General Equilibrium Techniques for Environmental Policy Analysis

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Abstract

Input-output datasets and economy-wide modelling have been widely used to investigate environmental externalities and policies. This thesis uses both to investigate plastic use by sector, the economy-wide impacts of tax on clothing produced from plastics, and the land use and broader economic impacts of including forestry in an emissions trading scheme.

To stop plastic pollution, policymakers and consumers should have an understanding of which industries are using a high value of plastic inputs. To estimate this, in the first paper of this thesis, I use an input-output database to calculate the plastic intensity (direct and indirect plastic use per dollar of output) of 415 industries in the USA across 13 types of plastic. I find that clothing and fabric related industries use a relatively high intensity of both aggregate plastics and polluting plastics, especially plastic fibres and filaments.

Given the high plastic use in the clothing industry, in the second paper of this thesis, I investigate the potential economic and land use change impacts from a shift to plastic and synthetic chemical free clothing. I do this using a bespoke global computable general equilibrium (CGE) model which represents both conventional clothing and plastic and synthetic chemical free clothing. In the policy scenarios for the model, a tax on conventional clothing sectors is introduced until all clothing production in taxed regions is plastic and synthetic chemical free. The results indicate that an increase in conventional clothing production in untaxed regions could have a negative impact on the effectiveness of a plastic clothing policy. They also indicate that there could be a significant amount of land use change from this policy, with land used for traditional plastic and chemical alternatives such as cotton, flax, natural rubber, and oleaginous fruits increasing at the expense of food-based agriculture.

Land use change should be an important consideration for environmental policies. Especially when those policies are directly related to farmer decision making, like the New Zealand Emissions Trading Scheme (NZ ETS). Accordingly, in the third paper of this thesis, I explore the economic and land use change impacts of production and permanent exotic forestry permits in the NZ ETS. I link a forestry model, a CGE model, and land use change functions to measure the expected proportion of foresters who will change land use from production to permanent forests at harvesting age from 2014 to 2050. The modelling analysis shows that this land use change increases carbon sequestration in New Zealand from 11 to 28 percent by 2050 (relative to the baseline), depending on farmers' responsiveness to the carbon price. Any increase in carbon sequestration, driven by the expansion in land used for permanent forests, increases both GDP and welfare relative to the baseline.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

The manuscripts in this thesis are co-authored between myself and Professor Niven Winchester. I was the principle author for each of the manuscripts and led the research, analysis, and write up.

Co-Author's signature: .... **Date**: **11/04/2024**

Student's signature: .... **Date**: **10/04/2024**

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Additional Information

This thesis uses the APA referencing style. The first paper 'The Plastic Intensity of Industries in the US: The Devil Wears Plastic' was published in *Environmental Modeling and Assessment* in 2022 and is available at: https://doi.org/10.1007/s10666-022-09848-z. The third paper 'Logs or permits? Forestry Land Use Decisions in an Emissions Trading Scheme' was published in *The Australian Journal of Agricultural and Resource Economics* in 2023 and is available at: https://doi.org/10.1111/1467-8489.12534.

Data Availability

The data analysed in 'The Plastic Intensity of Industries in the US: The Devil Wears Plastic' are available as part of the Eora Global Supply Chain Database, retrieved from https://worldmrio.com/. The data is referenced as Lenzen et al. (2012) and Lenzen et al. (2013) in the reference list.

The data analysed in 'Making a Material Difference: The Impacts of a Change to Plastic Free Clothing' and 'Logs or permits? Forestry Land Use Decisions in an Emissions Trading Scheme' are available as part of the Global Trade Analysis Project (GTAP) Database. To gain access to the GTAP data, users need to purchase a GTAP license.

Some results in 'Logs or permits? Forestry Land Use Decisions in an Emissions Trading Scheme' were derived from a version of the ENZ model, licensed to the authors by the Climate Change Commission and developed by the Climate Change Commission and Concept Consulting. Any modifications to the ENZ model and the production and interpretation of the results have not been quality assured by the CCC or Concept Consulting and are the responsibility of the authors.

1. Introduction

This thesis uses input-output data and computable general equilibrium (CGE) modelling to understand the impacts of plastic and climate change policies on GDP, welfare, output, and land use change. This includes an estimation of the plastic intensities of different industries in the US; a CGE analysis of the impacts of a switch to plastic and synthetic chemical free clothing on GDP, welfare, output, and land use in different regions around the world; and an estimation of the economic and land use impacts of forestry policy in the New Zealand Emissions Trading Scheme (NZ ETS).

These issues are analysed across three manuscripts and are all connected via the exploration of environmental issues using input-output data or CGE modelling. Plastics and climate change are inherently related due to the externality of environmental pollution as well as the similarities in the policies which could be used to reduce the extent of this pollution.

The first manuscript, 'The Plastic Intensity of Industries in the US: The Devil Wears Plastic' uses the Eora database (Lenzen et al., 2012; Lenzen et al., 2013) to estimate the plastic intensity of 415 different industries in the US. The aim of this analysis is to gain an understanding of the industries which use a large quantity of polluting plastics both directly and indirectly and indicate where potential policies could be targeted to effectively reduce plastic pollution. It finds that clothing and fabric industries use a high value of polluting plastics as an input, both directly and indirectly. This is particularly concerning given the microplastic pollution in waterways that clothing contributes to from the washing of clothes (Browne et al., 2011).

The second manuscript in this thesis, titled 'Making a Material Difference: The Impacts of a Change to Plastic Free Clothing' builds on the first manuscript by examining the impacts of a shift to plastic and synthetic chemical free clothing. To do this, I design a bespoke CGE model, calibrated to version 11 of the GTAP database (Aguiar et al., 2022) and introduce a tax on the conventional clothing sector in different regions until all clothing production in those regions is plastic and synthetic chemical free. The results indicate that clothing industries will favour the more traditional plastic alternatives such as plant-based fibres (e.g. cotton and flax), nuts, natural rubber, and forestry products. This causes land use change, with plastic alternatives being favoured over food-based crops like vegetables and fruits. The efficacy of the policy is hindered by clothing leakage, with untaxed regions increasing conventional clothing output relative to the benchmark due to the higher costs of plastic and synthetic chemical free clothing.

The third manuscript, titled 'Logs or Permits? Forestry Land Use Decisions in an Emissions Trading Scheme' estimates the economic and land use change impacts from the inclusion of forestry in the NZ ETS. It uses a forestry model called Energy and Emissions in New Zealand (ENZ) (CCC, 2021), a CGE model called the Climate PoLicy ANalysis (C-PLAN) model (Winchester & White, 2022) and sigmoid functions (S-curves) to estimate forestry land use change from production to permanent forest from 2014 to 2050 as incentivised by the NZ ETS. This builds upon the second manuscript by using a new method, S-curves, to represent land use change in a CGE model. It finds that forestry will reduce the cost of New Zealand meeting its net zero emissions target by 2050 and, due to the structure of land use change and the responsiveness of farmers to the carbon price, short run decision making by foresters has little impact on long run forestry land use change.

These manuscripts indicate the value of input-output data and economy-wide models for investigating a range of environmental issues and policies. They also demonstrate the complexity of impacts which environmental policies are related to including economic output, welfare, and land use change.

The rest of this thesis is split into eight further chapters. (1) A prelude to the first manuscript describing the main objectives. (2) The manuscript titled 'The Plastic Intensity of Industries in the US: The Devil Wears Plastic'. (3) A prelude to the second manuscript. (4) The manuscript titled 'Making a Material Difference: The Impacts of a Change to Plastic Free Clothing'. (5) A prelude to the third manuscript. (6) The manuscript titled 'Logs or permits? Forestry land use decisions in an emissions trading scheme'. (7) A high-level discussion of the thesis and concluding remarks.

2. Prelude to The Plastic Intensity of Industries in the US: The Devil Wears Plastic

The first manuscript in this thesis uses the Eora input-output database (Lenzen et al., 2012; Lenzen et al., 2013) to estimate the plastic intensity of industries in the USA. The aim of this paper is to identify sectors which use a relatively large amount of high polluting plastics. This is to help policy makers find sectors to target when creating plastic policies. In estimating plastic use, it is important to consider both the direct and indirect inputs of plastic for production. The direct use of plastics include the inputs of plastic products for production. Indirect use of plastics refers to inputs of products which, in turn, have directly used plastics. For example, if clothing products have inputs of textiles and those textiles use plastic fibres, clothing products are indirectly using those plastic fibres in production.

I use the Eora input-output database for this analysis due to its high level of plastic product disaggregation compared to other input-output databases. It also provides individual country datasets which allows for detailed regional analysis. I focus on the plastic intensity of industries in the USA and find that clothing and fabric related industries use a large value of polluting plastics both directly and indirectly as a proportion of output. This suggests that these industries present potential targets for policymakers to reduce plastic pollution.

3. The Plastic Intensity of Industries in the US: The Devil Wears Plastic

Abstract

Plastic pollution is a big source of concern around the world. Research to date has focused on the types of plastic in the environment and the processing of plastic waste. For policymakers and consumers to be informed decision makers, they need to understand the industries which use plastics and the plastic intensity of those industries. Using input–output data for the USA, we calculate the plastic intensity (the value of plastic inputs per dollar of output) of 415 non-plastic industries for 13 types of plastic. We find the most plastic intensive industries are related to clothing and fabric manufacturing. This is true for aggregate plastics as well as plastics most likely to contribute to pollution. The high plastic intensity of the clothing and fabric industries is consistent with the abundance of clothing-related microplastics found in waterways. The results indicate that policies focused on consumer-facing plastics such as plastic bags do not address key plastic pollution pathways and can help policymakers and consumers make decisions that improve environmental outcomes.

Additional Information

This work is published as White, D. & Winchester, N. (2023) The Plastic Intensity of Industries in the USA: The Devil Wears Plastic. *Environmental Modeling & Assessment, 28*, 15–28. https://doi.org/10.1007/s10666-022-09848-z

This is published under the Creative Commons Attribution 4.0 International License, details of which can be found here: https://creativecommons.org/licenses/by/4.0/. There have been some minor changes to the figure and table labelling and referencing style of the version of the paper included in this thesis compared to the published version.

3.1 Introduction

Plastics provide many practical uses but the treatment of plastics at the end of their product life cycle has come under much scrutiny. Plastic production for consumer-facing industries such as supermarkets has been subject to policies involving plastic bags and packaging (Saxton, 2019). This is due to the negative externality from the amount of plastic finding its way to the natural environment. The United Nations has recognised this issue by endorsing a resolution to end plastic pollution, with an aim to have a legally binding agreement in place by 2024 (UN, 2022; HAC, 2023). For this resolution to be effective, there should be accurate and detailed data on plastic use by industries.

There has been considerable research into the production of plastics, the generation of plastic waste, the recycling of plastics and plastic usage. Several studies including Geyer, Jambeck & Law (2017) focus on the waste management of plastics around the world. They compiled data from several sources on plastic resins, fibres and additives from 1950 to 2015 by sector and type of plastic. They found, of all plastics produced up to 2015, 30% are new plastics currently in use, 59% are in landfills or in the environment, 10% have been incinerated and 1% have been recycled and are currently in use. They estimate that 7% of all plastics produced have been recycled but 86% of this recycled plastic has now been disposed of in landfills and in the environment or incinerated. Further to this, they found that packaging plastics are the shortest used plastics before they are disposed of and have contributed the most to plastic waste. To show how much of a problem plastic waste is, Jambeck et al. (2015) estimated that 4.8 to 12.4 million tonnes of plastic enter the ocean every year, with that figure increasing year on year. Plastics are now so prevalent in the environment that Zalasiewicz et al. (2016) and Corcoran, Moore & Jazvac (2014) argue that they provide an effective means to measure the progress and impact of humans when analysing layers of sediment around the world.

Plastic pollution is increasing due to a number of factors including economic growth, the level of education, corruption and climate change (Cordier et al., 2021; Zapata, 2021). It is such a big problem in the Arctic that Abate et al. (2020) found, using a contingent valuation method, that the average Norwegian household is willing to pay 642 USD per year to reduce plastic pollution. McNicholas & Cotton (2019) have identified that plastic-related policies need to consider the perspectives of different stakeholders related to plastic including households, industries and government agencies to be successful. Further to this, Gielen & Moriguchi (2002) discuss the importance of considering product life cycles when designing environmental policies. This is particularly relevant for plastics as they become more of an issue as waste than in use. In managing waste, Cosmi et al. (2000) and Chambal, Shoviak & Thal (2003) demonstrate the value of data and accurate modelling as tools to determine environmental impacts from policies and improve decision making. In a review of the literature, Almroth & Eggert (2019) suggest future research areas which will help reduce marine plastic pollution. These areas include the development of plastics which are easier to manage as waste or recycle, a more thorough review of the health and environmental impacts of marine plastic pollution, an understanding of behavioural changes in relation to plastic policy and a deeper understanding of extended producer responsibility.

While there has been research into the application of input–output data to measure waste (Nakamura, 1999; Nakamura & Kondo, 2002a; Nakamura & Kondo, 2002b; Nakamura et al., 2007; Lenzen & Reynolds, 2014; Fry et al., 2015; Pomponi et al., 2022), and the use of an economy-wide model to estimate the impacts of potential widespread plastic policies (OECD, 2022a-c; OECD, 2023), to our knowledge, no previous study has estimated the disaggregated plastic intensity of different industries in the USA. Policy makers and consumers looking to reduce plastics would make better choices with detailed information on the plastic intensity of industries. Knowing plastic intensity would enable policy makers and consumers to focus their efforts on reducing output from or incentivising new technologies in industries where plastics make up a large proportion of inputs. We determine the plastic intensity of 415 non-plastic industries in the USA for 13 different types of plastic commodities, using the Eora Global Supply Chain Database (Lenzen et al., 2012; Lenzen et al., 2013). We focus on the USA, as, within the Eora Database, plastic products are described in detail; and it accounts for a significant proportion of global plastic consumption. This paper has five further sections. Section 3.2 describes the previous literature on plastic pollution. Section 3.3 describes the data and methods used for our analysis. Section 3.4 outlines the main results from our methodology. Section 3.5 provides some discussion and conclusions of those results.

3.2 Plastic Pollution

While plastic is widely reported as a large contributor to pollution, there are some forms of plastic that contribute disproportionately to the problem. There has been a large body of research which details the types of plastic that end up in the natural environment. We have focused our literature review on waterways, as that is where a significant quantity of plastic pollution is found (Parker, 2019).

Microplastics refer to microscopic pieces of plastic which contribute to pollution in the natural environment. This plastic usually has a high level of buoyancy when it enters the ocean, and over time, its buoyancy reduces and it sinks (Woodall et al., 2014). Due to its low rate of decomposition, it is often consumed by ocean fauna, or it builds up in the sediment on the ocean floor. Woodall et al. (2014) discuss the abundance of microplastic waste in the ocean, especially in the deep sea. By studying deep sea sediment cores, they found the most abundant microplastics in their samples to be rayon and polyester. Both of these plastics are predominantly found in clothing. Browne et al. (2011) also look at microplastics in waterways and the sources of those microplastics. Similar to Woodall et al. (2014), they discuss the large amount of polyester present as microplastics in the environment. They further explain that polyester ends up in waterways through the washing of clothes, when fibres are small enough to bypass filters in the sewerage system. One piece of clothing made with synthetic fibres can produce over 1900 fibres per wash. In addition to environmental impacts, there are also potential health impacts from man-made fibres. The concentration of these fibres indoors can be between 1 and 60 fibres/m^3 and between 0.3 and 1.5 fibres/m^3 outdoors. According to Dris et al. (2016), the potential health impacts from these fibres are not fully understood and should be researched further. In 2017, 70% of all fibres produced world-wide were artificial or synthetic, meaning there is a growing source of these microplastics and air pollution every year (The Fiber Year Consulting, 2017).

According to a meta-analysis on plastics in marine environments by Erni-Cassola et al. (2019), the most common types of plastic found in the ocean are polypropylene, polyethylene, polystyrene, polyester, polyamide and acrylic. This is backed up by an analysis from Morét-Ferguson et al. (2010) who took samples in the North Atlantic Ocean to study the size, mass, and distribution of plastic debris in that area. The main difference in their results was the specification of both high-density and low-density polyethylene, and the addition of polyvinyl chloride and polyethylene terephthalate.

Polypropylene refers to a form of thermoplastic which is used for a variety of purposes including the packaging of products, as parts in the motor vehicle industry, and in textiles (Creative Mechanisms, 2016a). Polyethylene refers to a type of plastic found as either high-density polyethylene or low-density polyethylene. High-density polyethylene can be found in products such as bullet proof vests and medical devices. Low-density polyethylene can be found in products such as plastic bags, plastic wrap and other packaging plastics (Rogers, 2015). Polyvinyl chloride, more commonly known as PVC, comes in two common forms, as a rigid polymer and as a flexible plastic. The rigid polymer is used as pipes for construction and plumbing. The flexible plastic is commonly used as insulation on wires, and flooring for homes and hospitals (Creative Mechanisms, 2016b). Polystyrene is a thermoplastic polymer that can be found as general polystyrene which is transparent or high impact polystyrene which is opaque. It is found in packaging, household appliances, building insulation, lighting fixtures, test tubes and petri dishes (PlasticsEurope, 2021). Polyester is a synthetic fibre used in products such as clothing, insulation, packaging products and recording tapes (Encyclopaedia Britannica, 2009a). Polyethylene terephthalate (PET) is part of the polyester family and is a clear, light and strong plastic used for drink bottles, food packaging and microwavable packaging (PETRA, 2015). Polyamide is a type of thermoplastic polymer used in products such as nylon, synthetic rubber and latex (Creative Mechanisms, 2016c). Acrylic refers to a range of synthetic resins commonly found in products such as plastic glass used in cooking, construction and motor vehicles (Encyclopaedia Britannica, 2009b).

We design our analysis around this research into polluting plastics. In the USA Eora Dataset, seven of the 13 plastic commodities represented contain plastics that contribute disproportionately to pollution in waterways. Our research focuses on these seven commodities.

3.3 Data and Methods

Our analysis employs the Eora Global Supply Chain Database which is comprised of a multi-region input–output table (MRIO) model that produces a time series of input–output tables for 190 countries (Lenzen et al., 2012; Lenzen et al., 2013). The data for the USA has more clear-cut commodities related to plastic compared to other countries, so we use the USA individual country basic price input–output table for our analysis. Specifically, the 13 plastic commodities represented in the USA data are significantly more than the number included for China (two plastic-related commodities), the UK (seven), Australia (one), Germany (one), Japan (eight) and Argentina (seven). The USA data contains information on primary inputs and final demand, and imports and exports in 2015 for 428 different industries and commodities. Plastics in this data are represented as 13 individual commodities, which are listed in Table 1.1. Each of these plastic commodities represents multiple plastic products.

Table 3.1: Plastic commodities in the US represented in the Eora Database.

Abbreviation	Commodity Name	Examples
Coated Paper and Plastic Film*	Coated and laminated paper, packaging paper, and plastics film manufacturing	Bread wrappers, waxed or laminated; coated paper for packaging; wrapping paper; and plastic film.
Plastic Plate Sheet	Laminated plastics plate sheet (except packaging), and shape manufacturing	Laminated plastic plate, rods, and sheets.
Other Plastics	Other plastic product manufacturing	Inflatable pool rafts, air mattresses, plastic gloves, plastic hardware, garbage containers, plastic bowls, and plastic bottle caps.
Plastic Bottles*	Plastics bottle manufacturing	Plastic bottles.
Polystyrene*	Polystyrene foam product manufacturing	Ice chests, cups, dinnerware, food containers, ice buckets, insulation and cushioning, packaging, and shaped cushioning.
Plastic Resin*	Plastics material and resin manufacturing	Acetal resins, nylon resins, polyester resins, PVC resins, PET resins, and elastomers.
Plastic Pipes	Plastics pipe and pipe fitting manufacturing	Plastic fittings and unions, plastic pipe, and rigid plastics.
Plastic Packaging Materials*	Plastics packaging materials and unlaminated film and sheet manufacturing	Unlaminated plastic film, flexible packaging, and packaging film.
Plastic Hoses and Belts	Rubber and plastics hoses and belting manufacturing	Conveyor belts, garden hose, fan belts, hydraulic hoses, water hoses, vacuum cleaner belts, and transmission belts.
Plastic Fibres and Filaments*	Artificial and synthetic fibres and filaments manufacturing	Acetate and acrylic fibre and filaments, polyester, cigarette filters, cellophane, nylon, PET fibres and filaments, artificial yarn, spandex fibre and filaments, and elastomeric fibres and filaments.
Synthetic Rubber*	Synthetic rubber manufacturing	Acrylic rubber, latex rubber, polyethylene rubber, silicone rubber, and polymethylene rubber.
Shaped Plastics	Unlaminated plastics profile shape manufacturing	Non-rigid plastics, plastic tubes, and plastic sausage casings.
Urethane	Urethane and other foam product (except polystyrene) manufacturing	Cushions, insulation, packaging, foam, carpet underlay, and coolers.

Note: The information provided is based on descriptions from NAICS (2018). Plastic commodities with a * after their abbreviation are plastics more likely to contribute to plastic pollution.

As discussed in Section 3.2, some types of plastic are more likely to end up in the environment as pollution than others. To understand the industries which use these types of plastic intensively, our analysis focuses on the high pollution plastic commodities in the Eora dataset. We identify these commodities by using the research from Erni-Cassola et al. (2019), Morét-Ferguson et al. (2010), and Geyer, Jambeck & Law (2017). These authors classify high pollution plastics as types of plastic which commonly end up in waterways, as described by Erni-Cassola et al. (2019) and Morét-Ferguson et al. (2010), as well as the short life cycle (mostly packaging) plastics described by Geyer, Jambeck & Law (2017). Using this classification, we identify seven plastic commodities from the Eora dataset which are relatively more likely to contribute to plastic pollution. These seven commodities are (1) coated paper and plastic film, (2) plastic bottles, (3) plastic packaging materials, (4) polystyrene, (5) plastic resin, (6) plastic fibres and filaments and (7) synthetic rubber.

To determine the plastic intensity of each industry, both the direct and indirect uses of plastic commodities need to be calculated. Direct use of plastic occurs when an industry uses inputs of a plastic commodity (e.g. fibre, yarn and thread mills use plastic fibres and filaments as an input). Indirect use of plastic occurs when an industry uses an input that was produced, in part, using plastics (e.g. carpet and rug mills use knit fabric as an input which is produced using plastic fibres and filaments).

The techniques we used to calculate direct and indirect use of plastics in this paper build on the methodologies developed for input–output analysis. The fundamental paper of Leontief (1970) describes how input–output data can be used to measure environmental impacts by industries. It specifies a set of simultaneous equations which need to be solved to calculate embodied pollution in an economy. Herwich and Peters (2009) provide an application of this methodology to determine embodied greenhouse gas emissions for final demand across 73 countries using the Global Trade Analysis Project (GTAP) database, an MRIO database commonly used in trade and policy analysis (Aguiar et al., 2019; Aguiar, Narayanan & McDougall, 2016). Input–output analysis has also been applied to other economic processes. Bullard, Penner & Pilati (1978) describe how direct and indirect energy use can be calculated using process analysis as well as input–output analysis and how the two approaches can be combined. Further to this, Heijungs & Suh (2002) provide a detailed description of life cycle assessment and how it can be used with input–output analysis in a hybrid analysis. Suh et al. (2003) explain how this hybrid analysis can extend the system processes included in life cycle assessment. An example of this comes from the use of input–output and hybrid analysis to research the generation of waste. Nakamura et al. (1999, 2002a, 2002b, 2007) show how input–output data can be used to generate waste input–output models that describe the direct and indirect generation of waste in relation to economic activities. Lenzen & Reynolds (2014) expand the research of Nakamura et al. (1999, 2002a, 2002b, 2007) by constructing a waste supply-use table which displays multiple types of waste such as recycling and aggregate plastics simultaneously. Fry et al. (2015) develop this further by designing a multi-regional waste supply-use framework for Australia which can calculate 'waste footprints' of industries and regions. It does this by combining a waste supply-use table based on the research by Lenzen & Reynolds (2014) with Australian waste data. Finally, Pomponi et al. (2022) use input–output data and life cycle assessment in a hybrid analysis to measure the potential environmental impact of a change in the design of plastic milk bottles. We extend these input–output methodologies to determine plastic intensity for industries in the USA using the Eora Dataset.

Three components of the Eora USA Dataset are used in our analysis: domestic output, domestic intermediaries, and aggregated imports of commodities by domestic industries. Domestic output includes data on the commodities produced by domestic industries. Domestic intermediaries include data on the domestic commodities used as inputs by domestic industries. Aggregated imports of commodities by domestic industries include, for each industry, data on the value of imported intermediate inputs (aggregated across commodities) from specific countries. For each commodity used by each sector, intermediate inputs are an aggregate of domestic and imported commodities. To determine imported plastic intensity, we set the intermediate input shares (across commodities) for imported intermediate inputs equal to the shares for domestically sourced intermediate inputs.[1] For example, 14.3% of the USA domestic inputs for the soft drink and ice manufacturing industry are plastic bottles. We then apply this percentage to the total value of imports used in soft drink and ice manufacturing to determine the approximate value of plastic bottles imported by this industry.

As input–output data measures transactions in values, we measure plastic intensity as the dollars of plastic inputs per dollar of output. This means that plastic intensity estimates will be higher for high-value plastic commodities (e.g. plastic packaging materials and plastic fibres and filaments) and/or low-value industries (e.g. scrap and used and second-hand goods). Pomponi et al. (2022) have a very effective method for converting the value of plastic milk bottles to weight and to environmental impacts. This conversion is unfortunately not possible for our research as the number of plastic commodities we examine and the aggregation of plastic types in these commodities makes it difficult to find a detailed and reliable database which we can use for this analysis. In the absence of detailed data on plastic volumes used by each industry for each plastic commodity (e.g. tonnes of plastic bottles used by soft drink and ice manufacturing), we use value-based plastic intensity estimates to approximate the plastic intensity of different commodities along with estimates of the overall value of plastic commodities used by each industry. The limitations of a value-based intensity measure are discussed in the conclusions.

[1] This assumption is necessary because data on imported intermediate inputs by commodity and sector is not available for the disaggregated USA input–output table that facilitates a detailed breakdown of plastic commodities.

To calculate the plastic intensity using MRIO data, our approach is based on the methodology introduced in Leontief (1970) and described further by Bullard, Penner & Pilati (1978), represented by Equation (3.1).

$$\pi = x(I - A)^{-1} \qquad (3.1)$$

Whereby π and x are vectors with entries π_i and x_i, for each industry i = 1, 2, …, N.[2] Specifically, π is the plastic intensity value of each industry; x is a vector of the direct plastic intensity of each industry; *I* is an identity matrix; and *A* is a *N*×*N* matrix of input–output coefficients which describes the commodities, *c*, needed to produce a unit of output by industry *i*. This approach assumes the MRIO data used has single-commodity output for each industry. Lenzen & Rueda-Cantuche (2012) explain how this methodology can be adapted for multi-commodity output MRIO data. We use this technique and apply it to the Eora dataset using Equation (3.2).

$$\pi = x(I - DB)^{-1} \qquad (3.2)$$

Where $D = VQ^{-1}$, and $B = UG^{-1}$. *V* is a *N*×*N* matrix which describes the output $V_{i,c}$ of commodity *c* by industry i, *U* is a *N*×*N* matrix which describes the direct input $U_{c,i}$ of commodity *c* for each industry i, Q is a diagonal matrix with diagonal entries of the total value of each commodity $\hat{q}_c$ produced, and *G* is a diagonal matrix with diagonal entries of the total value of output $\hat{g}_i$ produced by each industry. This approach takes into account the proportion of each commodity produced by each industry and is calculated separately for each of the 13 plastic commodities.

If desired, the methodology described by Lenzen & Rueda-Cantuche (2012) can also be used to calculate the plastic intensity of each commodity (π_c). Total plastic intensity of each industry is calculated by adding the 13 individual plastic intensity calculations together. This analysis is also used to determine the total value of each plastic commodity used by each industry, by multiplying both sides of Equation (3.2) by *G*.

3.4 Results

Using the methodology described in Section 3.3, we determine the plastic intensities for the 415 non-plastic industries described in the USA Eora Dataset. To provide a high-level understanding of differences in plastic intensities, we first calculate total plastic intensity (across all plastic types) for each industry. As a dollar of one plastic type does not have the same environmental impact as a dollar of another plastic type, we also calculate the plastic intensity of each industry separately for each plastic commodity. We report results for (1) total plastic intensity (aggregated across all plastic commodities); (2) total polluting plastic intensity (aggregated across all polluting plastic commodities, see Table 3.1); and (3) plastic intensity for each polluting plastic. To provide additional information,

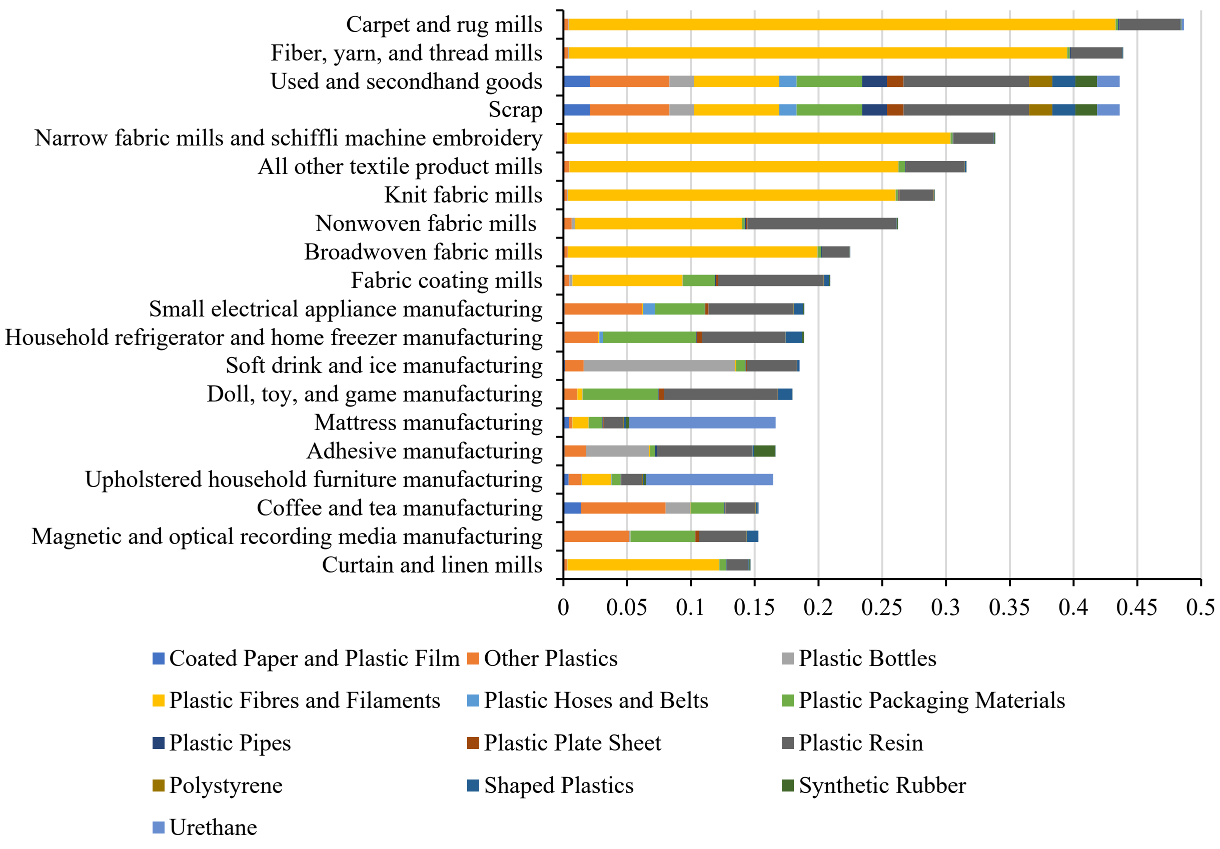
[2] In our work N = 428. This is the number of industries and commodities described by the USA Eora Dataset.

for each type of polluting plastic, we also calculate the total value used as an input by each industry. All industries presented in figures and tables are described in more detail in Appendix Table A3.1.

3.4.1 Total plastic intensity

Figure 3.1 shows the top 20 plastic intensive industries summed across the 13 plastic commodities, described in Table 3.1. Of the top 20 plastic intensive industries, nine of them can be categorised as clothing and fabric manufacturing–related industries, including the two most plastic intensive industries. The industry which has the highest plastic intensity is carpet and rug mills with a plastic intensity of 0.4865 (i.e. this industry uses 0.4865 dollars of plastic inputs per dollar of output). The next most intensive industries are fibre, yarn and thread mills (0.4390); used and second-hand goods (0.4362); and scrap (0.4362). Plastic fibres and filaments account for the largest share of plastic intensity in this figure, especially in the top ten industries.

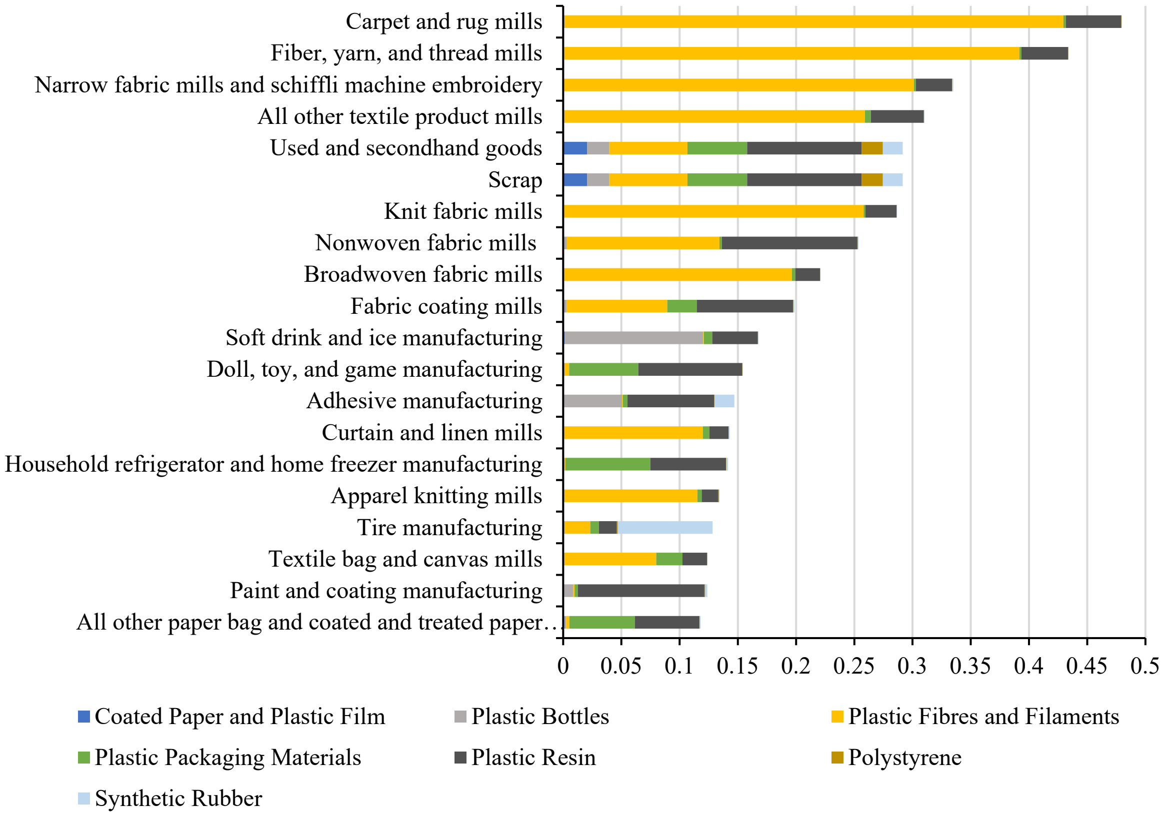
Figure 3.1: Plastic intensity by industry and plastic type (20 most aggregate plastic intensive industries).



3.4.2 Total polluting plastic intensity

The top 20 plastic intensive industries for aggregated polluting plastics (see Table 3.1) are shown in Figure 3.2. Of the top 20 polluting plastic intensive industries, 11 of them can be categorised as related to clothing and fabric manufacturing, including eight of the top ten industries. The plastic commodity used most intensively by these industries is plastic fibres and filaments. The industry most intensive in polluting plastics is carpet and rug mills (0.4798); followed by fibre, yarn and thread mills (0.4341); and narrow fabric mills and schiffli machine embroidery (0.3350). The 20th most intensive sector, all other paper bag and coated and treated paper manufacturing, has a plastic intensity of 0.1182.

Figure 3.2: Plastic intensity by industry and polluting plastic type (20 most plastic intensive industries).



3.4.3 Individual polluting plastic intensity and use

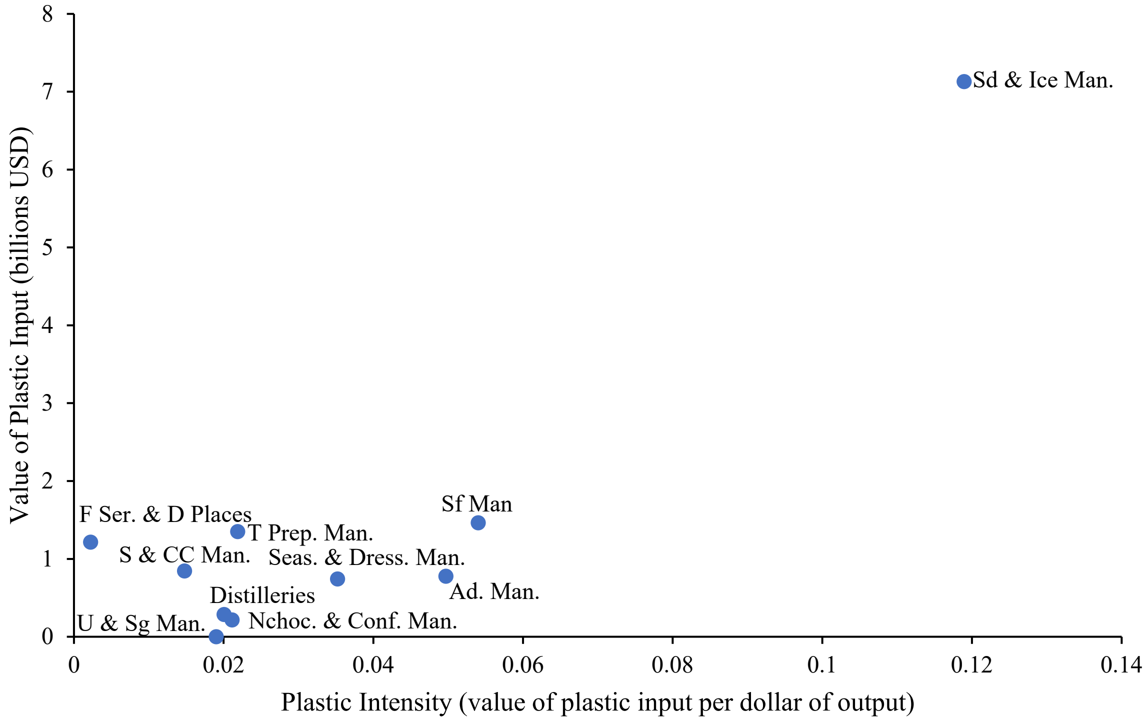
As noted in Section 3.3, comparing the plastic intensity across more than one plastic type is an issue as a dollar of one plastic commodity is not the same as a dollar of another plastic commodity. To address this issue, we report results for each of the seven polluting plastics individually and also calculate the total value of each polluting plastic used as an input by each industry.

Figure 3.3 shows a scatter plot of the five most plastic bottle intensive industries and the five industries which use the highest value of plastic bottles as an input.[3] Of these 10 industries, six are related to food and drink. The most plastic bottle intensive industry is soft drink and ice manufacturing (0.1190). There is then a relatively large drop in plastic bottle intensity, with the next

[3] In the case where industries were present in both top five lists, the industries chosen to make up the rest of the figure were based on the proportional difference between the fifth highest value or intensity and the next industry on the respective list. Where there was a smaller difference, that industry was chosen. This was also applied in Figures 1.4, 1.5, 1.6, 1.7, 1.8, and 1.9.

highest, snack food manufacturing (0.0541), being less than half the intensity of soft drink and ice manufacturing. Having a high plastic bottle intensity does not necessarily mean an industry uses the highest value of plastic bottles as an input. However, in this case, soft drink and ice manufacturing is the most plastic bottle intensive industry and accounts for the largest value of plastic bottles as an input. The next industry on the value list, snack food manufacturing, is about one fifth of the value of soft drink and ice manufacturing. This suggests that if policy makers and consumers wanted to reduce plastic bottles used, they should initially focus on incentivising changes in the soft drink and ice manufacturing industry, along with other food and drink–related industries.

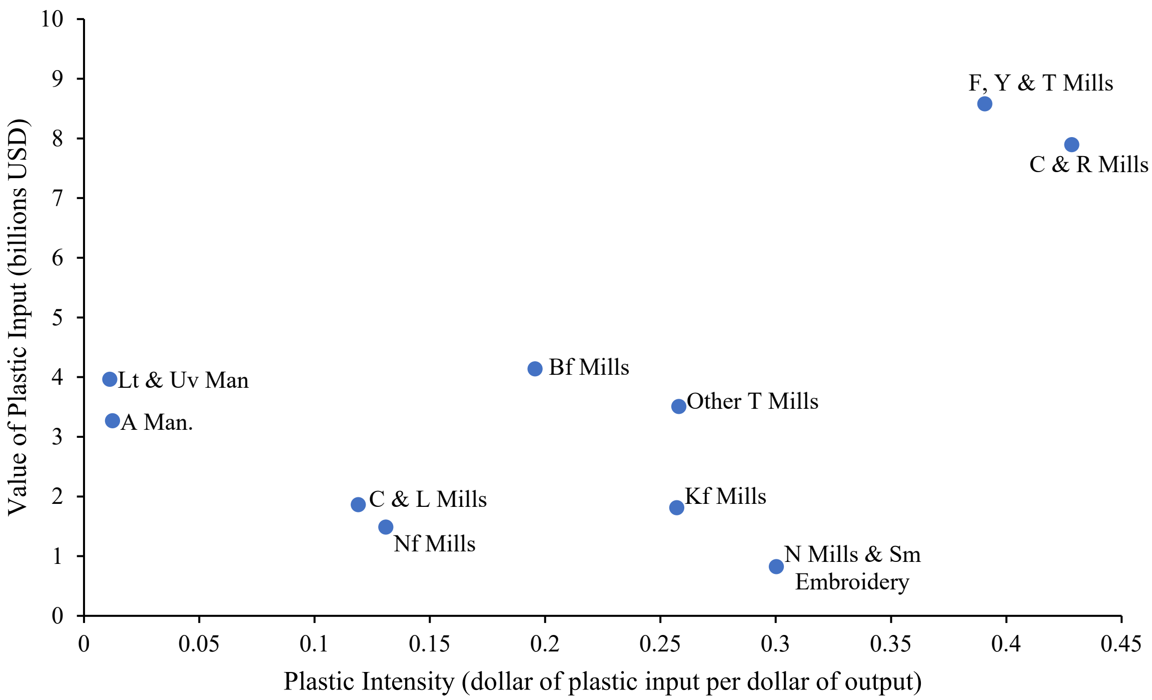
Figure 3.3: Plastic bottle intensity and value of plastic bottles used as an input (10 highest plastic intensive and value of plastic input industries).



Note: the industry names for the abbreviations used in the figure are as follows: soft drink and ice manufacturing (Sd & Ice Man.); snack food manufacturing (Sf Man.); toilet preparation manufacturing (T Prep. Man.); food services and drinking places (F Ser. & D Places); soap and cleaning compound manufacturing (S & CC Man.); adhesive manufacturing (Ad. Man.); seasoning and dressing manufacturing (Seas. & Dress. Man.); non-chocolate confectionery manufacturing (Nchoc. & Conf. Man.); distilleries (Distilleries); and used and second-hand goods (U & Sg Man.)

Figure 3.4 displays the five industries that use plastic fibres and filaments most intensively and the five industries which use the highest value of plastic fibres and filaments as an input. Eight of the 10 industries are related to clothing and fabric manufacturing. The most plastic fibres and filaments intensive industries are carpet and rug mills (0.4285) and fibre, yarn and thread mills (0.3908). These two industries also use the most plastic fibres and filaments in production (in value terms). Therefore, to reduce the plastic fibres and filaments used, policy makers and consumers should focus on prompting changes in production techniques of industries related to clothing and fabric manufacturing, especially carpet and rug mills and fibre, yarn and thread mills.

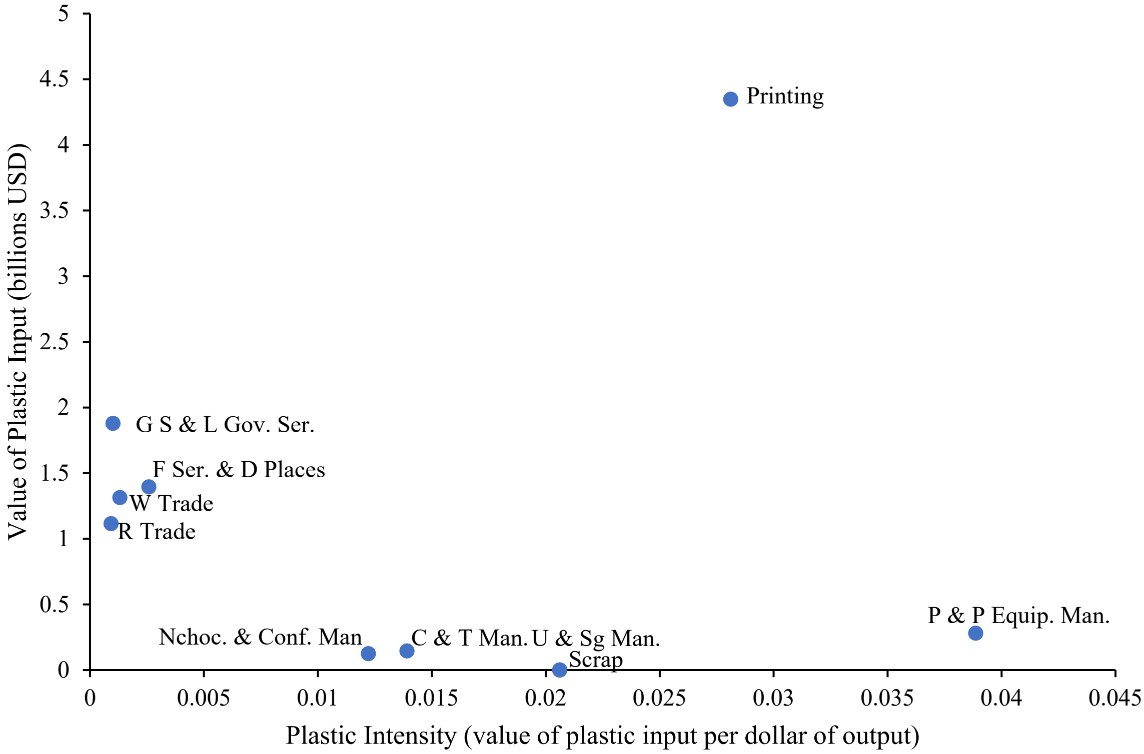
Figure 3.4: Plastic fibres and filaments intensity and value of plastic fibres and filaments used as an input (10 highest plastic intensive and value of plastic input industries).



Note: the industry names for the abbreviations used in the figure are as follows: fibre, yarn and thread mills (F, Y & T Mills); carpet and rug mills (C & R Mills); broadwoven fabric mills (Bf Mills); light truck and utility vehicle manufacturing (Lt & Uv Man.); all other textile product mills (Other T Mills); narrow fabric mills and schiffli machine embroidery (N Mills & Sm Embroidery); knit fabric mills (Kf Mills); nonwoven fabric mills (Nf Mills); curtain and linen mills (C & L Mills); and automobile manufacturing (A Man.)

The most coated paper and plastic film intensive industries and the industries which use the highest value of coated paper and plastic film as an input are shown in Figure 3.5. This figure is made up of a mixture of industries including food and drink–related industries, trade industries, printing and government services. Printing (0.0281) and photographic and photocopying equipment manufacturing (0.0389) are the two most plastic intensive industries. The printing industry also uses the highest value of coated paper and plastic film as an input. This means the printing industry is an efficient target for those seeking to reduce the amount of coated paper and plastic film used in production. However, to have a significant impact on plastic pollution, industries which use a relatively high value of coated paper and plastic film such as general state and local government services, food services and drinking places and wholesale and retail trade should also be incentivised away from using coated paper and plastic film.

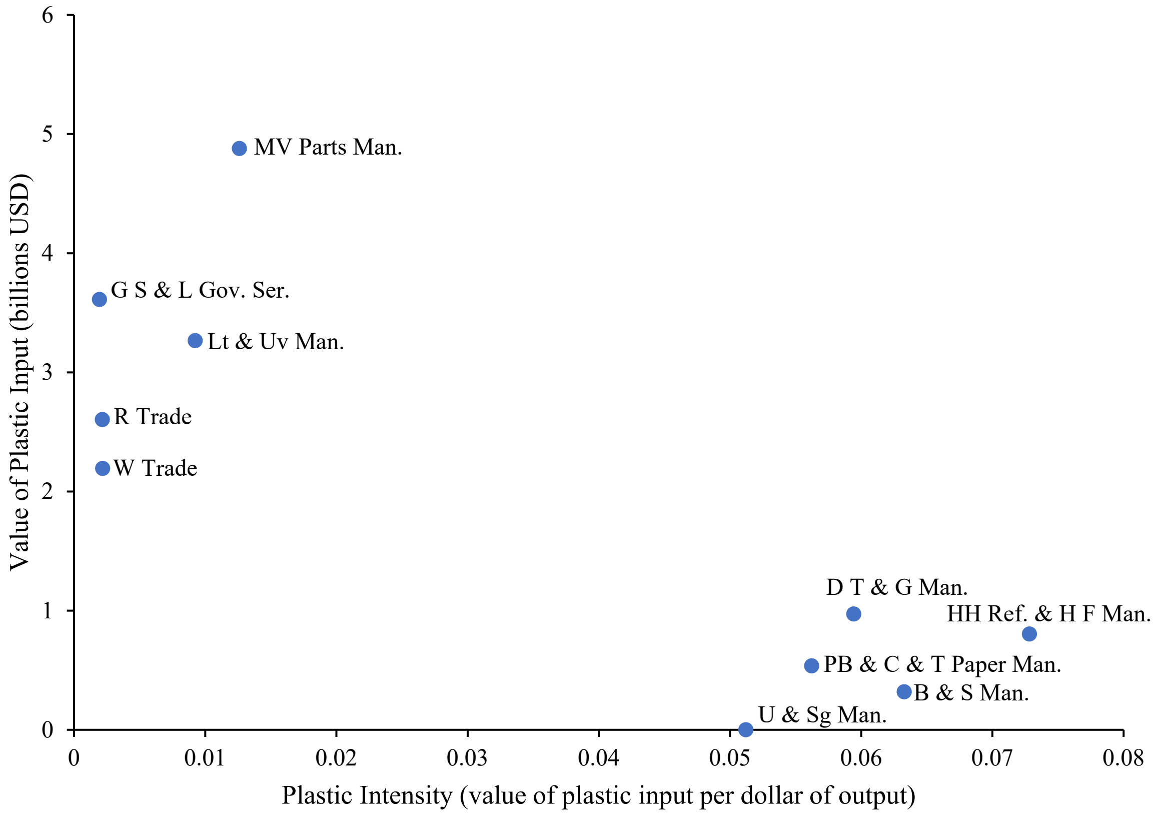
Figure 3.5: Coated paper and plastic film intensity and value of coated paper and plastic film used as an input (10 highest plastic intensive and value of plastic input industries).



Note: the industry names for the abbreviations used in the figure are as follows: photographic and photocopying equipment manufacturing (P & P Equip. Man.); printing (Printing); scrap (Scrap); used and second-hand goods (U & Sg Man.); coffee and tea manufacturing (C & T Man.); non-chocolate confectionery manufacturing (Nchoc. & Conf. Man.); general state and local government services (G S & L Gov. Ser.); food services and drinking places (F Ser. & D Places); wholesale trade (W Trade); and retail trade (R Trade).

As shown in Figure 3.6, the five most plastic packaging materials intensive industries and the five industries which use the highest value of plastic packaging materials as an input are related to trade, motor vehicles, government and household goods. There are no industries which have both a high plastic intensity and use a high value of plastic packaging materials as an input. Household refrigerator and home freezer manufacturing (0.0728) has the highest plastic intensity and motor vehicle parts manufacturing uses the highest value of plastic packaging materials in production. Policymakers wishing to reduce the amount of plastic packaging materials in the economy would need to target a diverse selection of industries as our results indicate that there is not an obvious industry or group of industries to focus on. It could be an effective strategy to focus on the industries which use a relatively high value of plastic packaging materials in production, including motor vehicle parts manufacturing, general state and local government services, light truck and utility vehicle manufacturing and retail and wholesale trade. Reducing plastic use in these industries would likely cause the largest reduction in the volume of plastic packaging materials entering the environment.

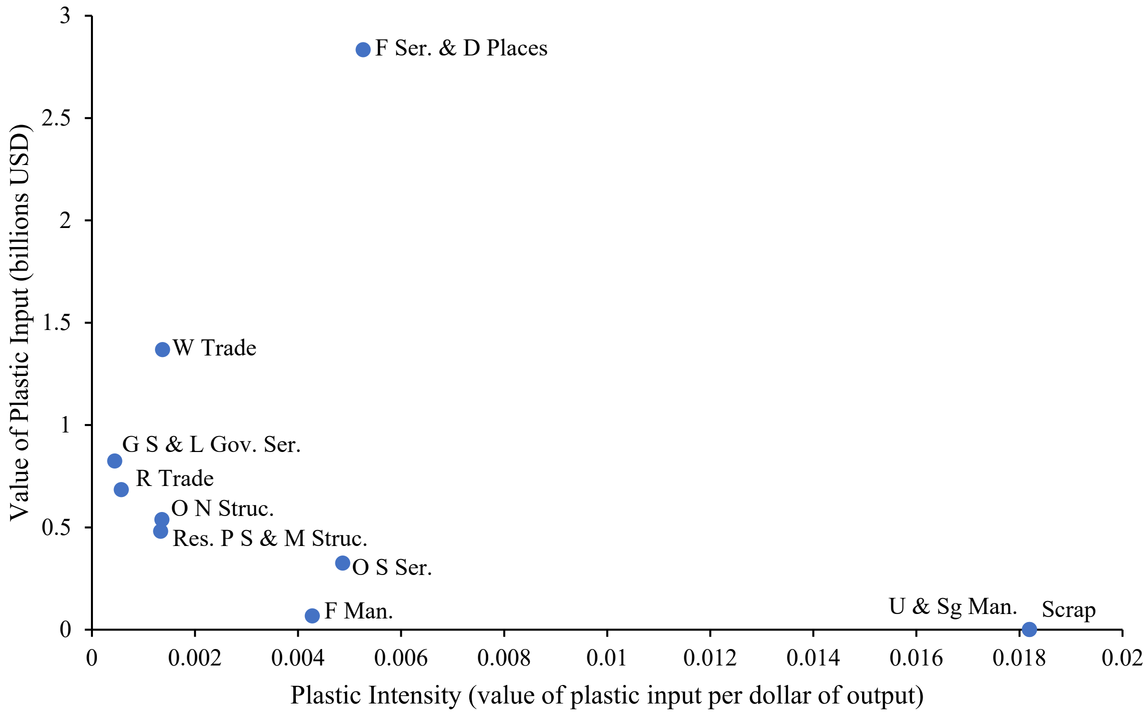
Figure 3.6: Plastic packaging materials intensity and value of plastic packaging materials used as an input (10 highest plastic intensive and value of plastic input industries).



Note: the industry names for the abbreviations used in the figure are as follows: household refrigerator and home freezer manufacturing (HH Ref. & H F Man.); blind and shade manufacturing (B & S Man.); doll, toy and game manufacturing (D T & G Man.); all other paper bag and coated and treated paper manufacturing (PB & C & T Paper Man.); used and second-hand goods (U & Sg Man.); motor vehicle parts manufacturing (MV Parts Man.); general state and local government services (G S & L Gov. Ser.); light truck and utility vehicle manufacturing (Lt & Uv Man.); retail trade (R Trade); and wholesale trade (W Trade).

Figure 3.7 plots the industries which use polystyrene the most intensively and use the highest value of polystyrene as an input. It includes a mix of industries related to trade, food and drink, clothing and support services. The two most polystyrene intensive industries are scrap (0.0182) and used and second-hand goods (0.0182). The next most intensive industry is food services and drinking places (0.0053) which also uses the highest value of polystyrene in production. Scrap and used and second-hand goods both use a very low value of polystyrene in production. An efficient way of reducing polystyrene in the economy would be to initially incentivise food services and drinking places away from using direct and indirect polystyrene inputs. A longer-term approach could then focus on other industries included in Figure 3.7, prioritising the industries which use a higher value of polystyrene first, such as wholesale trade, and working down until the majority of industries are incentivised to use non-plastic alternatives.

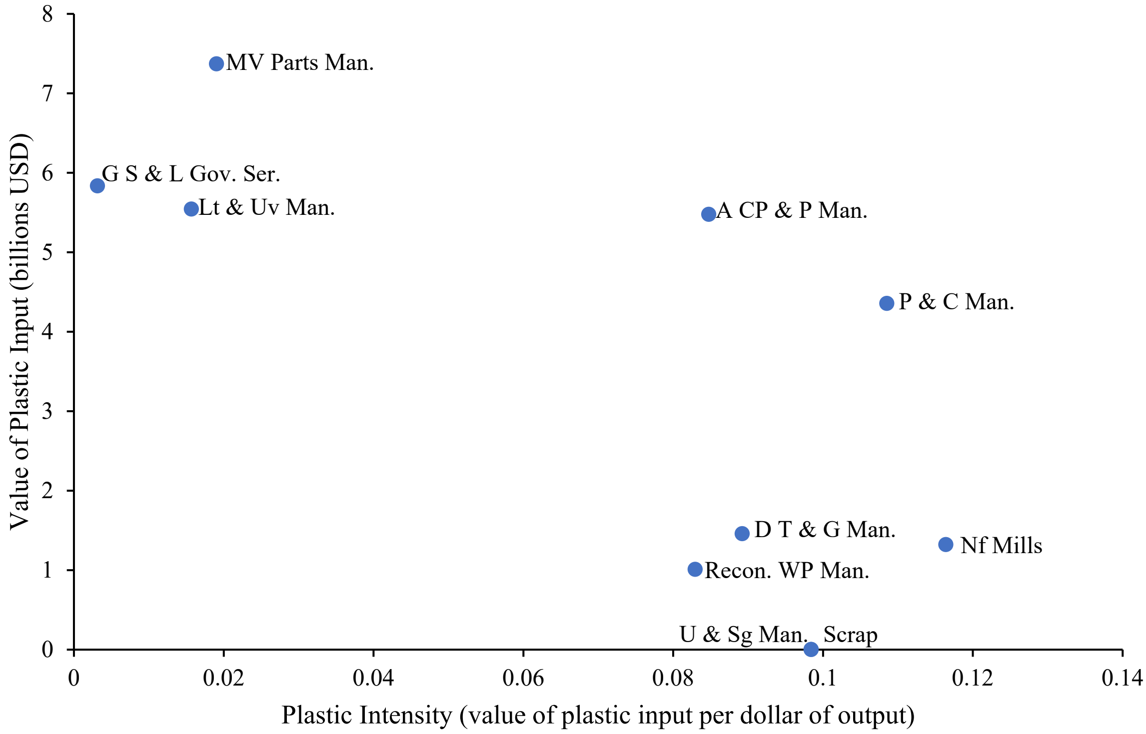
Figure 3.7: Polystyrene intensity and value of polystyrene as an input (10 highest plastic intensive and value of plastic input industries).



Note: the industry names for the abbreviations used in the figure are as follows: used and second-hand goods (U & Sg Man.); scrap (Scrap); food services and drinking places (F Ser. & D Places); other support services (O S Ser.); footwear manufacturing (F Man.); residential permanent site single- and multi-family structures (Res. P S & M Struc.); wholesale trade (W Trade); general state and local government services (G S & L Gov. Ser.); retail trade (R Trade); and other non-residential structures (O N Struc.).

Figure 3.8 shows the five most plastic resin intensive industries and the five industries which use the highest value of plastic resin as an input. The figure includes industries related to clothing and fabric manufacturing, chemical manufacturing, motor vehicles, scrap and government services. The most plastic resin intensive industry is nonwoven fabric mills (0.1164), followed by paint and coating manufacturing (0.1085) and used and second-hand goods (0.0984). The industries which use the highest value of plastic resin in production are motor vehicle parts manufacturing, general state and local government services and light truck and utility vehicle manufacturing. Policy makers and consumers looking to reduce the pollution from plastic resin should initially focus on all other chemical product and preparation manufacturing as well as paint and coating manufacturing, as they have a relatively high plastic resin intensity and use a relatively high value of plastic resin as an input.

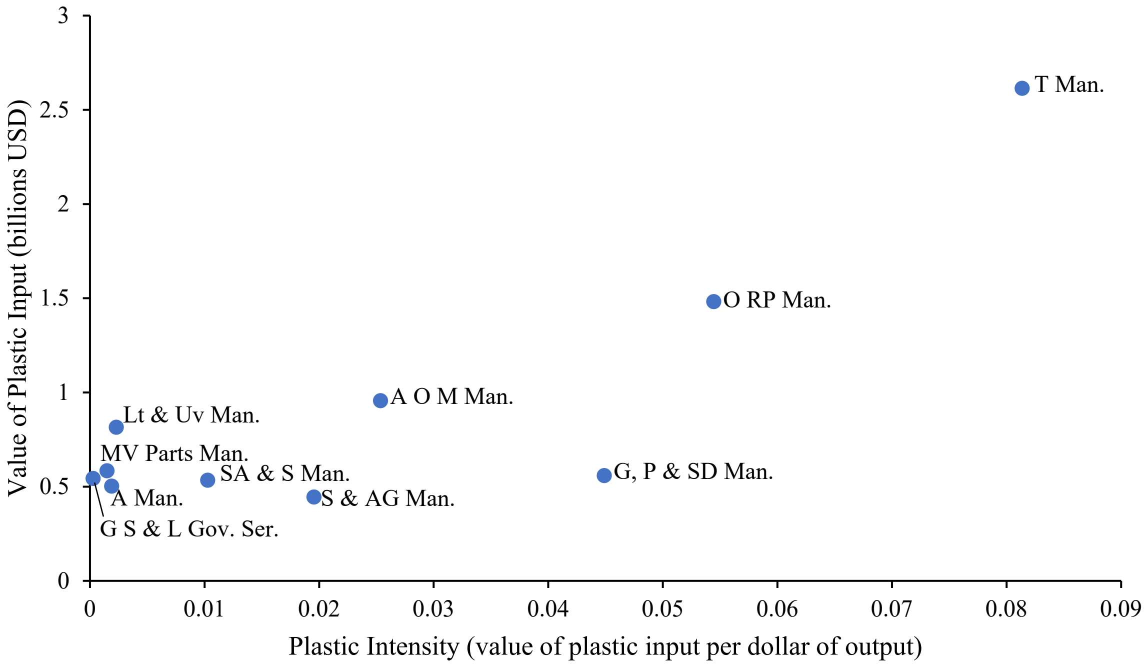
Figure 3.8: Plastic resin intensity and value of plastic resin used as an input (10 highest plastic intensive and value of plastic input industries).



Note: the industry names for the abbreviations used in the figure are as follows: nonwoven fabric mills (Nf Mills); paint and coating manufacturing (P & C Man.); scrap (Scrap); used and second-hand goods (U & Sg Man.); doll, toy and game manufacturing (D T & G Man.); motor vehicle parts manufacturing (MV Parts Man.); general state and local government services (G S & L Gov. Ser.); light truck and utility vehicle manufacturing (Lt & Uv Man.); all other chemical product and preparation manufacturing (A CP & P Man.); and reconstituted wood product manufacturing (Recon. WP Man.).

The industries which use synthetic rubber the most intensively and use the highest value of synthetic rubber as an input are shown in Figure 3.9. These industries are related to tire manufacturing, motor vehicles, plumbing, sporting goods and surgical equipment. The most synthetic rubber intensive industry and the industry which uses the highest value of synthetic rubber as an input is tire manufacturing (0.0814). Other rubber product manufacturing (0.0545) uses the second highest value of synthetic rubber and is the second most synthetic rubber intensive industry. There is then a relatively large decrease in both intensity and value of synthetic rubber used for the remaining industries. This indicates that to reduce the amount of synthetic rubber in the economy, tire manufacturing and other rubber product manufacturing would be efficient industries to incentivise away from using synthetic rubber as a direct and indirect input to production.

Figure 3.9: Synthetic rubber intensity and value of synthetic rubber used as an input (10 highest plastic intensive and value of plastic input industries).



Note: the industry names for the abbreviations used in the figure are as follows: tire manufacturing (T Man.); other rubber product manufacturing (O RP Man.); gasket, packing and sealing device manufacturing (G, P & SD Man.); all other miscellaneous manufacturing (A O M Man.); sporting and athletic goods manufacturing (S & AG Man.); light truck and utility vehicle manufacturing (Lt & Uv Man.); automobile manufacturing (A Man.); motor vehicle parts manufacturing (MV Parts Man.); general state and local government services (G S & L Gov. Ser.); and surgical appliance and supplies manufacturing (SA & S Man.).

3.5 Discussion and Conclusions

In recent years, there have been policies and actions around the world introduced to try and tackle plastic pollution. Examples of this, as described by Howard et al. (2019), include Canada's plan to remove single-use plastics by 2021 (e.g. plastic straws, plastic bags, plastic cutlery and plastic plates); Peru's policy to ban single-use plastics at its natural and cultural protected areas; the city of San Diego's ban on polystyrene food and drink containers; Washington D.C.'s ban on plastic straws; the approval of a reduction in single-use plastics by the European Union parliament (e.g. plastic straws, cotton buds, plastic cutlery and food containers); and the goal of American Airlines to reduce single-use plastics in its lounges. Policies to date may have been focusing on the wrong industries due to the lack of attention given to plastic-using industries which do not directly interact with the public. To adequately address this problem, there should be an understanding of the industries which produce the most plastic and the industries which use the most plastic in production. Highly intensive, high-value share products are the obvious plastic type-industry combinations for policy makers to address. We looked at plastic use in production by determining the plastic intensity of industries in the USA using an input–output dataset.

In determining these plastic intensities, we found that there is at least some use of plastics across all industries. We split our analysis into a general plastics overview and a polluting plastics investigation. Our results indicate that plastics are used intensively in clothing and fabric manufacturing–related industries.

The public perception, based on plastic-related policy, is that food and drink–related industries are the most plastic intensive due to their conspicuous use of packaging plastics such as plastic bags. Food and drink–related industries are most prominent in the plastic bottles analysis. They represent 10% of the top 20 plastic intensive industries and 5% of the top 20 polluting plastic intensive industries. Food and drink–related industries are plastic intensive for some plastic commodities but they do not dominate the list of the most plastic intensive industries as might be expected. They mostly use plastic bottles, coated paper and plastic film and polystyrene intensively. According to Geyer, Jambeck & Law (2017), Erni-Cassola et al. (2019), and Morét-Ferguson et al. (2010), these plastic commodities are contributors to environmental pollution, especially in the waterways. However, while their environmental impacts should not be understated, in our results, with regard to plastic intensity measured in value terms, plastic bottles, coated paper and plastic film and polystyrene are much less prevalent compared to plastic fibres and filaments.

Clothing and fabric manufacturing–related industries are highly plastic intensive, especially for plastic fibres and filaments. Collectively, they represent 45% of the top 20 plastic intensive industries and 55% of the top 20 polluting plastic intensive industries. Most of the clothing and fabric–related industries use a relatively large amount of plastic fibres and filaments as an input, which includes substances like polyester and nylon (NAICS, 2018). According to the research by Woodall et al. (2014), Browne et al. (2011) and Dris et al. (2016), these types of plastic are a major source of microplastics in the environment and they have potential human health impacts from their presence in the air. Given these negative impacts, it is concerning that plastic fibres and filaments have the highest plastic intensity value for a single industry and were the second most intensively used plastic commodity, on average, in the dataset. Our analysis indicates that, compared to other sectors, clothing and fabric–related industries are not only plastic fibres and filaments intensive but they use a relatively high value of these microplastics in production. Policies focused on reducing plastic inputs in clothing and fabric–related industries could cause a significant reduction in these man-made fibres.

The scrap industry and the used and second-hand goods industry are highly plastic intensive for a number of plastic commodities. This suggests that these industries could be relatively high users of plastics as inputs compared to their output and are potentially being overlooked when it comes to plastic-related policy. It is more likely that because scrap and used and second-hand goods are low-value industries, a dollar of plastic used in these industries will be a high proportion of output relative to other industries. This is why we compare plastic intensity with the value of plastic as an input for each of the polluting plastics.

The novelty of this research was using a multi-commodity input–output dataset to determine plastic intensity and total plastic use by plastic commodity and industry for 13 types of plastic. Industries that use plastic intensively and use a large amount of plastic as an input represent low hanging fruit for policy makers. Some of these industries include carpet and rug mills and fibre, yarn and thread mills for plastic fibres and filaments; soft drink and ice manufacturing for plastic bottles; printing for coated paper and plastic film; food services and drinking places for polystyrene; all other chemical product and preparation manufacturing and paint and coating manufacturing for plastic resin; and tire manufacturing and other rubber product manufacturing for synthetic rubber. A notable finding is that many clothing and fabric–related industries are highly plastic intensive. These industries have received less attention from policy makers and consumers wishing to reduce plastic pollution than industries that use a large amount of consumer-facing plastics.

Our results demonstrate the value of using input–output data to determine plastic intensity but future research could improve the calculation of embodied plastics in several ways. First, input–output datasets could display more detailed plastic commodities as well as provide a higher number of countries with plastic commodities described. Second, the development of a comprehensive auxiliary dataset for converting the value of plastic commodities into plastic volumes would assist the calculation of environmental impacts. Such data would, for different types of plastic, track plastic use in physical units (metric tonnes) as has been done for carbon dioxide emissions linked to fossil fuel use for climate policy analysis. Finally, future research would also benefit from more information on import and export flows of plastics including information on the specific plastics and countries involved.

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Appendix

Table A3.1: Descriptions of industries mentioned in Section 3.4, based on information from NAICS (2018).

Industry	Description
Adhesive manufacturing	Industries involved with manufacturing adhesives and caulk.
All other chemical product and preparation manufacturing	Industries involved with manufacturing chemical products. This includes lighter fluid, sugar substitutes, and swimming pool chemicals.
All other miscellaneous manufacturing	Industries involved with manufacturing goods not otherwise stated such as Christmas trees, cigarette lighters, and wigs.
All other paper bag and coated and treated paper manufacturing	Industries involved with manufacturing bags, coated paper, and laminates, as well as laminating and coating paper.
All other textile product mills	Industries involved with manufacturing textile products not otherwise specified. This includes adding decorative stitching to products.
Apparel knitting mills	Industries involved with knitting and finishing underwear, outwear, and nightwear.
Automobile Manufacturing	Industries involved with manufacturing vehicles and vehicle chassis.
Blind and shade manufacturing	Industries involved with manufacturing venetian blinds, as well as rods, poles, and fixtures for curtains.
Broadwoven fabric mills	Industries involved with weaving fabrics and felts.
Carpet and rug mills	Industries involved with manufacturing carpets and rugs including door mats, floor mats, and rugs.
Coffee and tea manufacturing	Industries involved with roasting coffee, and manufacturing coffee, tea, and coffee extracts.

Curtain and linen mills	Industries involved with manufacturing textiles including curtains, sheets, and towels.
Distilleries	Industries involved with distilling and blending liquors.
Doll, toy, and game manufacturing	Industries involved with manufacturing dolls, action figures, other children's toys, and games.
Fabric coating mills	Industries involved with coating and finishing textiles and clothing.
Fibre, yarn, and thread mills	Industries involved with manufacturing thread and yarn and winding natural and artificial fibres.
Food services and drinking places	Industries such as bars, nightclubs, and fast-food restaurants.
Footwear manufacturing	Industries involved with manufacturing shoes and slippers.
Gasket, packing and sealing device manufacturing	Industries involved with manufacturing gaskets and packing and sealing devices.
General state and local government services	Government organisations providing public services.
Hospitals	Industries providing emergency and specialist medical care.
Household refrigerator and home freezer manufacturing	Industries involved with manufacturing refrigerators and freezers.
Knit fabric mills	Industries involved with knitting and finishing fabric, and manufacturing lace.
Light truck and utility vehicle manufacturing	Industries involved with manufacturing light trucks and utility vehicles, and truck chassis.

Magnetic and optical recording media manufacturing	Industries involved with manufacturing magnetic and optical recording media. This includes blank tapes, and hard drives.
Mattress manufacturing	Industries involved with manufacturing mattresses.
Motor vehicle parts manufacturing	Industries involved with manufacturing and repairing motor vehicle parts.
Narrow fabric mills and schiffli machine embroidery	Industries involved in weaving fabrics and manufacturing elastic yarn and thread and Schiffli machine embroideries.
Non-chocolate confectionery manufacturing	Industries involved with manufacturing confectioneries not made of chocolate. This includes lollipops, bubble-gum, and cough drops.
Nonwoven fabric mills	Industries involved with manufacturing nonwoven fabric. This can involve bonding and interlocking fibres.
Offices of physicians, dentists, and other health practitioners	Industries offering health practitioner services.
Other non-residential structures	Industries involved with the construction of non-residential buildings.
Other rubber product manufacturing	Industries involved with manufacturing rubber products such as balloons and floor mats.
Other support services	Industries involved with providing business and other organisational support services including bartering services and lumber grading services.
Paint and coating manufacturing	Industries involved with mixing paints and other coatings, and manufacturing related paint products.
Photographic and photocopying equipment manufacturing	Industries involved with manufacturing photographic and photocopying equipment, projectors, film developing equipment, and photocopying equipment.

Printing	Industries involved with printing and binding. This includes the creation of books and pamphlets.
Reconstituted wood product manufacturing	Industries involved with manufacturing wood sheets and boards. This includes fibreboard and waferboard.
Residential permanent site single- and multi-family structures	Industries involved with construction and services of residential-permanent site single- and multi-family structures.
Retail trade	Industries involved with the retail sale of goods and services.
Scrap	Industries involved with assembling, breaking up, and sorting of scrap.
Seasoning and dressing manufacturing	Industries involved with making salad dressings, relishes, sauces, and seasonings.
Snack food manufacturing	Industries involved with manufacturing snack foods such as popcorn, potato chips and crackers.
Small electrical appliance manufacturing	Industries involved with manufacturing small electric appliances and housewares. This includes fans and vacuum cleaners.
Soap and cleaning compound manufacturing	Industries involved with manufacturing soaps and detergents. This includes laundry and dishwashing detergents, and toothpaste.
Soft drink and ice manufacturing	Industries involved with manufacturing soft drinks, sparkling water, and ice.
Sporting and athletic goods manufacturing	Industries involved with manufacturing sporting and athletic goods. This includes archery equipment, athletic goods, golf equipment, and footballs.
Surgical appliance and supplies manufacturing	Industries involved with manufacturing surgical appliances and supplies. This includes orthopaedic devices, crutches, and surgical dressings.

Textile and fabric finishing mills	Industries involved with finishing textiles, fabrics, and apparel. This can include bleaching, dyeing, and printing.
Textile bag and canvas mills	Industries involved with manufacturing textile bags, awnings, sails, and tents.
Tire manufacturing	Industries involved with manufacturing tires and inner tubes.
Toilet preparation manufacturing	Industries involved with manufacturing toilet products. This includes perfumes, shaving products, hair products, and face creams.
Upholstered household furniture manufacturing	Industries involved with manufacturing upholstered household furniture. This includes sofas and seats.
Used and second-hand goods	Industries involved with selling antiques, and second-hand goods. This includes books, clothing and sporting goods.
Wholesale trade	Industries involved with the wholesale distribution of goods.

4. Prelude to Making a Material Difference: The Impacts of a Change to Plastic Free Clothing

The second manuscript in this thesis expands upon the first by estimating the potential economic and land use change impacts from a plastic clothing tax. I do this by designing a bespoke CGE model which represents the conventional clothing sector, a plastics and synthetic chemical free clothing sector, and land use change. This is motivated by the United Nations (UN) endorsing a resolution to end plastic pollution, with an aim to have a legally binding agreement in place by 2024 (UN, 2022; HAC, 2023). Along with more traditional plastic pollution, plastic clothing also pollutes waterways from microfibres released from the washing of clothes (Browne et al., 2011). Therefore, for clothing to meet the UN's resolution, it needs to be made without plastic or synthetic chemicals.

Conventional clothing in the model is based on the clothing sector represented in version 11 of the GTAP database (Aguiar et al., 2022) which uses a mix of plastic, natural, and chemical inputs. To represent plastic and synthetic chemical free clothing, I create a clothing sector which uses agricultural alternatives rather than plastic and chemical inputs. I also use retail prices to estimate the production cost increases from using agricultural alternatives compared to conventional clothing.

5. Making a Material Difference: The Impacts of a Change to Plastic Free Clothing

Abstract

In 2022, the United Nations (UN) endorsed a resolution to end plastic pollution, with an objective to have a legally binding agreement in place by 2024 (UN, 2022; HAC, 2023). The clothing industry uses a significant amount of plastic which generates plastic pollution both through the mismanagement of clothing waste and microplastics released during the washing of clothes (Browne et. al, 2011). Consequently, clothing needs to be made without plastic fibres or synthetic chemicals to comply with the UN's resolution and stop contributing to plastic pollution. In this paper, we develop an economy-wide model and impose a tax on the conventional clothing sector in different regions until all clothing produced is free of plastics and synthetic chemicals. We analyse the impact of this change on GDP, welfare, output, and land use across three policy scenarios. If only some regions tax clothing production and not others, the production of conventional clothing increases in untaxed regions (i.e. there is conventional clothing 'leakage'). As clothing producers import some of their plastic inputs, increased production of conventional clothing in untaxed regions dampens the reduction in plastic production in regions with a clothing tax. Additionally, synthetic chemical and plastic free clothing production increases global demand for 'natural' alternatives such as plant-based fibres, oil seeds, natural rubber, and forestry products. This causes significant land use change in the model at the expense of food-based agricultural products.

5.1 Introduction

Plastic use is common across industries and continues to increase worldwide, with a cumulative 8300 million metric tonnes (Mt) of plastic estimated to have been produced by 2015 (Geyer, Jambeck & Law, 2017). Around 6300 Mt of this plastic has been incinerated, put in landfills, recycled, or exists as pollution in the environment (Geyer, Jambeck & Law, 2017). In 2010, approximately 4.8 to 12.7 Mt of plastic waste entered the ocean, with that number expected to rise over time (Jambeck et al., 2015). Plastic pollution has adverse effects on the natural environment such as ecosystem degradation from suffocation, dispersal, and starvation of plant and animal species. Consequently, there are also negative socio-economic impacts including the reduced productivity of fisheries, decreased tourism, and negative human health effects (Thushari & Senevirathna, 2020). Lau et al. (2020) used a Plastics-to-Ocean model to estimate the feasibility of policies to reduce plastic pollution. They found that 78 percent of plastic pollution can be reduced by 2040 with existing technologies, but it requires global cooperation to be achieved. A report by the OECD (2022a) found that if action is not taken, the use of plastics and production of plastic waste could triple by 2060. As recognition of this growing problem, in 2022, the United Nations (UN) endorsed a resolution to end plastic pollution, with an objective to have a legally binding agreement in place by 2024 (UN, 2022; HAC, 2023).

The clothing industry uses a large quantity of plastics both directly and indirectly via its use of intermediate inputs containing plastics such as textiles (White & Winchester, 2022). One of the main sources of plastic in clothing and textiles is plastic fibres such as polyester and polyamide (Textile Exchange, 2022). Synthetic chemicals are also used as an input, many of which are made using petrochemicals, plastics, and other toxins (HSE, 2016; Slama et al., 2021). This means that biodegradable fibres coated in synthetic chemicals (such as dyes) will have a similar impact as plastic fibres if they are released into the environment.

A unique form of plastic pollution from clothing is the microplastics released into waterways from the washing of clothes (Browne et al., 2011; Cai et al., 2020; Dalla Fontana, Mossotti & Montarsolo, 2020; Choi et al., 2021). It has been estimated by Browne et al. (2011) that in an average wash a single garment can produce over 1900 fibres and a number of these fibres reach waterways due to insufficient filters in sewerage systems. This is an example of non-point source pollution as it originates from many different sources and is difficult to manage (EPA, 2023). Consequently, clothing made with either plastic fibres or synthetic chemicals is likely to contribute to environmental pollution. To align with the UN's resolution to end plastic pollution, countries will have to make clothing without plastic fibres or synthetic chemicals (hereafter referred to as clean clothing).

There has been a significant amount of research on the environmental impacts of conventional clothing inputs and fast fashion (Kant, 2012; Dahlbo et al., 2017; Zamani, Sandin & Peters, 2017; Bick, Halsey & Ekenga, 2018; Niinimäki et al., 2020; Bailey, Basu & Sharma, 2022) as well as the potential benefits and costs associated with large scale production shifts towards biodegradable fibres and chemicals (Remy, Speelman & Swartz, 2016; Karimah et al., 2021; Palacios-Mateo, van der Meer & Seide, 2021; Sk et al., 2021; Pizzicato et al., 2023). There are some common themes and conclusions throughout this literature, including the potential high cost and seasonality of some biodegradable alternatives, the range of new technologies being developed in this space, and the benefits to clothing from using all 'natural' products.

Input-output datasets have been used to understand the interactions between plastic use, plastic waste, and the wider economy (Nakamura, 1999; Nakamura & Kondo, 2002a-b; Nakamura et al., 2007; Lenzen & Reynolds, 2014; Fry et al., 2015; Pomponi et al., 2022; White & Winchester, 2022). Economy-wide modelling has also been used to estimate the impacts of bioplastics (Escobar et al., 2018; Escobar & Britz, 2021), plastic waste management policies (Sjöström & Östblom, 2010; Freire-González, Martinez-Sanchez & Puig-Ventosa, 2022; Shih et al., 2024), and the impacts of potential widespread plastic policies (OECD 2022a-c; OECD 2023). To our knowledge, there has not been any economy-wide research into a shift in production to clean clothing or its potential impacts on land use change.

To examine the broader economic and environmental consequences of a policy on plastic clothing, we develop a global computable general equilibrium (CGE) model to estimate the impacts of a switch to clean clothing on GDP, welfare, output, and land use in different regions. In this model, both the conventional clothing sector and a clean clothing sector are represented in each region. In the policy scenarios, the conventional clothing sector is taxed in specific regions until all clothing produced in those regions is clean clothing. The plastic fibre and synthetic chemical alternatives included for the clean clothing sector are based on technologies/inputs which are already available and are almost exclusively agricultural products.

Our analysis indicates that if only some regions switch to clean clothing and not others there is clothing 'leakage'. This refers to an increase in conventional clothing output in regions not taxed due to the higher production costs of clean clothing. This causes changes in the trade of clothing, with untaxed regions increasing clothing exports. Under the scenario where the EU introduces a clothing tax, plastic production in the EU increases. This is driven, in part, by the high plastic intensity (plastic inputs as a proportion of output) in clothing and textile sectors outside of the EU. Accordingly, increased production of clothing in these untaxed regions increases exports of plastic from the EU.

Taxing conventional clothing also leads to an increase in the production of agricultural products such as plant-based fibres, natural rubber, oleaginous fruit, nuts, hides, and lumber. This leads to land use change in the model, with an increase in plastic and chemical alternatives resulting in a reduction in the land used for food related agricultural products such as vegetables, oats, barley, and raw milk.

This paper has three further sections. Section 5.2 provides an overview of clothing, textile, and chemical production. Section 5.3 describes the methods used for this analysis. Section 5.4 presents and discusses the results. Section 5.5 offers a discussion and some concluding remarks.

5.2 Clothing, Textile, and Chemical Production

Conventional clothing production uses plastic and synthetic chemical inputs through three main channels: (1) the direct use of plastic fibres and other plastic products, (2) the direct use of synthetic chemicals, and (3) the use of textiles that contain plastics and synthetic chemicals. Clean clothing needs to exclusively use both biodegradable (here after referred to as 'natural') fibre and chemical inputs. Available 'natural' input alternatives to plastics and synthetic chemicals and how they are made are discussed below.

5.2.1 Clothing and textile fibres

The Textile Exchange (2022) describes the products and materials used in the textiles sector in 2021 and 2022. Textiles are one of the main inputs for the clothing industry (Palacios-Mateo, van der Meer & Seide, 2021) so this report also provides information on the products and materials used to make clothing.

It reports that plastic and other synthetic fibres (e.g. polyester and polyamide) account for approximately 72.2 percent of global fibre production, with the rest being 'natural' alternatives. These alternatives include man-made cellulosic fibres, plant-based fibres, natural rubber, animal fibres, processed animal products, manmade non-fibre materials, biobased polyamide, manmade protein fibres, and CO_2-based fibres.

Man-made cellulosic fibres are created from crop and forestry products which are combined with water and chemicals in an energy intensive process (Seisl & Hengstmann, 2021; Hugill, Ley & Rademan, 2020). The main inputs into this process are from the pulp industry but it can also use raw biomass inputs from crops and forestry. Plant-based fibres include inputs from crops such as cotton, flax, bamboo, hemp, jute, coir, sisal, abaca, kapok, ramie, agave, rice, wheat, and sugar cane. Animal fibres include feather and down, sheep wool, mohair, cashmere, alpaca fibre, silk, and other animal hair. Processed animal products include leathers and other animal hides. Manmade non-fibre materials include products made from mycelium and other fungi, bamboo, cork, natural rubber, cactus, pineapple leaves, coconut, corn, grapes, and other biomass from crops. Biobased polyamide is a 'natural' alternative to polyamide and includes products made from castor oil, agricultural waste, and cotton. Manmade protein fibres are biobased fibres which are made from products such as sugar, water, salts, yeast, milk (Belkhir et al., 2021), sugarcane, corn, silk, and other plant biomass. CO_2-based fibres capture carbon dioxide from the atmosphere and use the carbon to create textiles, with this production able to substitute for polyester, manmade cellulosic fibres, and other fibres for textiles.

This information from Textile Exchange (2022) shows that most of the ‘natural’ alternatives to plastic fibres are made from raw or processed agricultural products and many of them are already used in the textile and clothing industries.

5.2.2 Chemicals

Chemicals are used in the clothing industry for the treatment, production and finishing of textiles (Lacasse & Baumann, 2004). Synthetic chemicals are used extensively and are typically made with petrochemical compounds and other environmentally damaging toxins (HSE, 2016; Slama et al., 2021). These chemicals are not all strictly plastic products, but they are made from the same or similar compounds as plastic. This means that any textiles or clothing made using synthetic chemicals could contribute to environmental pollution even if they are made with ‘natural’ fibres.

In this research, we use dyes in clothing as a representation of chemicals, and we estimate the products and costs required for them to be made from ‘natural’ materials. We focus on dyes due to their high frequency use in clothing and textiles and because of the high proportion of dyes which are synthetic (Hassaan & El Nemr, 2017). Approximately 10,000 dyes and pigments are used in the textile industry (Bharathi & Ramesh, 2013), and 800,000 tons of synthetic dyes are produced every year (Jamee & Siddque, 2019).

When considering alternatives to synthetic dyes, we only look at traditional processes due to the lack of large-scale uptake of new technology ‘natural’ dyes and uncertainties around production processes and costs. As described by Pizzicato et al. (2023), the traditional production of ‘natural’ dyes involves the use of animal (e.g. beetles and molluscs), plant (e.g. bark, roots, flowers, and leaves), microbe, or mineral (e.g. ochre) products. We do not consider microbes or minerals as ‘natural’ alternatives in this research as most ‘natural’ dyes come from plant products (Pizzicato et al., 2023) and we assume there are adequate plant or animal alternatives to these dyes.

An issue with dying clothes with ‘natural’ products is the inconsistent colour and spread of the dye due to difficulties fusing the dyes with textile and clothing fibres (Pizzicato et al., 2023). This often means that other processes or chemicals such as mordants need to be used to allow for an adequate level of bonding between the textiles and the dye. To account for this, and based on information from Palacios-Mateo, van der Meer & Seide (2021) and Sk et al. (2021), we assume that bonding procedures for ‘natural’ dyes require higher capital and labour costs than processes that use traditional chemicals.

Therefore, the ‘natural’ substitutes for synthetic chemicals in clothing are mainly sourced from raw or processed agricultural products, just like ‘natural’ fibres. However, while there is already a relatively high use of ‘natural’ fibres in the clothing industry (Textile Exchange, 2022), ‘natural’ chemicals are only a small segment of the market (Pizzicato et al., 2023).

5.3 Methodology

To understand the economic and land use impacts of a switch to clean clothing in different regions, we develop and deploy a bespoke CGE model. The model includes both a conventional clothing sector that uses plastics and synthetic chemicals (as represented in the base data) and a clean clothing sector, which is represented as a new technology. In the scenarios simulated in the model, a tax on the conventional clothing sector is endogenously chosen in different regions until all clothing produced in those taxed regions is clean. Salient modelling decisions, which are detailed below, include which regions to represent in the model and where to impose the tax, how to represent land use change, and how to calibrate inputs and production costs for the clean clothing sector. The remainder of this section is split into (1) an overview of the CGE model, (2) the calibration of the clean clothing and textile sectors, (3) a description of land use change in the model, and (4) a description of the policy scenarios simulated in the model.

5.3.1 The CGE model

The CGE model developed for this research is a global multisector, multi-region static model that builds on the core model set out by Lanz & Rutherford (2016)[1], which is a simplified version of the Global Trade Analysis Project (GTAP) model (Corong et al., 2018; van der Mensbrugghe, 2018). Key additions to the model, which are detailed below, include new technologies for producing clean clothing and textiles, and land use change. The model is calibrated using version 11 of the GTAP Data Base (Aguiar et al., 2022). It is written using the Mathematical Programming System for General Equilibrium (MPSGE) (Rutherford, 1999), which operates as a subsystem within the General Algebraic Modeling System (GAMS).

In each region, the model is structured into sectors and a representative agent for consumption, government expenditure and investment. Each sector in the model produces output from purchases of intermediate inputs from other sectors and by hiring primary factors (labour, capital, natural resources, and land). The representative agent in each region generates income from selling factor services, the net revenue from taxes and subsidies, and an exogenous net international transfer which represents the current account balance. International trade in the model follows an Armington specification (Armington, 1969) and assumes that goods produced in different regions are imperfect substitutes.

There are five regions represented in the model: the EU, China, other OECD countries, other clothing producers, and the rest of the world. These regions are selected either because they are more likely to introduce plastic policies, such as the EU and other OECD countries (OECD, 2022a; OECD, 2022b; and OECD, 2023), or they are large clothing manufacturers such as China and other clothing producers (Sabanoglu, 2024). The countries included in each region are described in Table 5.1.

[1] The algebraic description of the model by Lanz & Rutherford (2016), is the same as the base model used in this paper.

Table 5.1: Regions represented in the model.

Region in the Model	Countries and Regions Included
European Union (EU)	Austria, Belgium, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Norway, Romania, and the Rest of the European Free Trade Association.
China	China
Other OECD countries	Australia, New Zealand, Japan, Republic of Korea, Canada, Mexico, Chile, Colombia, Costa Rica, United States of America, United Kingdom, Switzerland, Israel, and Turkey.
Other Clothing Producers*	Bangladesh, Vietnam, India, Indonesia, Cambodia, Pakistan, and Sri Lanka.
Rest of the world (ROW)	All other countries/regions.

* This selection of regions is based on information from Sabanoglu (2024).

The model includes 48 sectors from the GTAP database along with new technologies for clean clothing and clean textiles to give a total of 50 sectors. Table 5.2 displays the sectors related to clothing and textile production, grouped into clothing and textiles, plastics and chemicals, plastic alternatives, chemical alternatives, other agriculture, and other industries. The rest of the economy is represented by 27 other industries, which are detailed in Appendix Table A5.1. The conventional clothing and textiles sectors include inputs of plastics products (referred to as rubber and plastics products in the GTAP database) and chemical products. The clean clothing and textile sectors include inputs of plastic alternatives and chemical alternatives instead of plastic and chemical products respectively. The sectors chosen as plastic alternatives are based on information from the Textile Exchange (2022) and chemical alternatives are based on Pizzicato et al. (2023) and Botanical Colors (2023a). All chemical alternatives are also plastic alternatives but not vice versa.

Table 5.2: Model sectors related to clothing and textiles.

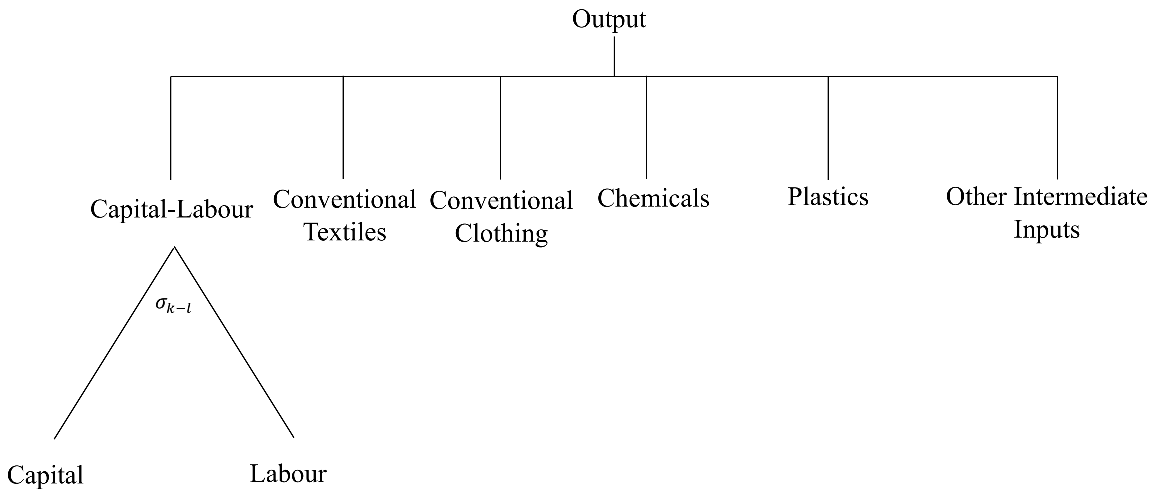
Sector Name	Sector Abbreviation
Clothing and Textiles	
Conventional Clothing	wap
Clean Clothing	wap_1
Conventional Textiles	tex
Clean Textiles	tex_1
Plastics and Chemicals	
Plastics Products	rpp
Chemical Products	chm
Plastic Alternatives	
Paddy Rice	pdr
Wheat	wht
Other Grains	gro
Cane and Beet	c_b
Plant-based fibres	pfb
Raw Milk	rmk
Wool and Silk	wol
Vegetables and Fruit	v_f
Oil Seeds	osd
Other Crops	ocr
Other Animal Products	oap
Lumber	lum
Leather Manufacturing	lea
Pulp and Paper Products	ppp
Chemical Alternatives	
Vegetables and Fruit	v_f
Oil Seeds	osd
Other Crops	ocr
Other Animal Products	oap
Lumber	lum
Other Agriculture	
Fishing	fsh
Cattle	ctl
Forestry	frs

The production structure used by both the conventional clothing sector and the conventional textile sector is displayed in Figure 5.1. These goods are produced by combining capital and labour in a constant elasticity of substitution (CES) nest, which is then combined with intermediate inputs in a Leontief nest. The conventional clothing sector uses plastics via inputs of plastic products, and conventional textiles (which are produced from plastic products, and chemicals) and it uses synthetic chemicals via inputs of chemical products. Both sectors also use within-sector intermediate inputs (e.g., the conventional clothing sector uses inputs of conventional clothing).

When representing clean clothing, we replace inputs of plastics, textiles, and synthetic chemicals with biodegradable alternatives. As the clothing sector uses a significant amount of textile inputs (Palacios-Mateo, van der Meer & Seide, 2021), the model also explicitly represents a clean textile sector.

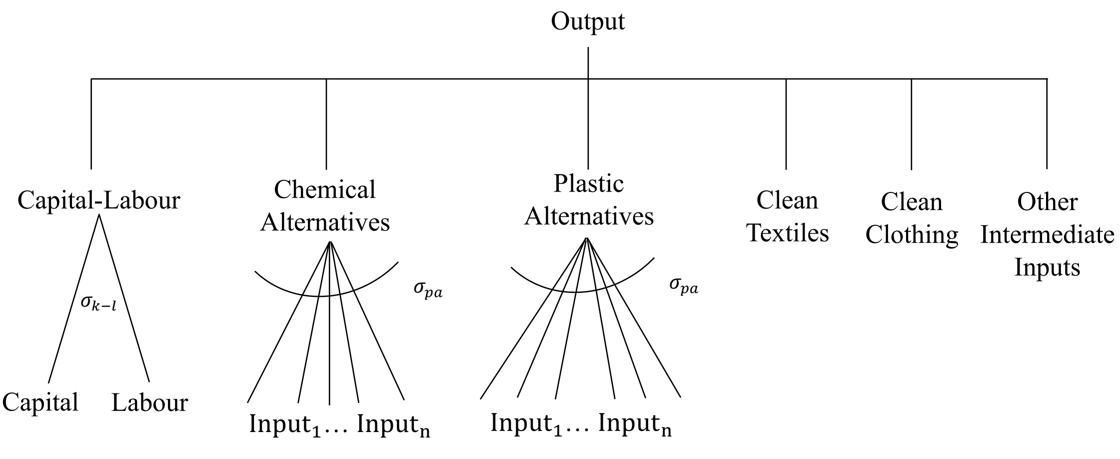
The production structure for the clean clothing and textiles sectors is described in Figure 5.2. A key difference relative to the conventional sectors is that inputs of plastics and chemicals are replaced by ‘natural’ fibres and an alternative chemicals composite. ‘Natural’ fibres and ‘natural’ chemicals are aggregated in separate CES functions to allow for the clean clothing and textile industries to have flexibility in the agricultural alternatives they use as inputs. Additionally, in the clean sectors, clothing and textile inputs are replaced by inputs of clean clothing and clean textiles. Clean clothing is a perfect substitute for conventional clothing in the model. The clean clothing and clean textile sectors are not included in the benchmark data but are included as backstop/new technologies. The calibration of these technologies is described below.

Figure 5.1: Production nest for conventional clothing and textiles.



Note: Vertical lines in an input nest represent a Leontief production structure where the elasticity of substitution is zero, and σ_{k-l} represents the sector specific elasticity of substitution between capital and labour.

Figure 5.2: Production nest for clean clothing and clean textiles.[2]



Note: Vertical lines in an input nest represent a Leontief production structure where the elasticity of substitution is zero, σ_{k-l} represents the sector specific elasticity of substitution between capital and labour, and σ_{pa} represents the elasticity of substitution between plastic and chemical alternatives and takes values of 0, 0.5, or 1.

[2] All other production nests for the model can be seen in Appendix Figures A5.1-5.4.

5.3.2 Calibration of clean clothing and textile sectors

Clean clothing and textiles are produced using different inputs to conventional clothing and textiles and are more costly to produce than their conventional counterparts (Palacios-Mateo, van der Meer & Seide, 2021; Sk et al., 2021). Input costs for conventional sectors are sourced from the GTAP Database. The clean sectors are based on the conventional sectors but do not use inputs of plastics or conventional chemicals (as noted above). The value of plastics from the conventional sectors is allocated between plastic alternatives in the clean sectors and the value of chemicals is split between chemical alternatives, labour, and capital. A key component of the calibration is the additional costs from making clothes and textiles with 'natural' fibres and 'natural' chemicals compared to the current mix of inputs. Based on several data sources (described below), the additional production cost from using 'natural' fibres is distributed across all inputs and the additional cost from 'natural' chemicals is distributed between chemical alternatives, capital, and labour.

To calculate the production cost increases for 'natural' fibres and 'natural' chemicals, we use retail prices on the basis prices reflect production costs in competitive markets.[3] For the production cost increases of 'natural' fibres, we use online prices from a fabric retailer (Spotlight, 2023a) and a leather retailer (New Zealand Leather Suppliers, 2023), along with information on global fibre use (Textile Exchange, 2022). To calculate the production cost increase for 'natural' chemicals, we use information from both 'natural' and synthetic dye retailers (Botanical Colors, 2023a; Botanical Colors, 2023b; Rit, 2023; Spotlight, 2023b). We estimate, for both clean textiles and clothing, that using 'natural' fibres results in a 3 percent total production cost increase compared to the conventional mix of fibres and using 'natural' chemicals results in a 90 percent cost increase for chemical inputs compared to the current mix of chemicals. More details on how we calculate these values are provided in Appendix B.

Equations (5.1) to (5.3) describe how these production cost increases are applied in the clean clothing sectors to estimate the value of plastic alternative inputs, chemical alternative inputs, and factor inputs respectively. Analogous equations are used for the clean textile sector and these calculations are implemented separately for each region.

[3] The relationship between prices and production costs have been widely discussed and it is clear that production costs have important role in dictating price (Karrenbrock, 1991; Neumark & Sharpe, 1992; Borenstein, Cameron & Gilbert, 1997; Jackson, 1997; Peltzman, 2000). Some research shows that market power, more than production costs, influence price differences (Hall 1988; Steenkamp, 1988; Klette, 2003; De Loecker & Warzynski, 2012; Raval, 2023). However, given that the majority of prices we use in our analysis are from products sold by the same company, we believe they are a reasonable predictor of input cost differences rather than market power. We also weight the prices of fibres using information from the Textile Exchange (2022) report which reduces the impact of price outliers on cost increases.

Equation (5.1) shows how the input values for plastic alternatives, x_i^*, used in the clean clothing and textiles sectors are calculated:

$$x_i^* = x_i + \delta_i^A P + \delta_i^T NC \qquad (5.1)$$

Where x_i is the value of plastic alternative *i* used in conventional clothing production, δ_i^A is the proportion of costs for plastic alternative *i* in total plastic alternatives for the conventional clothing sector, *P* is the value of plastic inputs in the conventional clothing sector, δ_i^T is the share of plastic alternative *i* in total costs (excluding plastics and chemicals) for the conventional clothing sector, N is the cost increase for replacing plastics with 'natural' fibres (0.03), and C is the total cost of conventional clothing production.

Equation (5.2) shows how the values of chemical alternative inputs in the clean clothing sector are calculated. Two key assumptions in the equation are that (1) the total cost increase for producing alternative chemicals is split evenly between (aggregate) alternative chemical inputs and capital-labour, and (2) the costs increase for conventional chemicals intermediate inputs is split evenly between the five chemical alternative inputs.[4] In the clean clothing sector, the cost of chemical alternative *z* (x_z^*) is:

$$x_z^* = \frac{1}{2}\delta_z^B \mathrm{H} + \frac{1}{2}\delta_z^B \mathrm{H}D \qquad (5.2)$$

Where *H* is the value of chemical inputs used in conventional clothing production, δ_z^B is the cost share of chemical alternative *z* in total alternative chemical costs (equal to 0.2 as there are five chemical alternatives), and *D* is the cost increase for replacing chemical inputs with 'natural' chemicals (0.90).

Equation (5.3) describes how the values of factor inputs for clean sectors, x_f^*, are calculated:

$$x_f^* = x_f + \delta_f^T NC + \frac{1}{2}\delta_f^E \mathrm{H} + \frac{1}{2}\delta_f^E \mathrm{H}D \qquad (5.3)$$

Where x_f is the value of factor *f* as an input into the conventional clothing sector, δ_f^T is the proportion of total costs (excluding plastics and chemicals) factor *f* accounts for in conventional clothing production, and δ_f^E is the proportion of total factor input costs *f* represents in the conventional clothing sector.

The costs of other intermediate inputs (excluding plastics and chemicals) are calculated by adjusting the production structures of the conventional sectors by adding the 'natural' fibres production cost increase (0.03).

[4] The even distribution of the value and markup of chemical inputs between the five chemical alternatives is based on an assumption that 'natural' dyes will require equal inputs of different agricultural products for each colour.

Table 5.3 illustrates initial input costs for both conventional and clean clothing and textile sectors in the EU. It shows that the greatest increase in input costs for clean sectors, relative to the conventional sectors, is for chemical alternatives. As shown in Figure 5.2, chemical alternatives enter in a separate CES nest which includes vegetables and fruits, oil seeds, lumber, other animal products, and other crops. All chemical alternatives are also plastic alternatives and there is a relatively high value of chemicals from the conventional sectors split between a small pool of agricultural products. This means they experience greater input cost increases compared to products which are only plastic alternatives. For example, the increase in costs for vegetables and fruits (which are plastic and chemical alternatives) for clean sectors is greater than the cost increase for wheat or paddy rice.

Table 5.3: Intermediate and factor inputs costs for conventional and clean clothing and textiles in the EU (cost per 1000 USD of output).

Inputs	**Conventional Clothing**	**Clean Clothing**	**Conventional Textiles**	**Clean Textiles**
		Plastic Alternatives		
Paddy Rice	0.005	0.006	0.003	0.003
Wheat	0.017	0.020	0.019	0.022
Other Grains	0.037	0.043	0.041	0.046
Cane and Beet	0.002	0.002	0.002	0.002
Plant-based fibres	0.054	0.063	1.270	1.408
Raw Milk	0.053	0.062	0.045	0.050
Wool and Silk	0.032	0.038	0.830	0.920
Leather Manufacturing	16.445	19.322	4.293	4.759
Pulp and Paper Products	18.816	22.108	20.283	22.486
		Plastic and Chemical Alternatives		
Vegetables and Fruit	0.057	3.463	0.195	25.227
Oil Seeds	0.068	3.476	0.205	25.238
Other Crops	0.774	4.306	3.542	28.937
Other Animal Products	0.099	3.514	0.104	25.125
Lumber	1.144	4.741	2.516	27.800
		Plastics and Chemicals		
Chemical Products	17.866	0	131.497	0
Rubber and Plastic Products	5.436	0	2.455	0
		Other Intermediate Inputs		
All Other Intermediate Inputs	660.304	680.366	545.252	564.310
		Factor Inputs		
Labour	164.250	181.863	167.114	264.370
Capital	114.542	126.825	120.332	190.361
Total	1000	1050.219	1000	1181.065

Note: input values in this table include ad valorum taxes.

The value of inputs for clean sectors in different regions is dependent on the value of plastic and chemical inputs in the conventional sectors. For selected sectors, Table 5.4 reports total plastic intensity (the value of direct and indirect plastic inputs per dollar of output), and direct chemical intensity (the value of direct chemical inputs per dollar of output) for each region.[5] China has the highest plastic intensity for conventional textiles (0.036) and conventional clothing (0.066). Sectors (other than plastics) have lower plastic intensities than textiles and clothing in all regions, other than the EU and the Rest of the World (ROW). Other OECD countries (0.153) and China (0.026) have the highest direct chemical intensity for conventional textiles and conventional clothing respectively. This translates to unique regional production cost increases for clean sectors. The lowest increases occur in China for textiles and in the ROW for clothing with 7.36 and 4.39 percent increases respectively (Table 5.4). The highest markup occurs in other OECD countries for textiles (17.47 percent) and in China for clothing (5.34 percent). When incorporating the cost increase for clean textiles, the production cost increase for clean clothing equates to 8.42, 8.50, 9.98, 8.10, and 7.99 percent for the EU, China, other OECD countries, other clothing producers, and the ROW respectively.[6]

Table 5.4: Plastic and chemical intensities by sector and production cost increases for clean textiles and clothing.

Region	Textiles	Clothing	Other Sectors*
Total Plastic Intensity for Conventional Sectors			
EU	0.016	0.021	0.022
China	0.036	0.066	0.034
Other OECD Countries	0.026	0.024	0.018
Other Clothing Producers	0.032	0.027	0.018
ROW	0.015	0.018	0.019
Direct Chemical Intensity for Conventional Sectors			
EU	0.131	0.018	0.010
China	0.049	0.026	0.023
Other OECD Countries	0.153	0.018	0.011
Other Clothing Producers	0.097	0.018	0.019
ROW	0.091	0.015	0.013
Production Cost Increase for Clean Sectors			
EU	15.56%	4.67%	-
China	7.36%	5.34%	-
Other OECD Countries	17.47%	4.66%	-
Other Clothing Producers	11.75%	4.58%	-
ROW	11.34%	4.39%	-

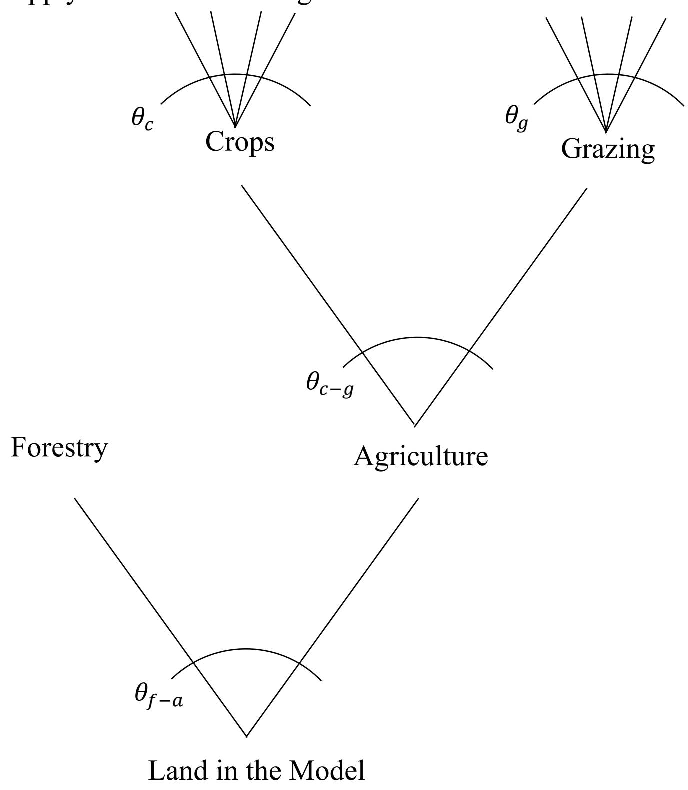
Note: production cost increases are calculated excluding ad valorum taxes.
*Calculations for other regions are a weighted average of all sectors other than clothing, textiles, plastics (for plastic intensities), and chemicals (for chemical intensities).

[5] For details on how we determined these values, please see Appendix C.
[6] These values are calculated by incorporating a weighted cost increase from clean textiles in clean clothing production.

5.3.3 Land use change

Land use change is represented in the model using the same elasticity of transformation structure as the GTAP Agro-Ecological Zone (GTAP-AEZ) model (Hertel et al., 2008), which is illustrated in Figure 5.3. This approach uses a constant elasticity of transformation structure with land use split into forestry and agriculture, and agriculture further split into cropland and grazing. Cropland in the model includes land for paddy rice, wheat, vegetables and fruit, oil seeds, cane and beet, plant-based fibres, other grains, and other crops. Grazing includes cattle, raw milk, wool and silk, and other animal products. The elasticity of transformation is -0.25 between forestry and agriculture, -0.5 between grazing land and crops, and -1 between crops and between grazing land. This approach allows for easier land transformations between similar land uses compared to dissimilar land uses. For example, it is more difficult for land to switch between forestry and agriculture, and grazing and cropland, than it is between different crops and between different grazing animals.

Figure 5.3: Land supply and land use change structure in the model.



Note: θ_c, θ_g, θ_{c-g}, and θ_{f-a} represent the elasticity of transformation between crops, grazing animals, crops and grazing animals, and forestry and agriculture respectively.

5.3.4 Modelling scenarios

Three policy scenarios are considered in the analysis. The scenarios tax the output of the conventional clothing sector until all clothing production is from the (new) clean clothing sector in the taxed region(s). In each region, the minimum value of the ad valorem tax is determined endogenously so that output from the conventional clothing sector is zero. The scenarios include (1) an EU clothing tax, (2) clothing taxes in the EU, China, and other OECD countries (hereafter referred to as the EU-China-OECD scenario), and (3) clothing taxes in all regions.

5.4 Results and Discussion

This section reports results from the three scenarios in the CGE model. This includes the impacts of conventional clothing taxes on GDP and welfare (Table 5.5); the output from individual sectors such as clothing and textiles (Table 5.6 and Figure 5.4), plastics (Figure 5.5), and alternatives to chemicals and plastics (Figure 5.6); as well as land use change (Figure 5.7 and 2.8). The results for each scenario are analyzed in separate sub-sections. The results shown are from the model structure where the CES between plastic and chemical alternatives is 0.5.[7]

Table 5.5: Percentage change in GDP, welfare, and clothing tax rates in each region relative to the benchmark.

Region	Scenario	Clothing Tax (%)	Welfare (% change from the benchmark)	GDP (% change from the benchmark)
EU	EU Tax	10.63	-0.17	-0.17
	EU, China, and OECD Tax	10.18	-0.24	-0.23
	All Regions Tax	9.77	-0.28	-0.27
China	EU Tax	-	0.02	0.02
	EU, China, and OECD Tax	10.53	-0.36	-0.35
	All Regions Tax	10.55	-0.35	-0.35
Other OECD	EU Tax	-	-0.01	-0.01
	EU, China, and OECD Tax	11.31	-0.10	-0.10
	All Regions Tax	11.10	-0.13	-0.14
Other Clothing Regions	EU Tax	-	0.04	0.05
	EU, China, and OECD Tax	-	0.18	0.23
	All Regions Tax	8.52	-0.02	0.00
ROW	EU Tax	-	-0.01	-0.01
	EU, China, and OECD Tax	-	-0.04	-0.05
	All Regions Tax	8.64	-0.23	-0.23

* Welfare in this model is defined as the Hicksian Equivalent Variation in income for consumption, investment, and the government.

5.4.1 The EU clothing tax

In the scenario where the EU is the only region to introduce a tax on conventional clothing, the tax rate determined by the model is 10.63 percent (Table 5.5). The tax has a negative impact on GDP and welfare in the EU; a positive impact in China and other clothing producers; and a negative impact in other regions. This result is caused by clothing 'leakage' which refers to changes in global clothing production. The higher cost of clean clothing incentivises regions with no clothing tax in place to increase clothing production and shift resources from other manufacturing sectors into the clothing sector. Regions with a clothing tax in place are incentivised to do the opposite. These changes benefit the untaxed regions where clothing is produced cheaply and in large quantities in the benchmark.

[7] We examine the sensitivity of the results to alternative values for this parameter in section 5.4.4.

Clothing leakage in the EU tax scenario can be seen in Table 5.6 and Figure 5.4. In the EU, the real change in clothing production (33 percent relative to the benchmark) and value change in exports (44 percent relative to the benchmark) decrease. All other regions increase clothing production. In China, for example, total clothing increases by 3.3 percent from the benchmark under the EU tax (Table 5.6). Reflecting production changes, China, other OECD regions, other clothing producers, and the ROW increase clothing exports by, respectively, 8, 13, 10 and 11 percent relative to the benchmark (Figure 5.4). This suggests that if the EU (or any other region) intends to introduce a unilateral tax on clothing, it should consider additional policy measures to avoid domestic plastic pollution gains being partially cancelled out by increases in clothing production in other countries. The model estimates 90 percent of the reduction in EU clothing is captured by clothing leakage.

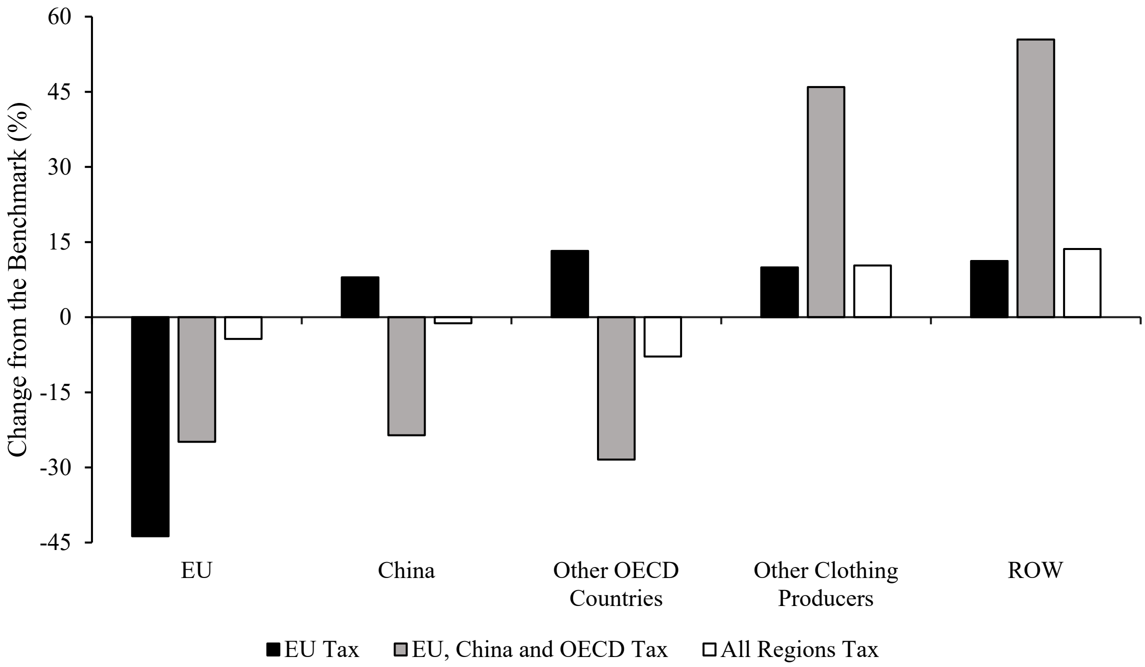
Table 5.6: Real clothing and textile output in each region and scenario, billions of USD.

Region	Scenario	Conventional Clothing	Clean Clothing	Total Clothing	Conventional Textiles	Clean Textiles*	Total Textiles
EU	Benchmark	136.1	0	136.1	154.8	0	154.8
	EU Tax	0	90.9	90.9	129.9	28.6	158.5
	EU, China, and OECD Tax	0	113.6	113.6	126.3	35.8	162.0
	All Regions Tax	0	138.1	138.1	121.2	43.5	164.7
China	Benchmark	446.4	0	446.4	699.5	0	699.5
	EU Tax	461.0	0	461.0	707.0	0	707.0
	EU, China, and OECD Tax	0	379.5	379.5	374.1	317.1	691.1
	All Regions Tax	0	416.2	416.2	329.5	347.7	677.1
Other OECD Countries	Benchmark	133.4	0	133.4	185.2	0	185.2
	EU Tax	141.1	0	141.1	185.3	0	185.3
	EU, China, and OECD Tax	0	106.8	106.8	152.9	42.2	195.1
	All Regions Tax	0	124.2	124.2	144.6	49.1	193.6
Other Clothing Producers	Benchmark	152.5	0	152.5	202.0	0	202.0
	EU Tax	163.9	0	163.9	202.8	0	202.8
	EU, China, and OECD Tax	206.5	0	206.5	202.1	0	202.1
	All Regions Tax	0	152.9	152.9	147.0	58.6	205.5
ROW	Benchmark	191.4	0	191.4	173.4	0	173.4
	EU Tax	198.6	0	198.6	174.6	0	174.6
	EU, China, and OECD Tax	232.0	0	232.0	178.6	0	178.6
	All Regions Tax	0	193.1	193.1	122.0	81.6	203.6

* These textiles are only used as intermediate inputs into the clean clothing and clean textiles sectors.

The introduction of the EU clothing tax also impacts textile production (Table 5.6). The output of textiles produced in the EU increases (158.5 billion USD) compared to the benchmark (154.8 billion USD). This is because clean textile inputs to both clean clothing and clean textiles is higher as a proportion of total inputs compared to conventional textiles in the conventional sectors (as shown in Table 5.3). There is also an increased use of conventional textiles by non-clothing sectors in the EU as well as overseas conventional clothing sectors. Mirroring changes in clothing output outside the EU, conventional textile production increases in all untaxed regions compared to the benchmark (Table 5.6).

Figure 5.4: Clothing exports in each region and policy scenario, percentage change from the benchmark.



Due to the high plastic intensity of clothing production, as discussed in White & Winchester (2022), there might be an expectation that the real output of plastics will decrease when regions produce clean clothing. As illustrated in Figure 5.5, when only the EU introduces a clothing tax, global plastic production decreases (0.02 percent) but plastic production in both the EU (0.17 percent) and other OECD countries (0.02 percent) increases compared to the benchmark. The increase in plastic production is driven by: (1) the relative plastic intensities of other manufacturing sectors compared to clothing and (2) clothing leakage.

Each region has different plastic intensities for their production sectors, as illustrated in Table 5.4. When the EU clothing sector is taxed, other EU manufacturing sectors increase their output and subsequently their demand for plastic inputs which mutes the impact on plastic demand.[8] Nevertheless, there may still be positive effects for plastic pollution. Washing clothes results in non-point source plastic pollution but plastic pollution from other sources could be considered point-source pollution (EPA, 2023). This includes leakage in the waste management system or the incorrect disposal of plastics by companies (OECD, 2022c). Point source pollution should be easier to target by

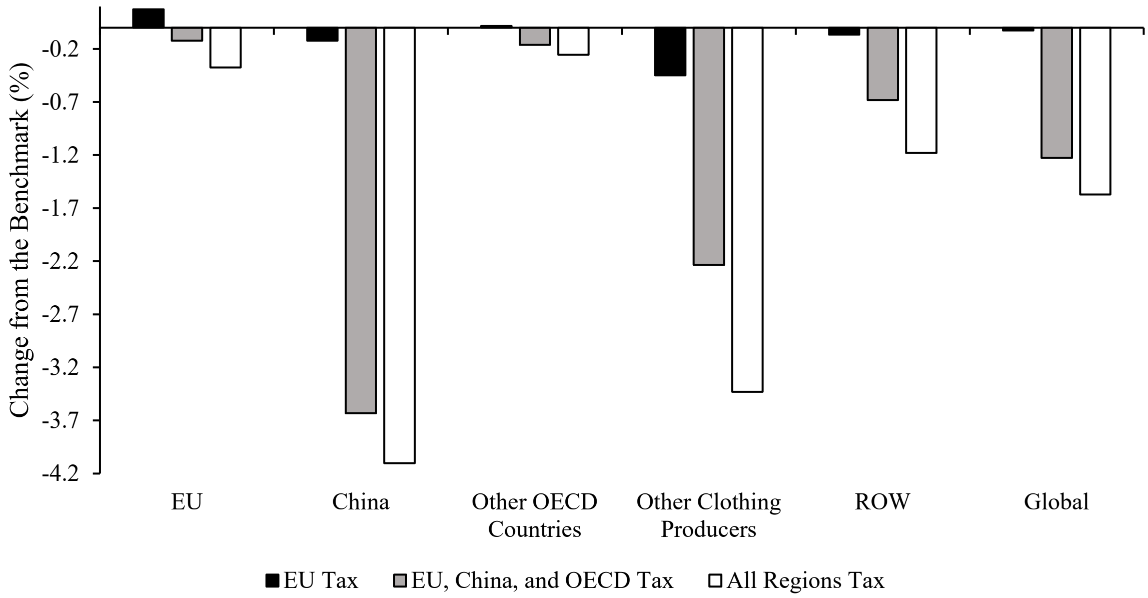
[8] This is an example of the targeting principle (Dixit, 1985; Kopczuk, 2003), where targeting one sector that uses plastics is inefficient, with plastics continuing to be used in other parts of the economy.

policymakers compared to non-point source pollution. Thus, a shift in plastic use from the clothing industry to other manufacturing sectors could reduce plastic pollution or make it more manageable.

Clothing leakage causes an increase in the demand for conventional clothing intermediate inputs, like plastic, in regions without a tax in place. Other regions (except the ROW) have higher plastic intensities for conventional clothing and textiles compared to the EU (Table 5.4). In the EU tax scenario, this leads to an increase in the exports of plastics from regions like the EU and other OECD countries to meet this demand.

Ultimately, once a clothing tax is in place, the plastic originally used for clothing in the benchmark could (1) go into the domestic manufacturing of other goods, (2) be exported overseas for non-taxed clothing manufacturers, or (3) no longer be produced. When the EU introduces a clothing tax, (1) and (2) outweigh (3) in the EU resulting in an increase in the production of plastics.

Figure 5.5: Plastic output in each region and scenario, percentage change from the benchmark.



Clean clothing production includes inputs of plastic and chemical alternatives which are made from raw or processed agricultural products (as described in Section 5.2.1 and 5.2.2). Figure 5.6 shows the percentage change in total global output of selected agricultural commodities under each of the policy scenarios. In the EU tax scenario, it indicates that changes in clothing production will increase output of 'natural' inputs including plant-based fibres (e.g. cotton), other crops (e.g. natural rubber), leather, oil seeds (e.g. nuts), wool and silk, other animal products (e.g. fur skins), and lumber. Increases in output for these commodities range from 0.12 percent for lumber to 0.57 percent for plant-based fibres. As the total supply of land is fixed in the model, production of other agricultural products decreases. This includes food products such as vegetables and fruit, paddy rice, wheat, cane and beets, other grains (e.g. barley), cattle, and raw milk. Decreases in output for these commodities range from 0.009 percent for vegetables and fruit to 0.048 percent for wheat.

Figure 5.6: Changes in the global output of selected agricultural commodities, percentage change relative to the benchmark.

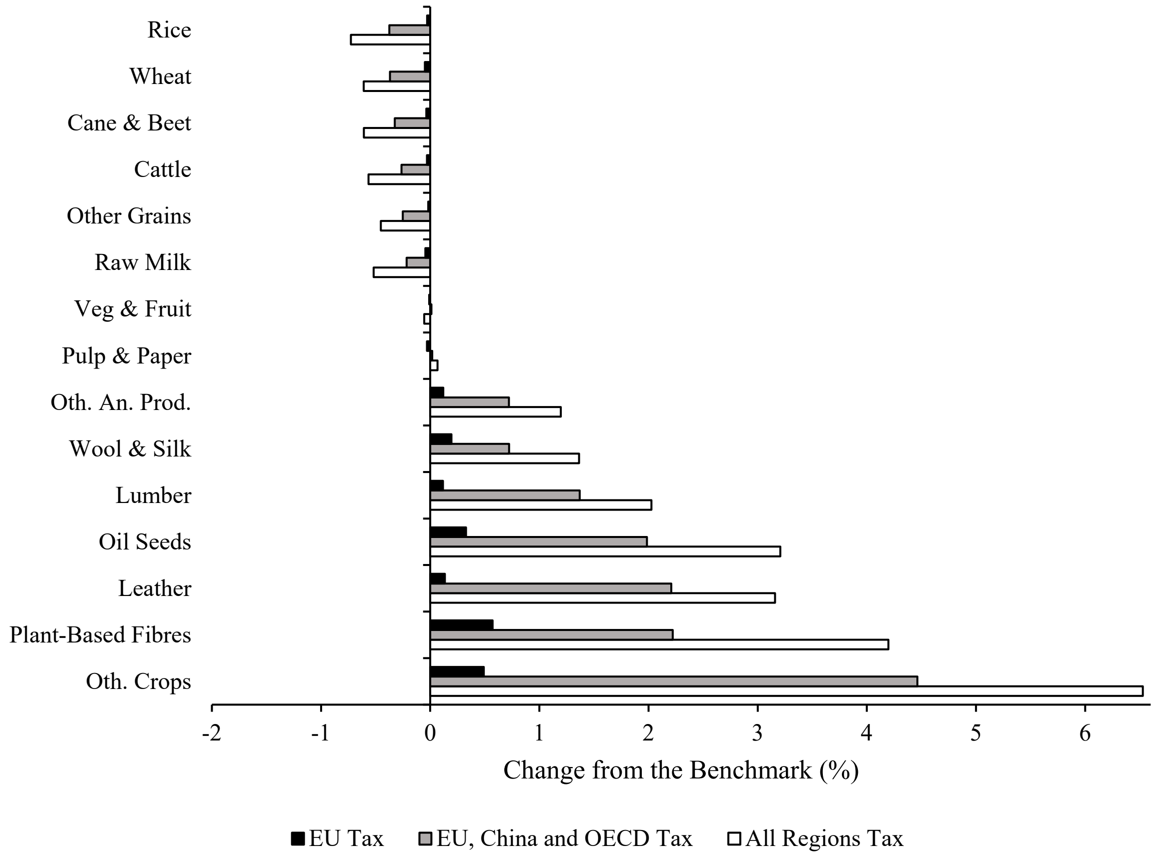


Figure 5.7 reports the proportional changes in land used for selected agricultural products. The results for the EU tax scenario show that the introduction of a clothing tax increases the land used for non-food crops and other animal products. It reveals that clean clothing and textile production in the EU will increase the amount of land used for products such as flowers, natural rubber, hides, fur skins, and nuts. It also shows that changes in conventional clothing production from clothing leakage will increase demand for products such as cotton, flax, hemp, and natural rubber.

In the EU, the land used for oil seeds, other crops, and other animal products increases by 1.79, 1.10 and 0.68 percent from the benchmark respectively. Whereas the land used for plant-based fibres, wool and silk, and forestry decreases by 0.30, 0.88, and 0.15 percent respectively. These results reflect the structure of land use substitution within the EU and the cost of 'natural' inputs in the model.

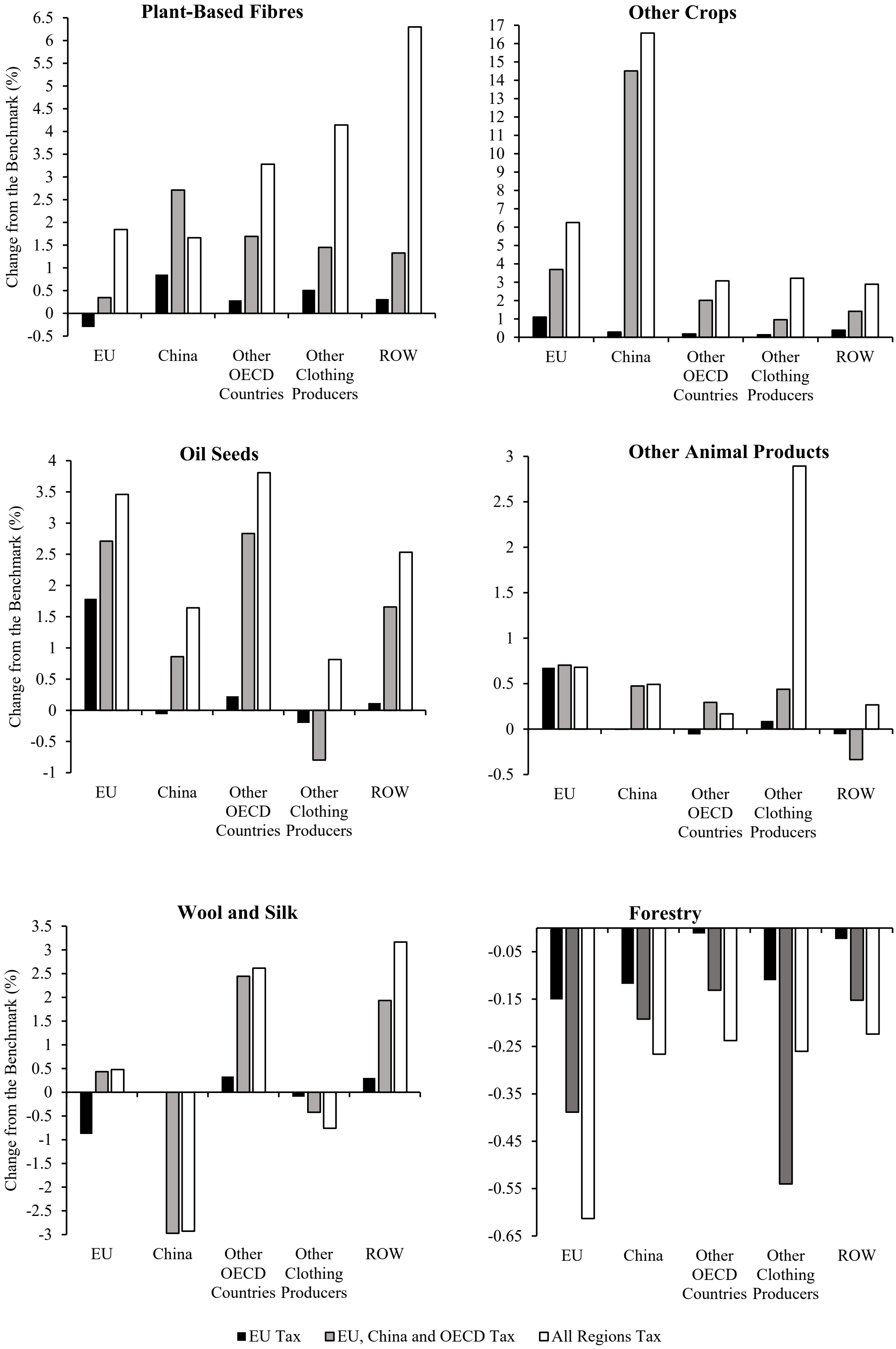
In the EU tax scenario, all other regions increase the land used for plant-based fibres and other crops. These changes are driven by both an increased output of conventional clothing in these regions and exports to the EU for its clean clothing industry. This indicates that conventional clothing still uses a relatively large value of 'natural' inputs alongside plastics and chemicals.

Increases in the land used by agricultural plastic and chemical alternatives reduce the land available for food-related agriculture in the model. The proportional change from the benchmark in the land used for vegetables and fruit, other grains, wheat, raw milk, cattle, and cane and beet in the EU tax scenario is shown in Figure 5.8[9]. In the EU, each of these food crops have reductions in land use with 0.26, 0.39, 1.14, 0.43, 0.45, and 0.26 percent decreases respectively. Most of the other regions have similar decreases in land use, apart from an increase for wheat in other OECD countries (0.22 percent) and the ROW (0.09 percent), and an increase for cattle in other clothing producers (0.11 percent). This translates to reductions in the output of processed food and beverage products including cattle meat, vegetable oils, dairy products, processed rice, and beverages and tobacco in most regions.

These changes in land use could result in environmental damages from more fertilizer and pesticide use, water use, and GHG emissions. For example, compared to other crops, cotton uses relatively large volumes of pesticides per crop area (Huang et al., 2002; Liu & Huang, 2013; Coupe & Capel, 2015) and accounts for approximately three percent of the globe's water footprint (Mekonnen & Hoekstra (2011).

[9]Land use change for paddy rice can be seen in Appendix Figure A5.5.

Figure 5.7: The land used for selected agriculture as percentage change from the benchmark.



5.4.2 The EU, China, and OECD countries tax

When there is a tax on conventional clothing in the EU-China-OECD scenario, the tax rate is 10.18 percent in the EU, 10.53 percent in China, and 11.31 percent in other OECD countries (Table 5.5). The lower tax rate in the EU compared to the EU tax scenario is due to the production of clean clothing in other regions. This makes clean clothing in the EU more competitive than it was in the EU tax scenario and means that conventional clothing requires a relatively lower tax rate to stop production.

This scenario causes welfare and GDP to decrease in the regions with a tax in place as well as the ROW and GDP and welfare to increase for other clothing producers (Table 5.5). This follows the same pattern as the EU tax, with a clean clothing tax benefitting regions which are not taxed but traditionally produce a large value of clothing. This is, again, due to clothing leakage. Clothing production increases in other clothing producers and the ROW and decreases in all regions with a clothing tax (Table 5.6). This is also illustrated in Figure 5.4, with clothing exports decreasing by 24 to 28 percent in the taxed regions and increasing by 46 and 55 percent in other clothing producers and the ROW respectively. The model estimates that 82 percent of the decrease in clothing production in taxed regions is captured by leakage.

Like the EU tax scenario, total textile production increases in most of the taxed regions, including the EU and other OECD countries (Table 5.6). It also increases in the ROW and other clothing producers because of a rise in domestic conventional clothing output. Textile production in China decreases due to a reduction in domestic clothing production and textile exports.

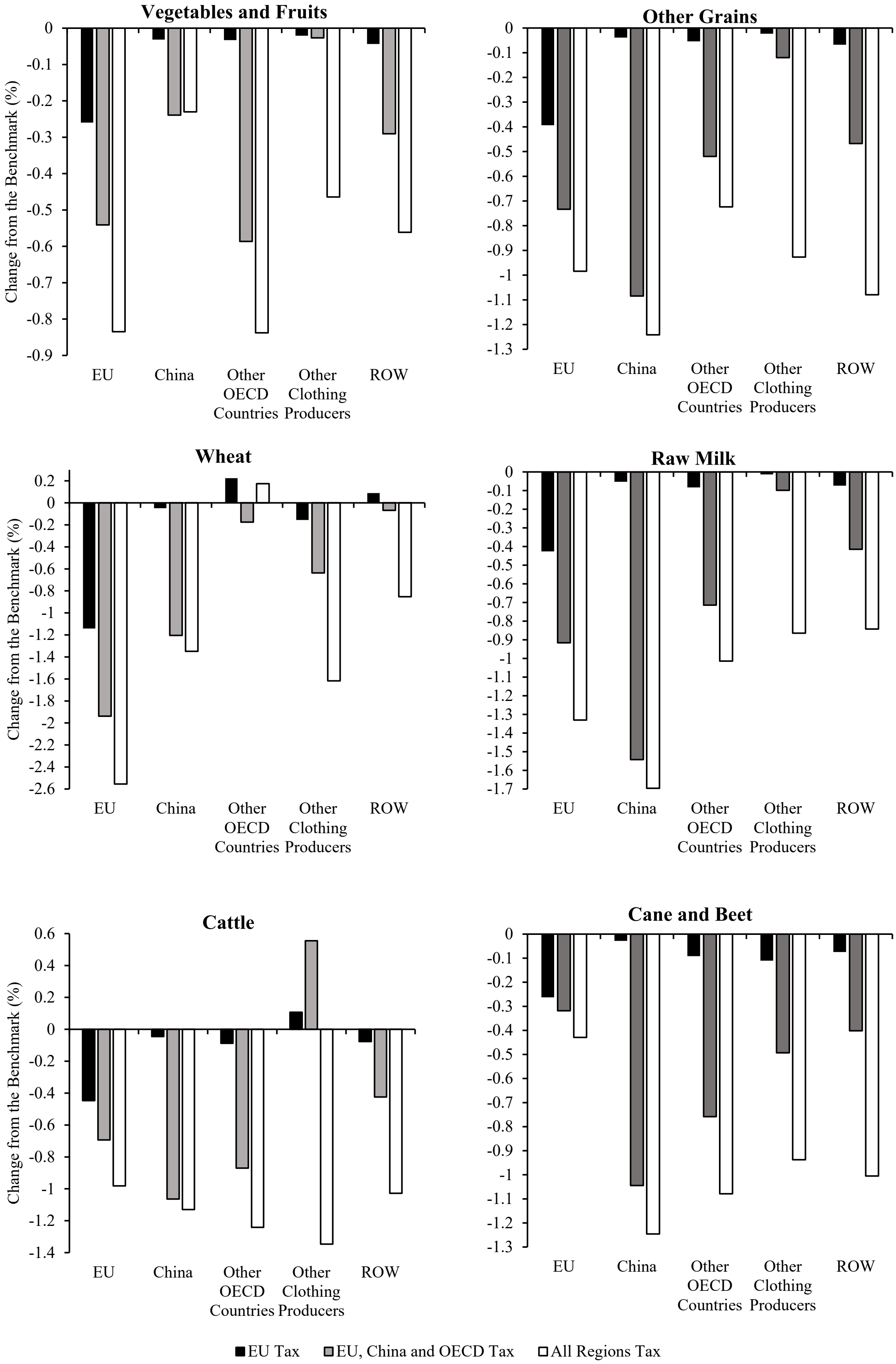
Plastic production in the EU-China-OECD scenario decreases in all regions. The proportional reduction in plastic output ranges from 0.12 to 3.63 percent. Compared to the EU tax scenario, this shows that if more regions tax conventional clothing, the effectiveness of a clothing policy on reducing plastic output increases. In the EU tax scenario, a significant amount of clothing leakage comes from an increase in conventional clothing production in China. In the EU-China-OECD tax scenario, this channel for clothing leakage is no longer available. This reduces international plastic demand and has a significant negative impact on plastic production in the EU and OECD. This is reflected in global plastic production, which decreases by 1.23 percent relative to the benchmark.

The change in global production of plastic and chemical alternatives in the model is similar to the EU tax scenario, but with larger magnitudes (Figure 5.6). The only notable change is that the global output of pulp and paper products (0.02 percent) and vegetables and fruit (0.01 percent) increase compared to the benchmark, rather than decreasing. The largest increase in production of 'natural' alternatives is in other crops (4.46 percent), followed by plant-based fibres (2.22 percent), and leather (2.21 percent). The largest reductions are in food-related agricultural products including rice (0.38 percent), wheat (0.37 percent), and cane and beet (0.33 percent).

The largest proportional increase in land in this scenario compared to the benchmark is in China for other crops and plant-based fibres (14.51 percent and 2.71 percent respectively), in the EU for other crops and oil seeds (3.70 percent and 2.71 percent respectively), and in other OECD countries for oil seeds (2.83 percent) (Figure 5.7). The land used for wool and silk increases in some taxed regions like other OECD countries and the ROW (2.45 and 1.93 percent respectively) but decreases in China and other clothing producers (2.97 and 0.42 percent respectively).

These changes in land use cause a decrease in the land used for food-based crops, with the largest proportional decreases in taxed regions. Examples of this include the 1.20, 1.54, 1.08, and 1.04 percent decreases in the land used for wheat, raw milk, other grains, and cane and beet respectively in China; the 1.94 percent decrease in the land used for wheat in the EU; and the 0.59 percent decrease in the land used for vegetables and fruits in other OECD countries (Figure 5.8).

Figure 5.8: The land used in selected food-related agriculture as a percentage change from the benchmark.



5.4.3 All regions tax

The final scenario is a tax on clothing in all regions that results in all clothing being made without plastic or synthetic chemicals. The tax rates for this scenario, as set endogenously by the model, reflect the differences in production cost increases and output taxes for clean clothing and textiles between regions. As described in Table 5.5, other OECD countries have the highest clothing tax (11.10 percent), followed by China (10.55 percent), the EU (9.77 percent), the ROW (8.64 percent), and other clothing regions (8.52 percent). All regions experience reductions in welfare and GDP compared to the benchmark apart from other clothing regions which experience a 0.002 percent increase in GDP.

Clothing production in this scenario is dependent on the relative competitiveness of clean clothing in different regions. As a result, compared to the benchmark, the EU, other clothing producers, and the ROW increase their clothing production and all other regions reduce their clothing production (Table 5.6). Due to the intermediate input demands of clean clothing, all regions except China increase their total textile production compared to the benchmark.

When there is a clothing tax in all regions, plastic production follows the same trend as the EU-China-OECD scenario, with a global reduction (1.57 percent) and a decrease in every region relative to the benchmark. Figure 5.5 shows that the largest decrease is in China (4.10 percent), followed by other clothing producers (3.43 percent), the ROW (1.18 percent), the EU (0.37 percent), and other OECD countries (0.26 percent).

The global output of plastic and chemical alternatives is also similar to the EU-China-OECD scenario. However, the magnitude of the change from the benchmark is larger, with other crops (6.53 percent), plant-based fibres (4.20 percent), and oil seeds (3.21 percent) having the greatest increases in output; and paddy rice (0.73 percent), wheat (0.61 percent), and cane and beet (0.61 percent) experiencing the largest decreases (Figure 5.6).

The largest increases in land use are for other crops in China (16.58 percent) and the EU (6.25 percent); plant-based fibres in the ROW (6.30 percent) and other clothing producers (4.14 percent); and oil seeds in other OECD countries (3.81 percent) (Figure 5.7). Wool and silk experience both increases and decreases in land use across different regions, with the directions and magnitudes dependent on the clean clothing and textiles production structure, as described in Section 5.3.2.

Some of the largest decreases in food-related land use include vegetables and fruit in other OECD countries (0.84 percent); other grains in China (1.24 percent); wheat in the EU (2.55 percent); raw milk in China (1.70 percent); cattle in other clothing producers (1.35 percent); and cane and beet in China (1.25 percent) (Figure 5.8). Not all food-related agricultural land decreases, with the land used for wheat increasing by 0.17 percent in other OECD countries. This is a function of increased exports of wheat from other OECD countries to food processing industries in other regions.

5.4.4 Sensitivity Analysis

In the core version of our model, CES between both products used as plastic alternatives and products used as chemical alternatives in clean clothing and textile production is 0.5 in all regions (σ_{pa} in Figure 5.2). In the absence of (to our knowledge) empirical estimates to guide this modelling choice, we test the sensitivity of the results to alternative values for this elasticity. Our sensitivity analysis considers elasticity values of 0 and 1.

Economy-wide outcomes for alternative elasticity specification are, in general, similar to those in our core analysis (reported above). At the sectoral level, there are some differences in the production of agricultural commodities, shown in Table 5.7. Notably, increasing the value of this elasticity decreases output of traditional chemical and plastic alternatives (e.g., plant-based fibres and oil seeds) and increases output of less traditional alternatives (e.g., pulp and paper products and lumber). This suggests that the ability of clean clothing producers to substitute between natural clothing and textile alternatives will have implications for food production and land use.

Table 5.7: Global output of chemical and plastic alternatives in the all regions tax scenario with different elasticity of substitution values for the chemical and plastic alternative nests in clean sectors (billions USD).

Sector	Elasticity of Substitution = 0	Elasticity of Substitution = 0.5	Elasticity of Substitution = 1
Paddy Rice	359.73	359.75	359.76
Wheat	187.93	187.94	187.95
Other Grains	284.64	284.65	284.66
Vegetables and Fruit	1346.47	1346.53	1346.58
Oil Seeds	323.79	323.79	323.79
Cane and Beet	133.95	133.95	133.96
Plant-based fibres	126.63	126.59	126.56
Other Crops	210.27	210.01	209.77
Other Animal Products	691.36	691.39	691.42
Raw Milk	367.09	367.1	367.11
Wool and Silk	19.05	19.05	19.06
Leather Manufacturing	466.67	466.68	466.69
Lumber	759.59	759.83	760.07
Pulp and Paper Products	1728.69	1728.8	1728.91

Our analysis measures the impacts from taxes which reduce conventional clothing production to zero in different regions. This is to comply with the UN's resolution to end plastic pollution and eliminate plastic pollution from clothing. To test if the results scale proportionally, we modify the EU tax scenarios by setting the target output for conventional clothing to 50 percent of its benchmark value.

In the EU tax scenario with a 50 percent conventional clothing production target, compared to a 0 percent target, there is a higher level of clothing leakage. This causes a relatively higher level of plastic production in the EU and other OECD countries, a global increase in plastic production, and a higher magnitude of land use change in regions without a tax in place. In this scenario the higher cost EU clean clothing sector struggles to compete with conventional clothing from all regions (including the EU) and it produces approximately 14.5 percent of the output it did under the 0 percent target scenario. This indicates that, due to clothing leakage, a tax on conventional clothing does not scale proportionally.

5.5 Conclusions

If the UN intends to end plastic pollution (UN, 2022; HAC, 2023), clothing needs to be made without any plastic fibres or synthetic chemicals. In this paper, we use a CGE model to impose a tax on the clothing industry and force a switch to clean clothing production in selected regions. To estimate the production costs for clean clothing, we use retail prices for fabrics, leather, and dyes. The modelling exercises consider three policy scenarios. We focus on the impact of clean clothing production on GDP, welfare, sectoral output, and land use change in five aggregated regions.

Our results show that if one region or a subset of regions introduce a clothing tax, there will be clothing leakage. This is where other regions increase their conventional clothing production as they are now more competitive than the high-cost clean alternatives produced in taxed regions. This indicates that a region, such as the EU, should also consider a plastic clothing border adjustment or encourage other regions to tax plastic clothing. Clothing leakage is similar to the carbon leakage issue that the EU aims to address using carbon border adjustments.

Under the EU clothing tax scenario, we find that, although global plastic production decreased, the total production of plastics in the EU increased. This is due to increased EU exports of plastics for use in clothing production in other regions, which use more plastic intensive production processes than the EU. The clothing tax also causes some of the plastic that was previously used in the EU clothing sector to divert to other domestic sectors with higher plastic intensities than clothing and textiles. Nonetheless, this shift could result in a decrease in total plastic pollution due to a transformation from non-point source pollution from the washing of clothes to point source pollution from more traditional waste in other sectors.

The modelling framework also allows for land use change. We find a tax on clothing favours the more traditional plastic-free agricultural alternatives such as plant-based fibres (e.g. cotton and flax), other crops (e.g. natural rubber and flowers), and oil seeds. Increases in the land used for these crops comes at the expense of food-based crops such as vegetables and fruit, grains, wheat, and cattle.

Given the complexity of this issue, there are some limitations to our analysis. One of these is the assumption that there is economy-wide availability for 'natural' chemical alternatives. This may not be possibly due to product seasonality and expense (Palacios-Mateo, van der Meer & Seide, 2021; Sk et al., 2021). Another limitation of this research is the estimation of production inputs for the clean clothing and textile sectors based on traditional alternatives without the representation of new technologies such as fibres made from CO_2 (Textile Exchange, 2022). Also, by focussing on the clothing industry, we are potentially underestimating impacts from wider reaching plastic policies on the economy and land use.

Our analysis enables us to trace out the channels through which reducing plastic and synthetic chemical use in clothing impacts economic and land-use outcomes. The results indicate that a shift towards the production of clean clothing leads to large-scale land use change. Also, they reveal the potential risks to plastic policy effectiveness from clothing leakage. While targeting plastic use is an important policy tool, to reduce plastic clothing pollution effectively, governments should invest in better microplastic filters for their sewerage systems (Browne et al., 2011) and take measures to increase the average lifecycle of clothing (Niinimäki et al., 2020). Future research in this area could compare the current levels of plastic, GHG emissions, and chemical pollution in the clothing industry with the potential pollution from land use change, plastic use in other industries, and emissions from 'natural' clothing production. There is also scope to represent new clothing and chemical technologies that are not reliant on traditional agricultural alternatives.

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Appendix A

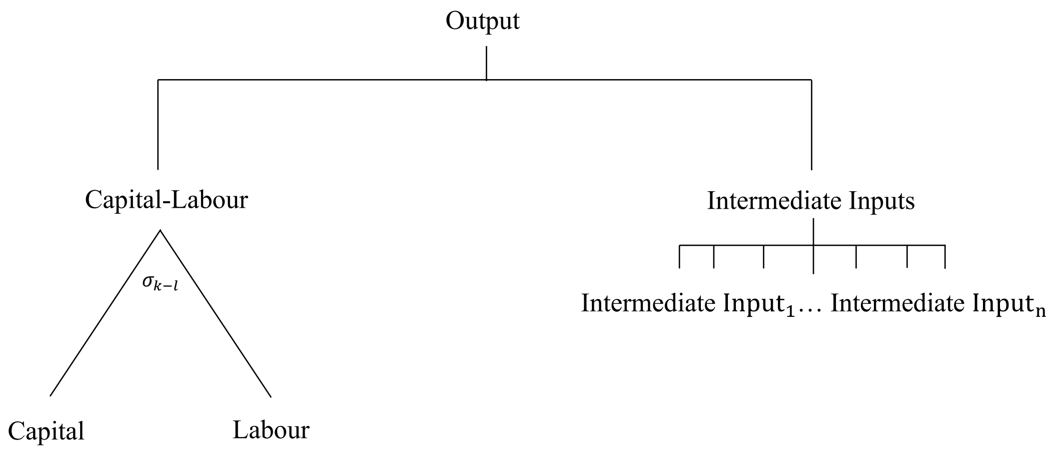
Table A5.1: Sector names and abbreviations represented in the model, mapped from version 11 of the GTAP database (Aguiar et al., 2022).

Sector Name	Sector Abbreviation
Clothing and Textiles	
Conventional Clothing	wap
Clean Clothing	wap_1
Conventional Textiles	tex
Clean Textiles	tex_1
Plastics and Chemicals	
Plastics Products	rpp
Chemical Products	chm
Plastic Alternatives	
Paddy Rice	pdr
Wheat	wht
Other Grains	gro
Cane and Beet	c_b
Plant-based fibres	pfb
Raw Milk	rmk
Wool and Silk	wol
Vegetables and Fruit	v_f
Oil Seeds	osd
Other Crops	ocr
Other Animal Products	oap
Lumber	lum
Leather Manufacturing	lea
Pulp and Paper Products	ppp
Chemical Alternatives	
Vegetables and Fruit	v_f
Oil Seeds	osd
Other Crops	ocr
Other Animal Products	oap
Lumber	lum
Other Agriculture	
Fishing	fsh
Cattle	ctl
Forestry	frs
Other Manufacturing Sectors	
Cattle Meat	cmt
Other Meat	omt
Vegetable Oils	vol
Dairy Products	mil
Processed Rice	pcr
Sugar and Molasses	sgr
Other Food	ofd
Beverages and Tobacco	b_t
Basic Pharmaceuticals	bph
Non-Metallic Minerals	nmm
Iron and Steel Manufacturing	i_s
Non-Ferrous Metals	nfm
Metal Products	fmp
Electrical Equipment	eeq
Machinery and Equipment Not Elsewhere Classified	ome
Motor Vehicles and Parts	mvh

Transport Equipment Not Elsewhere Classified	otn
Computer, Electronic and Optical Products	com
Manufacturing Not Elsewhere Classified	omf
Energy, Fossil Fuels and Mining	
Electricity Generation, Transmission and Distribution	ele
Crude Oil Extraction	cru
Coal Mining	col
Mining	min
Petroleum, Coal Products	oil
Natural Gas Extraction and Distribution	gas
Services	
Construction	cns
Services	ser

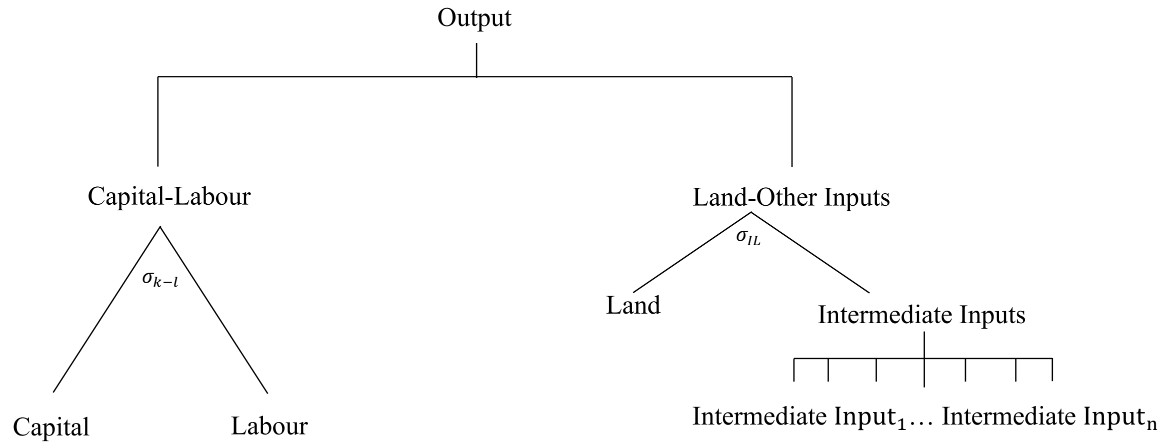
Note: Plastics products are the same as the rubber and plastics products in the GTAP database.

Figure A5.1: Production nest for all sectors other than agriculture, forestry, fossil fuel production, and clothing and textiles.



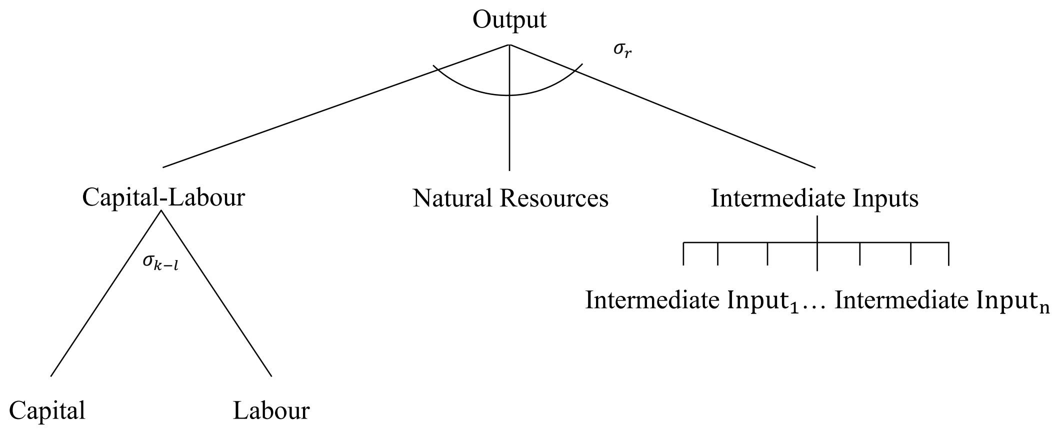
Note: Vertical lines in an input nest represent a Leontief production structure where the elasticity of substitution is zero and σ_{k-l} represents the sector specific elasticity of substitution between capital and labour.

Figure A5.2: Production nest for agriculture and forestry.



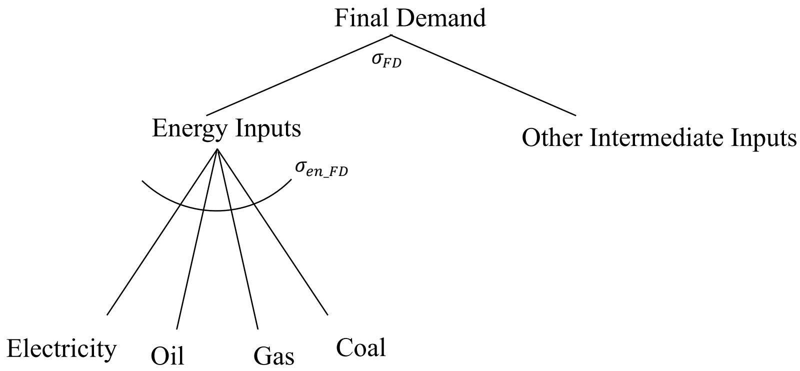
Note: Vertical lines in an input nest represent a Leontief production structure where the elasticity of substitution is zero, σ_{k-l} represents the sector specific elasticity of substitution between capital and labour, and σ_{IL} is equal to 0.05, based on information from White & Winchester (2022) and Chen et al. (2016).

Figure A5.3: Production nest for fossil fuel production.



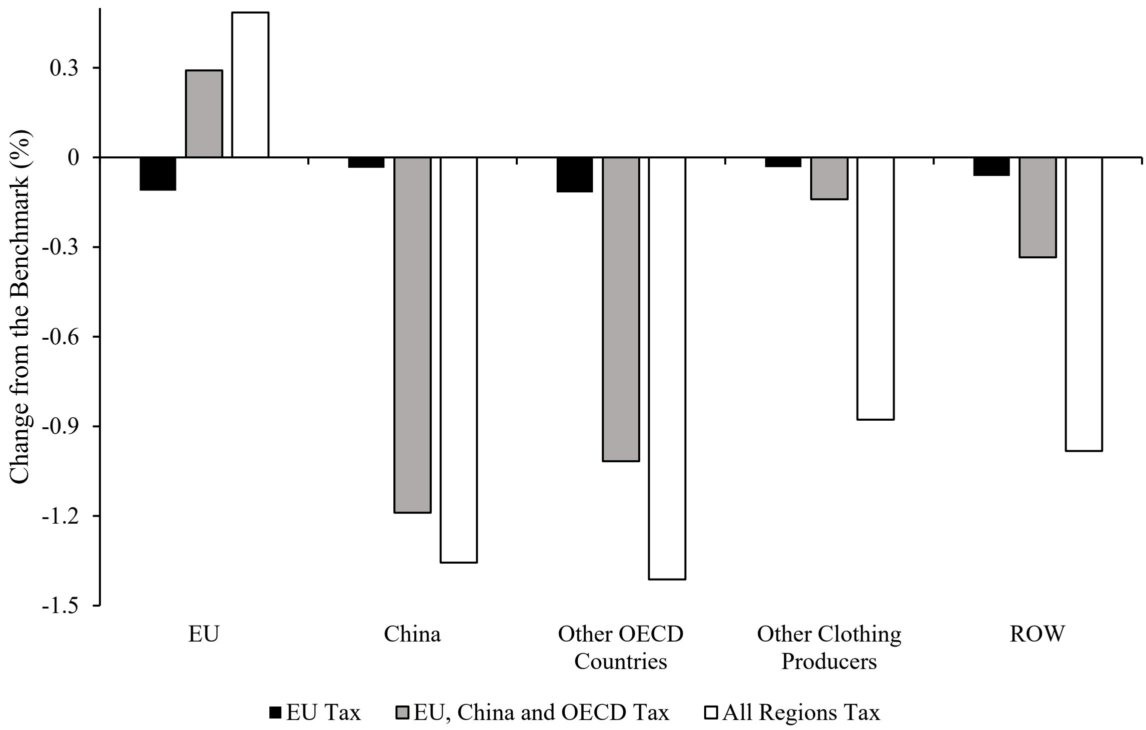
Note: Vertical lines in an input nest represent a Leontief production structure where the elasticity of substitution is zero, σ_r is equal to 0.5, and σ_{k-l} represents the sector specific elasticity of substitution between capital and labour.

Figure A5.4: Production nest for final demand.



Note: σ_{FD} is equal to 0.5 and σ_{en_FD} is equal to 1.

Figure A5.5: The land used by paddy rice as a percentage change from the benchmark.



Appendix B

'Natural' Clothing and 'Natural' Textiles Production Markup Estimation.

To estimate the increase in costs for clean clothing production, we use retail prices from fabric, leather, and dye manufacturers. Production markups are calculated separately for 'natural' fibres (here we categorise leather as a fibre) and 'natural' dyes before being applied to the overall production costs of clean clothing and textiles. For the 'natural' fibre markup, we use online prices from a fabric retailer (Spotlight, 2023a) and a leather retailer (New Zealand Leather Suppliers, 2023), along with information on global fibre use (Textile Exchange, 2022). To calculate the markup for 'natural' dyes we use information from 'natural' and synthetic dye retailers (Botanical Colors, 2023a; Botanical Colors, 2023b; Rit, 2023; Spotlight, 2023b). We chose this selection of retailers for the analysis because they each sell a wide range of products related to clothing. This limits any potential price differences driven by competition or brand recognition rather than production costs.

To estimate the costs of only using 'natural' fibres in textiles and clothing compared to the current mix of 'natural' and synthetic fibres, we use prices from plain fabrics in the "Dress Apparel and Fabrics" section of Spotlight (2023a). This provided per metre costs for a range of fibre types including polyester, cotton, linen, rayon/viscose, nylon, polyurethane, polyethylene, Tencel, acrylic, bamboo, polypropylene, acetate, jute, merino wool, and silk. We only use the 'pure' (100 percent cotton, 100 percent polyester etc.) per metre fabric cost for each material to inform our analysis[10]. The price per metre of leather is estimated using information from New Zealand Leather Suppliers (2023). They provided details on the price per metre of leather products used for bags, footwear, belts, garments, and linings. The fibres we categorized as non-plastic include cotton, linen, rayon/viscose, Tencel, bamboo, acetate, jute, merino wool, silk, and leather. To avoid outliers dominating the overall price, we calculate a weighted average price per metre of original and 'natural' fibres by combining the information from retailers with the weight of each type of fibre used globally, as estimated by the Textile Exchange (2022) report.

Table B5.1 illustrates how we calculate a 'natural' fibre markup based on the ratio of weighted prices from 'natural' fibres to original fibres. We calculate that 'natural' fibres cost approximately three percent more than the current mix of fibres. This approach assumes all fabrics are made with synthetic chemicals and is therefore only a representation of the additional costs associated with using 'natural' fibres.

[10] Spotlight New Zealand only has prices for bamboo when it is mixed with plastic. However, the fabric used for the price estimate in this analysis is made with 80 percent bamboo and should be representative of the bamboo price.

Table B5.1: A comparison of the weighted prices per metre of conventional clothing and textile fibres with prices of 'natural' clothing and textile fibres.

Product	Average Price (USD/m)	Global Fibre Use (Mt)	Proportion of Total Fibre Use	Weighted Price (USD/m)
	Conventional Clothing and Textile Fibres			
Synthetic Fibres				
Polyester	16.08	60.50	0.49	7.82
Polyamide (Nylon)	12.64	5.90	0.05	0.60
All Others	26.81	5.80	0.05	1.25
Manmade Cellulosic Fibres				
Viscose (Rayon)	14.20	5.80	0.05	0.66
Other	19.52	1.40	0.01	0.22
Plant Fibres				
Cotton	13.26	24.70	0.20	2.63
Other	24.08	6.70	0.05	1.30
Animal Fibres				
Wool	44.36	1.00	0.01	0.36
Silk	34.85	0.17	0.00	0.05
Leather	21.42	12.48	0.10	2.15
Total	-	124.45	1.00	17.03
	'Natural' Clothing and Textile Fibres			
Manmade Cellulosic Fibres				
Viscose (Rayon)	14.20	5.80	0.11	1.58
Other	19.52	1.40	0.03	0.52
Plant Fibres				
Cotton	13.26	24.70	0.47	6.27
Other	24.08	6.70	0.13	3.09
Animal Fibres				
Wool	44.36	1.00	0.02	0.85
Silk	34.85	0.17	0.00	0.11
Leather	21.42	12.48	0.24	5.12
Total	-	52.25	1.00	17.53
'Natural' Fibre Markup	-	-	-	1.03

Note: fibre prices are from Spotlight (2023a) and New Zealand Leather Suppliers (2023) and the tonnes of global fibre use is from Textile Exchange (2022). All prices are converted to US dollars based on the 2022 average exchange rates from IRS (2023).

To calculate the cost markup of 'natural' chemicals, we use the price difference between 'natural' and synthetic dyes. This is a similar approach to how we estimate the 'natural' fibre markup, however there are a number of assumptions underpinning this methodology: (1) all clothing currently uses synthetic chemicals, (2) synthetic chemicals are defined as those made with petrochemicals, (3) all dye colours are used in equal proportions, and (4) the cost increase for 'natural' dyes is representative of all chemicals used in clothing.

Rit (2023) and Spotlight (2023b) provide prices for synthetic dyes and Botanical Colors (2023) provides prices for 'natural' dyes. We only compare the prices of powdered rather than liquid dyes as many of the 'natural' dyes offered by Botanical Colors (2023) are powdered and it allows for a clearer price comparison.

For each of the dyes, we estimate the price per kilogram of fabric dyed based on product information from the company websites. The synthetic dye prices we use are classified by Rit (2023) and Spotlight (2023) as either 'all purpose', 'for natural fibres', or 'not for polyester'. 'Natural' dyes include plant extracts, animal extracts, and minerals, many of which require bonders to work properly (Pizzicato et al., 2023). Therefore, to accurately estimate the price of 'natural' dyes per kilogram of fabric, we add the price of 'natural' extracts and a chemical bonder called a mordant together. Both pieces of information are provided by Botanical Colors (2023). Mordants include chemical compounds such as aluminium triformate, aluminium sulfate, aluminum potassium sulfate, and aluminium acetate. In this analysis, we assume that the lowest cost mordant, aluminium triformate would be used by clothing industries and is the price included in our analysis.

Table B5.2 describes how we calculate the 'natural' chemical markup for the model using a ratio of 'natural' dye prices to synthetic dye prices. We estimate that 'natural' chemicals will cost an additional 90 percent compared to synthetic chemicals when used to make clean clothing and textiles.

Table B5.2: A comparison of the prices of 'natural' and synthetic chemicals per kilogram of clothing and textiles dyed.

Product	Price of Extract (USD/kg of fibre)	Average Mordant Price (USD/kg of fibre)	Total Price (USD/kg of fibre)
	'Natural' Dyes		
Premium Lac Extract	30.00	4.50	34.50
Textile Grade Cochineal Extract	24.65	4.50	29.15
Buckthorn Berry Extract	26.00	4.50	30.50
Chestnut Extract	3.19	4.50	7.69
Chlorophyllin Green Dye	44.00	4.50	48.50
Cutch Extract	11.66	4.50	16.16
Fustic Powder Extract	13.20	4.50	17.70
Gallo Tannin Extract	9.00	4.50	13.50
Himalayan Rhubarb Extract Powder	11.00	4.50	15.50
Lac Extract	27.50	4.50	32.00
Madder Extract	14.88	4.50	19.38
Myrobalan Extract	7.20	4.50	11.70
Organic Indigo	7.15	0.00	7.15
Pomegrannate Extract	8.25	4.50	12.75
Quebracho Moreno	8.00	4.50	12.50
Red Cochineal Extract	34.00	4.50	38.50
Rich Purple Logwood	50.00	4.50	54.50
Sappanwood Extract	20.90	4.50	25.40
Tara Powder	7.80	4.50	12.30
Walnut Hull Powder	94.50	4.50	99.00
Wattle Extract	3.08	4.50	7.58
Weld Extract	18.85	4.50	23.35
Organic Living Blue Indigo*	9.10	0	9.10
Marigold Mix	16.50	4.50	21.00
Average	20.85	4.13	24.98
	Synthetic Dyes		
Rit Powder Dye for all fibres apart from polyester	-	-	15.29
Jacquard iDye Fabric Dye	-	-	12.06
Jacquard iDye for 'Natural' Fabric	-	-	12.06
Average	-	-	13.14
'Natural' Chemical Markup	-	-	1.90

*Indigo does not need a mordant to bond to fibres Botanical Colors (2023).

Note: the prices for the synthetic chemicals come from Rit (2023) and Spotlight (2023) and the prices for synthetic chemicals come from Botanical Colors (2023). All prices are converted to US dollars based on the 2022 average exchange rates from IRS (2023).

Appendix C

Calculating the Plastic Intensity and Direct Chemical Intensity of Industries

To calculate the plastic intensity of industries using the GTAP database, our approach is based on the methodology introduced in Leontief (1970) and described further by Bullard, Penner & Pilati (1978). This is shown in Equation (C5.1).

$$\pi = x(I - A)^{-1} \qquad \text{(C5.1)}$$

Where π is a vector of the plastic intensity value for each industry i, x is a vector of the direct plastic intensity of each industry i, I is an identity matrix, and A is a $N \times N$ matrix (N for this analysis equals 48, the number of industries represented in the model) which describes the value of commodities, c, needed to produce a unit of output by industry i.

To estimate the weighted average plastic intensity, μ, for 'other industries', we use Equation (C5.2).

$$\mu = \sum_i \pi_i \theta_i^T \qquad \text{(C5.2)}$$

Where π_i is the plastic intensity of industry i and θ_i^T is the proportion of total output from all industries (excluding clothing, textile, and plastic sectors) the output from industry i represents.

To calculate the direct chemical intensity of each industry, σ_i, we use Equation (C5.3).

$$\sigma_i = \frac{x_{ci}}{V_i} \qquad \text{(C5.3)}$$

Where x_{ci} is the value of chemical inputs for sector i and V_i is the total value of output for industry i.

To estimate the weighted average direct chemical intensity of 'other industries', ρ, we use Equation (C5.4).

$$\rho = \sum_i \sigma_i \beta_i^T \qquad \text{(C5.4)}$$

Where β_i^T is the proportion of total output from all industries (excluding clothing, textile, and chemical sectors) the output from industry i represents.

6. Prelude to Logs or Permits? Forestry Land Use Decisions in an Emissions Trading Scheme

The final manuscript in this thesis seeks to estimate the land use and economic implications of the inclusion of production and permanent exotic forestry in the NZ ETS. This paper expands on the work of the first two manuscripts by examining land use change in a new context. This approach moves away from the constant elasticity of transformation approach used in the second manuscript and includes sigmoid functions linked to the CGE model. It shows an alternative way to represent land use change in economy wide models and the potential strengths of using sigmoid functions to represent farmer behaviour.

The NZ ETS is comprehensive and one of the first ETSs around the world to include forestry incentives (ICAP 2022a-b). These forestry incentives include the provision of permits by the New Zealand government for the carbon sequestered by production and permanent forests (Leining, 2022). Production forests refer to farms that aim to harvest their trees at maturity for forestry products. Permanent forests refer to trees planted with the aim to generate permits as part of the NZ ETS. Permits generated by forestry can be sold at auction to enterprises contributing to climate change. This means the profitability of permanent forests is directly related to the carbon price.

I estimate the impacts of foresters changing land use from production to permanent exotic forests at harvesting age using a modelling framework including a CGE model, a forestry model, and land use change functions. I find that the inclusion of permanent forests in the NZ ETS will result in a significant amount of land use change towards permanent forests.

7. Logs or Permits? Forestry Land Use Decisions in an Emissions Trading Scheme

Abstract

Negative carbon emissions options are required to meet long-term climate goals in many countries. One way to incentivise these options is by paying farmers for carbon sequestered by forests through an emissions trading scheme (ETS). New Zealand has a comprehensive ETS, which includes incentives for farmers to plant permanent exotic forests. This research uses an economy-wide model, a forestry model and land use change functions to measure the expected proportion of farmers with trees at harvesting age that will change land use from production to permanent forests in New Zealand from 2014 to 2050. We also estimate the impacts on carbon sequestration, the carbon price, gross emissions, GDP and welfare. When there is forestry land use change, the results indicate that the responsiveness of land owners to the carbon price has a measured impact on carbon sequestration. For example, under the fastest land use change scenario, carbon sequestration reaches 29.93 Mt CO2e by 2050 compared to 23.41 Mt CO2e in the no land use change scenario (a 28% increase). Even under the slowest land use change scenario, carbon sequestration is 25.89 Mt CO2e by 2050 (an 11% increase compared with no land use change). This is because, if foresters decide not to switch to permanent forests in 1 year, carbon prices and ultimately incentives to convert to permanent forests will be higher in future years.

Additional Information

This work is published as White, D. & Winchester, N. (2023) Logs or permits? Forestry land use decisions in an emissions trading scheme. *The Australian Journal of Agricultural and Resource Economics*, *67*(4), 558-575. https://doi.org/10.1111/1467-8489.12534.

This is published under the Creative Commons Attribution-NonCommercial-NoDerivs License, details of which can be found here: https://creativecommons.org/licenses/by-nc-nd/4.0/. There have been some minor changes to the figure and table labelling, and an update of information in 'The New Zealand ETS' section of the version included in this thesis compared to the published version.

7.1 Introduction

Mature production forests can provide nonmarket benefits for society including ecosystem services, natural disaster protection, recreational activities, agricultural productivity improvements, tourism and carbon sequestration (Figueroa & Pasten, 2015; Hanley et al., 2007). Due to the value of these nonmarket benefits and the impacts from climate change being felt around the world, the forestry industry has come under increasing scrutiny. Carbon sequestration from forests is a key tool to reduce greenhouse gas (GHG) emissions in the atmosphere (IPCC, 2022). It is therefore important for farmers to have incentives to incorporate the carbon sequestration of their forests into their harvesting decisions.

There are a variety of policies, explored by Englin and Klan (1990), which can incentivise production foresters to change their harvesting behaviour and increase the nonmarket benefits from each rotation. One policy intervention that could encourage farmers to stop harvesting altogether is an emissions trading scheme (ETS) where farmers earn permits for the carbon sequestration of their forests each year (Leining, 2022). One of the most comprehensive ETSs in the world is the New Zealand ETS (NZ ETS). This ETS was recently extended to include sequestration from forests, which incentivises farmers to plant permanent forests as the price of carbon increases (Leining, 2022). Exotic forests currently account for 2.1 million hectares of land in New Zealand, with approximately 1.7 million hectares being used for plantation forests and the remainder being unplanted or used as permanent forests (MPI, 2022a). This accounts for close to 8% of the total available land in New Zealand (MfE & Stats NZ, 2021). Out of the ETSs operating around the world—including those in Canada, China, Japan, the European Union, South Korea, Switzerland, Austria, Indonesia, Montenegro, Germany, Kazakhstan, Mexico and the United States (ICAP, 2022a)—the NZ ETS is the only scheme to include a forestry sector with both surrender obligations and the ability to earn carbon permits (ICAP, 2022b). In this paper, we use an economy-wide/computable general equilibrium (CGE) model and a forestry model to estimate the impact of the forestry rules in the NZ ETS on the land used for exotic permanent forests. We further investigate how this land use change affects the expected quantity of carbon sequestered, the amount of land harvested, the price of carbon and economic outcomes.

Previous research that has analysed the decision-making of foresters in the NZ ETS has focussed on afforestation, deforestation, land productivity and the optimal rotation age. Manley (2022) provided a comprehensive analysis of the impact the carbon price and timber price have on land value and afforestation decisions. He also explored the profitability of forest land under different carbon accounting systems and different carbon prices. Adams and Turner (2012) provided a model to represent the afforestation, deforestation and optimal harvest age decision-making for forestry farmers in New Zealand for carbon prices up to 50 NZD/tCO2. They also looked at land use change between other agricultural land uses and forestry with elasticities driving a probability of land use change at each carbon price. As expected, both found that as the carbon price increases, afforestation increases, and deforestation occurs in years where the carbon price is low and expected to increase in future years. Manley (2022) also found, under current NZ ETS rules, the optimal harvest age stays relatively constant even with an increasing carbon price. Hale et al. (2014) projected the changes in the land used for commercial forests as a response to the carbon price. They found that less productive forestry regions are the most efficient land areas to transition to permanent forests when the carbon price increases. Kerr et al. (2012) estimated the expected land use change elasticities between different agricultural land uses. They found a relatively low level of land use change to forestry from agriculture under the NZ ETS. A limitation of these studies is the low level of reactivity of the NZ ETS to forestry land use change, and, in some of the papers, the relatively low carbon price used. By connecting a forestry model with a CGE model, we can explore land use decision-making over a range of carbon prices to 2050 and the impact of those decisions on the economy and the NZ ETS.

To model forestry land use change, we need to represent farmers as risk-averse decision-makers (Binswanger, 1980). There is also a high level of uncertainty for farmers about factors outside their control such as natural disasters as well as unpredictable changes in government policy. In forestry, farmers must make costly decisions years before these uncertainties are resolved (Yousefpour et al., 2012). This is demonstrated by the common use of Faustmann's formula by both researchers and farmers (Crabbe & Long, 1989; Faustmann, 1849; Hartman, 1976; Loehle, 2023; Nakajima et al., 2017; Reed, 1984; Wang & van Kooten, 2001; Wilson et al., 1998). Under the NZ ETS, farmers now have an additional decision to make: whether to harvest their trees at maturity or keep them in the ground to earn carbon permits. This research examines the switch from production to permanent forests incentivised by changes in the carbon price. The choice farmers make will depend on the carbon price in the current year as well as the expected carbon price in future years.

We use sigmoid functions (also known as S-curves) to represent this forestry decision appropriately. Sigmoid functions have been used to represent the adoption of new technologies in agriculture (Beal & Bohlen, 1956; Beal & Rogers, 1960; Coleman et al., 1955; Kuehne et al., 2017; Llewellyn & Brown, 2020; Rogers, 2003; Swamila et al., 2020). This approach has the benefit of characterising heterogeneous decision-makers with segments of adopters that require different carbon prices to change production practices. The sigmoid functions also account for uncertainties felt by farmers surrounding climate change policy and embody long-run decisions around a short-run carbon price. To our knowledge, this is the first time S-curves have been used to represent land use change in a CGE model, and also the first CGE analysis to consider land use change caused by ETS incentives for permanent forests. The sigmoid functions allow us to avoid the land accounting issues, which come from using other CGE land use change techniques, whilst suitably representing forestry land use decision-making.[11]

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[11] See Taheripour et al. (2020) for a review of land use change in CGE models.

This paper has four further sections. Section 7.2 provides an overview of the NZ ETS. Section 7.3 describes the methods used for our analysis. Section 7.4 presents and discusses the results. Section 7.5 offers a discussion and some concluding remarks.

7.2 The New Zealand ETS

The NZ ETS operates through the generation and trading of carbon permits, which are limited by the government to meet emissions targets each year. As of 2022, this ETS included 52% of New Zealand's gross emissions (biogenic methane emissions from agriculture, which accounts for approximately 48% of New Zealand's gross emissions, are scheduled to be included in an external pricing system by 2025; MfE & MPI, 2022). Carbon permits can be acquired in the NZ ETS by receiving them from the government for free, purchasing them from other participants, purchasing them at auction, or receiving them from sequestration activities (Leining, 2022).

The NZ ETS was introduced in 2008 to help New Zealand meet its 2050 emissions target (Leining, 2022). Since its introduction, there have been several amendments to the structure and scope of the NZ ETS. A notable milestone in New Zealand climate policy was the Climate Change Response Amendment Act, more commonly known as the Zero Carbon Act, which was passed in 2019. This act set a new GHG emissions target for New Zealand, specifying that biogenic methane must be reduced by at least 10% below 2017 levels by 2035 and 24%–27% below these levels by 2050, and all other GHGs must be at net zero by 2050 (PCO, 2019). The act noted that the ETS is New Zealand's most important policy tool to achieve these targets. The most recent amendment to the NZ ETS was the Climate Change Response (Emissions Trading Reform) Amendment Act, passed in 2020. This act detailed changes in the structure of the ETS, including the future pricing of biogenic methane from agriculture and changes in forestry rules and accounting (PCO, 2020).

Forestry within the NZ ETS applies only to trees afforested after 1989 (Leining, 2022). Trees planted before 1990 cannot claim permits from carbon sequestration but do face emissions liability for deforestation. Since 2023, post-1989 foresters can claim permits as either permanent or production (also known as ‘standard’) forests. Previously, only production forests could claim permits[12]. Permits can be earned using either the stock change or the ‘averaging’ accounting approach. The stock change approach measures the creation and surrender of permits based on the change in carbon sequestration from a forest each year and is used for permanent forests. A condition of permanent forests claiming permits is they cannot change their land use for 50 years.[13] The ‘averaging’ approach, which is used by production forests, measures the change in carbon sequestration each year in the first rotation of the forests up until an ‘average’ age. The ‘average’ age is calculated as the long-run level of carbon

[12] Production foresters under the original scheme could keep their trees in the ground and claim permits under stock change accounting (MPI, 2023).

[13] It is possible for foresters to change their land use before 50 years under specific circumstances, with approval from the Minister for Climate Change (MPI, 2023).

sequestration achieved by production forests if they continue to be harvested and replanted. After the 'average' age, forest owners will no longer surrender or claim permits. The government tentatively mentioned that a redesigned permanent forest category could be introduced in 2025 to try and increase incentives for native forests to be planted (MPI, 2022b). It is unclear what these policy changes will be, so we model forestry land use change based on the NZ ETS policies, which have already been passed.

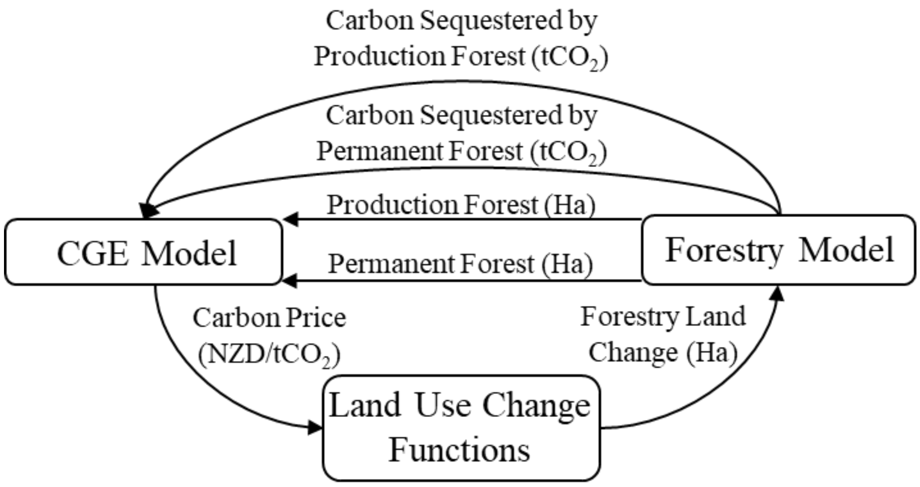
Native forest land use decision-making is not included in this research due to the lack of data available for private native forest landowners. Exotic forests, especially pine, also have a higher rate of carbon sequestration per hectare than native forests (PCO, 2008), so planting of native forests is largely carried out for noneconomic reasons.

7.3 Methodology

This paper combines a CGE model with a forestry model to estimate the impacts of land use change from exotic production forest to permanent forest at harvesting age from 2014 to 2050 in New Zealand.

In our approach, a CGE model augmented to include permanent and production forests provides a representation of the New Zealand economy and estimates the carbon price in each period. A forestry model estimates the sequestration from forestry based on the amount of land used for production and permanent forests. To connect the two models, we include a land use decision-making module for farmers, using sigmoid functions, which operates when the carbon price becomes high enough for the value of permanent forests to be greater than the value of production forests. At harvesting age, farmers can choose to either cut the trees down as planned or leave them unfelled and generate permits for the NZ ETS. This decision is a function of the carbon price from the year before, as calculated in the CGE model, and provides land use estimates for the forestry model to calculate carbon sequestration. Outputs from the forestry model also determine the amount of production and permanent forest land in the CGE model in the next year. Figure 7.1 illustrates how the models and functions are connected to each other.

Figure 7.1: How the CGE model, forestry model and land use change functions are connected via outputs.



We focus on land use change from production to permanent forests as there are strict rules within the NZ ETS, which make it difficult for permanent forestry farmers to change their land use (PCO, 2020). This decision only applies to forests about to be harvested as this is the youngest age a forest can be before production foresters can start earning money from permanent forests. We represent the decision to change land use based on the expected carbon price in 2050 and the carbon price from the year before. This is carried out under the assumption that, as detailed in Section 7.3.4, farmers do not have perfect information on the ETS and the carbon price and will make decisions on the long-run profitability of permanent forests using, among other intelligence, historical price information. This assumption is based on the papers by Yousefpour et al. (2012) and MPI (2019) who specify that farmers are particularly uncertain about climate change and climate change policies and will act differently compared with other land use decisions.

For the remainder of this section, the analysis is split into (1) an overview of the CGE model, (2) an overview of the forestry model, (3) a description of 'breakeven' carbon prices (used in the land use change model), and (4) a description of our land use change model.

7.3.1 The CGE model: Climate PoLicy Analysis (C-PLAN)

The CGE model used for this analysis is an augmented version of the C-PLAN model (Winchester & White, 2022), a global, recursive dynamic model built for the New Zealand Climate Change Commission (CCC). The C-PLAN model provides a representation of the New Zealand economy including climate change mitigation policies such as the NZ ETS. The model is solved annually from 2014 to 2050 and uses information from Version 10 of the Global Trade Analysis Project (GTAP) database (Aguiar et al., 2019; Chepeliev, 2020) and the New Zealand Government to supplement the benchmark data and calibrate the baseline. It is coded using the Mathematical Programming Subsystem for General Equilibrium (MPSGE) (Rutherford, 1999) a subsystem of the General Algebraic Modelling System (GAMS) (GAMS, 2021). We use the C-PLAN model to provide inputs to the forestry model and estimate the impacts of forestry land use change on the New Zealand economy. The land use change between production and permanent forests for this analysis is modelled outside the C-PLAN model, with updated amounts of land in permanent and production forests provided as exogenous inputs into the C-PLAN model each year. The model is packaged with a baseline scenario and three policy scenarios. In the baseline scenario, the carbon price is imposed as an exogenous carbon tax. Details on each scenario and more information on the model are available in Winchester & White (2022).

Our analysis uses the C-PLAN model policy scenario 'Transition Pathway 1' (TP1). This scenario models the NZ ETS (which includes all GHGs except biogenic methane) and a carbon pricing policy for biogenic methane emissions. The ETS in the model specifies targets for net emissions (other than biogenic methane) that are tightened over time so that they fall from 40.08 Mt CO2e in 2022 to zero Mt CO2e by 2050. The targets for each year are achieved by setting caps for gross GHG emissions (other than biogenic methane) accounting for the (exogenous) amount of emissions sequestered by forests in that year. In the policy scenario, carbon prices are determined endogenously by the supply and demand for emissions permits. The supply of permits is set exogenously each year according to the emissions cap in that period. Demand for permits reflects producers' operating decisions and is influenced by, for each sector, substitution possibilities between inputs, the availability of new technologies and the level of output. The carbon pricing policy for biogenic methane limits methane emissions to 24% below the 2017 level in 2050. There are also green technologies available in this scenario, which include electric vehicles, bioheat, electric heat, geothermal electricity with carbon capture and storage and methane-reducing technologies.

In the original version of the C-PLAN model, there is a single forestry sector that includes both production and permanent forests, with the hectares of land used and the carbon sequestered by forests exogenously determined using external estimates. In this research, the total land used for exotic forestry is still exogenously determined using estimates from the CCC (1.81 million hectares in 2014 up to 2.82 million hectares in 2050). However, the land used for permanent and production forests as well as the carbon sequestered and carbon permits produced by forestry are now endogenously determined in the modelling framework. These components are included in the C-PLAN model using two additional production activities. One production activity produces ETS permits from production forests (in their first rotation) and the other produces ETS permits from permanent forests. Both production activities use inputs of forestry land. The model also continues to represent a conventional production forestry sector that produces forestry products.

The value (and quantity) of land use in the new forest production activities is estimated from the value of land used in the original (conventional) forest production activity. The land inputs for the original production activity now represent rent paid on all production forest land not producing carbon permits. Accordingly, the value of land used as an input in the two new forest production activities represents the land used by permanent forests and the land used by first rotation production forests producing carbon permits, respectively. Both these values are calculated using the CCC's estimate of the total land used for forestry and projections of the area of forest land in each production activity. These value estimates are updated each year to reflect changes in land use due to changes in the carbon price. The carbon permits produced by production and permanent forests are based on the estimated carbon sequestration rates by these types of forestry and are also updated each year due to the differences in estimated carbon sequestration from each forest age group and the changing quantity of land in each of those age groups.

7.3.2 The forestry model: Energy and Emissions in New Zealand (ENZ)

The forestry model for this research comes from the ENZ model. This model was built for the CCC to provide policy advice for the government (CCC, 2021). A component of this model estimates the land used for different types of forestry, the emissions from afforestation and deforestation, as well as the carbon sequestered by exotic permanent and production forests. It estimates, without land use change at harvesting age, that 0.55 million hectares in 2014 and 0.83 million hectares of exotic forest in 2050 will be generating carbon permits in the NZ ETS. The carbon sequestered by production forests is calculated using the 'averaging' accounting approach.[14] The 'average' age of production forests in the ENZ model is 23 years and remains constant.[15] Carbon sequestration by permanent forests is calculated using the stock change approach. Based on advice from the CCC and the New Zealand Ministry for Primary Industries, the model assumes, in all years, that 6.1% of exotic trees planted per year are permanent forest, with the rest being production forest. This 6.1% accounts for 210 of 3435 ha of exotic trees planted in 2014, and 2537 of 41,595 ha planted in 2050. In our analysis, the total amount of forest land is exogenous, and we only consider the allocation of this land between production and permanent forests. Focussing on the decision to convert production forests into permanent forests at harvesting age is supported by the research by Kerr et al. (2012), which found that the change in land use from other types of agriculture into forestry as incentivised by the carbon price is negligible. Additionally, if any land use change occurs between production and permanent forests at afforestation, it will not affect the creation of carbon permits for 23 years due to the crossover between stocktake and averaging accounting. The ENZ model estimates the carbon dioxide sequestered by forests per hectare at each age and multiplies this by the hectares of forest at each age to calculate total carbon sequestration. This calculation only includes forests planted after 1989 to avoid double counting emissions and carbon sequestration from the pre-1990 Kyoto Protocol baseline.

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[14] In the ETS only forests planted after 2018 are eligible for average accounting (MPI, 2023) but we use it for all production forests here to be consistent with the CCC modelling and the C-PLAN baseline.

[15] This is an assumption made by the CCC and to remain consistent with the government baseline, we have maintained it in our analysis.

We convert the exotic forestry component of the ENZ model from Excel to GAMS and add this code to the C-PLAN model. This includes the amount of post-1989 forest land at each age group, the carbon dioxide emissions sequestered per hectare and emissions sequestered in each year. We use this module to determine how land use changes in forestry affect total carbon sequestration and feed that information into the C-PLAN model.

7.3.3 The 'breakeven' carbon price

All exotic forestry is treated the same in this analysis, with each tree assumed to have the same harvesting age, level of carbon sequestration and productivity. Carbon sequestration and productivity are based on the average levels for exotic trees in New Zealand as calculated by the ENZ model, and the harvesting age is assumed to be the average age of harvest for radiata pine. This is due to the limitations of the ENZ model, which does not have the functionality to look at different regions and different species of trees as well as the fact that radiata pine is the most abundantly planted species of exotic tree in New Zealand (MPI, 2021). Therefore, the change in land use between permanent and production forests modelled in this paper occurs at a harvest age of 28 years, based on the average age of harvest for radiata pine from 2017 to 2021 (MPI, 2021). We assume that this age of harvest does not change with the carbon price, based on the modelling by Manley (2022), who found that under averaging accounting, the age of harvest for production forests is not expected to change significantly.

In our model, farmers will only switch to a permanent forest when the carbon price increases to a level where permanent forests are more valuable than production forests. To calculate when this occurs, we use the 'breakeven' carbon prices estimated by Manley (2022). He used a forestry model to calculate the carbon price in New Zealand where the expected value of land in production forests is the same as permanent forests. This price is determined separately for forests less than 100 ha in size (that use the government-provided carbon look-up tables for their carbon sequestration calculations) and for forests larger than 100 ha in size (which have unique carbon look-up tables created for their carbon sequestration calculations). For these two forest sizes, Manley (2022) separated the forests into three levels of site productivity: 'low', 'medium' and 'high'. These productivity levels are based on the 300 index (the volume of stem growth for 300 trees at a predefined age) (Kimberley et al., 2005) and the site index (the height of the dominant tree at a predefined age) (Husch et al., 1982), which measure the productivity based on the change in tree biomass over time. Within these levels of site productivity, Manley (2022) further estimated three separate prices for different degrees of harvesting difficulty. This means the report estimated breakeven carbon prices, in New Zealand dollars (NZD) per tonne of carbon dioxide (tCO2), for 18 (two farm sizes, three types of site productivity and three types of harvesting difficulty) different types of forest land in New Zealand.

Manley (2022) further estimated area-weighted site index and 300 index values for New Zealand across 12 regions. He also provided examples of typical 300 index and site index values for 'low', 'medium' and 'high' productivity sites. The 12 regions described by Manley (2022) are similar to the aggregation used in MPI (2021), which estimated the total land used for production forests in New Zealand in 2021. Using the examples of site productivity from Manley (2022) as mid-points for each productivity level and the proportion of land in each of the 12 regions, as estimated by MPI (2021), we calculate the proportion of total production forest land at each site productivity level in New Zealand. From the information provided in MPI (2021), we also estimate the proportion of land for each productivity level that was below or above 100 ha in size. As seen in Table 1, approximately 19.2% of forest land in New Zealand is classified as small forests and 80.8% is classified as large forests.

Table 7.1: Carbon prices where the expected value of land is the same for production and permanent forests and the proportion of land in each farm size-productivity bucket.

Productivity	Breakeven CO_2 Price (NZD/tCO_2)	Proportion of Total Harvested Land
	Small Forests (Less than 100 ha)	
Low	102.33	5.3%
Medium	100.33	4.4%
High	106.67	9.5%
	Large Forests (Greater than 100 ha)	
Low	72.33	14.5%
Medium	76.00	16.4%
High	82.33	49.9%

Source: Authors' calculations based on information from Manley (2022) and MPI (2021).

Harvesting difficulty is challenging to determine for each region as there is a high level of heterogeneity in the harvesting costs for each site (West, 2019). There is also not a reliable data source, which estimates harvesting difficulty in the same regions used by Manley (2022). As a result, we average the 'breakeven' carbon price for each level of site productivity across harvesting difficulty. This means we use six 'breakeven' carbon prices (Table 7.1) compared with the 18 calculated by Manley (2022).

The baseline used in the C-PLAN and ENZ models assumes that there is a 35 NZD/tCO2 carbon price in the years the NZ ETS is active (CCC, 2021; Winchester & White, 2022). To avoid double counting any land use change estimated in these models, we add 35 NZD to the 'breakeven' carbon prices averaged from Manley (2022). The prices we use and the proportion of forest land at harvest age in each farm size–productivity 'bucket' are shown in Table 7.1.

7.3.4 Land use change

To represent land use change from harvest age production forest to permanent forest once the carbon price is above the 'breakeven' price, we use sigmoid functions (also known as S-curves). The use of S-curves to describe farming decisions was pioneered by Coleman et al. (1955), Beal and Bohlen (1956), Beal and Rogers (1960) and Rogers (2003) and continues to be used in more recent studies such as Kuehne et al. (2017), Swamila et al. (2020) and Llewellyn and Brown (2020). In using this function, we represent the switch to permanent forests as a similar process to the adoption of new technologies by farmers.

In other models, which use Faustmann's formula (Crabbe & Long, 1989; Hartman, 1976; Loehle, 2023; Nakajima et al., 2017; Reed, 1984; Wang & van Kooten, 2001; Wilson et al., 1998), forestry owners tend to be represented as rational decision-makers with full information. In reality, this is not the case and quite often each forestry owner makes decisions using different information and assumptions to their neighbours. As explained by Yousefpour et al. (2012), there is general knowledge within the industry on how to react to productivity risks using silvicultural methods but there are differences in how forestry owners react to the risks related to climate change. There is also scepticism regarding climate change-related policies by farmers in New Zealand (MPI, 2019), which will contribute to a slow adoption of technologies related to policy changes.

An S-curve can represent the heterogeneity in attitudes to switching to permanent forest at different carbon prices. This includes: (1) the small number of forest owners that are quick to make land use changes with the view of making more profit in the long term (innovators/early adopters); (2) the forest owners who take more time to make land use decisions but when profits for permanent forests are high enough they will make the change (early majority); (3) forest owners that wait until most of their peers in the industry have made the switch to permanent forests before they also change their land use (majority); and (4) the forest owners who are unlikely to change regardless of the carbon price (nonadopters) (Beal & Bohlen, 1956; Rogers, 2003).

The sigmoid functions used in this analysis determine the proportion of forest land that changes from production to permanent forests at harvesting age. Each carbon price above the 'breakeven' price corresponds to a probability of land use change. The S-curve functions include the carbon price from the previous period and the difference between an estimated 'high' carbon price (the maximum expected carbon price in 2050) and the breakeven carbon price. The estimated high carbon price is 337.79 NZD/tCO2, the 2050 (and highest) carbon price in the TP1 scenario estimated by Winchester and White (2022).[16] This is used under the assumption that foresters have access to this information (available on the CCC's website) and will internalise this as the expected high price.

Equation (7.1) shows the structure of the sigmoid function used in our analysis.

$$\sigma_{lyt+1} = \frac{0.95}{(1 + e^{-0.05(p_t - \hat{p}_{ly})})^a} \qquad (7.1)$$

where σ_{lyt+1} is the proportion of production forest land at harvesting age changing from production to permanent forests at forest size *l* (small or large), productivity level y (low, medium or high) and time

[16] The 2050 carbon price with no forestry land use change calculated in this study differs from what is reported by Winchester and White (2022) due to an update in the projected carbon sequestration from forestry in the ENZ model.

$t + 1$; p_t is the carbon price estimated by the C-PLAN model at time t; $\hat{p}_{ly}$ is the mid-point between the high carbon price calculated by the C-PLAN model (337.79 NZD/tCO2) and the breakeven carbon price for forest size l and productivity level y; and a is a parameter that controls the shape of the curve/responsiveness of land owners to increases in the carbon price. The total proportion of harvest land changing use is multiplied by 0.95 to represent the small proportion (5%) of landholders who will never change their land use to permanent forest regardless of the carbon price.[17]

The maximum amount of land that can change from production to permanent forests each year is based on the hectares of land expected to be harvested, as estimated by the ENZ model (between 42,087 and 72,327 ha each year). The amount of land that changes from production to permanent forests is a function of the maximum amount of land that can change use and a series of sigmoid function calculations (one for each productivity–farm size category). In each year, there are potentially six S-curves operating, each using a different 'breakeven' carbon price as its starting point, with the proportion of harvest land applying to each S-curve described in Table 7.2.

Equation (7.2) shows how the results from each of the six curves are added together to get the total area of harvest land changing use.

$$\varphi_{t+1} = \sum_l \sum_y \beta_{ly} \sigma_{lyt+1} \qquad (7.2)$$

where φ_{t+1} is the total hectares of land use change at time $t + 1$, and β_{ly} is the total hectares of harvest land available at each 'breakeven' carbon price based on land size l and productivity level y. Table 7.2 shows the area of land at harvest age (β_{ly}) available to change use under each breakeven carbon price in the model in 2022, 2035 and 2050.

Table 7.2: Hectares of harvest land available for change in each S-curve in 2022, 2035, and 2050.

Forest Land Characteristics (Breakeven Carbon Price NZD/tCO_2)	Area of Land Available for Change (ha)		
	2022	2035	2050
Small Forests Low Productivity (102.33)	3,156	2,727	3,833
Small Forests Medium Productivity (100.33)	2,620	2,264	3,182
Small Forests High Productivity (106.67)	5,657	4,889	6,871
Large Forests Low Productivity (72.33)	8,634	7,461	10,487
Large Forests Medium Productivity (76.00)	9,766	8,439	11,862
Large Forests High Productivity (82.33)	29,714	25,678	36,091
Total	59,548	51,458	72,327

Note: Due to rounding, the total harvest area may not equal the sum of the individual S-curve harvest areas.

To give a diverse representation of land use change, we consider a scenario with no endogenous land use change from production to permanent forests, and three separate S-curve parametrisations by

[17] We scale the aggregated S-curves by 0.95 based on research by Boscolo et al. (2009) and Flett et al. (2004). Boscolo et al. (2009) found that the average adoption rates by farmers in Bolivia are 88%, 96% and 93% for, respectively, sustainable forestry management practices, which have clear regulations, are easy to enforce and have clear and measurable changes on the farm. Flett et al. (2004) found similar new technology adoption rates for New Zealand farmers, but they did not explicitly consider sustainable forestry.

specifying alternative values for the a parameter in Equation (7.1). These scenarios are labelled: (1) no land use change, (2) fast adoption (a = 0.3), (3) moderate adoption (a = 1) and (4) delayed adoption (a = 5). As the total amount of forest land is exogenous in all scenarios, the area of harvest land available for land use change does not change between these adoption scenarios. The shape of the fast, moderate and delayed adoption land use change curves that determine the proportion of eligible forest land that is converted to permanent forest in a given year is illustrated in Figure 7.2.

Figure 7.2: The shape of the three S-Curves in the land use change model.

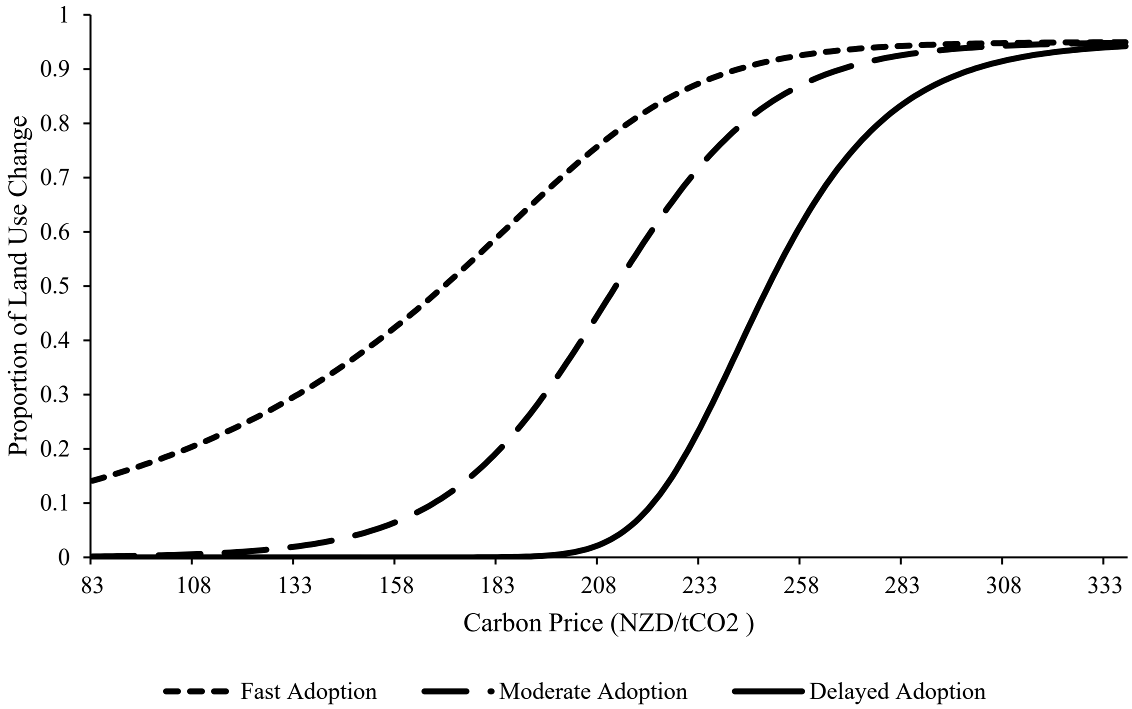


Table 7.3 provides an overview of forestry decisions in our modelling framework. As an ETS first operates in 2022 and forestry decisions are based on the carbon price from the previous year, endogenous land use change begins 2023. The table shows how the models are linked and how decisions in 1 year affect outcomes in subsequent years.

Table 7.3: Overview of forestry decisions in the modelling system.

Step	Action
1	If t = 2022: Simulate the C-PLAN model to estimate the carbon price in year t (p_t). If t > 2022: Go to Step 2.
2	Use p_t in Equation (7.1) to calculate the proportion of production forest land at harvesting age that changes from production to permanent forest for the six forest size-land productivity categories (σ_{lyt+1})
3	Use σ_{lyt+1} values in Equation (7.2) to calculate the total amount of land that changes from production to permanent forests at $t+1$ (φ_{t+1}).
4	Use φ_{t+1} to update the total amount of permanent forest land in the ENZ model.
5	Simulate the forestry component of the ENZ model to calculate land used for production and permanent forests, and CO_2 emissions sequestered by production and permanent forests.
6	Use the CO_2 sequestration estimates from the ENZ model to calculate the cap on gross emissions required to meet the ETS cap on net emissions in year $t + 1$.
7	Simulate the C-PLAN model with land use estimates from Step (5) and the gross emissions cap from Step (6) to estimate the carbon price in year $t + 1$. Go to Step (2) to calculate forest land use and sequestration for year $t + 2$.

7.4 Results

This section reports results for the TP1 simulation for four alternative land use scenarios: the (exogenous) land use scenario used by Winchester and White (2022), labelled no land use change, as well as the three S-curve scenarios: delayed adoption, moderate adoption and fast adoption. For each scenario, we report the carbon price, GDP, welfare, land used for permanent forests, output from the production forest sector and gross emissions (excluding biogenic methane) from 2014 to 2050.

Table 7.4 presents a summary of results in 2015, 2035 and 2050 for the no land use change and three S-curve scenarios. The table shows that, in all the S-curve scenarios, the carbon price decreases, gross GHG emissions increase, forestry removals increase and land used for permanent forests increase compared with the no land use change scenario (where forestry land use change is exogenous). Land use change begins to occur in the fast and moderate adoption scenarios by 2031, and for the delayed adoption scenario, this does not occur until 2043. Table 7.4 also shows that, compared with the no land use change scenario, land use change to permanent forests increases welfare and increases GDP by 2050. This is due to the increase in the gross GHG emissions cap caused by the additional carbon permits produced by permanent forests. The increase in land for permanent forests in the S-curve scenarios decreases output from the production forestry sector.

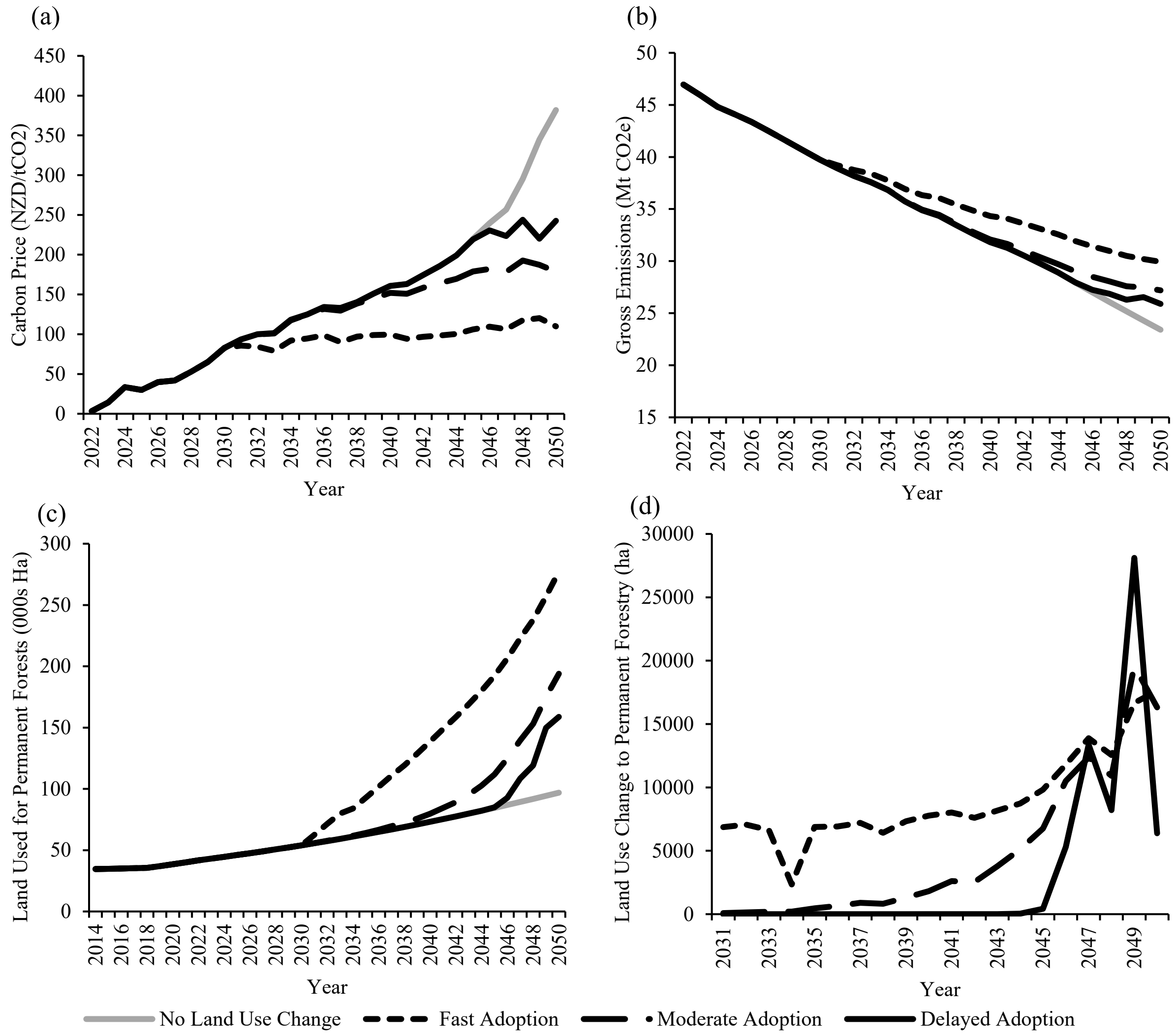
Table 7.4: Summary results for 2015, 2035 and 2050.

	2015	2035				2050			
		No Land Use Change	Delayed Adoption	Moderate Adoption	Fast Adoption	No Land Use Change	Delayed Adoption	Moderate Adoption	Fast Adoption
CO_2 Price, NZD/tCO_2	3.37	124.96	124.96	124.88	94.71	381.84	242.66	178.77	109.86
Gross GHG Emissions*, Mt CO_2e	45.45	35.74	35.74	35.78	36.93	23.41	25.89	27.19	29.93
Forestry Removals, Mt CO_2e	13.20	13.07	13.07	13.11	14.26	23.41	25.89	27.19	29.93
Total Permanent Forest Land, 000s ha	34.84	62.99	62.99	64.06	92.78	96.89	158.76	193.91	277.20
Production Forestry Output, billions 2017 NZD	3.84	5.51	5.51	5.51	5.42	6.34	6.16	6.05	5.79
Welfare, billions 2014 NZD	120.72	190.09	190.09	190.10	190.15	245.59	245.83	245.88	245.95
GDP, billions 2017 NZD	251.99	395.22	395.22	395.23	395.42	508.72	509.40	509.52	509.78

*: this measure is excluding biogenic methane emissions.

Results for each year are reported in Figure 7.3a–d. In the S-curve scenarios, the carbon price (Figure 7.3a) drives changes in forestry land use. As the carbon price increases, land changes use from production to permanent forests and carbon sequestration increases. Consequently, relative to the no land use change scenario, this allows for higher gross emissions within the NZ ETS cap (Figure 7.3b) and ultimately results in lower carbon prices. Gross emissions increase above the no land use change scenario in the fast adoption scenario and the moderate adoption scenario by 2031, and they do the same for the delayed adoption scenario in 2043. In all scenarios, net emissions are the same and (excluding biogenic methane) reach zero by 2050.

Figure 7.3: (a) Carbon price from 2022 to 2050 in each scenario. (b) Gross GHG emissions (excluding biogenic methane) from 2022 to 2050 in each scenario. (c) Total land used for permanent forests from 2014 to 2050 in each scenario. (d) Land use change from production to permanent forests each year from 2031 to 2050 in the S-curve scenarios.



As more land use change occurs in the fast adoption scenario than in the moderate and delayed adoption scenarios (Figure 7.3c), carbon prices are relatively high in the slower adoption scenarios. Specifically, when there is no land use change, the carbon price reaches 381.84 NZD/tCO2 in 2050. In the delayed adoption scenario, the 2050 carbon price is 242.66 NZD/tCO2; in the moderate adoption scenario, it is 178.77 NZD/tCO2; and in the fast adoption scenario, it is 109.86 NZD/tCO2. This means that if farmers delay their land use change to permanent forests, there will be higher carbon prices in future years that increase incentives to switch to permanent forests in those years.

The impact of delayed action on future land use change is illustrated in Figure 7.3d, which shows the annual changes from production to permanent forest land. Whilst the total amount of land in permanent forests is highest in the fast adoption scenario, the yearly amount of land converted to permanent forest is sometimes higher in other scenarios in later years. For example, in 2049, 16,662 ha of land are converted to permanent forests in the fast adoption scenario, and the corresponding numbers in the moderate and slow adoption scenarios are, respectively, 19,566 and 28,109. These relatively high levels of land use change then reduce carbon prices in future years (Figure 7.3a), which causes some volatility in the amount of land changing use from 2046 to 2050 in all scenarios.

As delayed action increases incentives to convert to permanent forests in future, there will be significant land use change in all scenarios by 2050 (Figure 7.3c). For example, even in the moderate and delayed adoption scenarios, there is 1.64 to two times more land used for permanent forests than the no land use change scenario by 2050. This delayed action effect also means that gross emissions start to converge across scenarios in later years (Figure 7.3b). In 2050, gross emissions in the fast adoption scenario are 1.28 times greater than the no land use change scenario, 1.16 times greater in the moderate adoption scenario and 1.11 times greater in the delayed adoption scenario. Due to land use change only occurring at harvesting age in this modelling, the total amount of land in permanent forests is only a small proportion of total exotic forest land in all scenarios. For example, in the fast adoption scenario, only 0.28 of 2.82 million hectares of exotic forests will be permanent forests in 2050.

Overall, our results illustrate that over the longer periods, short-run decisions by foresters have little impact on land use change to permanent forests in this model. If foresters decide not to switch to permanent forests in the current year, the carbon price will increase, and they will be incentivised to make the change in a later year.

7.5 Discussion and Conclusions

The core climate change policy tool in New Zealand is the NZ ETS (PCO, 2019). With the current rules around forestry, there are incentives for forestry owners to switch to permanent forests. We focus on land use change from exotic production forests to permanent forests when trees are at harvest age. We represent this choice using three S-curve scenarios. To estimate this land use change and the impacts from it, we simulated a modelling system that included an economy-wide model, a forestry model and land use change functions.

Our analysis considers land use change from production to permanent forest motivated by the ability to earn carbon permits rather than harvesting timber. To represent this change, we use S-curves. This is carried out under the assumption that farmers do not have perfect carbon price forecasting information and will make decisions on the profitability of permanent forests as if it is the adoption of a new technology. Our approach is based on the scepticism regarding climate change (Yousefpour et al., 2012) and climate change-related policies (MPI, 2019) by farmers, which will contribute to a slow adoption of new forms of land use related to policy changes. This is comparable with the methodology used by Adams and Turner (2012), who used transition probabilities to show that a higher carbon price leads to an increase in afforestation and carbon sequestration from forestry, but that optimal land use change is limited by uncertainty around the future carbon price. Manley (2022) reached similar conclusions regarding afforestation, although with a different methodology. Our analysis supports the results of these papers and has the additional robustness of an annually updating carbon price based on the change in carbon sequestration every year.

We found that when forestry owners respond to the carbon price, there is a noticeable increase in the amount of carbon sequestered and with more carbon permits produced in the NZ ETS, other sectors can emit more and stay within the emissions cap. Ultimately, this lowers the economic costs of meeting New Zealand's long-term climate goals.

We also found that feedback from the land use change to the carbon price means that the responsiveness of forest owners to the carbon price (as measured by the S-curves) has a relatively modest long-run impact. That is, a small response in the current year leads to a higher carbon price in future years, which incentivises more conversion to permanent forests, and ultimately offsets some of the small response in previous years. This is a consequence of the emissions cap imposed as part of the NZ ETS, with an increase in permanent forests (and their carbon sequestration) decreasing carbon prices in future years.

This suggests that if foresters are able to earn ETS permits for sequestering carbon, the long-run amounts of permanent forests and carbon sequestered are relatively insensitive to the responsiveness of farmers. To ensure foresters respond to the carbon price, the New Zealand Government should put resources into encouraging farmers to understand the potential benefits of including permanent forests in the ETS. These benefits include the potential additional profit foresters can make from being included in the NZ ETS and nonmarket benefits including the increased carbon sequestration from the trees and the benefits to soil and water quality they can provide (New Zealand Forest Service, 2021). The treatment of permanent forests in the NZ ETS should serve as a blueprint for other regions to incentivise forestry carbon sequestration.

A limitation of our approach is that we assume that foresters' trust in the longevity of the ETS is constant. As the NZ ETS is around for longer, there should be an expectation that farmer's trust of the policy and its potential benefits will increase. This means that the shape of the S-curves could change over time, and the switch to permanent forests could be higher than what is estimated here. Another limitation is the expectation that all land use change occurs at the age of 28, the age when radiata pine tends to be harvested in New Zealand (MPI, 2021). It is likely that land will change use at other mature forest ages, which impacts the amount of potential carbon sequestration (i.e. if a production forester changes land use at a harvesting age of 25, this will be included as three additional years of carbon permit production relative to our analysis). There may also be changes in forestry inputs (e.g. a preharvesting age decision to switch from production to permanent forests may result in less trimming for the affected trees). Also, this paper is potentially restricted in its analysis because it models all exotic forests as if it is radiata pine and excludes indigenous forests. Other species of trees in New Zealand, especially native trees, may not have as high a potential for ETS profitability but they do provide a host of other nonmarket benefits such as improvements in biodiversity, increased habitats for native species and increased cultural significance compared with what can be provided by radiata pine (New Zealand Forest Service, 2021).

Future studies could expand on this research by adding in a ‘trust component’ to the S-curves, including an analysis where species other than radiata pine are represented, and using a less rigid land use change age projection to estimate the changes in carbon permits produced over time. This work could also be augmented by including land use change between agricultural uses in the CGE model. This could be carried out by specifying additional S-curves or using an existing approach to represent land use change in CGE models.

Finally, policy-driven forestry incentives in New Zealand have been introduced in the past, including the One Billion Trees Program (New Zealand Forest Service, 2021). This project had the aim of helping meet the government's goal of planting 1 billion trees around New Zealand by 2028 through funding grants for planting native and exotic trees between 2018 and 2021. It incentivised 42 million trees to be planted around New Zealand, 80% of which were native species and 20% were exotic. The difference between this policy and the inclusion of forestry permits in the NZ ETS is the One Billion Trees Program was more focussed on increasing the incentives for native trees to be planted rather than trees with high levels of carbon sequestration. This provides an interesting dilemma for the government: whether to value the higher levels of carbon sequestration from exotic trees over the additional co-benefits and ecosystem service values from native forests. To increase incentives for native forests in New Zealand, the government would have to introduce a policy outside the NZ ETS.

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8. Discussion and Conclusions

This thesis explored the use of input-output data and economy-wide modelling to estimate the impacts plastic and climate change policies on the economy and land use change. The first manuscript in this thesis focussed on plastic use in industries. The second manuscript explored the potential economic and land use change impacts from regional switches to plastic and synthetic chemical free clothing. The third manuscript looked at climate change policy, estimating the economic and land use change impacts of the inclusion of forestry in the NZ ETS.

There have been several policies introduced around the world to try and combat plastic pollution. The majority of these have been plastic packaging policies (Howard et al., 2019). The first manuscript in this thesis aimed to identify industries in the USA which use a high value of high-polluting plastics both directly and indirectly. I used the Eora input-output database and an adjusted Leontief inverse to estimate the plastic intensity of products across different industries. This could help policy makers identify sectors which are using a large amount of plastic in production. The public perception, based on existing policies, is that food and drink related industries are the most plastic intensive due to their use of consumer-facing plastics in packaging. In this thesis, the industries which were found to use polluting plastics intensively include carpet and rug mills and fibre, yarn and thread mills for plastic fibres and filaments; paint and coating manufacturing for plastic resin; tire manufacturing for synthetic rubber; and soft drink and ice manufacturing for plastic bottles.

One of the key findings from the first manuscript was that clothing and fabric related sectors use polluting plastics intensively in production and at a relatively high value. The main plastic input for these sectors is plastic fibres and filaments which includes products such as polyester and polyamides (NAICS, 2018). As described by Woodall et al. (2014), Browne et al. (2011) and Dris et al. (2016) these plastics are a significant source of microplastics in the environment and they have potential human health impacts from their presence in the air.

In 2022, the UN endorsed a resolution to end plastic pollution, with the aim to have a legally binding agreement in place by 2024 (UN, 2022; HAC, 2023). Given the release of microplastics into waterways from the washing of clothes (Browne et al., 2011; Cai et al., 2020; Dalla Fontana, Mossotti & Montarsolo, 2020; Choi et al., 2021), for clothing to meet the UN's aim to end plastic pollution, better sewerage filtration systems will need to be developed or clothing will need to be made without plastic or synthetic chemicals. The second manuscript in this thesis explored the potential economic and land use change impacts from a switch to plastic and synthetic chemical free clothing in different regions. This involved the use of a CGE model which included a representation of the conventional clothing sector as well as a plastic and synthetic chemical free clothing sector for each region. A tax was endogenously introduced in the model until all clothing in the taxed region was plastic and synthetic chemical free.

The results from the model indicated potential risks to policy effectiveness from clothing leakage. This is where conventional clothing output increases in untaxed regions and decreases in taxed regions due to the higher production costs associated with clean clothing production.

In the tax scenario where the EU was the only region that introduced a clothing tax, total plastic output in the EU increased compared to the benchmark. This was caused by clothing leakage and by the relatively higher plastic intensities of some of the domestic EU industries. The demand from domestic industries means that even though plastic production is higher, plastic pollution in the EU may become more manageable as it is shifting from non-point source pollution from the washing of clothes to point source pollution from other sources of plastic leakage (EPA, 2023).

I found that shifting production towards clean clothing will also result in a significant amount of land use change. To estimate land use change, I used a constant elasticity of transformation function based on the GTAP-AEZ model (Hertel et al., 2008). Traditional agricultural clothing inputs such as plant-based fibres, natural rubber, oleaginous fruit, and hides will be favoured at the expense of food-based crops such as vegetables, oats, barley, and raw milk.

Since 2023, foresters can claim NZ ETS carbon permits as either permanent or production forests. The third paper in this thesis explored the potential impacts of this policy change on the economy and land use change. It used a CGE model, a forestry model, and land use change functions. I was specifically interested in the land use change from production to permanent forests at harvesting age in New Zealand. I focussed on this as the NZ ETS provides incentives for farmers wishing to plant trees with the sole purpose of generating revenue from carbon permits in the form of permanent forests. Also, the NZ ETS makes it difficult for permanent forestry owners to change their land use for 50 years.

Land use change in this modelling framework used sigmoid functions or S-curves to represent the risk averse nature of farmers (Binswanger, 1980; Yousefpour et al., 2012). To my knowledge, this was the first time this approach has been used in CGE modelling to represent land use change. The S-curves were used under the assumption that farmers do not have perfect carbon price forecasting information and will make permanent forest land use decisions as if it is the adoption of a new technology.

I found that when farmers switch to permanent forests as a response to the carbon price, there is a significant increase in the amount of carbon sequestered. This means that other sectors can emit more and stay within the emissions cap set by the NZ ETS. I also found that feedback from land use change to the carbon price means that the short-run decisions of farmers have little long-run impact on the land used for permanent forest. This is because, if the carbon price increases, more farmers will switch their forests to being permanent which will, in turn, decrease the carbon price from an increase in carbon sequestration, causing a reduction in land use change towards permanent forests.

All three manuscripts in this thesis contribute to the literature on the use of input-output and economy-wide modelling to investigate environmental issues. They show how these tools can identify problematic sectors which contribute to negative externalities and indicate the impacts of environmental policies on the economy, emissions, and land use change. They also show two different methodologies available within CGE models to represent land use change between agricultural products.

By investigating both plastics and GHG emissions policies, I show the parallels in addressing these pollutants, including the economic and land use implications. Future research could find a way of integrating S-curves with a constant elasticity of transformation structure to represent both typical land use change and land use change driven by new technologies. It could also study the interaction of a plastic clothing tax with an ETS or similar climate change mitigation policy.

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