Three Essays on Implementing a Sustainable Circular Economy for Plastics

by

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ABSTRACT

Plastic is a valuable part of the consumer economy, but it creates negative environmental externalities throughout its lifecycle. To reduce these effects, a sustainable circular economy is needed, where more plastic is diverted from landfill or environmental sinks through reduction, reuse, recycling, or composting, while addressing social needs. Although many different stakeholders (industry, academia, policymakers) are calling for a sustainable circular economy for plastics, globally, less than 20% of plastic is recycled with no data on reduction and reuse.

In this dissertation, a mixed methods approach is used to suggest how organizations related to the plastic industry can implement a sustainable circular economy. The first chapter identifies how firms across the plastic value chain can innovate to adopt a sustainable circular flow. A systematic review reveals over 300 examples, which are used to create a material flow typology. Findings summarize five critical points of innovation and indicate that innovation adoption is low. More concerted efforts are needed to improve innovation adoption and there is a need to shift innovation focus from resource efficiency to sustainability. The second chapters studies U.S. plastic recyclers' price signals to generate evidence for favorable recycling policies. A hedonic analysis reveals recyclers preferences for recyclability – plastic properties that enable recycling. Results suggest that adequate recycling infrastructure and absence of virgin plastic can play an important role in facilitating more recycling. In the third paper, the role of governments as consumers is studied. As the largest consumers in a market, governments can signal a large demand for circular products and services, however public administration literature has paid limited attention to it. A theoretical framework is created to fill the knowledge gap and suggest how governments can use sustainable public procurement for a circular economy. A systematic literature review of the top ten public administration journals over 32 years reveals critical knowledge gaps and the potential for important sustainable public procurement research.

DEDICATION

To my parents Shabana Naeem and Syed Muhammad Anzar for raising me to be ambitious and perseverant. Thank you for investing time and money into my education, and for instilling a love of books and critical thinking. Thank you for letting me write my own journey. And thank you for your help in the last leg of my journey – for looking after Ilhan to help me finish what I had started.

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Indeed, there are signs for those who reflect deeply (Surah Ar Rum, Verse 21)

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CHAPTER 1

INTRODUCTION

Plastic is lightweight, durable, and low cost, making it an attractive material choice for many applications. It is used in a diverse set of products, from toys to textiles to building materials. The production and disposal of consumer plastics however have negative externalities. GHG emissions from plastic production may account for as much as 15% of the global carbon budget by 2050 (Zheng & Suh, 2019) as the volume of plastic production roughly triples in that time frame (Lebreton & Andrady, 2019). If consumer plastic waste is landfilled, the value of the embedded material is lost. If landfill systems are inadequate, local water sources can become polluted. Plastic waste can be incinerated, and energy can be extracted, but incineration can create negative environmental impacts such as release of toxic gases (Jay & Stieglitz, 1995; Verma et al., 2016). If plastic waste is recycled, some of its value can be retained, but less than 10% of plastic of all plastic ever produced has been recycled (Geyer et al., 2017b). In addition, poorly managed plastic waste can contribute to land, water, and air pollution, impacting ecosystem services (Geyer et al., 2017a; Prata, 2017). According to one estimate, approximately 8 million metric tons of plastic is leaked into the oceans annually (J. R. Jambeck et al., 2015). Since plastic has a lifespan of 100-400 years, it can continue to adversely impact marine life for a long time (Chiba et al., 2018; James & Grant, 2005; D. E. MacArthur et al., 2016).

Given the potential environmental consequences and the volume of mismanaged plastic packaging, it is critical that the negative effects of plastic packaging production and use are prevented or sustainably managed. A sustainable circular economy for plastic seeks to do this via source reduction, reuse, and recycling. Contrary to the traditional linear economy, a sustainable circular economy aims to keep material in use forever while ensuring an equitable society, social and individual well-being, environmental quality, and economic prosperity (Velenturf & Purnell, 2021). Practically, it reduces material input by producing less, designs out waste through recycling and reuse, and regenerates nature by avoiding waste or using waste in ways that benefit the natural resources such as composting in a socially responsible manner (Blomsma & Brennan, 2017; Ellen MacArthur Foundation, 2017; Geissdoerfer et al., 2017; Ghisellini et al., 2016; Kirchherr et al., 2017). However, less than 9% of the plastic waste is recycled, and the data on plastic reduction and reuse is unknown (Geyer et al., 2017a).

Previous studies have focused on general implementation of circular economy in the electronic, food, fashion industry by evaluating the roles of different private firms (Geissdoerfer et al., 2018; Meherishi et al., 2019). However, a focus on plastic, seems to be missing (J. Jambeck et al., 2015; Meherishi et al., 2019). Since 42% of plastic is intended to be single-use and recycled, this omission is a significant gap in the research. As industries vary due to multiple factors, (Drazin & Van de Ven, 1985), it is important to account for this context, study product-specific circular economy, and identify concrete actions (Calisto Friant et al., 2020).

The current plastic value chain is divided into two independent parts: plastic manufacture and waste management. Typically, plastic manufacturing focusses on designing and producing desirable products for a global consumer base. In contrast, waste management is more local, and is subject to the local infrastructure and policies regarding waste management such that recycling of a product depends on how it was disposed, collected, and the presence of recyclers. Before a plastic product is circularized (reused or recycled), it influenced by multiple organizations. Thus, implementing the circular economy requires substantial improvements throughout plastic's value chain, and support from external stakeholders such as governments in the form of policy changes (Ellen MacArthur Foundation, 2017; Govindan & Hasanagic, 2018; Kirchherr et al., 2018; Merli et al., 2018).

Innovations – i.e. new ideas for institutions, product, process, technology, or policy that can facilitate the current system's transition from a linear to a circular economy are also known as circular innovations (Antikainen & Valkokari, 2016; de Jesus et al., 2016; Guzzo et al., 2019a; Pieroni et al., 2019). Potential circular innovations exist throughout the plastic value chain, from the design of biopolymers at the beginning of the value chain (Huang et al., 1990) to chemical recycling the end of the value chain (Rahimi & Garciá, 2017). While scholars have studied individual innovations, the full extent of plastic circular innovations and knowledge about their adoption remains unknown. To advance implementation of sustainable circular economy for plastics, it is important to identify how different organizations in the plastic value chain can innovate and what are key areas of innovation.

Other systemic barriers to circular economy implementation include support from stakeholders such as governments. Innovations across the value chain should also be supplemented with appropriate government regulations (Blomsma & Brennan, 2017a; Ghisellini et al., 2016; Homrich et al., 2018; Merli et al., 2018). For example, government policies can penalize non-recyclable plastic design, or encourage adequate reuse or recycling of plastics. Increasingly governments are developing policies like the British plastic tax or Break Free from Plastic Pollution Act (BFFPPA) that would tax the producer or provider a subsidy to recyclers (Aguilar-Hernandez et al., 2021; Lowenthal, 2020). These policies indicate a need for evidence that can quantify the penalty or subsidy.

One way to gather this evidence is by listening to recyclers' price signals. By purchasing plastic waste, recyclers send price signals in the market for regarding their demand for recyclable characteristics. Their purchases can be used to differentiate a plastic into its recyclable characteristics and used to identify the non-marginal willingness to pay for plastic waste characteristics. Using this evidence, plastic manufacturers and policymakers have an opportunity to identify the plastic characteristics that enable or hinder recycling and valuate them, which can be used to make effective policies that facilitate the implementation of a circular economy.

Governments can also help implement the sustainable circular economy as consumers in the plastic value chain (McCrudden, 2004). As the largest consumers in the market, government purchases can signal a demand for circular economy (UNEP, 2012). In the past, governments have used their purchasing power to stimulate innovation, empower small and minority owned businesses, and support local manufacture. This use of public purchasing to achieve sustainability goals is known as sustainable public purchasing. While governments are increasingly using sustainable public purchasing as a strategic tool, less is known about it in the public administration. Since public purchasing is a public administrative function, this is a critical omission and hinders the advancement of practical knowledge related to it. By studying sustainable public purchasing and its use in circular economy, public administration can play a critical role in implementing a circular economy.

Among others, there are three critical research gaps related to implementation of a sustainable circular economy: innovation across the plastic value chain, economics of plastic recycling, and the role of governments as policymakers and consumers. In this dissertation, I address these research gaps through a multi-method approach and by borrowing from three disciplines: organizational theory, economics, and public administration. In chapter 2, I conduct a systematic review for innovations across the plastic value chain. I use the to create a material flow typology that suggests how different actors across the plastic value chain can innovate to facilitate a transition to a circular economy. I also assess the level of adoption, to identify important areas of innovation. In chapter 3, use a scrap plastic price dataset from the U.S. to conduct a two-stage hedonic analysis. This reveals recyclers non-marginal willingness to pay for various plastic waste characteristics. In chapter 4, I create a theoretical framework to show how governments can use their purchasing power to implement a circular economy. I then conduct a systematic literature review on public purchasing and sustainable public purchasing across the top 10 public administration journals and use the results to validate the framework and identify research opportunities for public administration scholars.

CHAPTER 2

A TYPOLOGY AND ASSESSMENT OF CIRCULAR INNOVATIONS FOR PLASTIC PACKAGING

Many different stakeholders including scholars and the plastic industry are calling for the plastics sector to be more circular by reducing plastic usage, reusing, recycling, or composting the plastic that we consume (Ellen MacArthur Foundation, 2017). Plastic is called out compared to other materials as a particularly significant challenge given its pervasiveness. Plastic production creates GHG emissions (Zheng & Suh, 2019), and its inadequate disposal can pollute local water sources or generate air pollution (Jay & Stieglitz, 1995; Verma et al., 2016). If plastic waste leaks into the environment, it can impact ecosystem services for up to 400 years (Prata, 2017). These externalities can be prevented by circularizing plastic, however, less than 10 percent of plastic of all plastic ever produced has been recycled and data on plastic reduction and reuse remains unknown (Geyer et al., 2017a).

Among different plastic products, plastic packaging waste is of key concern (Ellen MacArthur Foundation, 2017). Plastic packaging constitutes 42 percent of plastic production and 47 percent of the plastic waste stream (Geyer et al., 2017a; Ritchie, 2018). Less than 20 percent of plastic packaging is recycled globally, the rest is either landfilled or incinerated (European Parliament, 2018; Ian Tiseo, 2020; U.S. EPA, 2017). Stakeholders recognize that the industry will need to increase the adoption of circular innovations - new or modified products, processes, business models, or technology that facilitate the current system's transition to a circular economy (American Chemistry Council, 2020; Blomsma & Brennan, 2017b; De Jesus et al., 2018; Ellen MacArthur Foundation, 2017; Guzzo et al., 2019b).

In this paper, I ask two research questions:

1. What are the types of circular innovations that the plastic packaging industry has adopted?
2. What is the level of adoption of these innovation types?

To identify the types of circular innovation that have been created, I used qualitative research methods. I led a team of graduate students to create an inventory of over 300 circular innovation examples relevant to plastic packaging. Inspired by the material flow of plastics, I observed that these circular innovations could be categorized by identifying the how they enable a circular value chain, i.e., how material ends up being recycled, composted, or reused, as opposed to being landfilled, incinerated, or littered. To answer the second research question, I manually assessed the level of adoption of each circular innovation.

There has been considerable work where scholars have examined the business models and critical success factors that enable firms to create value in a more circular economy. These studies have identified taxonomies and typologies of circular economy business models (Antikainen & Valkokari, 2016; Guldmann & Huulgaard, 2020) at the micro level (Blomsma et al., 2019) and macro level (Guzzo et al., 2019b). This body of research addresses how an individual firm or collection of firms can economically succeed within the new business landscape that emerges within a circular economy.

This study contributes to the literature by adopting a slightly different frame, namely, that of material flow through the whole value chain system. This research does not address which business models a firm can pursue to create value per se, but the innovations that enable those different business models to be successful. Circularity is a value chain level attribute (Konietzko et al., 2020), so this model illustrates how subsequent innovations are path dependent. For a value chain to deliver an outcome of packaging or packaging material that is recycled, composted, or reused, the model specifies that (1) packaging materials and design must be recyclable, compostable, or reusable; (2) the consumer must place packaging in the appropriate material recovery channel; (3) there must be convenient and efficient channels for successful packaging or packaging material recovery; (4) it must be profitable to recycle or compost recovered packaging material, or reuse recovered packaging; and (5) it must be profitable to use recycled or composted packaging material, or reused packaging. Circular innovations address one or more of these points in the overall value chain.

This study also differs from others in focus on a specific material and product category, plastic packaging. While there is value in models that address all sectors' opportunities in the circular economy, plastic packaging is a sector and category that, to date, has failed to achieve much circularity. Plastic packaging is generally only designed for single use, so many of the possible circular business models used in other product categories do not easily apply, or at least require significant innovation to make them feasible. Even in the realm of packaging, plastic has low circularity compared to metal, paper fiber, or glass. In that sense, plastic packaging is an "extreme case" (Flyvbjerg, 2006) that can serve to highlight circular innovations that may not be as significant or relevant in other sectors.

Literature Review

Circular innovations in plastic packaging

Plastic packaging waste has received significant attention in the last decade from multiple types of stakeholders, including corporations, non-profit organizations, consumers, retailers, and policymakers. Over 400 organizations including Unilever, Nestle, Coca-Cola and country level coalitions (US Plastics Pact, UK Plastics Pact) have committed to increase the use of recycled content as feedstock, reduce single use plastic, and experiment with reuse and bioplastics by 2025 through The New Plastics Economy

Global Commitment (Ellen MacArthur Foundation & UNEP, 2020). Non-profit organizations like Plastic Pollution Coalition continue to advocate for elimination of plastic packaging (Cohen, 2021), or increased recycling. Governments around the world, such as Hawaii, California, and most of Europe, have passed strict policies regarding packaging in the form of bans on single-use plastic packaging, or extended producer responsibility to increase recycling of plastic packaging (Bill 40, 2019, p. 40; Directive (EU) 2018/852, 2018). These commitments indicate a need for a circular economy of plastic packaging.

Concurrent with an increase in practitioner attention to these issues, scholars have asked the question, how can firms innovate to transition to a circular economy. Some scholars have answered this question by creating typologies and taxonomies, which provide testable theoretical concepts. Lüdeke-Fruend et al. (2019) studied 26 circular business models and found that businesses can innovate by adopting product or service models that slow the loop, close the loop, retain product value, or retain the material value. In 2019 Blomsma et al. concluded that manufacturing businesses become more circular by adopting innovative business models that reinvent, rethink, and reconfigure, restore, reduce, and avoid, or recirculate parts and products, and recirculate materials. While their taxonomy is focused on manufacturing, it can be generalized to represent a hierarchy of aspiration. At the broadest level, organizations can reinvent the product by changing it into a service and when more aspirant strategies are not feasible, firms can recirculate product by diverting from the landfill (Blomsma et al., 2019). In 2020 Kristensen and Mosgaard identified different ways organizations could adopt a circular economy - recycling, remanufacturing, reuse, resource-efficiency, disassembly, lifetime extension, waste management, and end-of-life management (Kristensen & Mosgaard, 2020). Henry et al.(2020) developed a typology on innovations in business models. They found that organizations can innovate that are design-based, waste based, platform-based, service-based, or nature based. When put together, these studies show that different scholars reached similar conclusions despite different methods. They indicate that organizations need to innovate the product design, end of life management, and adopt different business models.

More recently, in 2021, Aguilar-Hernandez, Rodrigues, and Tukker used meta-analysis to empirically examine the impact of over 300 circular economy scenarios from 2020 to 2050 on Gross Domestic Product (GDP), employment, and CO_2 emissions. They considered three types of circular innovations: resource taxes to reduce material extraction, technology changes to improve resource efficiency, and modification in consumption patterns (Aguilar-Hernandez et al., 2021). Unlike the other four studies, these innovations are implemented by an organization's stakeholders such as policy makers, suppliers in a value chain, and the consumers. The choice of innovations indicates that a transition to circular economy requires innovations from stakeholders like policymakers, suppliers, and customers.

Much like academic scholars, practitioner organizations have also been working on identifying areas of circular innovation and their work is more specific to plastic or plastic packaging. The Ellen MacArthur Foundation New Plastics Economy report (Ellen MacArthur Foundation, 2017) identified 10 key enabling technologies that are categorized under three strategies: creating an effective market for recovered materials, reducing environmental leakage, and decoupling plastics from fossil fuel feedstocks. The American Chemistry Council (American Chemistry Council, 2020) identified six focus areas for plastic innovation: value chain engagement, consumer engagement, access to recycling, collecting, and sorting, recycling efficiency, and end market economics. In a similar structure, The EU Commission report on a circular economy for plastics (Crippa et al., 2019) organized their recommendations into seven categories: new materials, bio feedstock, product and service design, collection and sorting, mechanical recycling, chemical recycling, and organic recycling. Closed Loop Partners identified three general types of innovations enabling circular systems: materials innovation, new business and delivery models (refill & reuse, rent & re-commerce), and transformational technologies (digital, material) (Closed Loop Partners, 2020). Together these reports suggest need for systemic innovation to transition to a circular economy for plastic packaging.

The existing relevant literature addresses which business model or product, or process innovation can create value for a firm. Circularity however is a value chain level attribute (Konietzko et al., 2020) – firms can play a role in making a value chain more circular but cannot do so by themselves. The plastic "problem" is indeed a problem at the level of the whole economy, so there is an opportunity to examine circular innovation not in terms of its value to individual firms, but rather as system-level solutions that enable circularity in the value chain and account for the path dependence of a supply chain. While the existing literature has identified need for innovative solutions from multiple actors, an explicit system level focus in missing. The existing literature also has a broad focus on all sectors' opportunities in the circular economy. This paper instead focuses on a single sector and category, plastic packaging. Because the global economy has not succeeded in making the plastic packaging value chain circular, this focus serves as an extreme case (Flyvbjerg, 2006) that can highlight circular innovations that may not be as significant or relevant in other sectors.

Plastic packaging circular innovation adoption

While identifying areas of innovation critical for a transition to a circular economy, it is also important to assess their level of adoption. The latter can help scholars and the industry recognize innovations areas that are lagging and require more effort. Innovation adoption is considered a system-based process (Adner, 2017; Rogers, 2003; Ven et al., 2008). According to innovation scholars, an innovation is adopted when an organization recognizes the need for innovation and makes changes to facilitate its implementation. It reaches a stage of diffusion when it has been implemented by a critical fraction of adopters in a social system. To reach a critical fraction, organizations need to rely on effective communication channel, characteristics of social networks, time, and enabling technology by other members of the system.

The studies cited above that have created typologies and taxonomies of circular innovation types have generally not studied how broadly these innovations are adopted. The ten “moonshot technologies” discussed in the Ellen MacArthur Foundation (2017) are categorized into four categories of maturity: research and development (reversable adhesives, removing additives, super-polymers, depolymerization, benign in marine environments, benign in freshwater environments); pilot (chemical markers, GHG-based feedstock); scaling (none identified); and mature (near infrared scanning, bio-based feedstock).

Other empirical data infers that the adoption of circular innovations for plastic packaging is probably low because recycling, reuse, and composting rates are so low, less than 10% (Geyer et al. 2017). Some adoption data exists for some relevant circular innovations (Closed Loop Partners, 2020; Schroeer et al., 2020; Tiseo, 2021). Bioplastics represented 5% of the global plastic market in 2020 and is expected to account for 40% by 2030 (Tiseo, 2021); Closed Loop Partners found 60 technology providers in the U.S. and Canada operating in the chemical recycling space (2020); according to Oceana (Schroeer et al., 2020), refillable bottle use went from 34% to 20% globally over the last twenty years (but that data is not material specific). While a few adoption estimates exist, I could not find any study that used a common means to compare levels of adoption.

This is especially true when the adoption rates are very low. Two innovations may be both at (e.g.) one percent adoption, but one may be in an experimentation stage and the other in a commercialization stage, so these methods will address this gap.

Methods

Finding and categorizing circular innovations

To answer the first research question**,** I employ qualitative and conceptual methods to create a typology. Typologies and taxonomies are types of classification; a typology is typically developed from a conceptual basis, whereas a taxonomy is developed from an empirical basis (Bailey, 1994). Classifications provide several theoretical and practical benefits: description, reduction of complexity, identification of similarities, identification of differences, presenting an exhaustive list of dimensions, comparison of types, management of types, study of relationships between types, criteria for measurement, and versatility.

I began with a search to identify circular innovations relevant to plastic packaging. Since innovations are typically associated with different stages of the plastic packaging value chain, I created a value chain model. This identified seven stages: polymer design and production, packaging design, packaging reuse, packaging disposal, waste collection and sorting, waste treatment, and recycled content use. An eighth type that can have impact across the value chain, policy, was added. I examined publicly available practices, policies, and technologies, such as journal articles, mass media, social media, company and industry web sites and reports, government, and NGO reports (but excluded patents) using Google search engine. I did not use patents or other proprietary information because I wanted to be able to publicly share these results. To find circular innovation examples, multiple researchers used a standardized key word template to find relevant citations. These innovations at the specific value chain level were new or modified product, processes, business models or technologies that could reduce, reuse, recycle plastic waste. They were not listed as "circular innovations"

The examples were presented to numerous subject matter experts from academia, corporations, NGOs, and governments to obtain additional examples of circular innovation. Representation from eight different webinars included over 150 participants, from organizations such as feedstock producers, polymer and monomer manufacturers and related associations, packaging designers and manufacturers, retailers, and environmental organizations.

The innovation examples differed in the way that they enabled and supported circular material flow in the value chain. For example, recycling labels are meant for the consumer of the packaging and are meant to ensure that the consumer places the packaging in the appropriate recovery channel (recycling, composting, or landfill). Conversely, optical sorting technology operates downstream from the consumer, and ensures that if a non-recyclable packaging was put into the recycling recovery channel, it is removed to ensure purity of the recovered recyclables. These are both "critical points" in the success of circular flow. These are also path dependent.

Applying this mapping to the inventory of circular innovations, I identified five such critical steps in the value chain. For a plastic packaging value chain to yield packaging or packaging material that is recycled, composted, or reused, (1) packaging materials and design must be recyclable, compostable, or reusable; (2) the consumer must place packaging in the appropriate material recovery channel; (3) there must be convenient and efficient channels for successful packaging or packaging material recovery; (4) it must be profitable to recycle or compost recovered packaging material, or reuse recovered packaging; and (5) it must be profitable to use recycled or composted packaging material, or reused packaging. Circular innovations were categorized as addressing one or more of these critical points in the material flow. Thus, this typology is in the form of critical material flow. It summarizes the value chain to five critical points that must happen to allow a successful circular economy.

Determining the adoption of circular innovation types

To answer the second research question, multiple coders used the results from question one to code how broadly adopted the innovation type is. For each innovation, I assessed whether the innovations were in a theoretical (only) stage, in experimentation, in commercialization but not widely adopted, or in an active innovation adoption and diffusion stage (Desouza et al., 2009; Schmidt-Tiedemann, 1982), as shown in Table 2.1.

Table 2.1

Rubric for Innovation Adoption Level

Adoption Level	Criteria
Theoretical	Untested idea found in an academic article, or news article
Experimentation	Idea was tested in an academic article, but no product page could be found
Commercialization	Innovation is in start-up phase, it has been tested, but is not being commercially sold
Diffusion stage	Innovation has been commercially adopted by more than one organization

For each innovation example, the publicly available information was examined according to the rubric in Table 2.1 to find evidence indicative on the different adoption levels. For example, if an innovation was discussed conceptually but had no evidence of being physically tested, it was considered in a theoretical stage. Conversely, if adoption was large enough for numerical estimates to be published about its adoption, it was considered in diffusion stage. I created two frequency charts to summarize the results from this analysis.

The first chart summarizes the number of innovations across each adoption level. This shows which adoption level is most prevalent among plastic packaging circular innovations. The second frequency chart groups the adoption level across the material flow typology. This chart demonstrates the variation in adoption level within each critical point.

Results

A typology of plastic packaging circular innovations

As mentioned in the Methods section, the plastic packaging value chain was chosen as the conceptual basis for constructing the critical material flow typology. The innovation types are summarized in Table 2.2. A detailed version with examples is listed in the appendix.

Table 2.2

A Typology of Plastic Packaging Circular Innovations

Material Flow Typology	Innovation	Example
Packaging design: Packaging materials and design must be recyclable, compostable, or reusable	Chemically recyclable polymers	Polydiketoenamine
	Straw-less lids	Starbucks
	Reversible Adhesives	DSM
	Bioplastics films for food packaging	BioPBS
	Single-layer packaging	PAXXUS
	Post-consumer recycled plastic	Epopak
	Reusable packaging	Starbucks
Consumer behavior: The consumer must place packaging in the appropriate material recovery channel	Educational labels	How2Recycle
	Consumer education program	Learning & Living Green
	Door-to-door collection program	Kabadiwalla Connect
	Bottle refund program	CalRecycle
	Food delivery in reusable boxes	Dabba Drop
	Stores that promote reusable containers	Miwa
	Rewards for reusable packaging	Target
Material recovery: There must be convenient and efficient channels for successful packaging or packaging material recovery	Collect waste from oceans	The Ocean Cleanup
	Efficient logistics for garbage trucks	FleetMind
	Automated waste sorters at MRFs	Max AI
	Online scrap trading platforms	Birch Plastic
	Informal cooperatives for waste collection	WEIGO
Material treatment: It must be profitable to recycle, or compost recovered packaging material, or reuse recovered packaging	Automated washer	Vecoplan
	Deinking	Cadel Deinking
	Twin extrusion	Coperion
	Low energy depolymerization	PET Hydrolase
Material reuse: It must be profitable to use recycled or composted packaging material, or reused packaging	Closed-loop recycling	Amcor
	Plastic roads	Plastic Road
	Local use of recycled materials	Plastic Bank
Policy: Impacts multiple failure modes	Extended Producer Responsibility (EPR)	Green Dot System
	Bag bans	Bag Ban
	Taxes on single-use plastics	UK Plastics Packaging Tax

Packaging design

Packaging design consists of selecting the format of the design as well as the material(s) to be used. These decisions are related in that different materials will be fit the purpose for any given packaging format. During packaging design, design for circularity is only one dimension of a complex decision. Cost and functionality must be considered, and the best packaging design may be format or material that is less than optimal in terms of its ability to be recycled, composted, or reused.

Monomer and polymer manufacturers can design polymers that remove barriers to circularity. Some examples include polymers that are safe for marine life, biodegradable (Dorgan et al., 2001), automatically sortable (Woidasky et al., 2020), chemically recyclable at low cost (Christensen et al., 2019), or biobased (Anjum et al., 2016). Manufacturers can also make bio-based plastics more circular by producing them using waste from food, agriculture, or fisheries industries (Tsang et al., 2019). They can also upscale their production using sustainable, micro-biorefineries such as wastewater treatment plants (Anjum et al., 2016).

The design and format of the packaging also makes it more or less likely to be circulated. Firms can redesign packaging to avoid components that are less likely to get recycled or reused. Brands can use straw-less lids (Warnick, 2019), reversible adhesives for labels (Hoex, 2018), bioplastic films for food packaging barriers, or single material instead of multiple materials that are easy to recycle. Firms can also keep material in the loop for longer by using recycled plastic instead of virgin plastic or developing products that can be reused such as trigger bottles.

Consumer behavior

After the packaging is used, it must get placed into an appropriate recovery channel for recycling, composting, reuse, or landfilling. A plastic package becomes either contamination, a societal cost rather than revenue, or creates less value from circularity, if the consumer does not place the packaging in the appropriate channel. Research shows that for people to adopt a behavior, they must be aware that action is required, they need to be motivated to take the action, and be capable of doing so (Chen et al., 2007). In this value chain, this means consumers must be aware that putting the packaging into a recovery channel other than landfilling is feasible and desirable, they need to be intrinsically or extrinsically motivated to do so, the need to know how to do so, and it needs to be convenient. For example, recycling is more likely to work if curbside pickup is available versus a consumer needing to travel to a recycling location.

To encourage reuse, retailers and product manufacturers can redesigning common items so that the need for single-use packaging is eliminated. Some examples include bulk grocery stores where customers bring their own reusable containers (Miwa, 2019), and food delivery in reusable tin-boxes (Hoole, 2019), which the company can circulate. Retailers can also use economic incentives and disincentive that discourage customers from using single-use packaging (Homonoff, 2018).

Packaging can have labels which inform consumers whether the package can be recycled or composted (Nemat et al., 2019), and sometimes, how it can be recycled. For example, a package may indicate that a cap should be retained on the beverage bottle when placing in the recycling bin. Additionally, companies and governments can provide recycling or composting education and ideas in web sites and in social media campaigns (So & Chow, 2019). Upstream manufacturers can motivate consumers by simplifying the decision-making process for them and reducing the decision fatigue related to recycling such as through mobile applications on recycling. Downstream waste collectors can motivate consumers by providing convenient waste collection such as door-to-door collection programs, or monetary incentives such as the bottle-refund program.

Material recovery

Waste collectors can facilitate a circular economy by making waste collection more efficient and monetizing it. More waste can be collected by accessing challenging areas such as oceans (Rochman, 2016); fewer resources can be consumed by using data-based logistics system for garbage trucks, so that they are only deployed when the waste container is full (Vicentini et al., 2009). Material Recovery Facilities can automate the waste sorting process to allow large volumes of plastic waste to be sorted in less time by using optical or AI based sorters (Gundupalli et al., 2017). In developing countries with informal economies, informal waste collectors have organized into waste cooperatives to increase their profit margins (Wilson et al., 2009). Some organizations in developed countries have created online trading platforms to trade scrap plastic waste on a global level (Suthar et al., 2016).

Material treatment

If all has succeeded to this point, a recyclable, compostable, or reusable package has made its way successful into the correct material recovery channel. Infrastructure and technology to perform recycling or composting, or logistics to enable reuse is necessary but not sufficient for the value chain to remain circular. These systems also must be profitable. When municipalities become financially stressed, they may cancel recycling services of certain materials that cost or have insufficient margins. For private operators in the system, low margins lead to challenges in serving smaller markets and likely less R&D investment. Thus, innovations that impact this failure mode tend to enhance profitability through efficiency improvements.

There are two main pathways for waste treatment of plastic packaging that leads to circular flow – mechanical and chemical recycling (which includes composting). Mechanical recycling is much more broadly adopted so its innovations are primarily around efficiency improvements, while chemical recycling is a less developed technology which is still exploring different dominant designs (Closed Loop Partners, 2020). For mechanical recycling, innovations in pre-recycling treatments play a key role by improving the quality and performance of the recycled product such as automated washing and deinking. Innovation in chemical recycling aims at optimizing design of the conversion processes, which includes achieving scale in an economically feasible way, purifying input streams, and reducing the amount of energy required (Closed Loop Partners, 2020).

Material reuse

Once waste is collected, a circular economy can be implemented by creating economies of scale for recycled plastic. For the circle to be complete, the recovered and recycled content needs to be used. In a true closed-loop system, plastic packaging is recovered and remanufactured as plastic packaging once again (Hahladakis & Iacovidou, 2018). This is practically uncommon, because of mixed waste streams and the high cost associated with separating plastic packaging from its products (Hopewell et al., 2009b). It is common however for packaging designs to include post-consumer recycled content, which will likely be a mix of packaging and non-packaging. So-called upcycling occurs when recycled content is used in a non-packaging application where the plastic increases the value of the material it is being added. These can include composite-based products like plastic roads using asphalt (Siddique et al., 2008), and precision tools with 3D printing (Pakkanen et al., 2017).

Policy

Policy can impact any stage of the plastic packaging value chain. For example, land-use policies may incentivize, or not, the adoption of renewable biomass feedstock (Jensen et al., 2007). R&D related policy may be targeted at perceived opportunities for economic growth and intellectual property, such as chemical recycling. Taxes, bans, and levies can be used to encourage consumers to reuse packaging, or as a form of extended producer responsibility to pay for waste treatment infrastructure (Abbott & Sumaila, 2019).

Figure 2.1

Adoption Level of Circular Innovations for Plastic Packaging

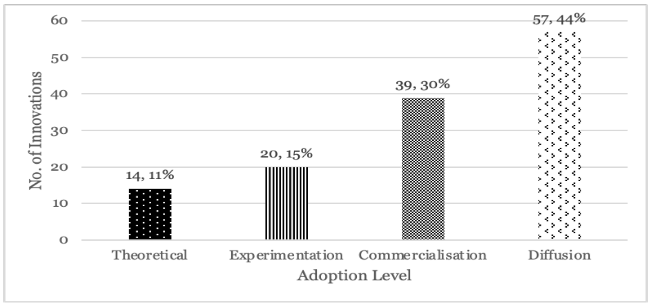


Figure 2.1 shows the typical level of adoption across all plastic packaging circular innovations: in a theoretical (only) stage, in experimentation, in commercialization but not widely adopted, or in an active innovation adoption and diffusion stage (Desouza et al., 2009; Schmidt-Tiedemann, 1982).

Out of 130 innovations, 11% are in the theoretical stage, 15% in experimentation, 30% in commercialization, and 44% in diffusion.

Figure 2.2

Adoption Level of Circular Innovations for Plastic Packaging Across Critical Material Flow Points

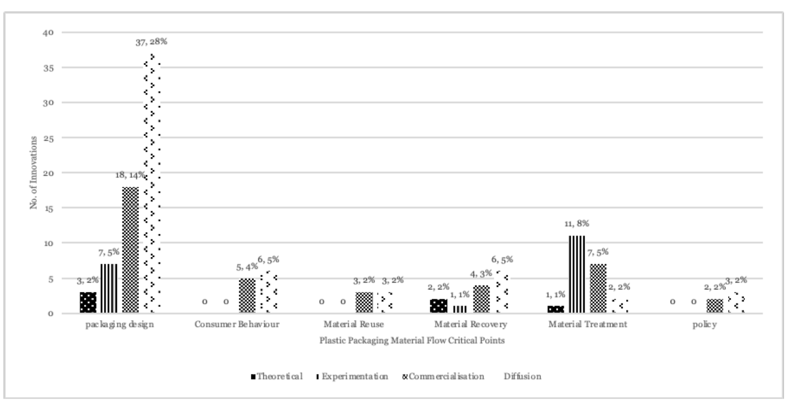


Figure 2.2 represents innovation adoption across the five critical material flow points. The highest number of innovations were at the packaging design stage, collectively making up 50% of the innovation categories. It was followed by material treatment,

which made up 16% of innovation categories. A lower number of innovations was observed for the other 4 critical flow points: consumer behavior (8 %), material reuse (5%), material recovery (10%), and policy (4%).

These results also show varying innovation adoption across each of the critical points. For example, within material treatment, 1% innovations are in theoretical stage, 8% in experimentation stage, 5% in commercialization stage, and 2% in diffusion stage. While Innovation diffusion appears to be the most dominant level of innovation adoption, it is not necessarily so across each of the critical material flow points.

Discussion

Here, I share a few other observations that are useful to share.

High circular flow requires synergies across the value chain

Successful circular innovation requires or benefits from complementary innovations, innovations needed to support the diffusion of another innovation (van Loon et al., 2021). Consider composting of bioplastic packaging – circular success depends on biopolymer design and production, but also the waste collection and composting infrastructure that makes, among other things. An innovation on its own is not enough, other actors must innovate to support it (Adner, 2017). In the case of bioplastics, these co-inventions are necessary to achieve circularity. Any attempt to study the full extent of product specific circular innovation must account for innovations by other actors. van Loon, Diener, and Harris indicate (2021) that studies of circular economy that don't consider synergistic effects between co-innovations probably don't accurately estimate the potential effects of sets of circular innovations.

In some cases, significant performance improvement (via innovation) in one performance dimension may reduce the need for performance improvement in another dimension. For example, recycling labeling and consumer awareness tend to tradeoff with innovations in automated sorting, where improvement in one lessens the need for improvement of the other.

Circular innovation types also act as mitigations against risks elsewhere in the value chain. For example, eliminating multi-format packaging (a packaging design innovation) helps mitigate a lack of waste sorting or waste treatment technology needed to recycle a multi-format design. Likewise, having sorting and treatment occur prior to recycling, but after initial sorting, can reduce contamination that was not captured in the first material sort. Because of these required or desired synergies, this suggests investment in one type of circular innovation without investments in others will leave significant circularity improvements on the table. Thus, future circular innovation studies should assess how important it is to adopt sets of related innovations in particular contexts.

Why is the rate of adoption low?

Despite the large number of technologically and economically feasible circular innovations in the plastic packaging industry, plastic recycling rates globally remain low. How can there be so much innovation with so little impact on overall circularity? According to diffusion of innovation theory, "diffusion is the process by which innovation is communicated through certain channels over time among members of a social system" (Rogers, 2003). Moore's "innovation chasm" phenomenon sheds more light on innovation adoption in the social system(Moore, 2014). In Moore's model, innovations get adopted by early adopters because of novel technological capabilities but fail to get adopted by the early majority because, as pragmatists, they are looking for other attributes to incentivize adoption.

For example, while innovation has existed for a long time in chemical recycling, there is still not broad adoption in part because of the excessively long time it has taken for companies in that area to reach business maturity (approximately 17 years) (Closed Loop

Partners, 2020). This leads to a lack of financial investment in the technology, which delays economies of scale that would make adoption more economically feasible. Some innovations are adopted broadly in developed economies but not in developing countries (e.g., AI-based waste sorting) simply because of the cost barrier to acquiring and operating the technology. Some circular innovations, such as upcycling of recycled plastic, are not broadly adopted largely because existing infrastructure and supply chains are not easily compatible with the innovation, and the initial capital expenditures needed to adopt the circular innovation are significant.

Scholars suggest that most firms target the top or middle tier of the market through their innovations, leaving the vast bottom tier, comprised of low-income customers, without access (Hart & Christensen, 2002). While this strategy is widely adopted for innovations, it prevents adoption of innovation on a vast scale. In order to ensure that an innovation is adopted across the globe, it is important that innovators pay close attention to affordable solutions for the "bottom of the pyramid" (Anderson & Billou, 2007; Hart & Christensen, 2002). An innovative affordable solution can be upscaled for the upper tiers of the market. However, an expensive innovation is very challenging to scale down for the bottom tier. A crisis like the plastic leakage, requires circular plastic innovation adoption across the value chain in all parts of the plastic-using world.

Should circularity include secondary material flows?

The innovations discussed in this paper focus on circularity of plastic packaging – but I came across other innovations that address circularity in secondary or tertiary material flows. For example, drill bits used to mine for fossil-fuel feedstock can be made to be repairable, extending their life (Tariq et al., 2017), and the refinery process itself uses waste from one process as input to another (Singh, 2019). Packaging can be designed so that it minimizes food loss, and it helps the consumer avoid use excess product. All processes in a value chain can be fueled by renewable energy, making their operations more circular. This system-level circularity is typically outside the scope of many CE discussions and studies. Scholars should broaden the scope and think about how plastic is produced or whether the way plastic is produced is circular.

Conclusion

This paper explores circular innovations for plastic packaging. In this paper, I have identified five critical points in the plastic packaging material flow that can enable circularity. A plastic packaging value chain can yield material flow that ends in recycling, composting, or reuse if packaging materials and design are made to be circular, the consumer handles the packaging correctly, there are convenient and efficient channels for material recovery, if it is profitable to treat recovered material, and if material can be profitably reused. Circular innovations support success at one or more of these critical points.

The paper also contributes to the literature by highlighting the level of adoption for circular innovations for plastic packaging. I find that adoption of innovation types is at various stages: experimentation, commercialization, and diffusion. Although some innovations are in use (at commercialization and diffusion stages), they seem stuck at current low levels of adoption, unable to rapidly grow as one would expect in a transition to a more circular economy. Among the six material flow points, packaging design is most popular.

Through these results, the paper provides justification for future research on innovation adoption of plastic packaging circular innovation. I also offer some insights about circular innovations, and their adoption. Circularity is systemic, so the plastic packaging industry should consider how different actors in the system can innovate to adopt circular innovations. This typology provides one lens to look at it. Scholars can ask other system-oriented questions such as what factors motivate organizations to adopt plastic circular innovations; what are barriers to adoption of plastic circular innovation; how can external stakeholders influence adoption of plastic circular innovations?

This study focuses on a single-use material – plastic packaging. While the typology derived from this study is generalizable, future research should investigate circular innovations in other plastic products that are more durable and other materials. Scholars have an opportunity to identify how circular innovations for various kinds of products can vary. This can reinforce a key point – different industries must adopt different approaches to transition to a circular economy.

The study also has other limitations that could be addressed in future research. The study did not incorporate patent data. There is academic debate as to whether patents are good (or complete) indicators of innovation (Gittelman, 2008). While I do not believe patent examples would have changed to typology, such data can indicate, for certain innovation types, trends in research and development investment.

It is also a limitation that my research questions do not have provable answers. A typology is not right or wrong, it is judged on validity and utility. The intent of this paper was to argue that the typology developed has logical, empirical, and face validity. Future use by academics and practitioners will judge the utility of it. Despite these limitations, these conclusions stand on a foundation of relevant theory and rigorous empirical methodologies.

CHAPTER 3

ESTIMATION OF RECYCLER DEMAND FOR RECYCLABILITY - EVIDENCE FOR RECYCLING POLICIES

Mechanical recycling is one way of circularizing plastic packaging. The waste industry currently recycles about 10% of the plastic waste (Geyer et al., 2017; WEF, 2016). Among other recycling options, chemical recycling and thermal recycling, mechanical recycling has been widely adopted around the world (Hopewell et al., 2009; MacArthur, 2013). Chemical recycling is still being commercialized and thermal recycling requires large scale infrastructure (CLP 2020). As compared to mechanical recycling, they are both resource intensive, as they require non-contaminated, clean material, high energy, and large-scale plants. In comparison, mechanical recycling is a widely adopted technology that is prevalent across developed and developing countries on both large scale and small-scale (CLP 2020). While recycling infrastructure is available across the world, less than 10% of all plastic waste is recycled (most through mechanical recycling).

Mechanical recycling is effective only when the consumers have adequately disposed plastic waste, waste collectors have collected plastic waste, and it has been cleaned, segregated adequately as required for the material, and there is a market for recycled plastic. Plastic is often not recycled because the costs of recycling are higher than the value of recycled plastics (Hopewell et al., 2009). It is cheaper to manufacture plastics than to recycle them. Anecdotal evidence suggests that recyclers often compete with the low virgin plastic prices to make recycled plastic profitable. To increase mechanical recycling and develop relevant policies, it is important to understand the cost and value of circularizing plastic waste, also known as scrap plastic.

Scrap plastic is usually a bundle of different properties. Scrap plastic bundles can look like a bundle of PET bottles collected from curbside or a bundle of plastic film made of

HDPE, LDPE, and PP. Among different kinds of scrap plastic, recyclers value some bundles more than others. For example, recyclers tend to prefer post-industrial plastic more than post-consumer plastics. In other cases, recyclers pay more for certain plastics that have low costs of recycling or higher potential for return. Similarly, recyclers pay more for non-colored, clear scrap plastic as compared to colored (Pacini & Golbeck, 2020). The variations in prices suggest that some scrap plastic is more desirable to recyclers than others or that some scrap plastic is more recyclable than others.

Economists suggest that scrap plastic can be broken down into its recyclable features using hedonic analysis (Bigelow et al., 2020; Lancaster, 1966; Ma & Swinton, 2012). The hedonic method is a revealed preference valuation technique which is specifically useful for cases where substitute market goods have different qualitative attributes in which consumers of the goods are aware of the characteristics and compete in a marketplace such that the traits lead to products commanding different prices in equilibrium. In the hedonic method, a market good such as scrap plastic can be broken down into its non-market characteristics (recyclability) that a firm might value (Lancaster, 1966; Ma & Swinton, 2012; Rosen, 1974). For scrap plastics, economists can use the method to assess the characteristics that recyclers value, their marginal willingness to pay (MWTP) for recyclable characteristics.

In the past, this technique has been applied to housing, farmland, and other differentiated goods like electronics or automobiles (Bajari & Kahn, 2005; Mendelsohn et al., 2006; Palmquist & Smith, 2003). However, to the best of my knowledge, such an analysis does not yet exist for distinct types of scrap plastic on a global scale.

To fill this gap, I ask the research questions:

- What are the recyclers' marginal willingness to pay for indicators of recyclability?

- What can policymakers, plastic industry, and waste managers learn from it?

Literature Review

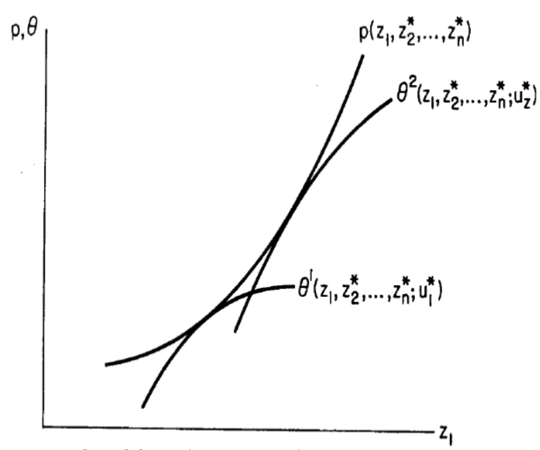
History of Hedonic Modeling

The hedonic model presumes that there is a market in equilibrium where a market good (x) such as scrap plastic can be described through a set of measurable characteristics $z = (z_1, z_2, \dots, z_n)$(material properties, physical condition), to reveal their characteristic prices $p(z) = p(z_1, z_2, \dots, z_n)$. The firm, recycler (k), maximizes their profit $V_k(x, z_1, z_2, \dots, z_n)$ subject to a cost constraint $y - p(z)$, which is the difference between firms costs and characteristics' prices. Using first order conditions for profit maximization, $p'_z(z) = V_z(x, z_1, z_2, \dots, z_n)/V_c(x, z_1, z_2, \dots, z_n)$. This condition provides two key pieces of information: characteristic prices, and their demand.

A simple two-step method can be used to estimate both prices and demand for characteristics. As a buyer of the scrap plastic, each recycler in the market has a demand function for a certain set of characteristics $\theta(z; u, y)$. The loci of maximums at each demand curve form the price function for the characteristics $p(z_1, z_2, \dots, z_n)$ as shown in Fig 3.1.

Figure 3.1

Demand Curve and Implicit Prices



Reproduced from (Rosen, 1974)

Although the demand function for recyclers is unknown, the implicit prices for each characteristic can be recovered through a regression. By regressing quantities of characteristics on the price of scrap plastic, implicit price of each characteristic can be identified. Since there is a relationship between goods and characteristics, it can be written as shown in (1).

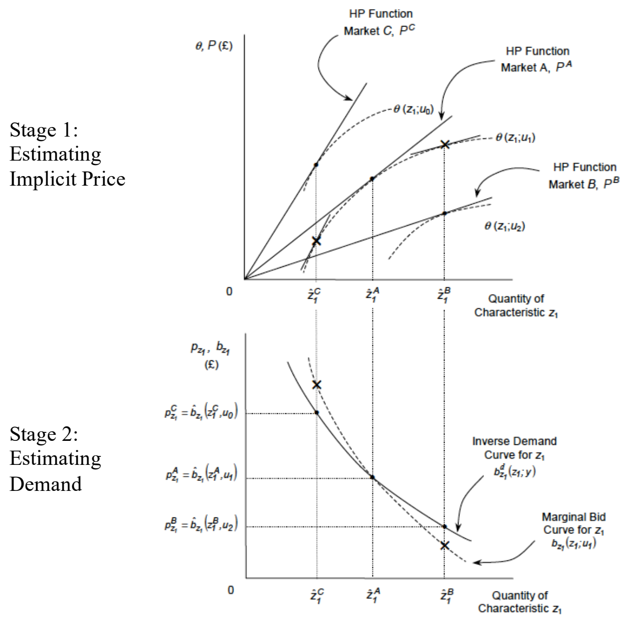
$$p_j = \alpha_{0,j^*} + \alpha_{1,j^*}\mathrm{z}_1 + \alpha_{2,j^*}\mathrm{z}_2 \ldots + \alpha_{n,j^*}\mathrm{z}_n + \xi_j \qquad (1)$$

(1) shows price on the left-hand side and observed characteristics ($\mathrm{z}_1 \ldots \mathrm{z}_n$) on the right. The coefficients from regression are represented by ($\alpha_{1,j^*} \ldots \alpha_{n,j^*}$), which indicate the price of one unit of characteristic, also known as characteristic price. α_{0,j^*} represents the minimum price when the characteristic value is set to 0. The error term (ξ_j) reflects unobserved characteristics, as there are many characteristics such as number of reuses of a plastic, that economists will not be able to observe.

The second step helps estimate the unknown demand function. It is known that the maximums on each individual demand curve form the characteristic price function as shown in Fig 3.1. Using this knowledge, price function can be decomposed econometrically to recover at least a few points on the demand curve. In theory, these points can be used to estimate the overall demand function. To estimate the demand function, quantity of characteristics can be regressed on to coefficients ($\alpha_{1,j^*} \ldots \alpha_{n,j^*}$) from the first regression and other demand instrumental variable, as shown in Fig 3.2 (Brown & Rosen, 1982; Palmquist, 1984).

Figure 3.2

Demand Curve from Implicit Prices



Reproduced from (Day, 2001)

Economists use this multi-market approach because an OLS regression significantly reduces the number of datapoints for a second regression. For example, if a scholar estimated scrap plastic characteristics prices in Atlanta for 7 characteristics, they would find one implicit price for each characteristic. Thus, making the second regression, impossible. To address this challenge, data from various locations can be used under the assumption that each location is an independent market, so that the price variation in the resulting characteristic prices can be used to identify points on the demand curve as shown in Figure 3.2.

It is challenging to assume that scrap plastic has independent markets because it is traded nationally and internationally. A single market model that gets around this limitation would be more reasonable. It is yet to be tested whether different regions are independent markets for scrap plastics or whether they can be reasonably assumed to be a single market.

However, this method of estimating prices and non-MWTP is controversial in the literature (Brown & Rosen, 1982; Ekeland et al., 2002; Heckman et al., 2003; Palmquist, 1984; Rosen, 1974). There are three main challenges with this technique: 1) identifying the correct functional form of characteristics' prices $p(z_1, z_2, \dots, z_n)$, 2) method's application in a single market, and 3) omitted variable bias (Abbott & Klaiber, 2011; Brown & Rosen, 1982; Ekeland et al., 2002).

New Techniques for Hedonic Modeling

To address the challenges, some economists have presented a new method of performing the hedonic analysis. They start by imposing restrictions on the indirect utility functions, and assuming that the relationship between utility, and preference parameters is known (Bajari and Kahn 2002).

$$v_{ij} = \beta_{i.1}x_1 + \beta_{i.2}\mathrm{x}_2 + \cdots + \beta_{i.n}\mathrm{x}_n + \mathrm{c} \tag{2}$$

v_{ij} represents a firm's indirect utility and $\beta_{i.1}$ represents the preference parameters. And $\beta_{i.1}$ can be shown through (3)

$$\beta_{i,k} = f_k(d_i) + \eta_{i,k} \tag{3}$$

$\beta_{i.1}$ is a function of instrumental demand variables (d_i) and firm-specifc residuals $(\eta_{i,k})$. When the indirect utility takes a linear form shown in (2), the first order condition for (2) becomes (4)

$$\frac{\partial \mathrm{v}\left(\mathbf{z}_{j^*}, \xi_{j^*}, y_i - p_{j^*}\right)/\partial z_{j,k}}{\partial v_i\left(\mathbf{z}_{j^*}, \xi_{j^*}, y_i - p_{j^*}\right)/\partial c} = \frac{\partial \mathbf{p}_m\left(\mathbf{z}_{j^*}, \xi_{j^*}\right)}{\partial z_{j,k}} = \frac{\beta_{i,k}}{z_{j*,k}} \tag{4}$$

Using these, and a two-stage regression the preference parameter for firms can be recovered. In the first regression, implicit prices for characteristics are observed, $\frac{\partial \mathbf{p}_m\left(\mathbf{z}_{j^*}, \xi_{j^*}\right)}{\partial z_{j,k}}$. These prices are multiplied by the quantity of characteristics, to estimate $\beta_{i,k}$, the unobserved preference parameter for each firm.

This parameter can be used to identify how tastes vary across a population or across time using the second stage regression. In the second stage, (3) is used such that instrumental variables for demand are regressed onto the $\beta_{i,k}$. Mathematically, this regression can be shown in (5).

$$\beta_{i,k} = \theta_{0,k} + \sum_s \theta_{k,s} d_{i,s} + \eta_{i,k} \quad (5)$$

Using this method, the first stage reveals MWTP, and the second stage shows non-MWTP or non-MWTA for various characteristics, given a demographic. $\beta_{i,k}$ on the left-hand side is the preference parameter and $d_{i,s}$ on right-hand side represents instrumental variables for demand. $\theta_{k,s}$ is the regression coefficient for the second regression and shows the non-MWTP, or non-MWTA for separate locations. And $\eta_{i,k}$ shows unobserved factors.

This new technique simplifies the interpretation of the hedonic estimates. It also addresses the challenges related to endogenous variables and single market data. Related to endogeneity, instead of using quantity, good instrumental variables that can predict shift in demand ($d_{i,s}$) are used. In the case of scrap plastics, price shocks such as change in price of virgin plastic (a related good) or changes in recycling policies can be used.

Related to single markets, there is much debate over the correct functional form of prices, Ekeland et al prove that it is always arbitrary and non-linear (Ekeland et al., 2002, 2004; Heckman et al., 2003; Keane, 2003). A linear price function cannot show the variation needed for second stage regression, as a regression coefficient from a linear equation is a single point on the curve and cannot take the form shown in (2). By using a non-linear functional form, economists can use the results to estimate a demand function as shown in (2). Furthermore, its arbitrary nature allows scholars flexibility with data and its estimation techniques.

Popular estimation techniques that allow users to assume a non-linear form include kernel regression, local polynomial regression, or nonparametric regression (Bajari &

Kahn, 2005; Bishop & Timmins, 2018; Fan et al., 1996). These techniques also help estimate the most appropriate conditional means for non-linear functions (Gutierrez et al., 2003). They also account for the heteroskedastic nature of most hedonic datasets by reducing the noise and variation in error.

These econometric techniques can also be used to apply the hedonic method to a single market. Some scholars have widely argued that it is not possible to estimate a hedonic demand function from a single market data because of lack of variation in prices in the market (Brown & Rosen, 1982; Ekeland et al., 2004). Ekeland et al (2004) prove that it is possible to introduce variance within a single market by using appropriate estimation techniques such as kernel regression, local polynomial regression, or nonparametric regression. These techniques, unlike ordinary least square regression, find characteristics' prices for each observation or a few groups of observations instead of a single price coefficient as was done in the past. The large number of prices provides enough variation to recover demand parameters for the second stage (Bajari & Benkard, 2005; Bajari & Kahn, 2005; Ekeland et al., 2004; Heckman et al., 2010).

In this analysis both multi-region ordinary least square regression and local polynomial regression are used following the new hedonic technique (Bajari & Benkard, 2005), and performance and implications of the two approaches are compared. For the second stage, non-marginal willingness to pay is estimated as function of instrumental supply shifter variables. A description of the methods is presented in the following sections.

Methods

Data

To implement this model econometrically a scrap plastic dataset from Recycle Markets Limited (RML) was obtained. RML dataset provides historical scrap plastic prices across eight regions in North America. This has been collected from purchasing officials across major recycling collection centers and consumers who report the information confidentially. The reporters share weekly reports on scrap plastic prices for 15 categories in an online portal. Each observation is a price that reflects the average price of a certain bundle of scrap plastic in a region for the specific date. The reports are then compiled and updated on the Recycling Markets Limited website. The specific data collected is tabulated in Table 3.1.

Table 3.1

Observations in the RML Scrap Plastic Dataset

Variable	No. of Unique Values	Unique Values	Description
Type of Plastic	16	PET - Premium	PET bottles from Deposit / Bottle Bill, Special Sort Baled Grades, picked up)
		PET	PET from curbside (Baled, picked up)
		PET - Thermoform	PET from Curbside, Post Consumer, (Baled, picked up) Southwest & Pacific regions
		PET Grade B	PET Curbside - It is considered Grade B in CA (Baled, picked up)
		Natural HDPE	Consists of uncolored, postconsumer #2 HDPE containers from household products typically collected in residential recycling programs. Examples include milk, vinegar, or ammonia bottles. Should be free of colored containers (including white) as well as any wide-mouth containers. Herbicide/insecticide bottles are not allowed.
		Colored HDPE	Consists of mixed colored, postconsumer #2 HDPE containers from household products typically collected in residential recycling programs. Examples include detergent, orange juice, and shampoo bottles. Should be free of wide-mouth containers such as margarine or whipped cream tubs. Motor oil and herbicide/insecticide bottles are not allowed.
		Commingled (1-7)	This grade primarily consists of PET bottles and HDPE bottles from residential recycling programs in which no positive sorting of any bottles has occurred and only the Mixed Bulky Rigid Plastics have been removed. Acceptable materials include soda bottles, milk jugs, shampoo bottles, yogurt cups, and other food and beverage containers. Non-bottle containers may consist of items such as cups, trays, clamshells, and tubs. Glass bottles and tin or aluminum cans are not allowed in this grade.
		Commingled (3-7)	This grade primarily consists of mixed bottles and containers from residential recycling programs in which most of the PET bottles, HDPE bottles, and Mixed Bulky Rigid Plastics have been positively sorted out. This grade may include some PET and HDPE but primarily consists of all leftover plastics materials remaining after they have been picked out. Non-bottle containers may consist of items such as cups, trays, clamshells, and tubs. Glass bottles and tin or aluminum cans are not allowed.
		HDPE Rigid	HDPE containers that are rigid and collected from curbside
		Mixed Bulky Rigid	This grade primarily consists of non-bottle PE and PP bulky rigid plastic items such as plastic drums, crates, buckets, baskets, toys, refuse totes, and lawn furniture typically collected in a residential recycling MRF. This grade should not contain any mixed 1-7 bottles and containers. They are most likely HDPE, PET, or PP
		FILM - Grade A	Grade A plastic films are 95% clean, dry, clear. They can be both post-commercial and post-industrial. They are typically LDPE or LLDPE. They are pre-sorted
		FILM - Grade B	Grade B plastic film consists of 80% clear, up to 20% color, clean, natural LDPE and/or LLDPE films. Any mix of post-commercial or post-industrial film is allowed. Minimal amounts HDPE or strapping allowed
		FILM - Grade C	Grade C film consists of 50% clear, 50% color, dry, LDPE or LLDPE films. It can be any mix of post-commercial or post-industrial film. HDPE or PP films are allowed.
		LLDPE-Stretch Film - prior to Feb 2016	Plastic films collected prior to 2016
		PP Post Consumer	Any Polypropylene (PP, #5) whole bottle, container product, generated through a positive sort from curbside, drop off or other public or private recycling collection program. Bulky Polypropylene (PP, #5) are items greater than 5 gallons, (e.g., buckets, crates, waste baskets, toys, and storage bins).
		Polystyrene EPS	Expanded Polystyrene
Region	8	Chicago	Midwest / Central USA
		New York	Northeast USA/Maritimes
		Ontario	Wester New York – up to Ontario in Canada
		Pacific	Northwest USA
		Quebec	Canada
		Atlanta	Southeast USA
		Los Angeles	Southwest USA
		Houston	Southcentral USA
Time			Weekly data from 2005-2021
Price	4	Low price	lowest price in the region during the reported week. All prices are in cents/lb
		High price	highest price in the region during the reported week. All prices are in cents/lb
		Average price	average price in the region during the reported week. All prices are in cents/lb
		National average	average price across the country during the reported week. All prices are in cents/lb

Table 3.1 shows how the data is collected. RML collects scrap plastic price data for 5 different types of plastics: Polyethylene Terephthalate (PET), High Density Polyethylene (HDPE), Polypropylene (PP), Low Density Polyethylene (LDPE), Polystyrene (PS). These prices were collected weekly from Midwest, Northeast, Northwest, Southeast, Southwest, Central, Ontario, and Quebec, between 2005-2021. For simplicity, the data from Canada was removed, and only 6 regions in the U.S. were used. As shown in Table 3.1, RML dataset distinguishes between the type of plastic in their definitions. These definitions were used to create the 29 variables as shown in Table 3.2.

Table 3.2

Variables from the RML dataset

Variable	Obs	Variable type	Mean	Std. Dev.	Min	Max
Date	62,111	Date/Time			12-Apr-05	3-Apr-21
Year	62,111	Year/Time	2015.72	4.02	2005	2021
Low price	56,963	Continuous	11.69	13.24	-8	112
High price	56,963	Continuous	13.55	13.37	-5	113
Average price	56,962	Continuous	12.62	13.29	-6.5	112.5
National Average Price	58,558	Continuous	12.38	12.96	-1.19	108.44
Region	62,111	Categorical	5.26	2.98	1	9
Plastic Type	62,111	Categorical	8.42	4.92	1	17
Contamination	62,111	Continuous	0.04	0.04	0	0.15
Color	58,566	Continuous	0.67	0.41	0	1
Bottle deposit	62,111	Binary	0.01	0.12	0	1
Curbside	62,111	Binary	0.17	0.37	0	1
Baled	62,111	Binary	0.80	0.40	0	1
Special baled	62,111	Binary	0.01	0.12	0	1
Food and Beverage	62,111	Binary	0.69	0.46	0	1
Household	62,111	Binary	1.00	0.00	1	1
Postcommercial	62,111	Binary	0.82	0.39	0	1
Bottles	62,111	Binary	0.76	0.43	0	1
Film	62,111	Binary	0.40	0.49	0	1
Other	62,111	Binary	0.36	0.48	0	1
Injection molding	48,552	Binary	0.49	0.50	0	1
Segregated	62,111	Binary	0.79	0.41	0	1
Rigid	56,222	Binary	0.73	0.45	0	1
HDPE	62,111	Binary	0.61	0.49	0	1
PET	62,111	Binary	0.33	0.47	0	1
PS	62,111	Binary	0.23	0.42	0	1
PP	62,111	Binary	0.42	0.49	0	1
LLDPE	62,111	Binary	0.40	0.49	0	1
LDPE	62,111	Binary	0.40	0.49	0	1

Table 3.2 shows the variables in the RML dataset. The variables copied as is from the dataset include date, year, and prices. The dataset ranges between Apr 12, 2005 – Dec 3, 2021. The prices are shown in cents/lb. Within the dataset, some scrap plastics are negative. These negative prices for scrap plastic indicate that the costs of recycling the respective scrap plastic is higher than the profit from the recycled product. This is comparable to the glass industry in the U.S., where the government gives subsidies to facilitate glass recycling. The negative prices indicate that under certain conditions, it is better to dispose the scrap material, instead of salvaging it. Anecdotal evidence suggests that these prices are typical of the scrap material industry. However, there is limited understanding of the industrial organization of recycling, and there is an opportunity to investigate the meaning behind negative scrap plastic prices.

The other variables describe the type of plastic (HDPE, LDPE, PET, PS, PP, LLDPE, LDPE), collection method (curbside, post-commercial, baled, bottle deposit), whether it was sorted (mixed), its condition (color, contamination), and the source of the plastic item (film, bottle, other). Almost all variables except color and contamination are binary. Color shows the proportion of color in a bundle. Contamination reflects the amount of acceptable contamination in a bundle of a given the type of scrap plastic such as Premium PET according to industry standards. This dataset does not provide information on quantity of characteristics and the material properties that may impact plastic recycling.

Research shows that plastic recycling is also dependent on plastic processability i.e., scrap plastic's ability to be processed based on its material properties such as tensile strength, shear strength, heat resistance etc. Therefore, the RML dataset was supplemented with material property data on mechanical recycling (Roosen et al., 2020). In this study, the scrap plastic is sampled, and their material properties determined. They find that plastic's processability is impacted by overall polymer composition of the plastic category. For example, PET bottle is typically composed of 80.7% PET, and other plastics and paper make up the remainder (Roosen et al., 2020). Scrap plastic also contains food metals, non-food metals, and halogens that can impact their material properties and recyclability. Their results were used to create four variables as shown in Table 3.3.

Table 3.3

Variables from Supplementary Data

Variable	Code	Observations	Variable Type	Min	Max
Percent of non-primary material	multi_material_p	17	Continuous	0.092	1
Non-food metals in ppm	metals_food_npm	17	Continuous	25.1	210.75
Food metals in ppm	metals_food_permitted	17	Continuous	512	3438
Halogen in ppm	halogen_ppm	17	Continuous	152	2941

Table 3.3 shows the four variables used from Roosen et al's papers. Their plastic categories matched most of the plastic categories reported in the RML dataset e.g., colored, and natural HDPE. In cases, where there was not an exact match, averages were used. For example, Rosoen's dataset provided material properties for PET trays and PET bottles. Since the RML dataset does not distinguish between bottle and other containers, a mean was calculated for PET to represent the material properties.

This data also covers the supply shifter variables: 2020 COVID-19 supply shifts, 2017 China import ban, and type of plastic. Since the data ranges from 2005-2021, it is possible to create dummy variables to represent these supply shifts. The analysis also recognizes that changes in oil prices can shift the supply for recycled plastic, so a quarterly oil price data across 2005-2010 from Energy Information Administration (EIA) was merged with the original data (EIA, 2022).

Finally, the scrap plastic prices were adjusted for inflation, using the inflation series for consumer prices prepared by the Research Department at the Federal Reserve of St. Louis from https://fred.stlouisfed.org/series/CPIAUCSL on Mar 5,2022 (FRED, 2022). The average prices for each observation were multiplied by the corresponding inflation rate for the respective year.

Plastic Model

Applying hedonic modeling to plastic recycling requires some formal theoretical structure. One piece is that the scrap plastic industry has many buyers and sellers of scrap plastic so that every firm is a price-taker, not a price setter. A second is that the scrap plastic industry is risk neutral. It is assumed that there is no market segmentation within the scrap plastic market by location as plastic waste generated in one region can be used by a recycler in another region. This is based on anecdotal evidence, during the literature review, no research was found that addressed this question. Nevertheless, market segmentation presents a future research opportunity. Firms are also assumed to have complete information about the market. This seems quite likely as the dataset relies on firms to report their prices and volumes of traded quantity. Finally, only structural market factors that influence recyclability during the period 2005-2021 are captured in the second stage shift variables.

Plastic waste is a bundle of three types of attributes: material properties, physical attributes from waste collection, and unobserved attributes (by the econometrician). The material attributes include percent of non-primary material, non-food metals, food metals (Hopewell, Dvorak, and Kosior 2009). The physical conditions in the model include color, contamination, type of material stream etc. The unobserved attributes include number of reuses of a plastic, exposure to type of contamination such as organic waste etc. Here $\mathbf{z}_j$ denote a 1xK vector of material and physical attributes and the unobserved attributes are represented by ξ_j.

The recyclers' willingness to pay will be estimated using instrumental supply shifter variables. This identifies how the recyclers' non-marginal willingness to pay varies when the supply of scrap plastic changes. These variables include import ban on scrap plastic, COVID-19, changes in oil prices, and type of plastic. In 2017, China imposed an import ban on scrap plastic. Since the U.S. waste management structure pre-dominantly relied on China to recycle its plastic waste, and did not have local infrastructure to support such volume of recycling, there was a higher supply of scrap plastic than the local recyclers demanded (Murphy et al., 2020; C. Wang et al., 2020). In 2020, during the COVID-19 pandemic, as manufacturing of virgin plastics slowed and their supply reduced, the demand for recycled plastics increased such that scrap plastic plastics rose (Issifu et al., 2021). Scholars have also proved that scrap plastic prices are closely associated with crude oil prices as oil is the primary raw material for virgin plastics (Issifu et al., 2021). Type of plastic is used as a supply shifter because anecdotal evidence suggests that the price or demand for characteristic is contingent on the plastic itself. For example, colored PET is acceptable up to a certain limit, but colored LDPE is not even reported in the dataset. Type of plastic is also used because this paper estimates the demand for indicators of recyclability and different plastics supply different characteristics. The plastic type is not an attribute of the scrap plastic as it is often mixed with other material. A bundle of PET bottles is also mixed with HDPE and LDPE film, and paper (Roosen et al 2020). A bundle of rigid plastics is a mixture of HDPE, PET, and PP (Roosen et al 2020). Thus, a scrap material known as PET bottle is not just PET bottle, scholars show that it only contains 50-80% of the primary material. The other materials in the bundle contribute to the recyclability. Variations in these bundles alter the recyclability attributes of the bundle e.g., color, nature of final product, rigidity, processability. These market changes are used as supply-shifter variables for recyclable characteristics in the second regression and are, represented by $d_{i,s}$.

The price of a ton of plastic waste is p_j, which is determined at equilibrium and adjusted for inflation across the years. Scrap plastic is traded globally by a large number of buyers and sellers, who determine these prices (Brooks et al., 2018; Pacini et al., 2021; Pacini &

Golbeck, 2020). Scrap plastic prices map recyclable characteristics as in (6) and the profit from these characteristics can be written as (7).

$$p_j = \mathbf{p}_m(\mathbf{z}_j, \xi_j) \tag{6}$$

$$v_{ij} = v_i\left(\mathbf{z}_j, \xi_j, \mathbf{y} - \mathbf{p}_m(\mathbf{z}_j, \xi_j)\right) \tag{7}$$

Plastic recyclers (i), who are profit maximisers, will choose a bundle of characteristics (j) that maximizes their indirect utility (profit) based on their cost constraint. Here p_m is a function that maps the recyclability characteristics into prices. A bundle j^*will be profit maximizing if condition (8) is met. This leads to the first order condition in (9)

$$j^*(i) = \arg\ max v_i\left(\mathbf{z}_j, \xi_j, y_i - \mathbf{p}_m(\mathbf{z}_j, \xi_j)\right) \tag{8}$$

$$\frac{\partial \mathrm{v}\left(\mathbf{z}_{j^*}, \xi_{j^*}, y_i - p_{j^*}\right)/\partial z_{j,k}}{\partial v_i(\mathbf{z}_{j^*}, \xi_{j^*}, y_i - p_{j^*})/\partial c} = \frac{\partial \mathbf{p}_m\left(\mathbf{z}_{j^*}, \xi_{j^*}\right)}{\partial z_{j,k}} \tag{9}$$

Following Bajari and Kahn (2002), a structure is imposed on the profit function, by assuming it takes a known parametric form (Bajari and Kahn 2002; Bajari and Benkard 2005). (10) shows a parametric profit function for the recycler,

$$v_{ij} = \beta_{i.,1-n}\text{material properties} + \beta_{i.,n-k}\text{physical condition} + \mathrm{c} \tag{10}$$

where

$$\beta_{i,k} = f_k(d_i) + \eta_{i,k} \tag{11}$$

$$E(\eta_i \mid d_i) = 0 \tag{12}$$

In (10)-(12), each recycler i's profit is linear for the various characteristics for a given bundle j. $\beta_{i,k}$ represents the preferences of different recyclers for a bundle j and it is assumed that preference parameters are identical across recyclers. (11) shows that $\beta_{i,k}$ is a function of supply-shift (d_i) and recycler-specific residuals $(\eta_{i,k})$. In this case, the residuals are assumed to be mean-independent of observed demand characteristics (12).

If the functional form assumption in (10) is made, then (9) becomes (13)

$$\beta_{i,k} = x_{j^*,k} \frac{\partial \mathbf{p}_m\left(\mathbf{x}_{j^*}, \xi_{j^*}\right)}{\partial x_{j,k}} \tag{13}$$

If a price derivative for a characteristic can be recovered, then recyclers preference can be recovered using (14). For estimation, (15) is used to recover implicit prices.

$$p_j(\mathbf{z_j}, \xi_j) = \alpha_{0,j^*} + \alpha_{1-x,j^*}\text{material properties} + \alpha_{y-z,j^*}\text{physical condition} + \xi_j \tag{15}$$

Using Bajari's method to estimate non-MWTP, $p(z) = p$, as shown in (15), allows the identification of the non-marginal firm WTP. Local polynomial regression is used to estimate the implicit price for each characteristic for all products (Bajari & Benkard, 2005; Bajari & Kahn, 2005). It is noted that the heterogeneity in firms' MWTP arises in equilibrium because of the highly non-linear nature of the hedonic price schedule and firm heterogeneity (in production and hence cost functions, varying levels of efficiency with respect to that technology) that leads them to choose different bundles along the same price function. Local polynomial is a form of non-parametric regression, which does not impose a functional form on to the data.

The local polynomial regression was run as shown in (16) and (17).

$$\alpha_{j^*} = \arg \min_{\alpha} (\mathbf{p} - \mathbf{z}\alpha)'\mathbf{W}(\mathbf{p} - \mathbf{z}\alpha) \tag{16}$$

$$\mathbf{p} = [p_j] \qquad \mathbf{z} = [\mathbf{z}_j] \qquad \mathbf{W} = \text{diag}\left\{K_h\left(\mathbf{z}_j - \mathbf{z}_{j*}\right)\right\} \tag{17}$$

Equations (16) and (17) illustrate the mathematics for a local polynomial regression. In this regression, an α – characteristic price is calculated for each observation and each characteristic by assigning weights, where α is a vector. Instead of fitting one coefficient (conditional mean) to the entire dataset, local polynomial regression is used to calculate coefficients for small sections of the data or for each observation. It assigns each observation a weight that minimizes its distance to a potential curve and calculates the corresponding coefficient. These coefficients address heteroscedasticity in the data and introduce the much-needed variation in first stage results for use the second regression. The heterogeneity in firms combined with non-linearity in the hedonic price function results in distinct bundles and implicit prices. However, this technique is computation intensive.

Over the last 30 years mathematicians have automated this process to facilitate its use. Now , in order to run such a regression a user only needs to select a kernel function and bandwidth that most closely fit the collected data for a pre-developed statistical code (Fan et al., 1996). The kernel function (K) is a weighting function that is used to estimate the weighted average of a data point. Users can choose between several types of kernel functions like Gaussian, triangle, quadratic, and the choice of function is dependent on the available data. The bandwidth (h) is a smoothing parameter – a high bandwidth allows the computer to account for distant neighbors of the observation, while a low bandwidth only allows points close to the observation. Like the kernel, the bandwidth is selected based on the data.

Using an automated local polynomial regression, α_{j^*} and error term ξ_j (unobserved characteristic prices) are recovered for each observation. The estimates from this regression, are used to identify firm MWTP for continuous characteristics as shown in (18).

$$\hat{\beta}_{i,k} = z_{j^*,k} \frac{\partial \hat{\mathbf{p}}_m\left(\mathbf{z}_{j^*}, \xi_{j^*}\right)}{\partial z_{j,k}} \tag{18}$$

In (18) $\frac{\partial \hat{\mathbf{p}}_m\left(\mathbf{z}_{j^*}, \xi_{j^*}\right)}{\partial z_{j,k}}$ on the right-hand side is equivalent to the coefficients calculated from the local polynomial regression. Then, mathematically, β on the left hand represents the total price a recycler pays for each characteristic. This β for each characteristic for each recycler, represents the MWTP for various characteristics.

The β can be modeled as shown in (19)

$$\hat{\beta}_{i,k} = \theta_{0,k} + \sum_s \theta_{k,s} d_{i,s} + \eta_{i,k} \tag{19}$$

Here, β is assumed to have a linear relationship for simplicity. The actual functional form may vary based on data. To assess the distribution of demand variables, an OLS regression was performed between MWTP and supply shifter variables. The results show how supply impacts consumer non-marginal WTP.

It should be noted that this technique is only applicable to continuous characteristics. For all dummy variables, the implicit price from stage 1 regression was used to identify a price threshold. For example, profit maximization implies, that if a recycler chooses segregated plastic over mixed plastic, their MWTP for segregated plastic is higher than the implicit price. If they do not choose segregated plastics, their MWTP for it is lower than the implicit price, which is observed on the first stage regression, as shown in (20) and (21).

$$[\text{ segregated } = 1] \Rightarrow \left[\beta_i > \frac{\Delta p_m}{\Delta \text{segregated}}\right] \tag{20}$$

$$[\text{ segregated } = 0] \Rightarrow \left[\beta_i < \frac{\Delta p_m}{\Delta \text{segregated}}\right] \tag{21}$$

Dichotomous variables were analyzed using maximum likelihood estimate of a probit as shown by Bajari and Kahn (2002). This estimates the recycler's likelihood of choosing to change the purchase decision for specific dichotomous characteristics change under a change in supply shift variable regimes. The likelihood of a recycler choosing segregated plastic is given in (22)

$$1 - N\left(\theta_{0,k} + \sum_s \theta_{k,s} d_{i,s} - \frac{\Delta p_m}{\Delta \text{segregated}}; \sigma\right) \tag{22}$$

Where N is the normal cumulative destiny function. And the likelihood function for the population distribution can be written as

$$L(\theta, \sigma) = \prod_{i=1}^{I} N\left(h(d_i; \theta_k) - \frac{\Delta p_m}{\Delta \text{segregated}}; \sigma\right)^{1-segregated_{j^*(i)}} \times \left(1 - N\left(h(d_i; \theta_k) - \frac{\Delta p_m}{\Delta \text{segregated}}; \sigma\right)\right)^{\text{segregated}_{j^*(i)}} \tag{23}$$

where

$$h(d_i; \theta_k) = \theta_{0,k} + \sum_s \theta_{k,s} d_{i,s}. \tag{24}$$

In this model (22) the implicit price of the dichotomous variable was standardized by subtracting the mean and dividing by the range (maximum-minimum) to make the interpretation of the results more straightforward. Following Bajari and Kahn (2002), Instead of normalizing on $\sigma = 1$, the model has been normalized on the observed implicit price, standard deviation can be calculated because the parameters of the cumulative density function are known.

Cross Validation and Aikake Information Criteria

The dataset consists of 62,111 unique observations. When missing values are accounted for, there are still 53,436 complete observations. Due to the size of this dataset, the probability of overfitting the data and Type 1 errors is high. If an explanatory model is used, it can be assumed that price of scrap plastic varies due to material properties, plastic conditions, and how it is collected. This hypothesis can be tested while controlling for some variables and it will be accepted if the p-values are significant. However, hypothesis testing through p-values only indicates whether each variable is a significant predictor on its own and does not imply whether the model works collectively for all the variables. Furthermore, excessive variables can overfit the data, such that the model might only work with the given dataset. To avoid this, and make the model generalizable, scholars suggest using predictive modelling (Shmueli, 2010). Scholars recommend using predictive modeling in conjunction with explanatory model. In some cases, where the causal model is unknown, scholars used the predictive model first to understand signals from the data and then from the causal model. In this case, the plastic model demonstrated above is considered the causal model. The predictive model is used to confirm the validity of the dataset, and the causal model, especially because the variables were not collected directly by the plastic purchasers. This approach helps confirm that the causal model holds up and avoids overfit (Belloni and Chernozhukov 2013).

Predictive modelling learns from the data, identifies the variables that are important predictors of the dependent variable, and assesses whether they work together as a model (Shmueli, 2010). Predictive modelling emphasizes the importance of the predictive power of a model to avoid overfit. To measure the predictive power of a model, cross-validation or information theory is used.

Cross validations examines the model performance on other datasets produced by the same underlying data generation process (Efron & Hastie, 2021; Lee et al., 2010). It is possible to cross validate the model by using multiple datasets or by sampling within a single dataset. Sampling allows the user to examine the model's performance using data which is known to be generated by the same underlying data generation process. Once the model has been fit, it can be tested over the remaining samples to examine the out of sample R^2, and deviance. Users should draw a representative sample without replacement instead of a random sample (Lee et al., 2010). For instance, in the case of the scrap plastic dataset which varies between 6 regions, weekly from 2005-2021, the sample should be representative of this temporal and spatial resolution. A sample that does not account for this will not result in a good model. It is also important to identify a sample size, which can be used to make adequate predictions about the population. A plot of predictive power or R^2 against sample sizes can be used to identify the smallest sample size with adequate predictive ability. In general, sampling is a low-cost tool for high-dimensional data that can be used to measure the model's performance on left out observations and ultimately avoid overfit.

Analysts can also use information criterion to compare non-nested models and choose the one with the highest predictive power (Efron & Hastie, 2021). Two information criteria are most popular in the literature: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). AIC assumes that there is a True model and assesses which model is closest to it. BIC assumes one of the compared models is the True model. Both AIC and BIC can be used to avoid overfit, as both penalize for too many parameters. However, BIC's penalty for complex models is much higher than AIC and it favors simpler models. In both cases, the lowest AIC or BIC corresponded to the highest likelihood that the model is close to the True model. While raw AICs and BICs can be used, they are difficult to interpret. Wagenmaker and Farrell (2004) suggest using AIC and BIC weights to determine the probability of each model. If the log likelihood of the model is known, Table 3.4 can be used to determine the information criteria ranking for each model as shown.

Table 3.4

Summary of Weighted AIC and BIC Calculation

Column Name	Description	
Model	Name of the Model	
No. of Parameters (V_i)	Number of predictors	
n	Number of observations	
log(L_i)	Natural log of maximum likelihood of the model (as calculated by the program)	
AIC_i	$\text{AIC}_i = -2\log L_i + 2V_i$	(25)
Δ_i(AIC)	$\Delta_i(\text{AIC}) = \text{AIC}_i - min\text{AIC}$	(26)
w_i(AIC)	$w_i(AIC) = \Delta_i(AIC)/\Sigma\Delta_i(AIC)$	(27)
BIC_i	$\text{BIC}_i = -2\log\ L_i + V_i \log\ n$	(28)
Δ_i(BIC)	$\Delta_i(B\text{IC}) = \text{BIC}_i - minB\text{IC}$	(29)
w_i(BIC)	$w_i(BIC) = \Delta_i(BIC)/\Sigma\Delta_i(BIC)$	(30)

Table 3.4 is adapted from Wagenmaker and Farrel (2004). It summarizes how each of the column in the original article was calculated. AIC is defined as (25) for large datasets,

where L is the maximum likelihood of the model and V is the number of parameters. (25) shows that AIC helps choose the model with the low information loss and high parsimony. BIC is defined as (28), and accounts for number of observations in the dataset in addition to L and V, implying that the penalty for choosing multiple parameters is much higher in the AIC.

While AIC and BIC raw values are useful, they are difficult to interpret when comparing models. For instance, even if a model has the lowest AIC or BIC, it is difficult to rank their importance. To make this task easier, Wagenmaker suggests using weights as shown in (27) and (30). To estimate weights, the difference between minimum AIC and each candidate model's AIC is calculated using (27), which is used to compute the relative likelihood of each candidate model as shown in (31).

$$L(M_i \mid \text{ data }) \propto \exp\left\{-\frac{1}{2}\Delta_i(\mathrm{AIC})\right\} \tag{31}$$

(31) implies that the Likelihood of the model is proportional to negative exponential of the AIC difference. The weight is then determined using (32).

$$w_i(\mathrm{AIC}) = \frac{\exp\left\{-\frac{1}{2}\Delta_i(\mathrm{AIC})\right\}}{\sum_{k=1}^{K} \exp\left\{-\frac{1}{2}\Delta_k(\mathrm{AIC})\right\}} \tag{32}$$

The sum of weights is equal to 1.

To estimate BIC weights, (28)-(30) from Table 3.4 are used. These weights simplify the process of assigning importance to a model. In this paper, the table from Wagenmaker and Farrel (2004) has been recreated to determine the model that is closest to the True model.

Another important tool is penalized regression and lasso regression is the most used version of the penalized regression (Gunes, 2015). A lasso regression takes the form shown in (33).

$$\mathcal{L}(\boldsymbol{\beta}; \lambda) = \| \mathbf{Y} - \mathbf{X}\boldsymbol{\beta} \|_2^2 + \lambda_1 \| \boldsymbol{\beta} \|_1 \tag{33}$$

(33) shows that the objective of the lasso is to minimize the residual sum of squares with a constraint. In (33) $\| \mathbf{Y} - \mathbf{X}\boldsymbol{\beta} \|_2^2$ shows the residual sum of squares between observed value and predicted value and λ_1 is a penalty for regression coefficients. This method is typically performed using a statistical software like Stata, which chooses the model with the least deviance among other candidate models. It starts with a set of variables and imposes a constraint that penalizes models for multiple variables. This penalty causes beta coefficients for some variables to shrink towards zero. Typically, such variables are not significant predictors, thus the resulting model is a simpler model with fewer variables that are collectively important predictors. The end goal of this tool is to avoid overfit and identify the variables that are most important predictors of the data (Tibshirani, 1996)..

In this chapter, all three tools (cross validation, information criteria, and lasso regression) have been used to determine the most appropriate predictors and model. To perform this analysis, the dataset was first split into a sample, a lasso regression was performed and cross validated for performance on other samples, followed by weighted information criteria calculation for all the models. All the modeling was performed using Stata 17.

To create samples, a power calculation was performed to estimate the smallest sample size with high predicting power and out of sample R^2 was 150 observations. Results show that the sample size did not matter beyond 150 observations and the predicting power and R^2 remained the same as shown in Figures 3.3 and 3.4.

Figure 3.3

Predicting Power Vs Sample Size (Small N)

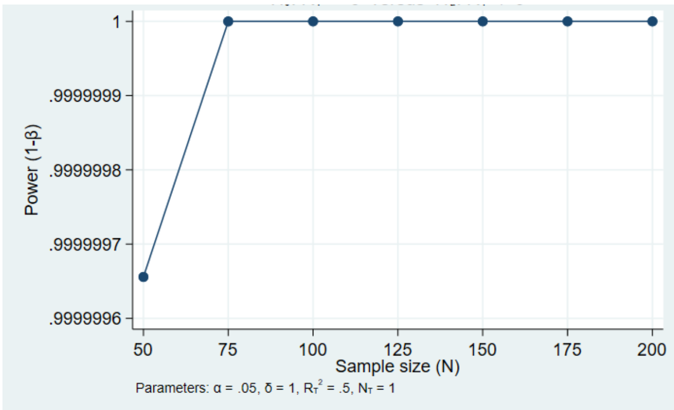
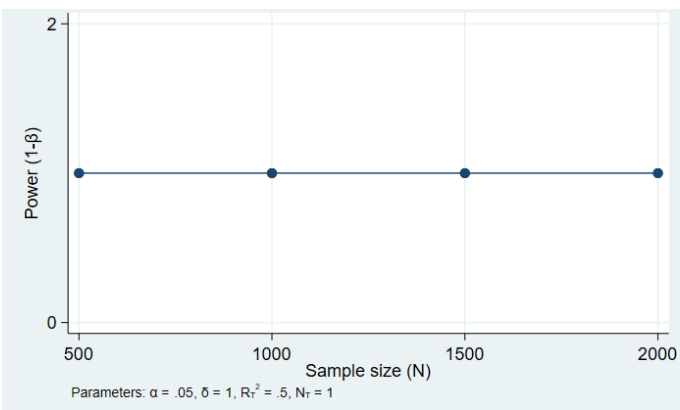


Figure 3.4

Predicting Power Vs Sample Size (Large N)



To achieve a sample that was representative of the time and location strata in the dataset, and to minimize the time for cross validation, the dataset into 3 samples stratified by region and quarter with approximately 17,000 observations in each, which would give massive predictive power.

Once samples were drawn, lasso regression was conducted for the variables in their raw form, as shown in Table 3.2 and 3.3 for stage 1. The lasso regression showed the 12 variables that would result in minimum deviance and high R^2 for the stage 1 implicit price model. These selected variables are rereferred as model 1. A lasso regression was also performed for stage 2 regression. The results from the lasso regressions are shown in Table 3.5 for stage 1, and stage 2 continuous, and stage 2 probit variables.

Table 3.5

Variables Selected from Lasso Regression

Stage 1: Implicit Price Variables	Stage 2: Non-marginal WTP variables
Curbside	import ban
baled	price of crude oil
Contamination	covid 19
Food and beverage	HDPE
Post-consumer	LDPE
Film	PET
Other	PP
Color	PS
Segregated Plastic	
Rigid	
Percent non-primary material	
Food metals in ppm	

While the cross validation suggests that 12 variables send strong signals towards price, two variables (baled and postconsumer) were omitted for simplicity. Almost all scrap plastic was baled or and generated from postconsumer waste, so these variables would be redundant and would not advance understanding of plastic characteristics. The variables in 3.5 (except baled and postconsumer), plus bottle deposit, were used to test develop six types of models – Model1.1, Model 1.2, Model 1.3, Model 2.1, Model 2.2, Model 2.3. Model 1.1 performs the stage 1 hedonic regression to recover implicit prices using and OLS regression. Model 1.2 conducts a stage 2 hedonic OLS regression, which estimates non-marginal WTP from implicit prices in Model 1.1. Model 1.3 is a stage 2 probit model, which estimates the recycler's likelihood of changing the purchase decision for binary characteristics. Model 2.1 recovers implicit prices through a local polynomial regression. Since Stata does not display or store results for this method, it is not possible to report them. The performance of this model is analyzed through the performance of its second stage regressions in Model 2.1 and Model 2.2. Model 2.2 uses implicit prices recovered from Model 2.1 to perform an OLS regression that estimates non-marginal WTP. Model 2.2 uses a probit model, like Model 1.2, except the implicit prices are recovered from a local polynomial regression. A summary is presented in Table 3.6.

Table 3.6

Summary of Models

Model	**Hedonic Stage**	**Method**
Model 1.1	Stage 1: implicit price	Multi-region OLS regression
Model 1.2	Stage 2: non-marginal WTP	OLS regression using model 1 estimates
Model 1.3	Stage 2: Likelihood of changing purchase decision	Probit regression using model 1 estimates
Model 2.1	Stage 1: implicit price	Local polynomial regression
Model 2.2	Stage 2: non-marginal WTP	OLS regression using model 4 estimates
Model 2.3	Stage 2: Likelihood of changing purchase decision	Probit regression using model 4 estimates

The variables selected from lasso regression were used to assess the predict the out of sample R^2. The results are shown in Table 3.6. Note: out of sample R^2 could not be recovered from Model 2.1 and Model 2.3 as Stata does not store them.

Table 3.6

Post-Selection Out of Sample R^2 for Model 1.1 And Model 1.2 using Sample 1

Name	Sample	MSE	R-squared	Observation
Model 1.1 - Stage 1- Multi-City Method	1	444.1999	0.4891	15,688
	2	428.7297	0.497	15,707
	3	435.7897	0.4941	15,674
Model 1.2 - Stage 2 - Multi-City Method	1	0.0509572	0.2609	5,935
	2	0.047797	0.2671	5,941
	3	0.0539228	0.2158	5,935
Model 2.2 - Stage 2: Local Polynomial Method	1	0.0024903	0.6931	5,935
	2	0.0024038	0.6873	5,941
	3	0.0023532	0.6976	5,935

Table 3.6 shows the out of sample performance for three models using only sample 1. Sample 1 was used for estimation and samples 2 and 3 were used for cross-validation. The table shows that in general, the out of sample R^2 stays consistent for all three samples in each model. Between model 1.2 and model2.2 the out of sample R2 is higher for model 2.2 (WTP estimates recovered from a local polynomial regression).

A weighted information criteria was also performed for the three models. The results for these are shown in Table 3.7, Table 3.8, and Table 3.9.

Table 3.7 shows the weighted information criteria for the cross validated model, obtained via a lasso regression, and the original causal model. It suggests the cross-validated model outperforms the causal model. While that may be the case, the causal model was chosen as Table 3.8 shows the weighted information criteria for Models 1.2, and 2.2 to estimate the information criteria for continuous variables. Model 1.2 is selected for color percent non-primary material, while model 2.2 is selected for contamination and food metals. Table 3.9 shoes the weighted information criteria for Models 1.3 and 2.3. Model 2.3 (estimates from local polynomial) has been selected for all variables. It is observed that local polynomial performs better than the multi-city approach 8 out of ten variables.

Table 3.7

Weighted AIC and BIC Estimates for Model 1.1

Model	n	V	$\log(L_i)$	AIC_i	$\Delta_i(AIC)$	$w_i(AIC)$	BIC_i	$\Delta_i(BIC)$	$w_i(BIC)$
Predictive Model (Lasso)	15688	13	-70079	140184.98	0	1	140284.568	0	1
Causal Model	15688	11	-70091	140205.9	20.92	2.866E-05	140290.167	5.59869726	0.06084969

Table 3.8

Weighted AIC and BIC Estimates for Model 1.2 and Model 2.2

Model	Variable	n	V	$\log(L_i)$	AIC_i	$\Delta_i(AIC)$	$w_i(AIC)$	BIC_i	$\Delta_i(BIC)$	$w_i(BIC)$
Model 1.2	color	16650	9	-21009.66	42037.32	0	1	421068015	0	1
Model 2.2	color	16650	9	-25538.64	51095.28	9057.96	0	51164.7615	9057.96	0
Model 1.2	contamination	17811	9	1252.613	-2487.226	54280.394	0	-2417.1379	54280.394	0
Model 2.2	contamination	17811	9	28392.81	-56767.62	0	1	-56697.532	0	1
Model 1.2	% non-primary material	17811	9	-33976.54	67971.08	0	1	68041.1681	0	1
Model 2.2	% non-primary material	2448	9	-45282.53	90583.06	22611.98	0	90635.2872	22594.1191	0
Model 1.2	Food Metals ppm	17811	9	-145662.9	291343.8	268182.3	0	291413.888	268182.3	0
Model 2.2	Food Metals ppm	17811	9	-11571.75	23161.5	0	1	23231.5881	0	1

Table 3.9

Weighted AIC and BIC Estimates for Model 1.3 and Model 2.3

Model	Variable	n	V	$\log(L_i)$	AIC_i	$\Delta_i(AIC)$	$w_i(AIC)$	BIC_i	$\Delta_i(BIC)$	$w_i(BIC)$
Model 1.3	bottle deposit	218	2	-248.789	501.578	0	1	508.34	0	1
Model 2.3	bottle deposit	444	2	-249.159	502.318	0.74	0.74	510.51	2.16	0.34
Model 1.3	food	9382	5	-6379.05	12768.1	1207.946	0	12803.8327	1207.946	0
Model 2.3	food	9382	5	-5775.077	11560.154	0	1	11595.8867	0	1
Model 1.3	film	17811	6	-7384.593	14781.186	758.476	0	14827.9114	758.476	0
Model 2.3	film	17811	6	-7005.355	14022.71	0	1	14069.4354	0	1
Model 1.3	other	17811	7	-7138.839	14291.678	2952.092	0	14346.191	2952.092	0
Model 2.3	other	17811	7	-5662.793	11339.586	0	1	11394.099	0	1
Model 1.3	segregated	17811	6	-7876.24	15764.48	784.592	0	15811.2054	784.592	0
Model 2.3	segregated	17811	6	-7483.944	14979.888	0	1	15026.6134	0	1
Model 1.3	rigid	16849	6	-11646.02	23304.04	793.26	0	23350.4323	793.26	0
Model 2.3	rigid	16849	6	-11249.39	22510.78	0	1	22557.1723	0	1

In addition to the cross-validation, Benjamini Hochberg correction was performed for all results to address the multiplicity problem caused by multiple testing. When multiple tests are performed at the same time such as by using multiple independent variables in an OLS regression, the potential for a type I error, false discovery, increases. The probability of not making an error in one test is $(1-\alpha)$, and the probability of making at least one error is $1-(1-\alpha)^m$, where α is the confidence interval and m shows the number of tests. For and $\alpha$of 0.05, and 10 tests for each variable, the probability of making at least one error is 0.401. To correct for this, the Benjamini Hochberg Procedure (BH procedure) is used, and p-values that are below a pre-determined confidence level are rejected. Using the BH procedure, p-values can also be adjusted to protect against false discovery. This is done by listing all the p-values in a model, ranking them (smallest to largest), and then calculating the adjusted value as shown in (34) adjusted p-value = p-value*number of tests/rank (34)

In the results sections, all results are shown with standard errors, p-values, and BH-adjusted p-values.

Results

The following tables capture the results for hedonic regressions for scrap plastic prices for all models except model 2.1. Table 3.10 is a summary of model 1. Table 3.11 and 3.12 show results from model 1.2 and model 1.3 respectively. The results from models 2.2 and 2.3 are summarized in tables 3.13 and 3.14.

Table 3.10

Implicit prices from Model 1.1 (cents/lb)

Region	% Primary Material	Food Metal	Color	Rigid	Food Grade	Film vs Bottle	Other vs Bottle	Segregated	Bottle Deposit	Contamination	Constant
Southeast (Georgia)	**-99.83*** **	**0.010*** **	**-28.79*** **	**10.13*** **	**24.37*** **	**-21.44*** **	**2.79**	**-63.06*** **	**(omitted)**	**68.04**	**100.03*** **
SE	(5.454)	(0.002)	(1.341)	(1.897)	(1.295)	(2.002)	(2.737)	(4.922)		(40.635)	(5.541)
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.308	<0.001		0.095	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.3076	<0.001		0.423	<0.001
Mid-West (Illinois)	**-96.01*** **	**0.010*** **	**-29.42*** **	**7.58** **	**24.07*** **	**-23.24*** **	**6.63**	**-57.39*** **	**(omitted)**	**46.92**	**97.01*** **
SE	(5.450)	(0.002)	(1.364)	(2.130)	(1.344)	(2.180)	(2.933)	(5.031)		(42.658)	(5.638)
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.024	<0.001		0.271	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001	0.0714	<0.001		0.611	<0.001
South Central (Texas)	**-112.42*** **	**0.012*** **	**-27.67*** **	**4.66**	**26.14*** **	**-28.61*** **	**9.76** **	**-65.92*** **	**-12.06** **	**61.77**	**107.36*** **
SE	(5.426)	(0.002)	(1.348)	(2.055)	(1.312)	(2.147)	(2.823)	(4.941)	(3.314)	(40.611)	(5.587)
p-value	<0.001	<0.001	<0.001	0.023	<0.001	<0.001	0.001	<0.001	0.0003	0.128	<0.001
BH p-value	<0.001	<0.001	<0.001	0.058	<0.001	<0.001	0.002	<0.001	0.0015	0.2568	<0.001
Southwest (California)	**-50.23*** **	**0.002**	**-27.96*** **	**1.59**	**21.67*** **	**-25.02*** **	**3.64**	**-30.10*** **	**-4.39**	**99.03**	**72.63*** **
SE	(4.800)	(0.0002)	(1.334)	(2.030)	(1.299)	(2.108)	(2.784)	(4.605)	(3.537)	(41.020)	(5.314)
p-value	<0.001	0.231	<0.001	0.434	<0.001	<0.001	0.191	<0.001	0.215	0.016	<0.001
BH p-value	<0.001	0.4642	<0.001	0.723	<0.001	<0.001	0.636	<0.001	0.5365	0.079	<0.001
Northeast (New York)	**-107.78*** **	**0.010*** **	**-27.39*** **	**6.74** **	**24.95*** **	**-23.88*** **	**4.81**	**-66.35*** **	**(omitted)**	**69.20**	**107.57*** **
SE	(5.451)	(0.011)	(1.411)	(2.105)	(1.383)	(2.220)	(2.923)	(5.037)		(43.007)	(5.725)
p-value	<0.001	<0.001	<0.001	0.001	<0.001	<0.001	0.100	<0.001		0.108	<0.001
BH p-value	<0.001	<0.001	<0.001	0.0063	<0.001	<0.001	0.300	<0.001		0.242	<0.001
Northwest (Washington)	**-65.23*** **	**0.005* **	**-27.82*** **	**4.82* **	**20.09*** **	**-20.29*** **	**2.52**	**-43.98*** **	**(omitted)**	**100.84* **	**79.16*** **
SE	(4.621)	(0.002)	(1.179)	(2.014)	(1.176)	(2.033)	(2.57)	(4.315)		(36.262)	(4.789)
p-value	<0.001	0.003	<0.001	0.017	<0.001	<0.001	0.328	<0.001		0.006	<0.001
BH p-value	<0.001	0.0153	<0.001	0.038	<0.001	<0.001	0.590	<0.001		0.0165	<0.001

Table 3.10 shows the implicit prices for 12 plastic properties by region from model 1.1. The columns show recyclability indicators, and the rows show the regions. Each cell shows the implicit price of recyclability characteristic in a region. For each characteristic, the standard error, p-value, and BH adjusted p-value is also reported. In general, the prices are consistent across the regions. The average price for primary % decrease in primary material is $-0.88/lb, for increase in color is $-0.28/lb, food grade is $0.237/lb.

The signs are as expected. For example, food grade plastics and rigid plastics have a positive price, while films have a negative price. However, the prices for bottle deposit and contamination have unexpected signs. It suggests that recyclers do not have a strong preference for a segregated material, which is untrue.

The results from Table 3.10 were merged with the original dataset. For continuous variables, the implicit prices from model 1.1 were multiplied by the respective characteristics for each observation to retrieve MWTP. The variables color, contamination, and percent of non-primary material were multiplied by 0.1, to interpret how the WTP will change with a 10% increase in these properties. The results from food metals were multiplied by 1000 to interpret how the WTP would change for a 1000 ppm decrease in food metals. These adjusted variables were used for the second stage regression with the supply shifter variables: import ban, covid 19, crude oil prices, and type of plastic. Table 3.11 summarizes these results.

Table 3.11

Non-Marginal WTP (cents/lb) from Model 1.2

Variable	% Primary Material	Food Metal	Color	Contamination
Import Ban	**-0.217*****	**115.992*****	**0.0977*****	**0.0230*****
SE	(0.0319)	(16.847)	(0.0172)	(0.0044)
p-value	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001
COVID 19	**-0.014**	**5.528**	**0.0295**	**-0.0002**
SE	(0.0394)	(20.818)	(0.0207)	(0.0054)
p-value	0.7164	0.7906	0.1531	0.9768
BH p-value	1	1	0.6124	1
Crude oil Prices	**0.0036*****	**-1.753*****	**-0.0016*****	**-0.0003*****
SE	(0.0006)	(0.2913)	(0.0003)	(7.62E-05)
p-value	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001
HDPE	**-6.975*****	**360.28*****	**-1.042*****	**0.0071**
SE	(0.0352)	(18.63)	(0.0185)	(0.0048)
p-value	<0.001	<0.001	<0.001	0.145
BH p-value	<0.001	<0.001	<0.001	0.29
LDPE	**-5.657*****	**-965.10*****	**-2.171*****	**-0.307*****
SE	(0.0383)	(20.29)	(0.0224)	(0.0053)
p-value	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001
PET	**-5.080*****	**472.82**	**-1.815*****	**0.0199***
SE	(0.0431)	(22.773)	(0.0226)	(0.006)
p-value	<0.001	<0.001	<0.001	0.0008
BH p-value	<0.001	<0.001	<0.001	0.002
PP	**-6.020*****	**-13.455**	**-0.008**	**-0.190*****
SE	(0.0531)	(28.103)	(0.0279)	(0.0074)
p-value	<0.001	0.6321	0.7769	<0.001
BH p-value	<0.001	1	1	<0.001
PS	**-7.506*****	**-154.26*****	**0.020**	**-0.0313*****
SE	(0.0604)	(31.98)	(0.0317)	(0.0084)
p-value	<0.001	<0.001	0.5279	0.0002
BH p-value	<0.001	<0.001	1	0.0008
Constant	**8.624*****	**-1747.21*****	**2.8333*****	**-0.056*****
SE	(0.0487)	(25.748)	(0.0265)	(0.0067)
p-value	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001
N	17811	17811	16650	17811
R^2	0.7144	0.2626	0.4745	0.2477

Table 3.11 shows the recyclers' non-marginal willingness to pay for each continuous characteristic for model 1.2, after the import ban, after COVID19, for variation in crude oil prices, and for each plastic type. Across the four characteristics, import ban and crude oil prices are statistically significant predictors at 99% confidence interval. The results suggest that after the Chinese import ban, recyclers were willing to accept 0.02 cents/lb for a 10% increase in contamination. Recyclers were also willing to pay 0.0008 cents/lb for contaminated plastic if oil prices increased. This willingness to pay varied based on the type of plastic with reference to mixed scrap plastic. Recyclers were willing to pay to recycle contaminated LDPE and PP, but they would have to be paid to recycle contaminated HDPE or contaminated PET as compared to mixed plastic.

For binary variables, the implicit prices from Table 3.10 were considered thresholds and they were normalized such that the mean was 0 and they varied between -1 and 1. A probit regression was performed for each binary characteristic to assess the impact of the import ban, COVID-19, variation in crude oil prices, and plastic type, at a constant implicit price of 1 cent/lb. The probabilities and their marginal effects were calculated for each characteristic. This helps interpret the model in straightforward manner. The results from these are shown in Table 3.12.

Table 3.12

Probit estimates from Model 1.3 (cents/lb)

Variable	Rigid	Food Grade	Film vs Bottle	Other vs Bottle	Segregated	Bottle Deposit
Import Ban	**-0.092****	**-0.121*****	**0.035*****	**0.061*****	**-0.089*****	**omitted**
SE	(0.007)	(0.010)	(0.005)	(0.005)	(0.006)	
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	
BH p-value	<0.001	<0.001	<0.001	<0.001	<0.001	
COVID 19	**0.040*****	**0.027**	**-0.006**	**-0.035*****	**0.062*****	**-0.0006**
SE	(0.009)	(0.013)	(0.007)	(0.006)	(0.007)	(0.001)
p-value	<0.001	0.039	0.3678	<0.001	<0.001	0.6578
BH p-value	<0.001	0.052	0.613	<0.001	<0.001	0.6578
Crude oil Prices	**0.001*****	**0.003*****	**-0.0004*****	**-0.0008*****	**0.002*****	**omitted**
SE	(0.0001)	(0.0002)	(0.0001)	(9.14E-05)	(0.0001)	
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	
BH p-value	<0.001	<0.001	<0.001	<0.001	<0.001	
HDPE	**-0.113*****	**0.0341*****	**-0.0006**	**-0.997**	**-0.0539*****	**omitted**
SE	(0.007)	(0.009)	(0.005)	(16.832)	(0.005)	
p-value	<0.001	<0.001	0.9083	0.9528	<0.001	
BH p-value	<0.001	<0.001	1	1	<0.001	
LDPE			**omitted**	**omitted**		
SE						
p-value						
BH p-value						
PET				**0.1285*****	**-0.3346*****	**omitted**
SE				(0.004)	(0.004)	
p-value				<0.001	<0.001	
BH p-value				<0.001	<0.001	
PP			**0.4614*****	**1.0923**		
SE			(0.002)	(16.832)		
p-value			<0.001	0.9483		
BH p-value			<0.001	1		
PS						
SE						
p-value						
BH p-value						
Mixed	**-0.0199***					
SE	(0.007)					
p-value	0.007					
BH p-value	0.0175					
Constant	**0.7040**	**0.7440**	**0.4177**	**0.3282**	**0.7869**	**0.4690**
SE	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.021)
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
N	16,849	9,382	17,811	17,811	17,811	218

Table 3.12 shows the marginal effect of supply shifters on the likelihood of paying 1 cent/lb for a binary characteristic from model 1.3. In this model all four variables are significant predictors across all characteristics. Following Bajari and Kahn (2002), the

marginal effects of the coefficients from the probit estimates of a known, standardized model can be interpreted in the following manner. After the import ban recyclers were less likely to pay 1 cent/lb to purchase rigid plastic. However, after COVID-19, the likelihood of paying more than 1 cent/lb to purchase rigid plastic increased .

Table 3.13

Non-Marginal WTP (cents/lb) from Model 2.2

Variable	% Primary Material	Food Metal	Color	Contamination
Import Ban	-0.0717***	$-2.65\text{x}10^{6}$	-0.0607*	-0.01262***
SE	(0.0091)	($1.40\text{x}10^{6}$)	(0.0226)	(0.001)
p-value	<0.001	0.059	0.0072	<0.001
BH p-value	<0.001	0.118	0.019	<0.001
COVID 19	-0.0094	$-1.97\text{x}10^{5}$	0.0292	0.001
SE	(0.0112)	($1.69\text{X}10^{6}$)	(0.0272)	(0.0012)
p-value	0.401	0.9075	0.2827	0.3827
BH p-value	1	1	0.565	1
Crude oil Prices	0.0014***	$5.99\text{X}10^{4}$*	0.0016***	0.0002***
SE	(0.0002)	($2.46\text{X}10^{4}$)	(0.0004)	(1.66E-05)
p-value	<0.001	0.0152	<0.001	<0.001
BH p-value	<0.001	0.04	<0.001	<0.001
HDPE	-1.777***	$-4.72\ \text{x}10^{6}$*	-0.844***	-0.0045***
SE	(0.0100)	($1.56\text{x}10^{6}$)	(0.0243)	(0.0011)
p-value	<0.001	0.0025	<0.001	<0.001
BH p-value	<0.001	0.01	<0.001	<0.001
LDPE	-1.451***	$174\ \text{x}10^{7}$***	-1.558***	0.1751***
SE	(0.0109)	($1.72\ \text{x}10^{6}$)	(0.0294)	(0.0016)
p-value	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001
PET	-1.276***	$-9.49\ \text{x}10^{6}$***	-1.452***	-0.0072***
SE	(0.0122)	($1.84\text{x}10^{6}$)	(0.0297)	(0.0013)
p-value	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001
PP	-1.545***	$1.51\ \text{x}10^{6}$	-0.1483***	0.1079***
SE	(0.0151)	($2.28\ \text{x}10^{6}$)	(0.0366)	(0.0016)
p-value	<0.001	0.5067	<0.001	<0.001
BH p-value	<0.001	0.81	<0.001	<0.001
PS	-1.925***	$1.71\ \text{x}10^{6}$	0.3529***	0.0043
SE	(0.0172)	($2.72\ \text{x}10^{6}$)	(0.0416)	(0.0018)
p-value	<0.001	0.5308	<0.001	0.0192
BH p-value	<0.001	0.707	<0.001	0.077
Constant	2.1613***	$2.49\ \text{x}10^{7}$***	1.940***	0.0302***
SE	(0.0138)	($2.19\ \text{x}10^{6}$)	(0.0348)	(0.0015)
p-value	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001
N	17811	2448	16650	17811
R^2	0.6683	0.1017	0.2371	0.6928

Tables 3.13 and 3.14 are results from models 2.2 and 2.3. Table 3.13 shows how non-marginal willingness to pay varies for continuous characteristics. For this model (model 2.2), implicit prices were recovered from a local polynomial regression, which were multiplied by respective characteristics for each observation to retrieve the MWTP. The MWTP was the dependent variable for OLS regressions. Like model 1.2, COVID-19 was not statistically significant. Table 3.13 shows that recyclers were willing to accept 0.06 cents/lb for a 10% increase in color after the import ban. And the recyclers were willing

to pay 0.0016 cents/lb for a 10% increase in color if oil prices increased. Across all types of plastics, recyclers would have to be given money to recycle plastic with more color. For LDPE and PET, recyclers were willing to accept ~1.5 cents/lb for a 10% increase in color.

Table 3.14

Probit Estimates from Model 2.3 (cents/lb)

Variable	Rigid	Food Grade	Film vs Bottle	Other vs Bottle	Segregated	Bottle Deposit
Import Ban	**-0.1157*** **	**-0.1404*** **	**0.0457*** **	**0.1942*** **	**-0.0918*** **	**omitted**
SE	(0.0076)	(0.0098)	(0.0055)	(0.0057)	(0.0059)	
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	
BH p-value	<0.001	<0.001	<0.001	<0.001	<0.001	
COVID 19	**0.0433*** **	**0.0287***	**-0.008**	**0.0206***	**0.0578*** **	**0.001**
SE	(0.0096)	(0.0123)	(0.0068)	(0.0074)	(0.0074)	(0.0011)
p-value	<0.001	0.019	0.224	0.005	<0.001	0.377
BH p-value	<0.001	0.038	0.56	0.015	<0.001	0.377
Crude oil Prices	**0.0015*** **	**0.0287***	**-0.0005*** **	**-0.002*** **	**0.0023*** **	**omitted**
SE	(0.0001)	(0.0123)	(0.0001)	(0.0001)	(0.0001)	
p-value	<0.001	0.019	<0.001	<0.001	<0.001	
BH p-value	<0.001	0.038	<0.001	<0.001	<0.001	
HDPE	**-0.0935*** **	**0.0181***	**-0.0018**	**-1.097756**	**-0.0551*** **	**omitted**
SE	(0.0071)	(0.0083)	(0.0051)	13.03048	(0.005)	
p-value	<0.001	0.029	0.731	0.933	<0.001	
BH p-value	<0.001	0.039	1	1	<0.001	
LDPE			**omitted**	**omitted**		
SE						
p-value						
BH p-value						
PET				**0.1374*** **	**-0.3265*** **	**omitted**
SE				(0.0043)	(0.0038)	
p-value				<0.001	<0.001	
BH p-value				<0.001	<0.001	
PP			**0.4612297**	**1.217685**		
SE			0.0016804	13.03048		
p-value			<0.001	0.926		
BH p-value			<0.001	1		
PS						
SE						
p-value						
BH p-value						
Mixed	**0.0151**					
SE	(0.0075)					
p-value	0.043					
BH p-value	0.108					
Constant	**0.7061*** **	**0.7361*** **	**0.4185*** **	**0.3292*** **	**0.7912*** **	**0.2233*** **
SE	(0.0031)	(0.004)	(0.0023)	(0.0024)	(0.0025)	(0.018)
p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
BH p-value	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
N	16859	9382	17811	17811	17811	444

Table 3.14 shows the impact of a supply shifter on recyclers probability of paying 1 cent/lb for a characteristic. This model was performed like model 1.3, but the implicit prices were recovered through a local polynomial regression. Once the probit coefficients were recovered, marginal effects of variables on probabilities was calculated using margins dydx(*) in Stata. In general import ban reduces the likelihood of paying, and COVID 19 and increase in crude oil prices, increases the likelihood of paying.

Discussion

The results from Table 3.10, 3.11, 3.12, 3.13, and 3.14 have important implications. In Table 3.10, the variation in implicit prices across regions indicate the differences in regulations on plastic collection and recycling. For example, there are no implicit prices for bottle deposit in four regions; and are only present in Texas and California. Even in California, where bottle deposit is popular, the price for bottle deposit -4.39 cents/lb. It is interesting that bottle deposit prices are not available for New York, which has a bottle bill. Bottle deposits are not significant predictors of recyclability. Even when they are present, recyclers do not associate a positive price with it. This hints at the recycling infrastructure. If all material must go through the same treatment, it does not matter whether a bottle deposit exists. Recyclers must treat a large volume of non-segregated plastics, so there is no marginal benefit from bottle deposits. Perhaps, if the volume of plastics from bottle deposits could increase, recyclers might value them more. Note that across 60,000 observations, only 400 were observed to be collected from bottle deposits.

Table 3.10 also shows that in general recyclers assign high positive values to food and beverage grade plastics. It is possible that food plastic is easier to clean and recycle or that the high standards for food-grade plastic help its recycling. Scholars have an opportunity to study food scrap plastic prices further and examine why recyclers assign a high positively value to them. The implicit prices for food contamination are positively related with the scrap plastic prices. Perhaps the industry has an opportunity to pay the same amount of thought and consideration when designing other types of plastic so that the resulting waste can be recycled easily. There is a positive relationship between plastic scrap prices and implicit prices for rigid plastics.

Interesting results are also observed from non-marginal willingness to pay. Take color from model 5 as shown in Table 3.13. For colored PET, recyclers were willing to accept

1.45 cents/lb for a 10% increase in amount of color. For 1 ton of colored PET (with a 10% increase in color), which costs approximately $725/ton, recyclers would have to be given $29 to recycle it. This is an important finding and suggests that colored plastics are hard to recycle. Perhaps the industry can self-regulate and implement tighter standards around use of color in plastic design. The industry and stakeholders can also adopt extended producer responsibility policy, as suggested in the Break Free From Plastic Pollution Act, where the producers can pool money ($29/ton of colored PET waste) and use it for research and development (Lowenthal, 2020). The government can also use these estimates to identify taxation. For example, the WTP can be recovered for different quantities of color. This can be used to tax the plastic producer, as their poor design leads to negative externality of plastic waste leakage.

This analysis also reveals important findings about two important predictors: Import ban and crude oil prices. Despite the differences in approaches, model 2,3,4, and5, share similar results across the two supply shifter variables. After the plastic import ban in 2017, many regions across the U.S. stopped collecting recyclable plastics as they could not recycle it anymore. U.S. recycling infrastructure did not have the capacity to recycle large volumes of plastics. As a result, recyclers either had low or negative preference for scrap plastic. In this case, subsidies that favor recycling infrastructure can help recyclers advance so that they are able to recycler larger volumes of domestic plastic waste.

Crude oil prices were another important predictor. As the raw material for virgin plastic, crude oil prices strongly influence virgin plastic prices such that low crude oil prices help keep virgin plastic prices low. Anecdotal evidence suggests that recyclers find it challenging to compete with these low virgin plastic prices so the demand for recycled plastic remains low. Recycled plastic demand increases only when oil prices hike, as shown by the results. In such cases, recyclers are willing to pay more for less desirable features such as contamination and color. This suggests that virgin plastic is not priced correctly to account for the waste it generates, especially when it cannot be recycled. Therefore, there is a need to price it correctly through a tax so that the negative externality can be accounted for. For example, in general, colored virgin PET should be priced at $29/ton more than recycled PET.

Conclusion

A hedonic analysis of scrap plastics in the U.S. is performed. Based on differentiated goods theory, it is proposed that the variations in scrap plastic prices stems from their recyclability – properties that enable recycling. This is tested using a two-stage hedonic regression on a large scrap plastic dataset from the U.S, which contains scrap plastic prices for 6 U.S. regions from 2005-2021. Instead of an explanatory model, a predictive modelling approach is used to let the data determine the most important variables.

The results confirm the general theory that scrap plastic prices vary based on properties that enable recycling. Furthermore, it confirms that both material properties and physical properties of scrap plastic influence recyclability and the price of scrap plastic. In general recyclers prefer clear, non-contaminated, segregated plastics that have been used in containers. In contrast, there is low preference for films, and mixed waste.

The results also show that changes in supply can influence how recyclers value scrap plastics. After the import ban on waste plastic, recyclers preferred not to buy scrap plastic. They would have to be paid money to recycle. However, after increases in oil prices, when the supply for virgin plastics reduces drastically, recyclers are willing to pay money to recycle even contaminated mixed waste. The results point at the need for more advanced recycling infrastructure so that U.S. recyclers can recycle. It also indicates the need for recycled plastic market that is more favorable than the one for virgin plastic.

The analysis suggests that scrap plastic and virgin plastic should be priced accurately to reflect the externalities caused by them. It reflects on the different approaches that the policymakers can use such as subsidy and tax to advance the goal of recycling scrap plastic.

These results should be treated with caution. They are limited because of the nature of the model. A popular version of the hedonics model, a consumer final market good model, has been used (Rosen 1974; Palmquist 1984; Bajari and Kahn 2005). However, scrap plastics are an intermediate good and are purchased by firms rather than consumers. Researchers have an opportunity to study how using an intermediate good theory can modify the results. Researchers also have an opportunity to conduct an in-depth evaluation of the industrial organization of the scrap plastics market, to interpret the scrap plastics better. The data collection also limits interpretation of these results. The original data did not capture the amount of color in each type of scrap plastic. This was recorded based on how much was allowed. It is possible the actual color varied across regions and type of plastic. Similarly, the dataset did not record material properties or information about recyclers. Future scholars have an opportunity to collect plastic scrap data such that it reflects all characteristics actual material properties. It is also noted that between the two approaches: multi-region approach and local polynomial approach, the latter performs better. For multi-region, scholars should investigate whether the market for scrap plastic is segmented into multiple regions, and if the assumption for market segmentation holds.

Future scholars can advance this research topic by analyzing other supply shifter variables, collecting more detailed data, and using advanced econometric methods. Policymakers can learn from these results and investigate more into the type of policies that can advance recycling – a circular economy pathway

CHAPTER 4

ROLE OF GOVERNMENT AS A CONSUMER TO INFLUENCE DEMAND FOR CIRCULARITY

Chapter 2 demonstrates the innovations required to transition to a circular economy for plastics. Although some innovations are in use, most innovations have low levels of adoption. Innovation adoption is more likely when stakeholders support it through financial capital, enabling policies and standards, and infrastructure (Garud et al., 2013; Rogers, 2003). For instance, plastic is recycled when the design is recyclable, consumer is aware and disposes the plastic, waste collectors have the tools to collect and recycle the plastic, and there is a market for recycled plastic. Stakeholders can play a critical role in enabling such innovations through finance, policies, social awareness, and market conditions (Garud et al., 2013; Rogers, 2003). Different stakeholders such as governments, financers, scientists, and competitors can facilitate innovations at different points in the value chain. Governments are especially critical stakeholders as they can influence innovations and the circular economy at both the supply and demand side.

Governments have been known to influence the supply side of the market in multiple ways. Governments can enforce design standards, impose taxes, or subsidize research and development efforts. Governments can also influence innovation through their demands in the form of public purchases, government purchase of goods and services (Edler et al., 2005; Edler & Georghiou, 2007). Many policymakers and policy scholars consider public purchases to be an effective policy tool. One analysis of innovations in Finland showed that 48% of successful innovators linked their success to public procurement (Edler & Georghiou, 2007). While much attention has been paid to supply side policies, demand side policies, particularly through public purchases remain understudied.

As shown in chapter 2, a circular economy will exist when circular product and services are purchased. Anecdotal evidence suggests that purchase of reusable, recyclable, and recycled goods has led to an increase in development of circular plastic products. While individual consumers can only purchase in limited amounts, governments as large institutions have enormous purchasing power. Public Purchasing accounts for about 20 percent of global Gross Domestic Product (GDP) and between 25 and 40 percent of all U.S. tax dollars collected (Coggburn, 2003). Their purchase of circular products sends strong signals in the market, creating a ripple effect. Recently, some governments are requiring the use of recycled plastic in construction of roads and buildings (Alhola et al., 2019). Such a purchase signals a demand to the builders, plastic waste collectors, and indicates a need for innovation. Due to the sheer size of such infrastructure projects, it facilitates the circular economy through capital, connections, and social awareness in a single project (Alhola et al., 2019). Thus, government purchase of circular products can trigger a large systemic change. Recognizing this, many governments see their purchasing power as a significant tool to stimulate innovation, and a transition to a circular economy. This use of public purchasing to achieve to meet their broader social objectives is also known as sustainable public purchasing (Alhola et al., 2019; Sönnichsen & Clement, 2020).

Sustainable public purchasing policies are government purchasing rules that explicitly value the economic, environmental, and societal impacts of their purchases. Examples of sustainable public purchasing policies include purchase of circular products, purchasing quotas for women- or minority-owned businesses, preferences for locally produced products, set asides for small business, expectations for fair labor practices, and purchasing criteria for products with reduced environmental impacts (Arrowsmith, 2010; Arrowsmith & Kunzlik, 2009; McCrudden, 2004; Stritch et al., 2018). While anecdotal information about these policies is emerging in fields such as economic policy, business administration, and innovation, public administration practitioners and scholars have given it far less attention, even though public purchasing is a central function of administrative government.

Historically, public purchasing has been at the periphery of public administration scholarship, accounting for about 1 percent of the total publications (Trammell et al., 2019). Among these publications, scholars have typically studied contracting concerns involving contract design (Kim & Brown, 2012; Malatesta & Smith, 2011), contract management (T. L. Brown et al., 2018; Romzek & Johnston, 2002), and accountability mechanisms in contracts (Allen et al., 2016; Girth, 2012; Romzek & Johnston, 2005). Less attention has been given to sustainable public purchasing (Trammell et al., 2019), such as buying local, green purchasing, or responsible supply chains. Additionally, very little is known about how the practitioner community is discussing sustainable public purchasing in their professional articles.

This research aims to understand how sustainable public purchasing has been regarded by the most influential outlets in public administration scholarship and practice and to pave a way forward for future research. It begins by describing the basic characteristics of public purchasing and sustainable public purchasing. It provides a theoretical framework for organizing research around sustainable public purchasing with a focus on circular economy. Next, it considers the historical evaluation of sustainable public purchasing policies enacted by the U.S. federal government and other OECD countries. I then review how public administration literature (scholarly and practitioner) addresses public purchasing and sustainable public purchasing. I pay special attention to prior research on sustainable public purchasing to assess what has been studied to date and to identify potential gaps that are important for public administration scholars to address. This will help understand how governments can use their purchasing power to facilitate a circular economy, and other big social goals.

The findings show that the landscape of sustainable public purchasing policies in the U.S. is rich and varied. While the federal government first implemented these policies in the 1800s, their use has increased especially since the mid-1970s, with no indication of a slowing trend. More recently, the European Union is even considering the use of circular public procurement. However, public administration publications have focused on other topics, with only 4.2 percent discussing issues of public purchasing. These articles focus exclusively on aspects of public purchasing, rather than discussing sustainable public purchasing. More specifically, these articles discuss the different aspects of contracting (T. L. Brown et al., 2018; T. L. Brown & Potoski, 2003; Kim & Brown, 2012), public private partnerships (Reynaers, 2014; H. Wang et al., 2018; Yang et al., 2013), and performance management (Koning & Heinrich, 2013; K. Yang et al., 2009). Although the proportion of public purchasing publications is greater in practitioner association publications, less than one percent discuss sustainable public purchasing. These results point to a critical void in the scholarly and practitioner literatures, especially given the potential promise that sustainable public purchasing policies have towards improving economic, environmental, and societal outcomes. I offer a justification for future research to consider the impact of these policies and identify several research questions to advance the field, especially related to circular economy.

Literature Review

Public Purchasing

Public purchasing is defined as the purchase of goods and services by all levels of government (Arrowsmith, 2010; OECD, 2017). Funded by taxpayers, these purchases facilitate government functioning and enable public agencies to provide public services such as education, healthcare, infrastructure, and waste management (Furneaux & Barraket, 2014).

Figure 4.1

Public Purchasing

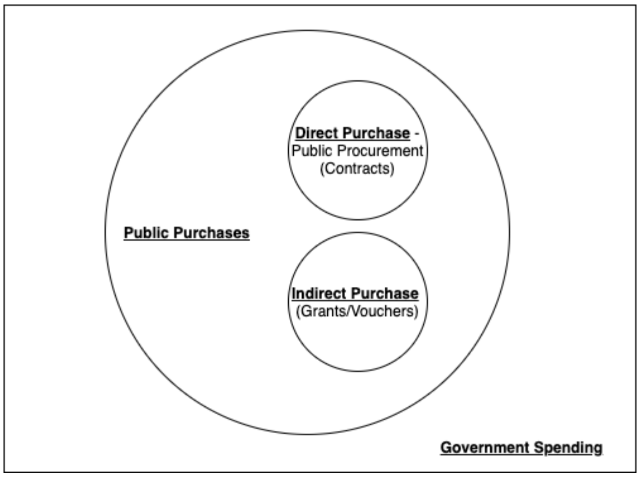


Figure 4.1 shows that governments conduct public purchasing through two mechanisms: direct purchases and indirect purchases. Direct purchasing, also commonly known as public procurement, refers to contract purchases that are conducted by government offices. For example, the Department of Defense uses direct purchasing to purchase equipment (Ruttan, 2006; Salamon & Elliott, 2002; U.S. Department of Treasury, 2020). Typically, scholars and practitioners have interpreted public purchasing to refer to only direct purchases (Boyne, 1998; T. L. Brown & Potoski, 2003; Romzek & Johnston, 2005). This interpretation ignores governments' indirect purchases where the government does not make the actual purchase. Rather, for indirect purchases, government offices transfer their purchasing authority to another organization or citizens. Examples include government grants to non-profit organizations to provide social services to citizens such as healthcare for the elderly, cash vouchers for food, and cash reimbursements for medicines (Ashley & Slyke, 2012; Beam

& Conlan, 2002; Breton, 1965; Buchanan, 1952; Colin, 2005; Department for International Development, 2011; Hipp & Warner, 2008; Lindert, 2013). While indirect purchases are an important form of public purchasing, scholars and practitioners typically have not considered indirect public purchasing in their assessments of public purchasing. Instead, they have focused on contracts with private sector vendors or service providers. When considering the government's overall purchasing power and influence, it is important to include both its direct and indirect purchases.

Government's purchasing influence is significant. Public purchasing amounts to approximately $9.5 trillion annually, accounting for one-fifth of the global GDP and one-fourth of all government spending (World Bank, 2017), making government the largest buyer in most economies (McCrudden, 2004; OECD, 2017). Within the Organization for Economic Co-operation and Development (OECD) countries, public purchasing accounts for between 15 and 30 percent of GDP (OECD, 2017). Even in developing countries, public purchasing accounts for between 10 and 15 percent of their national GDP (UNEP, 2017). Within the U.S., public purchases are approximately 24 percent of GDP (Hafsa et al., 2021).

Given its size and scope, all types of public purchases are susceptible to mismanagement and corruption which can lead to huge losses to governments and taxpayers. To reduce these problems, public purchases are heavily regulated. Over the past 100 years, local reform movements and international trade organizations have helped governments create systems of regulation-based laws and rules (Arrowsmith et al., 2011; OECD, 2017). Related to direct public purchases, these regulations guide the various stages of the process, which include budget plans, requests for bids, bid evaluation, contract design, and performance assessments (Arrowsmith et al., 2011; Thai, 2001). They also impose accountability on purchasers and vendors (Arrowsmith et al., 2011; Hettne, 2013; Schapper et al., 2017). Both purchasers and vendors are provided clear guidelines about due process including penalties for non-compliance. Purchasers are also typically required to practice transparency by documenting their selection criteria and the final choice of vendor, which helps ensure accountability. This documentation coupled with other regulations allows competing vendors to contest final decisions (Arrowsmith et al., 2011; Telgen et al., 2007; Thai, 2001). Although these regulations help ensure compliance, they also tend to add complexity to the public purchasing system and can increase administrative delays (Stritch et al., 2018).

Other forms of government purchasing are regulated to improve accountability. Related to indirect purchases, grants can account for up to 20 percent of state and local government's expenses (Beam & Conlan, 2002). To improve the accountability of these indirect purchases, governments require competitive applications and internal audits. Additionally, governments regulate indirect purchases by imposing restrictions on the types of goods and services that organizations or citizens can purchase. In each instance, citizens' or organizations' purchasing choices are constrained by government expectations or specific purchasing criteria. For instance, related to food vouchers, governments often restrict what types of food citizens can purchase with these vouchers. These restrictions can influence the production of certain types of food products. Similarly, government grants for social services place restrictions on the types of services provided. However, indirect purchases are less regulated than contracts (Beam & Conlan, 2002) and are generally awarded with limited scrutiny, as is the case for Medicaid grants (Breton, 1965). Some scholars therefore suggest that governments should be more transparent and critical regarding their award criteria (Ashley & Slyke, 2012; Dong & Lu, 2019; Zhao & Lu, 2020)

Other ways in which governments seek to reduce purchasing mismanagement and corruption involve imposing regulations such as eligibility criteria, purchase restrictions, and pre-approved vendor lists for voucher and cash transfer and reimbursement programs (Handa et al., 2016; Steuerle & Twombly, 2002). For instance, vouchers for housing are limited to qualified citizens who are either low-income or vulnerable (Handa et al., 2016; Steuerle & Twombly, 2002). Additionally, U.S. federal housing vouchers can only be used for housing that obtains a health and safety inspection. Similarly, in the case of food vouchers, governments limit eligibility and restrict the types of food that citizens can purchase, eliminating, for example, purchases of alcohol and unhealthy foods. Other programs that restrict the products that citizens purchase, include pre-approved vehicles in California's Hybrid and Zero-Emission Truck and Bus Voucher Incentive Project.

Regardless of whether purchases are direct or indirect, an important tension associated with reducing mismanagement and corruption is that regulations tend to diminish efficiencies related to the time it takes to award a contract, grant, or voucher (Arrowsmith et al., 2011). That is, as regulations increase, so too does process inefficiency. One way in which governments reduce this inefficiency is to require a singular criterion for purchases. Related to contracts, that criterion is often the lowest price bid for awarding contracts, and related to grants it is the highest number of beneficiaries (Arrowsmith et al., 2011; Beam & Conlan, 2002; Cravero, 2017; Hettne, 2013; Zhao & Lu, 2020). This incentive structure creates unintended outcomes. For instance, when a non-profit is motivated to increase the number beneficiaries to receive a grant, it will prioritize cases that are easier to process. As a result, vulnerable groups or more complicated recipients might get left behind. Single criterion approaches can also limit other benefits that could be derived from a product or service, such as product quality and timeliness of delivery. Governments, therefore, typically design purchasing regulations with multiple criteria to deliver social and economic benefits simultaneously.

Sustainable Public Purchasing

Government's use of public purchases to achieve social and environmental goals is known as sustainable public purchasing (Arrowsmith, 2010; Bengo, 2018; Brammer & Walker, 2011; Kanapinskas et al., 2014; Leiser & Wolter, 2017; McCrudden, 2004; Mendoza Jiménez et al., 2019; Sack & Sarter, 2018; Uttam & Roos, 2015; Wontner et al., 2020). Examples of sustainable public purchasing include set-asides that seek to address a single issue, such as the purchase of products from minority-owned businesses to address social inequalities, the purchase of environmentally friendly goods to reduce negative environmental impacts, and vouchers to encourage the adoption of low-carbon emitting vehicles to address climate change. Some forms of sustainable public purchasing address multiple social and environmental issues together, such as the purchase of environmentally friendly goods from a minority-owned, local business to reduce environmental impacts while empowering disadvantaged groups and supporting local economic development.

Two prominent bodies of literature address sustainable public purchases: public procurement of innovation (direct purchase of innovative solutions) and social public procurement (use of direct purchase for social outcomes). Both literatures typically have not been published in prominent public administration journals. The public procurement of innovation literature suggests that governments can solve large social problems created by inadequate public service and poor environmental management through direct purchase of innovative solutions (Edler et al., 2005; Edler & Georghiou, 2007; Hommen & Rolfstam, 2008; Uyarra & Flanagan, 2010). Since governments are large buyers, their purchase can encourage widespread adoption of innovative solutions that ultimately solve social problems (Edler & Georghiou, 2007; Edquist et al., 2015). The public procurement of innovation is currently limited to the direct purchase of innovative environmentally friendly technologies. It does not account for other types of public purchases and social outcomes, particularly social justice issues such as socioeconomic inequality.

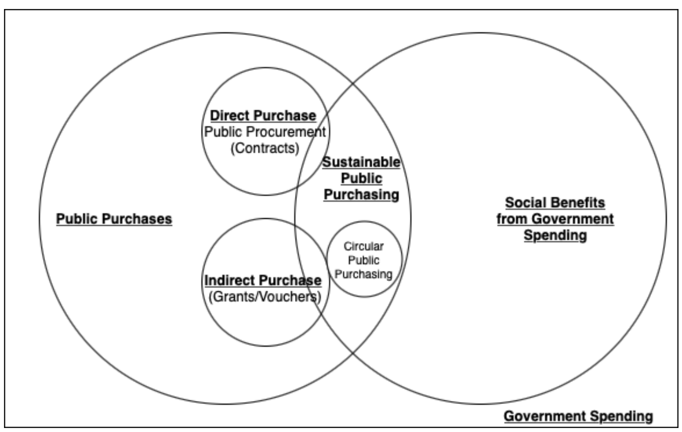
The second prominent body of literature addressing social public procurement focuses attention on how direct purchases can be used to address social justice issues such as women empowerment and labor rights, in addition to environmental issues (Arrowsmith, 2010; Barraket et al., 2015; Furneaux & Barraket, 2014). These scholars suggest that purchases can be categorized according to: 1) what governments' purchase (goods, services, or human services); 2) from whom it was purchased (private or non-profit organization); and 3) the type of social impact (direct or indirect) (Barraket et al., 2015; Furneaux & Barraket, 2014). While this literature advances understanding of sustainable public purchasing impacts, is it limited to direct public purchase and only considers social outcomes that can be achieved from contracts. What is missing from these discussions is how other public purchases, including grants, vouchers, and cash reimbursement, can affect sustainability outcomes. This limitation can impact how sustainable public purchasing is assessed more generally.

More recently, a small body of literature on circular public procurement has emerged. Circular public procurement is a part of sustainable public purchasing with an exclusive focus on the circular economy (Sönnichsen & Clement, 2020). Governments have an opportunity to use their purchasing power to demand innovative solutions such as road construction with recycled plastic (Alhola et al., 2019). Such demand can trigger a systemic response such that businesses will develop new circular products and services or collaborate to respond to government demand (Rainville, 2021). Scholars recognize that there is limited knowledge on circular public purchasing and that they can advance it by understanding sustainable public purchasing.

While the literatures on public procurement of innovation, social public procurement, and circular public procurement focus on different challenges, they can be collectively identified as sustainability challenges. The broader term “sustainable public purchasing” can account for social justice issues, environmental challenges, and the lack of circular economy. Therefore, I define sustainable public purchasing as all government purchases (direct and indirect) that improve social and environmental outcomes, as shown in Figure 4.2.

Figure 4.2

Sustainable Public Purchasing



I consider social outcomes to be different from public services (e.g., public education and public health) that governments typically provide. Social outcomes are societal benefits that can result from a public purchase, such as worker safety, harassment free workspaces, child labor free supply chains, women and minority empowerment, and accessible workspaces (Mendoza Jiménez et al., 2019; Missimer et al., 2017; Uttam & Roos, 2015; Wontner et al., 2020). They also include environmental concerns such as climate action through low emissions production, protection of natural resources through water-smart purchases, and reduction in use of single-use plastic (Daly, 1995; Wu, 2013). While environmental benefits are sometimes seen as distinct from social benefits, they directly impact the society. For example, if the local government uses reusable plastic bottle, it directly saves taxpayer money and reduces need for new material. This would also ultimately improve overall ocean health, public health, and well-being.

Table 4.1 elaborates on sustainable public purchasing by offering a theoretical typology. It distinguishes among two types of public purchases: direct (contract), and indirect (grants, vouchers, cash reimbursements). Direct purchases involve government making purchasing decisions that lead to exchanges between government and a vendor. By contrast, indirect purchases involve government transferring the purchasing decision to either individual citizens or to a non-profit that provides a social service. Both types of purchases can deliver immediate and deferred social outcomes. Immediate social outcomes are typically achieved shortly after government awards the contract, grant, voucher etc. Examples include savings that accrue after the purchase of reusable plastic bottles. Other outcomes are deferred and typically take multiple years to materialize. For instance, government's purchase of reusable plastic bottles can cause upstream manufacturers and distributors to redesign their single-use plastics to reduce their plastic footprint. These distinctions lead to four types of sustainable public purchasing: explicit contracts, contract spillovers, typical transfers, and transfer spillovers.

Table 4.1

Sustainable Public Purchasing Types

		Social Outcome Timing	
		Immediate	**Deferred**
Public Purchase Type	**Direct**	*Explicit contract*	*Contract spillover*
	Indirect	*Typical transfer*	*Transfer spillover*

Explicit Contract

Explicit contracts are direct, contractual, purchases. These contracts specify the nature of the good or service and the type of vendor. Social outcomes accrue at the point the contract is awarded, or shortly thereafter. As such, explicit contracts have an immediate social outcome. Examples include contracts for roads constructed with recycled plastics. These contracts directly reduce government's plastic footprint and encourage the use of recycled plastic (Alhola et al., 2019). Similarly, contracts involving set-asides for women-owned businesses address socioeconomic inequality by supporting women business-owners at the point the contract is awarded. and set-asides for women-owned businesses (Arrowsmith & Kunzlik, 2009; McCrudden, 2004).

Contract Spillover

Contract spillovers are direct purchases or contracts that have deferred social outcome in that they occur sometime after the point of purchase. For instance, governments often create purchasing contracts with statements of equal employment. These statements are intended to encourage contractors to hire more minority and female employees over time (Rice, 1991). Similarly, the UK requires contractors to take steps to prevent modern slavery in their supply chains (Butler, 2016). This condition is intended to eventually lead to elimination of modern slavery in supply chains. Governments can also require contractors to reuse and recycle. For example, a municipality in Denmark provided detailed guidelines to its contractors to facilitate the reuse of worker uniforms (Alhola et al., 2019). A similar guideline can be extended to plastics to require reusable food packaging or improved waste segregation infrastructure to encourage recycling.

Typical Transfer

Typical transfers are general purchases for social services that have immediate social outcomes for citizens. In some instances, typical transfers involve government cash vouchers to citizens for specific social outcomes, such as to assist low-income families with nutritious meals (Steuerle & Twombly, 2002). Typical transfers also involve governments giving grants to non-profits so they can purchase nutritious meals for low-income families (Beam & Conlan, 2002). In all cases, typical transfers offer social outcomes shortly after the transfer. In the past, the California government gave vouchers or rebates to encourage the purchase of electric vehicles (Steuerle & Twombly, 2002). In a comparable manner, governments can give vouchers to increase the market for recycled, and reusable products.

Transfer Spillovers

Transfer spillovers are typical transfers that offer deferred social outcome. For instance, food vouchers (a typical transfer) can specify healthier alternates to low-income families that reduce obesity over time. Additionally, food vouchers may allow the low-income family to spend their earnings on other family concerns, such as the purchase of medicine (Handa et al., 2016). Grants to non-profits can also have similar spillover outcomes. For example, a government grant that funds circular economy research can have long lasting impacts if government uses it to develop evidence-based policies.

Combined, these four types of sustainable public purchasing form a theoretical typology that articulates the variations in distinct types of government purchases (direct and indirect) and when social outcomes accrue (immediate or deferred). The typology also illustrates that while sustainable public purchasing may encourage the production of innovative products and services and contracting, this is only a small portion of its scope.

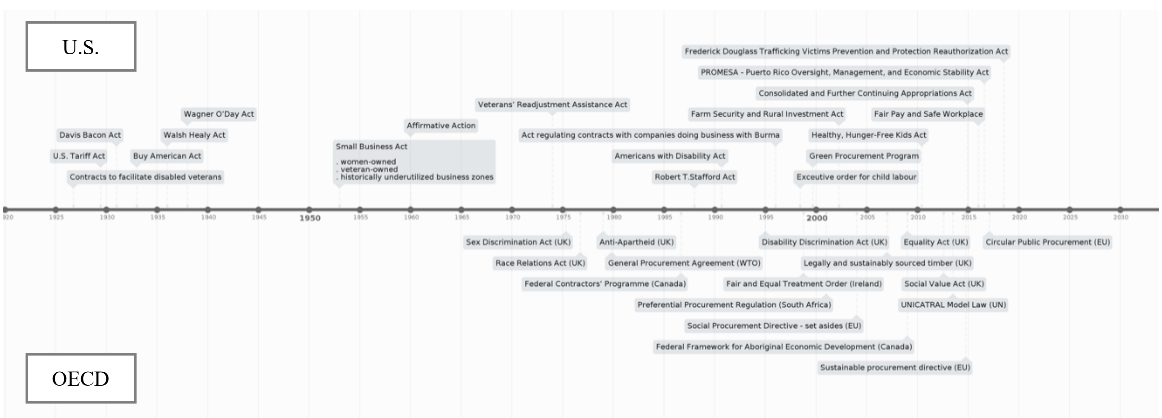
Sustainable Public Purchasing Policies

Sustainable public purchasing policies are purchasing rules or guidelines that deliver social benefits (Arrowsmith et al., 2011; Furneaux & Barraket, 2014). These benefits are derived from enhanced empowerment for women-, small-, or minority-owned businesses, local business growth, fair labor practices, and environmental improvements (Arrowsmith & Kunzlik, 2009; Cravero, 2017). Some governments set quotas for purchasing from minority-owned or small businesses to ensure equal access in the market (Arrowsmith et al., 2011; Furneaux & Barraket, 2014). In other instances, governments impose wage conditions on vendors when awarding contracts, such as fair wages, no child labor, or the prohibition against modern slavery labor (Furneaux & Barraket, 2014; McCrudden, 2004).

Sustainable public purchasing policies have been expanding significantly over time, as illustrated in Figure 4.3. The figure shows the evolution of sustainable public purchasing policies between 1900-2018 in U.S. and different OECD countries. The first U.S. sustainable public purchasing policy was adopted in 1840. It was an executive order by the President Van Buren, which imposed a 10 hour working day condition on all vendors contracted by federal government (Roediger & Foner, 1989). After 1930, the number of U.S. sustainable public purchasing policies steadily grew. Some of the more prominent U.S. sustainable public purchasing policies include Davis Bacon Act (1931) which ensured that federally contracted businesses paid minimum wages for all employees, the Buy American Act (1933) which prioritized local manufacturers when awarding contracts, and the Small Business Act (1958), which set aside contracts for small, women-owned, or minority-owned businesses (McCrudden, 2004). Other U.S. policies also encouraged set-aside contracts. These include the Wagner O'Day Act (1938) for people with disabilities, Veterans' Readjustment Assistance Act (1974) and Affirmative action policies in 1960s (McCrudden, 2004). In 1998, by way of executive order, the U.S. also adopted a federal green purchasing policy. In 2017, the European Union endorsed the use of public procurement to transition to a circular economy. To support public purchasers, EU also published a detailed guidelines demonstrating how circular public procurement can be implemented.

Figure 4.3

*Timeline of U.S. and OECD Sustainable Public Purchasing Policies (1900-2018) **



**Note: This timeline was produced by searching US laws using the US Congressional Database (govtrack) and Google search to identify similar policies for Australia, Canada, European Union (E.U.), New Zealand and the United Kingdoms (U.K.). Typical keywords used in both searches include women, minority, local, buy American, small businesses, green, environment, circular economy, and labor rights for the US; and women public purchasing policy, minority public purchasing policy, buy local public purchasing policy, small business public purchasing policy, green public purchasing policy, environmental public purchasing policy, circular public purchasing, and social public purchasing policy for other countries.*

Many policies were motivated by social movements (e.g., labor, ecology). For instance, the Davis Bacon Act and the Buy American Act reflected labor and business interests during the depression. Similarly, the Affirmative action policies of the 1960 reflect the civil rights movement and the 1998 Executive Order for federal green purchasing was created because of the growing environmental movement.

In contrast to the U.S., sustainable public purchasing policies across OECD countries began gathering momentum in the 1970s. The U.K. and Ireland passed legislations that required all public officers, including purchasing officers, to consider equality in their decision making. These legislations included the Race Relations Act (1976), Sex Discrimination Act (1975), Disability Act (1995), and Equality Act (2010). Like the U.S., the U.K. government also supported small businesses through direct purchases. However, instead of creating a formal purchasing policy, the U.K. government set up a council to advise small businesses (McCrudden & Doreen, 2007). Much of the E.U.'s sustainable public purchasing objectives were bundled into single legislations such as the 2008 and 2014 procurement directives. More recently, international governance bodies such as the United Nations and OECD have emphasized the importance of using public purchasing to achieve sustainability goals, including the circular economy.

Across all geographic settings, sustainable public purchasing policies hold enormous potential for improving numerous social outcomes even though, at present, they are largely limited to direct public purchases. As the largest buyers in the economy, governments can signal a significant demand for good and services that offer social benefits. Even if governments allocate a small portion of their purchases to sustainable public purchasing, they may be able to achieve significant social change directly within their communities and by shifting demand in the supply chain. If governments started considering the social impact of all types of public purchasing, the impact can be expected to be much larger. Yet, there is limited knowledge about how public administration scholars and practitioners are emphasizing it and whether its potential promise is being assessed.

Methods

In order to assess how public administration scholars and practitioners have regarded sustainable public purchasing, I conducted a systematic literature review (Tummers et al., 2015; Tummers & Karsten, 2012) of the scholarly and practitioner literatures that were published in the most widely recognized public administration outlets. A systematic review carefully examines publications on a specific topic and synthesizes their content. This approach enabled an understanding on what previous scholars have assessed related to public purchasing and sustainable public purchasing, and what gaps exist. Additionally, I reviewed both the scholarly and practitioner literatures to explore whether sustainable public purchasing has been addressed differently in scholarly and practitioner publications.

Assessing Scholarly Publications

I started with the scholarly literature. I constructed a dataset of public purchasing-related articles that were published in peer-reviewed public administration journals over 32 years. I focused on the top ranked public administration journals as identified by two prominent indexing platforms: Google Scholar Metrics and the Journal Citation Report Index. This approach was motivated by three factors. First, by focusing on indexed platforms, I identified journals with greater visibility, availability, and readership (Koushik, 2017). While non-indexed journals offer important scholarly contributions, they are less likely to be identified by search databases and tend to have lower citations and readership (Balhara, 2012).

Additionally, in incorporating two indexing platforms I further ensure that the analysis focuses on journals with greater prominence and that were available to a wider array of readers (Akhigbe, 2012). Moreover, indexed journals are ranked, which is how I was able to identify the top ranked public administration journals. This is important because faculty tenure, promotion, and other professional decisions, increasingly consider journal rankings as evidence for research quality (Corley & Sabharwal, 2010; Hodge & Lacasse, 2011; Lamb et al., 2018). Journal ranking is recognized as a measure of its importance within its field and provides a powerful incentive on what faculty decide to focus their research (Balhara, 2012).

After merging both lists, I identified the ten highest ranked journals that were identified more generally as being public administration journals – either a public affairs, public management, or public administration journal. These journals were characterized has having the highest h-indices, numbers of citations, and journal impact factors, as shown in Table 4.2.

Table 4.2

Top Ten Public Administration Journals

Journal	h-5 Index	Number of cites	Journal Impact Factor
Administration & Society (AS)	30	1877	1.564
American Review of Public Administration (ARPA)	38	1872	2.168
Governance (Gov)	38	2364	2.899
International Review of Administrative Sciences (IRAS)	30	1454	2.129
Journal of Policy Analysis and Management (JPAM)	36	2707	5.018
Journal of Public Administration Research and Theory (JPART)	46	5,222	3.289
Public Administration (PA)	40	3,941	1.825
Public Administration Review (PAR)	58	9,110	4.063
Public Management Review (PMR)	49	3,556	4.221
Public Money & Management (PMM)	24	1416	1.377

Table 4.2 shows 4 columns. The first column lists the names the top 10 public administration journals. The second column indicates their h-5 Index, which indicates that a journal has at least h articles with h citations in the last 5 years. For example Administrative Society (AS) has at least 30 articles with at least 30 citations in the last 5 years (Bornmann & Daniel, 2007; Google Scholar, 2021). The third column, number of cites, indicates the total cites for each journal for the year 2019. The fourth column lists

each journal's impact factor, which is the ratio of total citations in 2019 to the number of articles and reviews published in the last two years (2018 and 2017). A ratio higher than 1.0 implies that a journal's total number of citations in a year exceeded the number of articles published over the prior two years (Garfield, 2006). A journal's impact factor is a widely used proxy for the relative importance of a journal and is awarded to indexed journals (Balhara, 2012).

However, several biases are introduced by assessing only the work of indexed journals, which include: coverage and language preference of the database, procedures used to collect citations, citation distribution of journals, preference of journal publishers for articles of a certain type, citing behavior across subjects, and possibility of exertion of influence from journal editors (Balhara, 2011). For this reason, it is important to recognize that there are some limitations to our approach of focusing on indexed journals.

I restricted the assessment to publications in public administration journals as I wanted to understand how public administration scholars have discussed and assessed sustainable public purchasing. The top ten journals included in this assessment were: Administrative Society (AS), American Review of Public Administration (ARPA), Governance – an International Journal of Policy Administration and Institutions (Gov), International Review of Administrative Sciences (IRAS), Journal of Policy Analysis and Management (JPAM), Journal of Public Administration Research and Theory (JPART), Public Administration (PA), Public Administration Review (PAR), Public Money Management (PMM), and Public Management Review (PMR). Of the prominent public purchasing journals, only one was listed in the Journal Citation Report index for 2019: *Journal of Public Money Management*. Although journals like *Journal of Public*

Procurement and *Public Budgeting and Finance* also address public purchasing, as they are not indexed, I did not include them in this analysis.

The next step was to identify articles within the top ten public administration journals that addressed topics of public purchasing. The keywords are summarized in Table 4.3. To identify whether an article met the definition of public purchasing, I relied on keywords that included: purchase, procure, contract, outsourcing, grants, and cash vouchers. I used asterisks in keywords to increase the probability of identifying relevant articles. I relied on Web of Science for this search and considered only peer-reviewed articles published during the period, 1988-2020. Web of Science yielded 2,595 unique scholarly articles that had the keywords in the titles, abstract, or author listed keyword.

Table 4.3

Keywords for Public Purchasing and Sustainable Public Purchasing

Public Purchasing	Sustainable Public Purchasing
Auction*	Set-aside
Bid*	Women
Contract*	Minority
Privat*	Local business
Procur*	Small businesses
Purchas*	SME
Suppl*	Small medium enterprise
Set-aside*	Labor rights in supply chain
Tender*	Green purchasing
Vendor*	Environmental purchasing
Acquis*	Social
Capital	Ethics
Non-Profit*	Sustainable development
Cash	Gender
Voucher	Race
Expend*	Disability
Spend*	Public procurement of innovation
Award	Inequality
Grant*	Sustainability
Outsourc*	Sustainable development
Buy*	Nutrition
	Innovation
	Circular Economy

I manually screened each of the 2,595 articles for their relevance to *public purchasing*. Articles were considered relevant if they focused on contracting, tenders, vendors, purchasing, privatization or outsourcing of public service delivery, bidding or auctions, and government purchases for citizens through grants to non-profits, cash vouchers, or cash reimbursements. I coded articles as 1 if they were relevant to public purchasing and 0 if irrelevant. Articles that could not be easily categorized into either category, were coded as 2. For such articles, I assessed their abstracts and conclusions to verify their relevance and then coded them as either 1 or 0. If a publication was irrelevant to public purchasing, it was removed from the analysis. This process identified 515 publications that were relevant to public purchasing.

I then assessed each of the 515 articles for their relevance to *sustainable public purchasing*. If an article's title or abstract mentioned the following: social or environmental values, socioeconomic inequality, minority preference purchasing, women- or minority-owned business, buying local, small businesses, green/environmental purchasing, sustainable development, labor rights in supply chain, circular economy (as mentioned in Table 4.3) I considered it relevant. Additionally, I also identified public procurement of innovation as being relevant to sustainable public purchasing. A total of 65 articles from 1988-2020 met the criteria focusing on sustainable public purchasing.

To strengthen the validity of the results, I assessed the inter-coder reliability for the coding framework (available upon request). To do so, I gave another researcher in the field a randomly selected sample of 25 articles. I provided this individual with the coding definitions and asked them to determine whether the articles were relevant to either public purchasing or sustainable public purchasing. I then calculated the intercoder reliability as the proportion of the sample articles in which the independent researcher's coding matched mine. The inter-coder reliability across the independent researcher's coding and mine was 88 percent, in that coding for 22 of the 25 articles matched.

To determine the proportion of articles that were focused on public purchasing or sustainable public purchasing in the top ten public administration journals, I needed to know the total number of publications in each journal for each respective year. I collected these data by visiting each journal's website and manually counting its total number of articles in each year. Book reviews and editorial notes were omitted from the overall count. I then calculated: (1) the number of public purchasing articles as a percentage of the total publication, and (2) the number of sustainable public purchasing articles as a percentage of the total publications for each journal.

Assessing Practitioner Publications

For practitioner publications, I conducted a systematic review of publications that were produced by professional associations, since a critical part of their role is to impart information on cutting edge concerns that are relevant to their membership (ICMA, 2021; NCMA, 2021). For instance, if either the General Accountability Office or the General Services Administration develop new guidance related to sustainable public purchasing, professional associations would describe this guidance in their publications and convey how it is relevant to their members.

I focused on the largest public administration and public purchasing professional associations. I identified these associations by using internet searches on Google. Professional associations that were included in this analysis had to meet the following five criteria: (1) their primary mission that was focused on public administration; (2) they emphasized public purchasing in member communication; (3) their publications were published regularly via a report, magazine, blog, or newsletter; (4) their publications were in English; (5) publications were accessible to general audiences (and not just members). Since English is widely used for communication across their international membership, by focusing on professional associations that produce publications in English, I was able to target more influential international professional associations. The five inclusion criteria led to 34 professional associations, which were sorted based on their total membership. The top five largest professional associations had between 1,750 and 20,000 members (see Table 4.4). I limited my analysis to these associations because their large memberships are suggestive of their impact on the field. Additionally, memberships within other organizations were significantly lower (the next largest had 175 members). This approach necessarily excluded smaller, more regionally focused associations, associations that are not regularly communicating to members via publications. Additionally, because associations that either do not produce publications in English or are not regularly communicating to members via publications.

Table 4.4

Shortlisted Professional Public Purchasing Organizations

Organization	Membership
National Contract Management Association (NCMA)	20,000
Institute of Public Procurement (NIGP)	15,588
International City/County Management Association (ICMA)	11,881
National League of Cities (NLC)	2,000
ICLEI	1,750

I then reviewed professional association publications from *National Contract Management Association (NCMA)*, *Institute of Public Procurement (NIGP), International City/County Management Association (ICMA), National League of Cities (NLC),* and *ICLEI – Local Governments for Sustainability (ICLEI).* I visited the website for each professional association, and using the same keywords listed in Table 4.3, I manually screened each publication to determine whether it was relevant to public purchasing. Since the most recent publication began in 2015, I only considered articles published between 2015-2019 for all five organizations.

I determined each article's relevance to public purchasing and sustainable public purchasing using the criteria I used for assessing the scholarly publications. I identified 262 publications published between 2015-2019 that were relevant to public purchasing and, of these, 31 focused on sustainable public purchasing. I then calculated the proportion of public purchasing and sustainable public purchasing for each organization by manually counting the total number of professional association publications. Advertisements or editorial notes were omitted.

Content Analysis

To understand the general topics that are most addressed in the scholarly (515) and practitioner (262) publications, I used keyword analysis. For scholarly articles, I analyzed abstracts from publications. For practitioner articles, I only analyzed the article titles as many did not have formal abstracts. I used Antconc, a free text analysis software to find keywords (Anthony, 2019).

A keyword analysis compares distribution of words within a target text and a common English text (brown corpus) using a log-likelihood test. The software identifies keywords as words that have a high positive difference in distribution (Anthony, 2019; Kilgarriff, 2001). To ensure that the software only identifies key concepts, I excluded extensively used words from the analysis such as articles and pronouns, academic words such as theory and methods, and common public purchasing terms such as purchase, procurement, public, and government.

Antconc allows users to upload a stop list of words to exclude them from the analysis. I used the stop list by Natural Language Toolkit's and a modified version of Averil Coxhead's academic word lists (Coxhead, 2000). The academic wordlist includes words such as contract, minority, partnership that were key to the text under review. For this reason, I only included words such as research, lab, experiment, results that commonly appear in research papers. Since I expected the words public, governments, procurement, and purchasing to occur frequently throughout the text, I also added them to the stop list. By excluding these words, I was able to understand other topics besides public purchasing that were key to the public purchasing literature.

Once I obtained the keyword list, I manually screened for anomalies. I looked for words that share roots such as contract and contracting that were mentioned separately, and only used one of those words. I limited the analysis to the top fifty keywords.

In addition to keyword analysis, I used an n-grams analysis. An n-gram analysis helps identify clusters of words that frequently occur together such as public-private partnerships (Anthony, 2005; Nesselhauf & Tschichold, 2002). For this analysis, I only looked for 2- and 3-grams. Unlike the keyword analysis, I was unable to automate the n-gram analysis to exclude key concepts. Therefore, I manually screened for words that were helpful for the analysis, such as “set asides” and “small businesses” etc. I screened out phrases such as “guide to” and “state and local” as these did not advance understanding of the text. I combined the words from the top 50 keyword lists and the key phrases from top 50 n-grams to generate a word list. I used this word list to generate word clouds with a free, online word cloud generator.

I paid special attention to sustainable public purchasing scholarly articles and analyzed 57 for their type of sustainable public purchasing. I did not have full access to 8 of the 65 scholarly articles on sustainable public purchasing as they were behind a paywall. I mapped the 57 accessible articles on to the sustainable public purchasing typology. I used the definitions of type of public purchase (direct or indirect) and social outcome timing (immediate or deferred) to classify the article as explicit contract,

contract spillover, typical transfer, or transfer spillover. If the article referred to contracts or acquisition, it was coded as direct purchase. For other types of public purchases such as grants, and cash vouchers, I coded the articles as indirect purchase. If the article referred to an immediate social outcome such as empowering disadvantaged groups through set-asides or purchase of green goods, I coded it as immediate. If the article referred to spillover outcomes such as increasing minority employment in a contracted firm through set-aside, I coded it as deferred. For this coding, I asked a second coder to assess titles and abstracts for type of public purchase and social impact timing. I had a 100% intercoder reliability for type of public purchase. For timing, I had a 67% intercoder reliability, so I asked the coder to read more of the paper and conducted a second analysis, which resulted in a 100% match.

For all sustainable public purchasing scholarly articles, I also identified and categorized the social outcomes that they addressed. I conducted this exercise on MAXQDA and used grounded theory to categorize social outcomes.

Results

Figure 4.4 indicates the overall trend of scholarly publications in the top indexed public administration and public purchasing journals over the last 32 years (available upon request). The total journal publications are at the bottom, followed by public purchasing publications, and sustainable public purchasing publications are at the top. Since 1988 of the 12,164 total publications in all ten journals, less than four percent (515) of the publications addressed public purchasing. These results support earlier findings by Trammell et al (2019). Additionally, of these publications less than one percent (65) addressed sustainable public purchasing, suggesting that while there is a critical gap in public administration literature related to public purchasing, it is even bigger for sustainable public purchasing.

Figure 4.4

Public Purchasing Articles a in Public Administration Journals over Time

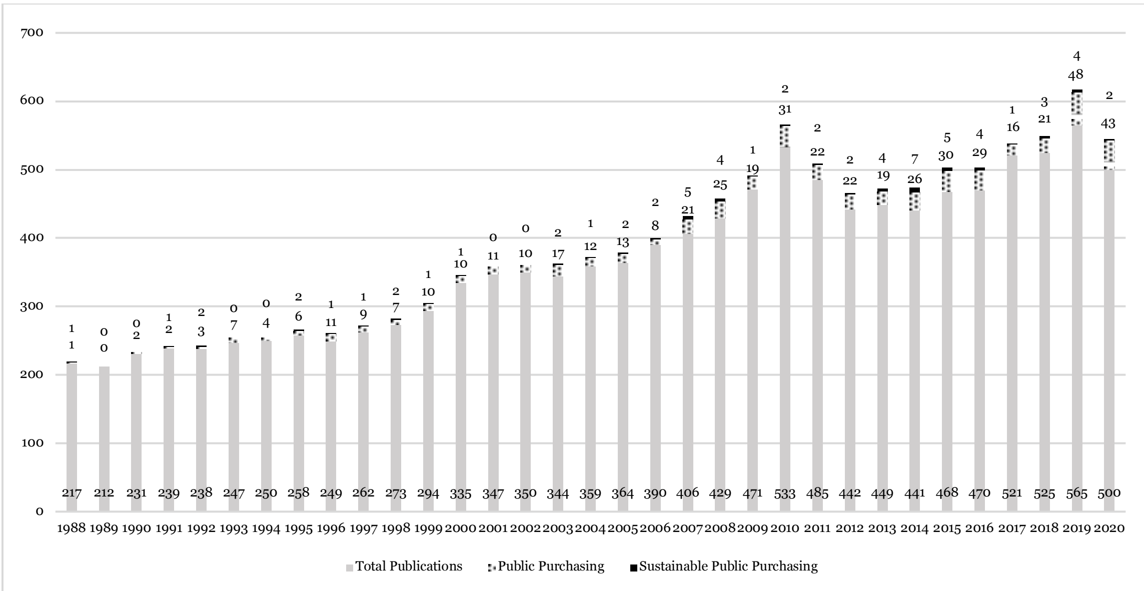
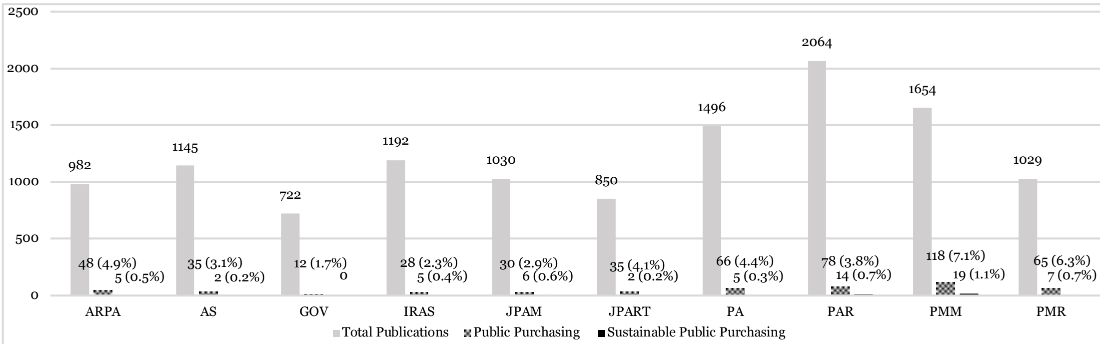


Figure 4.5 separates the scholarly publications by journal. Each journal's total publications are on the left, followed by its public purchasing publications and sustainable public purchasing publications. For example, PAR published 2,064 articles over 32 years. A total of 78 articles studied public purchasing (3.8 percent of all published content) and 13 studied sustainable public purchasing (0.7 percent of all published content). Among the top ten public administration journals, PMM published most articles on both public purchasing (118 articles) and sustainable public purchasing (19 articles). Among the top ten public administration journals, publications on public purchasing ranged between 1 - 7 percent of total content, and sustainable public purchasing made up less than 1 percent of all publications.

Figure 4.5

Public Purchasing Articles in Public Administration Journals by Journal



Similar trends are observed in the practitioner literature. Figure 4.6 indicates the overall trend of publications in the top public administration professional association publications between 2015-2019 (available upon request). The proportion of public purchasing publications is much higher in practitioner publications as compared to the proportion published in scholarly journals. However, of the 3,243 total publications (bottom) in all five practitioner publications, eight percent (262) publications have addressed public purchasing and only one percent (31) have addressed sustainable public purchasing.

Figure 4.6

Public Purchasing Articles *Practitioner Literature over Time*

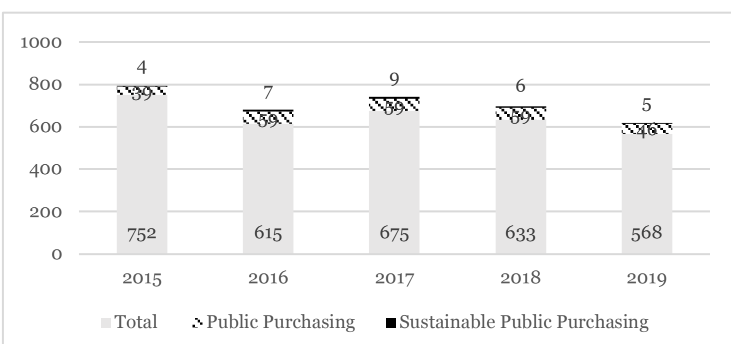


Figure 4.7 displays results of practitioner literature review by professional association. Note that NCMA and NIGP have a much higher share of public purchasing publications. These articles discuss topics such as contracting employees. Among other organizations,

ICLEI, ICMA, and NLC, the proportion of public purchasing and sustainable public purchasing publications matches the trend in scholarly publications.

Figure 4.7

Public Purchasing Articles in Practitioner Literature by Organization

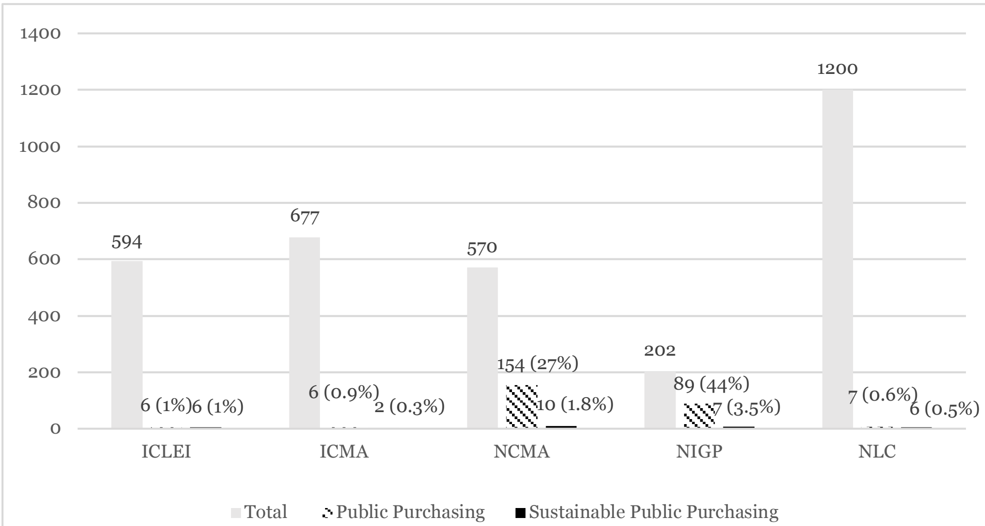


Figure 4.8 summarizes the results of our keyword analysis of the public purchasing and sustainable public purchasing publications in scholarly and practitioner literature, respectively. The publication type (scholarly article or practitioner publication) defines the vertical axis, and the purchasing topic (public purchasing or sustainable public purchasing) defines the horizontal axis. In each word cloud, the size of each word is proportional to its keyness (difference in distribution).

Figure *4*.8

Keywords Scholarly and Practitioner Literature

In general, there is a disproportional focus on the contracting process in direct public purchases in scholarly articles and practitioner articles of all sorts. Scholarly articles on public purchasing (quadrant a), focus prominently on topics related to “services,” “service delivery,” “private firms,” and “management.” Practitioner publications on public purchasing (quadrant c), focus more frequently on topics related to “technology,” “partnerships” and “subcontracts.” By contrast, scholarly articles on sustainable public purchasing (quadrant b) emphasize topics related to “minority” “policy” and “public private partnership (PPP)”. Finally, practitioner publications on sustainable public purchasing (quadrant d) emphasize topics related to “green”, “sustainability”, and “Small Business Innovation Research Program (SBIR)”. I did not come across any publications on circular economy or how to implement it using public purchasing.

Table 4.5 summarizes the type of sustainable public purchasing for scholarly sustainable public purchasing articles. A total of 51 out of 57 articles referred to direct public purchases. However, only 5 addressed indirect purchases. While articles were more inclines towards studying immediate outcomes, twenty-two articles studied both immediate and deferred outcomes of contracts. In general, scholars mostly studied explicit contracts and contract spillovers. There was little focus on typical transfer and transfer spillovers.

Table 4.5

Type of Public Purchase vs Outcome Timing in Scholarly Sustainable Public Purchasing Article

		Social Outcome Timing			Total Articles
		Immediate	Both	Deferred	
Public Purchase Type	Direct	*Explicit Contract* 22	17	*Contract Spillover* 12	51
	Indirect	*Typical Transfer* 1	5	*Transfer Spillover* 0	6
	Total Articles	23	22	12	

Table 4.6 is a summary of the social outcomes that scholarly sustainable public purchasing articles studied. For each type of public purchase, I identify the type of outcomes that the articles discussed. For example, for indirect public purchases (grants), scholars had studied grants to religious organizations run by religious minorities, which was an immediate social outcome. Similarly, use of religious groups to provide services to a diverse demographics was a deferred outcome. For each outcome, the number in bracket indicates the number of articles in which it was mentioned. In general, most articles studied explicit contracts which refer to immediate outcomes from contracts. The most studied outcome was contracting with minority-owned business and small

business. Other outcomes such as nutrition in meals and equal access were less studied. There was no mention of circular economy.

Table 4.6

Social Outcomes from Sustainable Public Purchasing Articles

	Immediate Outcome	Deferred Outcome

Direct Purchase Contracts	• Contract with minority-owned organization
	  ○ *General (13)*
	  ○ *Women (6)*
	  ○ *Indigenous (1)*
	  ○ *Racial or ethnic (8)*
	• Contracts with small businesses (15)
	• Contracts with local business (4)
	• Environmental impact of goods
	  ○ *Energy efficiency (1)*
	  ○ *Water footprint (1)*
	• Specifications for working conditions
	  ○ *Worker safety (2)*
	  ○ *Minimum wage (1)*
		• Contractor employs minorities
		  ○ *Equal employment (4)*
		  ○ *Women (2)*
		  ○ *Indigenous (1)*
		• Contractor addresses human rights in supply chain
		  ○ *General rights (1)*
		  ○ *Labor rights (1)*
		  ○ *Child labor (1)*
		• Contractor values process efficiency over
		  ○ *safety and well-being (1)*
		  ○ *ensuring all citizen's access to services (1)*
		• Environmental impact of goods
		  ○ *General (4)*
		  ○ *Climate action (1)*

Indirect Purchase Vouchers/Cash Reimbursement	Government provides vouchers for nutritious meals to low-income families (2)	Certain demographics do not have equal access to vouchers such as citizens with disabilities, or non-English speaking residents due to efficiency considerations (3)
Indirect Purchase Grants	Grants to non-profits run by religious minorities (1)	Grants to religious groups to ensure diverse groups of citizens have access to social services (1)

Discussion

While policymakers are developing sustainable public purchasing policies, the public administration field, responsible for the policy implementation, has understudied this topic. In the last 32 years, among all scholarly and practitioner articles, only a small portion (0.6%) has been dedicated to sustainable public purchasing. There is also bias in the type of purchase and social outcomes that have been studied.

Public administration scholarship has leaned heavily towards assessing direct public purchases. In comparison indirect public purchases have received little attention, which indicates that most top journals typically do not consider indirect purchases as a government purchasing activity. Indeed, 50 (88%) out of 57 scholarly articles assessed either explicit contracts, contract spillovers, or both. Due to this publication bias, scholars have focused on a narrow portion of social outcomes from public purchasing.

Most articles studied sustainability in contracting (Papanagnou & Shchaveleva, 2018), and set-asides for minorities (Fernandez et al., 2013; Martin et al., 2007; Rice, 1991) and small businesses (C. Smith & Fernandez, 2010; Walker et al., 2013). Even among the practitioner articles topics related to contracts were widely studied, including set-asides, local purchasing, and some emphasis on green/sustainable purchasing. For instance, each issue of NIGPs' publication includes a section related to green public purchasing. While these publications advanced a deeper understanding of contracts, extraordinarily little is understood about how indirect purchases can be used to address social needs. These are key research gaps that public administration scholars can fill.

Related to social outcomes of sustainable public purchasing, scholars have studied immediate outcomes, especially explicit contracts. Scholars have been concerned with the processes to award contracts, contract design, and contract effectiveness (Erridge & Hennigan, 2012; Gelderman et al., 2017; Young et al., 2016). This is mirrored in the practitioner literature, which primarily discusses various aspects of explicit contracts such as process innovation, and best practices for city government. As a result, a deeper understanding of deferred impacts is missing. In particular, there are no studies on transfer spillovers that can answer important questions such as can cash vouchers reduce obesity among citizens (Myers Jr & Chan, 1996; Sarter & Thomson, 2020). Therefore, assessing the deferred impact of sustainable public purchasing programs and policies, is another opportunity area for public administration scholars to study.

The existing research also raises concerns about the kind of social outcomes that are studied. I did not come across any articles in scholarly or practitioner literature on circular economy, even though this topic has been around since 1966 (Blomsma & Brennan, 2017b). Although the literatures have focused heavily on topics related to efficiency, effectiveness, and productivity, they did not refer to circularizing the economy, which also intends to promote efficiency in resource management and material use. Similarly, scholars needs to pay attention to distinct social, environmental, and economic priorities, and consider them together instead of a piecemeal fashion (T. L. Brown et al., 2006). Researchers have an opportunity to study, clarify, and evaluate the immediate and deferred social outcomes that public purchasing can achieve.

Scholars should also consider how competing values impact the implementation of sustainable public purchasing policies (Boyne et al., 1999; T. L. Brown et al., 2006). Most public purchasers are trained to consider best value for money, which can be a barrier when choosing circular or greener products which are typically more expensive (Loader, 2007; J. Smith et al., 2016; Sönnichsen & Clement, 2020). Alternatively, purchasing officers can be trained to consider multiple aspects of a purchase at the same time such as circularity, environmental impact, assistance to disadvantaged business communities. Thus research on meeting multiple objectives such as social values, process efficiency, and effectiveness can facilitate implementation of sustainable public purchasing (Stritch et al., 2020). To simplify the decision-making process for purchasers and providers and reduce the administrative burden, prospective research should identify different mechanisms to balance such conflicting objectives

Within sustainable public purchasing articles, the discussion on policy implementation is missing. For instance, it is unclear what type of organizational structures, information availability, software systems, and other factors can facilitate the implementation of sustainable public purchasing. In recent years, scholars have asked, but not answered, this question as it relates to sustainable public purchasing (Darnall, Stritch, Bretschneider, Hsueh, Duscha, et al., 2017; Grandia et al., 2015; C. Smith & Terman, 2016). However, less is known about the implementation challenges that organizations face for sustainable public purchasing more generally (Darnall, Stritch, Bretschneider, Hsueh, Duscha, et al., 2017). Future research should consider these issues more. One valuable approach might be assessing how different agencies, including the U.S. Department of Defense and the U.S. Environmental Protection Agency, are adopting, and implementing sustainable public purchasing. By comparing the implementation activities across agencies, prospective research would go a long way towards understanding the variations in implementation challenges as well as commonalities.

Although sustainable public purchasing policies are being implemented on a large scale, it is unclear whether these policies are achieving their desired goals (Brunjes & Kellough, 2018; Denes, 1997; Koning & Heinrich, 2013). For instance, about 28 percent of U.S. cities have adopted sustainable public purchasing policies (Darnall, Stritch, Bretschneider, Hsueh, & No, 2017), but scholars should consider whether they lead to more women or minority representation in contracted businesses, facilitate a higher market access for small businesses, or improve environmental outcomes? Similarly, scholars should ask whether the European Union policy on circular public procurement has facilitated a transition to circular economy. Answers to these questions can help us understand whether social objectives can be met using public purchasing policies. Scholars should consider expanding their scope to empirical studies for all kinds of public purchases, especially for transfers. With limited to no data on transfers, it is difficult to ascertain how policies related to them impact social well-being.

The list of gaps that have been identified in public administration research is not exhaustive. While there is room for more research sustainable public purchasing, existing knowledge gaps echo the existing debates in public administration relating to policy impact, competing values, and policy implementation.

Conclusion

Sustainable public purchasing is recognized as a strategic tool that is used by both national governments and international governance organizations around the world to influence social outcomes. Historically, since the 1800s, the U.S. government has been using public purchasing systems to address its broader social objectives, beyond price and quality. The U.S. has used sustainable public purchasing policies to address various disadvantaged communities, especially by using set-asides. Other countries have also used sustainable public purchasing policies to assist disadvantaged communities by establishing advisory councils. Globally, sustainable public purchasing policies have gained traction since 1970s with increased use. In 2017, the European Union recommended using public purchasing to achieve a circular economy. Despite the numerous sustainable public purchasing polices around the globe, the findings show that the scholarly and practitioner literature in public administration has been slow to respond.

In the last 32 years, of all publications in the top ten public administration journals, only 4.2 percent address public purchasing, and only 0.5 percent address sustainable public purchasing. In practitioner publications, while a greater proportion of content is dedicated to public purchasing (8 percent), only 1 percent of all content relates to sustainable public purchasing. I acknowledge that a literature review of the top ten public administration journals and top five professional association publications is not completely representative of the field. It is biased towards English language publications, more generalized public administration journals (as compared to specialized purchasing and finance journals), and larger publishing organizations with finances to invest in indexing or making their professional publications publicly accessible. The results therefore are not representative the entire field of public administration. They also are not representative of other fields, such as business administration, economic policy, and supply chain innovation, which may publish on the topic. This more targeted approach allowed a thorough assessment of the most widely recognized public administration journals and practitioner publications for a more systematic review. As such, these findings are representative of the state of the most influential public administration academic and professional outlets more generally. For public administration scholars, it is these public administration journals that receive considerable attention in tenure, promotion, and other professional decisions since journal rankings are regarded as evidence for research quality (Corley & Sabharwal, 2010; Douglas, 1996; Hodge & Lacasse, 2011) and journal importance (Balhara, 2012). Attention to journal quality during tenure, promotion, and other professional decisions also signals to faculty what their academic institutions considers important, which influences their choice of research topics and journal selection (Corley & Sabharwal, 2010; Douglas, 1996; Hodge & Lacasse, 2011). Based on the results of this research, I conclude that the top public administration outlets are not studying sustainable public purchasing, even though public purchasing is a critical function of public organizations. Public administration's neglect of public purchasing, and particularly sustainable public purchasing, has left a critical void in the knowledge about this increasingly important activity.

This void has important implications for social outcomes such as circular economy. While governments have the potential to spur innovation, and create a market for sustainable and circular products, public administration scholars have not responded to it. Scholars have an opportunity to facilitate a transition to circular economy, by learning from existing best practices on sustainable public purchasing, creating guidelines for public purchasers, and identifying which types of purchases are more effective than others. Scholars can advance theoretical development on sustainable public purchasing and sustainability challenges like circular economy, and help governments use public purchasing more strategically and more impactfully.

CHAPTER 5

CONCLUSION

This dissertation illustrates how a sustainable circular economy for plastics can be implemented in three ways 1) adopting circular innovations throughout the plastic value chain, 2) supporting recyclers through evidence-based policy changes, and 3) public purchase of sustainable and circular products and services.

Circular Innovations

The findings in chapter 2 reveal a material flow typology that shows that implementing a sustainable circular economy requires innovations at five critical points: packaging design, consumer behavior, material reuse, material recovery, material treatment, and policy. plastic packaging value chain can yield material flow that ends in recycling, composting, or reuse if packaging materials and design are made to be circular, the consumer handles the packaging correctly, there are convenient and efficient channels for material recovery, if it is profitable to treat recovered material, and if material can be profitably reused. Results also show that most innovations are at experimentation and commercialization and have not been diffused. Among other areas, most innovations exist in packaging design, and there are fewer innovations in policy and material recovery.

The results warrant a reflection on how adoption of innovation can be improved. While there is an abundance of innovation, less than 9% of plastic is recycled. How can there be so much innovation with so little impact on overall circularity? Scholars have an opportunity to study research questions such as what factors motivate organizations to adopt plastic circular innovations; what are barriers to adoption of plastic circular innovation; how can external stakeholders influence adoption of plastic circular innovations?

Evidence for Favorable Policies for Recycling

In chapter 3, recyclers' price signals for scrap plastic are interpreted to gather evidence for policymaking. A hedonic analysis is conducted to understand recyclers' demand for different plastic waste characteristics including physical conditions (segregated, contaminated), and material properties (food metals, percent of non-primary material, rigidity) under supply shift changes. The results show that recyclers' willingness to pay for a characteristic change according to the market conditions and type of plastic material.

In general, virgin plastic prices and adequate recycling infrastructure play a critical role in recycling. When virgin plastic prices are too high, the industry accepts recycled plastic as a low-cost substitute. In such cases, demand for recycled plastic increases such that recyclers are willing to pay for generally unacceptable characteristics like contamination. Presence of an adequate recycling infrastructure also impacts scrap plastic prices. If the volume of plastic waste exceeds recycling capacity, recyclers would have to be given money to recycle even desirable characteristics such as rigidity.

The type of plastic is an important predictor of willingness to pay. The recycling technology, material properties, or end-market of these plastics allows recyclers to process them more easily than others for a high profit. For example, recyclers are willing to pay money for contaminated polypropylene as compared to other plastics. Using these results, policymakers can develop policies based on the local context and end goal. For example, results show that recyclers would accept $29 to recycle a ton of colored PET, which is approximately 4% of the virgin-colored PET price ($725/ton). If the end goal is to increase recycling for colored PET, investment of $29/ton must be made to advance innovative technologies like de-inking that facilitates that. Another way is to tax plastic producers for at $29/ton manufacturing colored PET.

These results must be treated with caution. This chapter does not advocate for one policy over another. Future scholars have an opportunity to investigate what type of policies can be made using these results. Scholars also have an opportunity to improve data collection on plastic waste. The analysis revealed that limited efforts are made on recording historical plastic prices for scrap plastic and their corresponding properties.

Using Government Demand to Influence Circularity

Chapter 4 presents evidence that sustainable public procurement is a strategic tool that can be used to achieve a sustainable circular economy. While policymakers have developed sustainable public purchasing policies, the public administration literature has been slow to respond. Since public purchasing is a public administration function, this is a critical omission.

The chapter presents a theoretical framework to demonstrate how governments can use their purchasing power to achieve a sustainable circular economy. It is argued that governments can use both direct and indirect purchases to achieve immediate and deferred sustainability outcomes. For example, government can use public procurement contracts to commission circular products and services. Or governments can award a grant to a public university for research on implementation of a circular economy.

The systematic review of top ten public administration journals over the last 32 years reveals that only 0.5 percent publications study sustainable public purchasing and none have studied circular economy. The content analysis shows that the literature on sustainable public purchasing is also biased about the kind of outcomes that are studied. This indicates that the public administration field is wide open for scholars to study the use of sustainable public purchasing for circular economy. Scholars have an opportunity to facilitate a circular economy implementation, by learning from existing best practices, creating guidelines for public purchasers, and identifying which types of purchases are more effective than others. Such research will help governments influence the plastic life cycle as consumers in the market.

One limitation that was observed through all chapters limited to the use of sustainability within the circular economy field (Velenturf & Purnell, 2021). In practice, circular economy is often interpreted as a way to manage resources, especially waste and does not account for social responsibility (Blomsma & Brennan, 2017a). For example, plastic waste is recycled through the informal sector in some countries such as China and Pakistan. However, anecdotal evidence suggests that these recyclers are often marginalized, not equitably compensated for their labor, and do not have access to important services such as healthcare. While it can be argued that the overall waste management is circular, it comes as the cost of an unequal society. Chapter 2 shows that most innovations focused on operations and environmental management, with limited to no attention for social innovations. Chapter 4 shows that most social outcomes related to a certain group such as women, with no mention of other gender identities. This omission and bias hinder the achievement of sustainability goals. Thus, it is important for future scholars to be cognizant of these biases and help promote the concept of a sustainable circular economy.

Overall, this dissertation demonstrates three different ways that a sustainable circular economy for plastics can be implemented. As a systems issue, challenges like these require and inter-disciplinary and trans-disciplinary approach. Other disciplines such as material sciences, ocean sciences, management sciences etc. can explore this topic from different perspectives and help answer unanswered questions. The field is rife with opportunities.

REFERENCES

Abbott, J. K., & Klaiber, H. A. (2011). An Embarrassment of Riches: Confronting Omitted Variable Bias And Multiscale Capitalization In Hedonic Price Models. *The Review Of Economics And Statistics*, *93*(4), 1331–1342.

Abbott, J. K., & Sumaila, U. R. (2019). Reducing Marine Plastic Pollution: Policy Insights from Economics. *Review of Environmental Economics and Policy*, *13*(2), 327–336. https://doi.org/10.1093/reep/rez007

Adner, R. (2017). Ecosystem as structure: An actionable construct for strategy. *Journal of Management*, *43*(1), 39–58. https://doi/pdf/10.1177/0149206316678451

Aguilar-Hernandez, G. A., Dias Rodrigues, J. F., & Tukker, A. (2021). Macroeconomic, social and environmental impacts of a circular economy up to 2050: A meta-analysis of prospective studies. *Journal of Cleaner Production*, *278*, 123421. https://doi.org/10.1016/j.jclepro.2020.123421

Akhigbe, R. E. (2012). Scientific journals: Indexation and impact factor. *Lung India*, *29*(3), 300. https://doi.org/10.4103/0970-2113.99130

Alhola, K., Ryding, S.-O., Salmenperä, H., & Busch, N. J. (2019). Exploiting the Potential of Public Procurement: Opportunities for Circular Economy. *Journal of Industrial Ecology*, *23*(1), 96–109. https://doi.org/10.1111/jiec.12770

Allen, P., Hughes, D., Vincent-Jones, P., Petsoulas, C., Doheny, S., & Roberts, J. A. (2016). Public Contracts as Accountability Mechanisms: Assuring quality in public health care in England and Wales. *Public Management Review*, *18*(1), 20–39. https://doi.org/10.1080/14719037.2014.957341

American Chemistry Council. (2020). *The Roadmap to Reuse—Plastics Solutions for America 2020* (pp. 1–24). American Chemistry Council.

Anderson, J., & Billou, N. (2007). Serving the world's poor: Innovation at the base of the economic pyramid. *Journal of Business Strategy*, *28*(2), 14–21. https://doi.org/10.1108/02756660710732611

Anjum, A., Zuber, M., Zia, K. M., Noreen, A., Anjum, M. N., & Tabasum, S. (2016). Microbial production of polyhydroxyalkanoates (PHAs) and its copolymers: A review of recent advancements. *International Journal of Biological Macromolecules*, *89*, 161–174. https://doi.org/10.1016/j.ijbiomac.2016.04.069

Anthony, L. (2005). AntConc: A learner and classroom friendly, multi-platform corpus analysis toolkit. *Proceedings of IWLeL*, 7–13. https://www.researchgate.net/profile/Laurence-Anthony-2/publication/267631346_Proceedings_of_IWLeL_2004_An_Interactive_Workshop_on_Language_E-learning_2004/links/5458cd870cf26d5090acf212/Proceedings-of-IWLeL-2004-An-Interactive-Workshop-on-Language-E-learning-2004.pdf#page=7

Anthony, L. (2019). *AntConc* (3.5.8) [Computer software]. Waseda University. https://www.laurenceanthony.net/software

Antikainen, M., & Valkokari, K. (2016). A Framework for Sustainable Circular Business Model Innovation. *Technology Innovation Management Review*, *6*(7), 5–12. https://doi.org/10.22215/timreview1000

Arrowsmith, S. (2010). Horizontal policies in public procurement: A taxonomy. *Journal of Public Procurement*, *10*(2), 149–186. https://doi.org/10.1108/JOPP-10-02-2010-B001

Arrowsmith, S., & Kunzlik, P. (2009). Public procurement and horizontal policies in EC Law: General principles. In *Social and environmental policies in EC procurement law: New directives and new directions* (pp. 9–53). Cambridge University Press.

Arrowsmith, S., Treumer, S., Fejø, J., & Jiang, L. (2011). *Public Procurement: Basic Concepts and the Coverage of Procurement Rules* (pp. 1–32). University of Nottingham. http://eprints.nottingham.ac.uk/id/eprint/1689

Ashley, S. R., & Slyke, D. M. V. (2012). The Influence of Administrative Cost Ratios on State Government Grant Allocations to Nonprofits. *Public Administration Review*, *72*(s1), S47–S56. https://doi.org/10.1111/j.1540-6210.2012.02666.

Bailey, K. D. (1994). *Typologies and taxonomies: An introduction to classification techniques* (Vol. 102). Sage.

Bajari, P., & Benkard, C. L. (2005). Demand estimation with heterogeneous consumers and unobserved product characteristics: A hedonic approach. *Journal of Political Economy*, *113*(6), 1239–1276.

Bajari, P., & Kahn, M. E. (2005). Estimating Housing Demand with an Application to Explaining Racial Segregation in Cities. *Journal of Business & Economic Statistics*, *23*(1), 20–33.

Balhara, Y. P. S. (2011). Publication: An essential step in research. *Lung India: Official Organ of Indian Chest Society*, *28*(4), 324–325. https://doi.org/10.4103/0970-2113.85752

Balhara, Y. P. S. (2012). Indexed journal: What does it mean? *Lung India : Official Organ of Indian Chest Society*, *29*(2), 193. https://doi.org/10.4103/0970-2113.95345

Barraket, J., Keast, R., & Furneaux, C. (2015). Introduction. In *Social Procurement and New Public Governance* (pp. 1–12). Routledge. https://scholar.google.com/scholar?hl=en&as_sdt=0%2C3&q=Social+Procuremeny+and+New+Public+Governance+&btnG=

Beam, D., & Conlan, T. (2002). Grants. In *The tools of government: A guide to the new governance* (pp. 340–381). Oxford University Press.

Belloni, Alexandre, and Victor Chernozhukov. “Least Squares after Model Selection in High-Dimensional Sparse Models.” *Bernoulli* 19, no. 2 (May 2013): 521–47. https://doi.org/10.3150/11-BEJ410.

Bengo, I. (2018). Debate: Impact measurement and social public procurement. *Public Money & Management*, *38*(5), 391–392. https://doi.org/10.1080/09540962.2018.1471817

Bigelow, D. P., Ifft, J., & Kuethe, T. (2020). Following the Market? Hedonic Farmland Valuation Using Sales Prices versus Self-reported Values. *Land Economics*, *96*(3), 418–440. https://doi.org/10.3368/le.96.3.418

Bishop, K. C., & Timmins, C. (2018). Using Panel Data to Easily Estimate Hedonic Demand Functions. *Journal of the Association of Environmental and Resource Economists*, *5*(3), 517–543. https://doi.org/10.1086/696981

Blomsma, F., & Brennan, G. (2017a). The emergence of circular economy: A new framing around prolonging resource productivity. *Journal of Industrial Ecology*.

Blomsma, F., & Brennan, G. (2017b). The emergence of circular economy: A new framing around prolonging resource productivity. *Journal of Industrial Ecology*, *21*(3), 603–614. https://doi/pdf/10.1111/jiec.12603

Blomsma, F., Pieroni, M., Kravchenko, M., Pigosso, D. C. A., Hildenbrand, J., Kristinsdottir, A. R., Kristoffersen, E., Shabazi, S., Nielsen, K. D., Jönbrink, A. K., Li, J., Wiik, C., & McAloone, T. C. (2019). Developing a circular strategies framework for manufacturing companies to support circular economy-oriented innovation. *Journal of Cleaner Production*, *241*. https://doi.org/10.1016/j.jclepro.2019.118271

Bornmann, L., & Daniel, H.-D. (2007). What do we know about the h index? *Journal of the American Society for Information Science and Technology*, *58*(9), 1381–1385. https://doi.org/10.1002/asi.20609

Boyne, G. (1998). Bureaucratic Theory Meets Reality: Public Choice and Service Contracting in U. S. Local Government. *Public Administration Review*, *58*(6), 474–484. JSTOR. https://doi.org/10.2307/977575

Boyne, G., Gould-Williams, J., Law, J., & Walker, R. (1999). Markets, bureaucracy and public management: Competitive tendering and best value in local government. *Public Money and Management*, *19*(4), 23–29. https://doi.org/10.1111/1467-9302.00185

Brammer, S., & Walker, H. (2011). Sustainable procurement in the public sector: An international comparative study. *International Journal of Operations & Production Management*, *31*(4), 452–476. https://doi.org/10.1108/01443571111119551

Breton, A. (1965). A Theory of Government Grants. *The Canadian Journal of Economics and Political Science / Revue Canadienne d'Economique et de Science Politique*, *31*(2), 175–187. JSTOR. https://doi.org/10.2307/140062

Brooks, A., Wang, S., & Jambeck, J. (2018). The Chinese import ban and its impact on global plastic waste trade. *Science Advances*, *4*(6), eaat0131. https://doi.org/10.1126/sciadv.aat0131

Brown, J., & Rosen, H. (1982). On the Estimation of Structural Hedonic Price Models. *Econometrica*, *50*(3), 765–768. https://doi.org/10.2307/1912614

Brown, T. L., & Potoski, M. (2003). Contract–management capacity in municipal and county governments. *Public Administration Review*, *63*(2), 153–164. https://doi.org/10.1111/1540-6210.00276

Brown, T. L., Potoski, M., & Slyke, D. M. V. (2006). Managing Public Service Contracts: Aligning Values, Institutions, and Markets. *Public Administration Review*, *66*(3), 323–331. https://doi.org/10.1111/j.1540-6210.2006.00590.

Brown, T. L., Potoski, M., & Van Slyke, D. M. (2018). Complex Contracting: Management Challenges and Solutions. *Public Administration Review*, *78*(5), 739–747. https://doi.org/10.1111/puar.12959

Brunjes, B. M., & Kellough, J. E. (2018). Representative bureaucracy and government contracting: A further examination of evidence from federal agencies. *Journal of Public Administration Research and Theory*, *28*(4), 519–534. https://doi.org/10.1093/jopart/muy022

Buchanan, J. M. (1952). Federal Grants and Resource Allocation. *Journal of Political Economy*, *60*(3), 208–217. JSTOR. https://www.jstor.org/stable/1826452

Butler, J. (2016). *Procuring for good: How the Social Value Act is being used by local authorities*. Social Enterprise UK. https://www.socialenterprise.org.uk/wp-content/uploads/2019/05/Procuring_for_Good_FINAL.pdf

Calisto Friant, M., Vermeulen, W. J. V., & Salomone, R. (2020). A typology of circular economy discourses: Navigating the diverse visions of a contested paradigm. *Resources, Conservation and Recycling*, *161*, 104917. https://doi.org/10.1016/j.resconrec.2020.104917

Chen, M., Su, K.-H., & Tsai, W. (2007). Competitive Tension: The Awareness-Motivation-Capability Perspective. *Academy of Management Journal*, *50*(1), 101–118. https://doi.org/10.5465/amj.2007.24162081

Chiba, S., Saito, H., Fletcher, R., Yogi, T., Kayo, M., Miyagi, S., Ogido, M., & Fujikura, K. (2018). Human footprint in the abyss: 30 year records of deep-sea plastic debris. *Marine Policy*, *96*, 204–212. https://doi.org/10.1016/j.marpol.2018.03.022

Christensen, P., Scheuermann, A., Loeffler, K., & Helms, B. (2019). Closed-loop recycling of plastics enabled by dynamic covalent diketoenamine bonds. *Nature Chemistry*, *11*, 1–7. https://doi.org/10.1038/s41557-019-0249-2

Bill 40, no. 40(2019) (2019). http://www4.honolulu.gov/docushare/dsweb/Get/Document-238901/BILL040(19).pdf

Closed Loop Partners. (2020). *A Landscape of Transformational Technologies That Stop Plastic Waste, Keep Materials in Play and Grow Markets* (Accelerating Circular Supply Chains For Plastics). Closed Loop Partners. https://www.closedlooppartners.com/wp-content/uploads/2021/01/CLP_Circular_Supply_Chains_for_Plastics_Updated.pdf

Coggburn, J. D. (2003). Exploring differences in the American states' procurement practices. *Journal of Public Procurement*, *3*(1), 3–28. https://doi.org/10.1108/JOPP-03-01-2003-B001

Cohen, D. (2021). *Health and Environmental Impacts of Single-Use Plastics*. Plastic Pollution Coalition. https://singleuseplastics.plasticpollutioncoalitionresources.org/

Colin, F. (2005). Public service vouchers. *International Review of Administrative Sciences*, *71*(1), 19–34.

Corley, E. A., & Sabharwal, M. (2010). Scholarly Collaboration and Productivity Patterns in Public Administration: Analyzing Recent Trends. *Public Administration*, *88*(3), 627–648. https://doi.org/10.1111/j.1467-9299.2010.01830.

Coxhead, A. (2000). A new academic word list. *TESOL Quarterly*, *34*(2), 213–238. https://doi.org/10.2307/3587951

Cravero, C. (2017). Socially Responsible Public Procurement and Set-Asides: A Comparative Analysis of the US, Canada and the EU. *Arctic Review on Law and Politics*, *8*(2017), 174–192. https://doi.org/10.23865/arctic.v8.739

Crippa, M., Koopmans, R., Leyssens, J., Linder, M., Muncke, J., Ritschkoff, A.-C., Doorsselaer, K. V., Velis, C., & Wagner, M. (2019). *A circular economy for plastics- Insights from research and innovation to inform policy and funding decisions*. European Commission.

Daly, H. (1995). On Wilfred Beckerman's Critique of Sustainable Development. *Environmental Values*, *4*(1), 49–55.

Darnall, N., Stritch, J. M., Bretschneider, S., Hsueh, L., Duscha, M., Iles, J., No, W., Suarez, J., & Burwell, C. (2017). *Advancing green purchasing in local governments* (pp. 9–37). Center for Organization Research and Design, Sustainable Purchasing Research Initiative.

Darnall, N., Stritch, J. M., Bretschneider, S., Hsueh, L., & No, W. (2017). Going Green on Purchasing. *PM. Public Management; Washington*, *99*(8), 28–29.

Day, B. (2001). *The Theory of Hedonic Markets: Obtaining welfare measures for changes in environmental quality using hedonic market data* (p. 113).

Economics for the Environment Consultancy. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.473.8558&rep=rep1&type=pdf

de Jesus, A., Antunes, P., Santos, R., & Mendonça, S. (2016). Eco-innovation in the transition to a circular economy: An analytical literature review. *Journal of Cleaner Production*, *172*, 2999–3018. https://doi.org/10.1016/j.jclepro.2017.11.111

De Jesus, A., Antunes, P., Santos, R., & Mendonça, S. (2018). Eco-innovation in the transition to a circular economy: An analytical literature review. *Journal of Cleaner Production*, *172*, 2999–3018.

Denes, T. A. (1997). Do small business set-asides increase the cost of government contracting? *Public Administration Review*, *57*, 441–444. https://doi.org/10.2307/3109990

Department for International Development. (2011). *Cash Transfers* (Evidence Paper, Policy Division). UK Aid. https://www.who.int/alliance-hpsr/alliancehpsr_dfidevidencepaper.pdf

Desouza, K. C., Dombrowski, C., Awazu, Y., Baloh, P., Papagari, S., Jha, S., & Kim, J. Y. (2009). Crafting organizational innovation processes. *Innovation: Management, Policy and Practice*, *11*(1), 6. https://doi.org/10.5172/impp.453.11.1.6

Dong, Q., & Lu, J. (2019). What type of nonprofit organization is preferred in government contracting in China? *International Review of Administrative Sciences*, *87*(2), 328–346. https://doi.org/10.1177/0020852319862347

Dorgan, J. R., Lehermeier, H. J., Palade, L.-I., & Cicero, J. (2001). Polylactides: Properties and prospects of an environmentally benign plastic from renewable resources. *Macromolecular Symposia*, *175*, 55–66.

Douglas, J. W. (1996). Faculty, Graduate Student, and Graduate Productivity in Public Administration and Public Affairs Programs, 1986-1993. *Public Administration Review*, *56*(5), 433–440. https://doi.org/10.2307/977042

Drazin, R., & Van de Ven, A. H. (1985). Alternative forms of fit in contingency theory. *Administrative Science Quarterly*, 514–539. https://doi.org/10.2307/2392695

Edler, J., & Georghiou, L. (2007). Public procurement and innovation—Resurrecting the demand side. *Research Policy*, *36*(7), 949–963. https://doi.org/10.1016/j.respol.2007.03.003

Edler, J., Ruhland, S., Hafner, S., Rigby, J., Georghiou, L., Hommen, L., Rolfstam, M., Edquist, C., Tsipouri, L., & Papadakou, M. (2005). *Innovation and public procurement. Review of issues at stake*. Institute Systems and Innovation Research.

Edquist, C., Vonortas, N., Zabala-Iturriagagoitia, J. M., & Edler, J. (2015). *Public Procurement for Innovation*. Edward Elgar Publishing. https://charlesedquist.com/books/public-procurement-for-innovation/

Efron, B., & Hastie, T. (2021). Chapter 12: Cross-Validation and Cp Estimates of Prediction Error. In *Computer Age Statistical Inference: Algorithms, Evidence, and Data Science* (pp. 208–230). Cambridge University Press. https://hastie.su.domains/CASI_files/PDF/casi.pdf

EIA. (2022). *Spot Prices for Crude Oil and Petroleum Products*. https://www.eia.gov/dnav/pet/pet_pri_spt_s1_d.html

Ekeland, I., Heckman, J. J., & Nesheim, L. (2002). Identifying Hedonic Models. *The American Economic Review*, *92*(2), 304–309.

Ekeland, I., Heckman, J. J., & Nesheim, L. (2004). Identification and Estimation of Hedonic Models. *Journal of Political Economy*, *112*(S1), S60–S109. https://doi.org/10.1086/379947

Ellen MacArthur Foundation. (2017). The New Plastics Economy: Rethinking the Future of Plastics & Catalysing Action. *Ellen MacArthur Foundation*. https://doi.org/10.1103/Physrevb.74.035409

Ellen MacArthur Foundation & UNEP. (2020). *2020 Progress Report* (New Plastics Economy Global Commitment, pp. 1–76). Ellen MacArthur Foundation. https://www.newplasticseconomy.org/assets/doc/Global-Commitment-2020-Progress-Report.pdf

Erridge, A., & Hennigan, S. (2012). Sustainable procurement in health and social care in Northern Ireland. *Public Money & Management*, *32*(5), 363–370.

Directive (EU) 2018/852, 32018L0852, CONSIL, EP, OJ L 150 (2018). http://data.europa.eu/eli/dir/2018/852/oj/eng

European Parliament. (2018, December 19). *Plastic waste and recycling in the EU: Facts and figures | News | European Parliament*. https://www.europarl.europa.eu/news/en/headlines/society/20181212STO21610/plastic-waste-and-recycling-in-the-eu-facts-and-figures

Fan, J., Gijbels, I., Hu, T.-C., & Huang, L.-S. (1996). A Study of Variable Bandwidth Selection For Local Polynomial Regression. *Statistica Sinica*, *6*(1), 113–127.

Fernandez, S., Malatesta, D., & Smith, C. R. (2013). Race, gender, and government contracting: Different explanations or new prospects for theory? *Public Administration Review*, *73*(1), 109–120.

Flyvbjerg, B. (2006). Five Misunderstandings About Case-Study Research. *Qualitative Inquiry*, *12*(2), 219–245. https://doi.org/10.1177/1077800405284363

FRED. (2022). *Inflation, consumer prices for the United States*. FRED, Federal Reserve Bank of St. Louis; FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/FPCPITOTLZGUSA

Furneaux, C., & Barraket, J. (2014). Purchasing social good (s): A definition and typology of social procurement. *Public Money & Management*, *34*(4), 265–272.

Garfield, E. (2006). The History and Meaning of the Journal Impact Factor. *JAMA*, *295*(1), 90. https://doi.org/10.1001/jama.295.1.90

Garud, R., Tuertscher, P., & Van de Ven, A. H. (2013). Perspectives on Innovation Processes. *Academy of Management Annals*, *7*(1), 775–819. https://doi.org/10.5465/19416520.2013.791066

Geissdoerfer, M., Morioka, S. N., de Carvalho, M. M., & Evans, S. (2018). Business models and supply chains for the circular economy. *Journal of Cleaner Production*, *190*, 712–721. https://doi.org/10.1016/j.jclepro.2018.04.159

Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The Circular Economy – A new sustainability paradigm? *Journal of Cleaner Production*, *143*, 757–768. https://doi.org/10.1016/j.jclepro.2016.12.048

Gelderman, C. J., Semeijn, J., & Vluggen, R. (2017). Development of sustainability in public sector procurement. *Public Money & Management*, *37*(6), 435–442. https://doi.org/10.1080/09540962.2017.1344027

Geyer, R., Jambeck, J., & Law, K. L. (2017). Production, use, and fate of all plastics ever made. *Science Advances*, *3*(7), e1700782. https://doi.org/10.1126/sciadv.1700782

Ghisellini, P., Cialani, C., & Ulgiati, S. (2016). A review on circular economy: The expected transition to a balanced interplay of environmental and economic systems. *Journal of Cleaner Production*, *114*, 11–32. https://doi.org/10.1016/j.jclepro.2015.09.007

Girth, A. M. (2012). A closer look at contract accountability: Exploring the determinants of sanctions for unsatisfactory contract performance. *Journal of Public Administration Research and Theory*, *24*(2), 317–348. https://doi.org/10.1093/jopart/mus033

Gittelman, M. (2008). A Note on the Value of Patents as Indicators of Innovation: Implications for Management Research. *Academy of Management Perspectives*, *22*(3), 21–27. https://doi.org/10.5465/amp.2008.34587992

Google Scholar. (2021). *Google Scholar Metrics Help*. Google Scholar. https://scholar.google.com/intl/en/scholar/metrics.html#metrics

Govindan, K., & Hasanagic, M. (2018). A systematic review on drivers, barriers, and practices towards circular economy: A supply chain perspective. *International Journal of Production Research*, *56*(1–2), 278–311. https://doi.org/10.1080/00207543.2017.1402141

Grandia, J., Steijn, B., & Kuipers, B. (2015). It is not easy being green: Increasing sustainable public procurement behaviour. *Innovation: The European Journal of Social Science Research*, *28*(3), 243–260. https://doi.org/10.1080/13511610.2015.1024639

Guldmann, E., & Huulgaard, R. D. (2020). Barriers to circular business model innovation: A multiple-case study. *Journal of Cleaner Production*, *243*. https://doi.org/10.1016/j.jclepro.2019.118160

Gundupalli, S. P., Hait, S., & Thakur, A. (2017). A review on automated sorting of source-separated municipal solid waste for recycling. *Waste Management*, *60*, 56–74. https://doi.org/10.1016/j.wasman.2016.09.015

Gunes, F. (2015). Penalized Regression Methods for Linear Models in SAS/STAT®. *Proceedings of the SAS Global Forum 2015 Conference.*, 14. http://support. sas. com/rnd/app/stat/papers/2015/PenalizedRegression_LinearModels. pdf. 2015.

Gutierrez, R. G., Linhart, J. M., & Pitblado, J. S. (2003). From the Help Desk: Local Polynomial Regression and Stata Plugins. *The Stata Journal*, *3*(4), 412–419. https://doi.org/10.1177/1536867X0400300409

Guzzo, D., Trevisan, A. H., Echeveste, M., & Costa, J. M. H. (2019). Circular innovation framework: Verifying conceptual to practical decisions in sustainability-oriented product-service system cases. *Sustainability (Switzerland)*, *11*(12). https://doi.org/10.3390/su11123248

Hafsa, F., Darnall, N., & Bretschneider, S. (2021). Estimating the true size of public procurement to assess sustainability impact. *Sustainability*, *13*(3), 1448.

Hafsa, F., Dooley, K., Basile, G., & Buch, R. (In review). *Plastic packaging circular innovation framework – Assessing the innovations for a transition to a plastic packaging circular economy*.

Hahladakis, J. N., & Iacovidou, E. (2018). Closing the loop on plastic packaging materials: What is quality and how does it affect their circularity? *Science of The Total Environment*, *630*, 1394–1400. https://doi.org/10.1016/j.scitotenv.2018.02.330

Handa, S., Seidenfeld, D., Davis, B., Tembo, G., & Team, Z. C. T. E. (2016). The social and productive impacts of Zambia's child grant. *Journal of Policy Analysis and Management*, *35*(2), 357–387. https://doi.org/10.1002/pam.21892

Hart, S. L., & Christensen, C. M. (2002). The great leap: Driving innovation from the base of the pyramid. *MIT Sloan Management Review; Cambridge*, *44*(1), 51–56.

Heckman, J. J., Matzkin, R. L., & Nesheim, L. (2010). Nonparametric identification and estimation of nonadditive hedonic models. *Econometrica*, *78*(5), 1569–1591.

Heckman, J. J., Matzkin, R., & Nesheim, L. (2003). *Simulation and Estimation of Nonaddative Hedonic Models* (No. w9895). National Bureau of Economic Research. https://doi.org/10.3386/w9895

Henry, M., Bauwens, T., Hekkert, M., & Kirchherr, J. (2020). A typology of circular start-ups: An Analysis of 128 circular business models. *Journal of Cleaner Production*, *245*, 118528. https://doi.org/10.1016/j.jclepro.2019.118528

Hettne, J. (2013). *Strategic Use of Public Procurement–Limits and Opportunities* (European Policy Analysis, p. 20). Swedish Institute of European Policy Studies. https://lup.lub.lu.se/record/8166862

Hipp, L., & Warner, M. E. (2008). Market forces for the unemployed? Training vouchers in Germany and the USA. *Social Policy & Administration*, *42*(1), 77–101. https://doi.org/10.1111/j.1467-9515.2007.00589.x

Hodge, D. R., & Lacasse, J. R. (2011). Evaluating Journal Quality: Is the H-Index a Better Measure Than Impact Factors? *Research on Social Work Practice*, *21*(2), 222–230. https://doi.org/10.1177/1049731510369141

Hoex, L. (2018). This reversible glue puts a screw in manufacturing. *GreenBiz*, 1–7.

Hommen, L., & Rolfstam, M. (2008). Public procurement and innovation: Towards a taxonomy. *Journal of Public Procurement*, *8*(3), 17–56. https://doi.org/10.1108/JOPP-08-03-2008-B001

Homonoff, T. A. (2018). Can small incentives have large effects? The impact of taxes versus bonuses on disposable bag use. *American Economic Journal: Economic Policy*, *10*(4), 177–210. https://doi.org/10.1257/pol.20150261

Homrich, A. S., Galvão, G., Abadia, L. G., & Carvalho, M. M. (2018). The circular economy umbrella: Trends and gaps on integrating pathways. In *Journal of Cleaner Production* (Vol. 175, pp. 525–543). Elsevier Ltd. https://doi.org/10.1016/j.jclepro.2017.11.064

Hoole, G. (2019, March 7). *DabbaDrop: London's First Plastic-Free Takeaway*. Secret London. https://secretldn.com/dabba-drop-plastic-free-takeaway/

Hopewell, J., Dvorak, R., & Kosior, E. (2009a). Plastics recycling: Challenges and opportunities. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1526), 2115–2126.

Hopewell, J., Dvorak, R., & Kosior, E. (2009b). Plastics recycling: Challenges and opportunities. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1526), 2115–2126. https://doi.org/10.1098/rstb.2008.0311

Huang, J. -C, Shetty, A. S., & Wang, M. -S. (1990). Biodegradable plastics: A review. *Advances in Polymer Technology*, *10*(1), 23–30. https://doi.org/10.1002/adv.1990.060100103

Ian Tiseo. (2020). *EU-28: Plastic packaging waste treatment 2018*. Statista. https://www.statista.com/statistics/869674/plastic-packaging-waste-treatment-european-union/

ICMA. (2021). *Public Management (PM) Editorial Guidelines*. ICMA. https://icma.org/public-management-pm-editorial-guidelines

Issifu, I., Deffor, E. W., & Sumaila, U. R. (2021). How COVID-19 Could Change the Economics of the Plastic Recycling Sector. *Recycling*, *6*(4), 64. https://doi.org/10.3390/recycling6040064

Jambeck, J., Geyer, R., Wilcox, C., Siegler, T. R., Perryman, M., Andrady, A., Narayan, R., & Law, K. L. (2015). Plastic waste inputs from land into the ocean. *Science*, *347*(6223), 768–771. https://doi.org/10.1126/science.1260352

Jambeck, J. R., Geyer, R., Wilcox, C., Siegler, T. R., Perryman, M., Andrady, A., Narayan, R., & Law, K. L. (2015). Plastic waste inputs from land into the ocean. *Science*, *347*(6223), 768–771. https://doi.org/10.1126/science.1260352

James, K., & Grant, T. (2005). LCA of degradable plastic bags. *Centre for Design at RMIT University*.

Jay, K., & Stieglitz, L. (1995). Identification and quantification of volatile organic components in emissions of waste incineration plants. *Chemosphere*, *30*(7), 1249–1260. https://doi.org/10.1016/0045-6535(95)00021-Y

Jensen, K., Clark, C. D., Ellis, P., English, B., Menard, J., Walsh, M., & de la Torre Ugarte, D. (2007). Farmer willingness to grow switchgrass for energy production. *Biomass and Bioenergy*, *31*(11), 773–781. https://doi.org/10.1016/j.biombioe.2007.04.002

Kanapinskas, V., Plytnikas, Ž., & Tvaronavičienė, A. (2014). Sustainable Public Procurement: Realization of the Social Aspect in Republic of Lithuania. *Verslas: Teorija Ir Praktika*, *15*(4), 302–315. https://doi.org/10.3846/btp.2014.529

Keane, M. (2003, May). *Comment on "Simulation and Estimation of Hedonic Models" by Heckman, Matzkin and Nesheim* [MPRA Paper]. https://mpra.ub.uni-muenchen.de/55141/

Kilgarriff, A. (2001). Comparing corpora. *International Journal of Corpus Linguistics*, *6*(1), 97–133. https://doi.org/10.1075/ijcl.6.1.05kil

Kim, Y. W., & Brown, T. L. (2012). The importance of contract design. *Public Administration Review*, *72*(5), 687–696. https://doi.org/10.1111/j.1540-6210.2012.02537.x

Kirchherr, J., Piscicelli, L., Bour, R., Kostense-Smit, E., Muller, J., Huibrechtse-Truijens, A., & Hekkert, M. (2018). Barriers to the Circular Economy: Evidence From the European Union (EU). *Ecological Economics*, *150*(January 2019), 264–272. https://doi.org/10.1016/j.ecolecon.2018.04.028

Kirchherr, J., Reike, D., & Hekkert, M. (2017). Conceptualizing the circular economy: An analysis of 114 definitions. *Resources, Conservation and Recycling*, *127*, 221–232. https://doi.org/10.1016/j.resconrec.2017.09.005

Konietzko, J., Bocken, N., & Hultink, E. J. (2020). Circular ecosystem innovation: An initial set of principles. *Journal of Cleaner Production*, *253*, 119942.

Koning, P., & Heinrich, C. J. (2013). Cream-skimming, parking and other intended and unintended effects of high-powered, performance-based contracts. *Journal of Policy Analysis and Management*, *32*(3), 461–483. https://doi.org/10.1002/pam.21695

Koushik, A. (2017). Indexing and Impact Factor: Judging the Quality of a Journal. *Journal of Health & Medical Informatics*, *08*. https://doi.org/10.4172/2157-7420.1000285

Kristensen, H. S., & Mosgaard, M. A. (2020). A review of micro level indicators for a circular economy–moving away from the three dimensions of sustainability? *Journal of Cleaner Production*, *243*, 118531. https://doi.org/10.1016/j.jclepro.2019.118531

Lamb, J. B., Willis, B. L., Fiorenza, E. A., Couch, C. S., Howard, R., Rader, D. N., True, J. D., Kelly, L. A., Ahmad, A., Jompa, J., & Harvell, C. D. (2018). Plastic waste associated with disease on coral reefs. *Science*, *359*(6374), 460–462. https://doi.org/10.1126/science.aar3320

Lancaster, K. J. (1966). A new approach to consumer theory. *Journal of Political Economy*, *74*(2), 132–157.

Lebreton, L., & Andrady, A. (2019). Future scenarios of global plastic waste generation and disposal. *Palgrave Communications*, *5*(1), 1–11.

Lee, H. K. H., Taddy, M., & Gray, G. A. (2010). Selection of a Representative Sample. *Journal of Classification*, *27*(1), 41–53. https://doi.org/10.1007/s00357-010-9044-x

Leiser, M. S., & Wolter, S. C. (2017). Empirical evidence on the effectiveness of social public procurement policy: The case of the swiss apprenticeship training system. *Labour*, *31*(2), 204–222. https://doi.org/10.1111/labr.12089

Lindert, K. (2013). *Conditional & Unconditional Cash Transfers* (p. 36). The World Bank.

Loader, K. (2007). The challenge of competitive procurement: Value for money versus small business support. *Public Money and Management*, *27*(5), 307–314.

Lowenthal, A. S. (2020, February 12). *H.R.5845 - 116th Congress (2019-2020): Break Free From Plastic Pollution Act of 2020* (2019/2020) [Legislation]. https://www.congress.gov/bill/116th-congress/house-bill/5845

Lüdeke-Freund, F., Gold, S., & Bocken, N. M. P. (2019). A Review and Typology of Circular Economy Business Model Patterns. *Journal of Industrial Ecology*, *23*(1), 36–61. https://doi.org/10.1111/jiec.12763

Ma, S., & Swinton, S. M. (2012). Hedonic Valuation of Farmland Using Sale Prices versus Appraised Values. *Land Economics*, *88*(1), 1–15.

MacArthur, D. E., Waughray, D., & Stuchtey, M. R. (2016). The New Plastics Economy, Rethinking the Future of Plastics. *World Economic Forum*.

MacArthur, E. (2013). Towards the circular economy. *Journal of Industrial Ecology*, *2*, 23–44.

Malatesta, D., & Smith, C. R. (2011). Resource Dependence, Alternative Supply Sources, and the Design of Formal Contracts. *Public Administration Review*, *71*(4), 608–617. https://doi.org/10.1111/j.1540-6210.2011.02392.x

Martin, H., Berner, M., & Bluestein, F. (2007). Documenting disparity in minority contracting: Legal requirements and recommendations for policy makers. *Public Administration Review*, *67*(3), 511–520.

McCrudden, C. (2004). Using public procurement to achieve social outcomes. *Natural Resources Forum*, *28*(4), 257–267. https://doi.org/10.1111/j.1477-8947.2004.00099.x

McCrudden, C., & Doreen, M. (2007). Corporate social responsibility and public procurement. In *The New Corporate Accountability: Corporate Social Responsibility and the Law* (pp. 93–119). Cambridge University Press. https://ssrn.com/abstract=899686

Meherishi, L., Narayana, S. A., & Ranjani, K. S. (2019). Sustainable packaging for supply chain management in the circular economy: A review. *Journal of Cleaner Production*, *237*, 117582. https://doi.org/10.1016/j.jclepro.2019.07.057

Mendelsohn, R., Dinar, A., & Williams, L. (2006). The distributional impact of climate change on rich and poor countries. *Environment and Development Economics*, *11*(2), 159–178.

Mendoza Jiménez, J., Hernández López, M., & Franco Escobar, S. E. (2019). Sustainable Public Procurement: From Law to Practice. *Sustainability*, *11*(22), 6388. https://doi.org/10.3390/su11226388

Merli, R., Preziosi, M., & Acampora, A. (2018). How do scholars approach the circular economy? A systematic literature review. *Journal of Cleaner Production*, *178*, 703–722. https://doi.org/10.1016/j.jclepro.2017.12.112

Missimer, M., Robèrt, K.-H., & Broman, G. (2017). A strategic approach to social sustainability–Part 1: Exploring the social system. *Journal of Cleaner Production*, *140*(1), 32–41. https://doi.org/10.1016/j.jclepro.2016.03.170

Miwa. (2019). *Store shoppers*. Miwa.

Moore, G. A. (2014). *Crossing the chasm*. Harper business.

Murphy, E., Bernard, M., Helm, L., Hill, I., & Tuñas-Corzón, Á. (2020). Policy Recommendations to Reinvigorate Recycling in Arizona. *Journal of Science Policy & Governance*, *17*. https://doi.org/10.38126/JSPG170115

Myers Jr, S. L., & Chan, T. (1996). Who benefits from minority business set-asides? The case of New Jersey. *Journal of Policy Analysis and Management*, *15*(2), 202–226. https://doi.org/10.1002/(SICI)1520-6688(199621)15:2<202::AID-PAM3>3.0.CO;2-N

NCMA. (2021). *Contract Management Magazine Editorial Guideline*. NCMA. https://www.ncmahq.org/docs/default-source/cm-magazine-files/cm-editorial-calendar-2021.pdf?sfvrsn=d17033fc_0

Nemat, B., Razzaghi, M., Bolton, K., & Rousta, K. (2019). The role of food packaging design in consumer recycling behavior—A literature review. *Sustainability*, *11*(16), 4350. https://doi.org/10.3390/su11164350

Nesselhauf, N., & Tschichold, C. (2002). Collocations in CALL: An investigation of vocabulary-building software for EFL. *Computer Assisted Language Learning*, *15*(3), 251–279. https://doi.org/10.1076/call.15.3.251.8190

OECD. (2017). *Government at a Glance 2017* (pp. 171–182). OECD Publishing. 10.1787/gov_glance-2017-en

Pacini, H., & Golbeck, J. (2020). *Trade in scrap materials: Looking beyond plastics*.

Pacini, H., Shi, G., Sanches-Pereira, A., & da Silva Filho, A. C. (2021). Network analysis of international trade in plastic scrap. *Sustainable Production and Consumption*, *27*, 203–216.

Pakkanen, J., Manfredi, D., Minetola, P., & Iuliano, L. (2017). About the use of recycled or biodegradable filaments for sustainability of 3D printing. *International Conference on Sustainable Design and Manufacturing*, 776–785.

Palmquist, R. (1984). Estimating the Demand for the Characteristics of Housing. *The Review of Economics and Statistics*, 394–404.

Palmquist, R., & Smith, V. (2003). The international yearbook of environmental and resource economics 2002/2003. In *The Use of Hedonic Property Value Techniques for Policy and Litigation: Vol. VI* (p. United Kingdom of Great Britain and Northern Ireland). Edward Elgar.

Papanagnou, C. I., & Shchaveleva, N. (2018). Investigation of current perspectives for NHS Wales sustainable development through procurement policies. *Public Money & Management*, *38*(7), 493–502. https://doi.org/10.1080/09540962.2018.1527535

Pieroni, M. P. P., McAloone, T. C., & Pigosso, D. C. A. (2019). Business model innovation for circular economy and sustainability: A review of approaches. *Journal of Cleaner Production*, *215*, 198–216. https://doi.org/10.1016/j.jclepro.2019.01.036

Prata, J. (2017). Airborne microplastics: Consequences to human health? *Environmental Pollution (Barking, Essex : 1987)*, *234*, 115–126. https://doi.org/10.1016/j.envpol.2017.11.043

Rahimi, A. R., & Garciá, J. M. (2017). Chemical recycling of waste plastics for new materials production. In *Nature Reviews Chemistry* (Vol. 1, Issue 6, pp. 1–11). Nature Publishing Group. https://doi.org/10.1038/s41570-017-0046

Rainville, Dr. A. (2021). Stimulating a more Circular Economy through Public Procurement: Roles and dynamics of intermediation. *Research Policy*, *50*(4), 104193. https://doi.org/10.1016/j.respol.2020.104193

Reynaers, A.-M. (2014). Public values in public–private partnerships. *Public Administration Review*, *74*(1), 41–50. https://doi.org/10.1111/puar.12137

Rice, M. F. (1991). Government set-asides, minority business enterprises, and the Supreme Court. *Public Administration Review*, 114–122.

Ritchie, H. (2018). *Plastic Pollution—Our World in Data*. Published Online . https://ourworldindata.org/plastic-pollution

Rochman, C. M. (2016). Strategies for reducing ocean plastic debris should be diverse and guided by science. *Environmental Research Letters*, *11*(4), 041001. https://doi.org/0.1088/1748-9326/11/4/041001/meta

Roediger, D. R., & Foner, P. S. (1989). *Our own time: A history of American labor and the working day*. Verso.

Rogers, E. (2003). *Diffusion of innovations. Revised*. New York: Simon & Schuster.

Romzek, B. S., & Johnston, J. M. (2002). Effective contract implementation and management: A preliminary model. *Journal of Public Administration Research and Theory*, *12*(3), 423–453. https://doi.org/10.1093/oxfordjournals.jpart.a003541

Romzek, B. S., & Johnston, J. M. (2005). State social services contracting: Exploring the determinants of effective contract accountability. *Public Administration Review*, *65*(4), 436–449. https://doi.org/10.1111/j.1540-6210.2005.00470.x

Roosen, M., Mys, N., Kusenberg, M., Billen, P., Dumoulin, A., Dewulf, J., Van Geem, K. M., Ragaert, K., & De Meester, S. (2020). Detailed Analysis of the Composition of Selected Plastic Packaging Waste Products and Its Implications for Mechanical and Thermochemical Recycling. *Environmental Science & Technology*, *54*(20), 13282–13293. https://doi.org/10.1021/acs.est.0c03371

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34–55.

Ruttan, V. W. (2006). *Is war necessary for economic growth?: Military procurement and technology development*. Oxford University Press.

Sack, D., & Sarter, E. K. (2018). Strategic use and social taming–opening up the doctrine of market competition in public procurement. In *Handbook of European Policies* (pp. 371–387). Edward Elgar Publishing.

Salamon, L. M., & Elliott, O. V. (2002). *The tools of government: A guide to the new governance*. Oxford University Press.

Sarter, E. K., & Thomson, E. (2020). Fulfilling its promise? Strategic public procurement and the impact of equality considerations on employers' behaviour in Scotland. *Public Money & Management*, *40*(6), 437–445. https://doi.org/10.1080/09540962.2019.1684615

Schapper, P. R., Malta, J. N. V., & Gilbert, D. L. (2017). Analytical framework for the management and reform of public procurement. In *International handbook of public procurement* (pp. 119–136). Routledge.

Schmidt-Tiedemann, K. J. (1982). A New Model of the Innovation Process. *Research Management*, *25*(2), 18–21. https://doi.org/10.1080/00345334.1982.11756717

Schroeer, A., Lttlejohn, M., & Wilts, H. (2020). *Just one word: Refillables*. OCEANA. DOI: 10.5281/zenodo.3687106

Shmueli, G. (2010). To Explain or to Predict? *Statistical Science*, *25*(3), 289–310.

Siddique, R., Khatib, J., & Kaur, I. (2008). Use of recycled plastic in concrete: A review. *Waste Management*, *28*(10), 1835–1852. https://doi.org/10.1016/j.wasman.2007.09.011

Singh, S. (2019). Treatment and Recycling of Wastewater from Oil Refinery/Petroleum Industry. In R. L. Singh & R. P. Singh (Eds.), *Advances in Biological Treatment of Industrial Waste Water and their Recycling for a Sustainable Future* (pp. 303–332). Springer. https://doi.org/10.1007/978-981-13-1468-1_10

Smith, C., & Fernandez, S. (2010). Equity in federal contracting: Examining the link between minority representation and federal procurement decisions. *Public Administration Review*, *70*(1), 87–96. https://doi.org/10.1111/j.1540-6210.2009.02113.x

Smith, C., & Terman, J. (2016). Overcoming the Barriers to Green Procurement in the County: Interest Groups and Administrative Professionalism. *Journal of Public Procurement*, *16*(3), 259–285. https://doi.org/10.1108/JOPP-16-03-2016-B001

Smith, J., Andersson, G., Gourlay, R., Karner, S., Mikkelsen, B. E., Sonnino, R., & Barling, D. (2016). Balancing competing policy demands: The case of sustainable public sector food procurement. *Journal of Cleaner Production*, *112*, 249–256. https://doi.org/10.1016/j.jclepro.2015.07.065

So, W. W. M., & Chow, S. C. F. (2019). Environmental education in primary schools: A case study with plastic resources and recycling. *Education 3-13*, *47*(6), 652–663. https://doi.org/10.1080/03004279.2018.1518336

Sönnichsen, S. D., & Clement, J. (2020). Review of green and sustainable public procurement: Towards circular public procurement. *Journal of Cleaner Production*, *245*, 118901. https://doi.org/10.1016/j.jclepro.2019.118901

Steuerle, C. E., & Twombly, E. C. (2002). Vouchers. In *The Tools of Government: A Guide to the New Governance* (pp. 445–465). Oxford University Press. https://ebookcentral-proquest-com.ezproxy1.lib.asu.edu/lib/asulib-ebooks/detail.action?docID=729030.

Stritch, J. M., Bretschneider, S., Darnall, N., Hsueh, L., & Chen, Y. (2020). Sustainability Policy Objectives, Centralized Decision Making, and Efficiency in Public Procurement Processes in US Local Governments. *Sustainability*, *12*(17), 6934. https://doi.org/10.3390/su12176934

Stritch, J. M., Darnall, N., Hsueh, L., & Bretschneider, S. (2018). Green technology firms and sustainable public purchasing. *IEEE Engineering Management Review*, *46*(1), 128–131. https://doi.org/10.1109/EMR.2018.2810080

Suthar, S., Rayal, P., & Ahada, C. P. S. (2016). Role of different stakeholders in trading of reusable/recyclable urban solid waste materials: A case study. *Sustainable Cities and Society*, *22*, 104–115. https://doi.org/10.1016/j.scs.2016.01.013

Tariq, B., Duran, R., Hashmi, A., & Shafeiq, M. (2017, March 6). *An Approach to Use Refurbished Bits from Previous Wells that Involves Cost Savings and Effective Bit Utilization*. SPE Middle East Oil & Gas Show and Conference. https://doi.org/10.2118/183783-MS

Telgen, J., Harland, C., & Knight, L. (2007). Public procurement in perspective. In *Public procurement: International cases and commentary* (pp. 16–22). Routledge.

Thai, K. V. (2001). Public procurement re-examined. *Journal of Public Procurement*, *1*(1), 9–50. https://doi.org/10.1108/JOPP-01-01-2001-B001

Tibshirani, R. (1996). Regression Shrinkage and Selection Via the Lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267–288. https://doi.org/10.1111/j.2517-6161.1996.tb02080.x

Tiseo, I. (2021, January 27). *Bioplastics market share 2030*. Statista. https://www.statista.com/statistics/981791/market-share-bioplastics-worldwide/

Trammell, E., Abutabenjeh, S., & Dimand, A.-M. (2019). A Review of Public Administration Research: Where Does Public Procurement Fit In? *International Journal of Public Administration*, 1–13. https://doi.org/10.1080/01900692.2019.1644654

Tsang, Y. F., Kumar, V., Samadar, P., Yang, Y., Lee, J., Ok, Y. S., Song, H., Kim, K.-H., Kwon, E. E., & Jeon, Y. J. (2019). Production of bioplastic through food waste valorization. *Environment International*, *127*, 625–644. https://doi.org/10.1016/j.envint.2019.03.076

Tummers, L., Bekkers, V., Vink, E., & Musheno, M. (2015). Coping during public service delivery: A conceptualization and systematic review of the literature. *Journal of Public Administration Research and Theory*, *25*(4), 1099–1126. https://doi.org/10.1093/jopart/muu056

Tummers, L., & Karsten, N. (2012). Reflecting on the role of literature in qualitative public administration research: Learning from grounded theory. *Administration & Society*, *44*(1), 64–86. https://doi.org/10.1177/0095399711414121

UNEP. (2012). *The Impacts of Sustainable Public Procurement*. UNEP. http://www.unep.fr/scp/procurement/docsres/projectinfo/studyonimpactsofspp.pdf

UNEP. (2017). *Global Review of Sustainable Public Procurement*. United Nations Environment Programme.

U.S. Department of Treasury. (2020). *Analyst's Guide to Federal Spending Data*. U.S. Treasury Data Lab. https://datalab.usaspending.gov/analyst-guide/

U.S. EPA. (2017, September 7). *Containers and Packaging: Product-Specific Data* [Data and Tools]. US EPA. https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/containers-and-packaging-product-specific-data

Uttam, K., & Roos, C. L. L. (2015). Competitive dialogue procedure for sustainable public procurement. *Journal of Cleaner Production*, *86*, 403–416. https://doi.org/10.1016/j.jclepro.2014.08.031

Uyarra, E., & Flanagan, K. (2010). Understanding the Innovation Impacts of Public Procurement. *European Planning Studies*, *18*(1), 123–143. https://doi.org/10.1080/09654310903343567

van Loon, P., Diener, D., & Harris, S. (2021). Circular products and business models and environmental impact reductions: Current knowledge and knowledge gaps. *Journal of Cleaner Production*, *288*, 125627. https://doi.org/10.1016/j.jclepro.2020.125627

Velenturf, A. P. M., & Purnell, P. (2021). Principles for a sustainable circular economy. *Sustainable Production and Consumption*, *27*, 1437–1457. https://doi.org/10.1016/j.spc.2021.02.018

Ven, A. V. de, Polley, D., Garud, R., & Venkataraman, S. (2008). *The Innovation Journey* (1st edition). Oxford University Press.

Verma, R., Vinoda, K. S., Papireddy, M., & Gowda, A. N. S. (2016). Toxic pollutants from plastic waste-a review. *Procedia Environmental Sciences*, *35*, 701–708. https://doi.org/10.1016/j.proenv.2016.07.069

Vicentini, F., Giusti, A., Rovetta, A., Fan, X., He, Q., Zhu, M., & Liu, B. (2009). Sensorized waste collection container for content estimation and collection optimization. *Waste Management*, *29*(5), 1467–1472. https://doi.org/10.1016/j.wasman.2008.10.017

Wagenmakers, E.-J., & Farrell, S. (2004). AIC model selection using Akaike weights. *Psychonomic Bulletin & Review*, *11*(1), 192–196. https://doi.org/10.3758/BF03206482

Walker, H., Schotanus, F., Bakker, E., & Harland, C. (2013). Collaborative Procurement: A Relational View of Buyer-Buyer Relationships. *Public Administration Review*, *73*(4), 588–598. https://doi.org/10.1111/puar.12048

Wang, C., Zhao, L., Lim, M. K., Chen, W.-Q., & Sutherland, J. W. (2020). Structure of the global plastic waste trade network and the impact of China's import Ban. *Resources, Conservation and Recycling*, *153*, 104591.

Wang, H., Xiong, W., Wu, G., & Zhu, D. (2018). Public-private partnership in Public Administration discipline: A literature review. *Public Management Review*, *20*(2), 293–316. https://doi.org/10.1080/14719037.2017.1313445

Warnick, J. (2019). Say hello to the lid that will replace a billion straws a year. *Starbucks*.

WEF, E. (2016). McKinsey & Company.(2016). *The New Plastics Economy-Rethinking the Future of Plastics*.

Wilson, D. C., Araba, A. O., Chinwah, K., & Cheeseman, C. R. (2009). Building recycling rates through the informal sector. *Waste Management*, *29*(2), 629–635. https://doi.org/10.1016/j.wasman.2008.06.016

Woidasky, J., Sander, I., Schau, A., Moesslein, J., Wendler, P., Wacker, D., Gao, G., Kirchenbauer, D., Kumar, V., Busko, D., Howard, I. A., Richards, B. S., Turshatov, A., Wiethoff, S., & Lang-Koetz, C. (2020). Inorganic fluorescent marker materials for identification of post-consumer plastic packaging. *Resources, Conservation and Recycling*, *161*, 104976. https://doi.org/10.1016/j.resconrec.2020.104976

Wontner, K. L., Walker, H., Harris, I., & Lynch, J. (2020). Maximising "Community Benefits" in public procurement: Tensions and trade-offs. *International Journal of Operations & Production Management*, *40*(12), 1909–1939. https://doi.org/10.1108/IJOPM-05-2019-0395

World Bank. (2017). *Benchmarking Public Procurement 2017*. World Bank Publications.

Wu, J. (2013). Landscape sustainability science: Ecosystem services and human well-being in changing landscapes. *Landscape Ecology*, *28*(6), 999–1023. https://doi.org/10.1007/s10980-013-9894-9

Yang, K., Hsieh, J. Y., & Li, T. S. (2009). Contracting Capacity and Perceived Contracting Performance: Nonlinear Effects and the Role of Time. *Public Administration Review*, *69*(4), 681–696. https://doi.org/10.1111/j.1540-6210.2009.02017.

Yang, Y., Hou, Y., & Wang, Y. (2013). On the development of public–private partnerships in transitional economies: An explanatory framework. *Public Administration Review*, *73*(2), 301–310. https://doi.org/10.1111/j.1540-6210.2012.02672.x

Young, S., Nagpal, S., & Adams, C. A. (2016). Sustainable procurement in Australian and UK universities. *Public Management Review*, *18*(7), 993–1016. https://doi.org/10.1080/14719037.2015.1051575

Zhao, J., & Lu, J. (2020). Does Government Punish Nonprofits for High Administrative Costs in Contracting Decisions? *The American Review of Public Administration*, *50*(3), 286–296. https://doi.org/10.1177/0275074019893807

Zheng, J., & Suh, S. (2019). Strategies to reduce the global carbon footprint of plastics. *Nature Climate Change*, *9*(5), 374–378. https://doi.org/10.1038/s41558-019-0459-z

APPENDIX A

STATA CODE FOR CHAPTER 3

```
use "F:\Fatima_Scrap Plastic\Plastic_Scrap\RM\Data\plastic_master_vf_nomissingvalues.dta
//adjusting for inflation//
merge m:1 year using "E:\Users\shafsa\Scrap Plastic\inflation.dta"
replace inflation=1 if year==2021
gen adj_price=inflation*avgprice
sum adj_price
//generate a date variable for quarterly dates//
gen quarter = quarter(date)
gen year = year(date)
gen date_q = yq(year, quarter)
format %tq date_q
//estimate strata by region and quarterly date//
tab date_q region
egen strata_t_s = group (date_q region)
sum strata_t_s, det
sort strata_t_s
by strata_t_s: count
contract strata_t_s
save "F:\Fatima_Scrap Plastic\Plastic_Scrap\RM\Data\strata_t_s_freq.dta"
merge m:1 strata_t_s using "F:\Fatima_Scrap Plastic\Plastic_Scrap\RM\Data\strata_t_s_freq.dta"
merge m:m plastic_quality using "E:\Users\shafsa\RM\Data\plastic_properties.dta"
//generate a unique ID for each observation//
gen sort=uniform()
sort sort
gen id_random=_n
//crude oil prices//
merge m:m date_q using "E:\Users\shafsa\Scrap Plastic\crudeoil_p.dta"
** there are 402 strata**
//power testing - identify what the right sample size should be//
power rsquared (0.09(0.01)0.12), ntested(10) graph //graph power vs rsquare//
power rsquared 0.10, n(500 1000 1500 2000) ntested(10)  //graph power vs sample size at 0.10 Rsquare for large sample sizes//
power rsquared 0.10, n(50 75 100 125 150 175 200) ntested(10) ///graph power vs sample size at 0.10 Rsquare for small sample size//
power rsquared 0.12, n(50 75 100 125 150 175 200) graph ////graph power vs sample size at 0.12 Rsquare for large sample sizes//
power rsquared 0.12, n(500 1000 1500 2000) graph // //graph power vs sample size at 0.12 Rsquare for large sample sizes//
//GENERATING A STRATIFIED RANDOM SAMPLE BY REGION AND QUARTERLY DATE//
splitsample, generate(sample) balance(date_q region) nsplit(3)
tab strata_t_s sample //tally sample has correctly sampled from each stratum//
//CV - Cross Validation//
//generating lists of variable/
vl clear
vl create vlmaterial= (multi_material_p-halogen_ppm) //material properties//
vl create vlcondition=(bottledeposit-rigid) //material condition//
//cross validation for sample 1//
lasso linear adj_price $vlcondition $vlmaterial $injectionmolded if sample==1, rseed(1000)
cvplot
estimates store cv
lassoknots, display(nonzero osr2 aic)
lassoknots, display(nonzero aic bic)
**model 77 selected**
lassoselect id=77
lassocoef cv //display the variables selected by this process//
**does this work with other samples**
lassogof cv, over(sample) postselection
//stry 2 models//
reg adj_price curbside baled foodandbeverage postconsumer film contamination other color singlematerial rigid multi_material_p metals_food_permitted if sample==1 //chosen by CV
estimates store CV1
```

```
reg adj_price curbside foodandbeverage film contamination other color singlematerial rigid
multi_material_p metals_food_permitted if sample==1 // theoretically chosen
estimates store theory
reg adj_price curbside baled foodandbeverage postconsumer film contamination other color singlematerial
rigid if sample==1
estimates store nosup
estimates stats CV1 theory nosup
//graph cv variables against adj_price and lprice//
graph twoway (lfit adj_price bottledeposit) (scatter adj_price bottledeposit)
graph twoway (lfit adj_price curbside) (scatter adj_price curbside)
graph twoway (lfit adj_price specialbaled) (scatter adj_price specialbaled)
graph twoway (lfit adj_price contamination) (scatter adj_price contamination)
graph twoway (lfit adj_price foodandbeverage) (scatter adj_price foodandbeverage)
graph twoway (lfit adj_price postconsumer) (scatter adj_price postconsumer)
graph twoway (lfit adj_price bottles) (scatter adj_price bottles)
graph twoway (lfit adj_price film) (scatter adj_price film)
graph twoway (lfit adj_price other) (scatter adj_price other)
graph twoway (lfit adj_price color) (scatter adj_price color)
graph twoway (lfit adj_price singlematerial) (scatter adj_price singlematerial)
graph twoway (lfit adj_price rigid) (scatter adj_price rigid)
graph twoway (lfit adj_price multi_material_p) (scatter adj_price multi_material_p)
graph twoway (lfit adj_price metals_food_permitted) (scatter adj_price metals_food_permitted)
graph twoway (lfit adj_price metals_food_permitted) (scatter adj_price metals_food_permitted)
****gen supply shifter variables**
gen covid_19=1 if year>=2020
replace covid_19=0 if missing(covid_19)
gen import_ban=1 if year>=2018
replace import_ban=0 if missing(import_ban)
gen housing_crash=1 if year==2007
replace housing_crash=1 if year==2008
replace housing_crash=0 if missing(housing_crash)
**Hedonic Regression Using these results**
**Model 1: by region*
**Step 1: Identify implicit prices**
forvalues i=1/6{
        reg adj_price curbside foodandbeverage film contamination other color singlematerial rigid
multi_material_p metals_food_permitted if sample==1 & region==`i'
estimates store m`i', title(`i')
}
estimates dir
estimates drop cv
estimates table _all, se p
estimates table _all, star(0.05 0.01 0.001)
estimates table _all //for transposing results
estimates stats _all
**step 2**
**save transposed results in excel sheet,****merge two datasets on region**
merge m:m region using "E:\Users\shafsa\Scrap Plastic\beta_OLS_mar17.dta"
**estimate marginal preference - multipl implicit price by characteristic quantity**
        gen obeta_contam = b_contam * contamination
        gen obeta_color = b_color*color
        gen obeta_mmp = b_mmp*multi_material_p
        gen obeta_mfp = b_mfp*metals_food_permitted
**estimate WTP for continuous chracteristics**
gen wtp_contam=obeta_contam*(0.1)
gen wtp_color=obeta_color*(0.1)
gen wtp_mmp = obeta_mmp*(0.1)
gen wtp_mfp = obeta_mfp*(1000)
**estimate thresholds for dichotomous variables** standardise the variable by centering them so the mean is
0**
sum b_curb b_food b_film b_other b_single b_rigid //use means for table**
gen pt_curb= b_curb-(-5.909279 )
```

```
gen pt_food = b_food - 18.78944
gen pt_film = b_film - (-25.5608)
gen pt_other = b_other - 8.448498
gen pt_single = b_single - (-50.51966)
gen pt_rigid = b_rigid- 6.767585
sum pt_curb pt_food pt_film pt_other pt_single pt_rigid
**normalize**
gen p_curb = (2*(b_curb-(-21.44218)))/(3.780942-(-21.44218))-1
gen p_food = (2*(b_food-(4.367761)))/(27.04836-(4.367761))-1
gen p_film = (2*(b_film-(-31.33643)))/(-22.00077-( -31.33643))-1
gen p_other = (2*(b_other-(4.164687)))/(14.74035-(4.164687))-1
gen p_single = (2*(b_single-(-66.18358)))/(-9.489371-(-66.18358))-1
gen p_rigid = (2*(b_rigid-(3.900234)))/(10.39731-(3.900234))-1
**dummy variables frpm primary polymer**
gen HDPE1=1 if primary_polymer==1
gen LDPE1=1 if primary_polymer==2
gen PET1=1 if primary_polymer==4
gen PS1=1 if primary_polymer==6
gen PP1=1 if primary_polymer==5
gen mixed1=1 if primary_polymer==3
**CV second stage**
**sample within sample 1**
lasso linear wtp_contam import_ban covid_19 p_crudeoil ib3.primary_polymer if sample2==1 //
contamination
estimates store cv_1
lassoknots, display(nonzero osr2 aic)
lassoknots, display(nonzero aic bic)
lassoselect id=67
lassocoef cv_1
lassogof cv_1, over(sample2) postselection
lasso probit curbside import_ban covid_19 p_crudeoil i.primary_polymer if sample2==1, offset(p_curb)
//curbside sample 1
estimates store cv_2
lassoknots, display(nonzero aic bic)
lassoselect id=88
lassocoef cv_2
lasso probit curbside import_ban covid_19 p_crudeoil i.primary_polymer if sample2==2, offset(p_curb)
//curbside sample 2 because lassgof resulted in an error
estimates store cv_3
lassoknots, display(nonzero aic bic)
lassoselect id=88
lassocoef cv_3
**Step 3: Regressing prices on supply shifts**
**dichotomous variables**
probit curbside import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1, offset(p_curb)
estimates store m8
probit foodandbeverage import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1,
offset(p_food)
estimates store m9
probit film import_ban covid_19 p_crudeoil HDPE PP if sample==1, offset(p_film)
estimates store m10
probit other import_ban covid_19 p_crudeoil HDPE PET PP if sample==1, offset(p_other)
estimates store m11
probit single import_ban covid_19 p_crudeoil HDPE PET if sample==1, offset(p_single)
estimates store m12
probit rigid import_ban covid_19 p_crudeoil HDPE mixed if sample==1, offset(p_rigid)
estimates store m13
**continuous variables**
**change in mwtp**
reg wtp_contam import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1
estimates store m14
reg wtp_color import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1
```

```
estimates store m15
reg wtp_mfp import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1
estimates store m16
reg wtp_mmp import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1
estimates store m17
**Results: p value-se**
estimates table m1 m2 m3 m4 m5 m6, p se //first stage implict prices
estimates table m8 m9 m10 m11 m12 m13, p se //second stage dichotomous
estimates table m14 m15 m16 m17, p se //second stage continuous change in wtp**
**Results only p-values with ** **
estimates table m1 m2 m3 m4 m5 m6, star(0.05 0.01 0.001)
estimates table m8 m9 m10 m11 m12 m13, star(0.05 0.01 0.001) //second stage dichotomous
estimates table m14 m15 m16 m17, star(0.05 0.01 0.001) //second stage continuous change in wtp**
estimates stats m8 m9 m10 m11 m12 m13
estimates stats m14 m15 m16 m17
****Model 2:  Local Polynomial Regression (1500 observations) - NOTE: Takes about 1-2 hours to run***
**//Note:var_n is the resulting predictor
**only sample 1**
drop if sample==2
drop if sample==3
save "E:\Users\shafsa\Scrap Plastic\sample1_mar17.dta"
**step 1**
lpoly adj_price curbside, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(curb1_w curb1_n)
se(curb1_e)
lpoly adj_price contamination, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(contam_w
contam_n) se(contam_e)
lpoly adj_price bottledeposit, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(bdep_w bdep_n)
se(bdep_e)
lpoly adj_price specialbaled, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(sbale_w sbale_n)
se(sbale_e)
lpoly adj_price foodandbeverage, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(food_w food_n)
se(food_e)
lpoly adj_price postconsumer, bwidth(3) degree(2) kernel(gaussian)n(17811) generate(pc_w pc_n) se(pc_e)
lpoly adj_price other, bwidth(3) degree(2) kernel(gaussian)n(17811) generate(other_w other_n) se(other_e)
lpoly adj_price film, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(film_w film_n) se(film_e)
lpoly adj_price single, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(single_w single_n)
se(single_e)
lpoly adj_price color, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(color_w color_n) se(color_e)
lpoly adj_price rigid, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(rigid_w rigid_n) se(rigid_e)
lpoly adj_price multi_material_p, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(mmp_w
mmp_n) se(mmp_e)
lpoly adj_price metals_food_permitted, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(mfp_w
mfp_n) se(mfp_e)
lpoly adj_price halogen_ppm, bwidth(3) degree(2) kernel(gaussian) n(17811) generate(hal_w hal_n)
se(hal_e)
**step 2: generate marginal price**
**generate thresholds for dichotomous variables**
sum curb1_n food_n film_n rigid_n single_n other_n
gen pi_curb = (2*(curb1_n-(9.403238)))/(26.38472-(9.403238))-1
gen pi_food= (2*(food_n-(13.58066)))/(29.45018-(13.58066))-1
gen pi_film = (2*(film_n-(12.1004)))/(32.69612-(12.1004))-1
gen pi_other = (2*(other_n-(6.489145)))/(32.35192-(6.489145))-1
gen pi_rigid = (2*(rigid_n-(13.12564)))/(29.87232-(13.12564))-1
gen pi_single = (2*(single_n-(3.658515)))/(29.06399-(3.658515))-1
sum pi_curb pi_food pi_film pi_rigid pi_single
**generate marginal prices for continuous variables**
gen beta_contam = contam_n*contamination
gen beta_color = color_n*color
gen beta_mmp = mmp_n * multi_material_p
gen beta_mfp = mfp_n*metals_food_permitted
gen beta_hal = hal_n*halogen_ppm
**gen wtp for continuous variables
```

```
gen lwtp_contam=beta_contam*(0.1)
gen lwtp_color=beta_color*(0.1)
gen lwtp_mmp = beta_mmp*(0.1)
gen lwtp_mfp = beta_mfp*(1000)
**CV second stage**
**sample within sample 1**
splitsample, generate(sample2) balance(date_q region) nsplit(3)
lasso linear lwtp_contam import_ban covid_19 p_crudeoil ib3.primary_polymer if sample2==1 //
contamination
estimates store cv
lassoknots, display(nonzero osr2 aic)
lassoknots, display(nonzero aic bic)
lassoselect id=64
lassocoef cv
lassogof cv, over(sample2) postselection
lasso probit curbside import_ban covid_19 p_crudeoil i.primary_polymer if sample2==1, offset(pi_curb)
//curbside sample 1
estimates store cv2
lassoknots, display(nonzero aic bic)
lassoselect id=88
lassocoef cv2
lasso probit curbside import_ban covid_19 p_crudeoil i.primary_polymer if sample2==2, offset(pi_curb)
//curbside sample 2 because lassgof resulted in an error
estimates store cv3
lassoknots, display(nonzero aic bic)
lassoselect id=88
lassocoef cv3
**step 4: second-stage regression*
probit curbside import_ban covid_19 p_crudeoil ib3.primary_polymer, offset(pi_curb)
estimates store m18
probit foodandbeverage import_ban covid_19 p_crudeoil ib3.primary_polymer, offset(pi_food)
estimates store m19
probit film import_ban covid_19 p_crudeoil HDPE PP, offset(pi_film)
estimates store m20
probit other import_ban covid_19 p_crudeoil HDPE PET PP, offset(pi_other)
estimates store m21
probit singlematerial import_ban covid_19 p_crudeoil HDPE PET, offset(pi_single)
estimates store m22
probit rigid import_ban covid_19 p_crudeoil HDPE mixed, offset(pi_rigid)
estimates store m23
reg lwtp_contam import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1
estimates store m24
reg lwtp_color import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1
estimates store m25
reg lwtp_mfp import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1
estimates store m26
reg lwtp_mmp import_ban covid_19 p_crudeoil ib3.primary_polymer if sample==1
estimates store m27
**table outputs**
estimates table m18 m19 m20 m21 m22 m23, star(0.05 0.01 0.001)
estimates table m24 m25 m26 m27, star(0.05 0.01 0.001)
estimates stats m18 m19 m20 m21 m22 m23
estimates stats m24 m25 m26 m27
```

APPENDIX B

LOG FILES FROM CHAPTER 3

```
-------------------------------------------------------------------------------------------------------------------------------------------
------------------------------------------------
      NAME:  <UNNAMED>
       LOG:  E:\USERS\SHAFSA\SCRAP PLASTIC\MODEL 1.LOG
  LOG TYPE:  TEXT
 OPENED ON:   9 APR 2022, 15:50:24

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. LASSO LINEAR ADJ_PRICE $VLCONDITION $VLMATERIAL $INJECTIONMOLDED IF SAMPLE==1, RSEED(1000)
INVALID SYNTAX
   THE SYNTAX IS DEPVAR [(ALWAYSVARS)] OTHERVARS.
R(198);

END OF DO-FILE

R(198);

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. VL CLEAR

. VL CREATE VLMATERIAL= (MULTI_MATERIAL_P-HALOGEN_PPM) //MATERIAL PROPERTIES//
NOTE: $VLMATERIAL INITIALIZED WITH 4 VARIABLES.

. VL CREATE VLCONDITION=(BOTTLEDEPOSIT-RIGID) //MATERIAL CONDITION//
NOTE: $VLCONDITION INITIALIZED WITH 14 VARIABLES.

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. LASSO LINEAR ADJ_PRICE $VLCONDITION $VLMATERIAL $INJECTIONMOLDED IF SAMPLE==1, RSEED(1000)
NOTE: HOUSEHOLD OMITTED BECAUSE IT IS CONSTANT.
NOTE: BOTTLEDEPOSIT OMITTED BECAUSE OF COLLINEARITY WITH ANOTHER VARIABLE.
10-FOLD CROSS-VALIDATION WITH 100 LAMBDAS ...
GRID VALUE 1:     LAMBDA = 13.09873   NO. OF NONZERO COEF. =       0
FOLDS: 1...5....10   CVF = 868.8498
GRID VALUE 2:     LAMBDA = 11.93507   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = 836.8489
GRID VALUE 3:     LAMBDA =  10.8748   NO. OF NONZERO COEF. =       3
FOLDS: 1...5....10   CVF = 791.7367
GRID VALUE 4:     LAMBDA = 9.908708   NO. OF NONZERO COEF. =       3
FOLDS: 1...5....10   CVF = 753.0996
GRID VALUE 5:     LAMBDA = 9.028446   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 708.1311
GRID VALUE 6:     LAMBDA = 8.226384   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 669.2483
GRID VALUE 7:     LAMBDA = 7.495575   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF =  636.967
GRID VALUE 8:     LAMBDA = 6.829688   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 610.1663
GRID VALUE 9:     LAMBDA = 6.222958   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 587.9157
GRID VALUE 10:    LAMBDA = 5.670127   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 569.4427
GRID VALUE 11:    LAMBDA = 5.166409   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 554.1059
GRID VALUE 12:    LAMBDA = 4.707439   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF =  541.373
GRID VALUE 13:    LAMBDA = 4.289243   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 530.8017
GRID VALUE 14:    LAMBDA = 3.908199   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 522.0252
GRID VALUE 15:    LAMBDA = 3.561005   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 514.7387
GRID VALUE 16:    LAMBDA = 3.244655   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = 508.6892
```

GRID VALUE 17: LAMBDA = 2.956409 NO. OF NONZERO COEF. = 4
FOLDS: 1...5....10 CVF = 503.6667
GRID VALUE 18: LAMBDA = 2.69377 NO. OF NONZERO COEF. = 4
FOLDS: 1...5....10 CVF = 499.484
GRID VALUE 19: LAMBDA = 2.454463 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = 495.8416
GRID VALUE 20: LAMBDA = 2.236415 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = 492.7832
GRID VALUE 21: LAMBDA = 2.037738 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = 490.1769
GRID VALUE 22: LAMBDA = 1.856711 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = 487.9846
GRID VALUE 23: LAMBDA = 1.691766 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = 486.1643
GRID VALUE 24: LAMBDA = 1.541474 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = 484.6531
GRID VALUE 25: LAMBDA = 1.404534 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = 483.3983
GRID VALUE 26: LAMBDA = 1.279759 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = 482.3565
GRID VALUE 27: LAMBDA = 1.166069 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = 481.4915
GRID VALUE 28: LAMBDA = 1.062478 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = 480.7733
GRID VALUE 29: LAMBDA = .9680907 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = 480.0426
GRID VALUE 30: LAMBDA = .8820882 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = 479.3755
GRID VALUE 31: LAMBDA = .8037259 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = 478.7327
GRID VALUE 32: LAMBDA = .7323251 NO. OF NONZERO COEF. = 9
FOLDS: 1...5....10 CVF = 477.8614
GRID VALUE 33: LAMBDA = .6672674 NO. OF NONZERO COEF. = 9
FOLDS: 1...5....10 CVF = 476.8801
GRID VALUE 34: LAMBDA = .6079892 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = 476.0665
GRID VALUE 35: LAMBDA = .5539771 NO. OF NONZERO COEF. = 9
FOLDS: 1...5....10 CVF = 473.2994
GRID VALUE 36: LAMBDA = .5047633 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = 469.7037
GRID VALUE 37: LAMBDA = .4599215 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = 467.5996
GRID VALUE 38: LAMBDA = .4190633 NO. OF NONZERO COEF. = 9
FOLDS: 1...5....10 CVF = 465.8524
GRID VALUE 39: LAMBDA = .3818349 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 463.4065
GRID VALUE 40: LAMBDA = .3479138 NO. OF NONZERO COEF. = 9
FOLDS: 1...5....10 CVF = 460.5396
GRID VALUE 41: LAMBDA = .3170061 NO. OF NONZERO COEF. = 9
FOLDS: 1...5....10 CVF = 458.1627
GRID VALUE 42: LAMBDA = .2888441 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 455.9472
GRID VALUE 43: LAMBDA = .263184 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 454.0559
GRID VALUE 44: LAMBDA = .2398035 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 452.4857
GRID VALUE 45: LAMBDA = .2185 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 451.1823
GRID VALUE 46: LAMBDA = .199089 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 450.1003
GRID VALUE 47: LAMBDA = .1814025 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 449.2019
GRID VALUE 48: LAMBDA = .1652872 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 448.4561
GRID VALUE 49: LAMBDA = .1506036 NO. OF NONZERO COEF. = 10
FOLDS: 1...5....10 CVF = 447.8368
GRID VALUE 50: LAMBDA = .1372244 NO. OF NONZERO COEF. = 11
FOLDS: 1...5....10 CVF = 447.3228
GRID VALUE 51: LAMBDA = .1250337 NO. OF NONZERO COEF. = 11

```
FOLDS: 1...5....10   CVF =  446.896
GRID VALUE 52:    LAMBDA = .1139261   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 446.5417
GRID VALUE 53:    LAMBDA = .1038052   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 446.2475
GRID VALUE 54:    LAMBDA = .0945834   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 446.0014
GRID VALUE 55:    LAMBDA = .0861809   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 445.7817
GRID VALUE 56:    LAMBDA = .0785248   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 445.5868
GRID VALUE 57:    LAMBDA = .0715489   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 445.4246
GRID VALUE 58:    LAMBDA = .0651927   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 445.2901
GRID VALUE 59:    LAMBDA = .0594011   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 445.1783
GRID VALUE 60:    LAMBDA = .0541241   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 445.0872
GRID VALUE 61:    LAMBDA = .0493159   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 445.0118
GRID VALUE 62:    LAMBDA = .0449348   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 444.9498
GRID VALUE 63:    LAMBDA = .0409429   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 444.8992
GRID VALUE 64:    LAMBDA = .0373057   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 444.8574
GRID VALUE 65:    LAMBDA = .0339915   NO. OF NONZERO COEF. =      11
FOLDS: 1...5....10   CVF = 444.8229
GRID VALUE 66:    LAMBDA = .0309718   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.7947
GRID VALUE 67:    LAMBDA = .0282204   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.7711
GRID VALUE 68:    LAMBDA = .0257133   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.7517
GRID VALUE 69:    LAMBDA =  .023429   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.7354
GRID VALUE 70:    LAMBDA = .0213477   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.7219
GRID VALUE 71:    LAMBDA = .0194512   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.7107
GRID VALUE 72:    LAMBDA = .0177232   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.7014
GRID VALUE 73:    LAMBDA = .0161487   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.6938
GRID VALUE 74:    LAMBDA = .0147141   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.6876
GRID VALUE 75:    LAMBDA =  .013407   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.6825
GRID VALUE 76:    LAMBDA = .0122159   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF =  444.678
GRID VALUE 77:    LAMBDA = .0111307   NO. OF NONZERO COEF. =      12
FOLDS: 1...5....10   CVF = 444.6742
... CHANGE IN DEVIANCE STOPPING TOLERANCE REACHED ... LAST LAMBDA SELECTED
MINIMUM OF CV FUNCTION NOT FOUND; LAMBDA SELECTED BASED ON STOP() STOPPING CRITERION.

LASSO LINEAR MODEL                    NO. OF OBS      =     15,688
                                NO. OF COVARIATES =        16
SELECTION: CROSS-VALIDATION              NO. OF CV FOLDS   =        10

--------------------------------------------------------------------------
         |                            NO. OF      OUT-OF-      CV MEAN
         |                            NONZERO      SAMPLE   PREDICTION
      ID |     DESCRIPTION      LAMBDA     COEF.    R-SQUARED        ERROR
---------+----------------------------------------------------------------
       1 |    FIRST LAMBDA    13.09873         0      0.0006     868.8498
      76 |   LAMBDA BEFORE    .0122159        12      0.4885      444.678
    * 77 | SELECTED LAMBDA    .0111307        12      0.4885     444.6742
--------------------------------------------------------------------------
```

```
* LAMBDA SELECTED BY CROSS-VALIDATION.
NOTE: MINIMUM OF CV FUNCTION NOT FOUND; LAMBDA SELECTED BASED ON STOP()
    STOPPING CRITERION.

. CVPLOT

. ESTIMATES STORE CV

. LASSOKNOTS, DISPLAY(NONZERO OSR2 AIC)

-------------------------------------------------
       |              NO. OF     OUT-OF-
       |             NONZERO     SAMPLE
    ID |   LAMBDA     COEF.   R-SQUARED        AIC
-------+-----------------------------------------
     2 | 11.93507        2     0.0374   150098.7
     3 |  10.8748        3     0.0893   149226.7
     5 | 9.028446        4     0.1855   147476.4
    19 | 2.454463        5     0.4297   141887.9
    21 | 2.037738        6     0.4362     141709
    29 | .9680907        7     0.4478   141383.5
    31 | .8037259        8     0.4494   141341.7
    32 | .7323251        9     0.4504   141311.7
    34 | .6079892        8     0.4524   141251.2
    35 | .5539771        9     0.4556   141158.4
    36 | .5047633        8     0.4597   141038.8
    38 | .4190633        9     0.4642   140911.3
    39 | .3818349       10     0.4670   140828.5
    40 | .3479138        9     0.4703   140729.6
    42 | .2888441       10     0.4756   140574.8
    50 | .1372244       11     0.4855   140277.5
    55 | .0861809       12     0.4873     140225
    56 | .0785248       11     0.4875   140216.2
    66 | .0309718       12     0.4884   140190.4
  * 77 | .0111307       12     0.4885   140185.7
-------------------------------------------------
* LAMBDA SELECTED BY CROSS-VALIDATION.

. LASSOKNOTS, DISPLAY(NONZERO AIC BIC)

------------------------------------------------
       |              NO. OF
       |             NONZERO
    ID |   LAMBDA     COEF.        BIC        AIC
-------+----------------------------------------
     2 | 11.93507        2   150121.7   150098.7
     3 |  10.8748        3   149257.3   149226.7
     5 | 9.028446        4   147514.7   147476.4
    19 | 2.454463        5   141933.9   141887.9
    21 | 2.037738        6   141762.7     141709
    29 | .9680907        7   141444.8   141383.5
    31 | .8037259        8   141410.6   141341.7
    32 | .7323251        9   141388.4   141311.7
    34 | .6079892        8   141320.1   141251.2
    35 | .5539771        9     141235   141158.4
    36 | .5047633        8   141107.7   141038.8
    38 | .4190633        9   140987.9   140911.3
    39 | .3818349       10   140912.7   140828.5
    40 | .3479138        9   140806.2   140729.6
    42 | .2888441       10   140659.1   140574.8
    50 | .1372244       11   140369.4   140277.5
    55 | .0861809       12   140324.6     140225
    56 | .0785248       11   140308.2   140216.2
    66 | .0309718       12   140289.9   140190.4
  * 77 | .0111307       12   140285.3   140185.7
------------------------------------------------
* LAMBDA SELECTED BY CROSS-VALIDATION.

.
```

```
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. LASSOSELECT ID=77
ID = 77  LAMBDA = .0111307 SELECTED

. LASSOCOEF CV //DISPLAY THE VARIABLES SELECTED BY THIS PROCESS//

---------------------------------
                 |    CV
----------------------+----------
          CURBSIDE |     X
             BALED |     X
      CONTAMINATION |     X
    FOODANDBEVERAGE |     X
      POSTCONSUMER |     X
              FILM |     X
             OTHER |     X
             COLOR |     X
     SINGLEMATERIAL |     X
             RIGID |     X
    MULTI_MATERIAL_P |     X
METALS_FOOD_PERMITTED |     X
             _CONS |     X
---------------------------------
LEGEND:
  B - BASE LEVEL
  E - EMPTY CELL
  O - OMITTED
  X - ESTIMATED

. **DOES THIS WORK WITH OTHER SAMPLES**
. LASSOGOF CV, OVER(SAMPLE) POSTSELECTION

POSTSELECTION COEFFICIENTS
-------------------------------------------------------------
NAME          SAMPLE |        MSE    R-SQUARED       OBS
-----------------------+------------------------------------
CV                   |
                   1 |    444.1999      0.4891     15,688
                   2 |    428.7297      0.4970     15,707
                   3 |    435.7897      0.4941     15,674
-------------------------------------------------------------

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. FORVALUES I=1/6{
  2.        REG ADJ_PRICE MULTI_MATERIAL_P METALS_FOOD_PERMITTED COLOR RIGID FOODANDBEVERAGE
FILM OTHER SINGLEMATERIAL BOTTLEDEPOSIT CONTAMINATION IF SAMPLE==1 & REGION==`I'
  3. ESTIMATES STORE M`I', TITLE(`I')
  4. }
NOTE: BOTTLEDEPOSIT OMITTED BECAUSE OF COLLINEARITY.

     SOURCE |       SS           DF       MS      NUMBER OF OBS   =     2,741
-------------+----------------------------------   F(9, 2731)      =    309.59
      MODEL |  1272950.88         9  141438.986   PROB > F        =    0.0000
   RESIDUAL |  1247667.16     2,731  456.853591   R-SQUARED       =    0.5050
-------------+----------------------------------   ADJ R-SQUARED   =    0.5034
      TOTAL |  2520618.03     2,740  919.933589   ROOT MSE        =    21.374

-------------------------------------------------------------------------------------
          ADJ_PRICE | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
----------------------+--------------------------------------------------------------
    MULTI_MATERIAL_P |   -99.8252   5.454927   -18.30   0.000    -110.5214    -89.129
METALS_FOOD_PERMITTED |   .0104351   .0018462     5.65   0.000     .006815    .0140553
```

```
             COLOR |  -28.78674   1.341414   -21.46   0.000    -31.41703   -26.15645
             RIGID |   10.12921   1.896728     5.34   0.000     6.410048    13.84838
  FOODANDBEVERAGE |   24.37681   1.294697    18.83   0.000     21.83813     26.9155
              FILM |  -21.43604   2.002286   -10.71   0.000    -25.36219    -17.5099
             OTHER |   2.793604    2.73773     1.02   0.308    -2.574627    8.161835
   SINGLEMATERIAL |  -63.06108   4.922128   -12.81   0.000    -72.71255   -53.40961
    BOTTLEDEPOSIT |          0  (OMITTED)
    CONTAMINATION |   68.04799   40.63538     1.67   0.094     -11.6312    147.7272
             _CONS |   100.0279   5.540651    18.05   0.000     89.16362    110.8922
------------------------------------------------------------------------------------
NOTE: BOTTLEDEPOSIT OMITTED BECAUSE OF COLLINEARITY.

      SOURCE |       SS           DF       MS      NUMBER OF OBS   =     2,611
-------------+----------------------------------   F(9, 2601)      =    285.06
       MODEL |  1210490.95         9  134498.994   PROB > F        =    0.0000
    RESIDUAL |  1227217.06     2,601  471.82509    R-SQUARED       =    0.4966
-------------+----------------------------------   ADJ R-SQUARED   =    0.4948
       TOTAL |  2437708.01     2,610  933.987743   ROOT MSE        =    21.722

------------------------------------------------------------------------------------
          ADJ_PRICE | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
--------------------+---------------------------------------------------------------
   MULTI_MATERIAL_P |  -96.02824   5.450837   -17.62   0.000    -106.7167   -85.33983
METALS_FOOD_PERMITTED |  .0104011   .0018704     5.56   0.000     .0067334    .0140688
             COLOR |  -29.42482    1.36406   -21.57   0.000    -32.09957   -26.75006
             RIGID |   7.584874    2.13009     3.56   0.000      3.40803    11.76172
  FOODANDBEVERAGE |   24.07109   1.344125    17.91   0.000     21.43542    26.70675
              FILM |  -23.23539   2.179623   -10.66   0.000    -27.50937   -18.96142
             OTHER |     6.6311   2.932546     2.26   0.024     .8807401    12.38146
   SINGLEMATERIAL |  -57.38902   5.031492   -11.41   0.000    -67.25516   -47.52289
    BOTTLEDEPOSIT |          0  (OMITTED)
    CONTAMINATION |   46.92499   42.65754     1.10   0.271    -36.72118    130.5712
             _CONS |   97.01486   5.637896    17.21   0.000     85.95964    108.0701
------------------------------------------------------------------------------------

      SOURCE |       SS           DF       MS      NUMBER OF OBS   =     2,614
-------------+----------------------------------   F(10, 2603)     =    287.73
       MODEL |  1283820.41        10  128382.041   PROB > F        =    0.0000
    RESIDUAL |  1161450.09     2,603  446.196731   R-SQUARED       =    0.5250
-------------+----------------------------------   ADJ R-SQUARED   =    0.5232
       TOTAL |   2445270.5     2,613  935.809606   ROOT MSE        =    21.123

------------------------------------------------------------------------------------
          ADJ_PRICE | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
--------------------+---------------------------------------------------------------
   MULTI_MATERIAL_P |  -112.4177   5.425937   -20.72   0.000    -123.0573   -101.7781
METALS_FOOD_PERMITTED |   .012658   .0018572     6.82   0.000     .0090162    .0162997
             COLOR |   -27.6692   1.348304   -20.52   0.000    -30.31306   -25.02535
             RIGID |   4.667009   2.055342     2.27   0.023     .6367385     8.69728
  FOODANDBEVERAGE |   26.13693   1.312316    19.92   0.000     23.56364    28.71022
              FILM |  -28.60645   2.146668   -13.33   0.000     -32.8158    -24.3971
             OTHER |   9.758503   2.823282     3.46   0.001     4.222399    15.29461
   SINGLEMATERIAL |  -65.91768   4.940761   -13.34   0.000     -75.6059   -56.22946
    BOTTLEDEPOSIT |  -12.06327   3.313779    -3.64   0.000    -18.56118   -5.565367
    CONTAMINATION |   61.77117   40.61082     1.52   0.128     -17.8616    141.4039
             _CONS |   107.3562   5.587189    19.21   0.000     96.40041     118.312
------------------------------------------------------------------------------------

      SOURCE |       SS           DF       MS      NUMBER OF OBS   =     2,707
-------------+----------------------------------   F(10, 2696)     =    245.24
       MODEL |  1044168.82        10  104416.882   PROB > F        =    0.0000
    RESIDUAL |  1147873.33     2,696  425.769039   R-SQUARED       =    0.4763
-------------+----------------------------------   ADJ R-SQUARED   =    0.4744
       TOTAL |  2192042.15     2,706  810.067312   ROOT MSE        =    20.634

------------------------------------------------------------------------------------
          ADJ_PRICE | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
--------------------+---------------------------------------------------------------
   MULTI_MATERIAL_P |  -50.23435   4.799199   -10.47   0.000    -59.64484   -40.82387
```

```
METALS_FOOD_PERMITTED |  .0021898  .0018321    1.20  0.232   -.0014026   .0057822
               COLOR |  -27.95559  1.334018  -20.96  0.000   -30.5714   -25.33979
               RIGID |   1.589319  2.029877    0.78  0.434   -2.390954   5.569592
     FOODANDBEVERAGE |   21.67182  1.298597   16.69  0.000    19.12548   24.21817
                FILM |  -25.02044  2.107767  -11.87  0.000   -29.15344  -20.88743
               OTHER |   3.641941  2.783508    1.31  0.191   -1.816085   9.099967
      SINGLEMATERIAL |  -30.09587  4.604986   -6.54  0.000   -39.12553  -21.06621
       BOTTLEDEPOSIT |  -4.389975  3.53654    -1.24  0.215   -11.32458    2.54463
       CONTAMINATION |   99.03283  41.02002    2.41  0.016    18.59896   179.4667
               _CONS |    72.6282  5.313949   13.67  0.000    62.20837   83.04802
------------------------------------------------------------------------------------
NOTE: BOTTLEDEPOSIT OMITTED BECAUSE OF COLLINEARITY.

      SOURCE |       SS           DF       MS      NUMBER OF OBS   =     2,593
-------------+----------------------------------   F(9, 2583)      =    272.97
       MODEL |  1183505.27         9  131500.585   PROB > F        =    0.0000
    RESIDUAL |   1244321.4     2,583  481.734958   R-SQUARED       =    0.4875
-------------+----------------------------------   ADJ R-SQUARED   =    0.4857
       TOTAL |  2427826.67     2,592  936.661522   ROOT MSE        =    21.948

------------------------------------------------------------------------------------
           ADJ_PRICE | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
---------------------+--------------------------------------------------------------
    MULTI_MATERIAL_P |  -107.7845  5.451377  -19.77  0.000    -118.474  -97.09499
METALS_FOOD_PERMITTED |  .0107542  .0019073    5.64  0.000    .0070143   .0144941
               COLOR |  -27.39117  1.411047  -19.41  0.000   -30.15807  -24.62427
               RIGID |   6.740896  2.105037    3.20  0.001    2.613165   10.86863
     FOODANDBEVERAGE |   24.95421  1.382618   18.05  0.000    22.24306   27.66536
                FILM |  -23.87936  2.219751  -10.76  0.000   -28.23203  -19.52669
               OTHER |   4.807728  2.922622    1.65  0.100    -.923191   10.53865
      SINGLEMATERIAL |  -66.35425  5.037077  -13.17  0.000   -76.23137  -56.47714
       BOTTLEDEPOSIT |          0  (OMITTED)
       CONTAMINATION |   69.19908  43.00638    1.61  0.108   -15.13138   153.5296
               _CONS |   107.5668  5.725312   18.79  0.000     96.3401   118.7934
------------------------------------------------------------------------------------
NOTE: BOTTLEDEPOSIT OMITTED BECAUSE OF COLLINEARITY.

      SOURCE |       SS           DF       MS      NUMBER OF OBS   =     2,422
-------------+----------------------------------   F(9, 2412)      =    260.45
       MODEL |  773152.649         9  85905.8499   PROB > F        =    0.0000
    RESIDUAL |  795570.354     2,412  329.838455   R-SQUARED       =    0.4929
-------------+----------------------------------   ADJ R-SQUARED   =    0.4910
       TOTAL |     1568723     2,421  647.964892   ROOT MSE        =    18.161

------------------------------------------------------------------------------------
           ADJ_PRICE | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
---------------------+--------------------------------------------------------------
    MULTI_MATERIAL_P |  -65.23346  4.621135  -14.12  0.000   -74.29526  -56.17165
METALS_FOOD_PERMITTED |  .0046826  .0015951    2.94  0.003    .0015547   .0078106
               COLOR |  -27.82103  1.179446  -23.59  0.000   -30.13386  -25.50819
               RIGID |   4.824127  2.014091    2.40  0.017    .8745998   8.773654
     FOODANDBEVERAGE |   20.08881  1.176205   17.08  0.000    17.78233   22.39529
                FILM |  -20.29919  2.033271   -9.98  0.000   -24.28633  -16.31205
               OTHER |   2.517293  2.571056    0.98  0.328   -2.524413      7.559
      SINGLEMATERIAL |  -43.97792   4.31511  -10.19  0.000   -52.43963  -35.51621
       BOTTLEDEPOSIT |          0  (OMITTED)
       CONTAMINATION |    100.842  36.26212    2.78  0.005    29.73383   171.9501
               _CONS |   79.15563  4.789019   16.53  0.000    69.76461   88.54664
------------------------------------------------------------------------------------

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. ESTIMATES DIR

-------------------------------------------------------
             |           DEPENDENT  NUMBER OF
```

```
     NAME | COMMAND    VARIABLE    PARAM.  TITLE
-------------+----------------------------------------
       CV | LASSO    ADJ_PRICE       13  LASSO
       M1 | REGRESS   ADJ_PRICE       11  1
       M2 | REGRESS   ADJ_PRICE       11  2
       M3 | REGRESS   ADJ_PRICE       11  3
       M4 | REGRESS   ADJ_PRICE       11  4
       M5 | REGRESS   ADJ_PRICE       11  5
       M6 | REGRESS   ADJ_PRICE       11  6
------------------------------------------------------

. ESTIMATES DROP CV

. ESTIMATES TABLE _ALL, SE P

------------------------------------------------------------------------------------------
   VARIABLE |     M1         M2         M3         M4         M5         M6
-------------+----------------------------------------------------------------------------
MULTI_MATE~P | -99.825201  -96.028244  -112.41768  -50.234355  -107.7845  -65.233459
         |  5.4549271   5.4508372   5.4259365   4.7991988    5.451377   4.6211352
         |     0.0000      0.0000      0.0000      0.0000      0.0000      0.0000
METALS_FOO~D |  .01043515   .01040113   .01265798   .00218978    .0107542   .00468265
         |  .00184623   .00187043    .0018572   .00183207   .00190726   .00159513
         |     0.0000      0.0000      0.0000      0.2321      0.0000      0.0034
     COLOR | -28.786743  -29.424816  -27.669202  -27.955594  -27.391168  -27.821025
         |  1.3414143   1.3640595    1.348304   1.3340179   1.4110468   1.1794461
         |     0.0000      0.0000      0.0000      0.0000      0.0000      0.0000
     RIGID |  10.129215   7.5848743   4.6670093   1.5893187   6.7408961   4.8241268
         |   1.896728   2.1300903   2.0553423   2.0298772   2.1050369   2.0140907
         |     0.0000      0.0004      0.0232      0.4337      0.0014      0.0167
FOODANDBEV~E |  24.376814   24.071087   26.136927   21.671822    24.95421   20.088812
         |  1.2946971   1.3441252   1.3123159   1.2985966   1.3826185   1.1762054
         |     0.0000      0.0000      0.0000      0.0000      0.0000      0.0000
      FILM | -21.436044  -23.235395  -28.606446  -25.020438  -23.879361  -20.299187
         |  2.0022862   2.1796233   2.1466682   2.1077669   2.2197509   2.0332711
         |     0.0000      0.0000      0.0000      0.0000      0.0000      0.0000
     OTHER |  2.7936039      6.6311    9.758503   3.6419411   4.8077284   2.5172933
         |  2.7377297   2.9325457   2.8232816   2.7835082    2.922622   2.5710556
         |     0.3076      0.0238      0.0006      0.1908      0.1001      0.3276
SINGLEMATE~L | -63.061083  -57.389023  -65.917683   -30.09587  -66.354255  -43.977919
         |  4.9221275   5.0314918   4.9407613    4.604986   5.0370773   4.3151102
         |     0.0000      0.0000      0.0000      0.0000      0.0000      0.0000
BOTTLEDEPO~T |  (OMITTED)   (OMITTED)  -12.063275  -4.3899746   (OMITTED)   (OMITTED)
         |                          3.3137786     3.53654
         |                             0.0003      0.2146
CONTAMINAT~N |  68.047987   46.924991   61.771174   99.032826   69.199084   100.84195
         |  40.635376   42.657541    40.61082   41.020018   43.006378   36.262116
         |     0.0941      0.2714      0.1284      0.0158      0.1077      0.0055
     _CONS |  100.02791   97.014861    107.3562   72.628195   107.56677   79.155627
         |  5.5406514   5.6378965   5.5871893   5.3139492   5.7253123   4.7890189
         |     0.0000      0.0000      0.0000      0.0000      0.0000      0.0000
------------------------------------------------------------------------------------------
                                                                  LEGEND: B/SE/P

. ESTIMATES TABLE _ALL, STAR(0.05 0.01 0.001)

------------------------------------------------------------------------------------------------------------
   VARIABLE |      M1            M2            M3            M4            M5            M6
-------------+----------------------------------------------------------------------------------------------
MULTI_MATE~P | -99.825201***  -96.028244***  -112.41768***  -50.234355***  -107.7845***  -65.233459***
METALS_FOO~D |  .01043515***   .01040113***   .01265798***   .00218978      .0107542***   .00468265**
     COLOR | -28.786743***  -29.424816***  -27.669202***  -27.955594***  -27.391168***  -27.821025***
     RIGID |  10.129215***   7.5848743***   4.6670093*     1.5893187      6.7408961**    4.8241268*
FOODANDBEV~E |  24.376814***   24.071087***   26.136927***   21.671822***   24.95421***    20.088812***
      FILM | -21.436044***  -23.235395***  -28.606446***  -25.020438***  -23.879361***  -20.299187***
     OTHER |  2.7936039      6.6311*        9.758503***    3.6419411      4.8077284      2.5172933
SINGLEMATE~L | -63.061083***  -57.389023***  -65.917683***  -30.09587***   -66.354255***  -43.977919***
BOTTLEDEPO~T |  (OMITTED)      (OMITTED)     -12.063275***  -4.3899746     (OMITTED)      (OMITTED)
CONTAMINAT~N |  68.047987      46.924991      61.771174      99.032826*     69.199084      100.84195**
```

```
     _CONS |  100.02791***    97.014861***    107.3562***    72.628195***    107.56677***    79.155627***
--------------------------------------------------------------------------------------------------------------
                                      LEGEND: * P<.05; ** P<.01; *** P<.001

. ESTIMATES TABLE _ALL //FOR TRANSPOSING RESULTS

------------------------------------------------------------------------------------------
   VARIABLE |     M1         M2         M3         M4         M5         M6
-------------+----------------------------------------------------------------------------
MULTI_MATE~P | -99.825201  -96.028244  -112.41768  -50.234355   -107.7845  -65.233459
METALS_FOO~D |  .01043515   .01040113   .01265798   .00218978    .0107542   .00468265
       COLOR | -28.786743  -29.424816  -27.669202  -27.955594  -27.391168  -27.821025
       RIGID |  10.129215   7.5848743   4.6670093   1.5893187   6.7408961   4.8241268
FOODANDBEV~E |  24.376814   24.071087   26.136927   21.671822    24.95421   20.088812
        FILM | -21.436044  -23.235395  -28.606446  -25.020438  -23.879361  -20.299187
       OTHER |  2.7936039      6.6311    9.758503   3.6419411   4.8077284   2.5172933
SINGLEMATE~L | -63.061083  -57.389023  -65.917683   -30.09587  -66.354255  -43.977919
BOTTLEDEPO~T |  (OMITTED)   (OMITTED)  -12.063275  -4.3899746   (OMITTED)   (OMITTED)
CONTAMINAT~N |  68.047987   46.924991   61.771174   99.032826   69.199084   100.84195
       _CONS |  100.02791   97.014861    107.3562   72.628195   107.56677   79.155627
------------------------------------------------------------------------------------------

. ESTIMATES STATS _ALL

AKAIKE'S INFORMATION CRITERION AND BAYESIAN INFORMATION CRITERION

-----------------------------------------------------------------------------
       MODEL |          N   LL(NULL)  LL(MODEL)      DF        AIC        BIC
-------------+---------------------------------------------------------------
          M1 |      2,741  -13241.52  -12277.74      10   24575.48   24634.64
          M2 |      2,611  -12633.27  -11737.29      10   23494.58   23553.26
          M3 |      2,614  -12650.33  -11677.29      11   23376.57   23441.13
          M4 |      2,707  -12905.11  -12029.51      11   24081.01   24145.95
          M5 |      2,593  -12549.88  -11683.29      10   23386.58   23445.18
          M6 |      2,422  -11275.99  -10453.77      10   20927.53   20985.46
-----------------------------------------------------------------------------
NOTE: BIC USES N = NUMBER OF OBSERVATIONS. SEE [R] BIC NOTE.

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. PROBIT BOTTLEDEPOSIT IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1,
OFFSET(P_BDEP)

NOTE: IMPORT_BAN != 1 PREDICTS FAILURE PERFECTLY;
      IMPORT_BAN OMITTED AND 3459 OBS NOT USED.

NOTE: COVID_19 != 1 PREDICTS FAILURE PERFECTLY;
      COVID_19 OMITTED AND 1215 OBS NOT USED.

NOTE: 1.PRIMARY_POLYMER != 0 PREDICTS FAILURE PERFECTLY;
      1.PRIMARY_POLYMER OMITTED AND 297 OBS NOT USED.

NOTE: 2.PRIMARY_POLYMER != 0 PREDICTS FAILURE PERFECTLY;
      2.PRIMARY_POLYMER OMITTED AND 270 OBS NOT USED.

NOTE: 3.PRIMARY_POLYMER != 0 PREDICTS FAILURE PERFECTLY;
      3.PRIMARY_POLYMER OMITTED AND 287 OBS NOT USED.

NOTE: 4.PRIMARY_POLYMER != 1 PREDICTS FAILURE PERFECTLY;
      4.PRIMARY_POLYMER OMITTED AND 142 OBS NOT USED.

NOTE: 5.PRIMARY_POLYMER OMITTED BECAUSE OF COLLINEARITY.
NOTE: 6.PRIMARY_POLYMER OMITTED BECAUSE OF COLLINEARITY.
ITERATION 0:   LOG LIKELIHOOD = -248.91883
ITERATION 1:   LOG LIKELIHOOD = -248.78846
ITERATION 2:   LOG LIKELIHOOD = -248.78846
```

```
PROBIT REGRESSION                              NUMBER OF OBS =    218
                                          WALD CHI2(1)  =   0.20
LOG LIKELIHOOD = -248.78846                        PROB > CHI2   = 0.6550

------------------------------------------------------------------------------
 BOTTLEDEPOSIT | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
---------------+--------------------------------------------------------------
    IMPORT_BAN |          0  (OMITTED)
      COVID_19 |          0  (OMITTED)
    P_CRUDEOIL |  -.0023942   .0053583    -0.45   0.655    -.0128962    .0081078
               |
PRIMARY_POLYMER |
         HDPE  |          0  (EMPTY)
         LDPE  |          0  (EMPTY)
        MIXED  |          0  (EMPTY)
          PET  |          0  (OMITTED)
           PP  |          0  (EMPTY)
           PS  |          0  (EMPTY)
               |
         _CONS |  -.1076135   .3132709    -0.34   0.731    -.7216131    .5063861
        P_BDEP |          1  (OFFSET)
------------------------------------------------------------------------------

. ESTIMATES STORE M8

. MARGINS

PREDICTIVE MARGINS                               NUMBER OF OBS = 218
MODEL VCE: OIM

EXPRESSION: PR(BOTTLEDEPOSIT), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .4689548   .0212339    22.09   0.000     .4273371    .5105725
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                          NUMBER OF OBS = 218
MODEL VCE: OIM

EXPRESSION: PR(BOTTLEDEPOSIT), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL 1.PRIMARY_POLYMER 2.PRIMARY_POLYMER
4.PRIMARY_POLYMER 5.PRIMARY_POLYMER 6.PRIMARY_POLYMER

------------------------------------------------------------------------------
               |            DELTA-METHOD
               |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
---------------+--------------------------------------------------------------
    IMPORT_BAN |          0  (OMITTED)
      COVID_19 |          0  (OMITTED)
    P_CRUDEOIL |   -.000591   .0013238    -0.45   0.655    -.0031856    .0020035
               |
PRIMARY_POLYMER |
         HDPE  |          .  (NOT ESTIMABLE)
         LDPE  |          .  (NOT ESTIMABLE)
        MIXED  |          0  (EMPTY)
          PET  |          .  (NOT ESTIMABLE)
           PP  |          .  (NOT ESTIMABLE)
           PS  |          .  (NOT ESTIMABLE)
------------------------------------------------------------------------------
NOTE: DY/DX FOR FACTOR LEVELS IS THE DISCRETE CHANGE FROM THE BASE LEVEL.

. PROBIT FOODANDBEVERAGE IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1,
OFFSET(P_FOOD)
```

```
NOTE: 2.PRIMARY_POLYMER != 0 PREDICTS FAILURE PERFECTLY;
    2.PRIMARY_POLYMER OMITTED AND 3722 OBS NOT USED.

NOTE: 4.PRIMARY_POLYMER != 0 PREDICTS SUCCESS PERFECTLY;
    4.PRIMARY_POLYMER OMITTED AND 2505 OBS NOT USED.

NOTE: 5.PRIMARY_POLYMER != 0 PREDICTS SUCCESS PERFECTLY;
    5.PRIMARY_POLYMER OMITTED AND 1285 OBS NOT USED.

NOTE: 6.PRIMARY_POLYMER != 0 PREDICTS SUCCESS PERFECTLY;
    6.PRIMARY_POLYMER OMITTED AND 917 OBS NOT USED.

ITERATION 0:   LOG LIKELIHOOD = -6420.8978
ITERATION 1:   LOG LIKELIHOOD = -6153.6096
ITERATION 2:   LOG LIKELIHOOD = -6151.9995
ITERATION 3:   LOG LIKELIHOOD = -6151.9995

PROBIT REGRESSION                          NUMBER OF OBS =  9,382
                                          WALD CHI2(4)  = 490.69
LOG LIKELIHOOD = -6151.9995                PROB > CHI2   = 0.0000

------------------------------------------------------------------------------
FOODANDBEVERAGE | COEFFICIENT  STD. ERR.     Z    P>|Z|     [95% CONF. INTERVAL]
----------------+-------------------------------------------------------------
     IMPORT_BAN |  -.4464893   .0371002   -12.03   0.000    -.5192043   -.3737743
       COVID_19 |    .088024   .0456308     1.93   0.054    -.0014107    .1774588
     P_CRUDEOIL |   .0089505   .0007128    12.56   0.000     .0075535    .0103475
                |
PRIMARY_POLYMER |
          HDPE  |   .1666672   .0307601     5.42   0.000     .1063786    .2269558
          LDPE  |          0  (EMPTY)
           PET  |          0  (EMPTY)
            PP  |          0  (EMPTY)
            PS  |          0  (EMPTY)
                |
          _CONS |   .0387282   .0539729     0.72   0.473    -.0670567    .1445131
         P_FOOD |          1  (OFFSET)
------------------------------------------------------------------------------

. ESTIMATES STORE M9

. MARGINS

PREDICTIVE MARGINS                              NUMBER OF OBS = 9,382
MODEL VCE: OIM

EXPRESSION: PR(FOODANDBEVERAGE), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .7351755   .0037146   197.92   0.000      .727895    .7424559
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                        NUMBER OF OBS = 9,382
MODEL VCE: OIM

EXPRESSION: PR(FOODANDBEVERAGE), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL 1.PRIMARY_POLYMER 2.PRIMARY_POLYMER
4.PRIMARY_POLYMER 5.PRIMARY_POLYMER 6.PRIMARY_POLYMER

------------------------------------------------------------------------------
                |            DELTA-METHOD
                |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
----------------+-------------------------------------------------------------
```

```
    IMPORT_BAN |  -.1126562   .0092142   -12.23   0.000    -.1307157   -.0945967
      COVID_19 |   .0222098   .0115074     1.93   0.054    -.0003443    .044764
    P_CRUDEOIL |   .0022584   .0001764    12.80   0.000     .0019126    .0026041
               |
PRIMARY_POLYMER |
          HDPE  |   .0425416   .0079432     5.36   0.000     .0269733    .0581099
          LDPE  |          .  (NOT ESTIMABLE)
           PET  |          .  (NOT ESTIMABLE)
            PP  |          .  (NOT ESTIMABLE)
            PS  |          .  (NOT ESTIMABLE)
------------------------------------------------------------------------------
NOTE: DY/DX FOR FACTOR LEVELS IS THE DISCRETE CHANGE FROM THE BASE LEVEL.

. PROBIT FILM IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PP IF SAMPLE==1, OFFSET(P_FILM)

ITERATION 0:   LOG LIKELIHOOD = -14386.732
ITERATION 1:   LOG LIKELIHOOD = -7171.5625
ITERATION 2:   LOG LIKELIHOOD = -7127.5643
ITERATION 3:   LOG LIKELIHOOD = -7127.4383
ITERATION 4:   LOG LIKELIHOOD = -7127.4383

PROBIT REGRESSION                               NUMBER OF OBS =    17,811
                                                WALD CHI2(5)  = 11167.29
LOG LIKELIHOOD = -7127.4383                     PROB > CHI2   =    0.0000

------------------------------------------------------------------------------
        FILM | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |   .2105182   .0324463     6.49   0.000     .1469246    .2741117
    COVID_19 |   -.035502   .0396917    -0.89   0.371    -.1132963    .0422922
  P_CRUDEOIL |  -.0022205   .0006095    -3.64   0.000    -.0034151    -.001026
        HDPE |  -.0034079   .0296765    -0.11   0.909    -.0615728     .054757
          PP |   2.741818   .0261184   104.98   0.000     2.690627    2.793009
       _CONS |   -1.63284   .0525418   -31.08   0.000     -1.73582    -1.52986
      P_FILM |          1  (OFFSET)
------------------------------------------------------------------------------

. ESTIMATES STORE M10

. MARGINS

PREDICTIVE MARGINS                              NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(FILM), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .4177094   .0022192   188.22   0.000     .4133598     .422059
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                        NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(FILM), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PP

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |    .035423   .0054521     6.50   0.000      .024737     .046109
    COVID_19 |  -.0059738   .0066785    -0.89   0.371    -.0190635    .0071159
  P_CRUDEOIL |  -.0003736   .0001025    -3.65   0.000    -.0005745   -.0001728
        HDPE |  -.0005734   .0049937    -0.11   0.909    -.0103609     .009214
```

```
         PP |   .4613547   .0018826   245.06   0.000     .4576649    .4650445
------------------------------------------------------------------------------

. PROBIT OTHER IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PET PP IF SAMPLE==1, OFFSET(P_OTHER)

ITERATION 0:   LOG LIKELIHOOD = -13843.475
ITERATION 1:   LOG LIKELIHOOD = -7128.5056
ITERATION 2:   LOG LIKELIHOOD = -6540.0758
ITERATION 3:   LOG LIKELIHOOD = -6472.4732
ITERATION 4:   LOG LIKELIHOOD = -6462.0061
ITERATION 5:   LOG LIKELIHOOD = -6459.9834
ITERATION 6:   LOG LIKELIHOOD = -6459.7117
ITERATION 7:   LOG LIKELIHOOD = -6459.6719
ITERATION 8:   LOG LIKELIHOOD =  -6459.664
ITERATION 9:   LOG LIKELIHOOD = -6459.6624
ITERATION 10:  LOG LIKELIHOOD =  -6459.662
ITERATION 11:  LOG LIKELIHOOD =  -6459.662
ITERATION 12:  LOG LIKELIHOOD =  -6459.662

PROBIT REGRESSION                               NUMBER OF OBS =  17,811
                                                WALD CHI2(6)  = 1496.20
LOG LIKELIHOOD = -6459.662                      PROB > CHI2   =  0.0000

------------------------------------------------------------------------------
       OTHER | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |   .4370706   .0367245    11.90   0.000      .365092    .5090492
    COVID_19 |  -.2506761   .0449985    -5.57   0.000    -.3388716   -.1624806
  P_CRUDEOIL |  -.0059863   .0006612    -9.05   0.000    -.0072823   -.0046904
        HDPE |  -7.138479   120.4899    -0.06   0.953    -243.2944    229.0175
         PET |   .9201911   .0297914    30.89   0.000      .861801    .9785813
          PP |   7.819196   120.4899     0.06   0.948    -228.3368    243.9751
       _CONS |  -.6412801   .0574578   -11.16   0.000    -.7538953    -.528665
     P_OTHER |          1  (OFFSET)
------------------------------------------------------------------------------
NOTE: 6713 FAILURES AND 1805 SUCCESSES COMPLETELY DETERMINED.

. ESTIMATES STORE M11

. MARGINS

PREDICTIVE MARGINS                              NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(OTHER), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |    .328201   .0020717   158.42   0.000     .3241405    .3322614
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                        NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(OTHER), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PET PP

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |    .061057   .0050365    12.12   0.000     .0511857    .0709284
    COVID_19 |  -.0350185   .0062628    -5.59   0.000    -.0472933   -.0227436
  P_CRUDEOIL |  -.0008363   .0000914    -9.15   0.000    -.0010154   -.0006571
        HDPE |  -.9972173   16.83196    -0.06   0.953    -33.98726    31.99283
```

```
       PET |   .1285471   .0038396    33.48   0.000     .1210216    .1360725
        PP |   1.092311   16.83196     0.06   0.948    -31.89773    34.08235
------------------------------------------------------------------------------

. PROBIT SINGLEMATERIAL IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PET IF SAMPLE==1, OFFSET(P_SEG)

ITERATION 0:   LOG LIKELIHOOD =  -10762.37
ITERATION 1:   LOG LIKELIHOOD = -8008.1403
ITERATION 2:   LOG LIKELIHOOD = -7963.8293
ITERATION 3:   LOG LIKELIHOOD = -7963.6614
ITERATION 4:   LOG LIKELIHOOD = -7963.6614

PROBIT REGRESSION                               NUMBER OF OBS =  17,811
                                                WALD CHI2(5)  = 4726.34
LOG LIKELIHOOD = -7963.6614                     PROB > CHI2   =  0.0000

--------------------------------------------------------------------------------
SINGLEMATERIAL | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
---------------+----------------------------------------------------------------
    IMPORT_BAN |  -.4670223   .0309583   -15.09   0.000    -.5276995   -.4063451
      COVID_19 |   .3266282   .0384496     8.49   0.000     .2512685     .401988
    P_CRUDEOIL |   .0117618   .0006146    19.14   0.000     .0105573    .0129664
          HDPE |  -.2836518   .0255755   -11.09   0.000    -.3337788   -.2335248
           PET |  -1.761453   .0260432   -67.64   0.000    -1.812497   -1.710409
         _CONS |   1.534177   .0473661    32.39   0.000     1.441341    1.627013
         P_SEG |          1  (OFFSET)
--------------------------------------------------------------------------------

. ESTIMATES STORE M12

. MARGINS

PREDICTIVE MARGINS                                      NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(SINGLEMATERIAL), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .7869732   .0024066   327.01   0.000     .7822564      .79169
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                                NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(SINGLEMATERIAL), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PET

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |  -.0887353   .0058317   -15.22   0.000    -.1001652   -.0773054
    COVID_19 |   .0620601   .0072838     8.52   0.000      .047784    .0763362
  P_CRUDEOIL |   .0022348   .0001146    19.50   0.000     .0020101    .0024594
        HDPE |  -.0538945   .0049262   -10.94   0.000    -.0635497   -.0442393
         PET |  -.3346802   .0035033   -95.53   0.000    -.3415466   -.3278137
------------------------------------------------------------------------------

. PROBIT RIGID IMPORT_BAN COVID_19 P_CRUDEOIL HDPE MIXED IF SAMPLE==1, OFFSET(P_RIGID)

ITERATION 0:   LOG LIKELIHOOD = -11997.016
ITERATION 1:   LOG LIKELIHOOD = -11715.534
ITERATION 2:   LOG LIKELIHOOD = -11714.206
ITERATION 3:   LOG LIKELIHOOD = -11714.206
```

```
PROBIT REGRESSION                              NUMBER OF OBS = 16,849
                                    WALD CHI2(5)  = 521.20
LOG LIKELIHOOD = -11714.206                         PROB > CHI2   = 0.0000

------------------------------------------------------------------------------
       RIGID | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |  -.3244719   .0266674   -12.17   0.000    -.3767391   -.2722047
    COVID_19 |   .1417346   .0331062     4.28   0.000     .0768476    .2066216
  P_CRUDEOIL |   .0040601   .0004896     8.29   0.000     .0031006    .0050196
        HDPE |  -.3980745   .0247399   -16.09   0.000    -.4465639   -.3495852
       MIXED |  -.0701052   .0258773    -2.71   0.007    -.1208237   -.0193867
       _CONS |   .7545243   .0424529    17.77   0.000     .6713182    .8377305
     P_RIGID |          1  (OFFSET)
------------------------------------------------------------------------------

. ESTIMATES STORE M13

. MARGINS

PREDICTIVE MARGINS                              NUMBER OF OBS = 16,849
MODEL VCE: OIM

EXPRESSION: PR(RIGID), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .7040045   .0029999   234.68   0.000     .6981248    .7098841
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                        NUMBER OF OBS = 16,849
MODEL VCE: OIM

EXPRESSION: PR(RIGID), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL HDPE MIXED

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |  -.0919994    .007482   -12.30   0.000    -.1066638    -.077335
    COVID_19 |   .0401868   .0093758     4.29   0.000     .0218107     .058563
  P_CRUDEOIL |   .0011512   .0001381     8.34   0.000     .0008805    .0014219
        HDPE |  -.1128684   .0069148   -16.32   0.000    -.1264212   -.0993156
       MIXED |  -.0198773     .00733    -2.71   0.007    -.0342439   -.0055107
------------------------------------------------------------------------------

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. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. REG WTP_CONTAM IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1

      SOURCE |       SS           DF       MS      NUMBER OF OBS   =    17,811
-------------+----------------------------------   F(8, 17802)     =   5845.73
       MODEL |  1571.57615         8  196.447019   PROB > F        =    0.0000
    RESIDUAL |  598.23984     17,802  .033605204   R-SQUARED       =    0.7243
-------------+----------------------------------   ADJ R-SQUARED   =    0.7242
       TOTAL |  2169.81599    17,810  .12183133    ROOT MSE        =    .18332

--------------------------------------------------------------------------------
    WTP_CONTAM | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
---------------+----------------------------------------------------------------
```

```
   IMPORT_BAN |  -.0427778   .0035816   -11.94   0.000    -.0497981   -.0357574
    COVID_19 |   .0055292   .0044258    1.25   0.212    -.0031459    .0142042
   P_CRUDEOIL |    .000752   .0000619    12.14   0.000     .0006306    .0008733
             |
PRIMARY_POLYMER |
        HDPE  |  -.0115647   .0039601    -2.92   0.004    -.0193269   -.0038025
        LDPE  |   .7075288   .0043138   164.02   0.000     .6990733    .7159842
         PET  |   -.013527   .0048415    -2.79   0.005    -.0230167   -.0040372
          PP  |   .4507442   .0059746    75.44   0.000     .4390334     .462455
          PS  |  -.0035385   .0067979    -0.52   0.603     -.016863     .009786
             |
       _CONS |   .1174203   .0054734    21.45   0.000     .1066919    .1281487
------------------------------------------------------------------------------

. ESTIMATES STORE M14

. REG WTP_COLOR IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1

     SOURCE |       SS           DF       MS      NUMBER OF OBS   =    16,650
-------------+----------------------------------   F(8, 16641)     =   1892.20
      MODEL |  11224.7373         8  1403.09217   PROB > F        =    0.0000
   RESIDUAL |  12339.5052    16,641  .741512239   R-SQUARED       =    0.4763
-------------+----------------------------------   ADJ R-SQUARED   =    0.4761
      TOTAL |  23564.2425    16,649  1.41535483   ROOT MSE        =    .86111

------------------------------------------------------------------------------
     WTP_COLOR | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
----------------+----------------------------------------------------------------
   IMPORT_BAN |  -.1014116   .0173128    -5.86   0.000    -.1353465   -.0674766
    COVID_19 |  -.0302961   .0208491    -1.45   0.146    -.0711625    .0105703
   P_CRUDEOIL |    .001631   .0003142     5.19   0.000     .0010151     .002247
             |
PRIMARY_POLYMER |
        HDPE  |   1.053103   .0186499    56.47   0.000     1.016548    1.089659
        LDPE  |     2.1994   .0225668    97.46   0.000     2.155167    2.243633
         PET  |   1.832685   .0227895    80.42   0.000     1.788015    1.877354
          PP  |   .0018756   .0280654     0.07   0.947    -.0531355    .0568867
          PS  |  -.0005906   .0319331    -0.02   0.985    -.0631829    .0620017
             |
       _CONS |  -2.869404   .0266906  -107.51   0.000     -2.92172   -2.817087
------------------------------------------------------------------------------

. ESTIMATES STORE M15

. REG WTP_MFP IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1

     SOURCE |       SS           DF       MS      NUMBER OF OBS   =    17,811
-------------+----------------------------------   F(8, 17802)     =    661.21
      MODEL |  3.8235E+11         8  4.7794E+10   PROB > F        =    0.0000
   RESIDUAL |  1.2868E+12    17,802    72282815   R-SQUARED       =    0.2291
-------------+----------------------------------   ADJ R-SQUARED   =    0.2287
      TOTAL |  1.6691E+12    17,810  93718661.3   ROOT MSE        =    8501.9

------------------------------------------------------------------------------
       WTP_MFP | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
----------------+----------------------------------------------------------------
   IMPORT_BAN |  -1136.543   166.1105    -6.84   0.000    -1462.136   -810.9503
    COVID_19 |  -43.43946   205.2623    -0.21   0.832    -445.7736    358.8947
   P_CRUDEOIL |    17.9664   2.872299     6.26   0.000     12.33641    23.59638
             |
PRIMARY_POLYMER |
        HDPE  |  -3327.779   183.6629   -18.12   0.000    -3687.776   -2967.782
        LDPE  |   8518.866   200.0663    42.58   0.000     8126.717    8911.016
         PET  |  -4529.225   224.5389   -20.17   0.000    -4969.343   -4089.107
          PP  |  -29.16926    277.092    -0.11   0.916    -572.2965     513.958
          PS  |   1849.703   315.2737     5.87   0.000     1231.736     2467.67
             |
       _CONS |   15619.89   253.8464    61.53   0.000     15122.33    16117.46
------------------------------------------------------------------------------
```

```
. ESTIMATES STORE M16

. REG WTP_MMP IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1

     SOURCE |       SS           DF       MS      NUMBER OF OBS   =    17,811
-------------+----------------------------------   F(8, 17802)     =   8636.91
      MODEL |  125630.342         8  15703.7927   PROB > F        =    0.0000
   RESIDUAL |  32367.9457    17,802  1.81821962   R-SQUARED       =    0.7951
-------------+----------------------------------   ADJ R-SQUARED   =    0.7950
      TOTAL |  157998.287    17,810  8.87132438   ROOT MSE        =    1.3484

------------------------------------------------------------------------------
     WTP_MMP | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |   .2025558   .0263453     7.69   0.000     .1509165    .2541951
    COVID_19 |   .0246685   .0325548     0.76   0.449    -.0391421     .088479
  P_CRUDEOIL |  -.0034893   .0004555    -7.66   0.000    -.0043823   -.0025964
             |
PRIMARY_POLYMER |
        HDPE  |   7.173884   .0291291   246.28   0.000     7.116788     7.23098
        LDPE  |   5.822148   .0317307   183.49   0.000     5.759952    5.884343
         PET  |   5.169546   .0356121   145.16   0.000     5.099743    5.239349
          PP  |   6.193946    .043947   140.94   0.000     6.107806    6.280087
          PS  |   7.767291   .0500027   155.34   0.000     7.669281    7.865301
             |
       _CONS |  -8.880674   .0402603  -220.58   0.000    -8.959588    -8.80176
------------------------------------------------------------------------------

. ESTIMATES STORE M17

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. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD4EF4_000000.TMP"

. ESTIMATES TABLE M1 M2 M3 M4 M5 M6, P SE //FIRST STAGE IMPLICT PRICES

-----------------------------------------------------------------------------------------
    VARIABLE |     M1           M2           M3           M4           M5           M6
-------------+---------------------------------------------------------------------------
MULTI_MATE~P | -99.825201   -96.028244   -112.41768   -50.234355   -107.7845   -65.233459
             |  5.4549271    5.4508372    5.4259365    4.7991988    5.451377    4.6211352
             |     0.0000       0.0000       0.0000       0.0000      0.0000       0.0000
METALS_FOO~D |  .01043515    .01040113    .01265798    .00218978    .0107542    .00468265
             |  .00184623    .00187043     .0018572    .00183207   .00190726    .00159513
             |     0.0000       0.0000       0.0000       0.2321      0.0000       0.0034
       COLOR | -28.786743   -29.424816   -27.669202   -27.955594  -27.391168   -27.821025
             |  1.3414143    1.3640595     1.348304    1.3340179   1.4110468    1.1794461
             |     0.0000       0.0000       0.0000       0.0000      0.0000       0.0000
       RIGID |  10.129215    7.5848743    4.6670093    1.5893187   6.7408961    4.8241268
             |   1.896728    2.1300903    2.0553423    2.0298772   2.1050369    2.0140907
             |     0.0000       0.0004       0.0232       0.4337      0.0014       0.0167
FOODANDBEV~E |  24.376814    24.071087    26.136927    21.671822    24.95421    20.088812
             |  1.2946971    1.3441252    1.3123159    1.2985966   1.3826185    1.1762054
             |     0.0000       0.0000       0.0000       0.0000      0.0000       0.0000
        FILM | -21.436044   -23.235395   -28.606446   -25.020438  -23.879361   -20.299187
             |  2.0022862    2.1796233    2.1466682    2.1077669   2.2197509    2.0332711
             |     0.0000       0.0000       0.0000       0.0000      0.0000       0.0000
       OTHER |  2.7936039       6.6311     9.758503    3.6419411   4.8077284    2.5172933
             |  2.7377297    2.9325457    2.8232816    2.7835082    2.922622    2.5710556
             |     0.3076       0.0238       0.0006       0.1908      0.1001       0.3276
SINGLEMATE~L | -63.061083   -57.389023   -65.917683    -30.09587  -66.354255   -43.977919
             |  4.9221275    5.0314918    4.9407613     4.604986   5.0370773    4.3151102
             |     0.0000       0.0000       0.0000       0.0000      0.0000       0.0000
BOTTLEDEPO~T |  (OMITTED)    (OMITTED)   -12.063275   -4.3899746   (OMITTED)    (OMITTED)
             |                            3.3137786      3.53654
             |                               0.0003       0.2146
CONTAMINAT~N |  68.047987    46.924991    61.771174    99.032826   69.199084    100.84195
```

```
         |  40.635376   42.657541    40.61082   41.020018   43.006378   36.262116
         |     0.0941      0.2714      0.1284      0.0158      0.1077      0.0055
   _CONS |  100.02791   97.014861    107.3562   72.628195   107.56677   79.155627
         |  5.5406514   5.6378965   5.5871893   5.3139492   5.7253123   4.7890189
         |     0.0000      0.0000      0.0000      0.0000      0.0000      0.0000
------------------------------------------------------------------------------------------
                                                           LEGEND: B/SE/P

. ESTIMATES TABLE M8 M9 M10 M11 M12 M13, P SE //SECOND STAGE DICHOTOMOUS

------------------------------------------------------------------------------------------
    VARIABLE |     M8          M9         M10         M11         M12         M13
-------------+----------------------------------------------------------------------------
BOTTLEDEPO~T |
  IMPORT_BAN |  (OMITTED)
             |
             |
    COVID_19 |  (OMITTED)
             |
             |
  P_CRUDEOIL | -.00239423
             |  .00535825
             |     0.6550
             |
PRIMARY_PO~R |
        HDPE |    (EMPTY)
             |
             |
        LDPE |    (EMPTY)
             |
             |
       MIXED |    (EMPTY)
             |
             |
         PET |  (OMITTED)
             |
             |
          PP |    (EMPTY)
             |
             |
          PS |    (EMPTY)
             |
             |
             |
       _CONS | -.10761352
             |  .31327085
             |     0.7312
-------------+----------------------------------------------------------------------------
FOODANDBEV~E |
  IMPORT_BAN |             -.44648928
             |              .03710019
             |                 0.0000
    COVID_19 |              .08802405
             |              .04563082
             |                 0.0537
  P_CRUDEOIL |              .00895051
             |              .00071276
             |                 0.0000
             |
PRIMARY_PO~R |
        HDPE |              .16666719
             |              .03076005
             |                 0.0000
        LDPE |                (EMPTY)
             |
             |
             |
PRIMARY_PO~R |
         PET |                (EMPTY)
```

```
             |
             |
          PP |      (EMPTY)
             |
             |
          PS |      (EMPTY)
             |
             |
             |
       _CONS |       .0387282
             |      .05397289
             |         0.4730
-------------+----------------------------------------------------------------
FILM         |
  IMPORT_BAN |              .21051816
             |             .03244628
             |                0.0000
    COVID_19 |             -.03550204
             |             .03969166
             |                0.3711
  P_CRUDEOIL |             -.00222054
             |             .00060946
             |                0.0003
        HDPE |             -.00340786
             |             .02967652
             |                0.9086
          PP |              2.7418183
             |             .02611838
             |                0.0000
       _CONS |               -1.63284
             |             .05254177
             |                0.0000
-------------+----------------------------------------------------------------
OTHER        |
  IMPORT_BAN |                     .43707058
             |                    .03672445
             |                       0.0000
    COVID_19 |                    -.25067606
             |                    .04499854
             |                       0.0000
  P_CRUDEOIL |                    -.00598632
             |                    .00066122
             |                       0.0000
        HDPE |                    -7.1384791
             |                    120.48994
             |                       0.9528
         PET |                     .92019114
             |                    .02979142
             |                       0.0000
          PP |                     7.8191957
             |                    120.48994
             |                       0.9483
       _CONS |                    -.64128014
             |                    .05745775
             |                       0.0000
-------------+----------------------------------------------------------------
SINGLEMATE~L |
  IMPORT_BAN |                            -.46702229
             |                           .03095834
             |                              0.0000
    COVID_19 |                             .32662824
             |                           .03844956
             |                              0.0000
  P_CRUDEOIL |                             .01176183
             |                           .00061458
             |                              0.0000
        HDPE |                            -.28365179
             |                           .02557547
             |                              0.0000
```

```
         PET |                       -1.7614531
             |                       .02604324
             |                        0.0000
       _CONS |                        1.5341769
             |                       .04736611
             |                        0.0000
-------------+-----------------------------------------------------------------------------
RIGID        |
  IMPORT_BAN |                                  -.32447187
             |                             .02666743
             |                              0.0000
    COVID_19 |                                 .1417346
             |                             .03310622
             |                              0.0000
  P_CRUDEOIL |                                  .00406008
             |                             .00048955
             |                              0.0000
        HDPE |                               -.39807454
             |                             .02473993
             |                              0.0000
       MIXED |                                -.07010521
             |                             .02587725
             |                              0.0067
       _CONS |                                 .75452434
             |                             .04245289
             |                              0.0000
-------------------------------------------------------------------------------------------
                                 LEGEND: B/SE/P
```

. ESTIMATES TABLE M14 M15 M16 M17, P SE //SECOND STAGE CONTINUOUS CHANGE IN WTP**

```
-------------------------------------------------------------
    VARIABLE |    M14         M15         M16         M17
-------------+-----------------------------------------------
  IMPORT_BAN | -.04277777  -.10141157   -1136.543   .20255582
             |  .00358165   .01731282   166.11048   .02634527
             |     0.0000      0.0000      0.0000      0.0000
    COVID_19 |  .00552918  -.03029611   -43.43946   .02466848
             |  .00442583   .02084907   205.26233   .03255479
             |     0.2116      0.1462      0.8324      0.4486
  P_CRUDEOIL |  .00075195   .00163101     17.9664  -.00348934
             |  .00006193   .00031424   2.8722988   .00045555
             |     0.0000      0.0000      0.0000      0.0000
             |
PRIMARY_PO~R |
        HDPE | -.01156472   1.0531035  -3327.7793   7.1738841
             |  .00396011   .01864986   183.66295   .02912911
             |     0.0035      0.0000      0.0000      0.0000
        LDPE |  .70752879      2.1994   8518.8665   5.8221476
             |   .0043138   .02256685   200.06627   .03173069
             |     0.0000      0.0000      0.0000      0.0000
             |
PRIMARY_PO~R |
         PET | -.01352697   1.8326847  -4529.2248   5.1695458
             |  .00484147   .02278945   224.53886   .03561206
             |     0.0052      0.0000      0.0000      0.0000
          PP |  .45074418   .00187564  -29.169261   6.1939465
             |  .00597461   .02806536     277.092   .04394704
             |     0.0000      0.9467      0.9162      0.0000
          PS | -.00353854  -.00059056    1849.703    7.767291
             |  .00679788   .03193311   315.27367   .05000269
             |     0.6027      0.9852      0.0000      0.0000
             |
       _CONS |  .11742028  -2.8694038   15619.894  -8.8806741
             |  .00547339   .02669059   253.84636   .04026026
             |     0.0000      0.0000      0.0000      0.0000
-------------------------------------------------------------
                                          LEGEND: B/SE/P
```

```
. **RESULTS ONLY P-VALUES WITH ** **
. ESTIMATES TABLE M1 M2 M3 M4 M5 M6, STAR(0.05 0.01 0.001)

----------------------------------------------------------------------------------------------------------
   VARIABLE |     M1           M2           M3           M4           M5           M6
-------------+--------------------------------------------------------------------------------------------
MULTI_MATE~P | -99.825201***  -96.028244***  -112.41768***  -50.234355***  -107.7845***  -65.233459***
METALS_FOO~D |  .01043515***   .01040113***   .01265798***   .00218978      .0107542***   .00468265**
      COLOR | -28.786743***  -29.424816***  -27.669202***  -27.955594***  -27.391168***  -27.821025***
      RIGID |  10.129215***   7.5848743***   4.6670093*     1.5893187      6.7408961**    4.8241268*
FOODANDBEV~E |  24.376814***   24.071087***   26.136927***   21.671822***   24.95421***   20.088812***
       FILM | -21.436044***  -23.235395***  -28.606446***  -25.020438***  -23.879361***  -20.299187***
      OTHER |  2.7936039      6.6311*        9.758503***    3.6419411      4.8077284      2.5172933
SINGLEMATE~L | -63.061083***  -57.389023***  -65.917683***  -30.09587***  -66.354255***  -43.977919***
BOTTLEDEPO~T |  (OMITTED)     (OMITTED)     -12.063275***  -4.3899746     (OMITTED)      (OMITTED)
CONTAMINAT~N |  68.047987      46.924991      61.771174      99.032826*     69.199084      100.84195**
      _CONS |  100.02791***   97.014861***   107.3562***    72.628195***   107.56677***   79.155627***
----------------------------------------------------------------------------------------------------------
                                  LEGEND: * P<.05; ** P<.01; *** P<.001

. ESTIMATES TABLE M8 M9 M10 M11 M12 M13, STAR(0.05 0.01 0.001) //SECOND STAGE DICHOTOMOUS

----------------------------------------------------------------------------------------------------------
   VARIABLE |     M8           M9           M10          M11          M12          M13
-------------+--------------------------------------------------------------------------------------------
BOTTLEDEPO~T |
 IMPORT_BAN |  (OMITTED)
   COVID_19 |  (OMITTED)
 P_CRUDEOIL | -.00239423
            |
PRIMARY_PO~R |
       HDPE |    (EMPTY)
       LDPE |    (EMPTY)
      MIXED |    (EMPTY)
        PET |  (OMITTED)
         PP |    (EMPTY)
         PS |    (EMPTY)
            |
      _CONS | -.10761352
-------------+--------------------------------------------------------------------------------------------
FOODANDBEV~E |
 IMPORT_BAN |               -.44648928***
   COVID_19 |                .08802405
 P_CRUDEOIL |                .00895051***
            |
PRIMARY_PO~R |
       HDPE |                .16666719***
       LDPE |                 (EMPTY)
            |
PRIMARY_PO~R |
        PET |                 (EMPTY)
         PP |                 (EMPTY)
         PS |                 (EMPTY)
            |
      _CONS |                .0387282
-------------+--------------------------------------------------------------------------------------------
FILM        |
 IMPORT_BAN |                             .21051816***
   COVID_19 |                            -.03550204
 P_CRUDEOIL |                            -.00222054***
       HDPE |                            -.00340786
         PP |                             2.7418183***
      _CONS |                            -1.63284***
-------------+--------------------------------------------------------------------------------------------
OTHER       |
 IMPORT_BAN |                                          .43707058***
   COVID_19 |                                         -.25067606***
 P_CRUDEOIL |                                         -.00598632***
       HDPE |                                         -7.1384791
```

```
        PET |          .92019114***
         PP |          7.8191957
      _CONS |          -.64128014***
-------------+----------------------------------------------------------------
SINGLEMATE~L |
  IMPORT_BAN |          -.46702229***
    COVID_19 |          .32662824***
  P_CRUDEOIL |          .01176183***
        HDPE |          -.28365179***
         PET |          -1.7614531***
       _CONS |          1.5341769***
-------------+----------------------------------------------------------------
RIGID        |
  IMPORT_BAN |          -.32447187***
    COVID_19 |          .1417346***
  P_CRUDEOIL |          .00406008***
        HDPE |          -.39807454***
       MIXED |          -.07010521**
       _CONS |          .75452434***
------------------------------------------------------------------------------
                        LEGEND: * P<.05; ** P<.01; *** P<.001
```

```
. ESTIMATES TABLE M14 M15 M16 M17, STAR(0.05 0.01 0.001) //SECOND STAGE CONTINUOUS CHANGE IN
WTP**

----------------------------------------------------------------------
    VARIABLE |     M14          M15          M16          M17
-------------+--------------------------------------------------------
  IMPORT_BAN | -.04277777***  -.10141157***  -1136.543***  .20255582***
    COVID_19 |  .00552918     -.03029611     -43.43946     .02466848
  P_CRUDEOIL |  .00075195***   .00163101***   17.9664***  -.00348934***
             |
PRIMARY_PO~R |
       HDPE  | -.01156472**   1.0531035***  -3327.7793***  7.1738841***
       LDPE  |  .70752879***     2.1994***   8518.8665***  5.8221476***
             |
PRIMARY_PO~R |
        PET  | -.01352697**   1.8326847***  -4529.2248***  5.1695458***
         PP  |  .45074418***   .00187564    -29.169261     6.1939465***
         PS  | -.00353854     -.00059056     1849.703***   7.767291***
             |
       _CONS |  .11742028***  -2.8694038***  15619.894***  -8.8806741***
----------------------------------------------------------------------
                LEGEND: * P<.05; ** P<.01; *** P<.001
```

```
. ESTIMATES STATS M8 M9 M10 M11 M12 M13

AKAIKE'S INFORMATION CRITERION AND BAYESIAN INFORMATION CRITERION

-----------------------------------------------------------------------------
       MODEL |          N   LL(NULL)  LL(MODEL)      DF         AIC        BIC
-------------+---------------------------------------------------------------
          M8 |        218          .  -248.7885       2    501.5769   508.3459
          M9 |      9,382          .      -6152       5       12314   12349.73
         M10 |     17,811          .  -7127.438       6    14266.88    14313.6
         M11 |     17,811          .  -6459.662       7    12933.32   12987.84
         M12 |     17,811          .  -7963.661       6    15939.32   15986.05
         M13 |     16,849          .  -11714.21       6    23440.41    23486.8
-----------------------------------------------------------------------------
NOTE: BIC USES N = NUMBER OF OBSERVATIONS. SEE [R] BIC NOTE.
```

```
. ESTIMATES STATS M14 M15 M16 M17

AKAIKE'S INFORMATION CRITERION AND BAYESIAN INFORMATION CRITERION

-----------------------------------------------------------------------------
       MODEL |          N   LL(NULL)  LL(MODEL)      DF         AIC        BIC
-------------+---------------------------------------------------------------
         M14 |     17,811  -6525.088   4948.811       9   -9879.621  -9809.533
```

```
      M15 |     16,650  -26516.77  -21131.12      9   42280.24   42349.72
      M16 |     17,811  -188739.9    -186423      9     372864   372934.1
      M17 |     17,811  -44711.35  -30592.44      9   61202.87   61272.96
-----------------------------------------------------------------------------
NOTE: BIC USES N = NUMBER OF OBSERVATIONS. SEE [R] BIC NOTE.

.
END OF DO-FILE

. LOG CLOSE
    NAME:  <UNNAMED>
     LOG:  E:\USERS\SHAFSA\SCRAP PLASTIC\MODEL 1.LOG
 LOG TYPE:  TEXT
 CLOSED ON:   9 APR 2022, 15:54:11
```

```
------------------------------------------------------------------------------------------------------------------------------------------------------
--------------------------------------------------
    NAME:  <UNNAMED>
     LOG:  E:\USERS\SHAFSA\SCRAP PLASTIC\MODEL2_MERGIN RESULTS.LOG
 LOG TYPE:  TEXT
 OPENED ON:   9 APR 2022, 16:40:13

. DROP _MERGE

. MERGE 1:1 _N USING "E:\USERS\SHAFSA\SCRAP PLASTIC\SAMPLE1C.DTA"
(LABEL PRIMARY_POLYMER ALREADY DEFINED)
(LABEL REGION ALREADY DEFINED)
(LABEL PLASTIC_QUALITY ALREADY DEFINED)

    RESULT                    NUMBER OF OBS
    -----------------------------------------
    NOT MATCHED                             0
    MATCHED                            17,816  (_MERGE==3)
    -----------------------------------------

. DROP _MERGE

. MERGE 1:1 _N USING "E:\USERS\SHAFSA\SCRAP PLASTIC\SAMPLE1D.DTA"
(LABEL PRIMARY_POLYMER ALREADY DEFINED)
(LABEL REGION ALREADY DEFINED)
(LABEL PLASTIC_QUALITY ALREADY DEFINED)

    RESULT                    NUMBER OF OBS
    -----------------------------------------
    NOT MATCHED                             0
    MATCHED                            17,816  (_MERGE==3)
    -----------------------------------------

. DROP _MERGE

. MERGE 1:1 _N USING "E:\USERS\SHAFSA\SCRAP PLASTIC\SAMPLE1F.DTA"
(LABEL PRIMARY_POLYMER ALREADY DEFINED)
(LABEL REGION ALREADY DEFINED)
(LABEL PLASTIC_QUALITY ALREADY DEFINED)

    RESULT                    NUMBER OF OBS
    -----------------------------------------
    NOT MATCHED                             0
    MATCHED                            17,816  (_MERGE==3)
    -----------------------------------------

. DROP _MERGE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. SUM BDEP1_N FOOD1_N FILM_N RIGID1_N SINGLE1_N OTHER1_N CONTAM1_N COLOR1_N MFP1_N MMP1_N

    VARIABLE |        OBS        MEAN    STD. DEV.       MIN        MAX
-------------+---------------------------------------------------------
```

```
    BDEP1_N |     17,811    22.35509    .9820507   20.65427   24.05591
    FOOD1_N |     17,811    21.51542    4.581523   13.58066   29.45018
     FILM_N |     17,811    22.39826    5.945972    12.1004   32.69612
   RIGID1_N |     17,811    21.49898    4.834759   13.12564   29.87232
  SINGLE1_N |     17,811    16.36125    7.334546   3.658515   29.06399
-------------+---------------------------------------------------------
   OTHER1_N |     17,811    19.42053    7.466569   6.489145   32.35192
  CONTAM1_N |     17,811    18.65382    5.808394   13.42378   34.26771
   COLOR1_N |     17,811    19.57566    12.31974   8.554364   51.78507
     MFP1_N |      2,448    14.74005    12.58697   .3706165   69.21436
     MMP1_N |     17,811     21.6478    8.438851    3.22157   31.64632

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. GEN PI1_BDEP = (2*(BDEP1_N-(20.65427)))/(24.05591-(20.65427))-1
(5 MISSING VALUES GENERATED)

. GEN PI1_FOOD= (2*(FOOD1_N-(13.58066)))/(29.45018-(13.58066))-1
(5 MISSING VALUES GENERATED)

. GEN PI1_FILM = (2*(FILM1_N-(12.1004)))/(32.69612-(12.1004))-1
(5 MISSING VALUES GENERATED)

. GEN PI1_OTHER = (2*(OTHER1_N-(6.489145)))/(32.35192-(6.489145))-1
(5 MISSING VALUES GENERATED)

. GEN PI1_RIGID = (2*(RIGID1_N-(13.12564)))/(29.87232-(13.12564))-1
(5 MISSING VALUES GENERATED)

. GEN PI1_SINGLE = (2*(SINGLE1_N-(3.658515)))/(29.06399-(3.658515))-1
(5 MISSING VALUES GENERATED)

. SUM PI1_BDEP PI1_FOOD PI1_FILM PI1_OTHER PI1_RIGID PI1_SINGLE

   VARIABLE |        OBS        MEAN    STD. DEV.       MIN        MAX
-------------+---------------------------------------------------------
   PI1_BDEP |     17,811   -3.56E-07    .5773984  -.9999995   .9999988
   PI1_FOOD |     17,811   -1.51E-07    .5773991         -1          1
   PI1_FILM |     17,811   -1.15E-07    .5773988         -1   .9999998
  PI1_OTHER |     17,811    7.22E-08    .5773989  -.9999999          1
  PI1_RIGID |     17,811    2.91E-07    .5773991         -1   1.000001
-------------+---------------------------------------------------------
 PI1_SINGLE |     17,811   -5.26E-08    .5773989         -1   .9999999

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. GEN BETA1_CONTAM = CONTAM1_N*CONTAMINATION
(5 MISSING VALUES GENERATED)

. GEN BETA1_COLOR = COLOR1_N*COLOR
(1,166 MISSING VALUES GENERATED)

. GEN BETA1_MMP = MMP1_N * MULTI_MATERIAL_P
(5 MISSING VALUES GENERATED)

. GEN BETA1_MFP = MFP1_N*METALS_FOOD_PERMITTED
(15,368 MISSING VALUES GENERATED)

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"
```

```
. GEN LWTP1_CONTAM=BETA1_CONTAM*(0.1)
(5 MISSING VALUES GENERATED)

. GEN LWTP1_COLOR=BETA1_COLOR*(0.1)
(1,166 MISSING VALUES GENERATED)

. GEN LWTP1_MMP = BETA1_MMP*(0.1)
(5 MISSING VALUES GENERATED)

. GEN LWTP1_MFP = BETA1_MFP*(1000)
(15,368 MISSING VALUES GENERATED)

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. LASSO LINEAR LWTP1_CONTAM IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF
SAMPLE2==1 // CONTAMINATION
3B.PRIMARY_POLYMER OMITTED

10-FOLD CROSS-VALIDATION WITH 100 LAMBDAS ...
GRID VALUE 1:     LAMBDA = .0696335   NO. OF NONZERO COEF. =       0
FOLDS: 1...5....10   CVF = .0082717
GRID VALUE 2:     LAMBDA = .0634474   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0074904
GRID VALUE 3:     LAMBDA = .0578109   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0068061
GRID VALUE 4:     LAMBDA = .0526752   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0062379
GRID VALUE 5:     LAMBDA = .0479957   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0057662
GRID VALUE 6:     LAMBDA = .0437319   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0053745
GRID VALUE 7:     LAMBDA = .0398468   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0050493
GRID VALUE 8:     LAMBDA =  .036307   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0047793
GRID VALUE 9:     LAMBDA = .0330815   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0045551
GRID VALUE 10:    LAMBDA = .0301427   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0043689
GRID VALUE 11:    LAMBDA = .0274649   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF = .0042144
GRID VALUE 12:    LAMBDA =  .025025   NO. OF NONZERO COEF. =       1
FOLDS: 1...5....10   CVF =  .004086
GRID VALUE 13:    LAMBDA = .0228018   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0038682
GRID VALUE 14:    LAMBDA = .0207762   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0036612
GRID VALUE 15:    LAMBDA = .0189305   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0034893
GRID VALUE 16:    LAMBDA = .0172487   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0033466
GRID VALUE 17:    LAMBDA = .0157164   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0032281
GRID VALUE 18:    LAMBDA = .0143202   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0031297
GRID VALUE 19:    LAMBDA =  .013048   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF =  .003048
GRID VALUE 20:    LAMBDA = .0118889   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0029802
GRID VALUE 21:    LAMBDA = .0108327   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0029239
GRID VALUE 22:    LAMBDA = .0098704   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0028771
GRID VALUE 23:    LAMBDA = .0089935   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0028383
GRID VALUE 24:    LAMBDA = .0081946   NO. OF NONZERO COEF. =       2
```

```
FOLDS: 1...5....10   CVF =  .002806
GRID VALUE 25:    LAMBDA = .0074666   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0027792
GRID VALUE 26:    LAMBDA = .0068033   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF =  .002757
GRID VALUE 27:    LAMBDA = .0061989   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0027385
GRID VALUE 28:    LAMBDA = .0056482   NO. OF NONZERO COEF. =       2
FOLDS: 1...5....10   CVF = .0027231
GRID VALUE 29:    LAMBDA = .0051464   NO. OF NONZERO COEF. =       3
FOLDS: 1...5....10   CVF = .0027087
GRID VALUE 30:    LAMBDA = .0046892   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026929
GRID VALUE 31:    LAMBDA = .0042726   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026767
GRID VALUE 32:    LAMBDA = .0038931   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026632
GRID VALUE 33:    LAMBDA = .0035472   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026519
GRID VALUE 34:    LAMBDA = .0032321   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026426
GRID VALUE 35:    LAMBDA =  .002945   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026348
GRID VALUE 36:    LAMBDA = .0026833   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026284
GRID VALUE 37:    LAMBDA =  .002445   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF =  .002623
GRID VALUE 38:    LAMBDA = .0022278   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026185
GRID VALUE 39:    LAMBDA = .0020299   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026148
GRID VALUE 40:    LAMBDA = .0018495   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026118
GRID VALUE 41:    LAMBDA = .0016852   NO. OF NONZERO COEF. =       4
FOLDS: 1...5....10   CVF = .0026092
GRID VALUE 42:    LAMBDA = .0015355   NO. OF NONZERO COEF. =       5
FOLDS: 1...5....10   CVF = .0026071
GRID VALUE 43:    LAMBDA = .0013991   NO. OF NONZERO COEF. =       5
FOLDS: 1...5....10   CVF = .0026051
GRID VALUE 44:    LAMBDA = .0012748   NO. OF NONZERO COEF. =       5
FOLDS: 1...5....10   CVF = .0026035
GRID VALUE 45:    LAMBDA = .0011616   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0026021
GRID VALUE 46:    LAMBDA = .0010584   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0026008
GRID VALUE 47:    LAMBDA = .0009643   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0025997
GRID VALUE 48:    LAMBDA = .0008787   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0025987
GRID VALUE 49:    LAMBDA = .0008006   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0025979
GRID VALUE 50:    LAMBDA = .0007295   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0025973
GRID VALUE 51:    LAMBDA = .0006647   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0025967
GRID VALUE 52:    LAMBDA = .0006056   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0025963
GRID VALUE 53:    LAMBDA = .0005518   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0025959
GRID VALUE 54:    LAMBDA = .0005028   NO. OF NONZERO COEF. =       6
FOLDS: 1...5....10   CVF = .0025957
GRID VALUE 55:    LAMBDA = .0004581   NO. OF NONZERO COEF. =       7
FOLDS: 1...5....10   CVF = .0025955
GRID VALUE 56:    LAMBDA = .0004174   NO. OF NONZERO COEF. =       7
FOLDS: 1...5....10   CVF = .0025953
GRID VALUE 57:    LAMBDA = .0003804   NO. OF NONZERO COEF. =       7
FOLDS: 1...5....10   CVF = .0025951
GRID VALUE 58:    LAMBDA = .0003466   NO. OF NONZERO COEF. =       7
FOLDS: 1...5....10   CVF = .0025949
```

```
GRID VALUE 59:   LAMBDA = .0003158   NO. OF NONZERO COEF. =      7
FOLDS: 1...5....10   CVF = .0025948
GRID VALUE 60:   LAMBDA = .0002877   NO. OF NONZERO COEF. =      7
FOLDS: 1...5....10   CVF = .0025947
GRID VALUE 61:   LAMBDA = .0002622   NO. OF NONZERO COEF. =      7
FOLDS: 1...5....10   CVF = .0025945
GRID VALUE 62:   LAMBDA = .0002389   NO. OF NONZERO COEF. =      7
FOLDS: 1...5....10   CVF = .0025944
GRID VALUE 63:   LAMBDA = .0002177   NO. OF NONZERO COEF. =      7
FOLDS: 1...5....10   CVF = .0025943
GRID VALUE 64:   LAMBDA = .0001983   NO. OF NONZERO COEF. =      7
FOLDS: 1...5....10   CVF = .0025942
GRID VALUE 65:   LAMBDA = .0001807   NO. OF NONZERO COEF. =      7
FOLDS: 1...5....10   CVF = .0025941
GRID VALUE 66:   LAMBDA = .0001646   NO. OF NONZERO COEF. =      7
FOLDS: 1...5....10   CVF = .0025941
GRID VALUE 67:   LAMBDA =   .00015   NO. OF NONZERO COEF. =      8
FOLDS: 1...5....10   CVF =  .002594
... CHANGE IN DEVIANCE STOPPING TOLERANCE REACHED ... LAST LAMBDA SELECTED
MINIMUM OF CV FUNCTION NOT FOUND; LAMBDA SELECTED BASED ON STOP() STOPPING CRITERION.

LASSO LINEAR MODEL                    NO. OF OBS       =      5,935
                                 NO. OF COVARIATES =         8
SELECTION: CROSS-VALIDATION               NO. OF CV FOLDS   =        10

--------------------------------------------------------------------------
       |                         NO. OF     OUT-OF-     CV MEAN
       |                         NONZERO      SAMPLE   PREDICTION
    ID |     DESCRIPTION     LAMBDA    COEF.   R-SQUARED       ERROR
---------+----------------------------------------------------------------
     1 |    FIRST LAMBDA    .0696335       0      0.0033     .0082717
    66 |   LAMBDA BEFORE    .0001646       7      0.6874     .0025941
  * 67 | SELECTED LAMBDA      .00015       8      0.6874      .002594
--------------------------------------------------------------------------
* LAMBDA SELECTED BY CROSS-VALIDATION.
NOTE: MINIMUM OF CV FUNCTION NOT FOUND; LAMBDA SELECTED BASED ON STOP()
    STOPPING CRITERION.

. ESTIMATES STORE CV

. LASSOKNOTS, DISPLAY(NONZERO OSR2 AIC)

---------------------------------------------------
      |          NO. OF     OUT-OF-
      |         NONZERO     SAMPLE
   ID |   LAMBDA     COEF.   R-SQUARED       AIC
-------+-------------------------------------------
    2 | .0634474        1     0.0975  -12211.16
   13 | .0228018        2     0.5339  -16137.64
   29 | .0051464        3     0.6736  -18252.41
   30 | .0046892        4     0.6755  -18288.84
   42 | .0015355        5     0.6859  -18478.27
   45 | .0011616        6     0.6865  -18487.59
   55 | .0004581        7     0.6873  -18501.34
 * 67 |   .00015        8     0.6874  -18504.09
---------------------------------------------------
* LAMBDA SELECTED BY CROSS-VALIDATION.

. LASSOKNOTS, DISPLAY(NONZERO AIC BIC)

--------------------------------------------------
      |          NO. OF
      |         NONZERO
   ID |   LAMBDA     COEF.       BIC       AIC
-------+------------------------------------------
    2 | .0634474        1  -12197.78  -12211.16
   13 | .0228018        2  -16117.58  -16137.64
   29 | .0051464        3  -18225.65  -18252.41
   30 | .0046892        4   -18255.4  -18288.84
```

```
   42 | .0015355         5  -18438.14  -18478.27
   45 | .0011616         6  -18440.77  -18487.59
   55 | .0004581         7  -18447.83  -18501.34
 * 67 |   .00015         8   -18443.9  -18504.09
--------------------------------------------------------
* LAMBDA SELECTED BY CROSS-VALIDATION.

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. LASSOSELECT ID=67
ID = 67  LAMBDA = .00015   SELECTED

. LASSOCOEF CV

---------------------------
                |    CV
----------------+----------
     IMPORT_BAN |     X
       COVID_19 |     X
     P_CRUDEOIL |     X
                |
PRIMARY_POLYMER |
          HDPE  |     X
          LDPE  |     X
           PET  |     X
            PP  |     X
            PS  |     X
                |
          _CONS |     X
---------------------------
LEGEND:
  B - BASE LEVEL
  E - EMPTY CELL
  O - OMITTED
  X - ESTIMATED

. LASSOGOF CV, OVER(SAMPLE2) POSTSELECTION

POSTSELECTION COEFFICIENTS
-------------------------------------------------------------
NAME         SAMPLE2 |         MSE    R-SQUARED        OBS
---------------------+---------------------------------------
CV                   |
                   1 |     .002583       0.6888      5,935
                   2 |    .0025653       0.6781      5,941
                   3 |     .002465       0.6929      5,935
-------------------------------------------------------------

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. LASSO PROBIT CURBSIDE IMPORT_BAN COVID_19 P_CRUDEOIL I.PRIMARY_POLYMER IF SAMPLE2==1,
OFFSET(PI_CURB) //CURBSIDE SAMPLE 1

10-FOLD CROSS-VALIDATION WITH 100 LAMBDAS ...
GRID VALUE 1:     LAMBDA = .1400909   NO. OF NONZERO COEF. =       0
FOLDS: 1...5....10   CVF = .9083583
GRID VALUE 2:     LAMBDA = .1276456   NO. OF NONZERO COEF. =       3
FOLDS: 1...5....10   CVF = .8949853
GRID VALUE 3:     LAMBDA = .1163059   NO. OF NONZERO COEF. =       3
FOLDS: 1...5....10   CVF = .8734046
GRID VALUE 4:     LAMBDA = .1059736   NO. OF NONZERO COEF. =       3
FOLDS: 1...5....10   CVF =  .853758
GRID VALUE 5:     LAMBDA = .0965592   NO. OF NONZERO COEF. =       3
```

FOLDS: 1...5....10 CVF = .8369464
GRID VALUE 6: LAMBDA = .0879812 NO. OF NONZERO COEF. = 3
FOLDS: 1...5....10 CVF = .8225368
GRID VALUE 7: LAMBDA = .0801652 NO. OF NONZERO COEF. = 3
FOLDS: 1...5....10 CVF = .8101257
GRID VALUE 8: LAMBDA = .0730435 NO. OF NONZERO COEF. = 4
FOLDS: 1...5....10 CVF = .7980926
GRID VALUE 9: LAMBDA = .0665545 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = .7852386
GRID VALUE 10: LAMBDA = .060642 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = .7735593
GRID VALUE 11: LAMBDA = .0552547 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = .7634705
GRID VALUE 12: LAMBDA = .0503461 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = .7547513
GRID VALUE 13: LAMBDA = .0458735 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = .7472131
GRID VALUE 14: LAMBDA = .0417982 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = .7406942
GRID VALUE 15: LAMBDA = .038085 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = .7350559
GRID VALUE 16: LAMBDA = .0347016 NO. OF NONZERO COEF. = 5
FOLDS: 1...5....10 CVF = .7301696
GRID VALUE 17: LAMBDA = .0316188 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = .7256908
GRID VALUE 18: LAMBDA = .0288099 NO. OF NONZERO COEF. = 6
FOLDS: 1...5....10 CVF = .7216641
GRID VALUE 19: LAMBDA = .0262505 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .7178896
GRID VALUE 20: LAMBDA = .0239185 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .7142874
GRID VALUE 21: LAMBDA = .0217936 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .711025
GRID VALUE 22: LAMBDA = .0198575 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .7081611
GRID VALUE 23: LAMBDA = .0180934 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .7056451
GRID VALUE 24: LAMBDA = .0164861 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .7034329
GRID VALUE 25: LAMBDA = .0150215 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .7014865
GRID VALUE 26: LAMBDA = .013687 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6997724
GRID VALUE 27: LAMBDA = .0124711 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6982619
GRID VALUE 28: LAMBDA = .0113632 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6969295
GRID VALUE 29: LAMBDA = .0103537 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6957534
GRID VALUE 30: LAMBDA = .0094339 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6947145
GRID VALUE 31: LAMBDA = .0085958 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6937958
GRID VALUE 32: LAMBDA = .0078322 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6929829
GRID VALUE 33: LAMBDA = .0071364 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .692263
GRID VALUE 34: LAMBDA = .0065024 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6916263
GRID VALUE 35: LAMBDA = .0059248 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6910984
GRID VALUE 36: LAMBDA = .0053984 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6906484
GRID VALUE 37: LAMBDA = .0049189 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6902694
GRID VALUE 38: LAMBDA = .0044819 NO. OF NONZERO COEF. = 7
FOLDS: 1...5....10 CVF = .6899391
GRID VALUE 39: LAMBDA = .0040837 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6896493

GRID VALUE 40: LAMBDA = .0037209 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6893948
GRID VALUE 41: LAMBDA = .0033904 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6891595
GRID VALUE 42: LAMBDA = .0030892 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6889462
GRID VALUE 43: LAMBDA = .0028148 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6887584
GRID VALUE 44: LAMBDA = .0025647 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6885928
GRID VALUE 45: LAMBDA = .0023369 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6884466
GRID VALUE 46: LAMBDA = .0021293 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6883166
GRID VALUE 47: LAMBDA = .0019401 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6881752
GRID VALUE 48: LAMBDA = .0017677 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6880371
GRID VALUE 49: LAMBDA = .0016107 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .687914
GRID VALUE 50: LAMBDA = .0014676 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6878043
GRID VALUE 51: LAMBDA = .0013372 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6877064
GRID VALUE 52: LAMBDA = .0012184 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .687619
GRID VALUE 53: LAMBDA = .0011102 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6875408
GRID VALUE 54: LAMBDA = .0010116 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .687471
GRID VALUE 55: LAMBDA = .0009217 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6874085
GRID VALUE 56: LAMBDA = .0008398 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6873525
GRID VALUE 57: LAMBDA = .0007652 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6873024
GRID VALUE 58: LAMBDA = .0006972 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6872574
GRID VALUE 59: LAMBDA = .0006353 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6872171
GRID VALUE 60: LAMBDA = .0005789 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6871809
GRID VALUE 61: LAMBDA = .0005274 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6871484
GRID VALUE 62: LAMBDA = .0004806 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6871192
GRID VALUE 63: LAMBDA = .0004379 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .687093
GRID VALUE 64: LAMBDA = .000399 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6870694
GRID VALUE 65: LAMBDA = .0003635 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6870481
GRID VALUE 66: LAMBDA = .0003312 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .687029
GRID VALUE 67: LAMBDA = .0003018 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6870118
GRID VALUE 68: LAMBDA = .000275 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6869963
GRID VALUE 69: LAMBDA = .0002506 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6869824
GRID VALUE 70: LAMBDA = .0002283 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6869698
GRID VALUE 71: LAMBDA = .000208 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6869585
GRID VALUE 72: LAMBDA = .0001895 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .6869482
GRID VALUE 73: LAMBDA = .0001727 NO. OF NONZERO COEF. = 8
FOLDS: 1...5....10 CVF = .686939
GRID VALUE 74: LAMBDA = .0001574 NO. OF NONZERO COEF. = 8

```
FOLDS: 1...5....10   CVF = .6869307
GRID VALUE 75:    LAMBDA = .0001434   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6869232
GRID VALUE 76:    LAMBDA = .0001306   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6869164
GRID VALUE 77:    LAMBDA =  .000119   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6869103
GRID VALUE 78:    LAMBDA = .0001085   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6869048
GRID VALUE 79:    LAMBDA = .0000988   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868998
GRID VALUE 80:    LAMBDA = .0000901   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868953
GRID VALUE 81:    LAMBDA = .0000821   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868912
GRID VALUE 82:    LAMBDA = .0000748   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868876
GRID VALUE 83:    LAMBDA = .0000681   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868842
GRID VALUE 84:    LAMBDA = .0000621   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868812
GRID VALUE 85:    LAMBDA = .0000566   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868785
GRID VALUE 86:    LAMBDA = .0000515   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868761
GRID VALUE 87:    LAMBDA =  .000047   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868738
GRID VALUE 88:    LAMBDA = .0000428   NO. OF NONZERO COEF. =       8
FOLDS: 1...5....10   CVF = .6868718
... CHANGE IN DEVIANCE STOPPING TOLERANCE REACHED ... LAST LAMBDA SELECTED
MINIMUM OF CV FUNCTION NOT FOUND; LAMBDA SELECTED BASED ON STOP() STOPPING CRITERION.

LASSO PROBIT MODEL                      NO. OF OBS        =       5,935
                                        NO. OF COVARIATES =           9
SELECTION: CROSS-VALIDATION             NO. OF CV FOLDS   =          10

--------------------------------------------------------------------------
         |                                NO. OF      OUT-OF-
         |                               NONZERO      SAMPLE      CV MEAN
      ID |     DESCRIPTION      LAMBDA     COEF.   DEV. RATIO    DEVIANCE
---------+----------------------------------------------------------------
       1 |    FIRST LAMBDA    .1400909         0       0.0005    .9083583
      87 |   LAMBDA BEFORE     .000047         8       0.2442    .6868738
    * 88 | SELECTED LAMBDA    .0000428         8       0.2442    .6868718
--------------------------------------------------------------------------
* LAMBDA SELECTED BY CROSS-VALIDATION.
NOTE: MINIMUM OF CV FUNCTION NOT FOUND; LAMBDA SELECTED BASED ON STOP()
      STOPPING CRITERION.

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. ESTIMATES STORE CV2

. LASSOKNOTS, DISPLAY(NONZERO AIC BIC)

-------------------------------------------------
       |              NO. OF
       |             NONZERO
    ID |   LAMBDA      COEF.        BIC        AIC
-------+-----------------------------------------
     2 | .1276456          3   5345.389   5318.635
     8 | .0730435          4    4768.92   4735.477
     9 | .0665545          5   4698.771    4658.64
    17 | .0316188          6   4353.685   4306.865
    19 | .0262505          7    4315.36   4261.851
    39 | .0040837          8   4154.123   4093.925
```

```
  * 88 | .0000428         8   4134.699   4074.501
--------------------------------------------------
* LAMBDA SELECTED BY CROSS-VALIDATION.

. LASSOSELECT ID=88
ID = 88  LAMBDA = .0000428 SELECTED

. LASSOCOEF CV2

---------------------------
                |    CV2
----------------+----------
    IMPORT_BAN |     X
      COVID_19 |     X
    P_CRUDEOIL |     X
                |
PRIMARY_POLYMER |
          HDPE  |     X
          LDPE  |     X
         MIXED  |     X
            PP  |     X
            PS  |     X
                |
         _CONS |     X
---------------------------
LEGEND:
  B - BASE LEVEL
  E - EMPTY CELL
  O - OMITTED
  X - ESTIMATED

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. PROBIT BOTTLEDEPOSIT IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER, OFFSET(PI1_BDEP)

NOTE: IMPORT_BAN != 1 PREDICTS FAILURE PERFECTLY;
      IMPORT_BAN OMITTED AND 10724 OBS NOT USED.

NOTE: COVID_19 != 1 PREDICTS FAILURE PERFECTLY;
      COVID_19 OMITTED AND 3643 OBS NOT USED.

NOTE: 1.PRIMARY_POLYMER != 0 PREDICTS FAILURE PERFECTLY;
      1.PRIMARY_POLYMER OMITTED AND 891 OBS NOT USED.

NOTE: 2.PRIMARY_POLYMER != 0 PREDICTS FAILURE PERFECTLY;
      2.PRIMARY_POLYMER OMITTED AND 823 OBS NOT USED.

NOTE: 3.PRIMARY_POLYMER != 0 PREDICTS FAILURE PERFECTLY;
      3.PRIMARY_POLYMER OMITTED AND 786 OBS NOT USED.

NOTE: 4.PRIMARY_POLYMER != 1 PREDICTS FAILURE PERFECTLY;
      4.PRIMARY_POLYMER OMITTED AND 500 OBS NOT USED.

NOTE: 5.PRIMARY_POLYMER OMITTED BECAUSE OF COLLINEARITY.
NOTE: 6.PRIMARY_POLYMER OMITTED BECAUSE OF COLLINEARITY.
ITERATION 0:   LOG LIKELIHOOD = -274.91995
ITERATION 1:   LOG LIKELIHOOD = -274.53573
ITERATION 2:   LOG LIKELIHOOD = -274.53569
ITERATION 3:   LOG LIKELIHOOD = -274.53569

PROBIT REGRESSION                               NUMBER OF OBS =    444
                                                WALD CHI2(1)  =   0.01
LOG LIKELIHOOD = -274.53569                     PROB > CHI2   = 0.9411

------------------------------------------------------------------------------
  BOTTLEDEPOSIT | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
```

```
----------------+----------------------------------------------------------------
   IMPORT_BAN |          0  (OMITTED)
    COVID_19 |          0  (OMITTED)
   P_CRUDEOIL |  -.0003053   .0041346    -0.07   0.941    -.008409    .0077983
              |
PRIMARY_POLYMER |
        HDPE  |          0  (EMPTY)
        LDPE  |          0  (EMPTY)
       MIXED  |          0  (EMPTY)
         PET  |          0  (OMITTED)
          PP  |          0  (EMPTY)
          PS  |          0  (EMPTY)
              |
       _CONS |  -.8448312   .2410212    -3.51   0.000    -1.317224   -.3724383
    PI1_BDEP |          1  (OFFSET)
---------------------------------------------------------------------------------

. ESTIMATES STORE M18

. MARGINS

PREDICTIVE MARGINS                              NUMBER OF OBS = 444
MODEL VCE: OIM

EXPRESSION: PR(BOTTLEDEPOSIT), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |    .236708   .0179667    13.17   0.000     .2014939    .2719221
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                        NUMBER OF OBS = 444
MODEL VCE: OIM

EXPRESSION: PR(BOTTLEDEPOSIT), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL 1.PRIMARY_POLYMER 2.PRIMARY_POLYMER
4.PRIMARY_POLYMER 5.PRIMARY_POLYMER 6.PRIMARY_POLYMER

---------------------------------------------------------------------------------
              |            DELTA-METHOD
              |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
----------------+----------------------------------------------------------------
   IMPORT_BAN |          0  (OMITTED)
    COVID_19 |          0  (OMITTED)
   P_CRUDEOIL |  -.0000812    .001099    -0.07   0.941    -.0022352    .0020729
              |
PRIMARY_POLYMER |
        HDPE  |          .  (NOT ESTIMABLE)
        LDPE  |          .  (NOT ESTIMABLE)
       MIXED  |          0  (EMPTY)
         PET  |          .  (NOT ESTIMABLE)
          PP  |          .  (NOT ESTIMABLE)
          PS  |          .  (NOT ESTIMABLE)
---------------------------------------------------------------------------------
NOTE: DY/DX FOR FACTOR LEVELS IS THE DISCRETE CHANGE FROM THE BASE LEVEL.

. PROBIT FOODANDBEVERAGE IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER,
OFFSET(PI1_FOOD)

NOTE: 2.PRIMARY_POLYMER != 0 PREDICTS FAILURE PERFECTLY;
    2.PRIMARY_POLYMER OMITTED AND 3722 OBS NOT USED.

NOTE: 4.PRIMARY_POLYMER != 0 PREDICTS SUCCESS PERFECTLY;
    4.PRIMARY_POLYMER OMITTED AND 2505 OBS NOT USED.
```

```
NOTE: 5.PRIMARY_POLYMER != 0 PREDICTS SUCCESS PERFECTLY;
    5.PRIMARY_POLYMER OMITTED AND 1285 OBS NOT USED.

NOTE: 6.PRIMARY_POLYMER != 0 PREDICTS SUCCESS PERFECTLY;
    6.PRIMARY_POLYMER OMITTED AND 917 OBS NOT USED.

ITERATION 0:   LOG LIKELIHOOD = -6108.4819
ITERATION 1:   LOG LIKELIHOOD = -5842.5918
ITERATION 2:   LOG LIKELIHOOD =  -5840.999
ITERATION 3:   LOG LIKELIHOOD =  -5840.999

PROBIT REGRESSION                          NUMBER OF OBS =  9,382
                                           WALD CHI2(4)  = 492.06
LOG LIKELIHOOD = -5840.999                 PROB > CHI2   = 0.0000

--------------------------------------------------------------------------------
FOODANDBEVERAGE | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
----------------+---------------------------------------------------------------
     IMPORT_BAN |  -.4274964   .0368553   -11.60   0.000    -.4997314   -.3552614
       COVID_19 |   .0791608   .0453175     1.75   0.081    -.0096599    .1679816
     P_CRUDEOIL |   .0096584   .0007042    13.72   0.000     .0082782    .0110386
                |
PRIMARY_POLYMER |
          HDPE  |   .1282351   .0304078     4.22   0.000     .0686369    .1878332
          LDPE  |          0  (EMPTY)
           PET  |          0  (EMPTY)
            PP  |          0  (EMPTY)
            PS  |          0  (EMPTY)
                |
          _CONS |   .1669106   .0538214     3.10   0.002     .0614227    .2723986
       PI1_FOOD |          1  (OFFSET)
--------------------------------------------------------------------------------

. ESTIMATES STORE M19

. MARGINS

PREDICTIVE MARGINS                              NUMBER OF OBS = 9,382
MODEL VCE: OIM

EXPRESSION: PR(FOODANDBEVERAGE), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .7352874   .0039513   186.09   0.000      .727543    .7430318
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                        NUMBER OF OBS = 9,382
MODEL VCE: OIM

EXPRESSION: PR(FOODANDBEVERAGE), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL 1.PRIMARY_POLYMER 2.PRIMARY_POLYMER
4.PRIMARY_POLYMER 5.PRIMARY_POLYMER 6.PRIMARY_POLYMER

--------------------------------------------------------------------------------
                |            DELTA-METHOD
                |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
----------------+---------------------------------------------------------------
     IMPORT_BAN |  -.1155281   .0097766   -11.82   0.000    -.1346899   -.0963662
       COVID_19 |   .0213927   .0122411     1.75   0.081    -.0025995    .0453849
     P_CRUDEOIL |   .0026101   .0001862    14.02   0.000     .0022452     .002975
                |
PRIMARY_POLYMER |
          HDPE  |   .0350081   .0083746     4.18   0.000     .0185941    .0514221
          LDPE  |          .  (NOT ESTIMABLE)
```

```
         PET  |          .  (NOT ESTIMABLE)
          PP  |          .  (NOT ESTIMABLE)
          PS  |          .  (NOT ESTIMABLE)
------------------------------------------------------------------------------
NOTE: DY/DX FOR FACTOR LEVELS IS THE DISCRETE CHANGE FROM THE BASE LEVEL.

. PROBIT FILM IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PP, OFFSET(PI1_FILM)

ITERATION 0:   LOG LIKELIHOOD = -13957.362
ITERATION 1:   LOG LIKELIHOOD = -7043.7302
ITERATION 2:   LOG LIKELIHOOD = -6994.7623
ITERATION 3:   LOG LIKELIHOOD = -6994.6027
ITERATION 4:   LOG LIKELIHOOD = -6994.6027

PROBIT REGRESSION                               NUMBER OF OBS =   17,811
                                                WALD CHI2(5)  = 10709.26
LOG LIKELIHOOD = -6994.6027                     PROB > CHI2   =   0.0000

------------------------------------------------------------------------------
        FILM | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |   .2665768   .0321723     8.29   0.000     .2035203    .3296333
    COVID_19 |  -.0524086   .0394267    -1.33   0.184    -.1296836    .0248663
  P_CRUDEOIL |  -.0025985    .000608    -4.27   0.000    -.0037902   -.0014069
        HDPE |  -.0145482   .0295275    -0.49   0.622     -.072421    .0433246
          PP |   2.668271   .0259875   102.68   0.000     2.617337    2.719206
       _CONS |  -1.415769   .0524597   -26.99   0.000    -1.518589    -1.31295
    PI1_FILM |          1  (OFFSET)
------------------------------------------------------------------------------

. ESTIMATES STORE M20

. MARGINS

PREDICTIVE MARGINS                                      NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(FILM), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .4185939   .0022638   184.90   0.000     .4141569     .423031
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                                NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(FILM), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PP

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |    .046003   .0055435     8.30   0.000     .0351379     .056868
    COVID_19 |  -.0090441   .0068034    -1.33   0.184    -.0223785    .0042903
  P_CRUDEOIL |  -.0004484   .0001048    -4.28   0.000    -.0006539    -.000243
        HDPE |  -.0025106    .005096    -0.49   0.622    -.0124986    .0074775
          PP |   .4604617   .0016733   275.18   0.000      .457182    .4637414
------------------------------------------------------------------------------

. PROBIT OTHER IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PET PP, OFFSET(PI1_OTHER)

ITERATION 0:   LOG LIKELIHOOD = -12935.216
ITERATION 1:   LOG LIKELIHOOD = -6622.4664
```

```
ITERATION 2:   LOG LIKELIHOOD = -6050.7693
ITERATION 3:   LOG LIKELIHOOD = -5978.6933
ITERATION 4:   LOG LIKELIHOOD = -5967.4812
ITERATION 5:   LOG LIKELIHOOD = -5965.4341
ITERATION 6:   LOG LIKELIHOOD = -5965.0585
ITERATION 7:   LOG LIKELIHOOD = -5964.9975
ITERATION 8:   LOG LIKELIHOOD = -5964.9888
ITERATION 9:   LOG LIKELIHOOD =  -5964.987
ITERATION 10:  LOG LIKELIHOOD = -5964.9866
ITERATION 11:  LOG LIKELIHOOD = -5964.9866
ITERATION 12:  LOG LIKELIHOOD = -5964.9865

PROBIT REGRESSION                               NUMBER OF OBS =  17,811
                                                WALD CHI2(6)  = 1505.80
LOG LIKELIHOOD = -5964.9865                     PROB > CHI2   =  0.0000

------------------------------------------------------------------------------
       OTHER | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |   .4175875   .0366142    11.41   0.000     .3458251     .48935
    COVID_19 |  -.2126745    .044841    -4.74   0.000    -.3005611   -.1247878
 P_CRUDEOIL |  -.0069691   .0006588   -10.58   0.000    -.0082604   -.0056778
        HDPE |  -7.215447   120.0734    -0.06   0.952     -242.555   228.1241
         PET |   .9028425   .0296893    30.41   0.000     .8446525   .9610325
          PP |   7.911459   120.0734     0.07   0.947    -227.4281    243.251
       _CONS |  -.8889223   .0570549   -15.58   0.000    -1.000748   -.7770968
   PI1_OTHER |          1  (OFFSET)
------------------------------------------------------------------------------
NOTE: 6713 FAILURES AND 1978 SUCCESSES COMPLETELY DETERMINED.

. ESTIMATES STORE M21

. MARGINS

PREDICTIVE MARGINS                                NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(OTHER), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .3301104   .0021758   151.72   0.000     .3258459    .334375
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                          NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(OTHER), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PET PP

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |   .0618284   .0053143    11.63   0.000     .0514125    .0722442
    COVID_19 |  -.0314888    .006617    -4.76   0.000    -.0444578   -.0185198
 P_CRUDEOIL |  -.0010319    .000096   -10.75   0.000    -.0012199   -.0008438
        HDPE |  -1.068325   17.77816    -0.06   0.952    -35.91289   33.77624
         PET |   .1336756   .0039559    33.79   0.000     .1259223    .141429
          PP |   1.171377   17.77816     0.07   0.947    -33.67318   36.01594
------------------------------------------------------------------------------

. PROBIT SINGLEMATERIAL IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PET, OFFSET(PI1_SINGLE)

ITERATION 0:   LOG LIKELIHOOD = -10324.392
```

```
ITERATION 1:   LOG LIKELIHOOD = -7909.7498
ITERATION 2:   LOG LIKELIHOOD = -7873.9062
ITERATION 3:   LOG LIKELIHOOD = -7873.8277
ITERATION 4:   LOG LIKELIHOOD = -7873.8277

PROBIT REGRESSION                              NUMBER OF OBS =  17,811
                                               WALD CHI2(5)  = 4260.84
LOG LIKELIHOOD = -7873.8277                    PROB > CHI2   =  0.0000

------------------------------------------------------------------------------
SINGLEMATERIAL | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
---------------+--------------------------------------------------------------
    IMPORT_BAN |  -.3854774   .0307619   -12.53   0.000    -.4457696   -.3251852
      COVID_19 |   .2807773   .0381866     7.35   0.000     .2059329    .3556217
    P_CRUDEOIL |   .0103343   .0005993    17.24   0.000     .0091598    .0115089
          HDPE |   -.293579   .0253909   -11.56   0.000    -.3433442   -.2438139
           PET |  -1.648921    .025639   -64.31   0.000    -1.699172   -1.598669
         _CONS |   1.174048   .0468315    25.07   0.000      1.08226    1.265836
     PI1_SINGLE |          1  (OFFSET)
------------------------------------------------------------------------------

. ESTIMATES STORE M22

. MARGINS

PREDICTIVE MARGINS                                      NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(SINGLEMATERIAL), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .7894358   .0024588   321.06   0.000     .7846166     .794255
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                                NUMBER OF OBS = 17,811
MODEL VCE: OIM

EXPRESSION: PR(SINGLEMATERIAL), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL HDPE PET

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
  IMPORT_BAN |  -.0754732   .0059636   -12.66   0.000    -.0871617   -.0637848
    COVID_19 |   .0549738   .0074534     7.38   0.000     .0403655    .0695821
  P_CRUDEOIL |   .0020234   .0001151    17.58   0.000     .0017978    .0022489
        HDPE |  -.0574803   .0050477   -11.39   0.000    -.0673737   -.0475869
         PET |  -.3228448   .0037949   -85.07   0.000    -.3302827   -.3154069
------------------------------------------------------------------------------

. PROBIT RIGID IMPORT_BAN COVID_19 P_CRUDEOIL HDPE MIXED, OFFSET(PI1_RIGID)

ITERATION 0:   LOG LIKELIHOOD =  -11664.64
ITERATION 1:   LOG LIKELIHOOD = -11399.798
ITERATION 2:   LOG LIKELIHOOD = -11398.652
ITERATION 3:   LOG LIKELIHOOD = -11398.652

PROBIT REGRESSION                                       NUMBER OF OBS = 16,849
                                                        WALD CHI2(5)  = 497.89
LOG LIKELIHOOD = -11398.652                             PROB > CHI2   = 0.0000

------------------------------------------------------------------------------
       RIGID | COEFFICIENT  STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
```

```
-------------+----------------------------------------------------------------
 IMPORT_BAN |  -.3360041   .0266194   -12.62   0.000    -.3881773   -.2838309
   COVID_19 |   .1328407   .0330456     4.02   0.000     .0680725    .197609
 P_CRUDEOIL |   .0048029    .000487     9.86   0.000     .0038484    .0057574
       HDPE |  -.3324003   .0246808   -13.47   0.000    -.3807737   -.2840268
      MIXED |  -.0126867   .0257655    -0.49   0.622    -.0631862    .0378128
      _CONS |   .6600001   .0422719    15.61   0.000     .5771487    .7428514
  PI1_RIGID |          1  (OFFSET)
------------------------------------------------------------------------------

. ESTIMATES STORE M23

. MARGINS

PREDICTIVE MARGINS                              NUMBER OF OBS = 16,849
MODEL VCE: OIM

EXPRESSION: PR(RIGID), PREDICT()

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |     MARGIN   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
       _CONS |   .7053001   .0030577   230.66   0.000     .6993071    .7112932
------------------------------------------------------------------------------

. MARGINS, DYDX(*)

AVERAGE MARGINAL EFFECTS                        NUMBER OF OBS = 16,849
MODEL VCE: OIM

EXPRESSION: PR(RIGID), PREDICT()
DY/DX WRT:  IMPORT_BAN COVID_19 P_CRUDEOIL HDPE MIXED

------------------------------------------------------------------------------
             |            DELTA-METHOD
             |      DY/DX   STD. ERR.      Z    P>|Z|     [95% CONF. INTERVAL]
-------------+----------------------------------------------------------------
 IMPORT_BAN |  -.0973835   .0076291   -12.76   0.000    -.1123362   -.0824308
   COVID_19 |    .038501   .0095668     4.02   0.000     .0197505    .0572515
 P_CRUDEOIL |    .001392   .0001402     9.93   0.000     .0011172    .0016669
       HDPE |   -.096339   .0070555   -13.65   0.000    -.1101676   -.0825104
      MIXED |   -.003677   .0074664    -0.49   0.622    -.0183109    .0109569
------------------------------------------------------------------------------

. REG LWTP1_CONTAM IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1

      SOURCE |       SS           DF       MS      NUMBER OF OBS   =    17,811
-------------+----------------------------------   F(8, 17802)     =   4879.50
       MODEL |  99.0957099         8  12.3869637   PROB > F        =    0.0000
    RESIDUAL |  45.1916287    17,802  .00253857   R-SQUARED       =    0.6868
-------------+----------------------------------   ADJ R-SQUARED   =    0.6867
       TOTAL |  144.287339    17,810  .008101479   ROOT MSE        =    .05038

---------------------------------------------------------------------------------
  LWTP1_CONTAM | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
----------------+----------------------------------------------------------------
    IMPORT_BAN |  -.0116785   .0009844   -11.86   0.000     -.013608    -.009749
      COVID_19 |    .001828   .0012164     1.50   0.133    -.0005563    .0042123
    P_CRUDEOIL |    .000204    .000017    11.98   0.000     .0001706    .0002373
               |
PRIMARY_POLYMER |
          HDPE  |  -.0034654   .0010884    -3.18   0.001    -.0055989    -.001332
          LDPE  |   .1770548   .0011856   149.33   0.000     .1747309    .1793788
           PET  |  -.0051838   .0013306    -3.90   0.000     -.007792   -.0025756
            PP  |   .1130759   .0016421    68.86   0.000     .1098573    .1162946
            PS  |    .000358   .0018684     0.19   0.848    -.0033042    .0040203
               |
         _CONS |   .0294457   .0015045    19.57   0.000     .0264968    .0323947
```

```
--------------------------------------------------------------------------------

. ESTIMATES STORE M24

. REG LWTP1_COLOR IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1

    SOURCE |       SS           DF       MS      NUMBER OF OBS   =    16,650
-------------+----------------------------------   F(8, 16641)     =    533.28
     MODEL |  5405.00194         8  675.625242   PROB > F        =    0.0000
  RESIDUAL |   21082.955    16,641  1.26692837   R-SQUARED       =    0.2041
-------------+----------------------------------   ADJ R-SQUARED   =    0.2037
     TOTAL |  26487.9569    16,649  1.59096384   ROOT MSE        =    1.1256

--------------------------------------------------------------------------------
   LWTP1_COLOR | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
----------------+---------------------------------------------------------------
    IMPORT_BAN |   .0929656     .02263     4.11   0.000     .0486083    .1373229
      COVID_19 |    .008366   .0272524     0.31   0.759    -.0450515    .0617835
    P_CRUDEOIL |  -.0011804   .0004108    -2.87   0.004    -.0019856   -.0003752
               |
PRIMARY_POLYMER |
          HDPE  |  -.7126117   .0243776   -29.23   0.000    -.7603945    -.664829
          LDPE  |  -1.529588   .0294976   -51.85   0.000    -1.587407    -1.47177
           PET  |  -1.255456   .0297878   -42.15   0.000    -1.313844   -1.197069
            PP  |   .0432161    .036685     1.18   0.239    -.0286904    .1151225
            PS  |   -.035855   .0417405    -0.86   0.390    -.1176709    .0459609
               |
         _CONS |   1.982129     .03489    56.81   0.000     1.913741    2.050517
--------------------------------------------------------------------------------

. ESTIMATES STORE M25

. REG LWTP1_MFP IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1

    SOURCE |       SS           DF       MS      NUMBER OF OBS   =     2,448
-------------+----------------------------------   F(8, 2439)      =     23.73
     MODEL |  1.3328E+17         8  1.6660E+16   PROB > F        =    0.0000
  RESIDUAL |  1.7123E+18     2,439  7.0204E+14   R-SQUARED       =    0.0722
-------------+----------------------------------   ADJ R-SQUARED   =    0.0692
     TOTAL |  1.8456E+18     2,447  7.5422E+14   ROOT MSE        =    2.6E+07

--------------------------------------------------------------------------------
     LWTP1_MFP | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
----------------+---------------------------------------------------------------
    IMPORT_BAN |   -3971644    1453989    -2.73   0.006     -6822824    -1120464
      COVID_19 |    3547274    1744936     2.03   0.042     125563.6     6968985
    P_CRUDEOIL |   28255.99   24488.41     1.15   0.249    -19764.25    76276.22
               |
PRIMARY_POLYMER |
          HDPE  |   -2614337    1521386    -1.72   0.086     -5597678    369004.9
          LDPE  |   1.58E+07    1683675     9.39   0.000     1.25E+07    1.91E+07
           PET  |   -5359709    1851337    -2.90   0.004     -8990065    -1729353
            PP  |    2156236    2340899     0.92   0.357     -2434119     6746592
            PS  |    1157183    2739789     0.42   0.673     -4215371     6529737
               |
         _CONS |   2.53E+07    2146432    11.78   0.000     2.11E+07    2.95E+07
--------------------------------------------------------------------------------

. ESTIMATES STORE M26

. REG LWTP1_MMP IMPORT_BAN COVID_19 P_CRUDEOIL IB3.PRIMARY_POLYMER IF SAMPLE==1

    SOURCE |       SS           DF       MS      NUMBER OF OBS   =    17,811
-------------+----------------------------------   F(8, 17802)     =   4003.01
     MODEL |  7174.05387         8  896.756734   PROB > F        =    0.0000
  RESIDUAL |  3988.01557    17,802  .224020648   R-SQUARED       =    0.6427
-------------+----------------------------------   ADJ R-SQUARED   =    0.6426
     TOTAL |  11162.0694    17,810  .626730457   ROOT MSE        =    .47331
```

```
--------------------------------------------------------------------------------
    LWTP1_MMP | COEFFICIENT  STD. ERR.      T    P>|T|     [95% CONF. INTERVAL]
----------------+----------------------------------------------------------------
   IMPORT_BAN |  -.0140667   .0092475   -1.52   0.128   -.0321926   .0040592
     COVID_19 |  -.0295368   .0114271   -2.58   0.010   -.0519351   -.0071385
   P_CRUDEOIL |   .0006522   .0001599    4.08   0.000    .0003387    .0009657
              |
PRIMARY_POLYMER |
         HDPE  |  -1.706046   .0102246  -166.86   0.000   -1.726088   -1.686005
         LDPE  |  -1.385612   .0111378  -124.41   0.000   -1.407443   -1.363781
          PET  |  -1.187095      .0125   -94.97   0.000   -1.211596   -1.162594
           PP  |  -1.473783   .0154259   -95.54   0.000   -1.504019   -1.443547
           PS  |  -1.880945   .0175515  -107.17   0.000   -1.915348   -1.846542
              |
        _CONS |   2.130541   .0141331   150.75   0.000    2.102839    2.158243
--------------------------------------------------------------------------------

. ESTIMATES STORE M27

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. ESTIMATES TABLE M18 M19 M20 M21 M22 M23, P SE

------------------------------------------------------------------------------------------
    VARIABLE |    M18        M19        M20        M21        M22        M23
-------------+----------------------------------------------------------------------------
BOTTLEDEPO~T |
  IMPORT_BAN |  (OMITTED)
             |
             |
    COVID_19 |  (OMITTED)
             |
             |
  P_CRUDEOIL | -.00030533
             |  .00413459
             |     0.9411
             |
PRIMARY_PO~R |
        HDPE |    (EMPTY)
             |
             |
        LDPE |    (EMPTY)
             |
             |
       MIXED |    (EMPTY)
             |
             |
         PET |  (OMITTED)
             |
             |
          PP |    (EMPTY)
             |
             |
          PS |    (EMPTY)
             |
             |
             |
       _CONS | -.84483116
             |  .24102119
             |     0.0005
-------------+----------------------------------------------------------------------------
FOODANDBEV~E |
  IMPORT_BAN |              -.4274964
             |              .03685529
             |                 0.0000
    COVID_19 |              .07916084
```

```
             |     .04531753
             |       0.0807
  P_CRUDEOIL |            .00965839
             |     .00070418
             |       0.0000
             |
PRIMARY_PO~R |
     HDPE  |           .12823506
             |     .03040777
             |       0.0000
     LDPE  |            (EMPTY)
             |
             |
             |
PRIMARY_PO~R |
      PET  |            (EMPTY)
             |
             |
       PP  |            (EMPTY)
             |
             |
       PS  |            (EMPTY)
             |
             |
             |
     _CONS |           .16691062
             |     .05382137
             |       0.0019
-------------+----------------------------------------------------------------------------
FILM         |
  IMPORT_BAN |                      .26657682
             |              .03217227
             |                0.0000
    COVID_19 |                 -.05240861
             |              .03942672
             |                0.1838
  P_CRUDEOIL |                  -.00259855
             |              .00060802
             |                0.0000
       HDPE |                  -.01454821
             |              .02952747
             |                0.6222
         PP |                2.6682713
             |              .02598746
             |                0.0000
     _CONS |                  -1.4157695
             |               .0524597
             |                0.0000
-------------+----------------------------------------------------------------------------
OTHER        |
  IMPORT_BAN |                             .41758754
             |                     .03661419
             |                       0.0000
    COVID_19 |                          -.21267449
             |                     .04484095
             |                       0.0000
  P_CRUDEOIL |                           -.00696912
             |                     .00065884
             |                       0.0000
       HDPE |                         -7.2154472
             |                     120.07338
             |                       0.9521
        PET |                        .90284249
             |                     .02968932
             |                       0.0000
         PP |                       7.9114589
             |                     120.07339
             |                       0.9475
     _CONS |                          -.88892226
```

```
             |                              .05705485
             |                                0.0000
-------------+------------------------------------------------------------------------------
SINGLEMATE~L |
  IMPORT_BAN |                                          -.3854774
             |                                      .03076187
             |                                        0.0000
    COVID_19 |                                         .28077727
             |                                      .03818663
             |                                        0.0000
  P_CRUDEOIL |                                          .01033433
             |                                      .00059927
             |                                        0.0000
        HDPE |                                      -.29357904
             |                                      .02539086
             |                                        0.0000
         PET |                                      -1.6489208
             |                                      .02563904
             |                                        0.0000
       _CONS |                                          1.1740479
             |                                      .04683146
             |                                        0.0000
-------------+------------------------------------------------------------------------------
RIGID        |
  IMPORT_BAN |                                                   -.3360041
             |                                               .02661945
             |                                                 0.0000
    COVID_19 |                                                  .13284075
             |                                               .03304562
             |                                                 0.0001
  P_CRUDEOIL |                                                   .00480289
             |                                                 .000487
             |                                                 0.0000
        HDPE |                                               -.33240026
             |                                               .02468078
             |                                                 0.0000
       MIXED |                                                -.01268669
             |                                               .02576552
             |                                                 0.6224
       _CONS |                                                  .66000005
             |                                               .04227185
             |                                                 0.0000
--------------------------------------------------------------------------------------------
                                                    LEGEND: B/SE/P

.
END OF DO-FILE

. DO "C:\USERS\SHAFSA\APPDATA\LOCAL\TEMP\10\STD8914_000000.TMP"

. ESTIMATES TABLE M24 M25 M26 M27, P SE

-----------------------------------------------------------------
    VARIABLE |    M24         M25         M26         M27
-------------+---------------------------------------------------
  IMPORT_BAN | -.01167849   .09296558   -3971643.8   -.01406671
             |  .0009844   .02263004   1453988.6    .00924746
             |    0.0000      0.0000      0.0063      0.1282
    COVID_19 |  .00182801   .00836597   3547274.2   -.02953684
             | .00121643   .02725235   1744936.4   .01142714
             |    0.1329      0.7589      0.0422      0.0098
  P_CRUDEOIL |  .00020396   -.00118039   28255.985    .0006522
             | .00001703   .00041081   24488.412   .00015994
             |    0.0000      0.0041      0.2487      0.0000
             |
PRIMARY_PO~R |
      HDPE   | -.00346544   -.71261174   -2614336.7   -1.7060462
             | .00108843   .02437764   1521385.7   .01022464
             |    0.0015      0.0000      0.0859      0.0000
```

```
     LDPE  |  .17705481   -1.5295884    15804353   -1.3856118
           |  .00118563    .02949757   1683674.9    .01113778
           |     0.0000       0.0000      0.0000       0.0000
           |
PRIMARY_PO~R |
      PET  | -.00518382   -1.2554563   -5359708.9   -1.1870951
           |  .00133064    .02978779   1851337.2    .01249996
           |     0.0001       0.0000      0.0038       0.0000
       PP  |  .11307595    .04321608   2156236.4   -1.4737832
           |  .00164211    .03668496   2340898.9    .01542591
           |     0.0000       0.2388      0.3571       0.0000
       PS  |  .00035805   -.03585503   1157182.7   -1.8809449
           |  .00186838    .04174054   2739789.1    .0175515
           |     0.8480       0.3904      0.6728       0.0000
           |
    _CONS  |  .02944573    1.9821289    25274407    2.1305411
           |  .00150449    .03488999   2146431.9    .0141331
           |     0.0000       0.0000      0.0000       0.0000
----------------------------------------------------------------
                                LEGEND: B/SE/P

.
END OF DO-FILE

. SAVE "E:\USERS\SHAFSA\SCRAP PLASTIC\SAMPLE1A.DTA", REPLACE
FILE E:\USERS\SHAFSA\SCRAP PLASTIC\SAMPLE1A.DTA SAVED

. LOG CLOSE
      NAME:  <UNNAMED>
       LOG:  E:\USERS\SHAFSA\SCRAP PLASTIC\MODEL2_MERGIN RESULTS.LOG
  LOG TYPE:  TEXT
 CLOSED ON:   9 APR 2022, 16:49:42
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APPENDIX C

PREVIOUSLY PUBLISHED MATERIAL AND CO-AUTHORSHIP PERMISSION

Chapter 2

Is being peer-reviewed by Journal of Cleaner Productions

I declare that I have obtained permission from Kevin Dooley, George Basile, and Rajesh Bush to use material in this dissertation.

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Chapter 4

Has been published in Public Administration Review

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