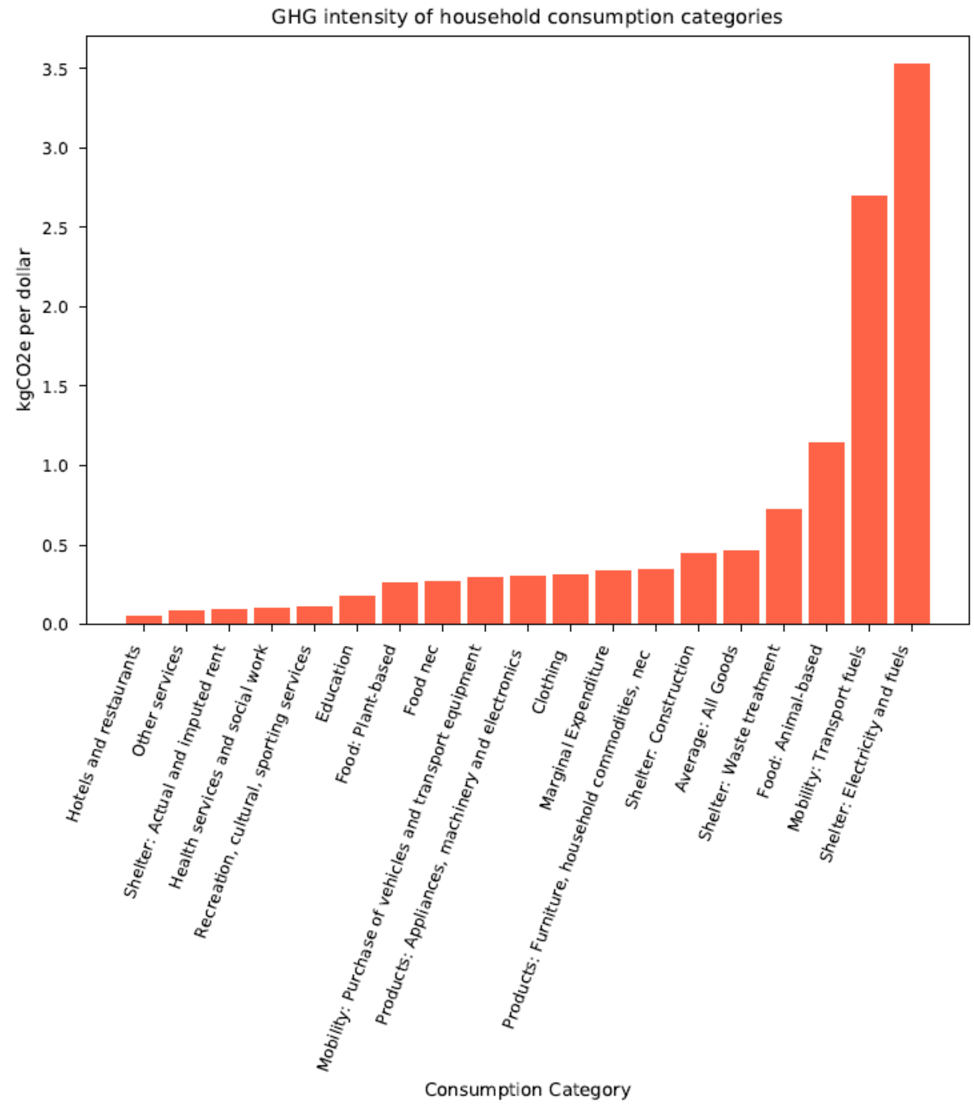

Figure 1.2: presents $\frac{kgCO2e}{\$}$ for a range of consumption categories for U.S. consumers.

1.5 Case studies

The following sections present five case studies that illustrate the importance of the subsequent stream of consumption in determining the choice with the least environmental impact, with particular focus on the global warming potential (GWP) of the outcomes. Rather than present deterministic outcomes for any particular case study, we calculate the break-even impact per dollar that would make the alternative consumption paths equivalent on a $kgCO_2e$ basis.

1.5.1 *Case study 1: conspicuous consumption?*

A consumer faced with the choice between iPhone models may be choosing between the new Apple iPhone 11 and the Apple iPhone Xr. Table 1.2 reports the carbon footprint of each product according to Apple's internal investigation [22]. Also reported is the retail sale price of both products in September of 2019, once the iPhone 11 was released.

	Price	$kgCO_2e$	$\frac{kgCO_2e}{\$}$
iPhone Xr (64gb)	\$599	68	0.11
iPhone 11 (64gb)	\$699	72	0.10

Table 1.2: reports the carbon footprint and price of the iPhone 11 (64gb) and the iPhone Xr (64gb).

In choosing the iPhone Xr the consumer saves \$100. If these savings are allocated to goods and services that in combination have an environmental impact greater than 4kg ($\Delta E_{subseq} > -(E_{iPhoneXr} - E_{iPhone11})$), then choosing the iPhone 11 has lower net environmental impact. In other words, if the spent savings are allocated in such a way that the impact per dollar is greater than 0.04kg/\$, then the iPhone 11 has lower net impact (Figure 1.3):

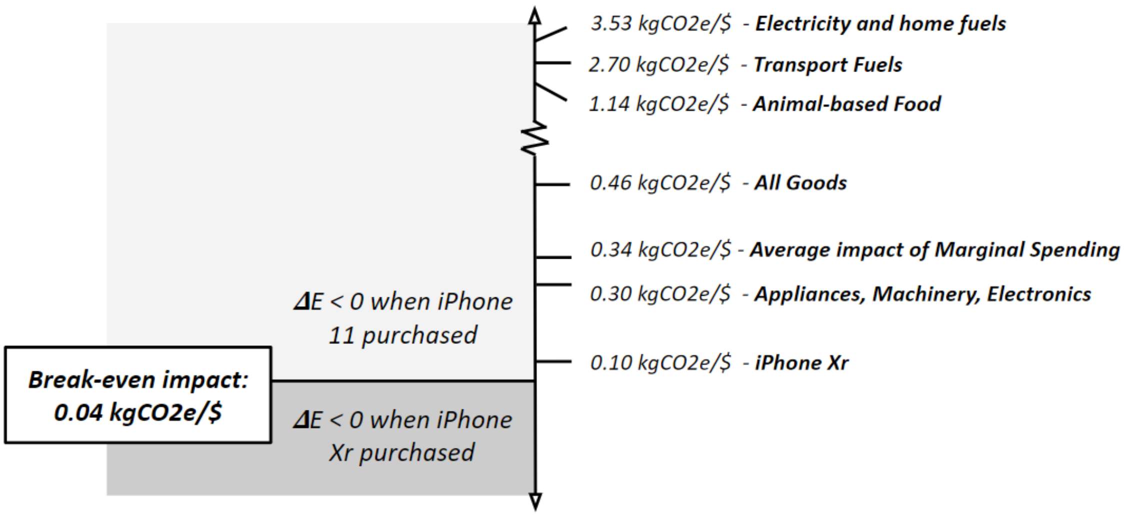

Figure 1.3: presents the breakdown of which choice results in less environmental impact as a function of the impact per dollar of spent savings.

First, why might the prices of the two goods be different? Surely, the service provided to the consumer by each alternative is different. For instance, the iPhone 11 has a better camera and is more water resistant. The consumer is likely also paying for intangibles. If smartphones are viewed as a status symbol this may drive the $100 price difference. In purchasing the benefits attributable to the $100 price premium, the consumer avoids the consumption of the goods that would have been purchased had the $100 been saved and spent elsewhere. Simply considering the carbon footprint of the products, the iPhone Xr appears to have lower environmental impact, assuming equal use and disposal impacts ($68kgCO_2e$ vs. $72kgCO_2e$). When prices are included, the decision involves a choice about how to allocate $699. Net environmental impact is co-determined by the prices and the production impacts of the goods, not simply the environmental profiles of the goods in question. Where conspicuous consumption has been lamented as a driver of environmental impact, as it often has [23], critics must contend with the acknowledgement that more expensive goods avoid larger baskets of alternative consumption.

1.5.2 *Case study 2: pre-made or do-it-yourself (DIY)?*

A recent peer-reviewed study compared the environmental performance of sandwiches made at home as compared to store bought sandwiches [24]. The authors do note that due to the difference in things like cost and taste, a direct comparison of the sandwiches may be unwarranted. Still, choosing the homemade sandwich is suggested to have a 'significantly' lower carbon impact, with the nuance lost in press reporting.

	Price	\$kgCO$_2e$	$\frac{kgCO_2e}{\$}$
Homemade H & C	\$2	0.622	0.311
Commercial-made H & C	\$7.52	1.35	0.18

Table 1.3: reports the carbon footprint and price of a homemade and a commercially made ham and cheese sandwich, as reported by Espinoza-Orias and Azapagic (2018).

Again, why might the prices of a homemade and a store bought sandwich be different? For one, convenience is a utility often monetized in consumer goods. The original paper focuses on understanding the climate impacts of convenience foods. The price of a pre-made sandwich purchased at the store includes consumers' willingness to pay for a sandwich on the go and without the need to prepare the food. Noting that the homemade sandwich has a smaller carbon footprint ($0.622kgCO_2e$ vs. $1.35kgCO2_e$) once again misses the implications of spending the savings associated with choosing to make the sandwich at home. In this case, if the savings of \$5.52 are spent in aggregate on goods and services with a combined footprint greater than 0.73kg, then the purchase of the store-bought sandwich leads to less environmental impact. As such, the break-even impact per dollar is $\frac{0.132kg}{\$}$ (Figure 1.4).

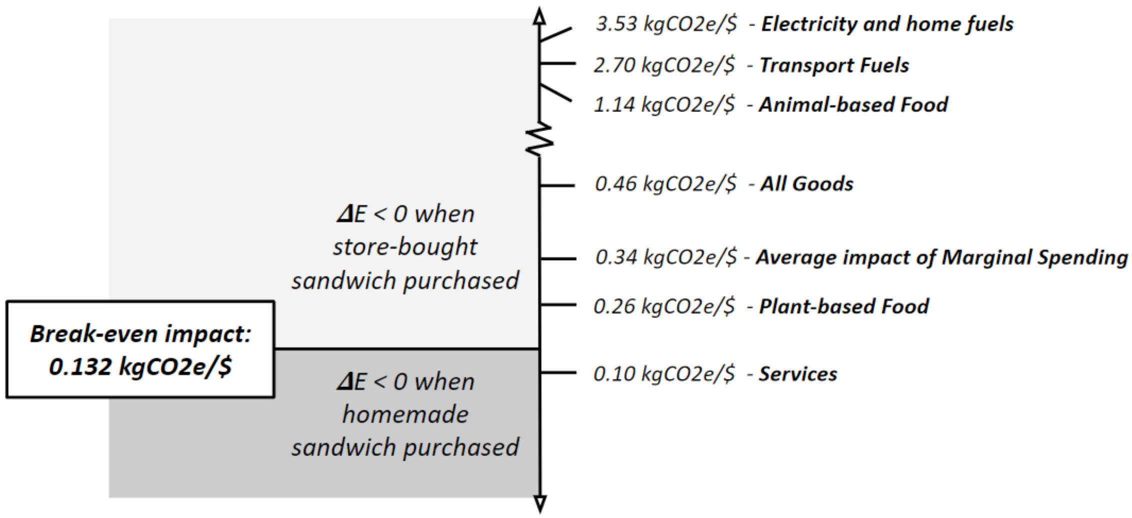

Figure 1.4: presents the breakdown of which choice results in less environmental impact as a function of the impact per dollar of spent savings.

This example brings to light an important consideration about the margins on which consumers adjust when making daily decisions. While it is true that the homemade sandwich is cheaper, it is also likely that making a sandwich at home is more time consuming than buying a convenience option. As a result, how the consumer allocates the time savings associated with the purchase of the store-bought sandwich may also have important environmental implications [18].

1.5.3 *Case study 3: reusable or single use goods?*

The use of reusable products in place of disposable, single-use alternatives is a commonly proposed environmental solution. In fact, one of the principal publications of comparative life cycle assessment was Hocking 1991's comparison of paper to polystyrene cups, with a follow up comparing reusable and disposable cups in 1994 [25, 26]. There is significant discussion in the literature regarding the environmental impacts of single use and multi-use cups [27, 28]. The question of interest has historically been "does the increased burden of production of reusable cups pay off environmentally as a function of reuse?" or alternatively "how many times must a reusable cup be reused for it to start accruing environmental benefits?". Some research has suggested that impacts of washing reusable cups alone outweigh the production impacts of disposable cups, indicating no payback period exists [29], here we ignore use phase impacts for clarity and simplicity. Let the lifetime of the reusable cup be quantified by n, the total number of single uses. The single use product has a price of p_{su}, while the reusable product has a price of p_{re}. We assume that reusing the cup has no additional cost. Let ΔE be the difference in environmental impact between the reusable cup and n single use cups. We can describe the environmental trade off between single use and reusable cups as follows, where ΔE is the net environmental impact of choosing the reusable option:

$$\Delta E = E_{re} + e_{savings}(np_{su} - p_{re}) - nE_{su} \tag{1.7}$$

If $\Delta E < 0$, then the choice of the reusable cup leads to less environmental impact. We can also characterize equation 1.7 using the per dollar environmental impact of the reusable cup and the single use cup, e_{re} and e_{su}, respectively.

$$\Delta E = p_{re}(e_{re} - e_{savings}) - np_{su}(e_{su} - e_{savings}) \tag{1.8}$$

The number of uses n for which impacts are equal is

$$n = \frac{p_{re}(e_{re} - e_{savings})}{p_{su}(e_{su} - e_{savings})} \tag{1.9}$$

As a result, there are four different cases:

	$e_{su} - e_{savings} < 0$ ΔE increases with n	$e_{su} - e_{savings} > 0$ ΔE decreases with n
$p_{re}(e_{re} - e_{savings}) > p_{su}(e_{su} - e_{savings})$	Single use cup always better	Single use better for low n, at some point reusable is better
$p_{re}(e_{re} - e_{savings}) < p_{su}(e_{su} - e_{savings})$	Reusable better for low n, at some point single use is better	Reusable cup always better

Table 1.4: outlines the framework for identifying the choice with the least environmental when one product functionally replaces more than one unit of the other product, given environmental impacts of the products, prices of the products, and the environmental impact of spent savings.

To parameterize this choice matrix, we compare a composite reusable cup with a paper single use cup using the life cycle impact results of KeepCup's recent sustainability report performed by Edge Environment [30]:

	Price	$kgCO_2e$	$\frac{kgCO_2e}{\$}$
Resusable cup (The Original)	\$13	0.5	0.038
Single use cup (paperboard with plastic lid) & C	\$0.2	0.034	0.17

Table 1.5: reports the carbon footprint and price of a single use cup and a reusable cup, as reported by Almeida et al. (2018).

Table 1.5 shows that the reusable cup has a greater production impact than the single use cup. If the subsequent stream of consumption was to be completely unaffected by cup choice, using the reusable cup at least 15 times would be sufficient for the higher initial impact of the reusable cup to be less than the recurring impact of the single use product (common idea of 'break-even' number of uses).

$$n^{break\text{-}even}_{without\ spent\ savings} = \frac{0.5kfCO_2e}{0.034kgCO_2e} = 15 \tag{1.10}$$

However, this ignores the effects of spent savings. Including the effect of spent cost savings not only changes the break-even number of uses, but also leads to some rather non-intuitive results.

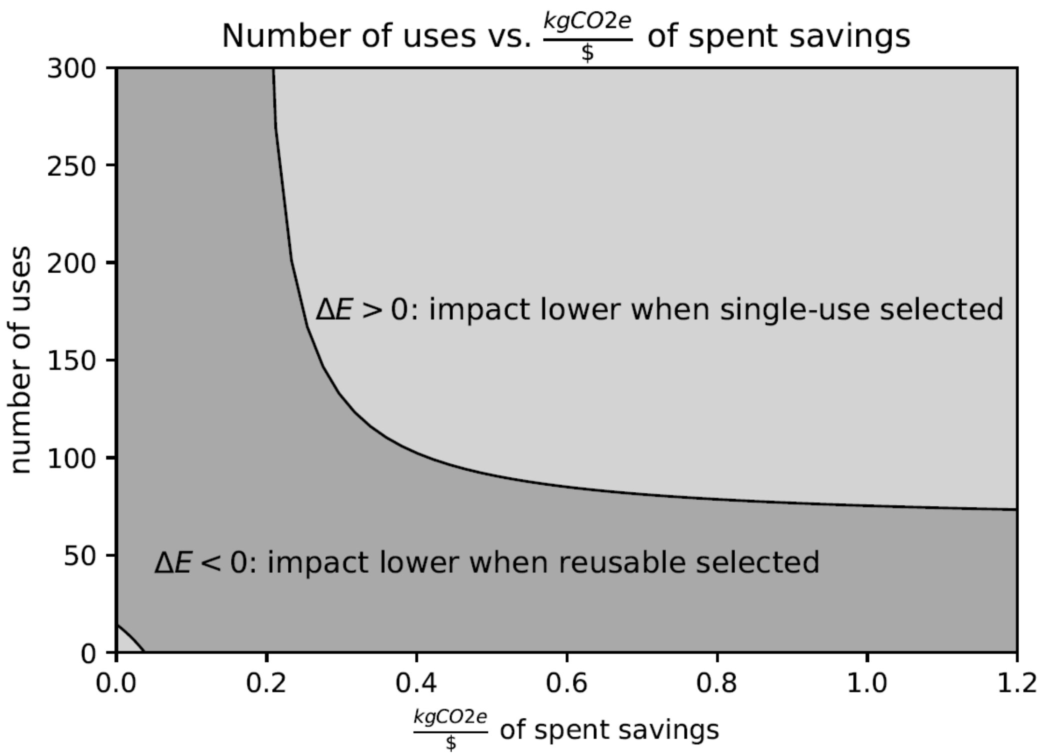

Figure 1.5: presents the graphical relationship between the number of uses of the KeepCup and the per dollar environmental impact of spent savings. $\Delta E < 0$ implies that the choice of the reusable bottle leads to less environmental impact, while $\Delta E > 0$ implies that the choice of the single use bottle leads to less environmental impact.

Figure 1.5 presents a graphical representation of equation 1.7, given the parameters in table 1.5. Whether the choice of the reusable cup leads to lower environmental impacts depends on the number of displaced single use cup uses and the environmental impact of spent savings. The recurring choice of the single use cup leads to less environmental impact under two sets of conditions. First, if the environmental impact of spent savings is relatively high, and the number of uses of the reusable alternative is relatively high, then the impacts of the spent savings dominate the environmental comparison, leading to the single use cup being preferred - as the savings from many uses of the reusable cup are spent on highly impactful goods. Conversely, if the environmental impact of spent savings is very low and the number of uses of the reusable cup is very low, then the single use cup leads to less environmental impact. This condition is consistent with the typical logic of the "break-even number of uses". If the environmental impact of spent savings is $\frac{0.34kgCO_2e}{\$}$, consistent with the average impact of marginal expenditure the reusable cup has lower net environmental impacts only if it is used less than 116 times. As the consumer saves money on each additional use of the reusable cup, this money is spent in a way that incurs more environmental impact than had that money been spent on a single use cup. With additional uses, the net environmental impact of choosing the reusable cup increases (ΔE increases with n in equation 1.7 when $e_{su} < e_{savings}$). After 116 uses, the cost savings of using the reusable cup incurs enough environmental impact to more than negate the environmental benefits of avoiding the production of 116 single use cups in the first place.

1.5.4 *Case study 4: building products that last?*

There is an intuitive appeal to the idea that longer lasting products are better for the environment since fewer units are needed to satisfy the same consumer needs. As a result, production lifetime extension (PLE) has been prescribed in sustainable design principles, suggestions for pro-environmental behavior, and environmental policies [31, 32]. Where research has addressed PLE and the environment, it has typically focused on optimal lifetime as a function of use phase environmental burdens [33].

Imagine a consumer purchased a pair of Allbirds wool runners three months ago and is contemplating replacing them with an identical pair. Is it better for the environment to make these shoes last another three months or buy a new pair? Table 1.6 summarizes data from a recently published sustainability report from Allbirds [34].

Shoes	Allbirds
price	\$95
carbon footprint (production)	$6.8kgCO_2e$
carbon footprint per dollar	$0.072\frac{kgCO_2e}{\$}$

Table 1.6: reports relevant information about Allbirds wool runners [34].

The intuitive comparison in this example is to imagine that, on one hand, buying a new pair of shoes results in 6.8 kg, while, on the other, not buying a new pair of shoes avoids this impact. However, when prices are included it becomes clear that spending \$95 dollars on a pair of Allbirds must be compared to the equal allocation of income elsewhere. If the \$95 is spent on goods and services with a total impact greater than 6.8kg, then buying a new pair of shoes leads to a lower net environmental impact. This is equivalent to the average impact per dollar of spent savings being greater than $\frac{0.072kgCO_2e}{\$}$ (Figure 1.6).

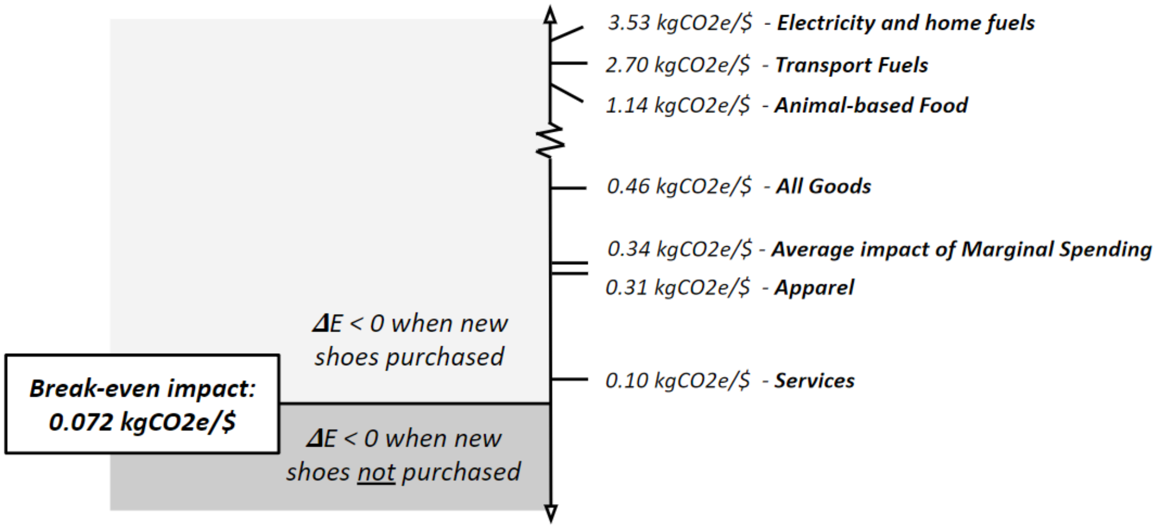

Figure 1.6: presents the breakdown of which choice results in less environmental impact as a function of the impact per dollar of spent savings.

Including prices in choice about extending product lifetime leads to a simple decision rule. Only when the impact per dollar of the good in question is higher than the impact per dollar of spent savings ($e_i > e_{savings}$) does product lifetime extension lead to lower environmental impacts.

1.5.5 *Case study 5: first class or coach?*

The carbon impact of air travel is notoriously high. A number of reports have claimed that flying first class is significantly worse for the environment than flying in an economy seat [35, 36]. The typical argument is that first class seats take up more space on the plane, so first class passengers should be responsible for more emissions than a person in coach. In fact, typically the space used by a single first class seat is sufficient to displace between 2 and 3 economy class seats [36]. If the environmental burdens of flying are allocated by floor space, then the carbon footprint of a first class seat is greater than an economy seat, but that doesn't always make the choice of the economy seat less environmentally impactful (Table 1.7).

Displaced Economy Seats	First Class Emissions	First Class Price	Economy Emissions	Economy Price	Break even impact of savings
s = 1	$465kgCO_2e$	$3486	$465kgCO_2e$	$587	$0\frac{kgCO_2e}{\$}$
s = 2	$930kgCO_2e$	$3486	$465kgCO_2e$	$587	$0.16\frac{kgCO_2e}{\$}$
s = 3	$1395kgCO_2e$	$3486	$465kgCO_2e$	$587	$0.32\frac{kgCO_2e}{\$}$

Table 1.7: reports the emissions of a first class seat and an economy seat for a direct flight from Los Angeles to London as calculated by the ICAO flight emissions calculator, with prices taken from Kayak.com [37]).

Table 1.7 reports the break-even impact of spent savings for three seat displacement scenarios. The table suggests that (depending on your accounting methods) it is wholly likely that the choice of a first class ticket leads to less environmental impact. Even where first class seats are worse, such a price effect attenuates the benefits of flying coach substantially. Notably, this result ignores long-run general equilibrium effects of seat choice, as discussed in Bofinger and Strand (2013), who conclude that the carbon impacts of a first class seat is 9 times worse than an economy seat, though their model ignores any environmental effects of spent savings [35]. Even in the case where each first class seat displaces three economy seats, the first class seat is environmentally preferred when spent savings has the impact of marginal expenditure ($0.34kgCO_2e$).

1.6 Conclusion

The prevailing logic in identifying the consumer choice with the least environmental impact has been to compare products based on their environmental profile and select the product with the smaller environmental footprint. The issue with such an approach is that isolating decisions as choices between alternatives ceteris paribus over-simplifies the environmental impacts of product choice to the point of pathology. Identifying the alternative with the smaller environmental profile is not the same as identifying the environmental choice because the real context of decision-making means other factors are at play that will affect the environmental impact of the decision maker. When decisions are economic in nature, prices are one such factor that plays a vital role in determining which choice has a lower environmental impact. When prices differ between alternatives, the choice cannot simply be between alternative A and alternative B (or not A) all else equal, since the savings of choosing the cheaper option will be used to buy other goods and services. Besides prices, product characteristic effects may also play an important role if alternatives have differing complementarity and substitutability with other goods. Decision making biases and heuristics may also be important, if for example decision makers experience moral licensing with regard to perceived environmental benefits of choices, the environmental benefits may be unwound in contexts where moral licensing occurs [38].

We consider the use of the environmental impact of spent savings as a useful approximation of the net environmental impacts that ensue from consumer choices outside the direct impacts of the products in question. Such an approximation could be improved by considering the preferences and characteristics of a subset of the population likely to be considering a particular choice, such as people with strong environmental preferences [39, 40]. Due to the general nature of this work, the implications are wide reaching. For instance, in product eco-labeling, we need clarity about how labels affect consumers' subsequent stream of consumption; and when motivating 'green' choices, we should be wary of the commonly proposed 'win-win' of environmental benefits and cost savings. One might ask, what can be done to avoid the potential complications of re-spent savings? First, decision makers can account for the impacts of re-spent savings in product choice. Second, savings can be spent on environmental goods, or goods with low environmental impacts per dollar, such as carbon offsets or services. Third, in the long run, income may be adjusted to account for significant cost savings. While it is outside the scope of this work, how and when consumers can be motivated to take the actions outlined above deserves further consideration and research.

In all, this work makes abundantly clear the insufficiency of our current understanding of the environmental impacts of product choice. Without understanding and quantifying the net effects on the subsequent stream of consumption, clear and persistent errors are made in evaluating the environmental impacts of consumer choices. Here we focus on one factor that influences ΔE_{subseq}, the difference in prices between choice alternatives, which we propose as a reasonable proxy for the total effect in absence of more robust estimates. The inclusion of just this one effect is sufficient to show that all is not well in our current understanding of the environmental impacts of product choice. We believe the investigation of E_{subseq} and the underlying factors and mechanisms that determine this net effect is a significant research opportunity for sustainability science at large. One such approach may be the empirical study of how interventions that influence product choice affect household environmental footprints. Our paper presents a framework for considering subsequent streams of consumption, which brings to bear the household-level perspective on product choice, since individual choices are placed in the context of their effect on household consumption and household impact as a whole. This is meant as a first step towards a more complete and robust theory of sustainable consumption, which is urgently needed to inform households, businesses, and environmental policy makers.

1.7 Supplemental information

The supplemental information for "The Role of Prices in Determining the Environmental Impacts of Product Choice" proceeds in two parts. First, we discuss the use of environmentally extended input-output LCA to estimate the GHG impacts per dollar of various product categories. Second, we discuss the estimation of the GHG impact per dollar of marginal expenditure.

1.7.1 *Calculating GHG impacts per dollar*

We use environmentally extended input-output life cycle assessment (EE-IOA) as the basis of our calculation of the GHG impacts per dollar of a modified set of COICOP (classification of individual consumption according to purpose) consumption categories, and supplement using other data sources as necessary. In the context of this research, EE-IOA is preferred because it produces environmental impacts per monetary unit, consistent with the needs of the current work. To do so, we rely on Exiobase 3, a multi-regional temporally environmentally extended input-output database [41]. We use Exiobase's 2011 model, as it is the most recent year available. We use the product x product characterization, as it is consistent with the classification structure for COICOP categories and the margin table's structure. As such, we rely on the product technology assumption [42] and constant returns to scale consistent with the underlying assumptions of EE-IOA in the product x product structure.

1.7.2 *Environmentally-extended input output LCA methodology*

We use the basic framework of EE-IOA to calculate impacts in each COICOP consumption category. First we calculate the total environmental impact for U.S. households for each product category x country as:

$$E = F(I - A)^{-1} y_{hh,U.S.}^{diag} \tag{1.11}$$

Where$E$ is then the matrix of total resources uses and emissions associated with final demand by U.S. households, given F per unit direct factor requirements matrix, I is the identity matrix, and A is the technological coefficients matrix, and $y_{hh,U.S.diag}$ is the diagonalized matrix of final demands by U.S. households. We then aggregate matrix E along two dimensions – first we sum the impacts over products in each COICOP category to generate total impacts by category, and second we aggregate emissions by contribution to climate change using the characterization factors of Traci 2.1 [43]:

$$E_{COICOP}^{GHG} = C \cdot E \cdot T \tag{1.12}$$

Where C is the COICOP to Exiobase products concordance matrix, and T is the Exiobase emissions to Traci 2.1 GHG impacts concordance matrix. This transformation creates a vector total GHG emissions for each COICOP category of interest. The concordance matrices are available upon request. Using the same logic, we create a final demand by COICOP category as follows:

$$F_{COICOP} = C \cdot F_{hh,U.S.}^{diag} \tag{1.13}$$

Thus, we can create a GHG impact per unit of expenditure for COICOP categories as $e_{COICOP,GHG} = E_{COICOP,GHG} \cdot F_{COICOP}$. However, before we do so, we must add the direct emissions by households, in accordance with their contribution to each COICOP. As Exiobase does not differentiate the source of direct household emissions, we disaggregated direct emissions into two categories "Shelter: Electricity and Fuels" and "Mobility: Transportation fuels, with ratio of 2.31:8.92 is accordance with Kammen and Jones (2014) [44]. The resulting vector of GHG impact per unit of expenditure are in 2011 producer euros. However, before we adjust to 2020 dollars, we must account for the margins of trade and transportation. We use Exiobase 2 trade and transportation margins due to their detailed nature, and assume these margins are consistent across the years. However, it is not a simple as just adjusting the expenditure, since trade and transportation margins have GHG impacts of their own. We use the margin tables to calculate the fraction of each dollar that goes to the COICOP category j, transportation industries trans, trade industries trade, and taxes and subsidies ts using the Exiobase 2 margin tables, then create purchaser price impacts per euro as follows:

$$e_{j,pp}^{GHG} = \alpha_j e_j^{GHG} + \alpha_{trans} e_{trans}^{GHG} + \alpha_{trade} e_{trade}^{GHG} + \alpha_{ts} e_{ts}^{GHG} \tag{1.14}$$

Where it is assumed that taxes and subsides have no environmental impact, and thus $e_{ts}^{GHG} = 0$. Finally we adjust $e_{j,pp}^{GHG}$ into 2020 U.S. dollars using average U.S. to Euro conversions for 2011 (European Central Bank) and average U.S. CPI (Bureau of Labor Statistics) [45]. The resulting measures are presented in Figure 1.2 of the main text.

1.7.3 *Calculating the GHG impact per dollar of marginal expenditure*

As an alternative to the GHG intensities of consumption categories, we also derive the overall GHG impact per dollar of marginal expenditure for the average American consumer from an estimate of the GHG impact elasticity of income, GWP, which describes the percentage change in the GHG emissions of a consumer as a function of a percentage change in income:

$$\epsilon_{GWP} = \frac{\partial GWP}{\partial I} \cdot \frac{I}{GWP} \tag{1.15}$$

From this equation, we can estimate the average GHG emissions per dollar of marginal expenditure for the average American household as:

$$e_{marginal\ expenditure} = \frac{\partial GWP}{\partial I} = \frac{I}{GWP} \cdot \epsilon_{GWP} \tag{1.16}$$

For the GHG elasticity of income, we use $GWP = 0.73$, implying a 1% increase in income increases emissions by 0.73% an estimate by Fremstad et al. (2018) [46]. For $\frac{GWP}{I}$, we use the average impact per dollar of expenditure by U.S. households ($0.46\frac{kgCO_2e}{\$}$) calculated using the EE-IOA methods described above. The result is a GHG impact per dollar of marginal expenditure equal to $0.34\frac{kgCO_2e}{\$}$, presented alongside other results in Figure 1.2 of the main text.

Chapter 2

Curbside Recycling Increases Household Consumption

Authors: Jason Maier, Roland Geyer, Doug Steigerwald

2.1 Abstract

The proposed environmental benefits of recycling rely on the assumption that total material throughput is unchanged by access to recycling programs. We leverage variation in the regional adoption of curbside recycling programs to compare similar communities with and without recycling programs, finding that household solid waste generation (and, thus, material consumption) increases by 7-10% in the presence of curbside recycling. This result shows that reducing the consumption of primary resources, not increasing secondary production through recycling, should be the focus of recycling programs and other circular economy activities.

2.2 Main

Recycling is perhaps the quintessential pro-environmental behavior, and it's presence in the public consciousness has only grown with the proliferation of the so called "circular economy" [47, 48]. There is an intuitive environmental appeal to the idea of closing material loops - since for many materials primary production is environmentally intensive compared to reprocessing activities [49]. As a result, a significant focus of policy and research has been on the mechanisms by which to increase secondary production (i.e. recycling), including but not limited to curbside recycling policies and program [50–52]. The assumed environmental benefits of recycling, however, depend on the assumption that material throughput is unaffected by recycling [53, 54]. In practice, recycling interventions may affect total material throughput, an idea termed circular economy rebound [53]. If, as we find here, total household material consumption increases as a result of access to curbside recycling, then the environmental merits of recycling are uncertain.

Households play a crucial role in the recycling supply chain - post-consumer recycling currently amounts to more than 40% by mass of the recycling waste stream in the United States, with much of this stream coming from curbside collection [55]. Across the United States, 59% of households have access to a curbside recycling program [56]. There is no fundamental reason to believe that household material consumption and solid waste generation are unaffected by the presence of a blue bin. In fact, there is literature to suggest otherwise. First, there is evidence that consumers experience a 'warm glow' from pro-environmental behavior [57, 58] and that this can affect consumption decisions [59]. Secondly, it has been noted anecdotally that the plastics industry considers recycling to be a 'guilt eraser' that allows consumers to purchase single-use plastic products without concern about waste generation [60].

The academic literature concurs that guilt can play a significant role in consumption decisions and that 'being wasteful' induces guilt [61, 62]. Finally, there is theoretical and experimental evidence that people consume more in the presence of recycling streams. Catlin and Wang (2013) demonstrate, in both a lab and a field experiment, that paper consumption increases in the presence of a recycling bin [63]. Ma et al. (2019) come to a similar conclusion using an online survey of Chinese consumers [64]. Sun and Trudel (2017) support these conclusions using a microeconomic model of consumer behavior and experimental evidence [65]. All together, previous research points to recycling being used as a justification for increased material consumption and solid waste generation. However, to date no study has empirically estimated the effect of curbside recycling on the levels of household material consumption and solid waste generation in an observational, real world setting.

The work here is possible due to a North Carolinian mandate beginning in 1999 compelling each municipality to report comprehensive information about their waste management practices annually to the North Carolina Department of Environment and Natural Resources (NCDENR). We leverage variation in the regional adoption of recycling programs and data on waste generation at the municipality level in North Carolina between 1999-2019. Since we cannot disaggregate the solid waste data into residential, commercial, or industrial sources, we analyze two different samples. First, we consider the whole sample, comprised of all municipalities regardless of the presence of industrial and commercial operations. Second, we consider a "households-only" sub-sample that only contains municipalities without industrial or commercial waste or recycling collection. This is done to isolate the effect of recycling programs on household material consumption and solid waste generation. More details on the data employed are presented in Supplemental Information Section 2.6.

The logic of the empirical model is to investigate the effect of the introduction of recycling programs on total solid waste generation, which we consider an imperfect proxy for material consumption. We employ fixed effects estimation where we control for municipality-specific effects and year-specific effects. The dependent variable of interest is total solid waste generation (i.e. municipal solid waste (MSW) + recycling). We apply this modeling approach to both the whole NCDENR sample and the "households-only" sub-sample. Given recent developments in causal inference using difference-in-differences (DID) methods, several robustness checks including additional sample restrictions, alternative estimators, and the estimation of dynamic treatment effects are presented in the supplemental information [66, 67]. As with all difference-in-differences designs, the causal interpretation of the estimates rely on the parallel trends assumption. Additional discussion of this assumption and suggestive tests are presented in Supplemental Information section 2.7. Table 2.1 presents the results of the DID estimation for the two sample sizes and one additional sample restriction. Model 1 shows the results for the full sample of North Carolinian municipalities. Model 2 shows the results for the "households-only" sample restriction, and model 3 presents the results for the "households-only" sample restriction under synthetic staggered adoption - only municipalities that are untreated at the beginning of the sample are considered, and municipalities are dropped if they remove curbside programs. This additional restriction of considering municipalities where adoption is staggered over time is used as robustness check to control for the potential concerns of heterogeneous treatment effects [66].

	model 1	*model 2*	*model 3*
any recycling program	0.0813** (0.0393)	-	-
residential curbside	-	0.0733*(0.0371)	0.0986* (0.0549)
residential drop-off	-	0.028 (0.0356)	0.0354 (0.0597)
time fe	*yes*	*yes*	*yes*
municipality fe	*yes*	*yes*	*yes*
cluster-robust se	*yes*	*yes*	*yes*
effective clusters	168	94	76
n	9648	4025	1653
restriction	*full sample*	*municipalities with no industrial or commercial collection*	*model 2 + only staggered adoption*

Table 2.1: shows regression results from several model and data specifications from the NCDENR panel. The dependent variable in all cases was the log of total municipal waste (disposal + recycling). *, **, *** correspond to significance at the 10%, %5, %1

Table 2.1 points to a strong relationship between recycling programs and total waste generation. Model 1 estimates the relationship between the presence of any type of recycling program (curbside or drop-off) and total waste generation - finding an 8.13% increase in solid waste generation for municipalities that start recycling programs. Whether this is driven by industrial, commercial, or residential collection is unclear. Model 2 presents the results of the same estimation, but for the sub-sample of data with no commercial or industrial MSW or recycling collection (i.e. municipalities where waste and recycling collection only occurs at the household). Here we see that curbside recycling programs are associated with a 7.33% higher level of total waste generation by households, controlling for residential drop-off programs.

In model 3, we repeat the analysis of model 2, finding a 9.86% increase, under the restriction that we only consider programs where the adoption is staggered (details about why staggered adoption may be important are presented in the SI). These results suggest that curbside recycling programs increase total solid waste generation of households, which reduces the environmental merits of recycling. As a robustness check, we perform the same analysis with the dependent variable as the log of *per capita* municipal solid waste and find qualitatively similar results (SI Section 2.7).

While this work provides compelling evidence that total solid waste generation increases in the presence of curbside recycling programs, it does little to help us understand why this might be the case. Future work should investigate the underlying mechanisms at play here. Additionally, which materials are consumed more and which are consumed less in the presence of curbside recycling affects the net environmental consequence of recycling programs, and future work should seek to investigate this. In a related sense, it is important to point out that this work does not answer the question of whether curbside recycling programs are a net benefit or cost to the environment. It's possible that even with increased consumption and waste generation, curbside programs still lead to environmental benefits, though this claim is harder to make given the above findings. In the presence of increased consumption, recycling must be that much more effective to lead to substantive benefits. The fact that household waste production increases in the presence of recycling waste streams should be taken in the context of recent work about circular economy rebound [53]; even without increases in consumption at the household level the merits of recycling rely on displaced production, which has limited empirical support [68, 69]. Future work may consider how best to avoid increasing household consumption when implementing recycling programs, though arguably efforts would be better spent focusing on shifting consumers towards more sustainable consumption patterns to begin with.

2.3 Methods

The data used for this study comes from the NCDENR and is a comprehensive self-reported annual survey of each municipality, generally completed by the municipality's waste management director. The data includes information about implemented MSW programs, including recycling, solid waste, composting, e-waste, and hazardous waste programs. Also included is information about the total weight of collection from each one of these streams. Since the data is self-reported, each form is not necessarily complete, and some forms are missing from the data. Relevant sample statistics are presented in Supplemental Information Section 2.6.

The survey reports curbside recycling programs, drop-off recycling programs, and 'other' recycling programs. Also, the data indicates whether residential, commercial, and industrial actors have access to curbside and/or drop-off recycling and MSW collection. Notably, programs may be run by government employees, or contracted with private haulers, and waste weights are reported in both cases. There are additional potentially relevant covariates worth detailing, see SI Table 1 and 2. At this time we do not investigate more detailed questions, such as the effect of single-stream recycling vs. multi-stream, but doing so may be fruitful.

We employ a difference-in-differences program evaluation design to estimate the effect of recycling programs on waste generation. Here, we present the results of a two-way fixed effects model of the form:

$$Y_{it} = \beta D_{it} + \alpha_i + \delta_t + \epsilon_{it} \tag{2.1}$$

where Y_{it} is the log of total waste generation (i.e trash + recycling in mass) in municipality i at time t, D_{it} is the treatment dummy, α_i is municipality level fixed effect,

δ_t is a time fixed effect. This model will be applied to both the whole sample and the "households-only" sample. Given recent developments in causal inference using DID methods, several robustness checks including additional sample restrictions, alternative estimators, and the estimation of dynamic treatment effects are presented in the supplemental information [66, 67]. The identification strategy in this context is to compare similar municipalities with and without curbside recycling. We use fixed effects to control for time and municipality specific effects, thus allowing us to reasonably make a comparison between municipalities with and without curbside recycling over time. Equation 1 combines the comparisons between treated and untreated municipalities into an average treatment effect. The basis of causal inference for difference-in-differences estimation is the assumption of parallel trends. This means that a causal interpretation of the resulting coefficient is only valid under the assumption that in the absence of the programs' implementation treated and control municipalities would see similar trends in waste generation.

As a robustness check in the main text, we provide model 3 which presents the results for the "household-only" sub-sample under the restriction of staggered adoption. This means that only municipalities that either are never treated or go from untreated (no curbside program) to treated (curbside program) and remain treated are included. This is done to control for the known, but relatively new, concerns about causal inference in the presence of treatment effect heterogeneity [66].

2.4 Supplemental information

2.5 Introduction

This section of the document is the supplemental information for the paper entitled "Curbside Recycling Increases Household Consumption". The document is organized as follows. First, we introduce additional background on the concept of circular economy rebound. The we describe the empirical setting of the study in more detail, including additional presentation of the data and sample statistics. Next we detail the empirical strategy. And finally, we present several alternative specifications and robustness checks.

2.5.1 *Circular Economy Rebound*

Typical engineering models of recycling simply assume secondary production *displaces* primary production on a one-to-one basis, akin to assuming that material throughput is unaffected by recycling. There is no a priori reason to believe this is the case, however. In practice, recycling interventions may affect total material throughput, since the relationship between secondary and primary production is market-mediated and subject to the context and specifics of the intervention in question, be it a policy, a new product, an information campaign, etc.

The idea that circular economy activities may change total material throughput is termed circular economy rebound (CER), due to its parallels to energy efficiency rebound [53]. A small but significant body of literature has focused on the theoretical and empirical underpinnings of CER. In particular, Zink et al. (2016, 2017a, 2017b) make foundational contributions to the concept by outlining the potential for circular economy rebound, describing a partial equilibrium framework for understanding CER, and applying it to the case of the U.S. aluminum industry [53, 68, 69]. In a similar vein, Dussaux and Glachant (2019) analyze the effects of domestic recycling of metals on domestic primary metal production and imports, finding that domestic metal recycling reduces the import of secondary materials, but has no conclusive effect on primary production [70]. Palazzo et al. (2019) outlines possible empirical frameworks for estimating CER, with a focus on introducing quasi-experimental methods to the discussion and Maier et al. (2021) provides the first quasi-experimental estimate of CER in the context of wastewater recycling [49, 71]. In general these approaches have focused on understanding and estimating circular economy rebound at the market-level, with a limited focus on understanding the underlying causal chain that might determine the observed outcomes. To date, no work has focused on the role that households may play in mediating CER.

2.6 Empirical Setting

In 1998, North Carolina passed 130A-309.09A, a general statute on local government waste responsibilities. Among the requirements of the statute is the yearly reporting by local governments on the state of solid waste management programs and waste reduction activities. This amounts to a form being submitted by every local government in North Carolina from 1999 to present. The form reports extensive information about recycling and municipal solid waste programs. The result of this reporting is a panel of information regarding recycling programs implemented by local governments over a 21 year period. The reporting is from 655 local governments (100 county and 555 municipal). Notably, there is not a single policy requiring curbside recycling or any recycling intervention, but a vantage point on a sequence of municipal policies, where curbside recycling is rolled out to residents, commercial entities, and industry across the state over time. The North Carolina Department of Energy and Natural Resources (NCDENR)'s annual report from 2018 suggests that between 2004 and 2018 there have been the addition of approximately 125 curbside recycling programs in North Carolina (Figure 2.1) [72]. It is worth highlighting that there is not a specific policy intervention that occurs affecting treated municipalities, and as a result it is important to consider the potential endogeneity of recycling programs with the outcome measures of interest. If areas where solid waste is increasing choose to adopt curbside programs because, for example, these areas are developing more quickly, this endogeneity challenges the causal interpretation of the result. It is also worth noting that recent results in causal inference call into question the causal interpretation of two-way fixed effects models in the context of treatment effect hetereogeneity [66, 67], which is the basis for our use of a staggered adoption sub-sample as an additional data specification. Future work should consider the specific context of each program adoption, which is possible given the extensive reporting on the program specifics.

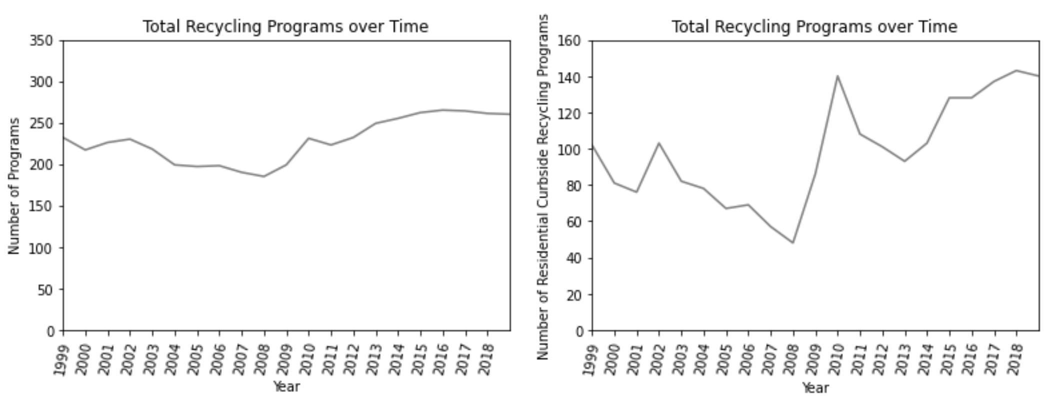

Figure 2.1: Panel A: Recycling programs over time (1999-2019). Panel B: Residential curbside recycling programs over time (1999-2019)

2.6.1 *NCDENR Data*

The data from the NCDENR is a comprehensive self-reported annual survey of each municipality, generally completed by the municipality's waste management director. The data includes information about implemented MSW programs, including recycling, solid waste, composting, e-waste, and hazardous waste programs. Also included is information about the total weight of collection from each one of these streams. Furthermore, there is information about waste reduction programs, such as programs to reduce 'junk mail', recycling brochures, and backyard composting programs. Program funding information is also available including the use of local or regional government grants to support programs and the use of (or absence of) tipping or collection fees. Since the data is self-reported, each form is not necessarily complete, and some forms are missing from the data. Relevant sample statistics are presented below in Table 2.2 for the whole sample and Table 2.3 for the "household-only" sample:

	All	*Recycling (any type)*	*No recycling (any type)*	*Recycling curbside (any type)*	*No curbside (any type)*
n (reported)	9648	9140	508	5167	4481
# municipalities	653	551	108	387	368
Years	21	21	21	21	21
garbage (MT)	16710	19525	802	10939	27303
	(+/ 367948)	(398118)	(2276)	(50737)	(565879)
recycling (MT)	1511	1702	6	1620	1787
	(9000)	(9610)	(32)	(10298)	(8473)
Compost (MT)	2919	3375	396	3789	2725
	(57319)	(62147)	(1005)	(72436)	(44980)
ln(population)	7.99	9.10	6.54	8.37	7.70
	(1.99)	(2.05)	(1.07)	(1.71)	(2.12)

Table 2.2: shows sample statistics from the whole NCDENR panel. Standard deviations are shown below mean estimates in parentheses.

	All	***Recycling (any type)***	***No recycling (any type)***	***Recycling curbside (any type)***	***No curbside (any type)***
n (reported)	4025	3747	278	2084	1941
# municipalities	492	482	85	326	289
Years	21	21	21	21	21
garbage (MT)	5746	6108	866	4089	7526
	(+/ 9384)	(9602)	(2573)	(6625)	(11373)
recycling (MT)	546	587	1.48	600	488
	(1433)	(1477)	(15)	(1551)	(1291)
Compost (MT)	1765	1814	339	2146	1328
	(26935)	(27393)	(756)	(36268)	(6907)
ln(population)	9.05	9.10	6.73	8.69	9.06
	(2.05)	(2.05)	(1.10)	(1.93)	(2.78)

Table 2.3: shows sample statistics from the constrained household from the NCDENR panel. Standard deviations are shown below mean estimates in parentheses.

There are some additional points worth making regarding the NCDENR panel. There are several ‘types’ of recycling programs, some of which are outlined in Table 2.2. We know whether residential, commercial, and industrial actors have access to curbside and/or drop-off recycling. In Table 2.2 we denote ‘any type’, which implies that curbside or drop-off recycling was available for residential, commercial, or industrial activities. Notably, programs may be run by government employees, or contracted with private haulers, and waste weights are reported in both cases. There are additional potentially relevant covariates worth detailing, see Table 2.4. At this time we do not investigate more detailed questions, such as the effect of single-stream recycling vs. multi-stream, but doing so may be fruitful.

Statistic	Value	Description
Percentage Mandatory CSR	19%	
Steam type	50% Carts	bins, carts, bags, other
Has waste reduction programs	11%	Junk mail, source reduction program
Has solid waste ordiance	47%	Disposal Bans, Illegal dumping, Littering,
C+D, other		
single stream	73%	
Precentage private contracting	77%	

Table 2.4: shows some additional information from the NCDENR panel

2.6.2 ***Empirical Strategy***

We employ a difference-in-differences design in this scenario. While simple two-way fixed effects models will be tested, we will also employ novel estimators that contend with issues of treatment effect heterogeneity and dynamic treatment effects. Additionally, several sample restrictions will be used to investigate the data. The primary two-way fixed effects model will take the following form:

$$Y_{it} = \beta D_{it} + \alpha_i + \delta_t + \epsilon_{it} \tag{2.2}$$

where Y_{it} is the log of total waste generation (i.e trash + recycling) in municipality i at time t, D_{it} is the treatment dummy, α_i is municipality level fixed effect, δ_t is a time fixed effect. This model will be applied to both the whole sample and the "households only" sample. There are notable concerns with the causal interpretation of this method, which will be discussed below. To overcome the issues with treatment effect heterogeneity in two-way fixed effects models, and given recent work showing the causal interpretation of the two-way fixed effects estimator with staggered adoption, a staggered panel is also selected, and eq. 2.6.2 is used to estimate the effect of treatment [66].

Second, a recent set of estimators will be deployed based on the work of De Chaisemartin and d'Haultfoeuille [67]. This estimation will be performed using the did_multiplegt function in stata. The purpose is to estimate the dynamic treatment effect without the assumption of a homogeneous treatment effect. Additional estimators of similar design may be employed at a future date. In all cases the identifying assumption is that in the absence of the initiated recycling programs the treated municipality (households) would have had similar trends in waste generation (consumption) to the municipalities (households) that are yet to be treated.

2.7 Alternative specification and results

As a first alternative set of specifications, we start by reporting the results of main text model specifications (Table 1) but with the dependent variable as the log of *per capita* municipal solid waste (garbage + recycling), presented in Table 2.5. The results are qualitatively similar to the results in the main text.

	model 1	*model 2*	*model 3*
any recycling program	0.0557** (0.0403)	-	-
residential curbside	-	0.0588**(0.0271)	0.0566 (0.0471)
residential drop-off	-	0.028 (0.0269)	-0.0192 (0.0485)
time fe	*yes*	*yes*	*yes*
municipality fe	*yes*	*yes*	*yes*
cluster-robust se	*yes*	*yes*	*yes*
effective clusters	168	94	76
n	9648	4025	1653
restriction	*full sample*	*municipalities with no industrial or commercial collection*	*model 2 + only staggered adoption*

Table 2.5: shows regression results from several model and data specifications from the NCDENR panel. The dependent variable in all cases was the log of per capita municipal waste (disposal + recycling). *, **, *** correspond to significance at the 10%, %5, %1

Second, Figure 2.2 presents the findings from the dynamic treatment effect estimation using the estimator of De Chaisemartin and d'Haultfoeuille [67]. This estimator is chosen because it controls for the challenges in estimating an average treatment effect in the presence of treatment effect heterogeneity, while still allowing for the use of the entire data sample - the estimator estimates the average treatment effect across all units whose treatment changes between time t and $t-1$. Other similar estimators have been proposed, and could be considered for additional robustness [65, 73]. The left panel presents the effect of any recycling program on the log of total waste generation, consistent with model 1 in Table 2.1, while the right panel presents the effect of curbside recycling on the log of total waste generation in the 'households only' sub-sample, consistent with model 2 in main text Table 1.

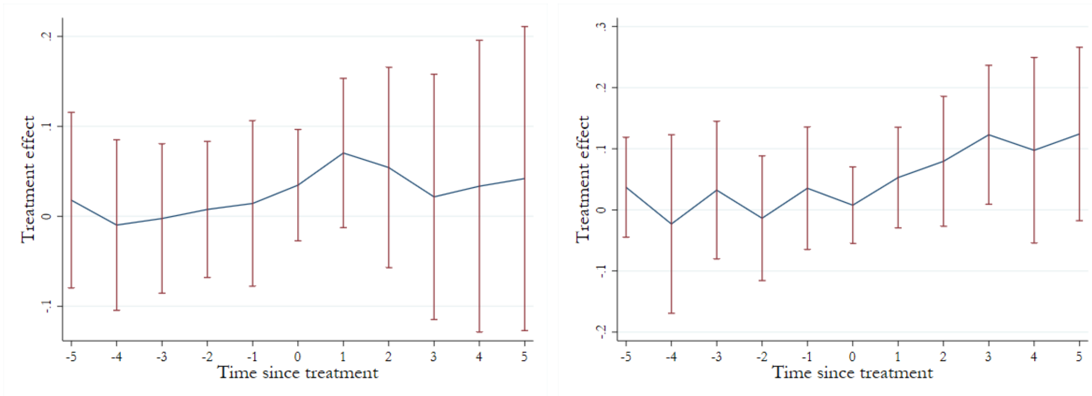

Figure 2.2: presents the results of the dynamic De Chaisemartin and d'Haultfoeuille estimator. The left panel investigates the effect of any recycling program on total waste generation. The right panel investigates the effect of curbside recycling on total waste generation in the 'households only' sub-sample.

Figure 2.2 does not show a statistically significant effect at the 5% level for any period in the whole sample, but does show significance during some following periods of the "households" only sample. This provides compelling evidence of a dynamic treatment effect. Future work should consider the possible implications of a dynamic effect.

Chapter 3

Demand-driven Conservation

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3.1 Main

Achieving conservation outcomes requires implementing conservation interventions. The conservation planner's instinct is often to rely on regulatory interventions. While regulatory interventions can clearly produce conservation benefits, there is increasing awareness of their limitations [74, 75]. Extraction limits, development restrictions, taxes, and technology constraints can force a certain amount of conservation, but may be limited to situations with well-measured stocks, formal markets, technological capacity, and in particular, good governance [76]. Since these interventions typically require formal policy action by governments, the significant and well-documented challenges of collective political action apply [77], as well as some conservation specific political challenges such as multi-lateral, migratory or even geographically shifting resource stocks [78]. Where regulations are implemented, conservation may be under-provided as a result of corruption, insufficient regulation, the beliefs of those with political power, or actors that aim to circumvent rules [79]. And while citizens may be able to create political change within their own country, a disconnect may arise between those who participate in a market and those who have any capacity to influence conservation regulations. As a result, the class of regulatory interventions may fall short in delivering conservation outcomes. This broad realization raises the question if other approaches can help improve conservation outcomes.

A promising alternative to regulatory interventions is the idea that a shift in consumer demand could *incentivize* conservation. This approach relies on individual consumers changing behavior – essentially by decreasing demand for products that rely on exploitation of natural resources. Under this mechanism, for example, people in the United States could plausibly protect the Amazon rainforest (by reducing consumption of Brazilian beef), reduce the extraction of primary materials (by buying recycled products), or reduce carbon emissions from electricity production (by switching to LED lights). To drive these demand shifts, individuals, communities, and corporations can pursue *demand-side* interventions, which often come in the form of information campaigns or new product introductions. This decentralized form of conservation intervention can create substantive change without the need for collective political action.

With this mechanism in mind, demand-side interventions have been introduced in a variety of markets: synthetic rhino horns a have been developed to decrease poaching [80], certified shade-grown coffee promotes biodiversity in tropical regions [81], water conservation campaigns are common, especially in draught-risk areas of the globe [82], totoaba are farmed for their swim bladder to reduce pressure on totoaba stocks and the ecologically linked vaquita [83, 84], and paper recycling seeks to reduce our need for primary forests [85]. All of these interventions rely on changes in demand as the vehicle for conservation.

Despite these, and countless other examples, the effectiveness of demand-side conservation interventions is difficult to ascertain. To our knowledge, no study fully captures the causal chain from demand-side intervention to conservation benefits to estimate the drivers, and efficacy, of a demand-side conservation intervention. Some environmental problems may be easily solved with a demand-side intervention, while others may find this approach utterly unproductive. But the scientific literature provides little to no guidance about which kinds of interventions are likely to be effective. For this reason, consumers who wish to pursue the demand-side mechanism are likely uninformed about the conservation implications of their actions. In this paper, we develop a general theory of the conservation efficacy of demand-side interventions, and apply that theory to a contemporary and salient real-world example.

While they surely differ in the details, all demand-side interventions require three steps to achieve conservation benefits. First, consumer demand must shift: a campaign warning of the ecological consequences of using tiger bones to treat ulcers must actually decrease demand for tiger bones. Shifting consumer demand can be challenging and research is mixed on the efficacy of demand-side interventions in motivating persistent changes in demand [86–88]. Second, the demand shift must interact with supply in a way that demonstrably changes price, and this price change must be passed through to resource extractors. Third, observing this reduction in price, resource extractors must change behavior and consequently the resource stock (or more broadly, environmental quality) must recover. In all, this causal chain is determined by the prevailing economic conditions of the resource stock and the market in which extraction occurs. For example, the extent to which extraction effort is affected by price is in part determined by the efficacy of current management. As a result, when a consumer chooses not to buy illegal tiger derivatives, it is unlikely that as a consequence one additional tiger is left to roam the forests. This framing applies equally to the case of renewable and nonrenewable resources, though in the renewable case the relationships are arguably more complex as stock growth dynamics complicate the relationship between extraction and conservation.

This paper attempts to shed light on this complex, but pervasive challenge. We aim to make three contributions to the discussion of demand-driven conservation. First, we propose a new statistic, called the "demand elasticity of conservation", or conservation elasticity (CE), which conveys the efficacy of a demand shift at producing a conservation outcome. It combines the underlying ecosystem dynamics with the supply and demand dynamics of relevant products to determine the efficacy of a demand shift at delivering a conservation improvement. Our second contribution is to apply the CE model to the case of marine fisheries as an exemplary case of the potential for demand-drive conservation. In that application, the conservation benefit is measured as the stock biomass of global marine fish. We estimate the CE for 27 classes of fish products, representing 83% of global marine fish catch. There, we find more than an order of magnitude difference in CE across these classes, suggesting that the same kind of demand side conservation intervention is likely to have dramatically different effects across fish classes. These empirical estimates of the CE allow us to estimate the demand shift required for each product class to reach a benchmark conservation outcome. While this analysis sheds light on how large demand shifts need to be, little evidence exists about how responsive consumers are to these interventions. Thus, our third contribution is to empirically estimate, using a choice experiment conducted on 969 fish consumers, the magnitude of the demand shift that is likely from a contemporary, real-world demand-side intervention. The specific case we study is the introduction of cellular seafood, meant to be a conservation-friendly alternative to eating wild-caught fish.

We begin by summarizing our model of the causal chain for a demand-side intervention to achieve a conservation outcome. This model gives rise to CE statistic, $\epsilon_{C,\alpha}$, which is interpreted as the percentage change in a conservation outcome that results from a one percent shift in demand. The derivation of this statistic is provided in the supplemental information (section 1.2), and the final statistic is given by:

$$\epsilon_{C,\alpha} = \frac{\epsilon_{D,\alpha}}{\epsilon_{S,p} - \epsilon_{D,p}} \cdot \epsilon_{C,p} \tag{3.1}$$

The conservation elasticity, $\epsilon_{C,\alpha}$, depends on three terms: First $\epsilon_{D,\alpha}$, which shows how responsive the demand shift is to a conservation intervention α; second the balance of price elasticities of demand and supply, $\epsilon_{D,p} - \epsilon_{S,p}$, determines how sensitive the market equilibrium price responds to a demand shift; and third $\epsilon_{C,p}$, which captures the conservation elasticity with respect to price. All these elasticities dynamically evolve over time, and especially the price elasticity of supply captures effects of possible regulatory interventions. We evaluate these elasticities at steady state, which allows for the interpretation of the CE as the long-run effect of a shift in demand on conservation. The parameter α can represent any exogenous demand shifter, including things like the price of a substitute, an information treatment, or an income shock. Further details are provided in the supplemental information (section 1.2). Any given conservation intervention (captured by α) will have a different set of relevant elasticities on the right hand side, and will thus give rise to a different conservation elasticity. In the special case of non-renewable resource, the result simplifies to $\epsilon_{C,p} = \epsilon_{S,p}$ (see SI 1.2).

While demand-side interventions are found in a variety of markets, we demonstrate the use of our framework in the context of global fisheries, where these interventions are extensively implemented. Consumers make purchase decisions at the fish counter based on sustainability status, seafood sustainability ratings help guide your restaurant order, and retailers regularly make commitments to purchase only sustainably caught fish. While many conservation outcomes could be considered, here, we measure conservation as the biomass of the fish population in the ocean. Using this metric, we can interpret the conservation elasticity as the percentage change in stock biomass that results from a one percentage change in demand for that fish. To understand demand-driven conservation for the particular case of fisheries, we first build a structural model of a fishery subject to regulatory interventions (SI 1). This model assumes that fisheries are, in part, driven by economic forces, so supply and demand influence the level of harvest and the price received.Not all fisheries operate in this manner. Consider for instance the case of fisheries managed through individual transferable quotas (ITQs) with a fixed cap. Barring significant demand changes that leave the quota non-binding, equilibrium fishing effort is fixed, and as a result, changes in demand will not affect equilibrium harvest or biomass (proof in SI section 1.3). To proceed, we parameterize the model for 4,713 global fish stocks, which we group into product categories using the International Standard Classification of Aquatic Animals and Plants (ISCAAP), and estimate the equilibrium steady-state supply curve for each fishery and product category (SI section 2.1). We then parameterize a demand curve for each product category (SI section 2.2.3) and estimate the conservation elasticity for each product class which we present alongside measures of current status ($\frac{B}{B_{MSY}}$)in Figure 3.6.

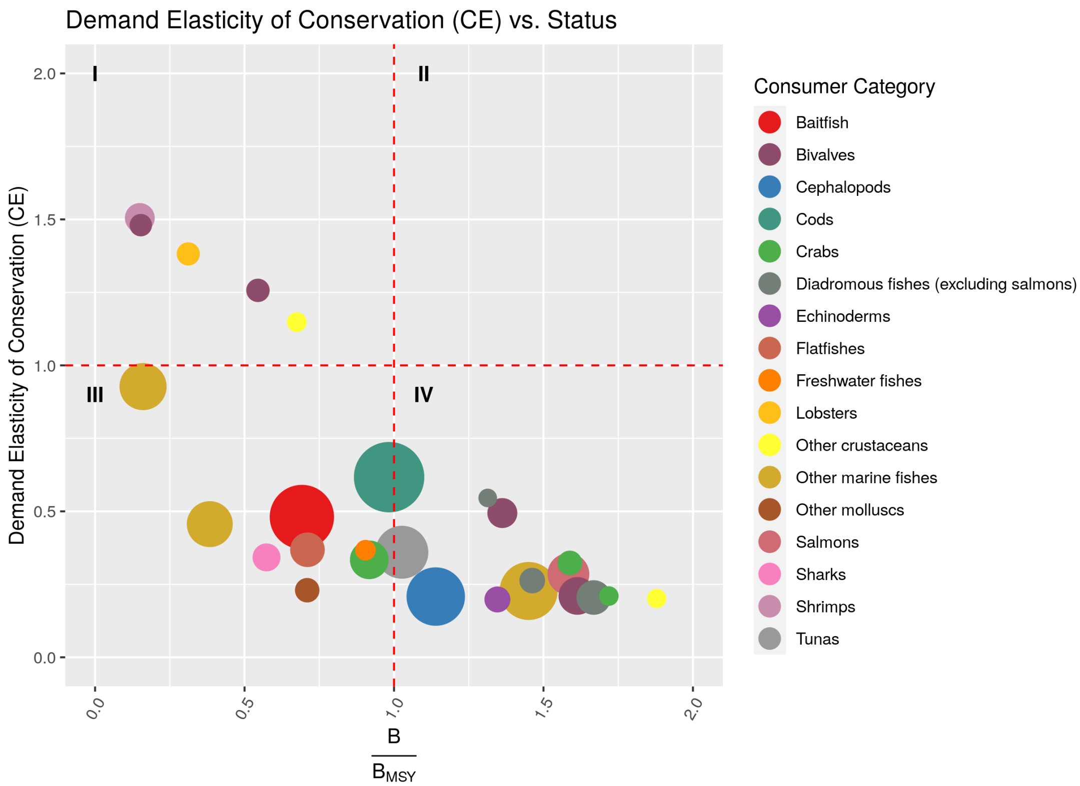

Figure 3.1: Vertical axis shows the demand elasticity of conservation for each ISSCAAP category. Horizontal axis measures the conservation status (biomass relative to a widely used benchmark) of each ISSCAAP category. CE values above 1.0 indicate that a 1% decrease in demand leads to a larger than 1% increase in biomass, where CE values below 1.0 indicates that a 1% decrease in demand leads to a less than 1% (but greater than 0%) increase in biomass. Stocks for which B/Bmsy<1.0 may indicate the stocks most in need of conservation interventions.

Figure 3.6 shows the CE for each ISCAAP product class, ranging from 0.16 to 1.6, with CE on the vertical axis and conservation status ($\frac{B}{B_{MSY}}$) on the horizontal axis. According to FAO [89], values of $\frac{B}{B_{MSY}} < 1$ indicate over-exploitation. This shows that the existing formal, regulatory efforts fail to achieve the desired conservation outcomes for many fish stocks. ISSCAAP categories are colored by a smaller set of 'consumer categories' for exposition. For most fish in the world, the conservation elasticity is well-below 1.0. This implies that even if an intervention can significantly shift demand, the ultimate conservation consequences will be somewhat muted. The average $\epsilon_{C,\alpha}$ across ISCCAAP categories is 0.55. However, there is significant heterogeneity in the CE across product classes. This suggests that demand interventions can be up to an order of magnitude more effective if targeted at a high-CE product class as compared to a low-CE product class. This finding points to the need to target demand interventions at product classes that will be highly affected, and suggests that our framework can provide valuable insight in contexts where interventions propose to maximize conservation benefits. The product categories fall into three quadrants: (I) stocks that are over-exploited and responsive to demand intervention, (III) stocks that are over-exploited but unresponsive to demand intervention, and (IV) stocks that are neither over-exploited nor responsive. To most effectively induce conservation, demand-side interventions should focus on stocks in quadrant (I) that are in need of conservation and amenable to changes in demand. Notably, for all over-exploited product types, the average demand shift required to induce maximum sustainable yield is 61.9%. This suggests that while certain product classes are amenable to demand intervention, significant shifts in demand are still necessary for a full recovery. In order to investigate which bio-economic parameters contribute most significantly to the determination of the CE, we perform a sensitivity analysis, presented in table 3.1. To do so we consider the a generic fishery parameterized with median values of all necessary modeling parameters. The median fishery CE, $\epsilon_{C,\alpha}$, is 0.28, resulting from a price elasticity of supply, $\epsilon_{S,p}$, equal to 0.148, a price elasticity of demand, $\epsilon_{D,p}$, equal to -1.15, and a price elasticity of conservation, $\epsilon_{C,p}$ equal to -0.38. The sensitivity analysis presented in table 3.1 shows the sensitivity of the median fishery CE to percentage changes in the several key modeling parameters. The results show that the effect of demand-side interventions strongly depends on ecological factors (growth rate and carrying capacity), as well as on economic parameters and the effectiveness of regulatory conservation interventions (fishery management).

parameter	percentage change in CE
price elasticity of demand, $p_{elast,D}$	-0.93%
management effectiveness, μ	0.01%
stock growth rate, g	-5.45%
marginal cost of fishing, c	1.85%
stock carrying capacity, k	-5.55%

Table 3.1: presents the results of the sensitivity analysis of the CE with regard to key modeling parameters. The results are calculated as the percentage change in the CE that results from a 1% change in the parameter of interest.

Stocks with low (marginal) costs and low management effectiveness are particularly prone to over-use, and general fisheries with less elastic demand, higher growth rate, and higher carrying capacities are more responsive to demand interventions. The results in table 3.1 that fisheries with these conditions are well suited for demand-side interventions.

We have shown that the efficacy of a demand-side conservation intervention depends on a complex interplay of economic, behavioral, and ecological effects, as well as pre-existing regulatory intervention. We have derived and empirically estimated the CE statistic for the near universe of commercially harvested global marine fisheries. But a significant question still remains: how large of a demand shift can we expect from real-world conservation interventions? To answer this question, we conducted a first-of-its-kind choice experiment with 969 fish consumers to estimate the demand shift for wild-caught bluefin tuna that would arise from a demand-side intervention. The intervention we chose is not hypothetical, it is a real-world technology called cellular seafood, which grows edible flesh from cellular cultures in a laboratory setting. Cellular seafood is a novel technology, currently under development by a variety of start-ups, that is touted as a conservation-promoting mechanism that works by providing lab-grown seafood alternatives to wild-caught products.

Our choice experiment presented consumers with realistic food consumption alternatives, where wild-caught bluefin steaks were presented alongside comparable cellular bluefin alternatives. Consumers were instructed to consider the alternatives to be qualitatively similar in taste, texture, etc. Cellular seafood alternatives were available at a range of retail prices similar to current prices for fresh bluefin tuna. More details about the consumer survey and the model estimation framework are given in the supplemental information (section 2.7). Figure 3.2 shows the estimated supply and demand curves for this bluefin choice experiment. The supply curve (in red) is based on stock assessment, catch, and price data and is derived based on the model presented above. The four demand scenarios (in blue) are estimated from the responses of consumers in the choice experiment. The demand scenarios are: (1) bluefin demand without a cell-based alternative, (2) bluefin demand with high price cell-based alternative, (3) bluefin demand with a medium price cell-based alternative, and (4) bluefin demand with a low price cell-based alternative. The current CE, $\epsilon_{C,\alpha}$, of bluefin is 0.5, resulting from a price elasticity of supply, $\epsilon_{S,p}$, equal to 0.63, a price elasticity of demand, $\epsilon_{D,p}$, equal to -1.15, and a price elasticity of conservation, $\epsilon_{C,p}$ equal to -0.89. Table 3.2 reports the equilibrium price, harvest and biomass that result from the introduction of cellular seafood at the three price points. For each demand scenario we use the resulting equilibrium price and quantity to determine the underlying biomass, consistent with an aggregation over the CE for the estimated demand shift.

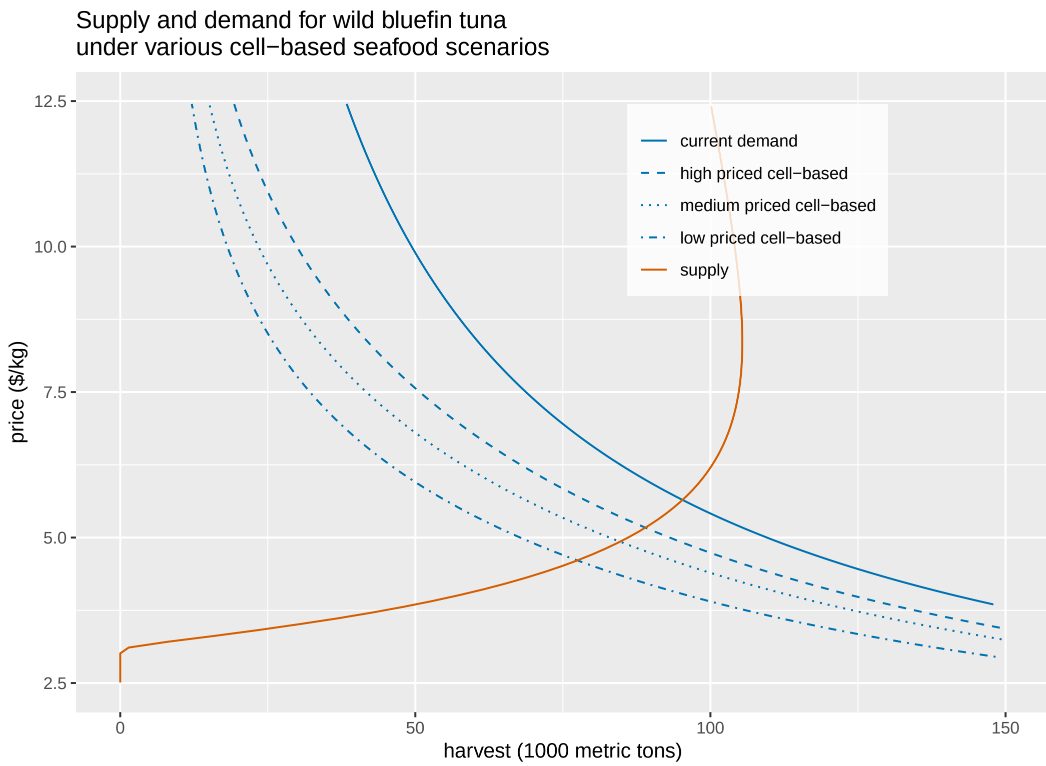

Figure 3.2: Supply and demand for bluefin tuna under alternative assumptions about a cell-based alternative.

Scenario	Cell-based Price Point ($/kg)	Bluefin Dock Price ($/kg)	Bluefin Harvest (1000 MT)	Bluefin Biomass (1000 MT)	Percent Change in Biomass
Current Demand	N/A	5.73	94.8	1,590	NA
High Priced Cell-based	91.98	5.24	88.5	1710	8%
Medium Priced Cell-based	61.98	4.99	84.1	1790	13%
Low Priced Cell-based	37.98	4.66	77.0	1910	20%

Table 3.2: presents the equilibrium price, harvest, and biomass that result from the various cell-based Bluefin introductions, as compared to current levels

Consider the scenario in which cell-based bluefin is available at the medium price (benchmarked to the median price of bluefin today, \$61.98/kg). There, the introduction of cellular bluefin has the potential to reduce demand for wild-caught bluefin by about 30%, leading to a 13% increase in wild-caught bluefin biomass. The high, medium, and low price scenarios correspond to a 8%, 13%, and 20% increase in the biomass of wild-caught bluefin stocks. These results suggest that as the price for cellular bluefin tuna is reduced, ecologically meaningful conservation benefits could ensue. However, at price parity, the conservation benefits are still modest. Future work investigating demand-side interventions should consider the drivers of consumers' willingness to substitute as well as levers that may be used to increase substitution.

Recognizing that formal regulatory policy solutions for environmental conservation are often elusive, there is great interest in demand-side interventions. Yet the scientific literature has little to offer about the efficacy of this increasingly wielded tool for conservation. We developed a general bioeconomic framework within which to study the efficacy of demand-side interventions in delivering conservation outcomes beyond preexisting regulatory interventions. In so doing, we developed a theoretically grounded new statistic, called the *demand elasiticty of conservation*, which can be calculated for nearly any conservation setting, and provides a summary statistic of the efficacy of a demand shift in achieving conservation outcomes. We applied that framework to the case of global fisheries, and uncovered a tremendous amount of heterogeneity; many of the world's fisheries are likely to be immune to demand-side interventions, while a few, which tend to be the most over-exploited, are likely to respond quite elastically to interventions that shift their demand.This indicates that demand-side conservation might be particularly useful when the conservation success of preexisting regulatory intervention is poor. Our choice experiment case study of bluefin tuna and its cell-based alternative showed that, at least for this iconic species, significant benefits may be possible. Outside of fisheries, we think a fruitful next step would be to empirically estimate the magnitude of the conservation elasticity. These, and subsequent results can help illuminate and guide the increasing practice of demand-side conservation interventions to tackle some of society's greatest environmental challenges.

3.2 Supplemental theory

The supplemental theory section covers in detail the theoretical model used as the basis for the results in the paper. We start by considering our definition of a shift in demand, the definition and derivation of the demand elasticity of conservation, $\epsilon_{C,\alpha}$. We then build the steady-state bio-economic model of a generic fishery under exogeneous imperfect management. Along the way we present important results and insights that underpin the conclusions of our work.

3.2.1 *Definition of a demand shift*

To consider the effects of demand interventions most generally, we specify the quantity demanded as a function of an arbitrary shift parameter α, which is affected by a demand intervention of interest:

$$D = f(p, \mathbf{x_D}, \alpha) \tag{3.2}$$

where p is price and $\mathbf{x_D}$ are other conventional demand shifters like income and the price of conventional substitute goods. We define a demand shift as occurring when an exogenous factor affects the level of α and thus affects the demand function, D. One can write the α elasticity of demand as $\frac{dD}{d\alpha} \cdot \frac{\alpha}{D}$

3.2.2 *Example: the price of a substitute as a demand shifter*

We can imagine the case that we are interested in the ability of a product substitute to shift demand. As such we might consider α as follows:

$$D = f(p, \mathbf{x_D}, \alpha(p_s^{\epsilon_s})) \tag{3.3}$$

In such a case,

$$\frac{dD}{dp_s^{\epsilon_s}} \cdot \frac{p_s^{\epsilon_s}}{D} = \frac{dD}{d\alpha} \cdot \frac{\alpha}{D} \cdot \frac{d\alpha}{dp_s^{\epsilon_s}} \cdot \frac{p_s^{\epsilon_s}}{\alpha} \tag{3.4}$$

$$\implies \epsilon_{C,p_s^{\epsilon_s}} = \epsilon_{D,\alpha} \cdot \epsilon_{\alpha,p_s^{\epsilon_s}} \tag{3.5}$$

3.2.3 *Definition of the demand elasticity of conservation,* $\epsilon_{C,\alpha}$

To inspect the conservation potential of demand shifts we first decompose the conservation elasticity of demand into two distinct effects: the effect of a change in equilibrium price on biomass and the effect of a change in α on equilibrium price. Since since the measure of conservation (think biomass) can be written as a function of price and constant parameters, where price is partially determined by the value of α, we have:

$$\epsilon_{C,\alpha} = \frac{dC}{d\alpha} \cdot \frac{\alpha}{C} \tag{3.6}$$

$$= \frac{\partial C}{\partial p}\frac{\partial p}{\partial \alpha} \cdot \frac{\alpha}{C} \tag{3.7}$$

$$= \frac{\partial C}{\partial p}\frac{\partial p}{\partial \alpha} \cdot \frac{\alpha}{p}\frac{p}{C} \tag{3.8}$$

$$\epsilon_{C,\alpha} = \epsilon_{C,p} \cdot \epsilon_{p,\alpha} \tag{3.9}$$

Furthermore, let's consider an arbitrary market equilibrium defined by $D(p(\alpha), \alpha, \mathbf{x_D}) = S(p(\alpha), \mathbf{x_S})$. We can define the elasticity of price with respect to α as follows:

$$S(p(\alpha)) = D(p(\alpha), \alpha)) \tag{3.10}$$

$$\implies \frac{\partial S}{\partial p}\frac{\partial p}{\partial \alpha} - \frac{\partial D}{\partial \alpha} - \frac{\partial D}{\partial p}\frac{\partial p}{\partial \alpha} = 0 \tag{3.11}$$

$$\implies \frac{\partial p}{\partial \alpha}\frac{\alpha}{p} = \frac{\frac{\partial D}{\partial \alpha}\frac{\alpha}{p}\frac{p}{D}}{\frac{\partial S}{\partial p}\frac{p}{S} - \frac{\partial D}{\partial p}\frac{p}{D}} \tag{3.12}$$

$$\implies \epsilon_{p,\alpha} = \frac{\epsilon_{D,\alpha}}{\epsilon_{S,p} - \epsilon_{D,p}} \tag{3.13}$$

Thus,

$$\epsilon_{C,\alpha} = \epsilon_{C,p} \cdot \frac{\epsilon_{D,\alpha}}{\epsilon_{S,p} - \epsilon_{D,p}} \tag{3.14}$$

3.2.4 *Definition of the conservation elasticity of demand,* $\epsilon_{C,\alpha}$ *for non-renewable resources*

The case of non-renewable resources is trivial in comparison to the renewable resource problem, in particular because conservation is more clearly related to supply in the case on nonrenewable resources. In the non-renewable case, the a decrease in supply is equivalent to an increase in conservation, since there is no growth and thus, conservation is simply avoided extraction. Such an intuition can be mathematized by the idea that for non-renewable resources $\epsilon_{C,p} = \epsilon_{S,p}$, that the price elasticity of conservation is equal to the price elasticity of supply. And hence,

$$\epsilon_{C,\alpha} = \epsilon_{S,p} \cdot \frac{\epsilon_{D,\alpha}}{\epsilon_{S,p} - \epsilon_{D,p}} \tag{3.15}$$

3.2.5 *The general conditions for a conservation-demand relationship*

We are interested in how demand-side interventions ultimately affect the conservation, which we consider here to be represented by the level of the stock. We focus specifically on the case of renewable resources, though this thinking could be applied to non-renewable resources as well. Increased stock size (over time) is our measure of conservation. The conservation mechanism we have in mind is that a demand-side intervention affects prices, and thus changes the incentives for extractors to exert more or less effort. We therefore assume that economic factors affect stock size *only* through their effect on extraction effort. This effect operates explicitly through the price channel, where extractors respond to changes in price by adjusting effort. Formally, the stock in time t is characterized by its stock size, B_t, harvest, H_t, and corresponding mortality rate, $F(t) = H(t)/B(t)$. Stock growth is given by the function $G(B_t, \mathbf{x_B})$ which is concave in B and where $\alpha \notin \mathbf{x_B}$. The growth of the stock depends on the level of the stock (B_t) and other biological and environmental parameters ($\mathbf{x_B}$), but not directly on economic factors such as α. For all $\mathbf{x_B}$ there is a biomass $B^{msy}(\mathbf{x_B})$ that maximizes $G(B)$, i.e. $G'(B^{msy}(\mathbf{x_B})) = 0$. Mortality is a choice that is made partly by managers, and partly by extractors themselves. Thus, we generally describe mortality as a function $F_t = f(B_t, p_t(\alpha), \mathbf{x_F})$ that depends on contemporaneous biomass and price of the resource, that latter of which is itself influenced by demand parameters α and $\mathbf{x_F}$. The change in stock is equal to the growth of the stock minus the harvest in period t: $\dot{B} = G(B_t) - H_t = G(B_t) - F_t B_t$, and steady-state is defined by $\dot{B} = 0$.

Under this setup, which conforms to the standard assumptions of bioeconomic models, we can derive a fairly simple result about demand-driven conservation:

Proposition 1: Steady-state size of a stock is responsive to changes in demand if and only if effort is responsive to changes in demand, where effort is responsive to changes in demand iff effort is responsive to changes in price.

proof: Since $\dot{B} = G(B_t) - F_t B_t$, where steady-state is $\dot{B} = 0$, then for every level of effort F_t there exists a steady-state biomass $\bar{B}$ such that $G(\bar{B}) - F_t\bar{B} = 0$. Thus, $\frac{d\bar{B}}{d\alpha} = \frac{\bar{B}\frac{dF_t}{d\alpha}}{G'(\bar{B}) - \frac{G(\bar{B})}{\bar{B}}}$. Since $G'(\bar{B}) - \frac{G(\bar{B})}{\bar{B}} < 0$ by the concavity of $G(\bar{B})$, $\frac{d\bar{B}}{d\alpha} \neq 0$ iff $\frac{dF}{d\alpha} \neq 0$. Furthermore, $\frac{d\bar{B}}{d\alpha} < 0$ iff $\frac{dF}{d\alpha} > 0$. Since $\frac{dF}{d\alpha} = \frac{\partial F}{\partial p_t}\frac{\partial p_t}{\partial \alpha}$, then $\frac{d\bar{B}}{d\alpha} \neq 0$ iff $\frac{\partial F}{\partial p_t} \neq 0$ and $\frac{\partial p_t}{\partial \alpha} \neq 0$.

Proposition 1 shows that for stocks to be responsive to changes in demand, it must be that changes in demand influence the market price *and* that effort responds to changes in price. Since extractors control biomass through changes in effort, if effort is unaffected by changes in α, then biomass will remain unchanged. Notably, there are stocks where harvest rules are not economic in nature. Consider for instance the case of fisheries managed through individual transferable quotas (ITQs) - barring significant demand changes that leave the quota non-binding, equilibrium fishing effort is fixed since effort is fixed. In such a case, changes in demand will clearly not effect equilibrium harvest or biomass.

3.2.6 *A general model of an economic fishery under exogenous management effectiveness*

In order to derive the general model of an economic fishery under exogenous management effectiveness we first consider next the case of an optimally managed fishery. We define a simple fisheries model where the underlying growth function is concave in biomass and described by $G(B_t)$ - growth is a function of the current biomass and other parameters which we exclude from the notation for convenience, with harvest, $H_t = F_t B_t$, and the following economic model. Using the notation from the previous section, profits from the fishery are given by:

$$\pi_t = p_t H_t - c\frac{H_t}{B_t} \tag{3.16}$$

where c is the marginal cost of effort. The current value Hamiltonian for the infinite-horizon optimal control problem is written as follows:

$$\mathcal{H} = p_t H_t - c\frac{H_t}{B_t} + \lambda_t (G(B_t) - H_t) \tag{3.17}$$

with the following necessary conditions:

$$\lambda_t = p_t - \frac{c}{B_t} \tag{3.18}$$

$$\frac{cH_t}{B_t^2} + \lambda_t G'(B) = -\dot{\lambda}_t + \rho\ \lambda_t \tag{3.19}$$

$$\dot{B}_t = G(B) - H_t \tag{3.20}$$

The optimal steady-state conditions are as follows, where we drop the superscript bar denoting steady-state for convenience, since all values are hereafter defined in steady-state:

$$\lambda^* = p - \frac{c}{B^*} \tag{3.21}$$

$$\frac{cH^*}{(B^*)^2} + \lambda^* G'(B^*) = \rho\ \lambda^* \tag{3.22}$$

$$H^* = G(B^*) \tag{3.23}$$

Combining these equations, we get the following condition for the optimal steady-state resource stock

$$p = \left(1 + \frac{G(B^*)}{B^*\,(\rho - G'(B^*))}\right) \frac{c}{B^*} \tag{3.24}$$

In this equation, the term $\frac{G(B^*)}{B^*\,(\rho - G'(B^*))}$ captures the resource rent as a fraction of marginal harvesting costs. It is strictly decreasing in the steady-state stock size,

$$\frac{d}{dB^*}\left(\frac{G(B^*)}{B^*\,(\rho - G'(B^*))}\right) = \frac{(G'(B^*)\,B^* - G(B^*))\,(\rho - G'(B^*)) + G(B^*)\,B^*\,G''(B^*)}{\left(B^*\,(\rho - G'(B^*))\right)^2} < 0, \tag{3.25}$$

due to the concavity of $G(B)$, i.e. $G''(B) < 0$ and $G'(B) < G(B)/B$. Implicitly differentiating (3.24) with respect to p, we thus conclude

$$\underbrace{\frac{B^* \frac{d}{dB^*}\left(\left(1 + \frac{G(B^*)}{B^*\,(\rho - G'(B^*))}\right)\frac{c}{B^*}\right)}{\left(1 + \frac{G(B^*)}{B^*\,(\rho - G'(B^*))}\right)\frac{c}{B^*}}}_{<0} \frac{p}{B^*}\,\frac{dB^*}{dp} = 1. \tag{3.26}$$

This implies that, under optimal management, $\frac{dB*}{dp} < 0$ (i.e., the steady-state stock sizes decreases with the price).

Since we are not concerned here specifically with an optimally managed fishery, but a fishery subject to some exogenous level of management, we define μ as the level of management effectiveness equal to the fraction of the external cost of fishing that is internalized by fishing behavior, rewriting equation 3.21 consistent with Quaas et al. 2016:

$$\mu\lambda_t = p_t - \frac{c}{B_t} \tag{3.27}$$

The harvest quantity is determined by the condition that the price (marginal benefit of catch) equals the marginal cost of catch, which is the sum of marginal harvesting cost and a fraction $\mu \in [0, 1]$ of the external costs of fishing. Equation 3.27 determines the supply of fish. In market equilibrium, supply is equal to demand, such that

$$P(H_t) = p_t = \frac{c}{B_t} + \mu\,\lambda_t \tag{3.28}$$

The external costs of fishing λ_t captures the dynamic stock externality, i.e. the opportunity costs of catching fish, i.e. the present value of future catches enabled by leaving an extra fish in the water.

3.2.7 *Quantifying the value of the dynamic stock externality*

There are (at least) three alternative possibilities to quantify the value of the dynamic stock externality:

1. λ_t^F is the value for the fishery that takes only a fraction μ of the externality into account.

2. $\lambda_t^\star$ is the value for a social planner who would optimize catches. (with derivation presented above).

3. λ_t^μ is the value for a social planner when the fishery internalizes only a fraction μ of λ^μ.

While we consider each of these alternatives below. But focus here on option 1, which we believe is most consistent with the modeling framework presented above, and as a result, it is the approach we have used in throughout the main text. The interpretation of this modeling choice is that the fishery is managed under imperfect management, and the external cost of fishing λ_t are determined under the acknowledgement of this imperfect management. We describe the mathematical formulation of this approach in Section 3.2.8

3.2.8 *Value of dynamic stock externality for the fishery that takes only a fraction μ of the externality into account*

Using $V^F(B_t)$ to denote the value of fish stock of size B_t for the fishery. The value of the dynamic stock externality is the marginal present value of next period's stock, i.e. the derivative of the value function, $\lambda_t^F = \delta\, V^{F'}(B_{t+1})$, where $\delta = 1/(1+\rho)$ is the discount factor.

In a discrete-time setting, the value function for the fishery is determined by the Bellman equation

$$V^F(B_t) = p_t\, H_t - \frac{c\, H_t}{B_t} + \mu\, \delta\, V^F\left(B_t + G(B_t) - H_t\right), \tag{3.29}$$

where we have considered that the fishery takes into account only a fraction μ of the future value of the fishery.

Differentiating (3.29) with respect to B_t, and using (3.23) with $\lambda_t = \lambda_t^F = \delta\, V^{F'}(B_{t+1})$, we get

$$\underbrace{V^{F'}(B_t)}_{=\lambda_{t-1}^F/\delta} = \frac{c\, H_t}{B_t^2} + \mu\, \delta\, \underbrace{V^{F'}\left(B_t + G(B_t) - H_t\right)}_{=\lambda_t^F/\delta} \left(1 + G'(B_t)\right). \tag{3.30}$$

Solving for λ and using this in (3.22), along with the steady-state condition $H = G(B_\mu)$, we obtain the following condition for the steady-state resource stock B_μ under limited management effectiveness:

$$\lambda^F = \frac{\delta\, c\, G(B^F)}{\left(B^F\right)^2\, \left(1 - \mu\, \delta\, \left(1 + G'(B^F)\right)\right)} \tag{3.31}$$

Using this in (3.27), we get the steady-state supply function

$$p^F = \left(1 + \mu\, \frac{G(B^F)}{B^F\, \left(\rho + 1 - \mu - \mu\, G'(B^F)\right)}\right)\, \frac{c}{B^F} \tag{3.32}$$

In this equation, the term that captures the resource rent is scaled by μ. For $\mu = 1$, we obtain $B_\mu = B^*$, for $\mu = 0$ we obtain $B_\mu = B^{OA}$. In between, for any given price p, B_μ is monotonically increasing with μ. This is found by implicitly differentiating 3.32 with respect to μ:

$$\underbrace{\frac{B_\mu\, \frac{d}{dB_\mu}\left(\left(1 + \mu\, \frac{G(B_\mu)}{B_\mu\, (\rho - G'(B_\mu))}\right)\, \frac{c}{B_\mu}\right)}{\left(1 + \mu\, \frac{G(B_\mu)}{B_\mu\, (\rho - G'(B_\mu))}\right)\, \frac{c}{B_\mu}}}_{<0}\, \frac{\mu}{B_\mu}\, \frac{dB_\mu}{d\mu} + \underbrace{\frac{G(B_\mu)}{B_\mu\, \left(\rho - G'(B_\mu)\right)}\, \frac{c}{B_\mu}}_{>0} = 0. \tag{3.33}$$

3.2.9 *Value of dynamic stock externality for the social planner who would optimize catches*

Using $V^\star(B_t)$ to denote the value of fish stock of size B_t for the social planner who optimizes catches. Again, the value of the dynamic stock externality is the marginal present value of next period's stock, i.e. the derivative of the value function, $\lambda^\star_t = \delta\, V^{\star\prime}(B_{t+1})$.

The social planner maximizes net social surplus, i.e. the difference between consumer benefit and fishing costs. The value function for the fishery is determined by the Bellman equation

$$V^\star(B_t) = \int_0^{H_t} P(h)\,dh - \frac{c\,H_t}{B_t} + \delta\,V^\star\left(B_t + G(B_t) - H_t\right), \tag{3.34}$$

where optimal catches are determined by

$$P(H_t) = \frac{c}{B_t} + \delta\,V^{\star\prime}\left(B_t + G(B_t) - H_t\right) \tag{3.35}$$

Differentiating (3.34) with respect to B_t, and using (3.35) with $\lambda_t = \lambda_t^\star = \delta\,V^{\star\prime}(B_{t+1})$, we get

$$\underbrace{V^{\star\prime}(B_t)}_{=\lambda^\star_{t-1}/\delta} = \frac{c\,H_t}{B_t^2} + \delta\,\underbrace{V^{\star\prime}\left(B_t + G(B_t) - H_t\right)}_{=\lambda^\star_t/\delta}\left(1 + G'(B_t)\right). \tag{3.36}$$

In steady state, $\lambda^\star_{t-1} = \lambda^\star_t = \lambda^F$, $H^F = G(B^F)$, and

$$\lambda^\star = \frac{\delta\,c\,G(B^\star)}{\left(B^\star\right)^2\,\left(1 - \delta\,\left(1 + G'(B^\star)\right)\right)} = \frac{c\,G(B^\star)}{\left(B^\star\right)^2\,\left(\rho - G'(B^\star)\right)} \tag{3.37}$$

Using this in 3.23, we get the steady-state supply function

$$p^\star = \left(1 + \mu\,\frac{G(B^\star)}{B^\star\,\left(\rho - G'(B^\star)\right)}\right)\,\frac{c}{B^\star} \tag{3.38}$$

3.2.10 *Value of dynamic stock externality for the social planner anticipating future limited management effectiveness*

Using $V^\mu(B_t)$ to denote the value of fish stock of size B_t for the social planner who takes for granted that future management effectiveness will be $\mu < 1$. Again, the value of the dynamic stock externality is the marginal present value of next period's stock, i.e. the derivative of the value function, $\lambda_t^\mu = \delta\, V^{\mu\prime}(B_{t+1})$.

The social planner maximizes net social surplus, i.e. the difference between consumer benefit and fishing costs. The value function for the fishery is determined by the Bellman equation

$$V^\mu(B_t) = \int_0^{H_t} P(h)\, dh - \frac{c\, H_t}{B_t} + \delta\, V^\mu \left(B_t + G(B_t) - H_t\right), \tag{3.39}$$

where catches are determined by (3.23) with $\lambda_t = \lambda_t^\mu$.

Differentiating (3.39) with respect to B_t, and using (3.23) with $\lambda_t = \lambda_t^\mu = \delta\, V^{\mu\prime}(B_{t+1})$, we get

$$\underbrace{V^{\mu\prime}(B_t)}_{=\lambda_{t-1}^\mu/\delta} = \frac{c\, H_t}{B_t^2} + \delta\, \underbrace{V^{\mu\prime}\left(B_t + G(B_t) - H_t\right)}_{=\lambda_t^\mu/\delta} \left(1 + G'(B_t)\right) - (1-\mu)\, \lambda_t^\mu\, \frac{dH_t}{dB_t}. \tag{3.40}$$

This equation contains the feedback of the stock on catches, dH_t/dB_t, which can be obtained by differentiating (3.28) with respect to B_t,

$$P'(H_t)\, \frac{dH_t}{dB_t} = -\frac{c}{B_t^2} + \delta\, V^{\mu\prime\prime}(B_{t+1}) \left(1 + G'(B_t) - \frac{dH_t}{dB_t}\right). \tag{3.41}$$

To determine steady-state supply, the full dynamic problem needs to be solved. This can be done numerically by applying value function approximation to (3.39) and (3.23).

3.2.11 *General model results*

The results presented below use the modeling framework above and the definition of the dynamic stock externality presented in section 3.2.8

Proposition 2: For economic fisheries (ones that are responsive to price signals), along a given supply curve, a lower (higher) equilibrium price implies higher (lower) steady-state biomass

proof: By eq. 3.32, for any given μ, B_μ is monotonically decreasing in the price p:

$$\underbrace{\frac{B_\mu \frac{d}{dB_\mu}\left(\left(1+\mu\,\frac{G(B_\mu)}{B_\mu\,(\rho-G'(B_\mu))}\right)\frac{c}{B_\mu}\right)}{\left(1+\mu\,\frac{G(B_\mu)}{B_\mu\,(\rho-G'(B_\mu))}\right)\frac{c}{B_\mu}}}_{<0}\ \frac{p}{B_\mu}\,\frac{dB_\mu}{dp}=1. \tag{3.42}$$

The steady-state biomass B_μ can be larger or smaller than the maximum sustainable yield biomass, depending on the price level. The critical price p_μ^{msy} is determined by

$$p_\mu^{msy}=\left(1+\mu\,\frac{G(B^{msy})}{B^{msy}\ (\rho+1-\mu-\mu G'(B^{msy}))}\right)\frac{c}{B^{msy}}=\left(1+\frac{\mu}{\rho+1-\mu}\,\frac{G(B^{msy})}{B^{msy}}\right)\frac{c}{B^{msy}}. \tag{3.43}$$

However, while decreases in price lead to biomass benefits, the effect is ambiguous for harvest:

Corollary 2: For economic fisheries (ones that are responsive to price signals), a lower equilibrium price implies higher or lower equilibrium levels of harvest depending on whether the current price is above or below p_μ^{msy}

proof: Since $H=G(B)$, $\frac{dH}{dp}=\frac{dG(B)}{dp}=G'(B)\cdot\frac{dB}{dp}$. Thus, $\frac{dH}{dp}\lesseqgtr 0$ if and only if $B_\mu \lesseqgtr B^{msy}(\mathbf{x_B})$, since $\frac{dB}{dp}<0$. In turn, $B_\mu \lesseqgtr B^{msy}(\mathbf{x_B})$ if and only if $p \gtreqless p_\mu^{msy}$.

Corollary 2 implies the potential for the supply curve of the fishery to "bend backwards". We can imagine several potential shapes of resulting supply curves, including a supply curve that bends backwards as first described by Copes 2007. Notably, the existence of a backward-bending supply curve, does not affect the monotonic and decreasing nature of the relationship between price and biomass described by proposition 2.

Using $p(H)$ to denote inverse demand, whereas (3.32) determines (inverse) supply in steady state, the full steady-state condition becomes

$$p(G(B_\mu);\alpha) = \left(1 + \mu \frac{G(B_\mu)}{B_\mu \, (\rho + 1 - \mu - G'(B_\mu))}\right) \frac{c}{B_\mu} \tag{3.44}$$

Stability requires that, at B_μ, inverse demand is steeper than inverse supply, both taken as functions of B_μ:

$$p'(G(B_\mu);\alpha)\, G'(B_\mu) > \frac{d}{dB_\mu}\left(\left(1 + \mu \frac{G(B_\mu)}{B_\mu \, (\rho + 1 - \mu - G'(B_\mu))}\right) \frac{c}{B_\mu}\right) \tag{3.45}$$

3.3 Supplemental data and empirics

This section details the construction of a parameterized model of global fisheries capable of estimating the demand elasticity of conservation for relevant fish products, as well as the detailed information regarding the bluefin tuna case study. We start discussing the parameterization of supply and curves for global fisheries, the proceed to discuss the case study experimental design and details, calibration and additional results.

3.3.1 *Parameterizing supply and demand for global fisheries*

The theory above confirms that reductions in demand manifest as increases in stock biomass. However, the extent to which any given shift increases biomass is unclear, given that the change in underlying biomass depends on biological, economic, and institutional factors that are stock and market dependent. We then ask - for a given stock or product class, how large would a shift in demand need to be for significant conservation benefits to be realized? To answer this question we link the most recent stock-level fisheries data from Costello et al. (2016) to a bio-economic supply and demand model capable of estimating the changes in biomass that result from decreases in demand.

3.3.2 *Data*

We parameterize supply curves for the worlds fisheries using data from Costello et al. (2016) which provides the following parameters (including appropriate adjustments) for 4,713 global fisheries. The parameters provided by this analysis are presented and described in table 3.3

parameter	description	value
c	harvest cost parameter	fishery specific
ϕ	Pella-Tomlinson scaling parameter	0.188
$B_{current}$	current level of biomass	fishery specific
$F_{current}$	current fishing effort	fishery specific
$H_{current}$	current harvest	fishery specific
k	stock carrying capacity	fishery specific

Table 3.3: Table outlining the parameters in Costello et al. 2016

3.3.3 *Building the supply curve*

We consider fish stocks to abide by a Pella-Tomlinson growth model[75], as follows:

$$B_{t+1} = B_t + \frac{\theta + 1}{\theta} g B_{eq} (1 - (\frac{B_{eq}}{k})^{\theta}) - H_t \ . \tag{3.46}$$

Furthermore, we define the fishers' profit function to be as follows:

$$\pi = p_k H_k - c_k F \tag{3.47}$$

for stock k. In order to understand how the underlying biomass of fish stocks responds to changes in demand, we parameterize the equilibrium supply and demand curves for global fisheries. There are approximately 4,713 unique fish stocks in the world's oceans. However, consumers do not view all of these stocks as being independent. Accordingly, we group stocks using the International Standard Classification of Aquatic Animals and Plants (ISSCAAP) structure in order to represent fish stocks as general consumer product categories. Stocks within a product class are treated as perfect substitutes in demand. We use the biological model and stock parameters from Costello et al. (2016) for each stock. To realistically represent current fisheries we must conceptualize and estimate current management status in a coherent manner. While several recent papers estimate management effectiveness for specific stocks [90] or report levels for a set of global stocks [91], to date there is no comprehensive measure available for stocks globally. We estimate and implement a measure of management effectiveness, μ_k, consistent with Quaas et al. (2016), where μ_k represents the fraction of the external cost of fishing that is internalized by current fishing behavior [92]. The calculation of μ_k and its integration into the estimation of the supply curve for a given stock under current management is discussed in detail in the supplemental information.

We estimate the equilibrium steady-state supply curve for each ISSCAAP category under three management scenarios: perfect economic management, open-access, and current management (see the supply curves in Figure 3.3 for an example considering the *tunas, bonitos, and billfishes* product category).

3.3.4 *Management effectiveness,* μ

To conceptualize a stock specific measure of management status we use Quass et al.'s (2016) management effectiveness. Management effectiveness is a measure of the fraction of external cost of fishing that is internalized in private fishing behavior. The external cost of fishing is equal to the shadow price, λ_k, where the shadow price can be derived from the first order condition that states the price as equal to the marginal cost of fishing (the private cost of harvesting plus the external cost of fishing). We estimate a fixed value for μ by determining the shadow value of the stock at it's current state as follows. For optimal control a manager maximizes:

$$\pi_t = \sum_{t=0}^{T-1} \left[p_t H_t - c(\frac{H_t}{B_t}) \right] s.t. \quad B_{t+1} = B_t + G_t - H_t, B_{t=0} = B_0, p_t = (\frac{A}{H_t})^{\frac{1}{\epsilon_p}} \tag{3.48}$$

The resulting solution defines $B(t), H(t), \lambda(t), \tau(t) = \frac{\lambda_k}{p_k}$. However, this simply defines the optimal policy function given a stating state of the stock. The first order condition of the optimal control problem thus states:

$$p_t = \frac{cH_t}{B} + \lambda_t \tag{3.49}$$

As in Quaas et al. (2015), we then consider the dimensionless value-added shadow price, $\tau_t = \frac{\lambda_t}{p_t}$ with management effectiveness measure μ measuring the fraction of the external cost of fishing that is internalized:

$$p_t(1 - \mu\tau_t) = \frac{c}{B_t} \tag{3.50}$$

So we can solve for the supply curve given a known level of management effectiveness using equation 3.3.4 and equation 3.3.3. For instance, to estimate the open-access supply curve for any fishery we must simply sole equation 3.3.4 given $\mu = 0$, since in open-access the external cost of fishing is not considered in harvesting decisions.

Costello et al. (2016) does not report a measure of management effectiveness for stocks. We estimate a fixed level of μ for each stock k, by using the observed level of effort in time $t = 0$ and the parameters at time $t = 0$ from the optimal control problem as follows:

$$\mu_k = \frac{1}{\lambda_0}\left[p_0 - \frac{cF_0^{\beta-1}}{B_0}\right] \tag{3.51}$$

Notably, such a calculation can also be framed as comparsion of the observed level of effort exerted in period $t = 0$ as compared to the level of effort that would have been excerted under optimal control:

$$1 - \mu_k = \frac{1}{\lambda_0}\left[\frac{A}{B_0}^{\frac{1}{\epsilon}}(\hat{F_0}^{-\frac{1}{\epsilon}} - \bar{F_0}^{-\frac{1}{\epsilon}})\right] \tag{3.52}$$

where $\hat{F_0}$ is the effort exerted in $t = 0$ under optimal control and $\bar{F_0}$ is the observed level of effort in $t = 0$.

3.3.5 *Aggregation of ISSCAAP categories*

We group stocks to the level of International Standard Statistical Classification of Aquatic Animals and Plants (ISSCAAP) categories. In order to aggregate the supply curves of stocks within a given category, the fundamental assumption is that the resulting products within each ISSCAAP category are perfect substitutes in demand. Under this assumption the aggregate supply curve of any ISSCAAP category is the horizontal aggregation of the individual stock supply curves.

3.3.6 *Building the demand curve*

We parameterize an iso-elastic demand curve using an assumed price elasticity of demand of -1.15 [89], with high and low price elasticity of demand scenarios considered in the supplemental information. The general demand function can be written as follows, for ISSCAAP category j:

$$H_j = A_j p_j^{\epsilon_j} \tag{3.53}$$

We calibrate current demand (estimate A_j) using the most recently observed price and harvest and the assumed price elasticity. More details about the calibration of the demand curve is presented in SI Section 3.3.6. The result of the model described above is the estimate of an equilibrium supply curve under current management and a demand curve for each ISSCAAP product category. Further details regarding this procedure are presented in the supplemental information (SI). Equilibrium supply and demand allow us to consider steady-state outcomes from changes in demand. Since the results of this model rely on steady state equilibrium outcomes, we estimate current equilibrium price, harvest, and biomass $(p_{eq,j}, H_{eq,j}, B_{eq,j})$ as the intersection of current demand and supply curves given current management, which may not represent the current state of the fisheries.

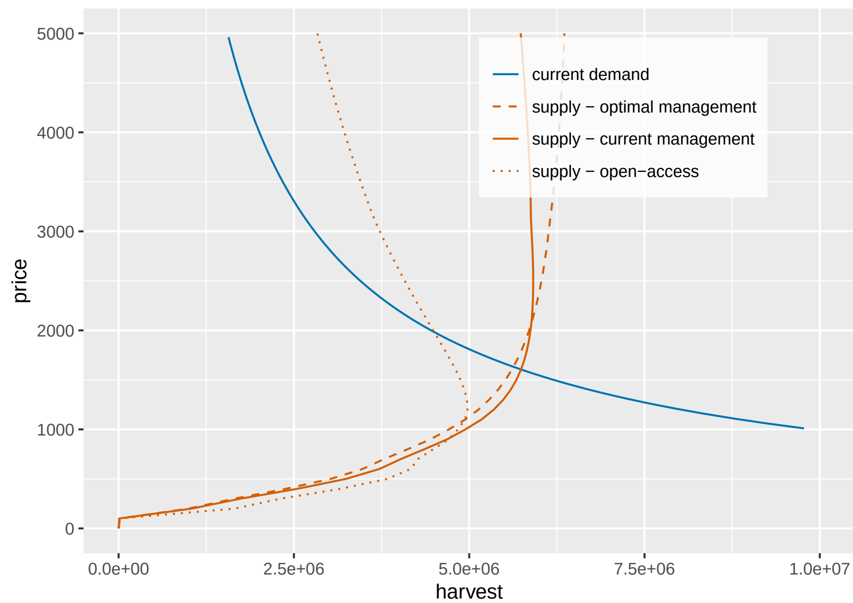

Figure 3.3: supply and demand for the *tunas, bonitos, billfishes* ISSCAAP category. current demand is presented alongside supply under current management, supply under open access, and supply under perfect economic management.

We conceptualize a shift in demand as a proportional shift in an isoelastic demand curve. As such, we define a demand shift parameter, α, where a 1% shift in α leads to a 1% change in quantity demanded:

$$H_j = \alpha A_j p_j^{\epsilon_j} \tag{3.54}$$

The purpose of describing a demand shift parameter in this way is to understand how a percentage change in demand manifests as changes in equilibrium biomass. In reality, a shift in demand may occur for many reasons, such as a change in income of the population, newly available products or information, or the change in the price of a substitute or complement product (see discussion in Section 3.2.1).

Given our estimation of current supply and demand curves, we can estimate the change in equilibrium biomass that results from a given shift in demand. Figure 3.6 presents the biomass elasticity of demand, $\epsilon_{C,\alpha}$, for each ISSCAAP category. This measure represents the percentage change in biomass induced by a 1% change in demand. The figure suggests that while it is possible that shifts in demand have proportional or magnified effects on biomass, for the majority of ISSCAAP categories, the biomass elasticity of demand is far below 1. The average $\epsilon_{B,D}$ across ISCCAAP categories is 0.51. We investigate factors that contribute to the estimated biomass elasticity of demand (such as management effectiveness, and current status) in the supplemental discussion.

3.3.7 *Demand curves*

We assume the demand for the ISSCAAP categories to be isoelastic with the functional form:

$$H_i = A_i p_i^{\epsilon_i} \tag{3.55}$$

We assume a constant price elasticity of -1.15, consistent with Costello et al. (2016), though we vary this assumption in the sensitivity analysis. Accordingly to parameterize demand for each ISSCAAP category we must simply estimate current price and harvest.

3.3.8 *Estimating the demand multiplier* A_J

Given current price and harvest for ISSCAAP category , we can simply estimate A_i:

$$A_J = \frac{H_J}{p_J^{\epsilon_J}} \tag{3.56}$$

The most recently reported price and harvest for a stock provided by version of Costello et al. (2016) is used to estimate A_J. Price for each ISSCAAP category is estimated as the median price of the stocks in the given ISSCAAP cateory, while harvest is estimated as the sum of the harvest over the stocks in the category:

$$p_J = median(p_i, ..., p_n) \quad for \quad i \in J \tag{3.57}$$

and

$$H_J = \sum_i^J H_i \tag{3.58}$$

3.3.9 *Shifts in demand*

In order to understand how possible shifts in consumer demand manifest as conservation benefits to wild fisheries we must conceptualize a shift in demand. As such, given isoelastic demand we can define a demand shift parameter, α, and define a demand shift by as a constant horizontal shifter of the iso-elastic demand function:

$$H_j = (\alpha)A_j p_j^{\epsilon_j} \tag{3.59}$$

To uncover the resulting change in biomass of the aggregated ISSCAAP product categories due to systematic shifts in the current demand curve, we estimate the resulting equilibrium price and harvest due to a shift in demand, $p_{J,\alpha}, H_{J,\alpha}$, then we equation 3.3.3 to solve for the equilibrium biomass.

3.3.10 *Sensitivity of the model to key parameters*

To perform the sensitivity analysis, reported in Table 1 of the main text, we do the following. First we define the median over-exploited fishery, as the fishery subject to the median value of all base modeling parameters, defined in table 3.3. Next we independently change key parameters by 1%, and report the change in the conservation elasticity, as a percentage change relative to the conservation elasticity of the median fishery.

3.3.11 *Case study methods: experimental design*

We designed our choice experiment to simulate a seafood purchase scenario for wild-caught bluefin tuna (*Thunnus thynnus*) before and after the introduction of cellular seafood. In both states of the world, information campaigns are present to communicate which tuna products are sustainably produced using a "traffic-light" color-scheme similar to Monterey Bay Aquarium Seafood Watch information program. Attribute levels were chosen based on current market availability prior to survey distribution.

We first designed the two choice experiments using a full factorial design. In the wild-caught choice experiment, there were four sustainability recommendation levels (None, Avoid, Good choice, Best choice) and five price levels ($18.99, $25.99, $30.99, $35.99, $45.99) while the second experiment included an additional production method attribute with two levels (wild-caught, cellular). Given these attribute levels, each experiment has twenty and forty total attribute combinations in a full factorial design, respectively. In the experiment that included cellular as an attribute, we eliminated choice questions in which one of the alternatives was a cellular tuna steak that was also assigned an "Avoid" sustainability recommendation. We made this decision based on the fact that cellular technology is expected to have minimal impact on the environment and would not likely be classified as unsustainable. This procedure reduced the number of total attribute combinations to thirty. We used the full factorial design in the wild-caught experiment.

Since fifty total choice questions (twenty in the wild-caught experiment and thirty in the cellular experiment) is far more than a single respondent could answer in one survey, we blocked the two designs to reduce the cognitive burden on our respondents. Each block contained five and six questions, respectively, in the wild-caught and cellular experiments. Each respondent was randomly assigned to one block in each experiment for a total of eleven choice questions. Each question included two choice alternatives plus a no purchase alternative. The order of each question in a given block was randomized for each respondent.

3.3.12 *Case study methods: sample*

We collected data in November 2020 from a sample of diverse food consumers via Amazon Mechanical Turk ("Mturk"). We specifically recruited Mturk workers with greater than zero approved tasks, task approval rating greater than 98%, and located in the United States. Only Mturk workers that fit the initial screening criteria saw the announcement for a "15-minute Academic Study". Participants were asked to answer a screener questionnaire to confirm eligibility prior to gaining access to the full the survey. Eligible participants were aged 18 years or older and lived in the United States. We paid participants $1.50 upon completion of the survey.

In addition to the screener questionnaire, we used methods to screen out respondents that attempted to take the survey from outside the United States. Recent studies identified a spike in workers using a Virtual Private Server (VPS), Virtual Private Network (VPN), or proxy server so that their internet activity cannot be traced geographically [93–95]. The majority of the VPS/VPN/proxy use cases on Mturk are international workers purposely running their activity through server farms or data centers in the United States to access tasks only made available to workers in the United States [93]. As an initial deterrent for those using some form of proxy server, we disclosed to potential respondents that we were screening IP addresses. If potential respondents did not leave the survey at this point, their IP address was screened using the protocol developed by Winter et al. 2019 and were deemed ineligible to participate in the survey if their IP address was flagged as being outside the United States and/or associated with known server farms.

We collected a total of 1,022 responses. We removed responses that either did not fully complete both sets of choice questions in the survey or completed the full survey in less than one-third the median completion time for the sample. This filtering procedure left a final sample of 969 for analysis. Summary statistics for the final sample are presented below.

Characteristic	**Sample estimates (N = 969)**	**Population estimates**[3]
Age[1] (years)	35.00 (11.25)	38.5
Sex[2] (%)		
Male	57.8	49.2
Female	42.1	50.8
Other	0.1	*Not reported*
Race[2] (%)		
White	77.5	60.0
Asian	6.40	5.6
Under-represented minority	11.1	32.0
Two or more races	5.1	2.5
Education[2] (%)		
Did not complete high school	0.2	9.6
High school graduate or GED	12.7	27.9

Characteristic	**Sample estimates (N = 969)**	**Population estimates**[3]
Some college	27.9	31.5
Bachelor's or higher	59.2	31.0
Income[2] (%)		
Less than $50,000	48.1	59.5
$50,000 to $74,999	26.0	16.9
$75,000 to $99,999	14.0	9.2
$100,000 to $149,999	8.6	8.4
$150,000 or higher	3.3	6.1
Household size[2] (%)		
1	20.9	28.3
2	31.7	34.3
3	22.0	15.3
4 or more	25.5	22.1
Political affiliation[2] (%)		
Republican	23.8	31.0
Democrat	49.0	36.0
Independent	23.7	31.0
Something else	3.4	2.0

[1] Statistics presented: Mean (SD)

[2] Category percentages are rounded and may not add exactly to 100.

[3] 2019 American Community Survey estimates except for "Political affiliation" which came from Gallup Poll Social Series interviews conducted on October 16-27, 2020.

Table 3.4: Sample summary statistics

3.3.13 *Case study methods: Random parameter logit specification and results*

We use a random utility framework to analyze our data and assume individual i makes choices between J alternatives in T choice situations by considering all available alternatives and chooses the alternative with the highest utility. The expression, $U_{ijt} = V_{ijt} + \epsilon_{ijt}$, characterizes the indirect utility associated with alternative J for individual i in choice situation T, where $V_{ijt} = \boldsymbol{\beta_i'} \boldsymbol{x_{ijt}}$ is the deterministic portion of utility with the individual parameter vector $\boldsymbol{\beta_i}$ assumed to be drawn from a population distribution, $g(\boldsymbol{\beta}|\boldsymbol{\theta})$, and the error term ϵ_{ijt} is independent and identically distributed extreme value type-1. Since each participant answered more than one choice question, we account for the panel structure of our data in the choice probability as discussed in Train (2009). We use maximum-likelihood methods to numerically evaluate the choice probability integral using 200 Halton draws.

We estimate two separate random parameter logit ("RPL") models for each of the two experimental designs to capture the with-in subject difference in demand for wild-caught bluefin after the introduction of cellular bluefin. The empirical models control for each alternative attribute (price, production method, and sustainability recommendation). Each parameter is assumed to follow a normal distribution which allows us to account for unobserved individual heterogeneity and also allows us to derive the demand curves discussed below as in Caputo et al. (2020). *Price* is specified as continuous while the other attributes are specified as dummy variables with no sustainability recommendation being the reference category in both models and additionally wild-caught being the reference category for production method in the "Post-Cellular" model. We also include an alternative specific constant to capture utility derived from selecting a "purchase" alternative ("ASC-Buy"). The coefficient for this parameter represents the utility derived from purchasing a wild-caught tuna steak with no sustainability recommendation in our experimental designs, and serves as the baseline for the demand curve derivation.

Table 3.3.14 presents the results of the two RPL models. Consistent with economic theory the *price* coefficient is negative indicating a downward sloping demand curve for bluefin steaks. The sustainability recommendations are also consistent with the expected effects in that a bluefin steak carrying an "Avoid" recommendation is associated with a negative marginal utility while a bluefin steak carrying either a "Good choice" or "Best choice" recommendation are associated with positive marginal utility. The relative ranking of the "Good choice" and "Best choice" are also consistent with expectations with the marginal utility of "Best choice" being strictly greater than the marginal utility of a "Good choice" recommendation since a "Best choice" recommendation requires more sustainable practices than a "Good choice." These results are consistent across both models. Focusing on the "Post-Cellular" model we find that cellular bluefin provides less utility to our respondents than wild-caught bluefin similar to previously proposed novel seafood products, such as genetically modified salmon [99].

3.3.14 *Demand curve derivation and calibration*

Using the two sets of RPL model parameters, we follow the methods of Lusk and Tonsor (2016) and Caputo et al. (2020) to derive the demand curves for fresh, wild-caught bluefin in the absence and presence of a cellular alternative. This is achieved by substituting the estimated RPL coefficients into probability equations with the prices of products of interest varied over the range of ex-vessel prices from the empirical demand estimates rescaled to retail price per pound, while the other choice experiment alternatives have price held constant at $30.99/lb. This exercise results in a vector of market shares for the product of interest relative to the other CE alternatives (including the outside option) at each price level. We determined the scaling factor for the empirical supply prices by dividing the median choice experiment price ($30.99) by the median ex-vessel price per pound ($3.35). Thus, we multiplied each ex-vessel price by 6.9 to adjust the prices to retail level for the market share simulation. This is necessary since the RPL estimates rely on choices made at retail price levels.

We next utilize the methods discussed in Section 3.3.7 to empirically derive the global demand curve for all bluefin tuna products (fresh, frozen, or live) coming from any of the three species (Atlantic bluefin (*Thunnus thynnus*), Pacific bluefin (*Thunnus orientalis*) and Southern bluefin (*Thunnus maccoyii*)). From here, we combine the market share estimates and the empirical global demand curve by multiplying the estimated market share of wild-caught bluefin products (relative to the outside option and/or cellular options) by the quantity demanded at each given price. The resulting curve represents the quantity demanded of fresh, wild-caught bluefin tuna. This procedure allows us to estimate the feasible demand shift given the introduction of cellular bluefin tuna products as measured by the percentage change in market share of wild-caughtbluefin products before and after the introduction of cellular bluefin.

	Pre-Cellular	Post-Cellular
ASC-Buy	4.77^{***}	5.67^{***}
	(0.26)	(0.26)
Price ($)	-0.12^{***}	-0.15^{***}
	(0.01)	(0.01)
'Avoid' recommendation	-5.23^{***}	-4.41^{***}
	(0.39)	(0.62)

'Good choice' recommendation	1.21^{***}	1.47^{***}
	(0.12)	(0.10)
'Best choice' recommendation	3.76^{***}	2.71^{***}
	(0.20)	(0.14)
Cell-based		-1.55^{***}
		(0.16)
SD ASC-Buy	2.58^{***}	2.43^{***}
	(0.18)	(0.22)
SD Price ($)	0.06^{***}	0.10^{***}
	(0.01)	(0.01)
SD 'Avoid' recommendation	3.60^{***}	3.81^{***}
	(0.34)	(0.56)
SD 'Good choice' recommendation	1.75^{***}	0.74^{***}
	(0.20)	(0.19)
SD 'Best choice' recommendation	2.09^{***}	1.52^{***}
	(0.24)	(0.17)
SD Cell-based		3.57^{***}
		(0.19)
Log-Likelihood	-3276.90	-3983.05
AIC	6573.79	7990.09
BIC	6638.65	8070.11
Number of choices	4845	5814
Sample size	969	969

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

3.4 Supplemental Discussion

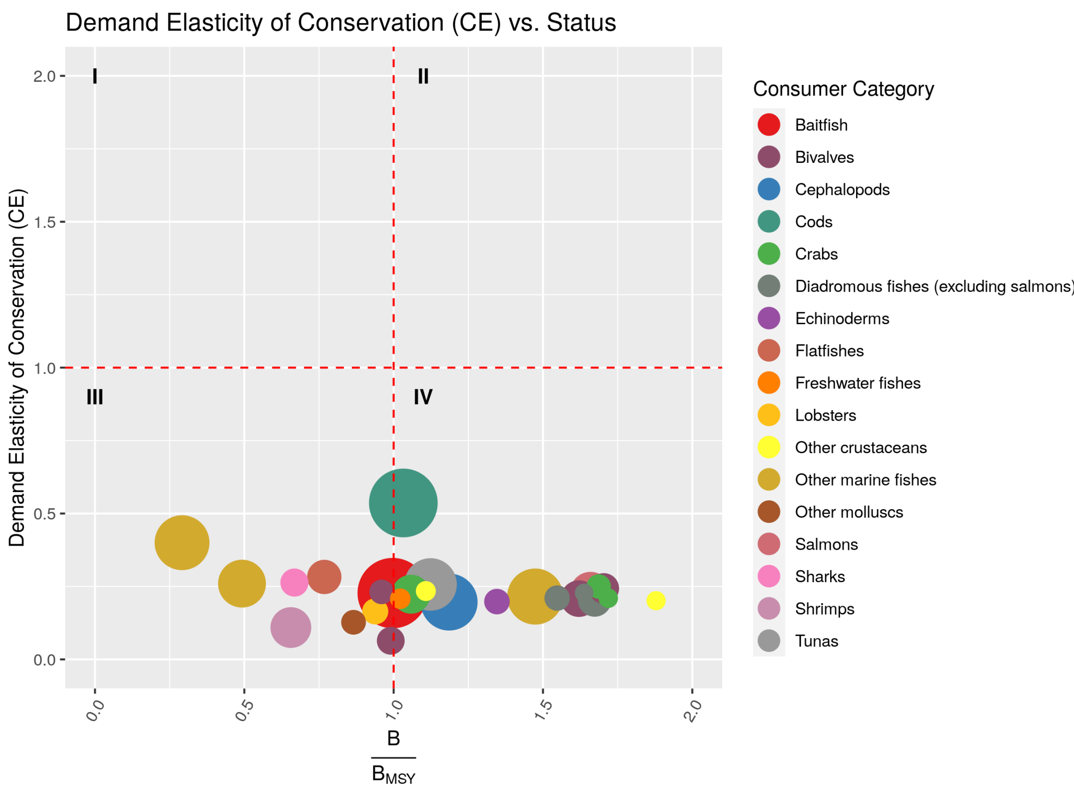

Figure 3.4: Figure 1 from main text but with the shadow value of the stock calculated using the social planners external cost of fishing. The absolute value of the conservation elasticity for each ISSCAAP category. Since biomass is decreasing in demand parameter, A, a measure above 1 indicates a 1% decrease in demand leads to a larger than 1% increase in biomass, where a measure below 1 indicates that a 1% decrease in demand leads to a less than 1% (but greater than 0%) increase in biomass. $\frac{B}{B_{MSY}}$ is considered a standard measure of exploitation where a measure below 1 indicates the stock is over-exploited.

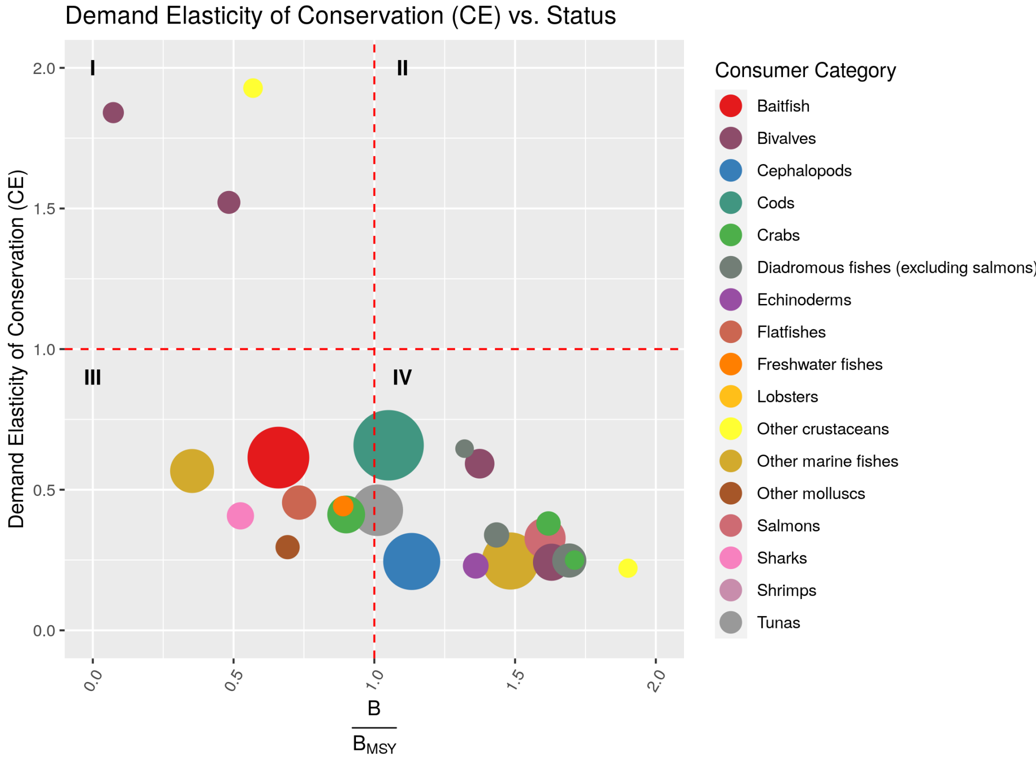

Figure 3.5: Figure 1 from main text but with an inelastic price elasticity of demand, $epsilon_{p,D} = -0.9$. The absolute value of the conservation elasticity for each ISSCAAP category. Since biomass is decreasing in demand parameter, A, a measure above 1 indicates a 1% decrease in demand leads to a larger than 1% increase in biomass, where a measure below 1 indicates that a 1% decrease in demand leads to a less than 1% (but greater than 0%) increase in biomass. $\frac{B}{B_{MSY}}$ is considered a standard measure of exploitation where a measure below 1 indicates the stock is over-exploited.

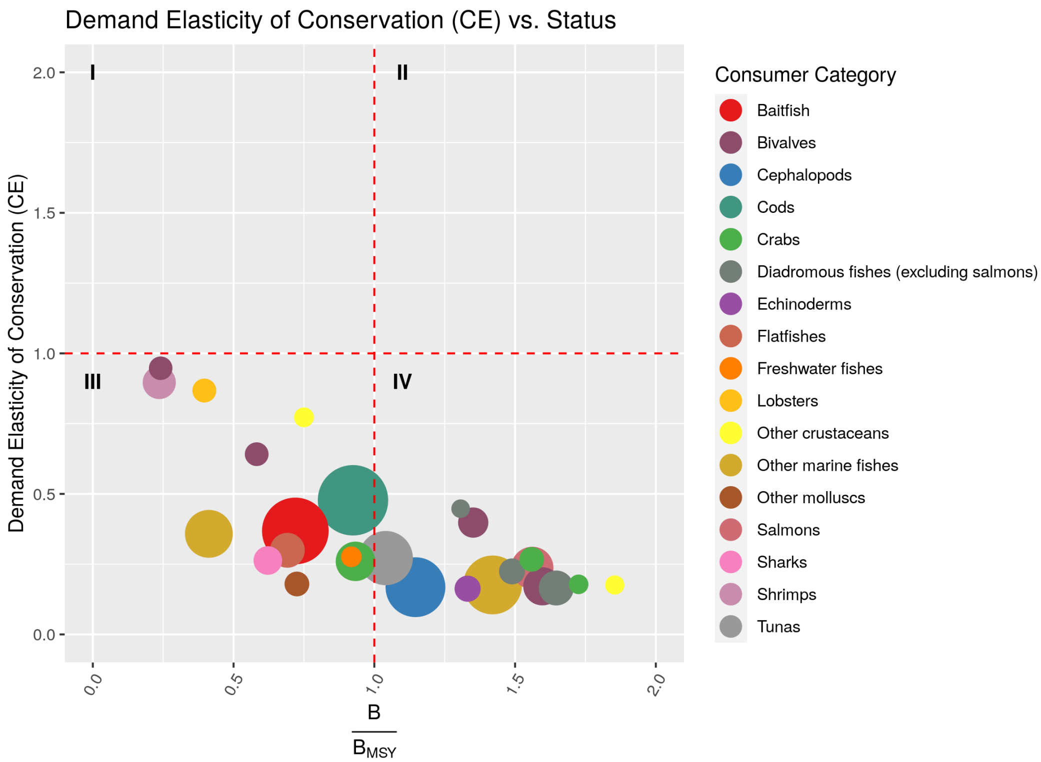

Figure 3.6: Figure 1 from main text but with an inelastic price elasticity of demand, $epsilon_{p,D} = -1.5$ The absolute value of the conservation elasticity for each ISSCAAP category. Since biomass is decreasing in demand parameter, A, a measure above 1 indicates a 1% decrease in demand leads to a larger than 1% increase in biomass, where a measure below 1 indicates that a 1% decrease in demand leads to a less than 1% (but greater than 0%) increase in biomass. $\frac{B}{B_{MSY}}$ is considered a standard measure of exploitation where a measure below 1 indicates the stock is over-exploited.

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