ABSTRACT

KAYA, ELISE TUGBA. Essays on Land Use, Environment and Policy. (Under the direction of Robert C. Abt.)

This dissertation consists of three essays in agricultural resource economics and forest economics. The first essay explores the impact of government policies on soil erosion. The U.S. government has created many programs to support farmers while trying to mitigate the unfavorable impacts of agricultural practices on environment. This paper focuses on two government programs: The Federal Crop Insurance Program (FCIP) and the Conservation Reserve Program (CRP).To examine, the effects of both programs on soil erosion, a system of five equations is estimated: soil erosion, CRP participation, insurance participation, fertilizer and chemical expenditures and conservation effort. The results indicate that CRP participation significantly reduces soil erosion, whereas crop insurance participation increases soil erosion. My results also indicate that farm diversification might reduce both crop insurance participation and fertilizer and chemical expenditures. The issue of moral hazard is a highly recognized problem and remains an important concern. My results find, as it is consistent with conventional wisdom, evidence of moral hazard in crop insurance participation, implying that insured farmers spend less on input expenditures. This research has implications for understanding government policies on environmentally sensitive lands because government subsidy programs may encourage crop expansion on environmentally sensitive lands while competing with itself by crowding out the CRP enrollment.

The second essay investigates the determinants of tree planting under the CRP in the U.S. South where more than 80% of tree planting have occurred as a resource conservation practice in the program. I estimate the predicted probability of a parcel converting from cropland to CRP tree planting by applying a probit panel model. Understanding the factors that influence tree-planting under the CRP is critical to design comprehensive conservation policies that target long-term conservation benefits such as reducing greenhouse gas emissions. I find empirical evidence that market forces and financial incentive payment impact land-use decisions in the U.S. South, where most of land is privately owned. Future extensions of this research will address if a low-cost carbon economy exists in tree-planting under the CRP in the US South. My research will improve the understanding of policy and market changes that drive tree planting under the CRP while quantifying

policy measurements to increase carbon sequestration on marginal lands.

The third essay examines the impacts of trade measure to address illegal fiber sourcing in the global forest market, using the Pseudo Poisson Maximum Likelihood model. The important contribution of this study is to quantify the effects of illegal logging trade measures on the global forest market by identifying key differences in trade regulations taken by countries to prevent illegal logging. Using a gravity model, I separately examine the impacts of trade measures on import values in each product group by focusing on four country groups: Australia, the EU, Japan, and the US. Because illegal logging persists, assessing the effectiveness of trade regulations and laws that target to the banning illegal importation of wood is important for effective policy design. Using the gravity model, I assess the economic aspects of trade measures on global forest products markets. Overall, I find a negative and significant effect of trade measures implemented by the countries on the importation of wood products though results vary by countries and product group.

Essays on Land Use, Environment and Policy

by
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DEDICATION

To my parents.

BIOGRAPHY

Elise Tugba Kaya was born in Izmir, Turkey and grew up in Istanbul, Turkey.She earned her Master of Business Administration at East Tennessee State University in 2012.She started PhD program in Forestry and Environmental Resources at North Carolina State University. She earned Master's in Economics in 2017 and is now completing her PhD at North Carolina State University.

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THE IMPACTS OF U.S. AGRICULTURAL POLICIES ON SOIL EROSION

1.1 Introduction

Agricultural practices may have unintended environmental outcomes that impact a wide range of environmental factors, including water, soil, and air quality; biodiversity; and greenhouse gas emissions (GHG). For instance, in the United States, agricultural practices that manage soil, livestock, and manure account for 9% of total GHG emissions, with crop cultivation being the main contributor (U.S. Environmental Protection Agency, 2019c). Increased agricultural pollution may also impair water quality, with impacts that could affect the surrounding ecosystems and human health. The magnitude of these environmental outcomes likely varies by region while some of these outcomes need attention at the federal level the other concerns such as water quality impairment in major estuaries deserve region-specific attention (Lichtenberg, 2018). For example, the Corn Belt and the Mississippi Delta regions have higher rates of sediment losses to water erosion due to agricultural land-use intensity while field erosion rates are higher in the southeastern U.S. because of its land attributes (Hellerstein et al., 2019). Thus, concerns with water quality would be more important in the regions where agricultural production is more prevalent. Region-specific concern also need attention and should be consolidated in government policy schemes.

The Federal Government has implemented many policy instruments to control agricultural pollution and meet region-specific environmental objectives. However, the level of environmental performance delivered by these policy instruments is diminished by existing farm income and support programs that spur farmers to engage in intensive cultivation on environmentally sensitive lands. Unintended environmental consequences of agricultural practices may be amplified when environmentally sensitive lands are brought to agricultural production. To understand how government farm policies impact the expansion of crop production on environmentally sensitive lands, the links between land use, policy, and the environment should be jointly analyzed. External forces and market forces, along with government farm policies, are likely to impact land-use change at both extensive and intensive margin(Lubowski, 2006).

The U.S. government has created many programs to support farmers while trying to mitigate the unfavorable impacts of agricultural practices on environment. This paper focuses on two programs that could be seen as having competing objectives on marginal agricultural lands: The Federal Crop Insurance Program (FCIP) and the Conservation Reserve Program (CRP). The FCIP has helped U.S. farmers manage production risks by providing financial support for them when they lose yields and revenue because of natural events and market conditions. Since 2000, the addition of new insurance products developed by private industry has substantially changed the program structure and subsidy levels. Higher subsidies have led to increased insured acres. The current status of insured acres is a total of 369 million acres and $ 110 billion in liabilities (U.S. Department of Agriculture, Risk Management Agency, 2019).

The CRP program is a long-term (10–15 years), voluntary land retirement program that pays an annual rental payment and provides cost-share assistance to enable landowners to retire environmentally sensitive lands from agriculture production and convert them into land uses that will improve environmental quality. The CRP has evolved since its establishment in 1985 and is a key environmental conservation program focusing on improving rather than just protecting environmental quality. Current enrollment is 22.6 million acres as of 2018, but the new farm bill increased capped acres to 27 million by 2023 (U.S. Department of Agriculture, Farm Service Agency, 2019).

The FCIP and the CRP may have conflicting objectives on environmentally sensitive lands. The FCIP may encourage cultivation on marginal land, whereas the CRP attempts to remove cropping on marginal lands and reduce agricultural pollution. I hypothesize that both the FCIP and the CRP will be more heavily utilized in counties with a higher proportion of marginal agricultural lands. This paper evaluates the impacts of both the FCIP and the CRP on soil erosion by updating and extending the previous work by Goodwin and Smith (2003). To examine the impact of enrollment in both programs on soil erosion, I estimate a structural model to consider the endogeneity potential among the variables. My empirical analysis consists of a system of five equations: soil erosion, CRP participation, insurance participation, fertilizer, and chemical expenditures and conservation effort. I estimate the impact of both policies on soil erosion by using county-level data for the period 2000–2012. Data used in this analysis come from various sources. Data on land use and land characteristics come from the National Resource Inventory (NRI) conducted by U.S Department of Agriculture (USDA), Natural Resources Conservation Services (NRSC). County-level crop yield and acreage data come from the (U.S. Department of Agriculture, National Agricultural Statistics Service, 2019). County-level insurance variables are collected from the USDA Risk Management Agency (RMA). County-level government payments, production revenues, and costs from crop and livestock production are obtained from regional economic accounts that are reported by the U.S. Department of Commerce's Bureau of Economic Analysis (BEA). The remainder of the paper is organized as follows. Section 1 provides an overview of the FCIP and the CRP. Section 2 reviews the relevant literature. Section 3 describes data and variable construction used in this study. Section 4 and 5 describe model specification. Section 6 presents estimations results. Finally, section 7 concludes.

1.2 Overview of U.S. Agricultural Policies

1.2.1 The Federal Crop Insurance Program

Agricultural production, by its nature, is subject to risk and uncertainty. Natural events or market fluctuations (such as shifts in demand and supply) result in volatility in commodity prices and can amplify the economic outcomes of agricultural production; thus, well-structured farm policies are advocated to manage risks and provide a safety net for farmers as they encounter yield and revenue losses. The Federal Crop Insurance Program (FCIP), which dates to the 1930s, is a pillar of farm support programs in the United States. It was initially introduced under the New Deal program by President Franklin Roosevelt to help financial recovery and alleviate the adverse impacts of the Great Depression and the Dust Bowl in the agriculture sector. Congress passed the Federal Crop Insurance Act in 1938 and established the Federal Crop Insurance Corporation (FCIC) to implement the FCIP. The first provisions of the program covered only major crops in the main regions. After its inception, the program has gone through substantial changes under different provisions (U.S Department of Agriculture, Risk Management Agency, nd). In particular, four significant provisions restructured context of the FCIP and made essential policy changes: the 1980 Federal Crop Insurance Act, the 1994 Federal Crop Insurance Reform Act (FCIRA), the 2000 Agricultural Risk Protection Act (ARPA), and the 2008 Food, Conservation, and Energy Act (FCEA). These acts were designed to benefit both private insurance companies and farmers.

The initial implementation of the program in 1938 was treated as an experiment and stayed limited, only covering certain commodities until the 1980 Federal Crop Insurance Act. The number of commodities insured, and the regions covered were extended in the Federal Crop Insurance Act of 1980. The enrollment cost was high, so premium rates were subsidized by 30% in order to make enrollment more accessible and affordable to the farmers and to enhance the scope of the program. This act also introduced the use of private insurance companies to manage the sales of federal crop insurance plans. Enrollment remained at modest levels until the mid-1990s when enrollment in the FCIP became mandatory to be eligible for deficiency payments under price support programs, certain loans, and benefits in the FCIRA of 1994. However, mandatory participation was repelled under the 1996 Federal Agricultural Improvement and Reform (FAIR) Act. One of the critical provisions created in the FCIRA of 1994 was the fully subsidized Catastrophic (CAT) coverage, which paid farmers for yield losses that exceeded 50% of historical average yield. It also increased premium subsidy rates, an average of 40%. The FAIR Act of 1996 made substantial changes. The FAIR of 1996 phased out mandatory participation requirements to be eligible for farm program benefits. Also, the Risk Management Agency (RMA) was created in the U.S. Department of Agriculture (USDA) in 1996 to manage the Federal Crop Insurance Corporation and support the U.S. agriculture industry (U.S Department of Agriculture, Risk Management Agency, nd).

The ARPA of 2000 made significant changes in program structures and introduced provisions for the funding of new product development and features provided by private insurance companies. The ARPA of 2000 aimed to increase insurance participation; thus, premium subsidies were increased to an average of 62 %. The FCEA of 2008 established the Average Crop Revenue Election (ACRE) and the Supplemental Revenue Assistance Payments (SURE). The ACRE gave farmers the option to replace Counter-Cyclical Payments (CCP) with an ACRE option. The eligibility of ACRE depended on the farm and revenues. The SURE provided a safety net to farmers in the event of revenue losses for their entire farming operations rather than compensating individual crop losses. The 2014 Farm Bill terminated these provisions and replaced the CCP and the ACRE with the Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC) programs. In addition to these provisions, the Supplemental Coverage Option (SCO) and the Stacked Income Protection Plan (STAX) were introduced and provided additional coverage on top of existing crop insurance coverage. SCO is available for the producers who already enrolled in PLC; on the other hand, STAX was established only for cotton producers (Smith et al., 2018).

The Agriculture Improvement Act (AIA) of 2018 has kept almost all the preceding provisions with small changes. provisions with small changes. However, due to low commodity prices, spending on commodity programs was increased. The introduction of new crop insurance provisions and increased subsidy rates have contributed to crop insurance participation, which tripled total enrolled acres in the program (Fig. 1.1). However, the cost of indemnities paid also increased with rising enrolled acres. Fig. 1.3 exhibits net indemnity payments between 1989 and 2018. As seen, crop insurance payments exceed farmer-paid premiums by one billion dollars starting from 2001 (except 2005, 2007, and 2016) with significant peaks occurring right after historic droughts of 2002, 2008, and 2012. In 2012, total crop losses payments reached their highest amount in the history of FCIP, accounting for 13.2 billion dollars due to severe drought. In the same year, that amount also exceeded total government farm payments, which accounted for 10.6 billion dollars in 2012. (See Fig. 1.2) 1989–2018.

The Federal Agriculture Improvement and Reform Act (FAIR) of 1996 enacted production-flexibility contact payments, which increased government direct farm program payments in the late 1990s. A critical year in the farm sector was 2005 because of agricultural production shocks; therefore, the government's direct program payments amounted to the highest historical figure: 24.3 billion dollars (See Fig. 1.3). In 2005, Hurricanes Katrina and Rita damaged agricultural production and caused crop losses, in particular to cotton and dairy producers. In the meantime, producers in the Midwest were facing a drought, which caused insect infestation and damaged corn and soybean production.

Fig. 1.3 indicates the importance of government farm programs to alleviate the adverse impacts of market fluctuations and provide income support as a safety net. Therefore, most of the debate on government farm programs have revolved around how to set an effective policy that integrates the cost of financing the program that does not distort production decisions on marginal lands and provides social benefits to producers and consumers. Effective policy design is the interest of both producers and taxpayers because taxpayers pay the cost of financing the program. Thus, new policies to address those concerns are vital to making informed decisions.

1.2.2 The Conservation Reserve Program

Like the FCIP, the history of farm conservation efforts also originates from the New Deal Program. The main objective was to retire highly erodible lands from agricultural production in order to prevent another Dust Bowl (which occurred in the 1930s); other objectives were to curb production supply and prevent increases in crop prices.

One of the most ambitious conservation efforts came as the Soil Bank Program. In 1956, the Soil Bank Program was established under the Agricultural Act of 1956 by President Dwight Eisenhower to curb commodity surpluses and protect farm income by retiring marginal lands from crop production and paying rental rates to participating farmers. The program included two subprograms targeted to reduce cropland production: The Acreage Reserve Program (ARP) and the Conservation Reserve Program (CRP). The ARP was targeted to curb commodity surpluses by idling lands that produced corn, cotton, wheat, rice, peanuts, and tobacco, whereas the CRP was designed to retire the land altogether from crop production and convert it to other land uses for the long term. As a result of both programs, 29 million acres were removed from crop production; the highest participation rates were in the Great Plains, Texas, and North Dakota. Tree planting under the CRP were concentrated in the Southeast U.S., whereas most of the grassland conversion occurred in the Great Plains (Helms, 1985).

In the 1970s, the agriculture industry expanded production levels because of the high international demand for grain exports from Russia, so conservation efforts faded during that time frame. Appreciation of US dollar and high interest rates led to the 1980s farm crisis. Following the 1980s farm crisis, conservation efforts were incorporated into the agenda of government farm policies again (Cain and Lovejoy, 2004). The Conservation Reserve Program (CRP), administered by the Farm Services Agency (FSA), was established in 1985 under the Food Security Act of 1985 by President Ronald Regan to form a long-term (10–15 years), voluntary conservation policy to address soil erosion. The program offers an annual payment and 50% of conversion cost-share assistance to the participants; in return, they remove highly erodible land from agricultural production and convert it into vegetative covers such as tree planting or grassland, which improve environmental quality.

When the CRP was introduced in 1985, the main goal of the program was to remove highly erodible lands from crop production; however, the context of the program has evolved with new provisions. It has become an important agri-environmental policy in the U.S. farm policy, currently enrolling 22.6 billion acres. The new Farm Bill of 2018 increases the acreage cap to 27 million (roughly the size of Virginia) by 2023. Current policy provisions focus on improving air and water quality, mitigating carbon emissions, enhancing wildlife habitats, and preserving soil productivity in addition to providing steady farm income support for landowners. The CRP has become the most extensive conservation and environmental policy in the United States and has been included in the Farm Bill since its inception and authorized under the conservation title. The CRP acres are limited to a certain amount under the new farm bills; the limits depend on many factors such as production, prices, and demand. Figure 5 illustrates the impact of government policy and commodity price changes on the CRP enrolled acres and capped acres. The program enrolled acres rapidly increased to 15.3 million acres from 1.9 million acres in 1987 (Fig. 1.4).

The conservation title officially started under the Farm Bill of 1985 with the Conservation Reserve Program. There were changes in the conservation title which was administered before under the USDA Soil Bank Program. Before the CRP was introduced under the Farm Bill of 1985, its participation had options of 3-, 5-, or 10-year contracts in the Soil Bank Program (Helms, 1985). Extending contracts to lengths of 10 to 15 years was one of the most significant changes compared with conservation provision under the USDA Soil Bank program, which provided more flexible contract lengths. In addition to the CRP, conservation compliances were amended, which prevented landowners from producing on highly erodible lands and wetlands. To be eligible for government farm program payments, including direct farm payments and conservation payments, a landowner is required to meet specific conservation objectives. This includes sodbuster and swampbuster programs which were implemented to remove highly erodible grasslands and wetlands from cropland use (Lichtenberg, 2018).

Enrolled acres increased to 32 million acres in 1990. Substantial changes also followed with increases in enrolled acres under the Food, Agriculture, Conservation, and Trade Act (FACT) of 1990. This act extended features of conservation compliance from the 1985 Farm Bill and created the Environmental Conservation Acreage Reserve Program (ECARP), including the Conservation Reserve Program (CRP) and the Wetland Reserve Program (WRP). The WRP, like the CRP, is a voluntary program offering financial incentives to landowners to protect and improve conservation and wildlife practices on their lands. The bill also added more provisions to meet environmental objectives, particularly emphasizing the relationship between agricultural production and the environment and establishing several incentive programs to meet environmental objectives: an agricultural water quality incentive, tree planting initiative, environmental easement program, and weed and pest control programs (Cain and Lovejoy, 2004). The consideration of environmental concerns led to the formulation of the Environmental Benefits Index (EBI), which also changes the nature of the program enrollment. The EBI is formulated to evaluate and score the offered lands for eligibility of CRP enrollment by incorporating many factors, including water and air quality improvement, and wildlife habitat enhancement. Therefore, eligibility in the program depends not only on an offered rental rate bid but also on the EBI, which made offers more competitive under the FACT of 1990 because the extent of eligibility increased.

As seen in Fig. 1.4, leading high commodity prices in the late 1990s and the Federal Agriculture Improvement Act (FACT) of 1996 decreased the capped acres to 36.4 million acres. The ECARP continued the CRP, and the WRP and introduced one of the significant provisions in conservation title: The Environmental Quality Incentives Program (EQIP), a voluntary program for adopting soil and water conservation practices on working lands. EQIP's primary goal was to encourage active farmers by providing cost-share assistance to implement conservation efforts while optimizing environmental benefits in agricultural production and forestry management. The EQIP not only extends the longevity of agricultural production but also helps landowners keep their land in production while increasing the profitability of adopting conservation practices. The bill also focused on conservation compliances and connected them to government farm program payments. The CRP continuous sign-up program was initiated for the lands in high-priority conservation areas such as riparian buffers, filter strips, grass waterways, or other areas that offer more significant environmental benefits. The CRP continuous sign up is more flexible than the CRP general sign up, allowing program participants to enroll in the program at any time. Enrolled acres under the program count toward the overall CRP capped acres.

As prices remained low after the late 1990s, the capped acres increased to 39.2 million acres under the Farm Security and Rural Investment Act (FSRI) of 2002. Congress also made substantial changes in the conservation title. FSRI of 2002 highlights the importance of EQIP by increasing the amount of funding for the program to 1.3 billion dollars for seven years. The bill also continued the WRP and increased capped acres to 2.275 million acres. The program reached its highest enrollment in 2007, accounting for 36.7 million acres where commodity prices had a downward trend. However, rising trends in commodity prices led to a decrease in the CRP capped acres, as seen in Fig. 1.4. Enrollment acres were capped at 32 million acres in the FCEA of 2008. The bill reauthorized the existing conservation provisions and established new conservation provisions such as The Conservation Stewardship Program (CSP). The CSP was targeted to address resource concerns on working lands while improving and building on existing conservation practices. It increased capped acres for the WRP to 3.014 million acres and extended the coverage of eligibility, including certain types of privates and tribal wetlands and grasslands.

The Agricultural Act of 2014 changed the context of the CRP and focused on the provision of working land programs (aiming to reconnect conservation compliance to crop insurance subsidies) and reduced the capped acres from 32 million acres to 24 million acres (25%). Direct spending outlays on conservation title also decreased to 3.9 billion dollars for the fiscal year 2014–2013[1]. The Agriculture Improvement Act of 2018 increased again to an acreage cap of 27 million acres and increased the EQIP funding from 1.75 billion in the fiscal year 2019 to 2.025 billion in the fiscal year 2023, thus re-emphasizing the link between conservation compliance and federal farm subsidy programs. The recent bill also has included different uses of the CRP land, by expanding grazing and commercial uses. Two new programs were introduced under the bill: The Clean Lakes, Estuaries, and Rivers (CLEAR) initiative and the Soil Health and Income Protection Pilot Program (SHIPP).

[1]More details can be found at http://www.cbo.gov/sites/default/files/cbofiles/attachments/hr2642LucasLtr.pdf

Landowners with expiring contracts can re-enroll their lands in the CLEAR 30 program (which covers high-priority wetland areas such as riparian buffers, grass sod waterways, and wetland buffers) or in other water quality conservation practices. Participants in the CLEAR program receive a 30-year annual payment. SHIPP provides landowners annual payments for 3–5 years for the establishment of grassland on less productive lands. To be eligible for participation in SHIPP, lands cannot be in the CRP during the previous three year (Stubbs, 2019). While introducing new pilot programs and expanding the CRP practices on new commercial activities, the new bill limits county average rental rates. Average rental rates must reflect market levels rental rates—county average soil rental rates (SRRs) for non-irrigated cropland for agricultural production of the annually tilled crop for each soil type. FSA determines the county average rental rate by multiplying the county average soil rental rate with a soil productivity index. Under the new provision, rental rates for general contracts cannot exceed 85% of the county average rental rate (or 90% of the county average rental rate for continuous contracts for the lands already in the CRP). Therefore, potentially low rental rates might discourage new lands from being enrolled in the CRP or might increase the likelihood of acceptance in the program.

The conservation title has had an essential role in the U.S. Farm Bills to address natural resource concerns while managing different land uses. Price fluctuations, changes in farm bill provisions, and exogenous factors would impact the future status of the conservation title in upcoming legislative farm program mechanisms. For instance, higher prices might incentivize farmers to keep marginal lands in agricultural production, and upward trends in prices might induce policymakers to reduce the CRP acreage cap, as seen in Fig. 1.4. Increases in government subsidies might dwindle participation in the program. Also, reductions in government support programs (such as crop insurance premium discounts) might alter landowners' intentions for abiding by conservation requirements. Both the FCIP and the CRP are risk management and income support programs for farmers and have a long history of providing income support for landowners to manage their lands. Examining the impact of agricultural policies on environmental quality requires examination from multiple perspectives. Knowledge of existing policy drivers is essential for policymakers to generate better future policy recommendations that address existing challenges and incorporate both economic and environmental goals.

1.3 Literature Review

The FCIP and the CRP have been cornerstones of U.S. agricultural policies; they provide financial support for farmers and link farm policies with environmental outcomes. Both programs have undergone significant changes over time. The FCIP has become a risk management tool for farmers, whereas the CRP has been an effective policy to create sustainable agricultural practices by providing incentives.

The CRP has been one of most extensive environmental programs since 1985, removing environmentally sensitive lands from agricultural production and converting the lands to resource-conserving practices to address conservation issues. The program currently has enrolled 22.6 million acres of environmentally sensitive cropland to conservation practices as of 2019, and the acreage cap has been increased to 27 million acres in the 2018 Farm Bill (U.S. Department of Agriculture, Farm Service Agency, 2019). Increasing concerns about the environment have changed the program's primary focus, which was soil erosion, and now it provides a broad range of economic and conservation benefits beyond erosion reductions. The CRP targets a variety of environmental indicators, including water quality improvements (Ribaudo, 1989), water and soil erosion reductions (Sullivan et al., 2004), carbon sequestration (Gebhart et al., 1994; Parks and Hardie, 1995), enhancements of wildlife habitat population, and recreational activities (Gleason et al., 2011; Feather et al., 1999).

The context of the FCIP also has been substantially changed since its inception in 1938. The primary objective of the FCIP was to mitigate the adverse impacts of the Great Depression and the Dust Bowl in agriculture. However, the program has evolved and has become a fundamental policy in the U.S. agriculture industry to provide a safety net for the management of farm risks. Program enrollment increased from 100 million acres in 1990 to 380 million acres in 2019. Total premium subsidies also grew from $215 million to $6.2 billion over the same period, meaning that increases in insured acres can be associated with premium subsidies. Besides, the total premium increased from $834 million to $10 billion over the same period, indicating that more enrollment led to more purchases of insurance (U.S. Department of Agriculture, Risk Management Agency, 2019).

While both programs have been key policy instruments in U.S. agriculture, the linkage between the CRP and the FCIP has been commonly debated. The main concern is that the FCIP might distort land-use decision-making and encourage crop production on unsuitable lands. Enrollment growth in the FCIP raises the underlying policy question: Does the subsidized crop insurance program distort farmers' decision-making at different margins? Increases in crop insurance subsidies might incentivize landowners to convert environmentally sensitive lands into cropland production, leading to more use of inputs and chemicals and resulting in more groundwater pollution, wildlife habitat loss, and soil erosion. For instance, a total of 23.7 million acres of grassland, shrubland, and wetlands were converted to cropland between 2008–2011, resulting in decreases in wildlife habitat in the Upper Midwest and Great Plains (Faber et al., 2012). Also, converting environmentally sensitive land into cropland might negate the benefits of the CRP, which include increased carbon sequestration, reduced erosion, and improved water quality. In that sense, government policies on environmentally sensitive lands may distort farmers' decision-making and diminish environmental benefits by making the production of insurable crops on marginal lands more lucrative and limiting potential CRP enrollments on those lands. Additional factors such as commodity prices, CRP rental payments, demand for land, and technology could also drive crop production on marginal lands. However, in the context of this study, we will focus only on the literature that studies how the FCIP impacts land-use decisions at both intensive and extensive margins.

Subsidized crop insurance programs may alter production decisions both at extensive and intensive margins. At the extensive margin, farmers may expand crop production, change crop allocation, or bring more lands into cultivation. At the intensive margin, farmers may grow the same crops on the same acreage but change production practices such as input use or conservation practices. Many studies have investigated the impacts of the FCIP on both extensive and intensive margins; however, one of the most common topics in the literature is the exploration of the effects of the FCIP on input use, focusing on the moral hazard issues because of the FCIP's environmental implications. Conventional wisdom indicates that insured farmers tend to use relatively less fertilizer and chemicals on crop production. However, previous empirical research on the moral hazard issue that investigates different crops and uses different methodologies suggests both positive and negative relationships.(Babcock and Hennessy, 1996; Goodwin and Smith, 2003; Goodwin et al., 2004; Horowitz and Lichtenberg, 1993; Mieno et al., 2018; Mishra et al., 2005; Weber et al., 2016). Results remain undetermined.

In their seminal work that used survey data of Midwest corn farmers, Horowitz and Lichtenberg (1993) found that contrary to conventional wisdom, crop insurance participation increased pesticide spending and nitrogen application by 19% and 21%, respectively. Several studies argued against their findings, applying different notions to their studies (Babcock and Hennessy, 1996; Mishra et al., 2005; Smith and Goodwin, 1996). For instance, Smith and Goodwin (1996) pointed out that the assumed recursive structure of decision-making in insurance purchase and input application ignores endogeneity in the model estimation in their study. They claimed that input use and crop insurance participation should be determined simultaneously because differences in crop practices and state legislative structures might impact the timing of crop insurance purchases and input application. Indeed, it could be possible that crop insurance purchase and input usage decisions are jointly determined and ignoring possible endogeneity in the model estimation creates simultaneity bias. Babcock and Hennessy (1996) found results similar to those of Smith and Goodwin (1996); by taking a different approach and using a farm simulation model, they showed that increasing crop insurance coverage leads to reduced nitrogen fertilizer applications.

Although these studies examined the impact of crop insurance participation on input use, they did not incorporate the environmental attributes of the land (such as soil quality, soil loss tolerance, leaching, and runoff potential) or conservation practices that farmers use to improve soil quality and decrease soil erosion. For instance, Mishra et al. (2005) included environmental attributes in their model and found that the purchase of insurance reduces fertilizer expenditures on highly erodible land (HEL), whereas pesticide expenditures on HEL are positive, but not significant. The potential for pesticide runoff also increases pesticide expenditures. Their results indicated how different input applications change the results of a moral hazard argument in the presence of environmental outcomes.

Improving soil quality is also important because it affects soil's long-term ability to sustain crop production without causing unintended environmental outcomes. Higher soil erosion, usually a proxy for poor soil quality, may require higher input use to compensate for the degradation on highly erodible lands (HEL), resulting in higher production costs. Goodwin et al. (2004) included land class capability as a proxy for land quality in their model, finding that higher-quality lands have lower input requirements. In a similar study, Goodwin and Smith (2003) found a positive and significant relationship between crop insurance participation and land quality.

In conclusion, the overall relationship between input use and crop insurance participation is ambiguous because many factors may affect the moral hazard argument, such as properties of applied input use, environmental attributes of the land, or the chosen crop mix. Some crops, such as corn, have higher fertilizer requirements than others, such as soybeans (Goodwin et al. (2004)). Thus, determining the effects of crop insurance on input usage is less clear.

While extensive literature has examined the effects of crop insurance at the intensive margin, a great deal of literature has investigated the effect of crop insurance at the extensive margin because of changes in land use and cropping allocations. Crop insurance subsidies distort farmers' decision-making in two ways at an extensive margin. The first way, distortionary impacts take the form of changing cropping patterns and encouraging the cultivation of more insured crops at an extensive margin. Previous research presents evidence that crop insurance subsidy programs have quite modest changes in the allocation of crop acreage (Claassen et al., 2017; Goodwin et al., 2004; Goodwin and Smith, 2013; Young et al., 2001; Yu et al., 2018).

For example, Young et al. (2001) showed a very modest impact of crop insurance subsidies on crop acreage; the results of their simulations show only a 0.4%increase in the total planted acreage under the crop insurance program. Similarly, Goodwin et al. (2004) found that when insurance premiums are reduced by 30%, acreage increases in corn and barley are small (0.28% and 1.1%, respectively) and there are no significant changes in soybean and wheat acreage in the Corn Belt and Upper Great Plains. Although previous literature suggests that the allocation of crop acreage is responsive to changes in crop insurance subsidies, the magnitude of that change might differ across regions and selected crop mixes (Goodwin and Smith, 2013; Yu et al., 2018). For example, by applying similar methods as in Goodwin et al. (2004), Yu et al. (2018) found that a 30% reduction in premium rates leads to a 1.1% acreage increase in planted acreage.

The extent to which subsidized crop insurance changes cropping patterns may depend on the crop and study region; for instance, an increased subsidy accounts for 63%planted acreage increases in the Plains states (Young et al., 2001) but only 0.06 percent in the Corn Belt region (Claassen et al., 2017). Likewise, subsidized crop insurance may alter cropping patterns and encourage farmers to expand production of certain crops (such as corn) and shift away from the production of soybeans, wheat, and hay (Claassen et al., 2017).

At the extensive margin, the second way examines the impact of subsidized crop insurance on land-use decisions and its unintended environmental impacts. Raising concerns about the environmental effects of agricultural production has been an ongoing and contentious issue. Agricultural production can represent a potential for non-point source pollutants, such as excessive uses of inputs from crop production, sediment transportation, and manure management. Surface and groundwater pollution are the most prevalent results of agricultural non-point source pollution because of sediment transportation and nutrient and pesticide applications by agricultural operations (U.S. Environmental Protection Agency, 2019b).

Negative impacts of agricultural operations would be more severe on lands that are prone to erosion because soil erosion can increase sediment delivery and potential runoff of nutrients and pesticides into surface water resources. Thus, the effects of soil erosion go beyond soil degradation and lead to increased pollution in water resources. Besides, lands prone to erosion and lower quality may need higher input applications (Goodwin et al., 2004) because they are less able to conserve soil fertility, and are severely limited for crop production. Crop insurance subsidies may encourage agricultural production on lands that have the potential for erosion because the insurance stabilizes the economic losses that are associated with low soil quality on these lands. As a result, policies that subsidize crop insurance could damage the environment (Lubowski, 2006). Therefore, understanding the linkage between crop insurance subsidies and targeted conservation programs on marginal lands is crucial to increasing the level of environmental benefits.

Previous literature on the environmental consequences of crop insurance subsidies and targeted conservation programs is limited; instead, it investigates the environmental impacts of crop insurance subsidies or crop insurance enrollment, pursuing moral hazard behavior and supporting the conventional wisdom. The literature on the unintended consequences of crop insurance subsidies on land allocation and CRP participation has not been fully examined in the literature. A handful of studies investigate the influence of crop insurance subsidies on CRP enrollment (Claassen et al., 2017; DeLay, 2019; Goodwin et al., 2004; Goodwin and Smith, 2003; Miao et al., 2016; Walters et al., 2012). Crop insurance subsidies may encourage farmers to plant insurable crops by reducing their out-of-pocket expenses and thus alter land-use decisions in a way that creates unintended consequences on the environment (DeLay, 2019). The magnitude of crop insurance's effect on land-use decisions and environmental indicators may differ across regions because of differences in land quality, region-specific concerns, and local farm policies. For example, DeLay (2019) found a minimal impact on land use, resulting in a 1%increase in crop insurance acres and a 0.03% decrease in CRP acres, while the simulated results of Claassen et al. (2017) implied only a 0.42%decrease in

CRP enrollment due to increases in crop insurance acres in the Corn Belt region. Another study by Feng et al. (2013) found that an increase of $1 per acre in crop insurance subsidies decreases the CRP enrollment by 6,000 acres in the Dakotas.

The overall environmental impact of crop insurance subsidies and CRP enrollment can be assessed by including environmental indicators in the studies. Relevant literature on investigating the effects of the CRP and FCIP on the environmental indicators has begun emerging in recent years (Claassen et al., 2017; Miao et al., 2016; Walters et al., 2012). Although previously mentioned studies reported a relatively modest impact of crop insurance on the CRP-enrolled acres, the environmental implications of crop insurance may be more severe at the extensive margin, leading to land-use change from hay and pastureland, which are used less intensively and have less chemical treatment, to more chemically intensive corn production and thus causing more non-point source pollution (Wu, 1999). More recently, Claassen et al. (2017) found small impacts on environmental indicators; however, their results suggest a 3.65%increase in wind erosion due to increases in crop insurance subsidies. Although their study shows a substantial increase in wind erosion, their region covers only the Corn Belt states where crop production is intense. As mentioned, environmental impacts of trade-offs between cropland expansion and land retirement may vary by region because of the characteristics of farm regions differ. For instance, environmentally sensitive lands in high production regions, such as the Corn Belt or Northern Plains, may present more competition between cropland and the CRP lands.

This literature review reveals several gaps that need further examination. The empirical research at both intensive and extensive margins focus on specific regions and commodity groups. Using comprehensive panel data (such as including a broader region and coverage crop mixes) enables policymakers and researchers to quantify the environmental impact of a policy-induced land-use change. Therefore, this study builds upon Goodwin and Smith (2003). I use panel data to link environmental indicators data from the National Resource Inventory (NRI) data to farm indicators from various resources to provide insights into how agricultural policies are impacting environmental quality and soil erosion. I formulate the model, acknowledging that crop insurance participation, input usage, conservation effort, soil erosion, and CRP participation are determined simultaneously.

1.4 Data and Variable Construction

The establishment of a structural model requires the integration of a variety of different data sources. Data included in this study combines both parcel-level data on land-use choices and land characteristics and county-level data on agricultural variables and socioeconomic indicators. In this section, data resources and variable construction are described using county-level data during the 2000–2012 time period to estimate a structural model that contains five equations: soil erosion, CRP participation, crop insurance participation, fertilizer and chemical expenditures and conservation effort.

1.4.1 National Resource Inventory Data

Parcel-level data on land-use choices and land characteristics were obtained from the National Resource Inventory (NRI), which was conducted by the U.S. Department of Agriculture National Resources Conservation Services (NRSC), formerly the Soil Conservation Service. The NRI is a statistical survey that evaluates and gives information about changes in the conditions and trends of natural resources on non-federal lands, including privately owned land, tribal and trust lands, and lands controlled by state and local governments across the conterminous United States. The NRI periodically obtains data on land-use patterns, land cover, soil characteristics, erosion, and conservation practices. Data were collected over five -year intervals from 1977 to 2000; since 1977, data have been collected annually, with major releases of data continuing to be reported at five-year intervals. This study uses variables between the 2000-2012 NRI data set, that is comprised of 1,362,936 unique parcels covering 3,096 U.S. counties.

The estimation methodology used in NRI data is based on a randomly stratified two-stage sampling procedure and a design-based analysis strategy. The longitudinal survey data contains repeated observations on sample primary sample units are areas of called “segments”, within which have detailed data on land use and land attributes are collected at a random sample of points. The 1997 NRI data included about 300,000 segments and about 800,000 sample points. After changing to the annual sample approach, 42,000 segments were selected as the “core segments” and are included in the annual survey along with 30,000 segments that are selected as a rotational subsample. The rotational subsample is chosen from the remaining 258,000 segments and rotates each year[2] (U.S Department of Agriculture, Natural Resource Conservation Service (2015)).

Repeated observations on each parcel are sample points that are assigned to the number of acres, indicated as *"expansion factor" (xfact)*. Expansion factors can be used as weighting factors to aggregate sample point data to a level of regional estimates such as a county-level or state-level estimates. In this study, both sample point data and county-level data were used. Using the expansion factor allows me to construct county-level estimates. The NRI provides extensive data on land attributes. The land attributes data were obtained from using the 2012 NRI data.

The NRI contains an estimate of the Universal Soil Loss Equation (USLE), which was proposed and developed by Wischemeier and Smith (1978) to measure soil erosion as a proxy for environmental quality. The USLE is defined as annual average soil loss caused by sheet and rill erosion. It also incorporates cropping and conservation management practices. The formula to estimate the USLE is given as $A = RKLSCP$, where A is the average annual soil loss (tons ha^{-1} year^{-1}) in tons per acre, R is the rainfall erosivity index (MJmm ha^{-1} h year), K is the soil erodibility factor (tons ha^{-1} R unit^{-1}) defined as k-factor in the NRI data, LS are the topographic factors (L is the slope–length factor and S is the slope=steepness factor), C is the cropping factor, and P is the conservation practice support factor also known as p-factor in the NRI data. Using the USLE, I included county level soil erosion (*SoilErosion*) in my data set.

Soil properties such as soil loss tolerance *(T-factor)* and soil erodibility factor *(K-factor)* were also considered in this study. Soil loss tolerance is the maximum rate of annual soil loss that will allow crop productivity to be sustained on a given soil. Inherent soil erodibility is a measurement of the inherent erodibility of a given soil. Further, the conservation practice factor *(P-factor)* was included to proxy the conservation effort (*ConvEff*) made by farmers. The conservation practice factor *(P-factor)* in the NRI data that measures the ratio of soil loss with specific treatment (such as when landowners use terracing or contouring) to soil loss without any special treatment (such as when landowners farm in straight-rows up and down the slope). Lower *P-factor* values indicate that better conservation practices are in place while the higher values imply poor (or lack of) conservation

[2]The NRI survey uses a stratified two-stage area sample. The total area of the states is divided according to the Public Land Survey (PLS), which includes primary sampling units (PSUs) in the land. Each PSU has sampling points. An expansion factor can be applied to each sampling point to allow aggregation of those survey unit points over county, state, region, and so on. See NUSSER and GOEBEL (1997) and Fuller and Breidt (1999) for detailed discussions of estimation and sampling procedure.

support practices. [3]

Land-use category data from the NRI included to construct variables to estimate the agricultural intensity and non-planted ratio. The NRI has 12 broad land-use categories: cropland (cultivated and non-cultivated), pastureland, rangeland, forestland, urban/built-up land, rural transportation, large and small water, federal, other rural lands, and CRP land. In the NRI data, the cropland land-use category has two different subcategories: cultivated and non- cultivated. Cultivated lands contain areas that are planted with row crops and close-grown crops in addition to other croplands such as pastureland and hayland in rotation with other crops. Non-cultivated lands include permanent haylands such as forage crops (grasses, legumes, or a mixture of both) and horticultural cropland, such as nurseries, vineyards, or land used to grow fruits. I used land-use choice estimates to construct both agricultural intensity (*AgIntensity*) and non-planted ratio (*NotPlanRatio*). I estimated the agricultural intensity as the ratio of total cropland (cultivated and non-cultivated) to total acres in the county. Non-planted ratio was estimated by obtaining the ratio of acres in non-cultivated lands to total cropland acres.

Finally, I obtained the land class capability (LCC) variable. LCC is one of the broadest categories in the NRI data, and it shows the classification of soil suitability for crop production and pasture plants. LCC has a total of eight categories; LCC I and LCC II indicate the highest-quality land classes, which have few or no limitations for agricultural production. LCC serves as a proxy for land quality and suitability in land economics studies. The LCC ratio (*LCC1&2*) was used, which is the proportion of agricultural land in LCC I or LCC II in the county, as an explanatory variable.[4]

1.4.2 Crop Insurance Data

I used the USDA Risk Management Agency's (RMA) summary of business data to construct crop insurance variables. RMA includes both county-level and crop-level premiums, subsidy, indemnity, liability payments, and insured acres. Barley, corn, cotton, soybeans, sorghum, and wheat were selected for the crops of interest in this study because they are major commodities in the U.S. and are

[3] If there are no control practices for soil erosion, *P-factor*1. If control practices eliminate all soil loss, then the *P-factor* is represented as 0. In my data set, the lowest value is 0.001 and the highest value is 0.94.

[4] The NRI data also has four different classes land capability subclasses that show concerns or limitations. Class code e denotes erosion problems, w indicates wetness limitations, s denotes root zone limitation, and c indicates climatic concerns. LCC I has no subclasses, so it was used as it is. LCC II has sub-classes, so it was aggregated at county level without considering subclasses because only the ratio of agricultural land that has few or no limitations is the focus of this research.

widely insured.[5] Data on premium and indemnity payments, liability amounts, and insured acres were aggregated at the county level for the crops of interest in the study.[6] Premium rate (*PreRate*) was estimated by dividing paid premiums (subsidy adjusted) by liability amounts. Premiums rates should influence insurance participation decisions. Higher premium rate might discourage farmers for crop insurance enrollment.

Loss ratio (*LossRatio*) was estimated by the same approach used in Goodwin (1993), where he defined loss-ratio as the loss-risk . The loss ratio of a given year (or loss-risk) in the county was obtained as the average of the county's preceding ten-year loss ratios, which was estimated by taking the average of the county's preceding ten-year loss ratios and then normalizing by dividing each year's loss ratios by the annual state average. This normalization process allows the consideration of any unexpected losses that occurred in any particular year. In an ideal environment, loss ratios would be expected to have an average value of 1, meaning that the total amount of losses (indemnity amount) is equal to the total premium amount. However, asymmetric information problems (such as adverse selection) may occur when high-risk farmers are more likely to enroll in crop insurance programs due to the high probability of losses.

Crop insurance participation (*InPar*) is estimated as the ratio of insured acres to total planted acres. There are two estimation strategies to calculate insurance participation. The first method estimates insurance participation as the ratio of insured acres to total planted acres in each county. The second approach estimates insurance participation for a crop as the ratio of actual liability in a county to the maximum possible liability of that county. The second method considers the coverage level on a field. I employed the first approach following Goodwin and Smith (2003) in constructing the crop insurance participation variable.

1.4.3 Farm Income and Yield Data

County-level data on crop yields and acreage were obtained from the USDA National Agricultural Statistical Service (NASS) annual survey data. I included county-level historical crop yields data to calculate yield risk (yield variability). Yield risk (*YieldRisk*) was estimated as the coefficient variation

[5] According to 2017 RMA data, 73% of barley acres, 89% of corn acres, 100% of cotton acres, 80% of sorghum acres, 90% of soybeans acres, and 85% of wheat acres are insured.More details can be found at https://www.fca.gov/template-fca/download/EconomicReports/CropInsuranceCoversMostMajorCrops.pdf

[6] Most of the variables are aggregated at county level. Therefore, county-level aggregated data on premium rate, loss ratio, and insured acres has been used instead of commodity level data.

(CV) from the historical yields for the preceding 20 years. Estimation of CVs can inform farmers' decisions on crop insurance purchases. Farmers who have high CVs are more likely to purchase crop insurance and would be less responsive to premium changes. The CV was constructed by detrending crop yields and normalizing them to a base year (2012) by using a quadratic time trend.[7]

County-level data on farm income, government payments, and production expenses were taken from the Bureau of Economic Analysis (BEA) to construct farm indicators variables. I included a county level aggregated fertilizer and chemical expenses to obtain input expenses variable (*InputExpen*). Government payments, total farm sales livestock sales and total gross farm income were obtained from the BEA to estimate government payment ratio(*GovPayRatio*) and livestock ratio(*LivesRatio*). Government payment ratio(*GovPayRatio*) was estimated as a proportion of government payments[8] to total gross farm income. Livestock ratio(*LivesRatio*) was the ratio of livestock sales to total farm sales and was included to proxy farm diversification. Farm diversification might impact crop insurance participation decisions.

Finally, the CRP participation (*CRPPar*) and rental rate (*RentalRate*) were taken from USDA's Farm Services Agency's (FSA). FSA collects CRP enrollment statistics by fiscal year. The CRP participation is the percentage of total agricultural acres[9] (including cultivated and non-cultivated cropland, pastureland, and rangeland) enrolled in the CRP. Rental rate is the county-level average payment. Also, I included county acres (*Size*) because I assume that acreage of counties also determine the CRP enrollment since larger counties would have more acres to participate in the program. Table 1.1 displays the summary statistics of variables used in this study.

[7]The coefficient variation is the ratio of standard deviation to the mean. The coefficient variation (CV) based on 20-year preceding crop yield data was estimated for 2000–2012. To construct the CV, crop yields were detrended to a base year's (2012) crop yield for each crop by using a quadratic detrend. The residuals from regressing the 20-year crop yield data on a year variable were added to a base year's (2012) predicted value for each county and year. For instance, a CV of 2012 for corn yields was constructed by adding residuals from the regression period from 1991 to 2011 and adding this value to the predicted value of base year (the predicted value of 2012) for each county. After estimating the CV of each crop, county-level weighted averages of the CVs were constructed.

[8]Note that these payments are based on USDA's national and state estimates in the BEA report. They are aggregate government payments for different programs.

[9]Total agricultural acres were taken from the NRI. Since NRI only has general sign-up acres information, the CRP enrolled acres were taken from FSA to estimate the CRP participation.

1.5 Model Specification

To estimate the joint impacts of CRP participation and crop insurance participation on soil erosion, a system of equations five equations was established: soil erosion, CRP participation, crop insurance participation, fertilizer and chemical expenditures and conservation effort. This approach allows us to consider possible endogeneity among these variables. Instruments in the model contain all exogenous variables. I follow Goodwin and Smith (2003) in obtaining a system of equations.

The soil erosion is expressed as follows:

$$SoilErosion_{i,t} = f(CRPPar_{i,t}, InPar_{i,t}, GovPayRatio_{i,t}, AgIntensity_{i,t}, ConvEff_{i,t}) \tag{1.1}$$

All variables in the model are at county-level. This equation is main interest of variable in this analysis. Country-level annual soil erosion, denoted as ($SoilErosion_{i,t}$).I hypothesize that the impacts of different government programs may vary on environmentally sensitive lands. Crop insurance subsidies may alter farmers' decisions and encourage cropland expansion, leading to more erosion on environmentally sensitive lands, whereas CRP enrollment may reduce soil erosion by removing environmentally sensitive lands from cropland.A negative coefficient for CRP participation (*CRPPar*) and a positive coefficient for crop insurance participation (*InPar*) are expected. (*GovPayRatio*) and(*AgIntensity*) represent government payments ratio and agricultural intensity, respectively. The conservation practices factor,(*P-factor*), (*ConvEff*) was considered in the soil erosion equation. Lower values of p-factor mean more conservation effort practices,hence will reduce soil erosion; thus, a positive coefficient for the conservation effort is expected.

The CRP participation equation is given Equation 1.2 below where (*CRPPar*) denotes country-level CRP participation in year (t). I hypothesize that CRP participation would be higher where lands are more susceptible to erosion. Rental rate(*RentalRate*) represents county-level average rental payment. Enrolled acres in the program are environmentally and economically marginal lands and are likely to have low soil quality; thus, I expect a negative coefficient for rental rate in contrast to Goodwin and Smith (2003). Soil inherent erodibility (*K-factor*) and soil loss tolerance (*T-factor*) were included in the model to account for the role of soil attributes that are pertinent in CRP participation decisions. Government payments ratio (*GovPayRatio*) was considered to understand the overall impact of other government policies on CRP enrollment. The total land area in county (*i*) denoted ($Size_i$) should matter in the model because no more than 25 percent of a county's cropland acreage can be participated in the program. Given its limitation on enrolled acres, I expect a positive sign on this variable in CRP participation equation.

$$CRPPar_{i,t} = f(RentalRate_{i,t}, K\text{-}factor_{i,t}, T\text{-}factor_{i,t}, GovPayRatio_{i,t}, Size_i) \tag{1.2}$$

The crop insurance participation equation is as follows:

$$\begin{aligned} InPar_{i,t} = f(&InputExpen_{i,t}, GovPayRatio_{i,t}, AgIntensity_{i,t}, LCC1\&2_{i,t}, PreRate_{i,t}, \\ &YieldRisk{*}PreRate_{i,t,}, LivesRatio_{i,t}, LossRatio_{i,t}, YieldRisk_{i,t}) \end{aligned} \tag{1.3}$$

The main parameter of interest in this equation is fertilizer & chemical expenditures (*InputExpen*). As discussed earlier, the previous literature found the evidence of moral hazard in input usage (or spending less on fertilizer and chemical expenses),indicating insured farmers tends to reduce the amount of input use and accept lower yields along with increased indemnity payments. If there is a supporting evidence in the model, I would expect a negative relationship between crop insurance participation (*InPar*) and fertilizer & chemical expenditures (*InputExpen*).

Changes in premium rates that result from changes in premiums paid by farmers also affect insurance participation decisions. Crop insurance participation increases if policies make it more affordable for farmers, so I expect that the premium rate (*PreRate*)is negatively associated with crop insurance. Yield variability also impacts risk-averse farmers' crop insurance enrollment decisions. Farmers who have high yield variation (*YieldRisk*) are more likely to enroll in the crop insurance program; however, they are less responsive to changes in premium rates. To account for this impact, an interaction term for yield risk and premium rate (*YieldRisk*PreRate*) is included. I also consider agriculture intensity(*AgIntensity*) as a proxy to measure the size of the agriculture industry in a county and expect a positive sign. Land quality also impacts insurance enrollment decisions. Higher quality lands (lands in LCC I and II) are more likely to engage in more intensive land uses such as cropland; hence, I expect that a positive coefficient sign on land class capability(*LCC1&2*). To reduce farm risks, farmers may diversify farm operations, relying on either livestock production or off-farm income; therefore, I hypothesize that crop insurance participation decreases in the level of farm diversification. Livestock ratio(*LivesRatio*) to account for this effect. Finally,Loss ratio (*LossRatio*) is the ratio of crop insurance payments to total premium paid. It was included to investigate its impact on crop insurance participation.

The fertilizer& chemical expenditures equation is expressed in equation 1.4. County-level fertilizer and chemical expenditures (*InputExpen*) were obtained from the BEA. As mentioned before, input expenditures may be jointly determined with insurance participation. The endogenous attributes of this effect should be considered to avoid simultaneity bias in the model estimation. Insured farmers may engage in moral hazard,hence decrease input use. I expect a negative relationship between The fertilizer& chemical expenditures (*InputExpen*) and crop insurance participation (*InPar*).

Input expenditures also vary by selected crop mixes because input requirements would be different for the chosen crop mixes. I included selected crop mix for this analysis:Barley acres (*BarleyAc*), corn acres (*CornAc*), cotton acres (*CottonAc*), sorghum acres (*SorghumAc*), soybean acres (*SoybeanAc*), and wheat acres (*WheatAc*)

Following Goodwin and Smith (2003), I hypothesize that acres left idle and fallow would require more input use so I included not planted ratio(*NotPlanRatio*) to determine this effect. Finally, the livestock ratio (*LivesRatio*) was considered to capture the fact that counties with high farm diversification would spend less on input use.

The fertilizer & chemical expenditures equation is expressed as follows:

$$\begin{aligned} \mathit{InputExpen}_{i,t} = f(&\mathit{InPar}_{i,t}, \mathit{K\text{-}factor}_{i,t}, \mathit{BarleyAc}_{i,t}, \mathit{CornAc}_{i,t}, \mathit{CottonAc}_{i,t}, \mathit{SorghumAc}_{i,t}, \mathit{SoybeanAc}_{i,t}, \\ &\mathit{WheatAc}_{i,t}, \mathit{LivesRatio}_{i,t}, \mathit{NotPlanRatio}_{i,t}, \mathit{YieldRisk}_{i,t}) \end{aligned} \tag{1.4}$$

The final equation includes conservation effort equation and can take form of

$$ConvEff_{i,t} = f(CRPPar_{i,t}, GovPayRatio_{i,t}, K\text{-}factor_{i,t}, T\text{-}factor_{i,t}, BarleyAc_{i,t}, CornAc_{i,t}, CottonAc_{i,t}, SorghumAc_{i,t}, SoybeanAc_{i,t}, WheatAc_{i,t}, LivesRatio_{i,t}, AgIntensity_{i,t}) \tag{1.5}$$

Conservation practices such as tillage and contouring are important in reducing the negative impacts of agricultural production. To capture this effect, the conservation effort variable, (*P-factor*), (*ConvEff*) was obtained from the conservation support practice factor (*P-factor*). It indicates the effect of conservation effort practices on soil loss. Lower values of the P-factor indicate good conservation effort, and higher values reflect poor conservation effort on the land, implying more soil loss on the lands.

Crop selection also affects conservation effort because conservation practice adoption rates may vary across different crop mixes. Some of the crop practices may require less conservation effort. To consider differences in the requirements of conservation efforts given various crop mixes, I included separate crop acres selected for this study.(*BarleyAc*),(*CornAc*),(*CottonAc*),(*SorghumAC*),(*SoybeanAc*),and (*WheatAc*) are the county-level planted acres in barley, corn, cotton, sorghum, soybean, and wheat acres,respectively.

The proportion of cropland acres to non-cropland acres within a county may also be related to conservation support practices and may reflect conservation efforts; thus, to account for this effect, agriculture intensity(*AgIntensity*) is included in the model estimation. To examine the effects of farm diversification on conservation effort, livestock ratio (*LivesRatio*) was included. Soil loss (*T-factor*) and soil erodibility factor (*K-factor*) were included in determining effects soil characteristics on conservation effort .

1.6 Empirical Strategy

A system of five equations explained in the previous section is used to consider the endogenous nature of independent variables in the model. All exogenous variables and farm resource regions are instruments in the model. Endogenous variables include CRP participation, insurance participation, soil erosion, conservation effort, and fertilizer and chemical expenditures. My empirical analysis combines both cross-sectional and time-series data for the 2000-2012 time period. Employing this kind of data can be a potential issue for heteroskedasticity due to the county-level unobserved form of spatial and temporal heterogeneity. To account for heteroscedasticity, I considered the White test for all equations explained in the previous section, and the results confirmed the evidence of heteroskedasticity. Also, the Hausman specification test results provided support for the joint determination of equations in the model;[10]Thus, to account for the endogenous nature of independent variables and the presence of heteroskedasticity, I employ instrumental variable (IV) methods within the context of the Generalized Method of Moments (GMM). Estimation of a system of equations can be expressed as follows (Wooldridge, 2010):

$$y_{it} = X_{it}\beta + \varepsilon_{it} \tag{1.6}$$

where y_{it} (N×1) denotes dependent variables, X_{it} is the (N×K) set of covariates includes both exogenous and endogenous variables, ε_{it} (N×1) is a random error term. Let Z_{it} (N×L) denote a set of instrumental variables, L ≥K, that are exogenous in a sense that $E(Z'_{it}\varepsilon_{it}) = 0 t = 1, ..., T$.

A set of moment conditions in the GMM estimator is expressed as follows:

$$g_{it}(\beta) = \frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T} Z'_{it}\left(y_{it} - X_{it}\beta\right), t = 1, ..., T and n = 1........, N \tag{1.7}$$

Let denote the sample average ofg_{it} (β) as $g_{it}(\hat{\beta}) = g_{it}\frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T} g_{it}(\beta)$

The GMM estimator of β for each equation is estimated by minimizing the following quadratic form:

$$\hat{\beta} = argmin\left[\frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T} Z'_{it}\left(y_{it} - X_{it}\beta\right)\right]' \hat{W}\left[\frac{1}{N}\frac{1}{T}\sum_{i=1}^{N}\sum_{t=1}^{T} Z'_{it}\left(y_{it} - X_{it}\beta\right)\right] \tag{1.8}$$

where $\hat{W}$ denotes an (M×M) positive semi-definite matrix.

[10]Model test results for Heteroskedasticity and Hausman Specification test are reported in Table 1.2.

1.7 Results and Discussion

This study provides an empirical analysis to evaluate the impacts of U.S. agricultural policies and their interactions on soil erosion. Table 1.3 and Table 1.4 display results from the IV- GMM parameter estimators for the system of equations across the counties in the U.S.

As the main question being examined in this paper is to evaluate the impacts of the U.S. agricultural policies on soil erosion, I first consider the impacts of the CRP participation and crop insurance participation on levels of soil erosion. As expected, the coefficient for CRP participation (*CRPPar*) is significant and negative. The results imply that a 1 % increase in CRP participation reduces soil erosion by 7.3 tons per acre. However, the results indicate that crop insurance participation (*InPar*) has an offsetting impact, implying that a 1 % increase in insurance participation increases soil erosion by an average of 4.4 tons per acre. This finding supports the evidence that the crop insurance program may expand cropland production on environmentally sensitive lands. The coefficient for government program payments (*GovPayRatio*) is negative and significant. This result reflects the nature of using aggregate cross-sectional data for government payments programs. I cannot distinguish direct payments from overall conservation payments due to a lack of program-specific payment data. The coefficient for agricultural intensity (*AgIntensity*) (a proxy for the size of the agriculture sector in a county) has a negative and significant impact on soil erosion, but the effect is very small. It reflects that a 1 % increase in agricultural activity decreases soil erosion by 0.07 tons per acre. Conservation effort (*ConvEff*) has a statistically significant and negative effect on soil erosion. Lower values of conservation practice factors are associated with higher levels of conservation management practices. This suggests that the adoption of conservation efforts reduces levels of soil erosion.

Estimation results for the CRP participation equation are statistically significant. The coefficient on the rental rate (*RentalRate*) is negative and significant, though the overall effect is very small. Rental rates are based on soil productivity and average cash rents for non-irrigated cropland. This result indicates that the percentage of agricultural acres that are participating in the CRP may be in counties with strong cash rent markets. Further, landowners go through a competitive bidding process under the general sign-up period; thus, they might bid lower than the established soil rental rates to be eligible in enrollment in the program. I consider land quality variables, i.e., soil erodibility factor(K-factor) and soil loss tolerance (T-factor). As expected, the soil erodibility factor(K-factor) is positive but has no significant effect on CRP participation. The coefficient estimate for soil loss tolerance(T-factor) is positive and significant. This finding suggests farmers adopt less conservation practices if soil loss tolerance is high. Therefore, it might lead to higher levels of soil erosion and more enrollment in the program. As expected, county size has a positive and significant sign because the larger counties would have more eligible acres to enroll in the program.

In the insurance participation equation, fertilizer and chemical expenditures display the expected sign and support the evidence of moral hazard in input use. It implies that crop insurance participation leads farmers to have less incentive to spend on input use. As expected, the agricultural intensity has a significant and positive sign, implying that counties with a large agricultural sector will be more likely to enroll in crop insurance. I also include the proportion of cropland in the county in land class capability I and II to proxy for higher quality lands. My results indicate that insurance participation is positively associated with higher quality lands. The coefficient for the premium rate (subsidy adjusted) is positive and significant. The sign of this term is not consistent with my hypothesis; however, the premium rate in my estimation is subsidy adjusted. Decreases in premium subsidies dissuade farmers to enroll in the crop insurance program and increase the risk faced by farmers. Therefore, the coefficient for premium rate suggests that a higher premium rate corresponds to the higher risk faced by producers. Using county-level aggregate data does not allow us to capture the farmers' risk. To account for this effect, we include an interaction term between yield risk and premium rates. The coefficient estimate for livestock ratio (a proxy for farm diversification) is negative and significant. It suggests that farm diversification would lead to decreases in crop insurance participation because it could help to mitigate risk. County size has a negative impact on crop insurance participation, indicating that the larger counties might have more land-use choices at an extensive margin. As expected, yield risk (higher coefficient variation) is positively associated with crop insurance participation.

Now, I turn to fertilizer & chemical expenditure equation. The crop insurance participation coefficient is negative but not significant in the fertilizer and chemical expenditures equation. I include per crop acres in the county for different crops to capture the impact of crop allocations on input use. Fertilizer and chemical expenditures on corn, cotton, sorghum, soybean, and wheat acres would be less. A negative and statistically significant coefficient of livestock ratio, suggest that farmers diversifying their farming operations spend less on fertilizer and chemical expenditures. Barley acres, the soil erodibility factor, and insurance participation are not statistically significant.

The final equation is the conservation effort equation. The conservation effort is associated with a county's crop allocations. The coefficient estimates for soybean and barley acres are positive and significant. This result indicates that counties, where soybean and barley production are high, are associated with lower levels of conservation effort, whereas counties where corn and sorghum production are prevalent, may engage in higher levels of conservation practices. The coefficient estimate for the livestock ratio is negative and significant. This estimate indicates that farm diversification plays an essential role in conservation management practices. As expected, the agricultural intensity is associated with lower conservation efforts. Insignificant parameter estimates in the conservation effort equation include government payments, cotton acres and wheat acres.

1.8 Concluding Remarks

Both the FCIP and the CRP have been cornerstones of U.S. agricultural policy to provide financial assistance to farmers. However, crop insurance subsidies may impact the CRP enrollment by altering farmers' production decisions and potentially encouraging cropland expansion on environmentally sensitive lands; thus, they may have unintended environmental consequences such as increased soil erosion. A broad literature has investigated the impacts of government farm policies on environmental indicators; however, many of the studies are dated and only focused on specific regions. In this paper, I examine the impacts of both the FCIP and the CRP on soil erosion by updating and extending the previous work by Goodwin and Smith (2003). I employ panel data during the 2000-2012 time period to estimate a system of five equations: soil erosion, CRP participation, crop insurance participation, conservation effort, and fertilizer and chemical expenditures.

My results confirm that CRP participation significantly reduces soil erosion, whereas crop insurance participation substantially increases soil erosion. This finding indicates that government farm policies may work at cross purposes in counties with a higher proportion of environmentally sensitive lands. My estimations also suggest that farm diversification reduces enrollment in the crop insurance program. This result points out the importance of specific risk mitigation practices in agriculture production from both financial and environmental aspects. Farm diversification may result in less crop cultivation on marginal agriculture lands and less the use of inputs; hence more environmental gains could be achieved.

The issue of moral hazard is a highly recognized problem in the literature and remains an important issue. My results find, as is consistent with conventional wisdom, evidence of moral hazard in crop insurance participation, implying insured farmers spend less on input expenditures. Proponents of moral hazard argument claim that moral hazard behavior leads to decreased input application; hence it may be less damaging to the environment. However, the presence of moral hazard may also encourage farmers to plant more acres of riskier crops on environmentally sensitive lands, often with adverse environmental outcomes. Crop insurance subsidies induce cropland expansion on environmentally sensitive lands. Perhaps, bringing those lands into cropland results in additional costs for taxpayers in case of a moral hazard issue. In addition to the environmental benefits, the CRP may also ease the burden of taxpayers and provide budgetary savings for the government farm programs.

As a result, the impact of government farm policies on soil erosion remains a valid empirical question. Knowledge of interactions between the FCIP and the CRP is helpful to address conflicting objectives of these programs on marginal lands. Otherwise, the government may work at cross purposes by providing financial support for competing interests in farm policy. Many policy questions are involved in this context, and existing programs need careful examination of overtime in order to produce new policy mechanisms that support agricultural producers by recognizing environmental indicators.

Table 1.1: Summary Statistics

Variable	Mean	Std.Dev.
Land Attributes		
T-Factor	4.0239	0.7008
K-Factor	0.2881	0.0718
ConvEff	0.9617	0.0637
LCC1 & LCC 2	0.3575	0.2298
AgIntensity	1.0967	1.3509
SoilErosion(tons/acre)	2.2024	1.5458
CRPPar	0.0514	0.0617
NotPlanRatio	0.44	0.2816
Economic Indicators and Acres Yield Variables		
RentalRate (Real $/acre)	82.2497	40.1029
GovPayRatio	0.0022	0.002
CornAc	0.2565	0.2179
BarleyAc	0.0153	0.0498
CottonAc	0.0315	0.0958
WheatAc	0.1141	0.1054
SorghumAc	0.2241	0.1944
SoybeanAc	0.0112	0.0275
LivesRatio	0.4991	0.2565
Size (100,000 acres)	5.8557	5.5775
YieldRisk	13.0808	3.7207
InputExpen (Real $100,000)	136.9846	123.0452
Crop Insurance Variables		
PreRate	0.0524	0.0234
InsurancePar	0.4722	0.2114
LossRatio	0.8825	0.9695

Table 1.2: Model Tests

Heteroskedasticity and Hausman Tests	Statistic	p-value
Hausman Specification Test: OLS vs.2SLS	777.7*	<.0001
White's Test: CRP Participation	429.7*	<.0001
White's Test: Soil Erosion	980*	<.0001
White's Test: Insurance Participation	1257*	<.0001
White's Test: Fertilizer and Chemical Expenditures	792.9*	<.0001
White's Test: Conservation Effort	2012*	<.0001

Table 1.3: GMM Estimation Results

Variable	Estimate	Standard Error	t-Ratio
	Soil Erosion		
Intercept	14.52511*	0.5713	25.42
CRPPar	-7.34041*	0.7088	-10.36
InPar	4.466711*	0.147	30.38
GovPayRatio	-63.127*	13.4242	-4.7
AgIntensity	-0.07639*	0.0181	-4.23
ConvEff	-14.3757*	0.6167	-23.31
	CRP Participation		
Intercept	0.002503	0.00712	0.35
RentalRate	-0.00025*	0.000019	-12.99
K-factor	0.024763	0.0132	1.88
T-factor	0.014113*	0.00141	9.98
GovPayRatio	-2.29866*	0.4444	-5.17
Size	0.000713*	0.000158	4.52
	Insurance Participation		
Intercept	0.583408	0.0328	17.78
InputExpen	-0.00038*	0.000092	-4.09
GovPayRatio	-12.4914*	2.7369	-4.56
AgIntensity	0.01684*	0.00347	4.86
LCC1&2	0.131988*	0.0139	9.52
PreRate	2.390155*	0.3964	6.03
YieldRisk*PreRate	-0.19192*	0.0273	-7.03
LivesRatio	-0.33525*	0.0177	-18.91
LossRatio	0.014415*	0.00247	5.84
YieldRisk	0.008831*	0.00194	4.55

Table 1.4: GMM Estimation Results

Variable	Estimate	Standard Error	t-Ratio
	Fertilizer & Chemical Expenditures		
Intercept	333.657*	13.0272	25.61
InPar	-15.8275	20.2747	-0.78
K-factor	74.86196	21.6104	3.46
BarleyAc	106.0303	40.8679	2.59
CornAc	-51.3643*	9.3257	-5.51
CottonAc	-178.33*	18.32	-9.73
SorghumAc	-185.517*	34.8477	-5.32
SoybeanAc	-170*	13.6573	-12.45
WheatAc	-136.228*	19.435	-7.01
Livestock Ratio	-79.3363*	7.7911	-10.18
NotPlanRatio	-234.129*	5.8374	-40.11
	Conservation Effort		
Intercept	1.021905*	0.00717	142.54
CRPPar	0.058536	0.0342	1.71
GovPayRatio	-0.40934	0.4974	-0.82
K-factor	-0.16922*	0.0112	-15.18
T-factor	-0.00291	0.00156	-1.86
BarleyAc	0.101742*	0.0166	6.15
CornAc	-0.02582*	0.00663	-3.9
CottonAc	-0.02131	0.01	-2.13
SorghumAc	-0.1619*	0.0309	-5.23
SoybeanAc	0.069476*	0.00503	13.81
WheatAc	0.02601	0.0107	2.43
LivesRatio	-0.01961*	0.00382	-5.13
AgIntensity	0.002696*	0.000641	4.21

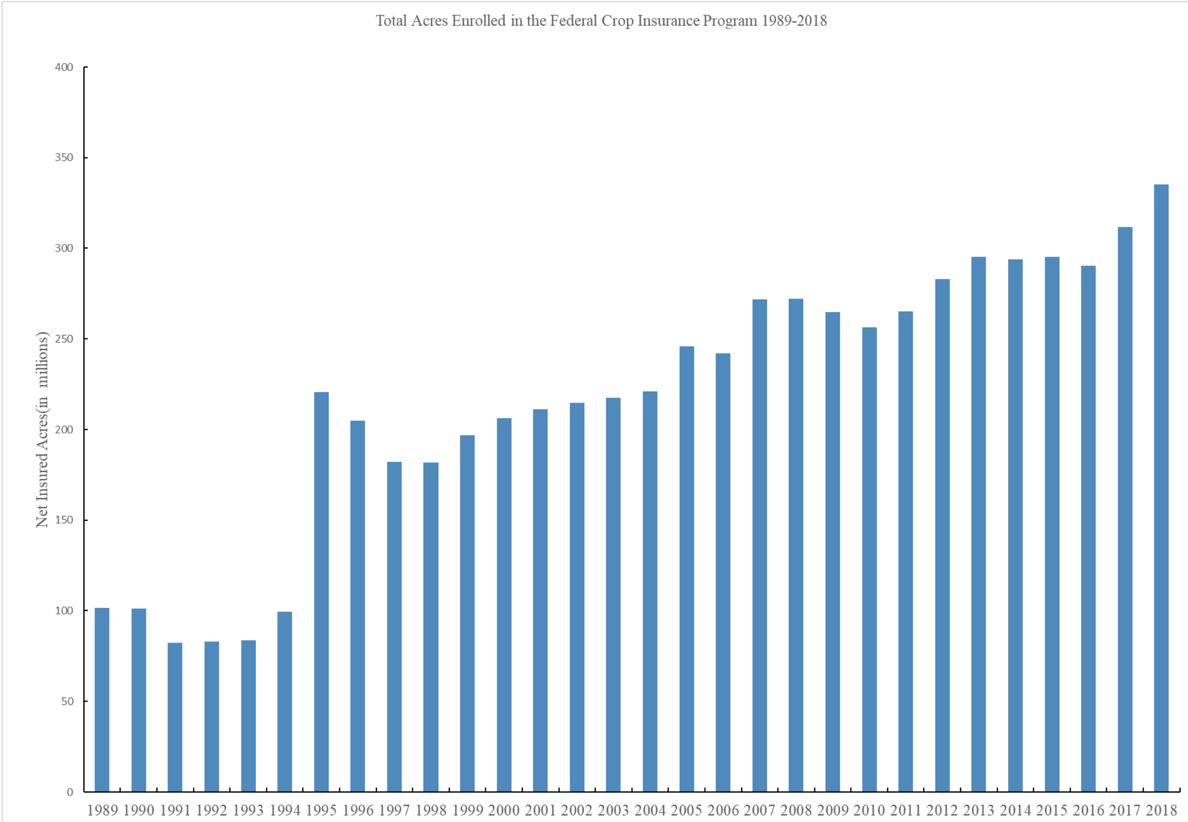


Figure 1.1: Total Net Insured Acres by FCIP,1989-2018. Source: USDA, Risk Management Agency, Summary of Business

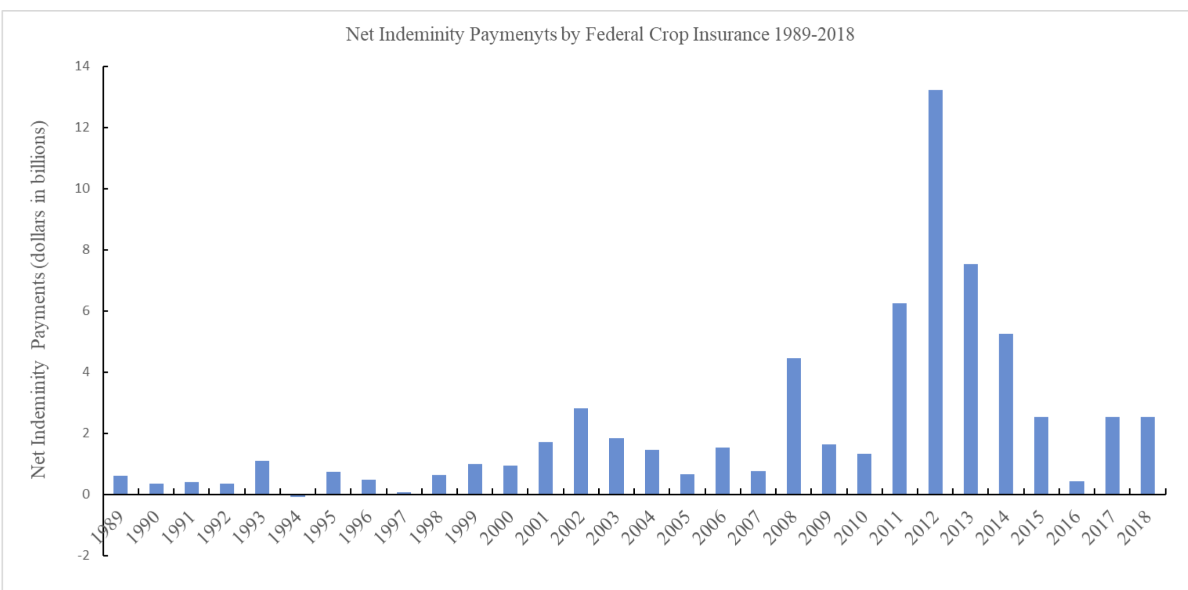


Figure 1.2: Net Indemnity Payments by FCIP 2000–2018 Source: USDA, Risk Management Agency, Summary of Business Reports

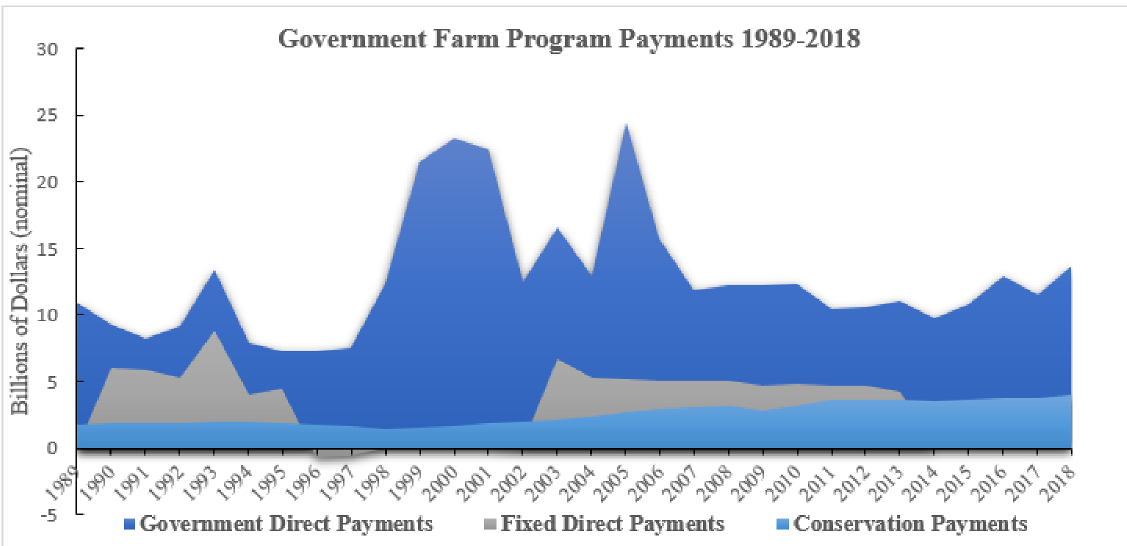


Figure 1.3: Source: USDA, Economic Research Service, Farm Income, and Wealth Statistics.

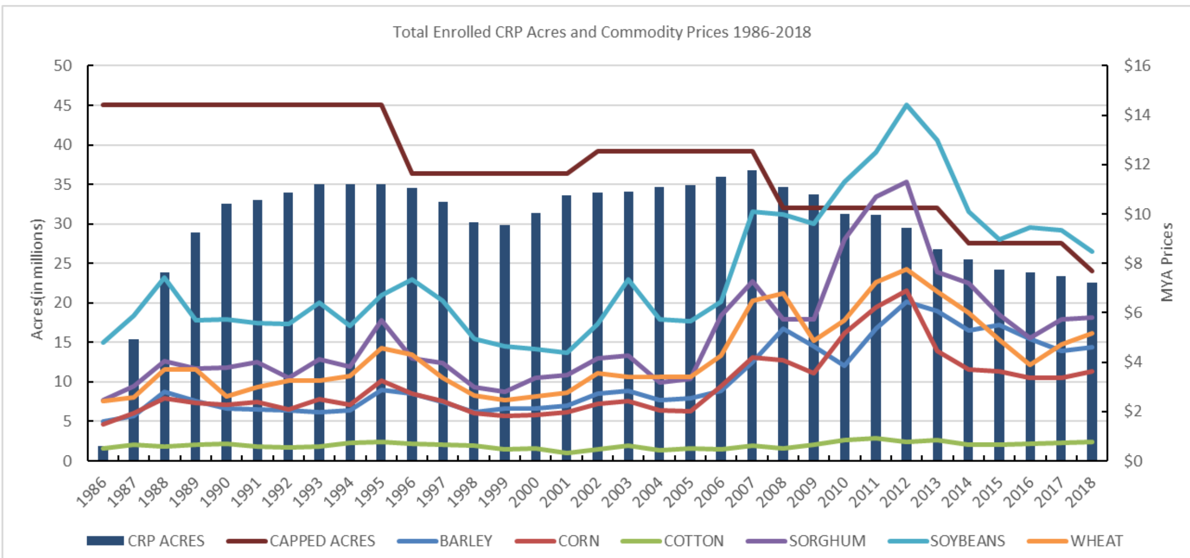


Figure 1.4: Enrolled acres in the CRP 1986 and Market Average Prices by Commodity–2018 Source: USDA, Farm Services Agency, and USDA, NASS.

CHAPTER

2

THE DETERMINANTS OF CRP TREE PLANTING IN THE U.S. SOUTH

2.1 Introduction

Climate change and increases in greenhouse gas emissions (GHG) continue to be a global issue. Growing concerns about the consequences of climate change have made policymakers search for alternative ways to mitigate GHG emissions at a low cost. In particular, significant policy efforts in understanding the role of land use, land-use change and forestry (LULUCF) activities on climate change have stipulated in international agreements. For instance, Article 3.3 of Kyoto Protocol refers that emissions and removals of GHG from the human-induced land use change and forestry activities (e.g., afforestation, reforestation, and deforestation) should be included in national greenhouse gas account inventories (United Nations, 1998).

While LULUCF activities have been sources of either removal or emissions of GHG on global scale, LULUCF activities have been a net carbon sink in the U.S. since 1990, accounting for 12%

of total GHG emission reductions in 2018 (U.S. Environmental Protection Agency, 2019a). Indeed, forests in the U.S. have a substantial carbon mitigation potential, removing 15 percent of the annual total carbon emissions that stem from fossil fuel combustion (Woodall et al., 2015) and can be used as a low-cost natural carbon solution often with co-benefits such as providing ecosystem enhancements, protecting soil, water, and air quality, and improving wildlife habitat.

Therefore, policy approaches in the U.S. seek to improve common forest-based carbon mitigation options such as either afforestation or reforestation policies and cost-effectiveness of these policy options has been the underlying motivation in the previous studies. Past research has focused either on the role of afforestation or reforestation in mitigation carbon storage (Wear and Coulston, 2015; Kline et al., 2002; Newell and Stavins, 2000). Within the previous research strand, afforestation has been a viable cost-effective option to ascertain sustainability of natural resources by preventing soil erosion and contamination of air and water resources while sequestering carbon stocks (Adams et al., 1999; Lubowski et al., 2006; Haight et al., 2020; Plantinga et al., 1999).

Various forest incentive programs have been implemented for non-industrial private forest owners to promote afforestation and forest restoration by offering policy tools such as financial incentives, technical assistance, and educational support to influence the management of their lands. The initial intent of these programs was to increase timber supply and improve timber stands; however, growing environmental concerns about biodiversity and forest fragmentation has catalyzed a reformulation of incentive programs, making them more environmentally focused (Straka et al., 2006). Table 2.1 briefly summarizes existing forest incentive programs.

Currently, three federal programs provide conservation incentives for forestland owners: The Conservation Reserve Program (CRP), the Environmental Quality Incentives Program (EQUIP) and the Wetland Reserve Program (WRP). These are the main conservation programs that promote afforestation by providing financial incentives and technical assistance for private landowners to improve production practices on existing forest lands or non-forest lands such as in the CRP. For spending allocation, the CRP and the EQUIP are the largest conservation programs in the USDA, accounting for more than 90% of government conservation spending as of 2018. The CRP is a land retirement program, established in 1985 which provides financial incentives and cost-share assistance to the participants for converting the lands to resource conserving practices such as tree planting. Majority of tree planting in the program, almost 80% of them, have occurred in the U.S.

South.[1] Therefore, U.S. South provides an ideal example to investigate the enrollment criteria in CRP tree planting.

Expansion of forestland through tree planting is of particular interest in the US South. This region, sometimes referred to as the “wood basket” of the nation, have the largest proportion of timberland (71% of all planted timberland) (Oswalt et al., 2019). Regional carbon estimates indicate, mostly, that forests in the South have substantial forest carbon stocks, with largest annual forest carbon accumulation in the South (Woodall et al., 2015). Forests in the US South has the ability to sequester carbon and provide other co-benefits listed above. However,the combined effects of land use change and forest may pose a threat to trajectory of carbon sequestration capacity in the region.

Land use in the South has gone through changes because the geography and land access has made land suitable for multiple land uses. Majority of land use transitions have occurred between forest land and agricultural land (Alig et al., 2010). Forest land has substantially risen (by 34 million acres between 1987 and 2012), whereas cropland has dwindled, mostly in the Southeast states where the cropland is more concentrated in the Delta States and the Southern Plains. Declines in crop profitability and increasing pressures on urbanization are the main contributing factors of agricultural land-use change in the region (Bigelow and Borchers, 2017).[2] Urbanization also poses a potential threat to forest fragmentation in the Southern U.S. (Wear and Greis, 2002). However, pressures from urbanization on forestland would have been more significant if federal and state-level forestry incentive programs (FIP) that spur landowners to plant trees had not been in place (Smith et al., 2009).

As stated earlier, various policy programs have been presented both at federal and state-level. Of these programs, the CRP may present opportunities for policymakers to strengthen carbon sequestration rates at low-cost on marginal agricultural lands. Indeed, such efforts could be an effective way to serve as a natural carbon solution and to avoid losses in forestland acres while keeping marginal lands on resources conserving practices. For instance, Wear and Coulston (2015) find that afforestation and restoration of 19.1 million acres through the Conservation Reserve Program (CRP) would enhance sequestration by 188 million metric tons over the 25-year simulation period.

[1] This estimation is based on the latest release of NRI 2015 data.

[2] Bigelow and Borchers (2017) divide the Southern U.S. into four regions: Appalachian (VA, WV, NC, KY, TN), Southeast (SC, GA, FL, AL), Delta States (MS, AR, LA), and Southern Plains (OK, TX).

Although tree planting acres in the CRP are low, with only 1.2 million acres of planted trees on the 24.1 million CRP acres, the U.S. South has the largest CRP tree planting acreage in the nation. Most of the tree planting in the program has concentrated in the Delta and the Southeast region (see Fig. 2.7-Fig. 2.24) because of dynamics of the region as mentioned previously. In fact, most of the tree planting as conservation cover practice either re-enrolled or converted into forestland (see (Bigelow et al., 2020)) , therefore, the tree establishments on the CRP land may be a mitigation option to address climate change and provide environmental benefits in the U.S. South. Using CRP tree planting as a case study gives impetus to the development of integrated approaches that include both conservation goals and climate change objectives.

However, one needs to consider that private landowners who invest in tree planting are likely to be profit-motivated; hence, the means of influencing their behavior should be through understanding socioeconomic drivers of land use. Understanding the factors that influence land conversion decisions from cropland to CRP tree planting on marginal agricultural lands is important because it helps with what type of components can be factored into more broader policy frameworks that integrates both climate change and conservation goals.

In this paper, I examine the determinants of tree planting under the CRP in the U.S. South, where more than 80% of tree planting have occurred as a resource conservation practice in the program. I estimate the predicted probability of a parcel converting from cropland to CRP tree-planting by using plot-level National Resource Inventory (NRI) data between 2005 and 2015 in the U.S. South as a function of timber prices, land attributes, government payments, and socioeconomic variables. My findings suggest that market forces and conservation incentives are important factors to incentivize landowners to enroll in CRP tree planting in the U.S. South.

The findings of this study will be useful to evaluate current policies and make policy recommendations on the expansion of continued conservation policies and designing new integrated strategies to improve the nation's carbon sinks without harming the environment. Notably, in the light of recent policy developments in the U.S. that target reforestation and afforestation of public and private lands such as the "Trillion Trees Act", (U.S House, 2019) this kind of information could be vital to understanding timber market dynamics from the landowner's perspective.

The remainder of the paper is organized as follows. Section 2 provides a brief background on previous studies. Section 3 describes the data used and variable construction. Section 4 outlines the empirical strategy. Section 5 presents the empirical results and discusses the robustness check. Finally, section 6 concludes and discusses future research.

2.2 Literature Review

There are many factors that impact CRP enrollment decisions. Socioeconomic drivers and policy structures continue to impact enrollment decisions in the program. The previous literature has focused on identifying these factors that are pertinent to the CRP enrollment decision. Several studies have investigated the effects of various policy instruments that incentivize and retain private landowners in the CRP enrollment: farm financial characteristics (Mishra and Khanal, 2013); property taxes (Polyakov and Zhang, 2008); commodity prices (Rashford et al., 2010); and economic benefits and land values of the CRP (Wu and Lin, 2010).

For instance, Mishra and Khanal (2013) pointed out that financial constraints (liquidity and solvency) negatively impact the adoption of the CRP, indicating the importance of financial assistance to boost farm income when addressing environmental concerns with the CRP. On the other hand, Wu and Lin (2010) found that CRP participation increases farmland values by between $18 and $25 per acre, while developed land values are increased by between $6 and $274 per acre, with the most significant effects in the Mountain, Southern Plains, Appalachian, and Corn Belt regions.

While these studies focused on the influential factors for the CRP enrollment decisions, post-enrollment decisions have been explored in the previous literature (Bigelow et al., 2020; Hellerstein and Malcolm, 2011; Hendricks and Er, 2018; Johnson et al., 1997; Skaggs et al., 1994; Rashford et al., 2010; Roberts and Lubowski, 2007). For instance, farmers who participated in the program for economic reasons (Johnson et al., 1997) and have previously irrigated acres (Skaggs et al., 1994) are more likely to return to crop production. Increasing commodity prices can make economic returns to cropland more profitable, and thus could drive post-CRP land-use conversion into cropland (Hellerstein and Malcolm, 2011; Rashford et al., 2010). On the contrary, Hendricks and Er (2018) argued that government policies that respond to changing market conditions rather than commodity prices determine land conversion from CRP land to cropland.

Post -CRP land- use decisions may vary by region. Most CRP lands in the Midwest and the Corn Belt converted back to cropland where crop production is common and lucrative (Bigelow et al., 2020; Lubowski et al., 2006).However,77% of land enrolled land in CRP tree planting remained in the program (particularly in Georgia and Mississippi, where forestland is dynamic, productive, and timber value is high) (Bigelow et al., 2020).

Although much of the previous literature examined the impacts of economic and environmental factors that influence a landowner's decision-making about the CRP enrollments, understanding the policy drivers that affect tree planting under the CRP has not received much attention in the literature. I combine the factors that are pertinent to both the determinants of CRP enrollment on marginal lands and forest land expansion, using the CRP tree planting on marginal lands as a case to examine components that influence interactions between agricultural and forestland use. Mainly, three studies are closely related to my research regarding approaches used and regions covered (Hardie et al., 2000; Kim et al., 2018; Kim and Langpap, 2016).

Since this research aims at understanding land use change at extensive margin, an important consideration in land use economics is given to the positive relationship between land-use conversion and land rents. As consistent with Ricardian rent theory, timber rents (Kim et al., 2018; Lubowski et al., 2008) or stumpage prices (proxy for forest rents), (Hardie et al., 2000; Mauldin et al., 1999) have found to be the most prominent factors that influence forestland expansion at extensive margin. Although stumpage prices are the main explanatory variables in this study, I also investigate the impacts of forest rents on CRP tree planting because the determinants of CRP tree planting may differ from other land use conversion decisions. I explore this idea by estimating the model including both stumpage and forest rents (or pine plantation rents) separately.

The effects of financial incentives and cost-share assistance on land conversion decisions between forest land and agricultural land also has been examined (Kim and Langpap, 2016; Plantinga and Ahn, 2002). Considering regional forces and differences, the policy aspects of financial incentives may not be uniform. For example, landowners in the Southeast are more responsive to financial incentives for afforestation compared with those in other regions (Kim and Langpap, 2016). Conversely, Lubowski et al. (2008) found that policy incentives are less likely to spur new forest establishment. However, such results may stem from not accounting for regional variations that impact the responsiveness of financial incentives by landowners.

The impact of population and income have also been documented in the literature as being contributors of urban land expansion (Alig et al., 2010; Hardie et al., 2000; Kim et al., 2018). Population and income growth may prompt urban land and developed land use expansion and may differ across regions in the South. In fact, the Southeast[3] has more population pressure on the land than the South-Central area, leading to a decline in forest area by 6 million acres (Alig and Plantinga, 2004). In a recent study, Terando et al. (2014) project that urban growth in the Southern U.S. will cause forest losses of 7% –12%, with the most significant expansion occurring in the Blue Ridge, Ridge and Valley, Southern Coastal Plain, and Piedmont ecoregions[4]. All of these studies provide information about the link between socioeconomic attributes (e.g., population and income) and urban land expansion, however it would be worth examining the effects of CRP enrollment on population and income. For instance,Sullivan et al. (2004) found evidence that CRP enrollment is negatively correlated with income, meaning that program enrollment provides the guaranteed financial income for landowners. CRP enrollment tends to occur in more rural areas than urbanized regions, so I expect that population density would have a negative effect on the enrollment of CRP tree planting.

This study contributes to land-use economics in several ways: (1) by measuring farmers' enrollment decisions in CRP tree planting based on actual land-use observations rather than relying on survey data, (2) by constructing a novel data set to precisely estimate forest rents based on pine plantation data from Forest Inventory Analysis (FIA), and (3) by developing a discrete choice model that combines both timber prices and forest rents to estimate determinants of CRP land use.

2.3 Data

I construct a novel data set from numerous data sources. My study area covers only the states in the U.S. South and includes the years from 2005 to 2015. In the next section, I provide details of data sources and variable construction used in this study.

2.3.1 National Resource Inventory (NRI) Data

Plot-level data on land-use patterns and land characteristics were compiled from the National Resources Inventory (NRI) data, conducted by the U.S. Department of Agriculture National Resources

[3]The authors define the Southeast region to include the states FL, GA, NC, SC, and VA while the South-Central region consist of the states AL, AR, KY, LA, MS, OK, TN, and TX.

[4]These projected ecoregions overlap projections of Alig and Plantinga (2004).

Conservation Service (NRSC). The NRI is a statistical survey data of land-use patterns, land cover, soil characteristics, erosion, and conservation practices to evaluate the conditions and trends of natural resources in the conterminous U.S. My data analysis is limited to the years 2005–2015.

Repeated observations on each parcel are sample points and are assigned to the number of acres, indicated as “expansion factor” (xfact). Expansion factors can be used to weigh factors to aggregate sample-point data to obtain a level of regional estimates such as county-level or state-level estimates. In this study, I used expansion factors to construct county-level estimates.

The NRI has land-use data on each plot, consisting of 12 broad land-use categories: cropland (cultivated and non-cultivated), pastureland, rangeland, forestland, urban/built-up land, rural transportation, large and small water, federal, other rural lands, and CRP land. It also includes data on the type of CRP cover practices for enrolled lands under the CRP general enrollment [5]. Although the NRI does not include data about the CRP continuous enrollment, 77% of enrolled lands in the program are already under general enrollment[6].

Enrolled acres in pine planting are covered under CRP general enrollment; hence, I was able to capture land-use decisions precisely for pine plantations[7]. I combined both broad land-use choice (cropland and CRP land use) and CRP cover practices (tree planting) to estimate land-use conversion decisions under the general enrollment period. The initial plot must be in cropland use at time t to enroll in the tree planting at time $t+1$. Hence, the dependent variable for each plot is equal to 1 at time $t+1$ if a plot was in cropland at time t and converted into tree planting and 0 otherwise.

Soil properties, such as the soil loss tolerance (T-factor) were also considered in this study. Soil loss tolerance is the maximum rate of annual soil loss that will allow crop productivity to be sustained on a given soil. It ranges from 1 to 5 where soil with a tolerance level of 1 indicates soils susceptible to erosion (fragile soils), and a tolerance level of 5 represents soils least subject to erosion.

Finally, I obtained the land class capability (LCC) variable to proxy for land quality. LCC is one of the broadest categories in the NRI data; it indicates the classification of soil’s suitability for crop

[5]The CRP has two enrollment options: the general and the continuous enrollment choice. Under the general enrollment, participants have the opportunity to enroll in the program annually during announced enrollment periods while under the continuous enrollment, only environmentally sensitive land devoted to certain conservation practices can enroll in the program at any time.

[6]Only 23% of enrolled lands were under the continuous CRP sign up between 2005 and 2015, whereas 77% of lands participated in the CRP general sign-up (U.S. Department of Agriculture, 2015)

[7]There are three different practice codes for tree planting in the program: CP3 Softwoods, CP3A Longleaf Pine, and CP3A Hardwoods. CP3 Softwoods (Pine Plantations) are offered in the CRP general sign-up (U.S. Department of Agriculture (2015)).

production and pasture plants. LCC has eight categories ranging from I to VIII; where LCC I and LCC II indicate the highest-quality land classes with few or no limitations for agricultural production and LCC VII represents the lowest quality land. Lands in LCC III and LCC IV have severe restrictions for crop cultivation and require special conservation management. Lands in LCC V and LCC VI are not suitable for cultivation and have restrictions for pastureland, rangeland, forestland and wildlife food and cover uses. LCC VII and LCC VIII contain lands that are unsuitable for cultivation and limit their uses for grazing, forestland, wildlife, and recreation. I obtained the share of land in LCC I and LCC II in the county, using the "expansion factor" to proxy land quality impact on the CRP tree planting enrollment[8].

2.3.2 Farm Indicators Data

County-level data on crop revenues, government payments, per-capita income, and population were obtained from the Bureau of Economic Analysis (BEA). The BEA collects data for economic activity and growth at the county, state, metropolitan area, or BEA economic areas since 1969[9].

Farm income and expense accounts were obtained to calculate crop net income to proxy for both crop rents and composite crop prices. The BEA has separate data for cash receipts from crops and livestock and livestock products sales. These figures represent values of gross revenues that are received from both crops and livestock and livestock product sales during a given calendar year.

Crop revenues consist of income received from grains (such as corn, wheat, and soybeans), hay, vegetables, fruits and nuts, greenhouse and nursery products, tobacco, cotton, and other miscellaneous crops. Livestock revenues include sales of meat (such as cattle and calves, hogs and pigs, sheep, and lambs), poultry and poultry products (including eggs), dairy products, the marketing of horses, bees, animal aquaculture, and other miscellaneous animal species raised on agricultural operations[10].

Although cash receipts from crop and livestock product sales are reported separately, farm expense variables are not distinguished by use. Thus, I made an adjustment to obtain crop net

[8] The NRI data also has four different classes of land capability and subclasses that show concerns or limitations. Class code e denotes erosion problems, w indicates wetness limitations, s denotes root zone limitation, and c indicates climatic concerns. LCC I have no subclasses, so it is used as is. LCC II has subclasses, so it is aggregated at the county level without considering subclasses because only the ratio of agricultural land that has few or no limitations is the focus of this research.

[9] I used farm income and expenses data and it can be obtained from https://apps.bea.gov/iTable/iTable.cfm?reqid=70

[10] More details on a complete list of statistics can be found from https://apps.bea.gov/regional/definitions/

income to proxy for both crop rents and composite crop prices. I estimated the ratio of crop cash receipts to total cash receipts and then applied this ratio to total net income to derive crop net income. Per acre crop rent is obtained by dividing county level net crop income (proxy for crop rents) by the total number county acres . Then, following Hardie et al. (2000), I estimated a county-level composite crop price by dividing crop net income by farmland acres in a county.

Government payments were obtained from the BEA's farm income and expense accounts, and includes support program payments, disaster payments, conservation payments, and direct payments to farmers. I excluded conservation reserve program payments that are obtained from USDA's Farm Service Agency to precisely derive county-level per acre government payment estimates. Finally, the CRP payments were taken from the USDA's Farm Services Agency's (FSA). FSA collects CRP enrollment statistics by fiscal year.

County-level estimates of per capita income and population were compiled from the BEA's economic profiles account. All values of per-capita income are inflated to 2018 values by using the consumer price index (CPI)[11] . Population density is estimated as the ratio of population to land area. The land area was taken from the U.S. Census Bureau to estimate population density[12].

2.3.3 Forest Inventory and Analysis (FIA) Data

Raw data on growth values (volume per acre) and stand age of 7,292 unique survey units in pine plantations were obtained from the USDA Forest Service, Forest Inventory and Analysis to estimate timber yield equations for each county.

The Forest Inventory and Analysis (FIA) program, a survey of forest area, is conducted by the USDA's U.S. Forest Service to provide information on the status and trends of forest resources in the United States. Its objective is to improve the understanding of forest ecosystems by informing policymakers and land managers about formulating and incentivizing sustainable management practices that are both economically and ecologically feasible. The FIA data includes information about forest inventories such as size, location, and site features such as species, health, growth, and mortality of trees.

[11]All values were inflated to 2018 values using the consumer price index for all urban consumers obtained from https://fred.stlouisfed.org/series/CPIAUCSL

[12]Data on land area was obtained from https://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk

The FIA also reports parcel-level data on current management types (for example, natural stands vs. plantations) which was critical for my analysis to construct forest yields for estimation of forest rents[13]. The 1998 Farm Bill, (the Agricultural Research, Extension, and Education Reform Act of 1998), made conceptual changes in the sampling approach of FIA data and introduced an annual forest inventory program. An annual inventory approach required that 20% of plots within a state be measured each year, while all plot inventories are reported every five years. An annual inventory program also strengthens the capacity to measure the impacts of natural events such as hurricanes and storms. The bill also combined the FIA program with the Forest Health Monitoring (FHM) program, which was established in 1990 to monitor forest ecosystem conditions to predict where and how future forest areas might change under environmental and management conditions.

The FIA's sampling procedure consists of three phases, with each having populations and sub-populations of interest. Phase 1 is aimed at classifying land area in a population of interest and assigning plots in that area by using aerial photography or satellite images. Phase 2 includes spatial distribution of plots across the landscape with the assignment of one plot per every approximately 6,000-acre hexagonal cell, having one permanent ground plot each visited by the field crew. In Phase 2, non-forest uses are also measured to quantify potential conversion to forest use. Phase 3 contains all procedures of Phase 2, obtaining additional measurements on soil sampling, tree-crown conditions, vegetation structure, ozone bioindicators, and downed wood material. The sampling procedure is based on one plot per every 96,000 acres (McRoberts et al., 2005).[14].

2.3.4 Forest Rent Estimations Data

Timber Price and Establishment Cost Data

Timber price data was obtained from bi-monthly surveys of Forest2Market (2016), which provides a comprehensive data set based on actual timber sales (stumpage values). I used two different timber prices (pulpwood and sawtimber[15] prices) for each quarter from 2005 to 2015 of 39 micro-markets that include country clusters in three regions(west-south,mid-south and east-south) in the U.S.

[13] I estimated forest rents from pine plantations in the U.S. South by using stumpage price and forest yield data.

[14] More details on the sampling procedure can be found from https://www.srs.fs.usda.gov/pubs/gtr/gtr_srs080/gtr_srs080.pdf

[15] Pulpwood is the wood suitable for making pulp and paper and sawtimber are defined as trees that can be cut into lumber

South. [16]Using a simple average of these quarterly timber prices of micro-market regions, I obtained annual timber price data for each micro-market. Micro-market timber prices were assigned to counties, so I was able to derive county-level prices using micro-market specific timber prices.

County-level CRP tree establishment cost data was taken from Nielsen et al. (2014). Their estimates rely on the observed county average cost shares for tree establishment costs between 1986–1993[17].

2.3.5 Timber Yield Data

I used FIA plot data on growing stock volume (cubic feet per acre) and stand age of 7,292 survey units of pine plantations in the U.S. South to calculate region-specific timber yield equations within each state. Data set was partitioned in two regions: coastal and non-coastal region which enabled me to quantify differences in environmental conditions such as climate, vegetation, and soils that might impact mean volume and growth of pine plantations[18].

Using empirical models in the estimation of timber yield values (e.g., polynomial equations) may not produce meaningful parameter estimates for timber growth functions because forest conditions varies across regions. Usually, non-linear growth functions are employed in natural science because it explains biological behavior better than empirical models (Fekedulegn et al., 1999). To estimate timber growth functions, the Bertalanffy (1938) growth model, a specific case of logistic function, was applied in fitting FIA plot data. The von Bertalanffy growth function takes the form of

$$Vol(age)_{r,s} = \alpha_{r,s}\left(1 - e^{-\beta_{r,s} * age}\right)^3 \tag{2.1}$$

where $\alpha_{r,s}$ and $\beta_{r,s}$ are the parameters to be estimated by each region r within state s, and *age* is the stand age. The coefficient α is the asymptote (or growth limiting value) and β is the growth

[16]Forest2Market collects and reports micro-market specific timber price data in the US South,combining three regions (west-south,mid-south and east-south). Each micro market includes different county groups so I was able to obtain county level timber prices

[17]There is a 50% cost-share assistance in the CRP for practice covers. Nielsen et al. (2014) multiplies cost share assistance by 2 to derive forest establishment costs (per acre) for each county during the period 1986–1993.They mention that the CRP data provide better establishment cost information about planting.It is an outdated data and it does not reflect current land values because the context of the CRP has undergone many changes.

[18]Due to lack of observations, I was able to generate timber yield data only by each region (coastal or non-coastal) within a state. However, not every state had both coastal and non-coastal regions, so I ended up using only non-coastal region for those states (such as Arkansas). Also, I excluded Kentucky from our analysis because the FIA data were missing (the data had only four observations).

rate. Growth function $Vol(age)_{r,s}$ is calculated for each region within a state using non-linear estimation in R.[19]

Fig. 2.1 shows the difference between the coastal and non-coastal regions in Alabama. In the coastal region (α=3501.67, β=0.08) of Alabama, temperatures tend to be warmer and more precipitation is received, whereas in non-coastal areas ($\alpha = 2600.46$, $\beta = 0.10$), particularly in the Appalachian Mountains and in the Northeast, the environment tends to be cooler.

2.3.6 Forest Rent Estimation

Using timber yields developed by the von Bertalanffy growth function and timber prices from Forest2Market (2016), I estimated a bare land expectation value which is the net present value of an infinite stream of forest revenue for a pine plantation based on optimal timber rotation age using the Faustmann formula with a discount rate of 5%.

A bare land expectation value (*LEV*) for pine plantation in each county i and conversion year t (2005-2015) was calculated by selecting the harvest age (a) in the following equation which maximizes the land expectation value:

$$LEV_{i,t}(a) = (1 - e^{-ra})^{-1}[(P_{i,f,t} * Q_{i,f,a})^{e^{-ra}} - C_i] \tag{2.2}$$

where *LEV* is the land expectation value,i represents the county,t is the conversion year;$P_{i,f,t}$ is timber price by product,county and conversion year;$Q_{i,f,a}$ is the volume final harvested at age a by county i and conversion year t, C_i is the per-acre establishment cost for county i; and r is the continuous discount rate, which is assumed to be 5%.

I considered the differences in the age of stand by given timber products;thus,the product was determined by the age of the stand in the optimization.For instance ,if the stand age a is less than 12 years, then the product volume is 100% pulpwood and the price applied to that volume is the pulpwood price.Similarly, if the stand age in the optimization is between 12 and 18, then chipnsaw and greater than 18 the sawtimber.Therefore,optimization in land expectation value can be expressed as follows:

[19]The von Bertalanffy growth function was estimated using non-linear least squares algorithm in R. Assigning the initial values are critical in non-linear regression so I used self-started values and plotted them to see how close starting values fit in yield curves.

$$
LEV_{i,t}(a) = max \begin{cases} (1-e^{-ra})^{-1}[(P_{i,pulpwood,t} * Q_{i,f,a})^{e^{-ra}} - C_i] if\ t \leq 12 \\ (1-e^{-ra})^{-1}[(P_{i,cnipnsaw,t} * Q_{i,f,a})^{e^{-ra}} - C_i] if\ 12 < t < 18 \\ (1-e^{-ra})^{-1}[(P_{i,sawtimber,t} * Q_{i,f,a})^{e^{-ra}} - C_i] if\ t \geq 18 \end{cases} \tag{2.3}
$$

It should be also noted that only final harvest revenues are included in the land expectation value estimation. Intermediate harvests,e.g., thinning, could return some revenue above the cost of the thinning but data were not available on thinning volumes to be removed without use of a growth and yields model, which brings its own issues and complication for modeling and analysis that would likely not improve land expectation value calculation. Therefore, I only considered the landowners' final harvest decision that maximize the land expectation value.

Finally, I obtained annualized county-level forest rents by multiplying the land expectation value by interest rate as follows:

$$
ForestRent_{i,t} = LEV_{i,t}(a) * r \tag{2.4}
$$

I obtained forest rents based on pine plantations for CRP tree planting, considering differences in observed prices for the U.S. South. Although the main objective of this study is to quantify the determinants of CRP tree planting with the focus on the relationship with timber prices and the likelihood of program participation, I also created different sample to estimate a different (named as alternative model in 2.4) model only using forest rents as the main explanatory variables to explain the determinants of CRP tree planting decisions.

Table 2.2 and Table 2.5 reports separately summary statistics of the variables used in main (the preferred model) and alternative model specification.

2.4 Model Specification

I begin from the assumption that a profit-maximizing landowner has static expectations (without considering option values on the lands) and chooses a land-use k that maximizes the present value of an infinite stream of expected net returns less conversion cost. Given the assumption of static expectations, I suppose that a landowner converts from land-use j to k at time t only if the economic net return minus conversion cost for land use k exceeds net returns from the current land use j.

This assumption can be expressed as follows:

$$\left(R_{kt} - rC_{jkt}\right) \geq R_{jt} \tag{2.5}$$

where R_{kt} is the economic net return from land-use conversion to k on parcel i at time t, r is the discount rate, and C_{jkt} is the cost of converting from land-use j to k on parcel i at time t.

Land use decisions faced by landowners are discrete events, so it involves discrete choice framework. Discrete choice frameworks are derived from random utility maximization. To examine the probability that a landowner's land is allocated to specific land use, I employ the random utility maximization (RUM) model introduced by (McFadden (1977)).

A landowner chooses land use k over land use j on parcel i at time t if land-use k provides the highest utility. This choice can be specified as $U_{ikt} > U_{ijt} \forall j \neq k$. However, from the researcher's standpoint, some factors that influence landowners' utility are unobservable. Thus, utility is separated into two parts; a deterministic component and an error component (idiosyncratic error term) that captures random, unobservable factors (Train, 2009):

$$U_{ijk} = V_{ijkt} + \varepsilon_{ijkt} \tag{2.6}$$

V_{ijkt} is expressed as the simple form as follows:

$$U_{ijk} = \beta_k X'_{ijkt} + \varepsilon_{ijkt} \tag{2.7}$$

where β_{jk} is a vector of unobserved variable parameters to be estimated, X_{ijkt} is a vector of explanatory variables that impact the land-use choice k (land rents, land quality, socioeconomic factors, etc.), and ε_{ijkt} is a random error term. Given this, the probability that a landowner converts land-use j to land-use k on parcel i at time t is:

$$Pr_{ijkt}(y_{ikt} = 1|X) = Pr(\beta_k X'_{ijkt} + \varepsilon_{ikt} > \beta_j X'_{ijkt} + \varepsilon_{ijt}) \forall j \neq k \tag{2.8}$$

Or

$$Pr_{ijkt}(y_{ikt}=1|X)=Pr(\beta_k X'_{ijkt}-\beta_j X'_{ijkt}>\varepsilon_{ijt}-\varepsilon_{ikt})\forall j\neq k \tag{2.9}$$

Assume that ε_{ijkt} are independent and identically distributed with a normal cumulative distribution function of the probit model of land-use choice and that the probability that a landowner converts cropland j to CRP tree planting use k on parcel i at time t in the probit structure can be expressed as (Greene, 2003):

$$Pr_{ijkt}(y_{ikt}=1|X)=\Phi(X'_{ijkt}\beta_k)=\int_{-\infty}^{X'\beta}\phi(z)dz\forall j\neq k \tag{2.10}$$

where $\phi(z)$ is the standard normal density.

$$\phi(z)=2\pi^{-1/2}exp(-z^2/2)$$

To estimate the probability that landowners participate in CRP tree planting, we employ two distinct identification strategies: a timber price model (our preferred model or main empirical strategy) and a forest rent model. The dependent variable used in each model is the probability that a landowner converts cropland into tree planting.

2.4.1 Main Empirical Strategy: Timber Price Model

I apply a probit panel model to examine the determinants of CRP tree planting where I use timber prices[20] as the main explanatory variable. Under this strategy, Pr_{ijkt} is defined as a function of timber prices, composite crop prices, land quality, land attributes, and socioeconomic variables:

$$\begin{aligned} Pr_{ijkt}(y_{ikt}=1)=\Phi(&\beta_0+\beta_1 P_{pulpwood}+\beta_2 P_{sawtimber}+\beta_3 ConserPay+\beta_4 GovPay\\ &+\beta_5 EstabCost+\beta_6 CropP+\beta_7 LCC_{1\&2}+\beta_8 Pop\\ &+\beta_9 PerCap+\beta_{10}\,T\text{-}factor)\end{aligned} \tag{2.11}$$

[20] I only used pulpwood and sawtimber prices in our analysis because pulpwood and sawtimber prices dominate stumpage markets in the U.S. South; thus, I excluded chipnsaw prices from our analysis.

where the dependent variable (y_{ikt}) is the probability that a landowner converts cropland (land-use j) into tree planting (land-use k) on parcel i at time t, $P_{pulpwood}$ and $P_{sawtimber}$ denotes county-level pulpwood and sawtimber prices at time t, *ConserPay* is county-level conservation payments, *GovPay* denotes country level government payments, and *EstabCost* is the tree establishment cost, *CropP* is county-level composite crop price ,$LCC_{1\&2}$ is the proportion of lands in LCC 1 and 2 in a county, Pop and *PerCap* are county-level population and per-capita income. Finally, (*T-factor*) is the parcel-level soil loss tolerance.

As discussed earlier, there are several factors that could influence landowners' enrollment decisions in CRP tree planting; these factors include stumpage prices, land characteristics, and socioeconomic factors. Pulpwood ($P_{pulpwood}$) and sawtimber ($P_{sawtimber}$) prices, main variables of interest, were included as proxies for forest revenues from future timber harvest on marginal lands. Future demand for pulpwood and sawtimber might impact tree planting decisions. I hypothesize that increased pulpwood and sawtimber prices will lead to increased tree planting under the CRP. For instance,Hardie et al. (2000) used sawtimber prices and found that sawtimber prices positively impacted land conversions into forestland.

To account for the relationship between government farm program payments and land-use decisions, I included two variables: county-level per acre estimates of conservation reserve program payments $\left(ConserPay\right)$ and per acre government program payments $\left(GovPay\right)$. Conservation program payments are excluded from government program payments.

Evidence of a previous study suggests that tree establishment cost (*EstabCost*) negatively influences tree planting (Li and Zhang, 2007). Conversion cost (or tree establishment cost) is also one of the determinants that affect land-use decisions at an extensive margin. I expect that the likelihood of CRP participation will decrease with increases in tree establishment costs. County-level composite agriculture prices (*CropP*) were included because changes in crop prices might impact landowners' decisions at the extensive margin and encourage an expansion of crop cultivation; therefore, I expect a negative sign for that variable.

The proportion of land in land class capability 1 and 2 ($LCC_{1\&2}$) was included as a proxy to capture the soil's suitability for crop cultivation. I assume that it would be negatively associated with enrolling the land in the CRP because high-quality lands would likely remain in agricultural production. Population density (Pop) and per capita income (*PerCap*) were included as explanatory variables to consider how socio-economic factors play a role in rural land-use decisions in the U.S. South. The population density is a proxy for urbanization, and I hypothesize that less urbanized counties are more likely to participate in the CRP. I expect that per capita income might be negatively associated with CRP participation because low-income counties are more likely to enroll in the program because CRP rental payments provide a steady income source to the participants whose financial stability relies heavily on off-farm income (Sullivan et al., 2004). Plot conditions also influence the decisions to convert from cropland to CRP tree planting, so I included soil loss tolerance (*T-factor*) to capture those conditions.

I also included a year dummy variable in my model specifications (models 4 and 5 in Table 2.3) to consider the effects of economic circumstances on the program enrollment. The economic recession of 2007–2008 already decreased planted acres and impacted the forest industry due to a downturn in the construction industry. To capture the regional differences that are not explained by explanatory variables, I run separate models by region (Appalachian, Delta, and Southeast)[21].

2.4.2 Alternative Empirical Strategy: Forest Rent Model

I employ another sample that uses only pine plantation rents as the primary explanatory variable instead of timber prices. Although my preferred model is the previous identification strategy, as discussed previously, I explore the impacts of forest rents on the CRP tree planting because land conversion decisions on marginal agricultural lands might be different. I also use crop rents (*CropRent*) instead of composite crop prices to be consistent with forest rents, keeping other explanatory variables the same.

My estimation equation becomes as follows:

$$\begin{aligned} Pr_{ijkt}(y_{ikt}=1) = \Phi(&\beta_0 + \beta_1 \mathit{ForRent} + \beta_2 \mathit{CropRent} + \beta_3 \mathit{ConserPay} + \beta_4 \mathit{GovPay} \\ &+ \beta_5 \mathit{EstabCost} + \beta_6 LCC_{1\&2} + \beta_7 LCC_{1\&2} \mathit{CropRev} \\ &+ \beta_8 \mathit{PerCap} + \beta_9 \mathit{Pop} + \beta_{10} \mathit{T\text{-}Factor}) \end{aligned} \tag{2.12}$$

where *ForRent* represents county-level estimated pine plantation rents, and *CropRent* represents

[21] Due to lack of observations in CRP tree planting, I excluded Southern Plains from this study. Results for regional estimates are shown separately.

county-level crop rents derived from using data from BEA. These are the only different variables added in the equation 2.12 while keeping other explanatory variables, the same as those in the first identification strategy. I expect that the probability of enrolling in tree planting under the CRP would be positively related to pine plantation rents, while the likelihood of tree planting in the program might decrease with increasing crop returns.

2.5 Estimation Results

2.5.1 Main Empirical Strategy: Timber Price Model

Table 2.3 displays the results of the first identification strategy for a random effects probit model where I use timber prices as main explanatory variables to explain the determinants of the conversion of cropland to CRP tree planting on marginal agricultural lands. I estimated a series of models to isolate the impacts of different prices and economic recession on the land conversion decision in the CRP tree planting program. The first column of Table 2.3(the preferred model(model 1)) includes all the explanatory variables to explain the determinants of cropland conversion to CRP tree planting. The second and third columns of Table 2.3 show the results of running the model by separating pulpwood and sawtimber prices to ensure that I have proper estimates from the preferred model, considering possible collinearity that may exist between pulpwood and sawtimber prices[22].

To account for the impact of the economic recession that may affect the likelihood of CRP tree planting, I estimated the model by including a year dummy for 2007, and results are shown in the fourth column of Table 2.3. Intuitively, it is less likely that landowners enroll in tree planting under CRP because of an economic downturn in the housing industry. Finally, I estimated the model by excluding variables that are not significant in the preferred model to check whether our results would change. Results, shown in the fifth column of Table 2.3, support the preferred model in terms of sign direction and significance. Table 2.3 and Table 2.4 present estimated parameters and average marginal effects, respectively, of the model across all alternative specifications

Coefficient values for the preferred model (Table 2.3, column 1) are difficult to interpret; unlike

[22] I looked at whether any collinearity exists between pulpwood and sawtimber prices to ensure that I have proper inferences from the preferred model specification (column 1 in Table 1.2). I used both Pearson correlation and variance inflation factors (VIFs) to verify multicollinearity. The Pearson correlation coefficient was 0.2702 and the VIF values for all variables were below 10, indicating no collinearity between pulpwood and sawtimber prices and among other variables.

linear regression models, the estimated coefficients do not have direct interpretation. Therefore, I focus on the results of average marginal effects for the preferred model. Results of the average marginal effects of the preferred model are reported in Table 2.4 (see column 1)

Discussion of the estimated parameters may be useful to indicate whether the independent variables have a significant positive or negative effect on the dependent variable, *ceteris paribus*. The coefficient values generated by the preferred model for stumpage prices, conservation and government payments, establishment cost, and per capita income are all statistically significant(see Table 2.3, column 1). The probability of enrolling in CRP tree planting increases with pulpwood price ($P_{pulpwood}$) while increases in sawtimber prices($P_{sawtimber}$) are less likely to increase the probability of participation in the CRP tree planting program. This is a confounding result and I interpret this result as there might be undiscovered collinearities between pulpwood and sawtimber prices or as a result of other left-out variables in this analysis.

As expected, the coefficient values for conservation payments (*ConserPay*) and government payments (*GovPay*) are significant and positive, indicating that increases in both program payments are more likely to increase the probability of CRP tree planting while decreases in tree establishment cost (*EstabCost*), (or conversion cost), increase the likelihood of land conversion from cropland to CRP tree planting. As expected, lower-income counties are more likely to enroll in the CRP tree planting program. In summary, the estimated coefficients indicate that pulpwood prices, conservation, and government payments, sawtimber prices, and establishment cost are the factors affecting the probability of a landowner's decision to enroll in the CRP tree planting program.

As indicated earlier, I continue with the results of the average marginal effects to ease the interpretation since they provide a better understanding of how individual effects of explanatory variables could impact the probability that a landowner converts cropland to CRP tree planting under the CRP.

The average marginal effects with respect to pulpwood prices ($P_{pulpwood}$) are positive and statistically significant at a 1% level, suggesting that a $1 increase in pulpwood prices would increase the probability of cropland being converted into CRP tree planting by 0.0343%. The average marginal effects of sawtimber prices ($P_{sawtimber}$) are negative and significant, meaning that increases in sawtimber prices are likely to decrease to the probability of cropland conversion to CRP. This finding challenges my hypothesis. Perhaps, there might be other left-out factors that could yield such result in this analysis such as current trends in timber prices and financial crisis. As illustrated in Fig. 2.2, sawtimber prices have been declining since 2005, and the gap between sawtimber and ChipNSaw and pulpwood prices has shrunk. If spatial and time trends of sawtimber prices in the U.S. South are considered (see Fig. 2.3 and Fig. 2.4), sawtimber prices have experienced a significant decline over the last 13 years and have been on a slow recovery path for the post-recession period.

The average marginal effect of conservation payments (*ConserPay*) on tree planting is positive and significant. The positive sign confirms that landowners are potentially more responsive to incentive payments when deciding whether to enroll in CRP tree planting. Also, the average marginal effects of conservation payments are significantly higher than other independent variables (by 0.10317%). This finding suggests that providing higher incentives for landowners to convert environmentally sensitive lands into CRP tree planting has a more significant impact than other factors in the model.

The average marginal effects with respect to government payments (*GovPay*) are positive but statistically not significant. The positive sign suggests that increases in government payments increase the CRP the tree planting enrollment. The relationship between establishment cost (*EstabCost*) and the probability of cropland conversion to CRP tree planting is negative and statistically significant at a 1% significance level, suggesting that lower tree establishment cost on land makes landowners more likely to enroll in the CRP tree planting. Such a result is expected; the establishment cost would impact the future expected earnings and low conversion costs increases the future expected returns.

The average marginal effect of crop prices suggests that crop prices (*CropP*) do not have a significant impact on the probability of land conversion to CRP tree planting; however, the negative sign indicates that higher commodity prices decrease the likelihood of cropland conversion to CRP tree planting on marginal lands. The probability of CRP tree planting on high -quality land($LCC_{1\&2}$) is negative, but not significant.

The average marginal effects of the population (Pop) are negative, although not significant, suggesting that rural areas and less populated counties are more likely to enroll CRP tree planting. The average marginal effect for per capita income (*PerCap*) has a negative sign and is significant, which supports the notion that lower-income counties are more likely to participate in CRP tree planting because CRP payments might provide a stable income source for poorer landowners. Finally, the average marginal effect of soil loss tolerance (*(T-Factor*) on CRP tree planting is positive and insignificant which means that soil loss tolerance has no impact on the enrollment decisions.

2.5.2 Alternative Empirical Strategy: Forest Rent Model

The results for this strategy, which uses pine plantation rents as the primary explanatory variable to explain the probability of cropland conversion to CRP tree planting, are displayed in Table 2.6. The first column of Table 2.6 reports the estimated parameters from the random effects probit model, and the second column of it provides the average marginal effects of independent variables used in the model. Since the interpretation of the coefficient generated by the random effect probit model is not straightforward, I begin the discussion by analyzing the average marginal effect to assist the understanding, as I did in the previous section. Summary statistics for this specification are presented in Table 2.5.

The average marginal effects of pine plantation rents (*ForRent*) are negative and significant at 1% level. The negative coefficient seems counterintuitive. However, my primary objective is to build a model to explore what incentivizes landowners to enroll in tree planting programs under the CRP; thus, this study departs from previous research that finds a positive relationship between timber rents and forestland expansion (Kim et al., 2018; Lubowski et al., 2008).

The coefficient estimates on the crop rent (*CropRent*) variable produces a negative but not significant. A possible explanation for the lack of significance may be attributed to regional heterogeneity in crop rent estimations.

The average marginal effect of conservation payments (*ConserPay*) is positive and significant at a 1% level, supporting the hypothesis that landowners might respond to incentive payments that may encourage the program enrollment. Similar to the previous identification strategy, I find that conservation payments are a useful policy tool in incentivizing landowners to adopt CRP tree planting practices on marginal croplands. While conservation payments are positively (statistically significant) associated with the enrollment decisions, the average marginal effects of government program payments (*GovPay*) are negative and significant. These results give evidence that government programs may work at cross-purposes on marginal agricultural lands.

The coefficient on tree establishment (*EstabCost*) cost is negative and significant, suggesting that higher establishment costs matter for land-use decisions on marginal agricultural lands. The average marginal effect of land quality of class 1 and 2 ($LCC_{1\&2}$) is negative, as expected, but not significant. The average marginal effects of per capita income (*PerCap*) and population (Pop) remain negative as in the previous strategy; however, there are no statistically significant effects of income and population on enrolling in the CRP tree planting program. The negative sign suggests that rural counties are more likely to enroll in the program. Finally, the coefficient of soil loss tolerance (*T-Factor*) is positive but insignificant.

2.5.3 Robustness Check

Given the nature of panel data in this study, I conduct alternative model specifications to test the robustness of parameter estimates considering the unobservable characteristics of independent variables. I employ the traditional random-effects probit model to estimate a probability of converting cropland to the CRP tree planting as our primary empirical strategy.

The traditional random effects (RE) probit model produces efficient and consistent estimates if individual effects are uncorrelated with other explanatory variables in the model, assuming zero correlation between observed explanatory variables and time-invariant variables (Wooldridge, 2010). However, if time-invariant variables are correlated with explanatory variables, then the unobserved random effect may lead to inconsistent estimators because of uncontrolled unobserved heterogeneity. Thus, the RE probit model may not be a viable option as an estimation strategy because unobserved characteristics of land may be correlated with other explanatory variables, and we cannot control endogeneity using the traditional RE probit model.

To remedy this impact, the standard fixed effect (FE) model usually is used in the estimation procedure because it can control unobserved heterogeneity (Allison, 2009; Wooldridge, 2010). The FE model provides a means for alleviating the bias of omitted variables and has been an appealing approach in panel data studies. However, the disadvantage of using the FE model is that it eliminates time-constant variables (e.g., soil loss tolerance, establishment cost in this study) from the model, so the effects of these variables cannot be estimated in the model.

Furthermore, using the FE model in the context of a binary response model introduces the incidental parameters problem, and estimation can create a bias (Wooldridge, 2010). Therefore, I consider the correlated random effects (CRE) framework—or Chamberlain-Mundlak approach—as a remedy for the limitations of FE and RE models in estimating nonlinear panel models. The CRE approach, first introduced by Mundlak (1978), has been a preferred method in panel data to address the shortcomings of traditional FE and RE models. Mundlak (1978) and Chamberlain (1980) show that the FE estimator can be estimated by adding the averages of time-variant variables as explanatory variables in the model and allowing for correlation between the individual effects and explanatory variables. Wooldridge (2010) shows how the CRE framework can be applied to the unobserved effects probit model as follows.

Assume that FE estimators of a binary outcomes model take the following form Wooldridge (2010):

$$Y_{it} = X_{it}\beta + c_{i+}\varepsilon_{it} \tag{2.13}$$

where X_{it} is 1x k and can include explanatory variables that change across t but not i, variables that change across i but not t and variables that change across i and t. c_i is individual effect and ε_{it} is an idiosyncratic error.

The Chamberlain-Mundlak approach assumes that $c_i|X_i \sim N(\psi + \overline{X}_i\xi, \sigma_\alpha^2)$, where σ_a^2 is the variance of a_i in the equation $c_{i=}\psi + \overline{X}_i\xi + \alpha_i$.Then the CRE probit model can be specified as

$$Y_{it} = X_{it}\beta + \psi + \overline{X}_i\xi + \alpha_i + e_{it} \tag{2.14}$$

where $e_{it}\, are\, independent, e_{it}|X_i, \alpha_i \sim N(0, \sigma_\alpha^2)$, and $a_i|X_i \sim N\left(0, \sigma_\alpha^2\right)$.

Adding the average overtime for the cross-sectional unit i, X_i $\overline{X}_i$=$T_i^{-1}\sum_{r=1}^{T} X_i$, as a set of explanatory variables controls unobserved heterogeneity c_i and consistently estimates parameter estimates and the average marginal or average partial effects (APEs).

In the context of a CRE framework, I can estimate our model by introducing $\overline{X}_i$ as a set of explanatory covariates shown in Equation 2.11 and Equation 2.12 and specify a probit response function (Wooldridge, 2019) [23]:

[23]The CRE model framework can be extended to unbalanced panel data. Wooldridge (2019) shows that Equation 2.13 also holds for unbalanced panels and nonlinear models. Given the nature of the data set used in this study, I follow the pertinent estimation approach, which is the strategy proposed by Wooldridge (2019). Also, Wooldridge mentions that using the CRE approach in estimating small T and large N panel data (as in this study) outperforms the conditional maximum likelihood.

$$Pr_{ijkt}(X_i, c_i) = \Phi\left(X_{it}\beta + c_i\right), t = 1, \ldots.., T \tag{2.15}$$

I follow the compact form of the CRE probit approach above to circumvent the unobserved heterogeneity problem in the random effects assumption. Including group means of time-varying variables corrects for unobserved heterogeneity and serves as a form of fixed effect (See Equation 2.14).

First, I estimate the model using the traditional RE probit model, CRP probit model, and pooled probit model with standard errors clustered at the plot level. The parameter estimates and the average marginal effects of both preferred and alternative models are displayed in Table 2.7 and Table 2.8, respectively. To check the robustness of the RE probit model and whether the CRE approach is preferred to initial empirical strategy, I perform the likelihood ratio test to test the null hypothesis $c_i = 0$ by comparing the random effects probit model.

The likelihood ratio test[24] (LR) fails (please see Table 2.7) to reject the null hypothesis that $c_i = 0$, implying that adding the mean of time-varying regressors does not impact the estimates, and thus the estimates of the random effects probit model are robust.[25]

2.5.4 Regional Estimations for Timber Price Model

To capture differences across regional patterns of the likelihood of cropland conversion to CRP tree planting, I estimate the preferred model separately by region (Appalachian, Delta, and Southeast) except for the Southern Plains region. Only a small amount of cropland conversion to CRP tree planting occurred in that region, and therefore I excluded that region from the regional analysis. CRP acres in that region are more concentrated in CRP grassland practices.

The estimated parameters and the average marginal effects are presented in Table 2.9 and Table 2.10, respectively. The average marginal effects of pulpwood prices ($P_{pulpwood}$) is positive and significant except for the Delta region. Appalachian and Southeast regions have experienced pulpwood prices increases due to high demand (see Fig. 2.3 and Fig. 2.5).The average marginal effects of sawtimber prices ($P_{sawtimber}$) are consistently negative and significant across all regions, which is consistent with the preferred model estimation. The forementioned declines in sawtimber

[24]The LR test results are shown in Table 2.7. I only perform LR test for preferred (timber price model) model.

[25]I also run the robustness check for regional estimates. Results are shown in Appendix A.

price since 2005 both Southwide and by state could be one of possible explanations of this result (see Fig. 2.6). Sawtimber prices have experienced declines across all regions in the U.S. South despite housing market recovery after recession.

The average marginal effects of conservation payments (*ConserPay*) on the probability of enrolling in CRP tree planting are positive and significant for the Appalachian and Delta regions. However, the effects of conservation payments(*ConserPay*) are relatively larger in the Appalachian region. The impact of government payments (*GovPay*) are positive but not significant across all regions. Such a result might stem from regional differences in government programs. Tree establishment cost (*EstabCost*) is negative and significant for the Appalachian and the Delta regions; however, it is positive and not significant for the Southeast region. Tree establishment cost would matter more in the Appalachian and Delta regions because there is more competition between agriculture and forest land uses

The average marginal effects of crop prices (*CropP*) in the Appalachian and Southeast regions are positive and not significant; however, they are negative and significant for the Delta region. The negative sign suggests that higher commodity prices decrease the likelihood of cropland conversion to CRP tree planting on marginal lands. Such a result is expected given that the Delta region has the highest percentage of cropland compared to the other two regions; therefore, higher crop prices are more likely to lead to restrained increases in CRP tree planting.[26]

The average marginal effects of land quality of class 1 and 2 ($LCC_{1\&2}$) are negative, as expected, but are not significant across all regions, suggesting that high-quality lands are less likely to be converted to CRP tree planting on average. The average marginal effects of the population (*Pop*) remain negative but not significant for the Appalachian and Delta regions while remaining positive and not significant for the Southeast region. The average marginal effect of per capita income (*PerCap*) suggests that poorer counties in the Southeast region are more likely to enroll in the CRP tree planting. The average marginal effects are positive for the Appalachian region and negative and not significant for the Delta region. Finally, the average marginal effects of soil loss tolerance *T-factor* on the probability of CRP tree planting enrollment is positive but not significant across all regions.

[26]According to Bigelow and Borchers (2017) data about major land uses, 20% of land is used as cropland in the Delta region while only 18.3% and 10.1%, respectively, is used as cropland in the Appalachian and Southeast regions.

2.6 Discussions / Conclusions

Though tree planting acres in the CRP are low, with only 1.2 million acres of planted trees on the 24.1 million CRP acres, the U.S. South has the largest CRP tree planting acreage in the nation. In fact, most of the tree planting as conservation cover practice either reenrolled or converted into forestland. From that standpoint, the CRP tree planting can contribute to forestland expansion in the U.S. South, and tree planting under the CRP can be used as climate policy to tackle climate change and provide environmental benefits.

Implementing such a policy that aims to provide multiple benefits (such as reducing emissions and enhancing ecosystem benefits) in the U.S. South requires understanding what incentivizes landowners to enroll in the CRP and how market forces impact such decisions. The findings of this research help inform policymakers for the development of better policy tools that consider CRP tree planting both as a long-term conservation policy and as a climate change policy by providing financial incentives to retain and promote lands in tree planting while increasing forest carbon sinks on marginal agriculture lands.

In this study, I estimated a model to explain the determinants of converting cropland to CRP tree planting as a function of timber prices, land attributes, conservation, and government payments, and socioeconomic variables by using a random-effects probit model as our main specification. In the preferred model, marginal effects derived from the model are robust, statistically significant.

Estimation results suggest that pulpwood prices significantly and positively impact landowner decisions about enrolling in the program, while sawtimber prices negatively impact those decisions. Although this finding confronts my hypothesis, there might be other external factors that affects such result. For instance, increases in bioenergy demand and other paper products have increased pulpwood prices and trends in pulpwood markets.Also, financial crisis and decreased sawtimber demand might put downward pressures on sawtimber prices.

As discussed earlier, financial incentives are one of the influential determinants in afforestation policies. Given that, the marginal effects of conservation payments have a larger magnitude than other variables in the preferred model, suggesting that conservation payments are the most significant explanatory variable in explaining the probability of cropland conversions to CRP tree planting. This finding is also consistent with the results of the forest rent model. Higher conservation payments are more likely to induce afforestation of marginal lands.

Results of average marginal effects of establishment cost provide evidence that higher conversion costs reduce the likelihood of cropland conversion to CRP tree planting. This result suggests that land conversion decisions may be delayed, or CRP lands may be either re-enrolled in the program or converted into forestland upon the contract termination. Another significant factor that influences tree planting decisions on marginal agricultural land is per capita income. High enrollment in CRP tree planting is more likely to be associated with a low-income level, indicating that rural counties are likely to enroll in the program because CRP payments can be viewed as a stable income source for landowners.

In conclusion, I find empirical evidence that market forces impact land-use decisions in the U.S. South, where most of the land is privately owned. My results suggest that rising pulpwood prices and conservation payments are key indicators that could impact the likelihood of converting cropland to tree planting under the CRP in this study.

Quantifying the determinants of land-use conversion decisions in our study would be useful for policy development to address low-cost carbon sequestration on marginal lands. The findings of this research are timely as policymakers seek to implement efficient policy tools (e.g., the Trillion Trees Acts) that promote afforestation of environmentally sensitive lands and increase carbon sequestration on those lands.

Future extension of this research will address whether a low-cost carbon economy exists in tree planting under the CRP in the U.S. South such as linking the CRP rental rate payments to the amount of sequestrated carbon, could be more efficient for enduring conservation benefits on the lands at a low cost. Such work could provide better insights for the efficacy of a policy design requires understanding the factors which can facilitate private landowners' decision making in environmental policy context.

Table 2.1: Forest Incentive Programs

Forest Stewardship Program (FSP)—Established in 1991 to assist private forest owners to keep forestland and resources in healthy condition and increase the economic and environmental benefits it provides. The FSP is not a cost share program; cost-share assistance program in which participating forestland owners receive technical assistance to implement a Forest Stewardship plan and must make a good faith effort to implement the plan. Administered by the U.S. Forest Service.
Conservation Reserve Program (CRP)—Established in 1985 to promote conversion of highly erodible farmland and other environmentally sensitive land to a long-term resource conserving cover practice. It is a voluntary program for agriculture landowners. Participating landowners receive annual payments duration of their contract based on the converted land's agricultural rental value and environmental benefit index. They also can receive a cost share of up to 50% of the cost of establishing the resource conserving cover. Administered by the USDA Farm Service Agency.
Environmental Quality Incentives Program (EQIP)—Established in 1996 to provide technical and financial assistance to address environmental concerns and improve environmental benefits such as air, water quality, increase soil health and reduce soil erosion. Participating agriculture producers receive technical assistance, cost share, and incentive payments to implement conservation practices. Administered cooperatively by the USDA NRCS and Farm Service Agency.
Forest Land Enhancement Program (FLEP)—Established in 2002, to provide technical and financial assistance to promote long-term sustainable forest practices for non-industrial private forestland owners. The FLEP replaces two earlier programs: The Forest Incentives Program (FIP) and the Stewardship Incentives Program (SIP). To be eligible for cost-share assistance, a forest resource management plan should be submitted by forestland owners. Administered by the U.S. Forest Service in partnership with state forestry agencies.
Forest Legacy Program (FLP)—Created in 1990 to encourage the protection of environmentally important private forestland through conservation easements or land purchases Administered by the U.S. Forest Service in partnership with individual states.
Landowner Incentive Program (LIP)—Established in 2003 to provide cost-share assistance to protect and restore the decline of habitats on private lands. Administered by the USDI Fish and Wildlife Service in cooperation with state wildlife agencies. To participate, the states must provide a minimum 25% nonfederal match for federal funding.
Southern Pine Beetle Prevention and Restoration Program (SPBPR)—Initiated in 2003, to help public and private landowners in southern states to reduce the Southern Pine Beetle (SPB) damage and restore damaged forest areas. Participating forestland owners receive both educational support and cost-share payments for management activities such as thinning to improve forest health. Administered by the U.S. Forest Service.

Table 2.1: Forest Incentive Programs Continued

Wetlands Reserve Program (WRP)—Established in 1985 to provide technical and financial assistance to private landowners to promote long-term conservation efforts and wildlife practices. Eligible lands for the WRP includes wetlands farmed under natural conditions; farmed wetlands; prior converted cropland; farmed wetland pasture; certain lands that have the potential to become a wetland as a result of flooding; rangeland, pasture, or forest production lands where the hydrology has been significantly degraded and can be restored; riparian areas which link protected wetlands; lands adjacent to protected wetlands that contribute significantly to wetland functions and values; and wetlands previously restored under a local, State, or Federal Program that need long-term protection. Lands established to trees under the CRP are not eligible for WRP participation. ***The Wildlife Habitat Incentives Program (WHIP)***—Established in 1998 to encourage the development and improvement of wildlife habitat on private land. Participating owners receive technical assistance to develop a wildlife habitat management plan, plus cost share payments under an agreement lasting 5–10 yr. Cost shares cannot exceed 75% of the cost of the practices performed. Administered by the USDA NRCS.

Table 2.2: Summary Statistics and Variable Definitions for Timber Price Model

Variable	Description	Mean	Std. Dev
$P_{pulpwood}$	County-level pulpwood prices	8.8941	2.4698
$P_{sawtimber}$	County-level Sawtimber prices	32.2073	11.4391
ConserPay	Conservation Payments ($/acre)	1.0299	1.0299
GovPay	Government Payments ($/acre)	22.9212	26.4489
EstabCost	County-level CRP Tree Establishment Cost	156.2949	70.4069
CropP	Farm Revenues/Farm Acres	366.0245	280.8559
LCC1&2	Proportion of Land in LCC 1 and 2	0.2975	0.1353
Pop	Population Density	98.8032	137.2041
PerCap	Per-capita Income($1000s)	34.6900	6.9568
T-Factor	Soil Loss Tolerance	4.6365	0.7957

Table 2.3: Parameter Estimates Random Effects Probit Model for Timber Price Model

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
$P_{pulpwood}$	0.0866***	0.1221		0.1068***	0.0812**
	(0.0203)	(0.0145)		(0.2144)	(0.0173)
$P_{sawtimber}$	-0.0995***		-0.0906***	-0.1153***	-0.0821***
	(0.007)		(0.0066)	(0.0117)	(0.0055)
ConserPay	0.2619***	0.2735***	0.2156***	0.2403***	0.2547***
	(0.0451)	(0.0415)	(0.0468)	(0.0451)	(0.0459)
GovPay	0.0057**	-0.0222***	0.0059*	0.0057**	0.0048**
	(0.0026)	(0.002)	(0.0025)	(0.0024)	(0.0022)
EstabCost	-0.0052***	-0.0026	-0.0060***	-0.0042**	-0.0037**
	(0.002)	(0.0017)	(0.002)	(0.0018)	(0.0016)
CropP	-0.0001	0.0011***	0.00002	-0.0001	
	(0.0002)	(0.0001)	(0.00029)	(0.0002)	
LCC1&2	-0.6415	0.0296	-0.2626	-0.3094	
	(0.6273)	(0.5729)	(0.649)	(0.5962)	
Pop	-0.0007	-0.0025*	0.0005	-0.0007	
	(0.0013)	(0.0012)	(0.0013)	(0.0014)	

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 2.3: (Continued) Parameter Estimates Random Effects Probit Model for Timber Price Model

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
PerCap	-0.0258*	-0.0037	-0.0289*	-0.0221	-0.0246**
	(0.0152)	(0.0126)	(0.0153)	(0.0143)	(0.0125)
T-Factor	0.0189	0.0816	0.0704	0.00644	
	(0.1172)	(0.1213)	(0.1209)	(0.1131)	
Year_2007				-0.5388**	
				(0.2455)	
Constant	-12.0518	-16.3324	-11.1575	-10.1785	-8.0122
	(0.8667)	(0.8247)	(0.8781)	(0.9078)	(0.5279)
Log-Likelihood	-1539.8088	-1657.9042	-1555.912	-1570.56	-1668.48
χ^2	814.48	250.98	782.27	752.98	557.13
AIC	3103.618	3337.808	3133.824	3167.118	3352.96
BIC	3109.082	3450.856	3246.872	3300.72	3435.18
Pseudo R-Square	0.21	0.15	0.20	0.20	0.15
Observations	214709	214709	214709	214709	214709

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 2.4: Average Marginal Effects of Random Effects Probit Model for Timber Price Model

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
$P_{pulpwood}$	0.000341***	0.000047		0.000398***	0.000296***
	(0.000097)	(0.000067)		(0.000098)	(0.000070)
$P_{sawtimber}$	-0.000392***		-0.000344***	-0.000430***	-0.000300***
	(0.000069)		(0.000060)	(0.000075)	(0.000038)
ConserPay	0.0010317***	0.001042***	0.000818***	0.000895***	0.000930***
	(0.000212)	(0.000236)	(0.000194)	(0.000186)	(0.000169)
GovPay	0.000023	-0.000085***	0.000022*	0.000021**	0.000018**
	(0.000011)	(0.000019)	(0.000010)	(0.000010)	(0.000008)
EstabCost	-0.000021**	-0.000010	-0.000023***	-0.000016**	-0.000014**
	(0.000008)	(0.000007)	(0.000008)	(0.000007)	(0.000006)
CropP	-0.000001	0.000004***	0.0000001	0.0000004	
	(0.000001)	(0.000001)	(0.0000011)	(0.0000010)	
LCC1&2	-0.002527	0.000113	-0.000996	-0.001152	
	(0.002518)	(0.002182)	(0.002472)	(0.002232)	
Pop	-0.000003	-0.000010*	-0.000002	-0.000003	
	(0.000005)	(0.000005)	(0.000005)	(0.000010)	
PerCap	-0.000102*	-0.000014	-0.000110*	-0.000082	-0.000090**
	(0.000061)	(0.000049)	(0.000060)	(0.000054)	(0.000046)
T-Factor	0.000075	0.000311	0.000267	0.000240	
	(0.000461)	(0.000463)	(0.000457)	(0.000421)	
Year_2007				-0.002007**	
				(0.000948)	
Observations	214709	214709	214709	214709	214709

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 2.5: Summary Statistics and Variable Definitions of Forest Rents Model

Variable	Description	Mean	Std.Dev.
ForRent	County-level Forest rents ($/acre)	1008.138	404.677
CropRent	County-level crop rents ($/acre)	31.6318	40.6034
ConserPay	Conservation Payments($/acre)	0.9759	1.1633
GovPay	Government Payments($/acre)	17.8922	20.5915
EstabCost	County-level CRP Tree Establishment Cost	144.3643	49.1350
LCC1&2	Proportion of Land in LCC 1 and 2	0.3180	00.1344
Pop	Population Density	98.8081	132.3949
PerCap	Per-capita Income ($1000s)	34.7148	66.6467
T-Factor	Soil Loss Tolerance	4.6701	0.7666

Table 2.6: Estimated Parameters and Average Marginal Effects for Forest Rents Model

Variables	Random Effects Probit	Average Marginal Effects
ForRent	-0.0024***	-0.000011***
	(0.0002)	(0.000002)
CropRent	-0.0036	-0.000016
	(0.0046)	(0.000021)
ConserPay	0.2651***	0.001195***
	(0.0746)	(0.000335)
GovPay	-0.0084**	-0.000038*
	(0.0042)	(0.000021)
EstabCost	-0.0063**	-0.000029**
	(0.0025)	(0.000012)
LCC1&2	-0.4253	-0.001918
	(0.8890)	(0.004008)
LCC1&2*CropRent	0.0082	0.000037
	(0.0115)	(0.000052)
PerCap	-0.0267	-0.000121
	(0.0185)	(0.000085)
Pop	–0.0010	-0.000005
	(0.0013)	(0.000006)
T-Factor	0.0824	0.000372
	(0.1429)	(0.000644)
Log-Likelihood	-1086.21	
χ^2	530.89***	
AIC	2196.42	
BIC	2314.43	
Pseudo R -square	0.20	
Observations	137,837	

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 2.7: Robustness Check: Parameter Estimates of Alternative Models: Timber Price Model

Variables	Random Effects Probit	CRE Probit	Pooled Probit
$P_{pulpwood}$	0.0866***	0.0638**	0.0191***
	(0.0203)	(0.0248)	(0.0071)
$P_{sawtimber}$	-0.0995***	-0.0985***	-0.0130***
	(0.007)	(0.0076)	(0.0018)
ConserPay	0.2619***	0.4888***	0.1336***
	(0.0451)	(0.110)	(0.0146)
GovPay	0.0057**	0.0084***	0.0006
	(0.0026)	(0.003)	(0.0009)
EstabCost	-0.0052***	-0.0040**	-0.0018**
	(0.002)	(0.0019)	(0.0007)
CropP	-0.0001	0.0003	0.00006
	(0.0002)	(0.0004)	(0.0001)
LCC1&2	-0.6415	0.1139	0.1743
	(0.6273)	(0.6221)	(0.0794)
Pop	-0.0007	0.0250**	-0.0009
	(0.0013)	(0.0108)	(0.0006)
PerCap	-0.0258*	-0.0599**	-0.0077
	(0.0152)	(0.0296)	(0.0058)
T-Factor	0.0189	0.0651	0.0576
	(0.1172)	(0.1172)	(0.045)
$\overline{P_{pulpwood}}$		0.0526	
		(0.0668)	
$\overline{P_{sawtimber}}$		-0.0102	
		(0.0317)	
$\overline{ConserPay}$		-0.3135**	
		(0.122)	
$\overline{GovPay}$		-0.0045	
		(0.0059)	
$\overline{CropP}$		-0.0003	
		(0.0007)	
$\overline{Pop}$		-0.0282**	
		(0.0123)	
$\overline{PerCap}$		0.0505	
		(0.0375)	
Intercept	-12.0518***	-12.6893***	-2.1893***
	(0.8667)	(1.0955)	(0.2966)
Log-Likelihood	-1539.81	-1535.54	-8098.91
	814.48***	365.94***	308.09***
AIC	3103.61	3226.94	16219.81
BIC	3109.08	3304.34	16332.86
LR test (H0:ci=0)	8.54		
	0.2878		
Observations	214709	214709	214709

Table 2.8: Robustness Check: The Average Marginal Effects of Alternative Models for Forest Rents Model

Variable	Random Effects Probit	CRE Probit	Pooled Probit
ForRent	-0.000011***	-0.000013***	-0.000006***
	(0.000002)	(0.000002)	(0.000001)
CropRent	-0.000016	-0.000018	-0.000014
	(0.000021)	(0.000023)	(0.0000035)
ConserPay	0.001195***	0.003411***	0.003012***
	(0.000335)	(0.00101)	(0.000473)
GovPay	-0.000038*	-0.000016*	-0.000023
	(0.000021)	(0.000022)	(0.000027)
EstabCost	-0.000029**	-0.000012**	-0.000029*
	(0.000012)	(0.000013)	(0.000015)
LCC1&2	-0.001918	-0.002278	-0.002759
	(0.004008)	(0.004349)	(0.005987)
LCC1&2*CropRent	0.000037	0.000045	0.000085
	(0.000052)	(0.000055)	(0.000088)
PerCap	-0.000121	-0.00022	-0.000173
	(0.000085)	(0.00019)	(0.00014)
Pop	-0.000005	0.000304	-0.000020*
	(0.000006)	(0.000086)	(0.000012)
T-Factor	0.000372	0.000271	0.000885
	(0.000644)	(0.000636)	(0.000986)
$\overline{ForRent}$		0.000008***	
		(0.000003)	
$\overline{CropRent}$		0.000001	
		(0.000021)	
$\overline{ConserPay}$		-0.002402**	
		(0.001002)	
$\overline{GovPay}$		-0.000024	
		(0.000051)	
$\overline{CropP}$		-0.000328***	
		(0.000096)	
$\overline{Pop}$		0.000155	
		(0.000213)	
$\overline{PerCap}$		-0.0123	
Observations	137837	137837	137837

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 2.9: Parameter Estimates of Random Effects Probit Model for Regions: Timber Price Model

Variable	Appalachian	Delta	Southeast
$P_{pulpwood}$	0.0942**	0.0218	0.0892**
	(0.0435)	(0.0473)	(0.0369)
$P_{sawtimber}$	-0.0787***	-0.127***	-0.0998***
	(0.0121)	(0.0145)	(0.0132)
ConserPay	0.6048***	0.160***	0.1695
	(0.1289)	(0.0611)	(0.1351)
GovPay	0.0056	0.0052	0.0079
	(0.0042)	(0.00459)	(0.0113)
EstabCost	-0.0102**	-0.0108***	0.00008
	(0.0047)	(0.00318)	(0.00273)
CropP	0.0002	-0.00148***	0.00002
	(0.0003)	(0.000562)	(0.00049)
LCC1&2	-0.5168	-1.229	-0.9718
	(1.2122)	(1.261)	(1.2065)
Pop	-0.0003	-0.00177	0.0002
	(0.0015)	(0.00312)	(0.0025)
PerCap	0.009	-0.0246	-0.0855**
	(0.0184)	(0.0243)	(0.0417)
T-Factor	0.0736	0.132	0.0984
	(0.1455)	(0.272)	(0.2898)
Intercept	-10.2239***	-11.3416***	-8.5345
	(1.2188)	(1.739)	(1.9159)
Log-likelihood	-450.98	-684.64	-383.31
	161.57***	305.1***	165.77***
AIC	925.96	1393.28	790.63
BIC	1037.54	1504.84	897.05
Pseudo R-square	0.16	0.19	0.18
Observations	80,699	80,569	52,487

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 2.10: The Average Marginal Effects for Regions: Timber Price Model

Variable	Appalachian	Delta	Southeast
$P_{pulpwood}$	0.000189***	0.000101	0.000335***
	(0.000094)	(0.000222)	(0.000164)
$P_{sawtimber}$	-0.000158**	-0.000590***	-0.000375***
	(0.000039)	(0.000133)	(0.000114)
ConserPay	0.001217**	0.000746***	0.000637
	(0.000317)	(0.000283)	(0.000513)
GovPay	0.000011	0.000024	0.000030
	(0.000009)	(0.000022)	(0.000043)
EstabCost	-0.000020***	-0.000050***	0.0000003
	(0.0000102)	(0.000016)	(0.000010)
CropP	0.0000004	-0.000007**	0.0000001
	(0.0000006)	(0.000003)	(0.000002)
LCC1&2	-0.001040	-0.005717	-0.003649
	(0.002459)	(0.005925)	(0.004572)
Pop	-0.000001	-0.000008	0.000001
	(0.000003)	(0.000015)	(0.000010)
PerCap	0.000018	-0.000114	-0.000321*
	(0.000037)	(0.000115)	(0.000169)
T-Factor	0.000148	0.000616	0.000370
	(0.000293)	(0.001252)	(0.001092)
Observations	80,699	80,569	52,487

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

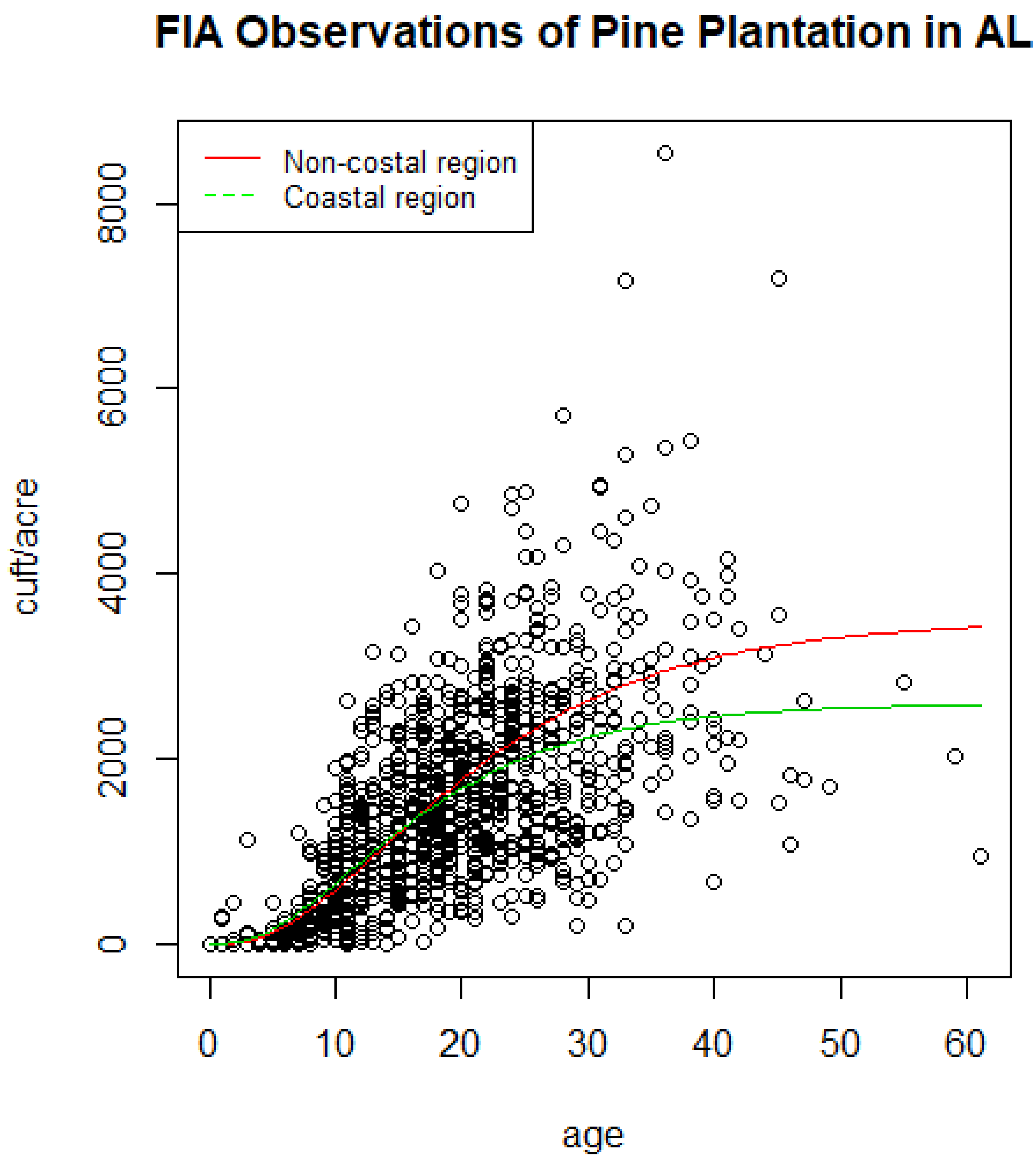


Figure 2.1: Example of the empirical yield curve in Alabama by region.

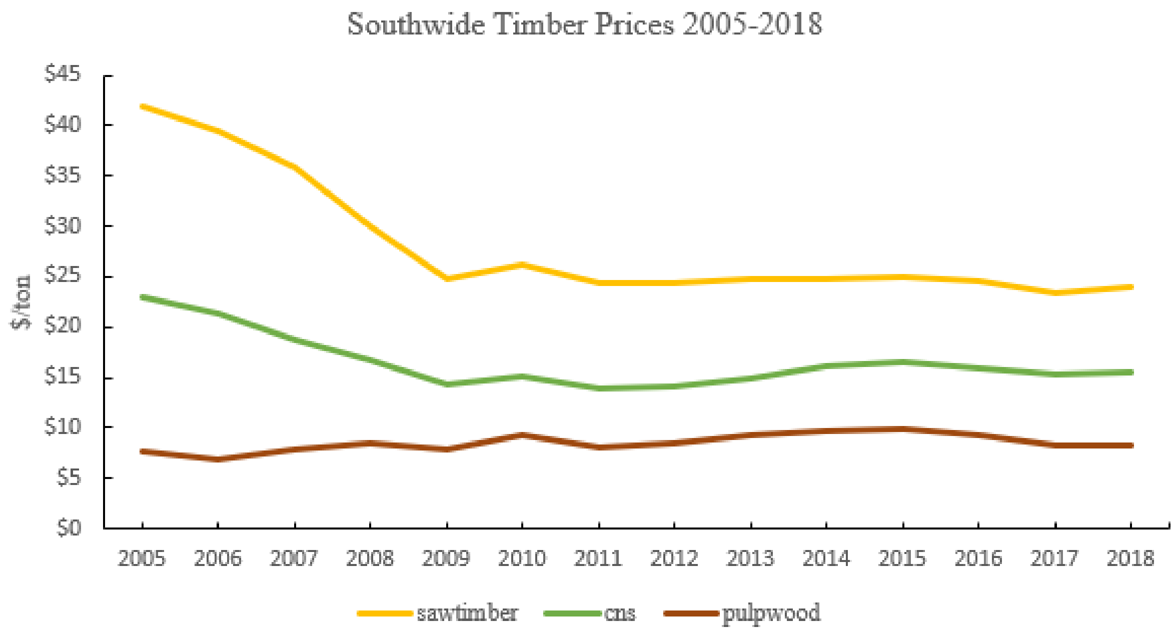


Figure 2.2: Southwide Timber Prices 2005-2018 Source: Forest2Market (2016)

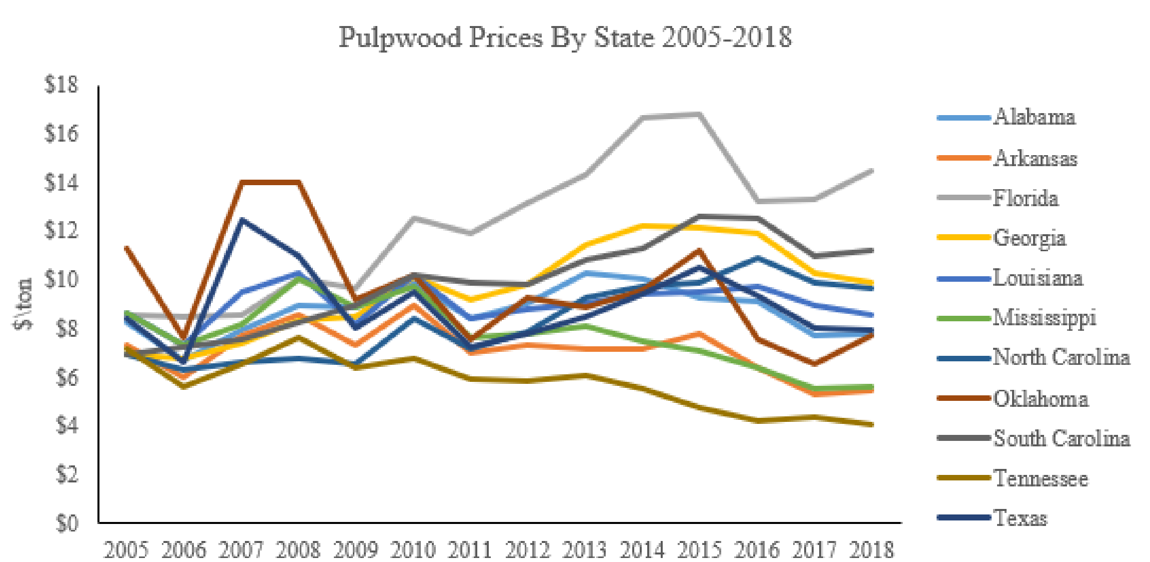


Figure 2.3: Pulpwood Prices 2005-2018 Source:Fores2Market

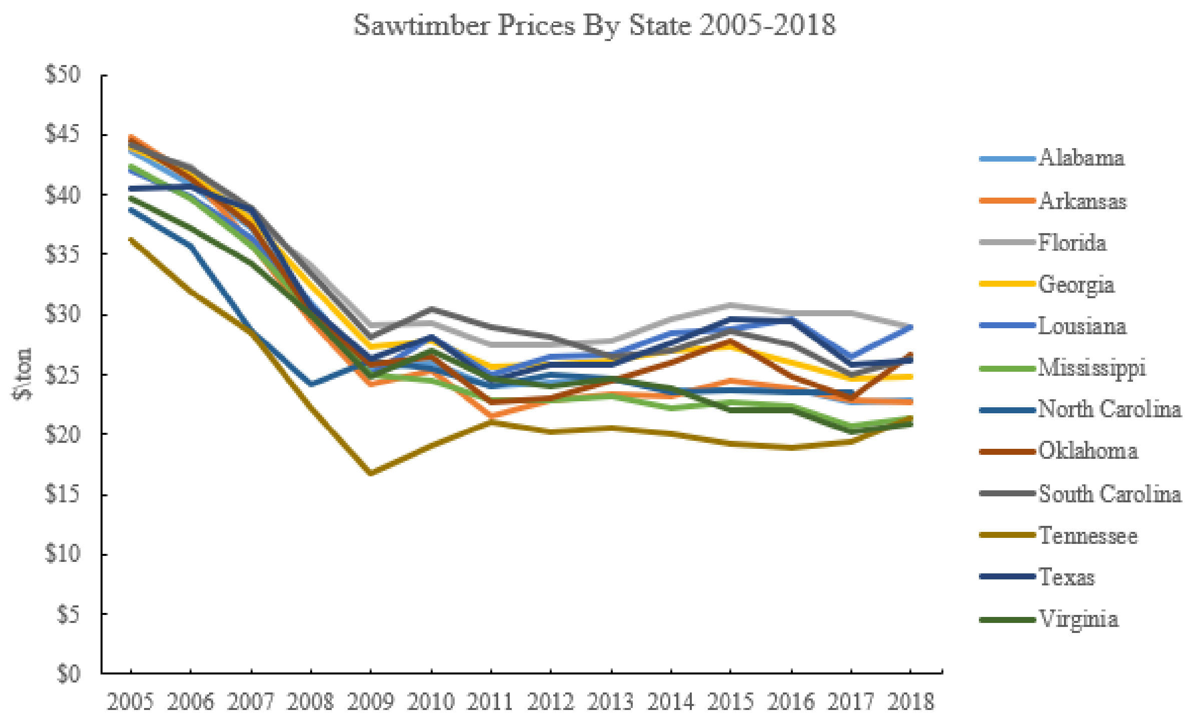


Figure 2.4: Sawtimber Prices 2005-2018 Source:Forest2Market (2016)

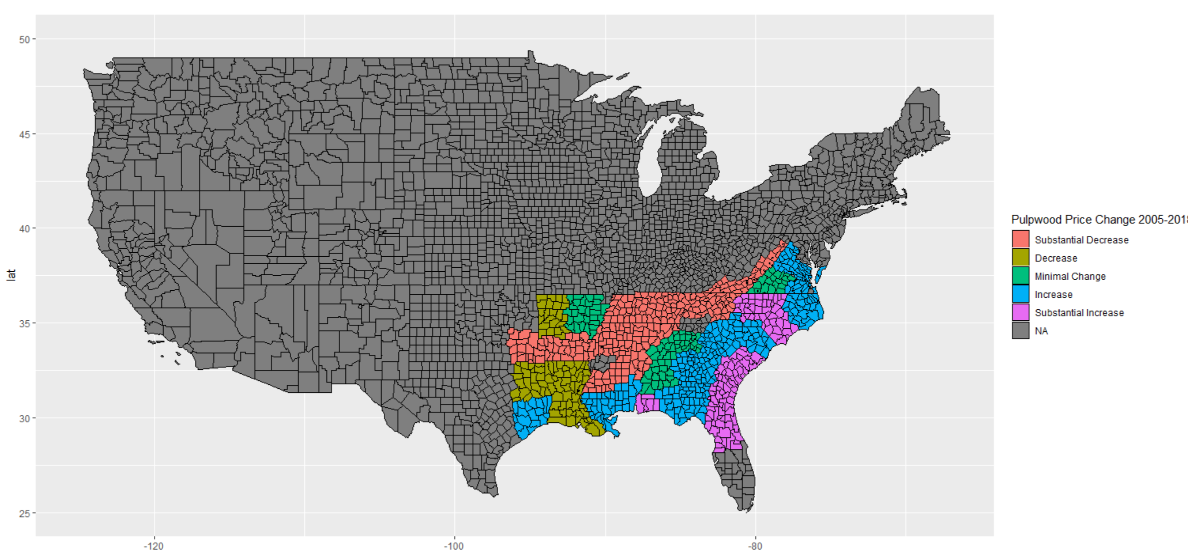


Figure 2.5: Pulpwood Price Changes between 2005-2018

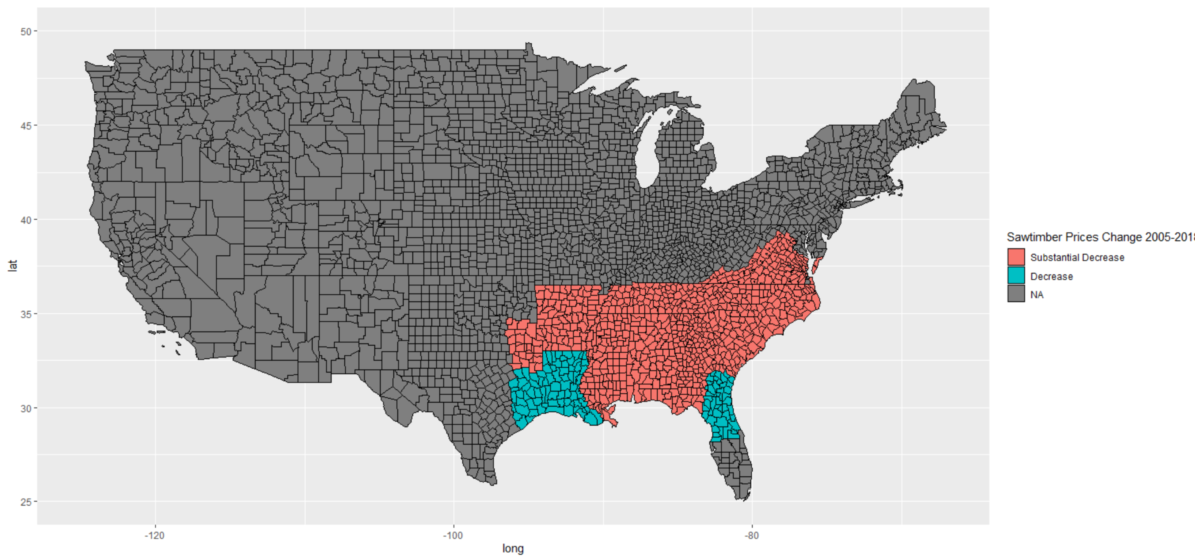


Figure 2.6: Sawtimber Price Changes between 2005-2018

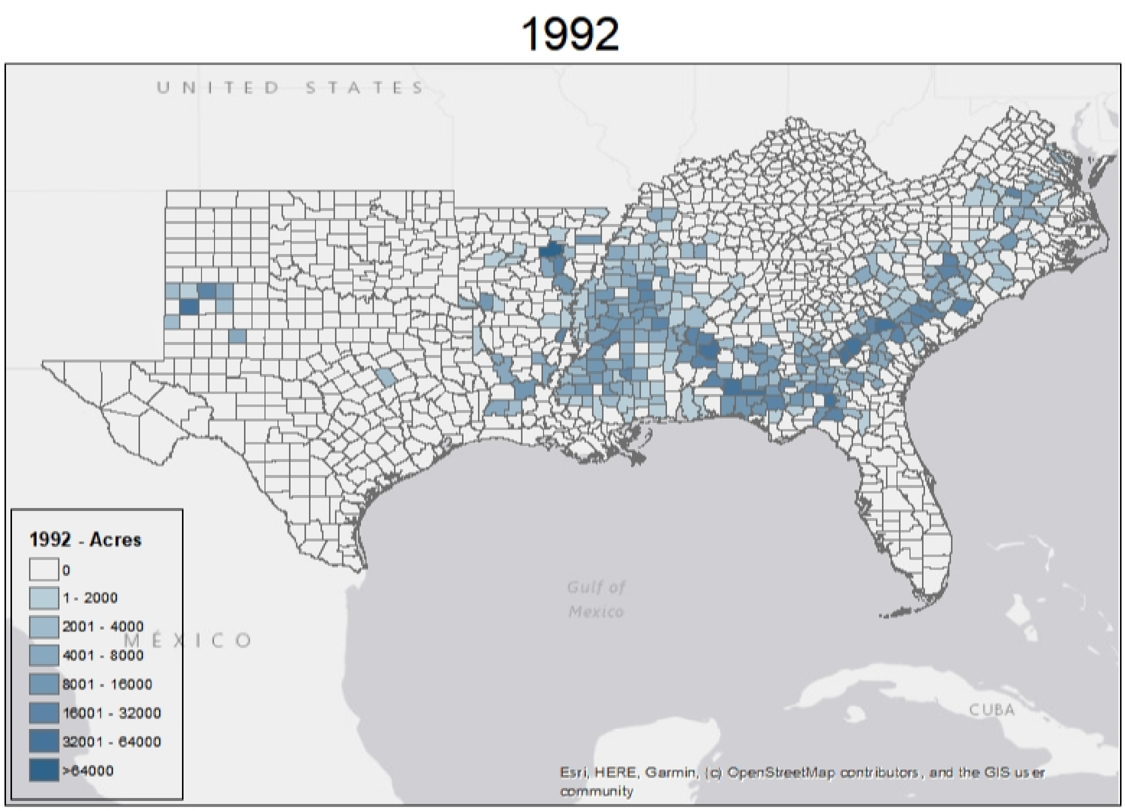


Figure 2.7: NRI CRP Tree Planting in 1992

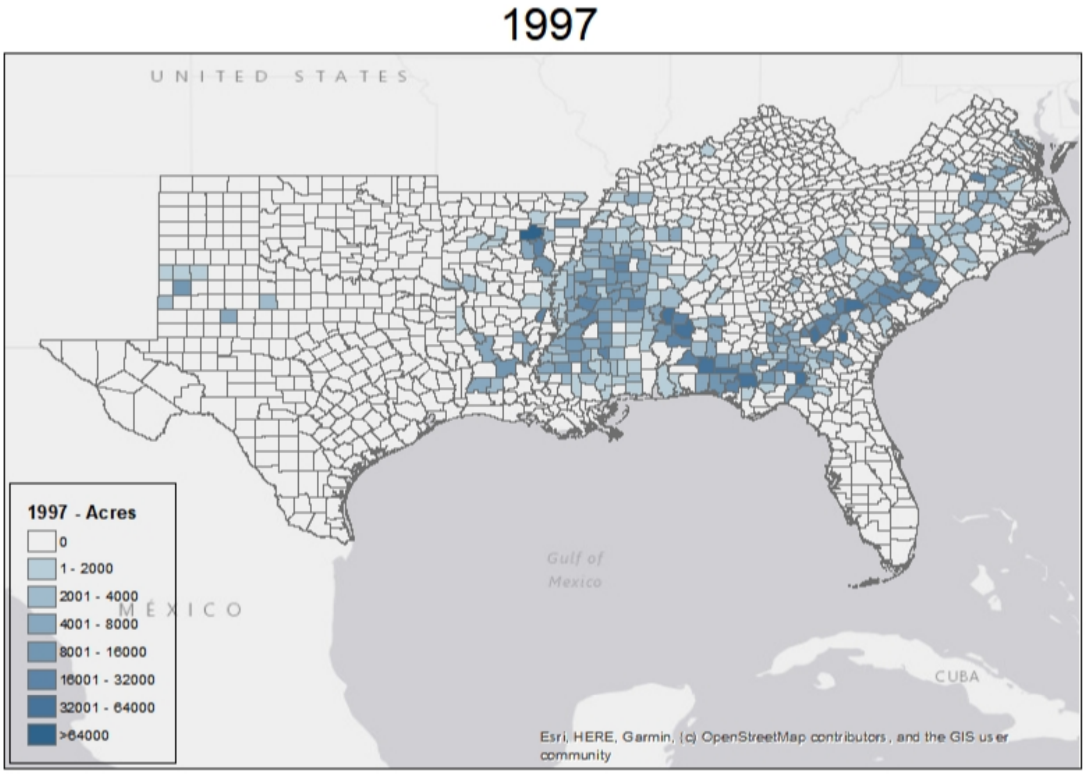


Figure 2.8: NRI CRP Tree Planting in 1997

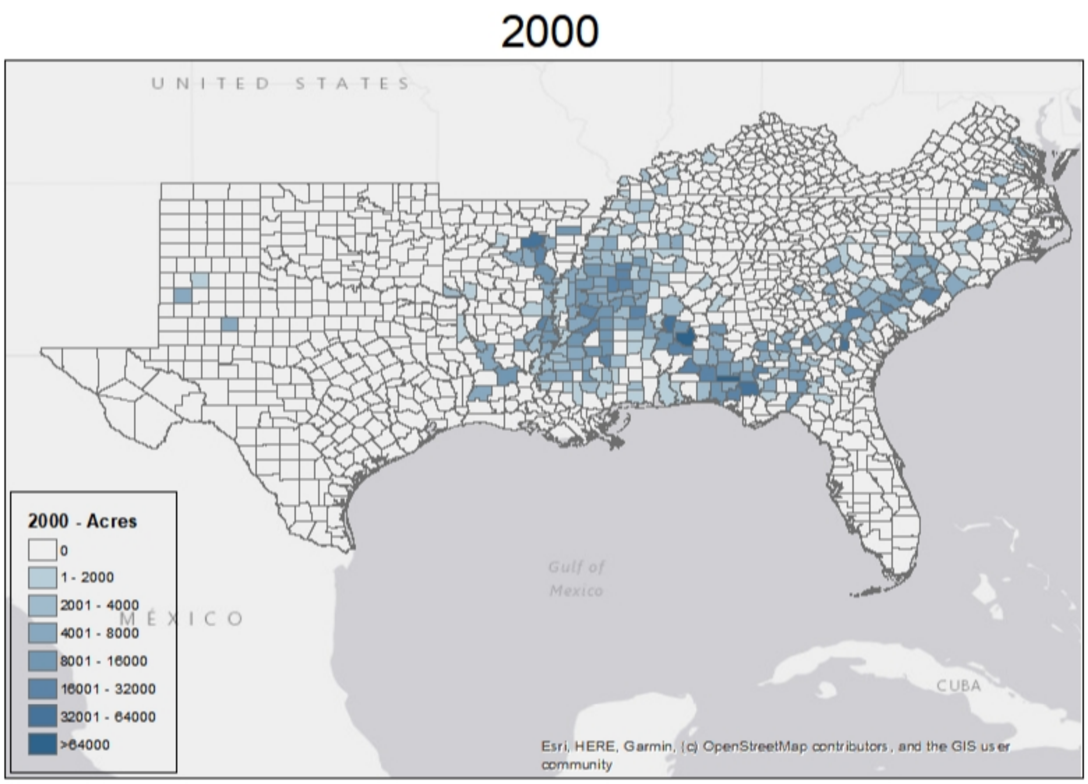


Figure 2.9: NRI CRP Tree Planting in 2000

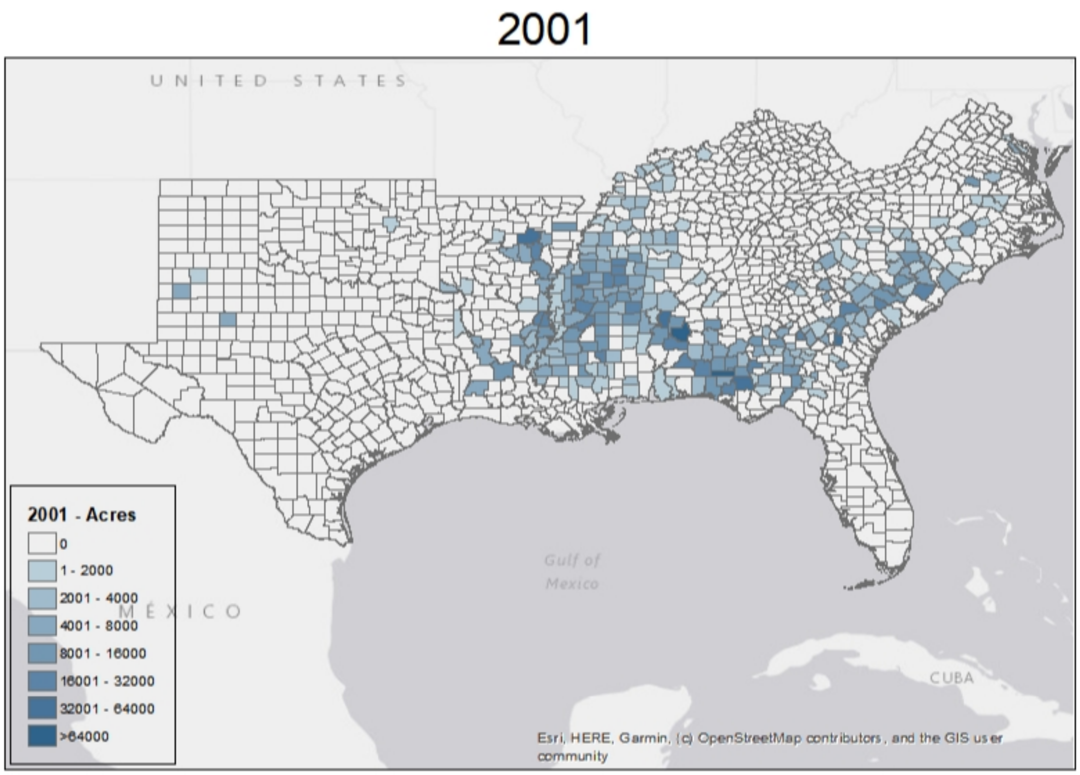


Figure 2.10: NRI CRP Tree Planting in 2001

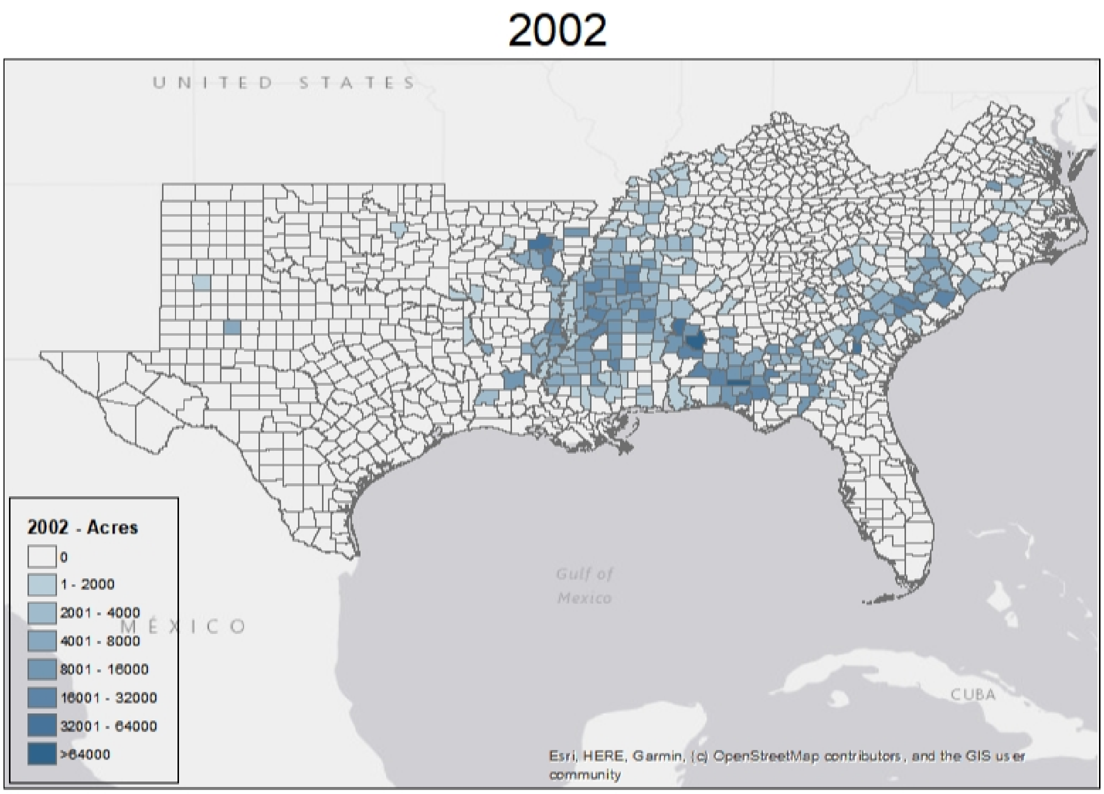


Figure 2.11: NRI CRP Tree Planting in 2002

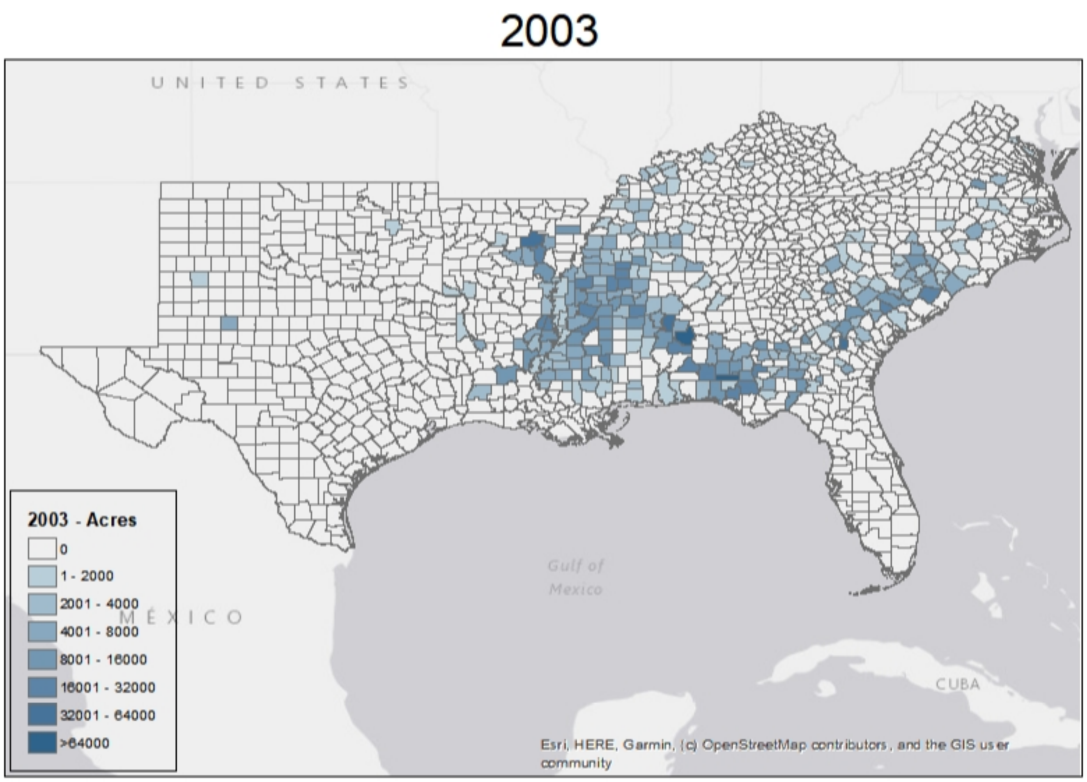


Figure 2.12: NRI CRP Tree Planting in 2003

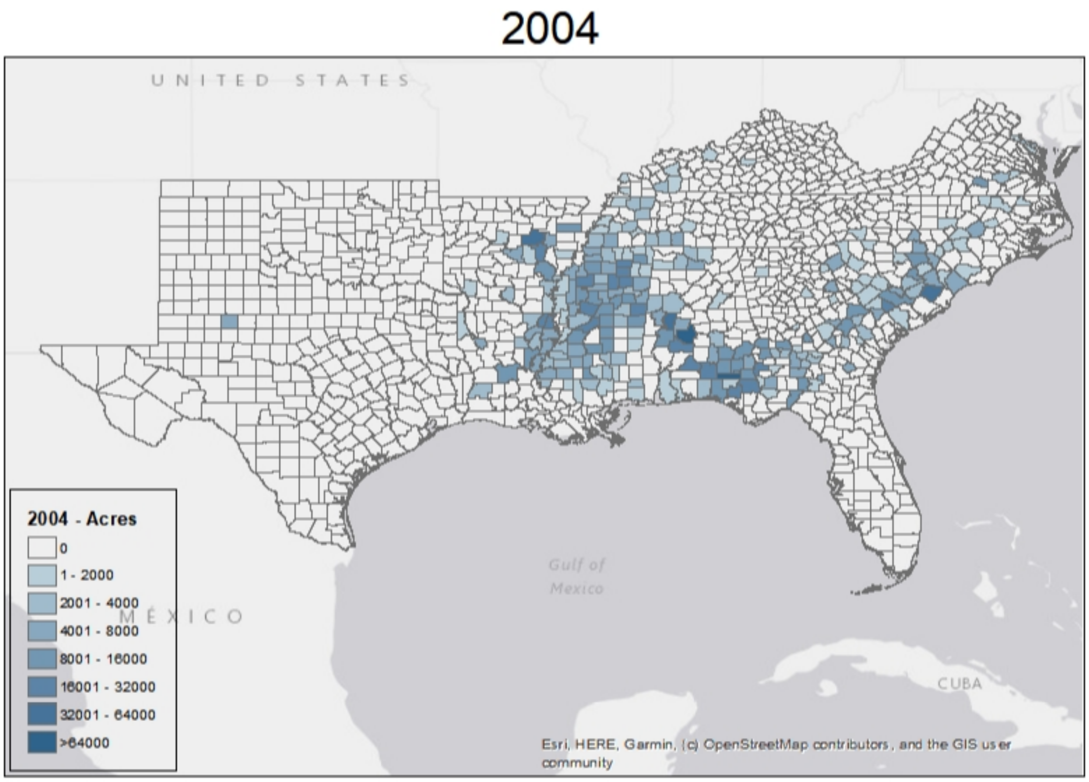


Figure 2.13: NRI CRP Tree Planting in 2004

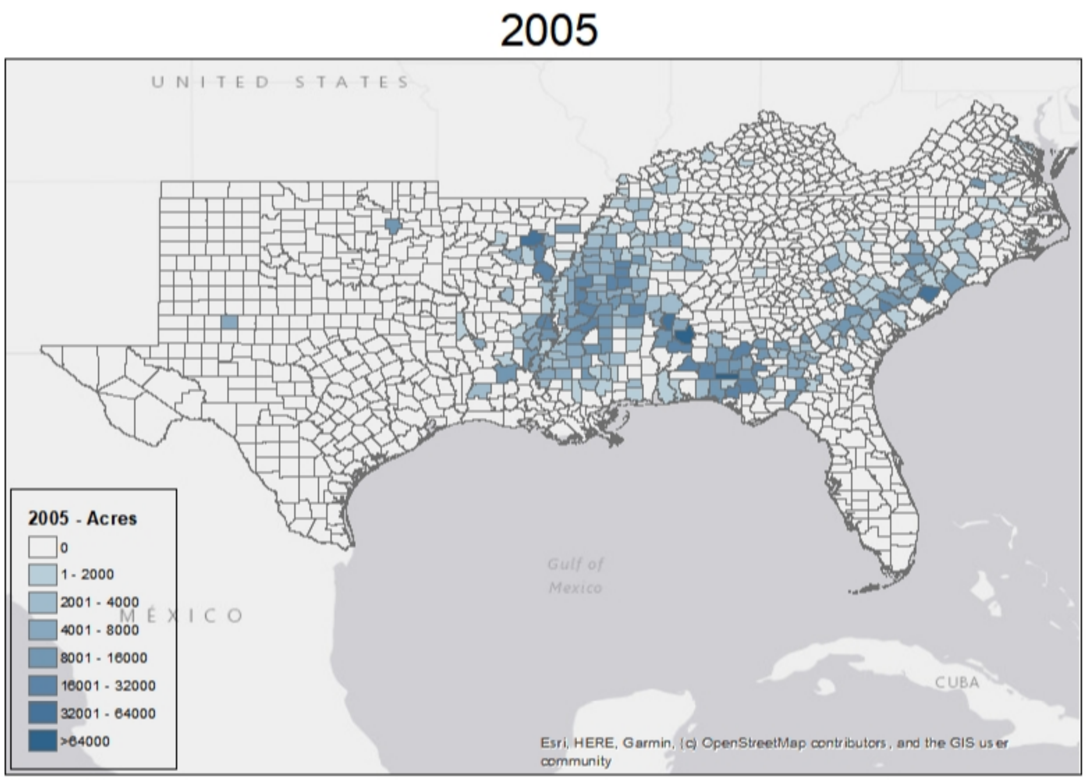


Figure 2.14: NRI CRP Tree Planting in 2005

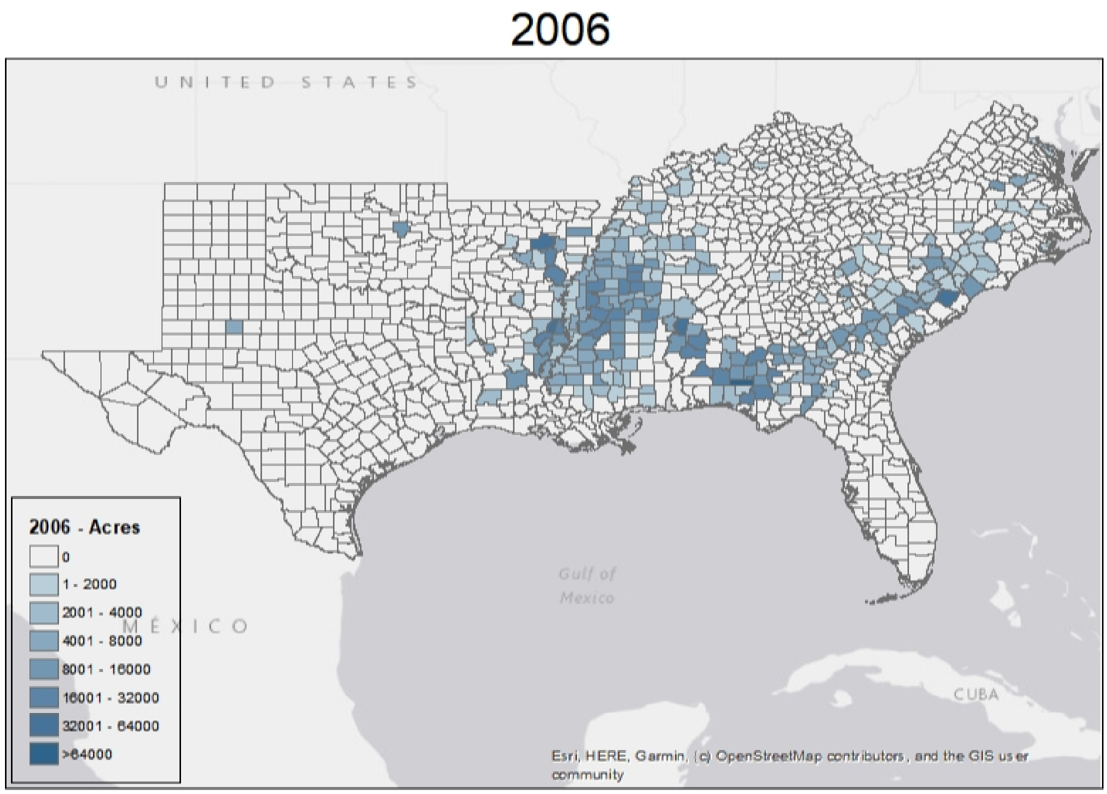


Figure 2.15: NRI CRP Tree Planting in 2006

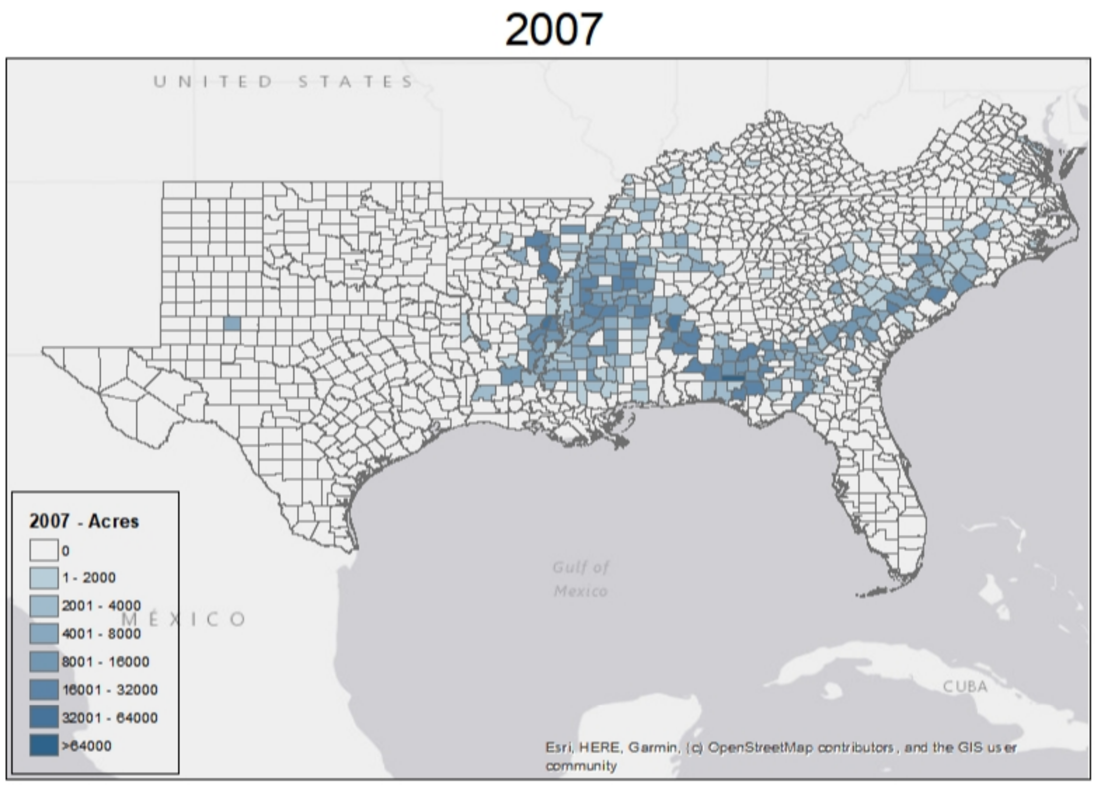


Figure 2.16: NRI CRP Tree Planting in 2007

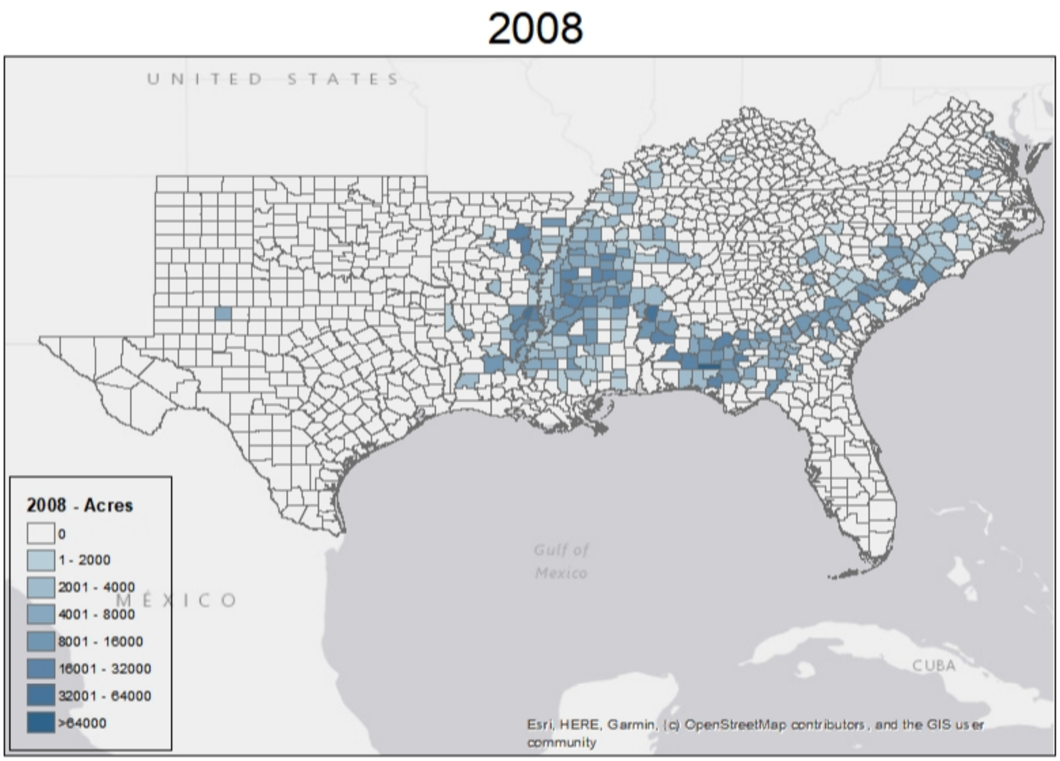


Figure 2.17: NRI CRP Tree Planting in 2008

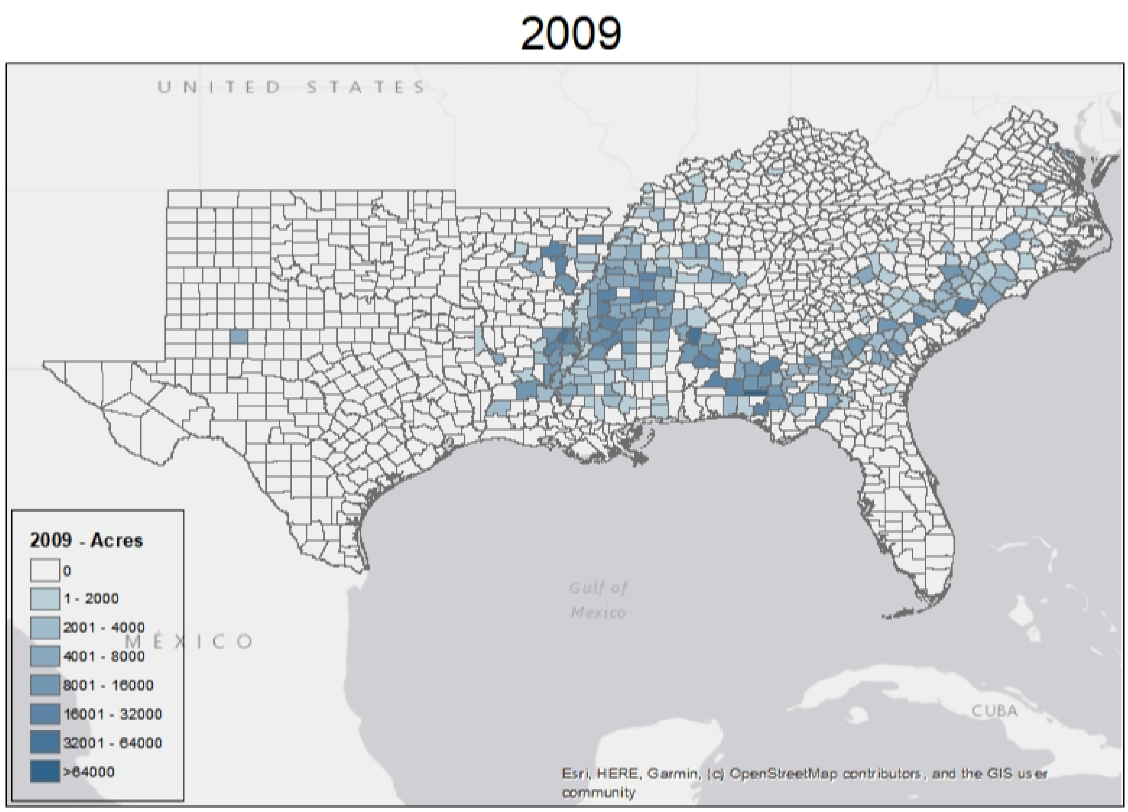


Figure 2.18: NRI CRP Tree Planting in 2009

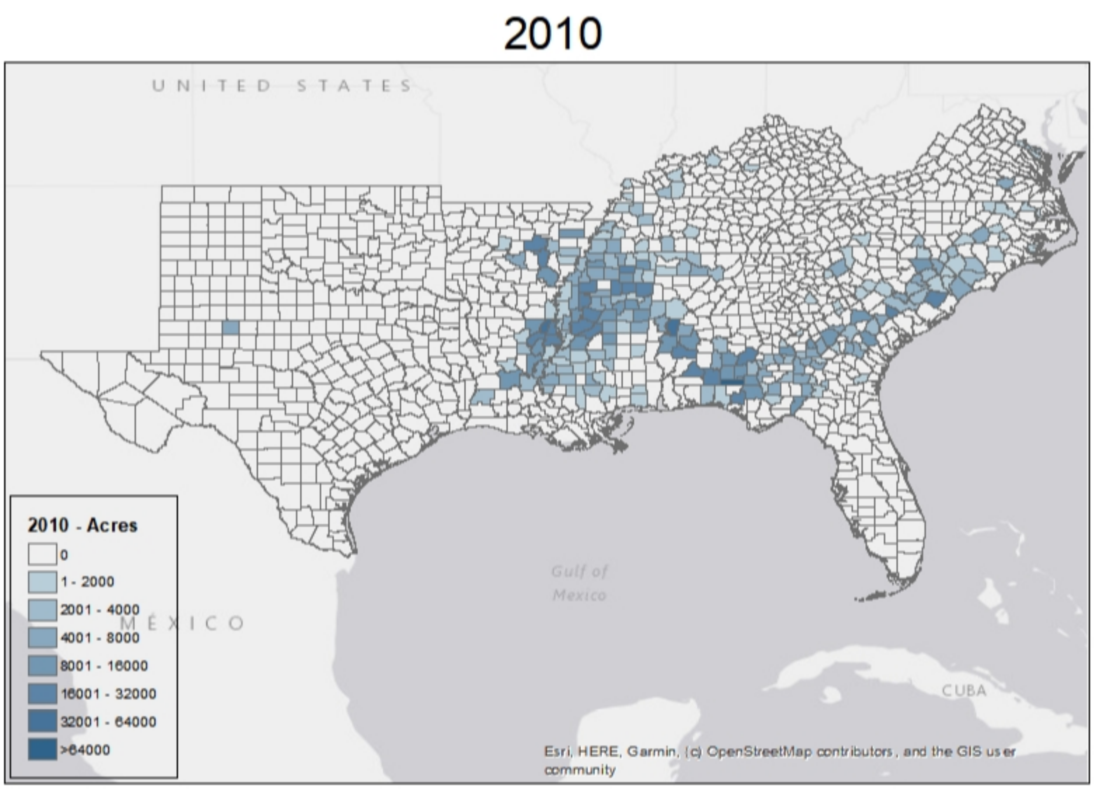


Figure 2.19: NRI CRP Tree Planting in 2010

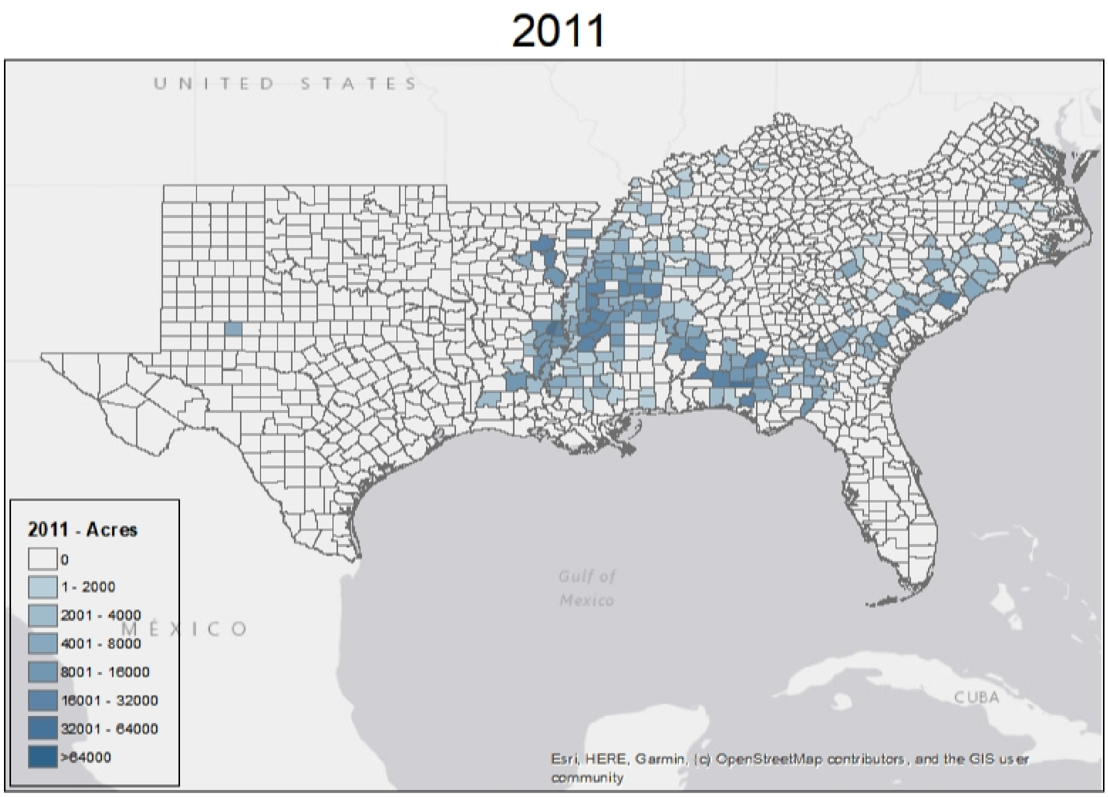


Figure 2.20: NRI CRP Tree Planting in 2011

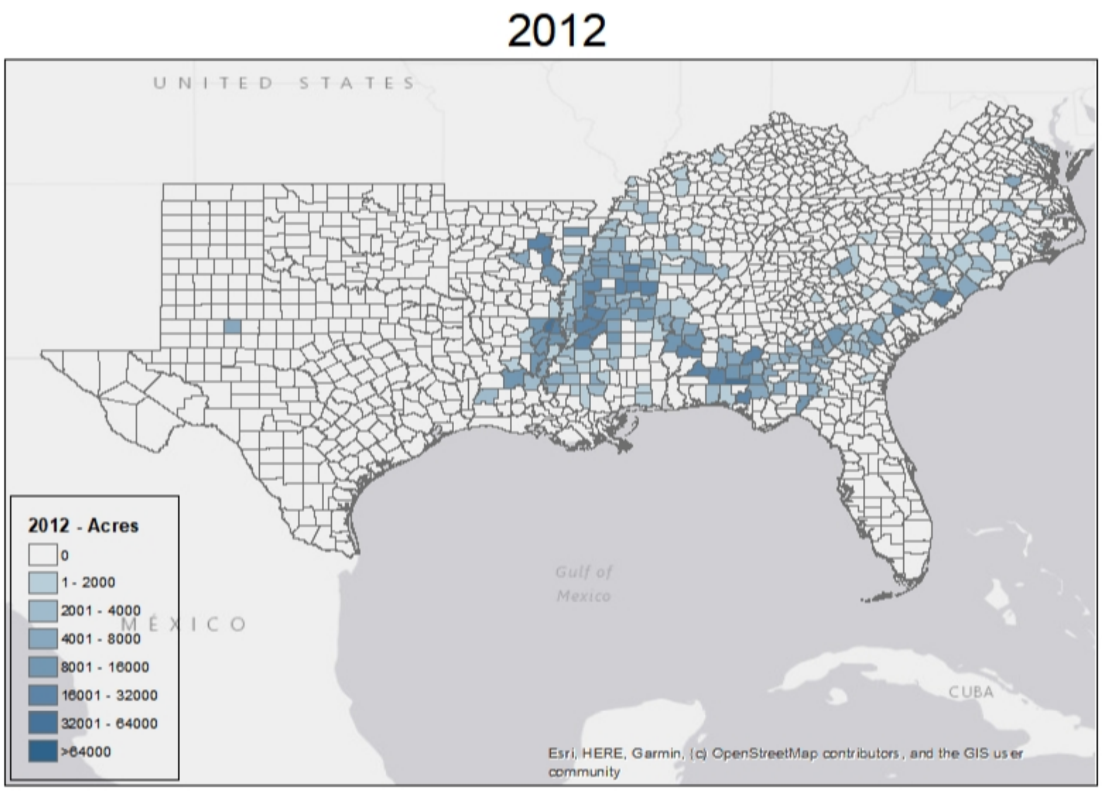


Figure 2.21: NRI CRP Tree Planting in 2012

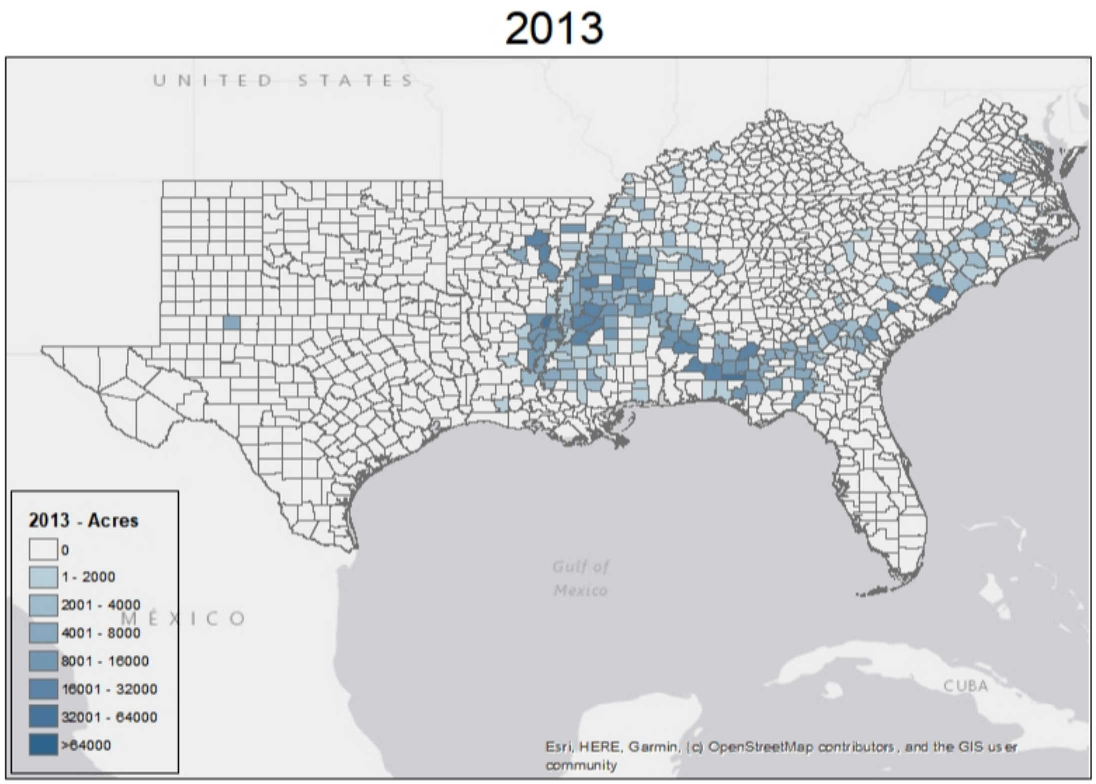


Figure 2.22: NRI CRP Tree Planting in 2013

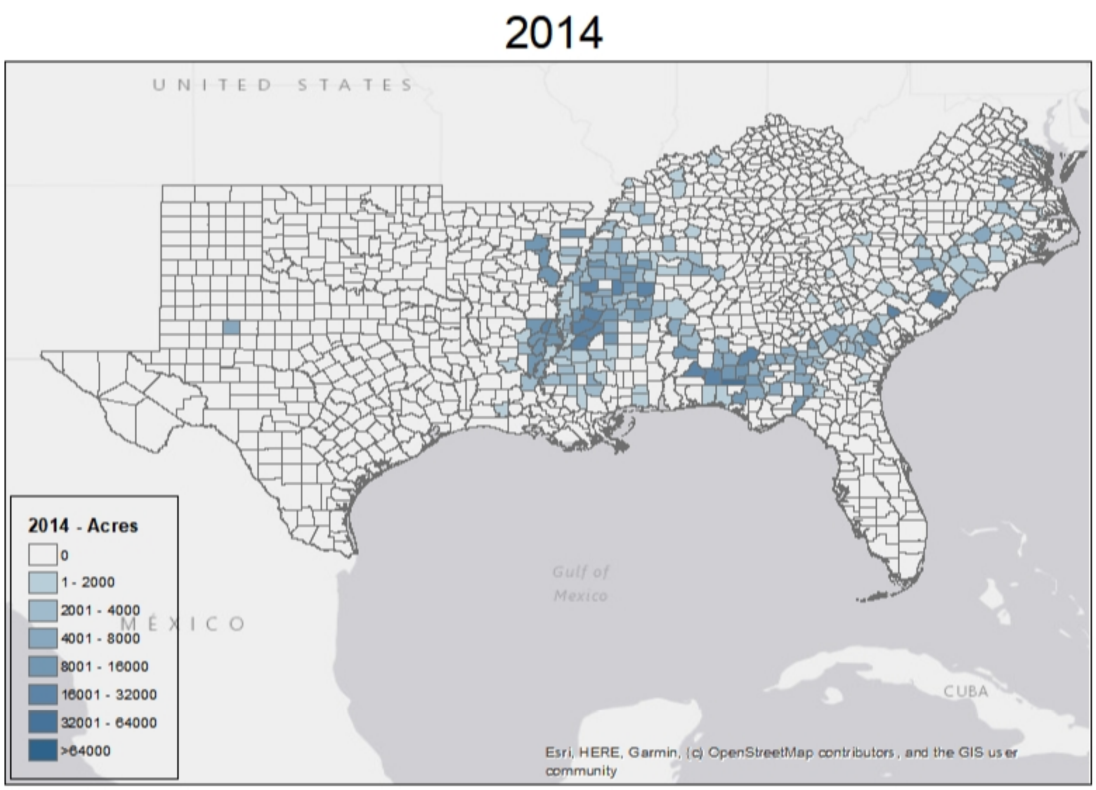


Figure 2.23: NRI CRP Tree Planting in 2014

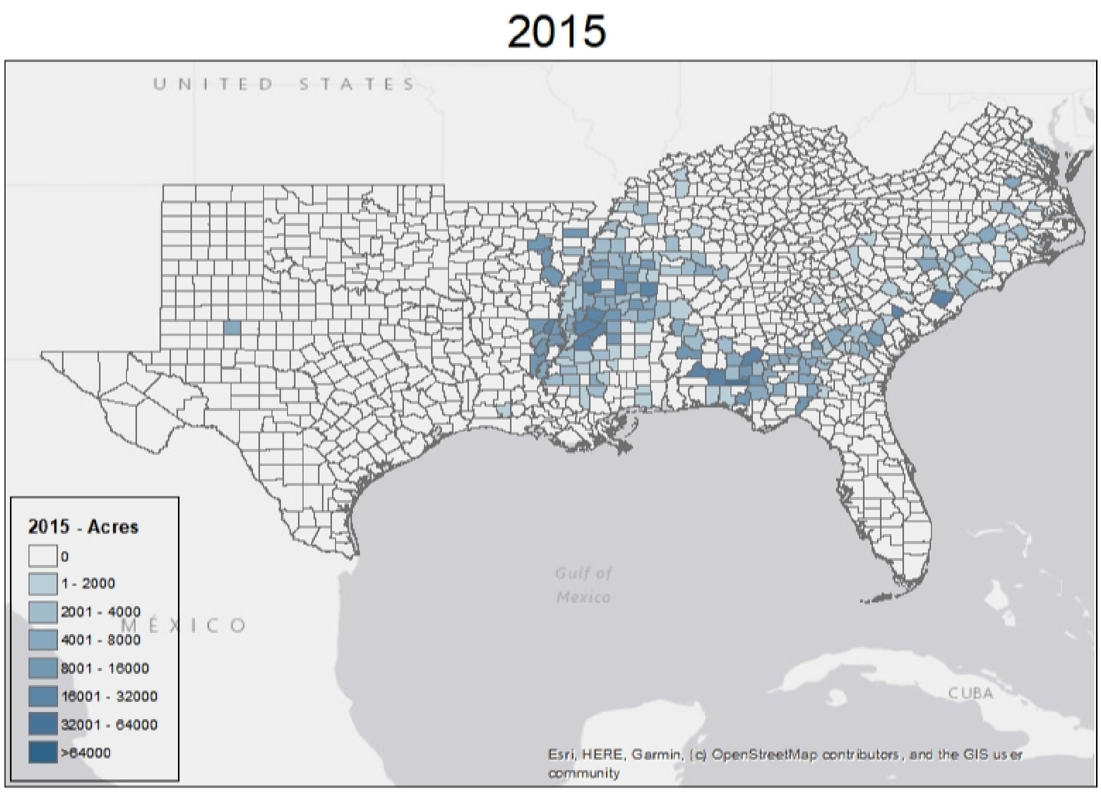


Figure 2.24: NRI CRP Tree Planting in 2015

CHAPTER

3

THE IMPACTS OF TRADE MEASURES TO ADDRESS ILLEGAL LOGGING ON THE GLOBAL FOREST PRODUCTS MARKET

3.1 Introduction

The exploitation of forest resources through illegal logging has been a growing concern and significant challenge on the global agenda. In recent years, illegal logging has gained considerable attention because activities associated with illegal logging are symptoms of environmental abuses that have international implications. Seneca Creek Associates (2004) defines major environmental abuses related to illegal logging as "(1) harvesting without authority in designated parks or forest reserves, (2) harvesting without authorization or in excess of concession permit limits, (3) failing to report harvesting activity to avoid royalty payments or taxes, and (4) violating international trading rules and agreements". These unfavorable activities related to illegal logging and trade have become more prevalent and they drive numerous problems that cause economic losses, environmental destruction, and social issues.

The illegal logging has a high economic cost because it causes loss of revenue that could have been earned by the legal forest sector could have contributed to the economic livelihood of local communities. Even though it is difficult to obtain a direct estimate of economic losses that illegal logging causes, those losses are large; illegal logging accounts for one of largest environmental crimes by value. Interpol (2019) estimates that $15–150 billion flows into illegal activity channels and results in economic losses in the legal forestry industry. The World Bank indicates that illegal logging causes economic losses of $10–15 billion, which includes losses in government revenues of $5 billion per year (Pereira et al., 2012). The entrance of illegal wood products into both global and domestic forest product supply chains puts pressure on timber prices and market shares, endangering the future sustainability of the forest industry and distorting timber markets. Besides economic losses, environmental ramifications of illegal logging include destruction of biodiversity and the ecosystem, greenhouse gas emissions, deforestation, and degradation of water quality (Moiseyev et al., 2010). These are the significant factors that could lead to global climate change and cause animal and plant species to become extinct.

Characteristics of rural communities and government structure also play a prominent role in forest governance and management. Social and government impacts of illegal logging coincide because illegal logging driven by profits is often facilitated by government corruption and institutional weakness, inoperable rule of law, money laundering, organized crimes, social instability, and civil wars (Reboredo, 2013).As a result, illegal logging also puts pressure on the legitimacy of the forest industry and threatens its sustainable practices. Social impacts of illegal logging particularly affect forest losses in countries where the rule of law is absent. For instance, lower middle-income and low-income countries, where 25 percent of forest resources are located, account for the highest forest losses (Keenan et al., 2015), making illegal logging and trade a more pervasive and entrenched concern because of weak law enforcement and institutions in these countries.

The factors that contribute to illegal logging are complicated because illegal logging is often an indication of more complex social issues mentioned above; therefore, concerns about illegal logging have prompted a series of policy instruments that take different forms. For instance, the Convention on Trade in Endangered Species of Wild Fauna and Flora (CITES) was established in 1973 to facilitate legal and sustainable trade by limiting trade in certain species. (Seneca Creek Associates, 2004). However, only a few timber species are regulated under CITES; it does not cover a wide variety of commercial wood. [1]. CITES requires only an export permit, stating that the legality of timber has been verified; no further due diligence is required.The holes in the implementation process of CITES has persuaded policy makers that other policy measures are needed. Additional regulatory measures were introduced with the primary focus on improving and promoting the sustainable use of forest resources. Such policy tools can work as remedies of symptoms of illegal logging and they can promote sustainable and legal forest governance.

In particular, to promote sustainable use and management of timber resources and tackle the issues related to illegal exploitation of timber resources, voluntary certification schemes—the Forest Stewardship Council (FSC) and the Program for the Endorsement of Forest Certification (PEFC)—have been implemented for ensuring timber legality in the international trade of forest products (Brack, 2013). The primary purposes of these standards, as voluntary and market-based approaches, are to serve as an incentive and encourage sustainable forest use and management practices in the marketplace and to provide information to the countries regarding the due diligence process.

Indeed, forest certification programs as a policy instrument have been an effective tool to contribute to sustainable forest management by promoting productivity (Rametsteiner and Simula, 2003), biodiversity enhancement (Johansson and Lidestav, 2011), conservation (Gullison, 2003), and air pollution reduction (Miteva et al., 2015). However, in the absence of uniform forest certification standards followed by all certifying authorities, these standards potentially may cause laxness of forest certification standards (Cerutti et al., 2011), resulting in limited effectiveness and might not go very far in addressing illegal logging issue. Also, certification is less likely to be effective in countries where forest governance has limited capacity and lacks incentives to promote sustainable forest resource management. The effectiveness of international certification policies remains unclear. To improve forest governance, these efforts should be a part of a broader and cohesive set of strategies as they are in illegal trade measures (Brack, 2013). Although forest certification practices help with requirements of illegal trade measures, they cannot be considered as proof of timber legality. In fact, main suppliers in major Lacey Act penalties [2] were FSC-certified so clearly certifications could

[1]Current listings of tree species can be found at https://www.fws.gov/international/plants/current-cites-listings-of-tree-species.html

[2]Johnson and Gehl (2019) suggest three high-profile Lacey Act penalty cases: Gibson Guitars, Lumber Liquidators,

not prevent illegal wood from being placed in trade flows (Johnson and Gehl, 2019). Certification systems are not legally binding; hence they might be ineffective as a policy tool for tackling illegal logging.

In addition to forest certification efforts, countries have enacted strict demand-side trade regulatory measures in pursuit of reducing illegal logging on the global supply chain. These measures prohibit the trade of illegal timber in their market and promote supply-side improvements in forest governance by forming bilateral agreements with wood-exporting countries. Addressing illegal logging has been a collaborative effort of importing countries such as the United States, the European Union (EU), Australia, and Japan. Such importing countries collectively have taken concrete steps toward curbing illegal logging in the global forest products market by enacting various trade measures. Although the implementation of these trade measures differs, they share the same goal: reduce illegal logging and increase forest governance in timber-exporting countries. Key trade measures include the Australian Illegal Logging Prohibition Act (ILPA), the European Union Timber Regulation (EUTR) within the framework of the EU Forest Law Enforcement Governance and Trade (FLEGT) Action Plan, the Japanese Clean Wood Act (JCAW), and the Lacey Amended Act (LAA) in the United States.

These attempts taken by countries impose stringent requirements to prohibit trade of illegal wood products and require companies in wood-producing countries to execute due diligence processes to manage and mitigate risks. The federal Lacey Act of the United States,as amended in 2008(herein,"LAA") to ban the importation and interstate transport, purchase, sale, or acquisition of any illegal plant product, including wood fiber, and to require a declaration of the plant species and its provenance)has been a pioneer in setting an example of how to execute due diligence processes on imported wood and is followed by other countries(U.S Fish& Wildlife Services,n.d.).Additional efforts have been carried out by countries to strengthen due diligence processes. For this reason, countries also formed bilateral trade agreements with wood-producing countries to support their efforts in legal assurance systems and forest governance. As a centerpiece of its strategy, the European Union (EU), for instance, has established bilateral voluntary partnership agreements (VPAs) to support timber legality enforcement in timber-exporting countries, many of which lack capacity to control trade flows. The US and Australia have taken similar approaches and work closely other governments

and Young Living Essential Oil. For details of the cases, see (Johnson and Gehl, 2019).

to strengthen their forest governance efforts and tackle illegal logging. For instance, the US-Peru Free Trade Agreements (PFTA) includes an environmental chapter that addresses the environmental and economic implications of illegal logging and ensures the protection of conservation and biodiversity.

Previous studies have investigated the effects of policy measures on global forest products, providing evidence on changes in prices and import quantities (Bosello et al., 2013; Li et al., 2008; Moiseyev et al., 2010; Prestemon, 2015) and on trade diversion (Masiero et al., 2015). For instance, Prestemon (2015) found that implementation of the LAA resulted in significant increases in hardwood lumber and plywood prices along with decreases in import quantities of hardwood lumber and plywood. Introducing trade measures for controlling international trade in illegal wood activities may affect trade patterns, causing trade diversion (Lawson and MacFaul, 2010); for example, Masiero et al. (2015) provided evidence on trade diversion, indicating that imports of tropical wood diminished in the US, the EU, and Australia while they increased in emerging economies such as China, India, and Vietnam.

Although various aspects of trade measure have been addressed by the previous literature with special emphasis on either single trade measures and/or countries, no empirical study, to my knowledge, has examined separately the effects of trade measures by focusing on the same specific product groups for each importing country. Hence, it would be important to compare dissimilarity among these policies because changes in trade flows for specific product groups could be attributed to implementation differences in legislation in importing countries. The important contribution of this study is to quantify the effects of illegal logging trade measures on the global forest market by identifying key differences in trade measures taken by countries to prevent illegal logging.Using a gravity model,I separately examine the impacts of trade measures on import values in each product group by focusing on four country groups: Australia, the EU, Japan, and the US.Because illegal logging continue to be a burden, assessing the effectiveness of trade regulations and laws that target to the banning illegal importation of wood would be important to shape long-term solutions.

The remainder of this chapter proceeds as follows. Section 3.2 provides a brief background on trade measures implemented by countries to prevent illegal logging. Section 3.4 describes the data used for this study, and section 3.3 outlines the empirical strategy. Section 3.5 presents the results of the empirical strategy. Section 3.6 discusses the robustness check. Finally, section 3.7 concludes.

3.2 Trade Measures on Illegal Fiber Sourcing

Illegal logging and illegal wood fiber sourcing activities threaten the sustainability of biodiversity, result in losses in government revenues, undermine the rule of law by encouraging corruption and social instability, and destroy the legality of forest industry. To address the negative aspects of illegal logging and illegal wood fiber sourcing, countries have designed and implemented numerous policy instruments that aimed to deter the flow of illegal logging and illegal wood fiber sourcing into their trade and to increase forest law enforcement in wood-exporting countries. In this study, I consider demand-side major trade measures that are enforced by countries for curbing illegal fiber sourcing in global forest products markets: the Australian Illegal Logging Prohibition Act (ILPA), the EU Timber Regulation (EUTR), the Japanese Clean Wood Act (JCWA) and the US Lacey Amended Act (LAA). Of these trade measures, only the JCWA is a voluntary policy framework while the other three pieces of legislation are mandatory in nature. Although these policies differ in practices, they all seek to tackle illegally sourced wood fiber activities and endeavor to increase forest governance in wood-exporting countries.

Additional measures have also been taken by other countries to address the scale of illegal fiber sourcing issues; for example, South Korea has recently amended the Act on the Sustainable Use of Timbers in 2017. Although there is high expectation of the potential of these trade measures to address illegal logging activities, it is difficult to estimate the extent of effectiveness of these policies on tackling illegal logging because estimating the amount illegal wood is a challenging task. One can compare the impacts of these policies given structural differences in the implementation process.

3.2.1 Australian Illegal Prohibition Act

Australia's Illegal Logging Prohibition Act (ILPA) was enacted in 2012 to prohibit the trading of illegal timber and timber products as well as the processing of domestic raw logs that have been illegally sourced. Both importers and domestic processors are obliged to exercise due diligence requirements. Regulated products include wood, pulp, paper, furniture, and raw logs.[3] The ILPA places different due diligence obligations on importers and domestic processors.[4] Timber producers

[3] The whole list of HTS codes for regulated products can be found at https://www.agriculture.gov.au/forestry/policies/illegal-logging/importers/regulated-timber-products

[4] More detail on due diligence obligations for importers and processors can be obtained from https://www.legislation.gov.au/Details/C2012A00166

and domestic processors need to comply with due diligence processes by (1) gathering information for the purposes of evaluating risk, (2) evaluating and defining risk, (3) mitigating risk, and (4) keeping a record of the processes taken (Australian Government, 2018). In addition to due diligence obligations, the ILPA also imposes a penalty system: if parties breach the act, they are liable to civil penalty, including five-year imprisonment and monetary civil penalties.

Australia also implemented bilateral cooperation agreements to support the engagement of governments in the Asia-Pacific regions in order to strengthen timber legality standards.[5] These arrangements provide technical assistance, offer guidelines on recognizing the need to address illegal logging and promote sustainable forest management practices, and identify the areas that need further cooperation on forestry matters (Department of Agriculture, Water and the Environment, nd).

It is also important to note import trends by product groups and key trading partners of Australia after the implementation of the ILPA.Fig. 3.1 displays import trends by various product groups during 1997–2017. Among product categories, the largest share of import values consists of coniferous sawnwood and plywood followed by non-coniferous sawnwood after the enactment of the ILPA while largest decrease has been occurred in non-coniferous sawnwood imports, accounting for approximately a 47.7 percent decline after the ILPA. Consistent with trends in the EU and the US as seen Fig. 3.2 and Fig. 3.3 , the import values of newsprint have been declining since the 2010s. Compared with other product groups, the value of industrial roundwood imports has been relatively flat. Panels A and B of Fig. 3.7 show the primary trading partners of Australia for coniferous and non-coniferous sawnwood. New Zealand is the largest trading partner of coniferous sawnwood ($ 118 million) followed by Canada, the US, and other EU countries as key trading partners of Australia for coniferous sawnwood. For non-coniferous sawnwood, Australia tends to import more from Asian countries. Key trading partners for coniferous and non-coniferous plywood are shown in Panels A and B of Fig. 3.8, which include a wide range of regions.

[5] These countries include Papua New Guinea, Indonesia, Malaysia, the Republic of Korea, China, and New Zealand.

3.2.2 The European Timber Regulation

The EU's policy of tackling illegal logging activities dates back to 2003. The EU Action Plan on Forest Law Enforcement (FLEGT) was enacted in 2003 to facilitate both demand-side and supply-side trade measures to curb illegal logging activities. In particular, it targeted Central Africa, Russia, Tropical South America, and Southeast Asia, which account for nearly 60% of the world's forest and supply a large proportion of internationally traded timber (European Comission, nd a). As a key component of the FLEGT, bilateral agreements,called Voluntary Partnership Agreements (VPAs), have been implemented on timber-producing countries to support forest law enforcement and ensure the flow of legal timber in the EU market. Currently, six countries have ratified and signed VPAs—Ghana, the Republic of Congo, Cameroon, Indonesia, the Central African Republic, Liberia, and Vietnam. Negotiations with nine countries are still in process (European Commission, nd b). Implementation of VPAs has been a core element in addressing illegal logging and associated trade in the EU.

As an integral part of the FLEGT Action Plan process, the EU Timber Regulation (EUTR), which was first adopted in 2010, came into effect in March 2013. The EUTR prohibits placing of illegally harvested timber on the EU market and requires EU operators to exercise due diligence to mitigate the risks of placing illegal timber in EU trade flows. Although the due diligence provisions in the EUTR context are similar to the idea of due care in the LAA, the implementation processes are more binding and the steps in the due diligence processes are more specific. The due diligence requirement has the following three components (European Commission, nd c):

- Information: The operator must have access to information describing the timber and timber products, country of harvest, species, quantity, details about the supplier, and information about compliance with national legislation.
- Risk assessment: The operator should assess the risk of illegal timber in his supply chain, based on the information identified above and considering criteria set out in the regulation.
- Risk mitigation: When the assessment shows that there is a risk of illegal timber in the supply chain, that risk can be mitigated by requiring additional information and verification from the supplier.

The EUTR applies to a wide range of wood products such as solid wood, furniture, plywood, pulp and paper.[6] Futhermore, timber products that comply with requirements of FLEGT and CITES are also considered as legal under the EUTR.

Import trends are presented in Fig. 3.2 and Fig. 3.7 and Fig. 3.8 display primary trading partners of the EU. [7] As seen in Fig. 3.2, coniferous sawnwood and plywood followed by non-coniferous sawnwood account for a large share of import values during the period 2000–2017. The economic crisis of 2007–2008 severely impacted hard wood-based industries such as construction. The values of sawnwood and plywood import values were decreased between 2007 and 2010. The enactment of the EUTR has introduced more strict regulations in trade, reflecting an 8 percent decrease in non-coniferous sawnwood imports. There is a sharp decrease in import values of newsprint. Perhaps an increase in use of online platforms has contributed to that trend. Fig. 3.7 panels A and B show the top trading partners of coniferous and non-coniferous sawnwood. Fig. 3.8 panels A and B display the key trading partners of coniferous and non-coniferous plywood in the EU. European countries such as Sweden, Finland, and Latvia constitute primary trading partners of coniferous sawnwood, whereas key trading partners of non-coniferous sawnwood include African and Asian countries, more precisely countries that either ratified VPAs or are in the process of negotiation. For coniferous and non-coniferous plywood imports, the EU tends to import from a wider range of countries.

As stated earlier, the enactment of VPAs has been a key element of the EU's efforts to address illegal timber trade. Although the effects of both VPAs and the EUTR have been studied by the previous literature, there is only a handful of research studies that examine the implications of both components and the existing research does not use empirical econometric analysis. It is still worth mentioning them here because previous research has focused on different aspects of the EUTR. For instance, the implementation of VPAs accounted for reductions in wood harvest and production and for price increases in industrial roundwood in the VPA region (Moiseyev et al., 2010). With enactment of the EUTR, a moderate decline on illegal logging was reported (Bosello et al., 2013; Gan et al., 2013). However, the joint implementation of both the LAA and the VPAs could lead to increased reduction rates of illegal logging (Gan et al., 2013). Moreover, recent study by (Brusselaers and Buysse, 2021) found that the implementation of the EUTR does not leverage legal

[6]The list of timber and timber products covered can be found at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32010R0995

[7]Import trends and key trading partners presented in these figures are based on the selected EU countries in this study;hence,they do not reflect overall trends and trading partners of the EU countries.

wood production and consumption at global level while finding that tropical wood production showed a modest increase.

3.2.3 The Japanese Clean Wood Act

The Japanese Clean Wood Act (JCWA), mandated in 2016, is the first legislation to encourage domestic operators to use and distribute legally harvested wood and wood products. The scope of regulatory framework is different from previously mentioned policies because of its voluntary nature, unlike the policies in Australia, the EU, and the US. Practically, the operators who register must undertake due diligence. The JCWA applies only to domestic operators, and foreign suppliers are not subject to it. Its approach is based on registration, rather than being a compulsory piece of legislation, as compared with previous trade regulations discussed above. The only penalty for trading illegal timber and timber products is revocation of registration. The JWCA is more flexible in its application, but its provisions may be extended in time.

Fig. 3.3 shows the import trends by countries. Import values for coniferous sawnwood and plywood have been on the decline since 2014. Panels A and B in Fig. 3.9 display primary trading partners of coniferous and non-coniferous sawnwood flows. While Canada, the US, the Russian Federation, and the EU countries have been the key partners of Japan for coniferous sawnwood, primary partners of non-coniferous sawnwood have been more concentrated in different parts of the world. Fig. 3.10 (Panels A and B) displays the top trading partners of coniferous and non-coniferous plywood import. The largest partners of coniferous plywood are Canada, New Zealand, and Philippines. Significant partners for non-coniferous plywood include mostly Asian countries.

3.2.4 The Lacey Act of Amendments of 2008

The Lacey Act, first enacted in 1900, is a conservation law that prohibits illegal harvesting, trading, transporting, and purchasing of wildlife, plants, and fish in contravention of any US or state law or regulation or in contravention of any foreign law. The Lacey Act is the oldest federal wildlife protection law in the US. The 2008 Farm Bill (also called the Food, Conservation, and Energy Act of 2008) enacted the Lacey Act Amendment (LAA) and expanded previous provisions by covering a wide range of plant and plant products. With the LAA of 2008, declaration of a particular plan and plant products, including wood products, was mandated and prohibited trade importation of these products.[8] The LAA became the world's first trade measure that bans the trade of illegal wood products. The ban on illegally sourced wood products applies to all products, including standard products such as raw logs, sawn timber, plywood, composite materials, furniture, pulp, paper, and musical instruments. The LAA is administered by the USDA's Animal and Plant Health Inspection Service (APSIS), the National Marine Fisheries Service, and the US Fish and Wildlife Service.

The LAA also provided the basis for legal action by other countries to reduce illegal logging. Thus, expectations that the LAA would address illegal logging and deter illegal trade flows were high. However, implementation of the LAA has been questioned because of the interpretation of what accounts for "due care" (Momii, 2014). In fact, there is no obligation in the "due care" process; the policy offers flexibility to the operators to exercise due care. The penalty provisions are allocated on the information about the product sources so that penalties would be higher for those who intentionally place illegal wood in trade flows and would be lower for operators who unknowingly trade illegal wood. As stated above, the due care process gives operators flexibility, which opens the way for violations of the LAA.

Despite the caveats of the due care process in the LAA, the policy has been successfully applied to a wide range of wood and wood products. The phased-in enforcement schedule has been designed to include a variety of Harmonized Tariff Schedule (HTS) chapters. The most recent phase, phase VI, contains two products from Chapter 44 (Wood and Articles of Wood) and Chapter 92 (Musical Instruments).[9]

Fig. 3.4 shows the import trends of wood products during the period of 1997–2017. After establishment of the LAA, the trend for the importation of coniferous sawnwood and plywood values has increased whereas import values of newsprint have sharply decreased. Panels A and B of Fig. 3.11 illustrate key trading partners of both coniferous and non-coniferous sawnwood. Canada has been the top trading partner of the US for coniferous sawnwood, followed by the EU countries. For non-coniferous sawnwood imports, Canada is still the top key partner of the US, but other important

[8]Only specific Harmonized Tariff Schedule (HTS) chapters are scheduled for the import declaration, including chapter 44 (wood and articles of wood and wood charcoal). More details on certain chapters can be found at https://www.aphis.usda.gov/aphis/ourfocus/planthealth/import-information/lacey-act/implementaton-schedule/hts.

[9]More information about the current phase of the LAA can be found athttps://www.federalregister.gov/documents/2020/03/31/2020-06695/implementation-of-revised-lacey-act-provisions

key partners include countries such Brazil, Peru, Malaysia, and Ecuador, which are known to be suspected countries for illegal logging. Asian and South American countries account for a large share of both coniferous and non-coniferous plywood imports (see Fig. 3.12).

Previous literature has documented the impacts of the LAA (Gan et al., 2013; Lu et al., 2015; Prestemon, 2015; Sun and Bogdanski, 2017); however, each of these studies looked at the effects of the LAA from different perspectives by focusing on various policy parameters such as prices, quantities, welfare impacts, etc. For instance, Prestemon (2015) sought to measure price and quantity impacts of the primary imported products from suspected countries while Sun and Bogdanski (2017) explored the impacts of the LAA (among other factors) on non-tropical hardwood plywood sector, pointing out welfare impacts. Neither Prestemon (2015) nor Sun and Bogdanski (2017) explored the impacts of the LAA on illegal logging which was the focus of (Bridegame and Eastin, 2014; Gan et al., 2013).For example Gan et al. (2013) showed that the LAA has small effect on reducing illegal logging. Perhaps, differences in results can be attributed to the methodologies and product aggregation levels used in these studies. More detailed empirical analysis focusing on broader scope is needed to explain the impacts of the LAA on US imports. As discussed earlier, the implementation of the LAA (such as concerns about performing the due care processes) might also affect the efficacy of the program. In this analysis, I look at precisely how the LAA has affected the imports of coniferous and non-coniferous sawnwood and plywood between 1996 and 2019.

3.3 Estimation Strategy

To quantify the impacts of trade measures to address illegal logging on the global forest market, I employ the gravity model which was pioneered by Tinbergen (1962).The gravity model has proven to be a successful and consistent econometric approach to evaluate the patterns of bilateral trade in international trade studies. Tinbergen (1962) proposed the gravity model to explain the size of bilateral trade between two countries; it is based on the economic size of two countries and the geographic separation (distance) between two countries. According to the gravity model, the size of bilateral trade is positively associated with economic size (respective national incomes such as GDPs) while it depends inversely on the distance between two countries i and j. A simple form of

Tinbergen's gravity equation can be shown as

$$M_{ij} = A\frac{Y_i Y_j}{D_{ij}} \tag{3.1}$$

where M_{ij} is the trade flow between country i and country i, Y_i and Y_j are the respective economic sizes of countries (i and j), D_{ij} is a measure of the distance between country i and j, and A is a constant of proportionality.

Although the earlier specification of the traditional gravity model introduced by Tinbergen (1962) has been a robust estimation approach to explain the patterns of international trade, it lacked theoretical foundations. Subsequent studies demonstrated model improvements on the theoretical front. The absence of micro-foundations of the gravity model have been challenged by linking various theoretical foundations in the gravity model (Anderson, 1979; Anderson and van Wincoop, 2003; Bergstrand, 1985; Deardorff, 1998; Eaton and Kortum, 2002; Helpman et al., 2008). Seminal work by Anderson (1979) was the first to offer a theoretical foundation of the gravity model, using Cobb-Douglas expenditure and constant-elasticity substitution (CES) preferences, which had illustrated imperfect product substitution. Following studies have shown that gravity models can be derived in the presence of a various micro-foundations: monopolistic competition, (Bergstrand, 1989; Deardorff, 1998), firm heterogeneity (Helpman et al., 2008), and a Ricardian model (Eaton and Kortum, 2002). Anderson and van Wincoop (2003), following and proposing an augmented version of Anderson (1979), argue that the gravity model should control for the multilateral resistance (or fixed effects) in order to avoid misspecification of the model. The augmented gravity equation is

$$X_{ij} = \frac{y_i y_j}{y_w}\left(\frac{t_{ij}}{P_i P_j}\right)^{1-\sigma} \tag{3.2}$$

whereX_{ij} denotes the trade flow between country i and j, y_i and y_j are the respective economic sizes (GDP) of countries i and j, $y_w$is global income, t_{ij} represents the bilateral trade barriers, and P_i and P_j are price indices or "multilateral resistance." According to the equation 3.2, the bilateral trade, considering economic size, depends on the bilateral trade barriers and the product of multilateral trade resistance in countries i and j.

The log-linearization of gravity equation (3.2) with an additive error term can be characterized by the following form (Anderson and van Wincoop (2003)),

$$lnX_{ijt} = k + lny_{it} + lny_{jt} - lny_{wt} + \rho(1-\sigma)lnd_{ij} + R_{ij} + \varepsilon_{ijt} \tag{3.3}$$

where X_{ijt} denotes the trade flow from country i to j; k is a positive constant; y_i and y_j are the respective economic sizes in countries i and j; d_{ij} is the geographic distance between countries i and j; ε_{ijt} is the error term; and R_{ij} measures the sum of multilateral resistance terms (explained in equation 3.2) as follows:

$$R_{ij} = (1-\sigma)lnt_{ij} - (1-\sigma)lnP_{it} - (1-\sigma)lnP_{jt} \tag{3.4}$$

A theoretical gravity equation followed in this empirical analysis is based on equation 3.2.

The traditional gravity model given in equation 3.2 is estimated by using the ordinary least squares (OLS) approach. However, using the OLS approach introduces two drawbacks in estimates of the model. First, incidence of zero trade flows (lnX_{ijt}) is a particular concern because it eliminates zero trade observations since the natural logarithm of zero is undefined. One can argue that it could be legitimate to discard zero trade values; hence they might not be economically meaningful (Anderson, 2011). Elimination of zero trades should be avoided because such elimination naturally introduces omitted variable biases in estimating trade flows. In the forest trade flows, as in this study, zero trade flows are prevalent and might convey important information that potentially explains trade patterns under new policy changes , so the truncation of zero trade flows may cause standard sample selection bias in the model (Heckman, 1979). The second caveat is the presence of heteroskedasticity in the error term (ε_{ijt}); the estimated parameters can be significantly biased and inconsistent (Silva and Tenreyro, 2006).

To overcome the estimation challenges presented above, Silva and Tenreyro (2006) proposed the Poisson Pseudo Maximum Likelihood (PPML) model, which has been a well-recognized estimation method of choice in empirical international trade studies. Silva and Tenreyro (2006) demonstrate that the PPML estimator accounts for zero trade flows because the error term in equation 3.2 takes a multiplicative form and estimates the model in levels instead of taking the natural logarithm of trade flows. Also, an important assumption of the PPML estimator is that the conditional variance is proportional to the conditional mean. Hence, the PPML estimator generates unbiased and consistent parameter estimators. The PPML estimator given in equation 3.2 can be expressed as follows:

$$X_{ijt} = exp[lny_{it} + lny_{jt} - lny_{wt} + \rho(1-\sigma)lnd_{ij} + R_{ij}]\varepsilon_{ijt} \tag{3.5}$$

Anderson and van Wincoop (2003) pointed out that the absence of a multilateral resistance term in the model estimation, as in equation 3.5, can lead to two problems: omitted variable bias and incorrect comparative static analysis. Because multilateral resistance terms (the price indices, P_i and P_j, given in equation 3.2) are unobservable by the researcher, they should be accounted for in the correct specification of the model. Baldwin and Taglioni (2006) also referred to the omission of multilateral resistance terms as a "gold medal mistake" and presented a way of overcoming this issue. Using directional (exporter and importer) or pairwise fixed effects in the estimation can control for the multilateral resistance terms; hence, the omitted variable bias can be avoided (Anderson and van Wincoop, 2003; Baldwin and Taglioni, 2006; Feenstra, 2004; Piermartini and Yotov, 2016). The usual application in empirical research is to introduce both importer and exporter fixed effects to absorb both observable and unobservable country-specific characteristics that may impact trade flows.[10, 11]

Following the previous literature, this study also includes fixed effects to capture multi-resistance terms. However, the introduction of directional (both importer and exporter) or pairwise fixed effects in this study presents difficulty in the estimation because my data set does not have the entire set of country pairs for both directions(exporter and importer) and it focuses on a trade measure of a single importing country. For this reason, inclusion of country-specific exporter fixed effects is suitable in this study. Using time fixed effect also is not feasible for this study because importer-specific variables such as GDP or production are constant across all exporters and would be perfectly collinear; hence, it would be dropped in the estimation. Therefore, I employ an alternative approach and use only exporter fixed effects to capture unobserved country heterogeneity that may stem from trade measures, and I exploit the advantage of estimating importer-specific variables in my model.

[10] In addition to fixed effects estimation, Baier and Bergstrand (2009) proposed an alternative strategy to estimate the model using a first-order Taylor's series expansion. See Baier and Bergstrand (2009) for further details.

[11] Westerlund and Wilhelmsson (2011) proposed the use of a Poisson fixed-effects estimator.However, implementing such a model has the drawback of not excluding time-invariant variables.

The empirical specification of the PPML[12] equation in this study is[13]

$$
\begin{aligned}
X^{k}_{ijt} = &\beta_0 + \beta_1 lnDist_{ij} + \beta_2 ComLan_{ij} + \beta_3 Cont_{ij} + \beta_4 lnForEx_{jt} + \beta_5 lnForIm_{it} \\
&+ \beta_6 lnGDPEx_{jt} + \beta_7 lnGDPIm_{it} + \beta_8 lnExRate_{ijt} + \beta_9 lnProEx^{k}_{jt} + \beta_{10} lnProIm^{k}_{it} \\
&+ \sum_{n=1}^{3} \gamma_m d^{m}_{ijt} + \pi_j + \varepsilon_{ijt}
\end{aligned}
\tag{3.6}
$$

where X^{k}_{ijt} denotes the nominal imports value of country i from country j at time t for forest product k[14]; $Dist_{ij}$ stands for the geographical distance between trading partners; $ComLan_{ij}$ is a dummy variable for whether country i and country j share a common language; $Conti_{ij}$ is a dummy variable equal to 1 if trading partners share a common border, $ForEx_{jt}$ represents the exporter's forest rent at time t, $ForIm_{it}$ is the forest rent in year t in the importing country; $GDPEx_{jt}$ stands for the exporter's GDP at time t; $GDPIm_{it}$ is the importer's GDP at time t; $ExRate_{ijt}$ is the ratio of the exporter's local currency per importer's local currency; $ProEx^{k}_{jt}$ is the production quantity of product k in year t in the exporting country; $lnProIm^{k}_{it}$ denotes the importer's production quantity for product k at time t; d^{m}_{ijt} is the mth dummy for destination i at time t;π_j represents the country-specific exporter fixed effects; and ε_{ijt} is the error term.

Three dummy variables were introduced in this study: (1) a trade measure (ILPA, EUTR, LAA, or JCWA), which takes the value 1 by effective year of trade policy in importing countries and is otherwise 0; (2) restriction, which takes the value 1 if the exporting country has a timber measure to curb illegal logging in place; and (3) WTO membership, which takes the value 1 if the exporter is a member of WTO. More specifically, I use the first two dummies to capture the impacts of their incidence at the product level.

Given the estimation issues raised by using a conventional OLS estimator, I implement the PPML fixed effects (PPML FE) to estimate the product level[15] (k =1...4) gravity model for each importing country as the preferred specification, because the PPML FE simultaneously addresses both issues

[12]The coefficients are the elasticity of trade flows with respective continuous explanatory variables.

[13]All covariates take the natural logarithm, except for dummy variables in the model. The dependent variable is import values and is measured in levels.

[14]I estimated the PPML estimator separately for each of the four product groups: *k=1* is coniferous sawnwood, *k=2* denotes non-coniferous sawnwood, *k=3* indicates coniferous plywood, and *k=4* is non-coniferous plywood.

[15]I run the model by product group for each country.

of zero trade flows and heterogeneity in the estimates and it also controls for omitted variable bias. However, I also document the results of additional specifications for comparison: the PPML, OLS FE, and OLS. In addition to the preferred and alternative specifications, several robustness checks also were conducted to investigate econometric issues discussed above and will be discussed in Section 6.

3.4 Data

In this study, I use annual data on bilateral import values of four product commodity groups for Australia, the EU, Japan, and the US and their trading partners[16].My data set covers the period 1996–2019 for Australia, Japan, and the US. For the EU data, it spans from 1999 to 2019.[17] For the EU analysis, I considered 10 major importing countries in the EU, using the average value of imports between 1999 and 2019.[18] Data on import values for Australia, the EU, and Japan were collected from the United Nations (UN) Comtrade data, using both the Harmonized Tariff System (HTS) 6-digit codes and the Standard International Trade Classification (SITC) (Rev.3) 4- and 5-digit codes. The EU and Japan data were assembled using HTC classification while Australian data was combined using SITC because SITC is the primary classification used in Australia's international trade statistics. For the US import values, data was obtained from the United States International Trade Commission (USITC) database using HTS 6-digit codes.

Four commodity groups that were considered in this study are: (1) coniferous sawnwood, (2) non-coniferous sawnwood, (3) coniferous plywood, and (4) non-coniferous plywood. Table 3.1 and 3.2 display how such product groups were assembled using both the HTS and SITC classification codes. I selected these product categories because they are regulated timber products by their HTS and SITC codes and they also represent major product groups by import values between 1997 and 2017 in Australia, the EU, Japan, and the US as previously mentioned. In contrast with previous empirical studies that used aggregate level HTS classification codes for timber products (Guan and Gong, 2015; Morland et al., 2020; Larson et al., 2018), this study employs the disaggregated data at

[16] Trading partners of the countries are listed in the Appendix tables B9 through B12,respectively.

[17] The EU adopted the euro as their currency in 1999, so I used data between 1999 and 2019 in order to be consistent with the exchange rate.

[18] For the EU data, I selected 10 major importing countries based on average import values between 1999 and 2019. The selected countries are Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Poland, Spain, and the United Kingdom.

HTS 6-digit and SITC 4- and 5-digit codes to empirically evaluate the impacts of trade measures on the global forest market for the implication of gravity model.

As previously mentioned, the SITC is the primary trade classification code for Australian trade statistics. For sawnwood trade flows, 4-digit SITC codes were used. To obtain import values of non-coniferous (hardwood) plywood, total plywood (6343) was subtracted from coniferous plywood (63439) (see Table 3.1).The HTS classification system was used to obtain trade flows for the US, EU, and Japan. To obtain import values of non-coniferous (hardwood) plywood, coniferous (softwood) plywood was subtracted from total plywood (4412). HTS codes have been redefined after 2007, so 4412.19 and 4412.39 were used for periods of 1996–2006 and 2007–present, respectively, to obtain non-coniferous plywood import values[19] (see Table 3.3).

Independent variables used in this study include forest rent, gross domestic product (GDP), exchange rate, the quantity of timber production for selected wood products,gravity variables and three dummy variables. Data on forest rents, GDP, and exchange rate were obtained from the World Bank's World Development Indicators (WDIs). Forest rents (%GDP) were included to be a proxy for both forest endowment resources and the contribution of the forest sector to economic outputs. Previous literature has used either the ratio of per capita forestland area between exporter and importer (Guan and Gong, 2015) or wood production per capita (Zhang and Li, 2009) to proxy for forest resource endowment in considering the importance of forest abundance in the countries. Forest rents can also be a proxy for forest sector capacity; for instance, Morland et al. (2020) used forest rents to account for forest sector production potential. As gravity theory suggests, GDP is the most commonly used variable to account for economic size of a country in the literature; therefore, GDP data were included as a proxy for the economic size. The effect of exchange rate on forest products trade has been documented by previous studies(Buongiorno, 2015; Zhang and Li, 2009; Zhang et al., 2019) because movements in exchange rate and exchange rate volatility bring uncertainty in trade flows and could influence trade patterns.The exchange rate used in this study is the importing country's exchange rate per exporter's local currency.

Home bias, the phenomenon in which consumers favor domestic products over foreign alternatives, has been an important puzzle in the international trade literature along with the border puzzle, tariff and non-tariff barriers, and exchange rate risk (Obstfeld and Rogoff, 2000). I included

[19]Coniferous plywood is described in the HTS code system as plywood in which both outer plies are coniferous wood.

both exporter's and importer's production data to control for multilateral trade resistance (Anderson and van Wincoop, 2003) and quantity if trade induces such bias in forest products flow. Further, countries may adjust their production capacity to control the trade balance and increase domestic production as well. However,many factors (such as heterogeneity in demand across countries) might contribute to home bias, and often it is hard to distinguish demand-side home bias from costs associated with trade. Timber production data for selected wood products were obtained from the International Tropical Timber Organization (ITTO) [20]

Adding commonly used gravity variables such as distance, common language, contiguity, or colony usually accounts for differences in demand trade costs (Anderson, 2011). More specifically, distance and contiguity are the most commonly used variables to account for trade costs and market accessibility in the international trade literature (Anderson and van Wincoop, 2004). I include these variables to consider both bilateral trade cost and market accessibility. For this reason, I included distance, common language, contiguity, and the WTO membership to consider both trade cost and market accessibility Data on gravity variables were collected from USICT's gravity database to proxy market accessibility because USITC gravity data is more detailed and addresses limitations from Centre d'Etudes Prospectives et d'Informations Internationales (CEIP).[21]

In addition, I introduced three dummy variables in this study: (1) trade measures, namely ILPA, EUTR, JCWA, and LAA, which capture the impact of trade policies imposed by the importing countries in this study and is equal to 1 by the effective year of related policy; (2) restriction that takes a value of 1 if the exporting country has a trade measure in effect at time t; and (3) WTO membership, which takes a value of 1 if the exporter is a member of WTO.A negative (and significant)coefficient of trade measure and a positive (and significant) coefficient of restriction suggest trade diversion toward the markets where trade measures are in place. Moreover, a positive(and significant) coefficient of WTO membership indicated that being a member of WTO facilitates trade.

My final data set spans (annually) from 1996 to 2019 for the US, Australia, and Japan and covers the period 1999 to 2019 for the EU. All monetary values and exchange rates are in current US dollars. I particularly used nominal values because the incorrect deflation of monetary values might cause

[20]ITTO has provided information about timber production and trade flows data for primary timber products since 1990. Data collection is based on data submitted by ITTO members countries through the Joint Forest Questionnaire. Historical data can be found athttps://www.itto.int/biennal_review/.

[21]More details can be found at https://www.usitc.gov/data/gravity/dgd.htm.

biases in the estimations (Baldwin and Taglioni, 2006).Data descriptions and sources as well as a summary statistic of all variables included in the countries are exhibited in Appendix B. Tables B.1 through B.4 present the definition of variables used in this study and detailed information about data resources for each country. Summary statistics of country-specific variables are displayed in Tables B.5 through B.8.Country lists for each importing country that is studied in this analysis are displayed in Tables B.9 through **??**.

3.5 Estimation Results

The estimation results of model specifications for each importing country and product group are discussed in this section. First, I present the estimation results for Australia; then I continue with the EU, Japan, and the United States. I refer to the estimates from the PPML FE model as my preferred specification because it deals with zero trade flows and heteroskedasticity and accounts for unobserved heterogeneity. However, I also consider three separate estimations as my alternative specifications: PPML, OLS FE, and OLS.

3.5.1 Australia

The Impacts of ILPA on Coniferous Sawnwood Import Values

The estimation results of PPML estimators from both preferred specification (PPML FE) and alternative PPML specification are reported in columns 1 and 2 of Table 3.3. Columns 3 and 4 of Table 3.3 present alternative specifications (OLS FE and OLS) from the OLS estimator, where the dependent variable is in logarithmic form. In general, estimation results of PPML estimators are similar in terms of direction and significance whereas OLS estimators (OLS FE and OLS) reduce the magnitude of coefficients. However, the signs of coefficients are similar to those obtained from the PPML estimators (PPML FE and PPML). I also implemented the Reset specification test (Ramsey (1969)) and reported the results in Table 3.3. Based on the drawback of PPML and OLS estimators as mentioned earlier, I will refer to the results of the PPML FE as my preferred specification.

First, I start with discussion of gravity variables. Contiguity ($Cont_{ij}$) is omitted from the estimation because Australia has no shared border with any country because it is an island country. Therefore, I refer only to results of the estimated coefficients for distance ($lnDist_{ij}$) and common language ($ComLan_{ij}$) across all product groups for Australia. The estimated coefficient for distance ($lnDist_{ij}$)is negative and statistically significant, indicating that distance deters trade. Contrary to my expectations, the estimated coefficient for common language is negative but not statistically significant.

As for the coefficient of exporters' forest rents ($lnForEx_{jt}$), the estimate of forest rents (0.980) is positive and statistically significant. It suggests that forest rents in the exporting country are positively associated with Australia's coniferous sawnwood imports. I interpret this result to indicate that Australia imports more from countries that have higher forest rents and where forest sector could be an important contributor of economy. The coefficient of Australia's forest rents ($lnForIm_{it}$) is negative but not statistically significant.

The estimated coefficient of the exporter's GDP ($lnGDPEx_{jt}$) is positive and the parameter estimate of Australia's GDP ($lnGDPIm_{it}$) is negative, but neither is statistically significant. The exchange rate is the local exporter's currency per Australian dollar. The depreciation of the Australian dollar makes the import value more expensive, hence decreasing the value of imports. However, the exchange rate ($lnExRate_{ijt}$)has a significant negative impact on Australia's coniferous sawnwood imports, which contradicts my expectation explained above. As expected, the coefficient on the exporter's production ($lnProEx^k_{jt}$)is positive and statistically significant, suggesting that production volume in the exporting countries would have a positive impact on coniferous sawnwood imports. However, the estimated impact of Australia's coniferous sawnwood production ($lnProIm^k_{it}$) is positive but not statistically significant.

As indicated earlier, the main variable of interest in this study is the dummy variable constructed for each trade measure mentioned earlier because the purpose of this study is to quantify the impacts of trade measures on import values in each country. Now,I turn to the main focus of this study, the impact of the ILPA on coniferous sawnwood import values in Australia. The estimated coefficient of ILPA is negative and statistically significant. In other words, implementation of such a policy would reduce imports of coniferous sawnwood by 22.8 percent.[22] On the other hand, the coefficient of restriction is positive, economically large, and statistically significant. More precisely, if the exporting country applies a trade measure, imports of coniferous would increase by 97.1

[22]The coefficients on indicator variables are semi-elasticities that are equal to [exp(β)-1] *100), so the rest of paper follows this equation to interpret the impact of country-specific trade measures on import values. It is computed as [exp (-0.259)-1] *100.

percent.[23] The economic impact is quite large. I interpret the combined effects of both findings as suggesting evidence of trade diversion for coniferous sawnwood import values in Australia and moving trade flows towards countries that have trade laws in place. By having a trade restriction, the exporting country has made itself a preferred source of coniferous sawnwood imports. The partner membership of WTO *(Member_WTO)* has a positive and significant influence on import values of coniferous sawnwood, suggesting that being a WTO member facilitates trade.

The Impacts of ILPA on Non-coniferous Sawnwood

Table 3.4 reports the impacts of ILPA on non-coniferous sawnwood import values. Column 1 of Table 3.4 and columns 2 through 4 of Table 3.4 display the results of the preferred and the alternative specifications, respectively. I pursue the results of the PPML FE (the preferred specification) for reasons explained previously.

As expected, the estimated coefficients for distance ($lnDist_{ij}$) and common language have the expected signs: negative and positive, respectively but only the coefficient of distance ($lnDist_{ij}$) is statistically significant. The significant and negative coefficient of distance ($lnDist_{ij}$) indicates that import values of non-coniferous sawnood decrease as geographic distance between Australia and the exporting country increases.

The estimated coefficients of both the exporting country's forest rent ($lnForEx_{jt}$) and Australia's forest rent ($lnForIm_{it}$)are negative but not statistically significant. The impact of the exporter's GDP ($lnGDPEx_{jt}$) on import values is positive but not statistically significant. However, the estimated coefficient of Australia's GDP ($lnGDPIm_{it}$)is positive and statistically significant, indicating that non-coniferous sawnwood imports would increase with higher GDP because larger economic size increases the potential demand for non-coniferous imports.The impact of exchange rate ($lnExRate_{ijt}$) is positive but not statistically significant, suggesting that appreciation of the Australian dollar against the exporter's currency makes imports cheaper and hence will increase the value of non-coniferous sawnwood imports. The estimated coefficients for both the exporter's production ($lnProEx^{k}_{jt}$) and Australia's production ($lnProIm^{k}_{it}$) are positive, but only the coefficient of Australia's production ($lnProIm^{k}_{it}$) is statistically significant. I interpret this as suggesting that an increase in import values induces domestic production of non-coniferous sawnwood in

[23] Again, this estimation is based on [exp (0.679)-1] *100.

Australia, suggestion evidence of home bias.

The impacts of ILPA on non-coniferous sawnwood is, as expected, negative but not statistically significant. The coefficient of restriction is positive and statistically significant. This finding suggests a trade diversion for non-coniferous sawnwood imports, indicating that Australia trades 60.3[24] percent more with countries where trade measures apply. As expected, membership in the WTO *(Member_WTO)* has a positive and statistically significant impact on the import values of non-coniferous sawnwood.

The Impacts of ILPA on Coniferous Plywood

Estimation results of the preferred model and the alternative model are reported in Table 3.5. Column 1 of Table 3.5 presents results of the PPML estimator, and columns 2 through 4 show the results of the alternative specification. In general, the signs of estimated coefficient are similar across all specifications but the magnitudes of the estimated coefficients of OLS estimators are slightly greater than those of PPML estimators (PPML FE and PPML).I refer to the results of the preferred model, the PPML FE.

The coefficient estimate of distance ($lnDist_{ij}$) is statistically significant and has the expected sign (negative), whereas the impact of common language ($ComLan_{ij}$) is negative but not statistically significant. As expected, distance would reduce imports of coniferous plywood in Australia.

The estimated coefficient of the exporter's forest rent ($lnForEx_{jt}$) is positive but not statistically significant, whereas the parameter estimate of Australia's forest rent ($lnForIm_{it}$) is negative and statistically significant, suggesting that demand for coniferous plywood import has a negative impact on forest rents in Australia.The impact of the exporter's GDP ($lnGDPEx_{jt}$) is positive but not statistically significant. The estimated coefficient of Australia's GDP ($lnGDPIm_{it}$) is negative and not statistically significant. The impact of exchange on coniferous plywood is negative but not statistically significant. The coefficient estimates of both the exporter's production quantity ($lnProEx^{k}_{jt}$) and Australia's production ($lnProIm^{k}_{it}$) are positive but not statistically significant.

The estimated coefficient of ILPA is negative and statistically significant, as expected. This result indicates that implementation of the ILPA reduces the value of coniferous plywood imports by 43.22

[24] It is estimated as [exp (0.472)-1]*100.

percent.[25] On the other hand, the impact of restriction is positive and statistically significant. Altogether, the results suggest a trade diversion in coniferous plywood imports. Finally, if the exporting country is a member of WTO *(Member_WTO)*, the import value of coniferous plywood increases.

The Impacts of ILPA on Non-coniferous Plywood Imports

Table 3.6 reports the impacts of ILPA on non-coniferous plywood import values. The first column of Table 3.6 displays results of the PPML FE. The alternative specification results are presented in columns 2 through 4. The signs and the magnitudes of both PPML estimators (PPML FE and PPML) are similar.

The coefficient estimate of distance($lnDist_{ij}$)is negative and statistically significant. However, the impact of whether an exporting country and Australia share a common language ($ComLan_{ij}$)has a negative but not statistically significant impact on import values of non-coniferous plywood.

The coefficient of the exporter's forest rent ($lnForEx_{jt}$) is negative and statistically significant, implying that if the exporter's forest rent increases by 10 percent, decrease import values by 4.75 percent. The impact of Australia's forest rent ($lnForIm_{it}$) is positive and statistically significant. The coefficient of the exporter's GDP ($lnGDPEx_{jt}$) is negative but not statistically significant. Although it is not significant, it indicates that Australia imports more from smaller economies. As expected, the estimated coefficient of Australia's GDP ($lnGDPIm_{it}$)is positive, economically large, and statistically significant. It suggests that 10 percent increase in Australia's GDP would lead to a 17.41 percent increase in import of non-coniferous plywood. Contrary to my expectations, the coefficient on exchange rate ($lnExRate_{ijt}$)is negative and statistically significant, indicating that a low exchange rate will increase the import prices of non-coniferous plywood. Coefficient estimates of production quantity are statistically significant and positive for both the exporting country ($lnProEx^{k}_{jt}$) and Australia ($lnProIm^{k}_{it}$). However, the magnitude of the coefficient for an exporter's production quantity ($lnProEx^{k}_{jt}$) is larger. I interpret this result as suggesting that Australia consumes more imported non-coniferous plywood than domestically produced non-coniferous plywood.

Parameter estimates of the ILPA are negative but not statistically significant, whereas the coefficient on restriction is positive and statistically significant. This result suggests that the impact

[25] It is estimated as [exp (-0.566)-1]*100.

of the ILPA has a negative effect on non-coniferous imports and that Australia imports more from countries where trade policies are in place. Finally, the exporter's WTO membership has a positive and statistically significant impact.

3.5.2 The European Union

The Impacts of EUTR on Coniferous Sawnwood Imports

Results of the preferred specification (PPML FE) and the alternative specifications are displayed in Table 3.7. Column 1 reports the results of PPML FE, and columns 2 through 4 display results obtained from the alternative specifications. The estimated coefficients produced by the PPML FE estimator are similar to those obtained from the PPML estimator. The magnitude of coefficients from both OLS estimators (OLS FE and OLS) are less than those from the PPML estimators.

As for distance ($lnDist_{ij}$) and common language ($ComLan_{ij}$),the estimated coefficients are statistically significant and have the expected signs: negative and positive, respectively. I interpret this as suggesting that larger distance between the exporting countries and the EU deters trade whereas sharing a common language facilitates trade. Although the impact of contiguity ($Cont_{ij}$) on coniferous sawnwood import value is positive, it is not statistically significant, indicating that the EU imports more from countries in close proximity.

The estimated coefficient for the exporter's forest rent ($lnForEx_{jt}$) is statistically significant and has the expected sign: positive. This finding indicates that the EU imports more from countries where forest endowment is abundant, or the forest industry is an important economic contributor to GDP. The coefficient of the EU's forest rent ($lnForIm_{it}$) is negative and statistically significant, implying that if the EU's forest rent decreases by 10 percent, import values of coniferous sawnwood would decrease by 7.16 percent.

The impact of GDP in the exporting country ($lnGDPEx_{jt}$) is positive but is not statistically significant. The positive and significant coefficient of the EU's GDP ($lnGDPIm_{it}$) indicates that increases in economic size would lead to more coniferous sawnwood imports because GDP is representative of the economic size of the EU. The parameter estimate for exchange rate ($lnExRate_{ijt}$) is negative, contrary to my expectation, but not statistically significant. The coefficient of the exporter's production quantity ($lnProEx^k_{jt}$)is positive but not statistically significant. On the other hand, the estimated effect of the EU's production ($lnProIm^k_{jt}$) is positive and statistically significant. This finding implies supporting evidence of home bias, suggesting that increases in import values would stimulate domestic production of coniferous sawnwood production in the EU.

The estimated coefficient of the EUTR is negative and statistically significant, indicating that implementation of the EUTR has a negative impact on coniferous sawnwood imports. In other words, the EUTR reduces coniferous sawnwood import values by 37.93 percent in the EU.[26] Also, the coefficient on restriction is negative but not statistically significant. The coefficient of WTO membership *(Member_WTO)* is negative, contrary to my expectation, but not statistically significant.

The Impacts of the EUTR on Non-coniferous Sawnwood Imports

The estimation results of the impact of the EUTR on non-coniferous sawnwood imports are displayed in Table 3.8. Column 1 reports results of the preferred model, and results of alternative specification are shown in columns 2 through 4.

The coefficients of gravity variables such as distance ($lnDist_{ij}$), common language ($ComLan_{ij}$) and contiguity ($Cont_{ij}$) have the expected signs (negative, positive, and positive, respectively), but only distance ($lnDist_{ij}$) is statistically significant. Distance, as a proxy for transportation cost, reduces the import values of non-coniferous sawnwood in the EU.

The estimated coefficient of the exporter's forest rent ($lnForEx_{jt}$) is positive and statistically significant, indicating that forest rents of exporters are positively associated with non-coniferous import values. The negative and statistically significant coefficient for the EU's forest rent ($lnForIm_{it}$) suggests that a 10 percent increase in forest rents would reduce non-coniferous sawnwood imports by 5.52 percent. The coefficients of both the exporter's GDP ($lnGDPEx_{jt}$) and the EU's GDP ($lnGDPIm_{it}$) are positive but not statistically significant. The impact of exchange rate ($lnExRate_{ijt}$) is positive, as expected, but not statistically significant. The positive and statistically significant impact of the exporter's production ($lnProEx^k_{jt}$) suggests that the potential demand of non-coniferous sawnwood demand would increase production volume in the exporting countries. The coefficient of the EU's production ($lnProIm^k_{it}$) is positive and statistically significant. It supports the home bias—that is, increases in import values would provide an impetus for domestic production of non-coniferous sawnwood production as well.

[26]This value is quantified by estimating [exp (-0.477)-1] *100.

The impact of EUTR is positive, contrary to my expectation, but not statistically significant. I interpret this as suggesting that the implication of EUTR may stimulate the exporting countries to ratify the VPAs because countries such as Cameroon and Ghana have already adopted the VPA as being top trading partners of non-coniferous sawnwood imports (see Panel B of Fig. 3.7) Negotiations are still going on with other trading partners such as Malaysia, Côte d'Ivoire, and Gabon. The parameter estimate of restriction is positive, economically large, and statistically significant, indicating that the EU imports more from the countries that apply trade measures to curb illegal logging. Finally, the WTO membership *(Member_WTO)* has positive and statistically significant import values for non-coniferous sawnwood.

The Impacts of the EUTR on Coniferous Plywood

The first column of Table 3.9 reports results of the preferred specification (PPML FE), and columns 2 through 4 display results of the alternative specification. The estimation results of PPML estimators from both the preferred specification (PPML FE) and the alternative specification (PPML) yield similar results while the magnitudes of the estimated coefficients of the OLS estimators are small comparing to those of the PPML estimators.

The estimated coefficients of distance ($lnDist_{ij}$)and common language ($ComLan_{ij}$) are statistically significant and have the expected sign: negative and positive, respectively. Larger distance between the exporting country and the EU impedes the trade, whereas sharing the same language facilitates the trade. The coefficient of contiguity ($Cont_{ij}$) is negative but not statistically significant.

The impact of the exporting country's forest rent ($lnForEx_{jt}$) is positive and statistically significant, implying that if exporter's forest rent increases by a 10 percent, coniferous plywood imports increase by 5.91 percent. The estimated coefficient of the EU's forest rent ($lnForIm_{it}$) is negative but not statistically significant. The impact of the exporter's GDP ($lnGDPEx_{jt}$) is positive but not statistically significant, As expected, the positive and significant coefficient of EU's GDP ($lnGDPIm_{it}$)indicates that 10 percent increase in economic size (GDP) would raise import values of coniferous plywood by 9.37 percent. The estimated coefficient of exchange rate ($lnExRate_{ijt}$) is negative but not statistically significant. The coefficient for the exporter's production ($lnProEx^{k}_{jt}$) is positive and statistically significant, suggesting that a higher production volume would increase imports of coniferous plywood . On the other hand, the negative and statistically significant coefficient of the EU's production ($lnProIm_{it}^{k}$) implies that decreases in production quantity of coniferous plywood would increase the value of coniferous plywood imports.

As expected, the estimated coefficient of the EUTR is negative but not statistically significant. This finding indicates that implementation of the EUTR decreases the import value of plywood because it tries to prevent inflow of illegal timber flows in the European market. The impact of whether the exporting country has trade measures is negative and statistically significant. I interpret this finding as suggesting that the EUTR would not cause a trade diversion for coniferous plywood imports. The parameter estimate of WTO membership *(Member_WTO)* is positive but statistically significant.

The Impacts of the EUTR on Non-coniferous Plywood Imports

The first column of Table 3.10 reports the estimates for the preferred specification, and columns 2 through 4 display the estimated coefficients of alternative specifications. As consistent with the previous results, the PPML FE (column 1 of Table 3.10) and the PPML (column 2 of Table 3.10) produce similar estimates. The results of OLS estimators (columns 3 and 4 of Table 3.10) are inferior to those of PPML estimators. I focus on the results of the PPML FE estimator since it controls for the estimation challenges mentioned earlier.

The estimated coefficients of distance ($lnDist_{ij}$) and common language ($ComLan_{ij}$) indicate that distance has a negative and statistically significant impact on import values of non-coniferous plywood while common language has a positive and statistically significant effect on non-coniferous plywood imports in the EU. The impact of contiguity ($Cont_{ij}$) on import is positive but not statistically significant.

The exporter's forest rent($lnForEx_{jt}$) has a negative but not statistically significant impact on non-coniferous imports. The estimated coefficient of the EU's forest rent ($lnForIm_{it}$) is positive but not statistically significant. The exporter's GDP ($lnGDPEx_{jt}$)has a negative, economically small, and statistically significant effect on imports, suggesting that the EU imports more from the countries that have smaller economies. The positive and statistically significant impact of the EU's GDP ($lnGDPIm_{it}$)suggests that a 10 percent increase in economic size of the EU would lead to 9.37 percent more non-coniferous plywood imports. The estimated coefficient of the exchange rate ($lnExRate_{ijt}$) is negative but not statistically significant. Coefficient estimates of the exporter's production ($lnProEx^k_{jt}$) and the EU's production ($lnProEx^k_{jt}$) are statistically significant and have the expected signs: positive and negative, respectively. As expected, the exporting country's production of non-coniferous plywood is positively related to the EU's import values whereas domestic production is negatively associated with non-coniferous plywood imports.

As expected, the impact of the EUTR is negative and statistically significant, indicating that implementation of the EUTR would decrease import values of non-coniferous plywood by 26.06 percent in the EU.[27] The estimated coefficient of restriction is positive but not statistically significant. Combined effects of both results suggest that the EUTR reduces non-coniferous import values; however, it is not necessarily creating a trade diversion toward countries that apply legal structures to curb illegal logging. The coefficient on WTO membership *(Member_WTO)* is positive and statistically significant, suggesting that being a WTO member country would facilitate non-coniferous plywood imports between the exporting country and the EU.

3.5.3 Japan

The Impacts of JCWA on Coniferous Sawnwood Imports

The estimation results of the preferred specification (PPML FE) are presented in column 1 of Table 3.11, and columns 2 through 4 report the results of the alternative specifications. I focus on the results of the preferred specification.

Since Japan, like Australia, is an island country, and therefore share no borders with other countries, the contiguity ($Cont_{ij}$)variable is omitted from all specifications across all product groups. The estimated coefficients of distance ($lnDist_{ij}$) and common language ($ComLan_{ij}$) are not statistically significant but have the expected signs: negative and positive, respectively.

The estimated coefficient of the exporter's forest rent ($lnForEx_{jt}$)is positive and statistically significant, suggesting that if forest rent in the exporting country increases by 10 percent, imports would rise by 5.46 percent. The coefficient variable of Japan's forest rent ($lnForIm_{it}$) is positive but not statistically significant. Both the exporter's GDP($lnGDPEx_{jt}$) and Japan's GDP ($lnGDPIm_{it}$) have a positive and statistically significant impact on coniferous sawnwood imports. The parameter estimate of exchange rate ($lnExRate_{ijt}$) is negative but not statistically significant. The coefficient

[27] It is estimated as [exp (-0.302)-1] *100.

of the exporter's production quantity ($lnProEx^k_{jt}$) is positive and statistically significant, indicating that increased exporter's production would lead to more coniferous sawnwood imports. The positive and statistically significant coefficient of Japan's production quantity ($lnProIm^k_{it}$) suggest that increase in import demand of coniferous sawnwood would stimulate domestic production.

The estimated coefficient of JCWA is negative and statistically significant, whereas the parameter estimate of restriction is positive and statistically significant. The implementation of such a policy reduces coniferous sawnwood import values by 55.42 percent.[28] The positive and statistically significant coefficient of restriction indicates that Japan imports 25.23 percent[29] more from countries where trade measures are established to curb illegal logging. Altogether, the results point out a significant trade diversion with the implementation of JCWA in coniferous sawnwood imports. As expected, the parameter estimate of WTO membership *(Member_WTO)* is positive but not statistically significant.

The Impacts of JCWA on Non-coniferous Sawnwood Imports

Estimated results of the impact of JCWA on non-coniferous sawnwood imports from both the preferred specification and alternative specifications are reported in Table 3.12. The first column displays results of the PPML FE (preferred specification) estimator, and columns 2 through 4 report results of the alternative specifications (PPML, OLS FE, and OLS estimators). In general, PPML estimators (PPML FE and PPML) result in larger coefficients compared with the OLS estimators (OLS FE and OLS).

The estimated coefficients of distance ($lnDist_{ij}$) and common language ($ComLan_{ij}$) are statistically significant and have the expected sign: negative and positive, respectively. As expected, distance impedes trade whereas sharing a common language facilitates trade.

The impact of the exporter's forest rent ($lnForEx_{jt}$) is negative but not statistically significant. The coefficient of Japan's forest rent variable ($lnForIm_{it}$) is positive and statistically significant, suggesting that increases in forest rent would lead to higher import values for non-coniferous sawnwood in Japan.The estimated coefficient of the exporting country's GDP ($lnGDPEx_{jt}$) is negative and statistically significant. This result indicates that Japan imports more from low-income

[28]Hence, its value is interpreted by [exp (-0.808)-1] *100, which is a –55.42 percent reduction.

[29]It is quantified as [exp (0.225)-1] *100.

countries. Japan's GDP ($lnGDPIm_{it}$) has a positive and statistically significant impact on bilateral trade flows of non-coniferous sawnwood, implying that if GDP rises by 10 percent import values of non-coniferous sawnwood would increase by 12.75 percent. The parameter estimate of exchange rate ($lnExRate_{ijt}$) is negative but not statistically significant. The coefficient of the exporter's production ($lnProEx^{k}_{jt}$) is positive but not statistically significant. The estimated effect of Japan's production ($lnProIm^{k}_{it}$) (0.196) is positive and statistically significant, indicating that increases in imports would provide an impetus for domestic production in Japan.

The Japanese trade measure *(JCWA)* has a negative and statistically significant impact on non-coniferous sawnwood imports. The introduction of JCWA which aims to curb illegal logging and related trade reduces trade flows by 40.49 percent.[30] The estimated coefficient of restriction is negative but not statistically significant. The impact of WTO membership is positive and statistically significant, indicating that such agreements facilitate trade in non-coniferous sawnwood imports.

The Impact of JCWA on Coniferous Plywood Imports

The first column of Table 3.13 reports the estimation results of the preferred specification (PPML FE), and columns 2 through 4 display results of alternative specifications. I refer to the result of the PPML FE estimator in discussion here.

The coefficient estimate of distance ($lnDist_{ij}$) is negative but not statistically significant, whereas the coefficient of ($ComLan_{ij}$) is negative and statistically significant.

The parameter estimate of the exporter's forest ($lnForEx_{jt}$) is positive, economically large and statistically significant, suggesting that if forest rents increase by 10 percent in the exporting country, the value of coniferous imports would rise by 19.41 percent in Japan. The impact of Japan's forest rent ($lnForIm_{it}$) is positive but not statistically significant. The effect of the exporter's GDP ($lnGDPEx_{jt}$) is positive but not statistically significant on imports, whereas the positive and significant coefficient of Japan's GDP ($lnGDPIm_{it}$) suggest that a 10 percent increase in GDP would lead to 11.65 percent more imports. The higher GDP, the more imports in Japan.

As expected, the coefficient of exchange rate ($lnExRate_{ijt}$) is positive and statistically significant, indicating that appreciation in Japanese yen against foreign currency would lead to an increase in coniferous plywood (a 10 percent appreciation in the Japanese yen would increase

[30]This value is estimated as exp ((-0.340)-1) *100.

import values by 4.96 percent). The impact of the exporter's production ($lnProEx^k_{jt}$) on coniferous plywood import values is positive and statistically significant, indicating that increases in quantity of coniferous plywood production would raise imports. The negative and statistically significant coefficient of Japan's production ($lnProIm^k_{it}$) suggest that domestic production of coniferous plywood tends to decline as import demand for coniferous plywood increases.

I now turn to the main variable of interest in this study: the implementation of JCWA has a negative and statistically significant impact on coniferous plywood import values, suggesting that such a policy impedes trade and decreases import values by 43.33 percent.[31] The estimated coefficient of restriction is positive, economically large (0.709), and statistically significant. If combined effects of both JCWA and restriction are considered, I find supporting evidence of import diversion toward countries that impose trade measures on illegal logging. Finally, the coefficient of WTO membership is positive but not statistically significant.

The Impact of JCWA on Non-coniferous Plywood Imports

The estimation results of the preferred specification (PPML FE) and alternative specifications are displayed in Table 3.14.I focus on the results of the PPML FE estimator. The negative and significant coefficient of distance ($lnDist_{ij}$) implies that larger distance between Japan and the exporting country reduces imports as transportation costs increase. The estimated coefficient of common language ($ComLan_{ij}$) is positive and statistically significant, suggesting that sharing the same language is a trade facilitating factor.

The estimated coefficient for the exporter's forest rent ($lnForEx_{jt}$) is positive but not statistically significant. On the other hand, the negative and statistically significant coefficient of Japan's forest rent ($lnForIm_{it}$) indicates that if Japan's forest rent increase by 10 percent, non-coniferous imports would decline by 5.08 percent. The effect of the exporter's GDP ($lnGDPEx_{jt}$) on imports is positive and statistically significant, indicating that Japan tends to import from larger economies. The estimated coefficient of Japan's GDP ($lnGDPIm_{it}$) is negative but not statistically significant. Contrary to my expectation, the coefficient of exchange rate ($lnExRate_{ijt}$) is negative and statistically significant at a 1 percent level. The coefficient estimates for both the exporter's non-coniferous production ($lnProEx^k_{jt}$) and Japan's non-coniferous plywood production ($lnProIm^k_{it}$) are posi-

[31] This interpretation is estimated by [exp (-0.568)-1] *100.

tive and statistically significant. Increases in imports of non-coniferous plywood tend to raise both domestic production and production volume in the exporting country; however, the response of the exporter's production is larger.

The impact of both the JCWA and restriction on imports are negative but not statistically significant. I cannot find supporting evidence of trade diversion for the implementation of the JCWA; however, the negative coefficient of the JCWA tends to decrease import values. As expected, the positive and statistically significant impact of WTO membership *(Member_WTO)* suggests that being a member of WTO is a trade-facilitating factor.

3.5.4 The United States

The Impact of the LAA on Coniferous Sawnwood Imports

The first column of Table 3.15 reports the estimation results of the preferred specification (PPML FE), and columns 2 through 4 display results of the alternative specifications (PPML, OLS FE, and OLS). Results of the Reset test show that the PPML FE and PPML specify the model, but I focus on the results of the PPML FE estimation. In general, the PPML FE generates a larger magnitude of coefficients compared with other estimators; results of it are similar to those obtained from the PPML estimator.

The estimated coefficients of distance ($lnDist_{ij}$) and contiguity ($Cont_{ij}$) are positive. Contrary to my expectations, distance is trade-facilitating rather than trade-deterring, which is not consistent with what gravity theory suggests. However, the impact of distance on coniferous sawnwood imports might be different; in fact, Canada, Chile, New Zealand, Germany, and Brazil account for the top five major exporters for US's coniferous sawnwood imports in my sample (see Panel A of Fig. 3.11). Of these countries, only Canada is in proximity to the US. As expected, the impact of sharing the same language ($ComLan_{ij}$) is positive and statistically significant.

The estimated coefficient of the exporter's forest rent ($lnForEx_{jt}$) is negative but not statistically significant. The estimated coefficient of the US's GDP ($lnForIm_{it}$) is positive and statistically significant. This finding indicates that if forest rents in the US increase by 10 percent, coniferous sawnwood imports would rise by 6.48 percent. The estimated coefficient of the exporter's GDP ($lnGDPEx_{jt}$) is negative and statistically significant, suggesting that the US imports more from smaller economies. As expected, the US's GDP ($lnGDPIm_{it}$) is positive and statistically significant, suggesting that a higher economic size results in more imports of coniferous sawnwood. The estimated coefficient of exchange rate ($lnExRate_{ijt}$) is negative and statistically significant. It suggests that appreciation of the US dollar against the exporter's currency would lead to a decrease in import values, which does not match my expectation. However, the estimated effect is not larger in magnitude (0.367).

The estimated effect of the exporter's production ($lnProEx^{k}_{jt}$)is positive and statistically significant, indicating that increases in production volume of coniferous sawnwood in the exporting country would tend to increase imports as well. The impact of the US's production ($lnProIm^{k}_{it}$) on import values of coniferous sawnwood is also positive and statistically significant; however, this result yields a larger response compared to production in the exporting country. I find evidence of home bias; a 10 percent increase in US production tends to raise import values by 14.95 percent at a 1 percent significance level.

The effect of LAA is positive and significant, contrary to my expectation; the LAA would tend to increase imports by 28.53 percent.[32] The implication is that LAA is not trade-deterring but instead has a trade-creation effect. Also, the negative and statistically significant coefficient of restriction implies that trade measures applied by the exporting country decreases US imports of coniferous imports by 46.42 percent. As expected, the estimated coefficient of WTO membership *(Member_WTO)* is positive and statistically significant.

The Impact of the LAA on Non-coniferous Sawnwood Imports

Table 3.16 reports the results of both the preferred specification and alternative specifications. Results of the Reset test indicate that both the PPML FE and the PPML approaches properly specify the model. I pursue the results of the PPML FE. In general, both the PPML FE and the PPML estimations produce similar responses in terms of direction; however, the responses of the PPML FE are larger in magnitude.

The estimated coefficients of distance ($lnDist_{ij}$) and common language ($ComLan_{ij}$) are statistically significant and positive. Both results suggest that neither reducing distance nor having a common language facilitate trade. On the other hand, the impact of contiguity ($Cont_{ij}$) on

[32] It is estimated as [exp (0.251)-1] *100.

non-coniferous sawnwood is negative but not statistically significant.

The estimated coefficient of the exporter's forest rent ($lnForEx_{jt}$) is positive and statistically significant, as expected, indicating that higher forest rents in the exporting country would increase US non-coniferous sawnwood imports. The impact of forest rent in the US ($lnForIm_{it}$) has a negative but not statistically significant on import values. The estimated coefficient for the exporter's GDP ($lnGDPEx_{jt}$) is positive but not statistically significant. The impact of the US GDP ($lnGDPIm_{it}$) is positive and statistically significant, suggesting that US imports would increase 14.24 percent if the US GDP would rise by 10 percent. The parameter estimate of exchange rate ($lnExRate_{ijt}$) is negative and statistically significant, although it has small impact (0.132) on non-coniferous sawnwood imports. The estimated coefficients of both the exporter's production ($lnProEx^k_{jt}$) and the US production ($lnProIm^k_{it}$) have a positive impact on non-coniferous imports, but only the exporter's production ($lnProEx^k_{jt}$) is statistically significant.

The introduction of the LAA has a negative and statistically significant impact on non-coniferous sawnwood imports, as expected, implying that enactment of the LAA reduces imports by 46.9.[33] The estimated coefficient of restriction is positive and statistically significant, suggesting that the US would import 68.81[34] percent more from countries where trade measures to reduce illegal logging are in effect. I can conclude that the implementation of the LAA reduces non-coniferous sawnwood imports more than it reduces coniferous sawnwood imports. Although trade diversion is remarkably high, this high level is not surprising given that the five trading partners of the US include Canada, Brazil, Peru, Malaysia, and Ecuador in my entire sample for non-coniferous sawnwood flows (see Panel B of Fig. 3.11). All these countries, except Canada, are suspected source countries for illegal logging and associated trade (Seneca Creek Associates (2004)); my results are also consistent with Prestemon (2015). The positive and statistically significant impact of WTO membership *(Member_WTO)* indicates that WTO membership facilitates trade.

The Impact of the LAA on Coniferous Plywood

The first column of Table 3.17 reports the estimation results of the preferred specification (PPML FE), and columns 2 through 4 display results of the alternative specifications (PPML, OLS FE, and

[33]The interpretation is computed as [exp (-0.633)-1] *100.
[34]This figure is estimated as [exp (0.524)-1] *100.

OLS). I focus on the results of the PPML FE (preferred specification).

The estimated coefficients of distance ($lnDist_{ij}$) and common language ($ComLan_{ij}$) are statistically significant and have the expected signs: negative and positive, respectively. Contiguity ($Cont_{ij}$) is omitted from both the PPML FE and OLS FE estimations. I interpret this result as suggesting that the fixed-effect estimator absorbs the contiguity variable in my sample.

The estimated coefficient for the exporter's forest rent ($lnForEx_{jt}$) is negative but not statistically significant. The US's forest rent ($lnForIm_{it}$) is positively associated with import values of coniferous plywood but is not statistically significant. The negative and statistically significant coefficient of the exporter's GDP ($lnGDPEx_{jt}$) suggests that the US is inclined to import more from countries that have small economies. The estimated coefficient of the US's GDP ($lnGDPIm_{it}$) is positive and statistically significant, as expected.If US GDP increases by 10 percent,coniferous plywood imports would rise by 4.88 percent. As expected, the coefficient of exchange rate ($lnExRate_{ijt}$) is positive, but not statistically significant. The effect of both the exporter's production quantity ($lnProEx^{k}_{jt}$) and the US production quantity ($lnProIm^{k}_{it}$) are positive and statistically significant. The level of estimated effects of both variables are also quite large, suggesting that if coniferous plywood production in the exporting country increases by 10 percent, imports would rise by 19.42 percent more imports. Increase in US imports also stimulates domestic production of coniferous plywood. These results suggest that import values might stimulate domestic production, providing evidence of home bias.

The estimated coefficient of the LAA and restriction are negative, as expected, but not statistically significant, while the impact of WTO membership is positive but not statistically significant. As discussed before, I assume that inclusion of exporter-specific fixed effects might cause such a result overall my entire sample. Although estimated effects of the LAA and restriction do not yield significant responses, the direction of the LAA is correctly estimated.

The Impacts of the LAA on Non-coniferous Plywood Imports

The estimation results of the preferred specification (PPML FE) are presented in column 1 of Table 3.18, and columns 2 through 4 report the results of the alternative specifications. To determine whether the estimated models are correctly specified, the Reset specification test was carried out. The results suggest that all specifications except the OLS estimation are appropriate, but I focus on the results of preferred specification in discussion here. The estimated coefficient of distance ($lnDist_{ij}$) is positive and statistically significant. The negative and statistically significant coefficient of common language ($ComLan_{ij}$) indicates that sharing a common language does not facilitate trade. The impact of contiguity ($Cont_{ij}$) on imports is positive and statistically significant.

The effect of the exporter's forest rent ($lnForEx_{jt}$) on import values is positive but not statistically significant, whereas the positive and statistically significant coefficient of US forest rent ($lnForIm_{it}$) suggests that if a 10 percent increase in US forest rent would lead to 3.58 percent more imports of non-coniferous plywood. The estimated coefficient of the exporter's GDP ($lnGDPEx_{jt}$) is positive but not statistically significant. As expected, the positive and statistically significant coefficient of the US GDP ($lnGDPIm_{it}$) indicates that a 10 percent increase in US GDP would raise import values by 14.30 percent. The estimated effect of the exchange rate ($lnExRate_{ijt}$) on import values is negative and not statistically significant. The impact of production quantity in the exporting country ($lnProEx^{k}_{jt}$) on imports is positive and statistically significant (0.865). These results imply that US import demand for non-coniferous plywood may induce an increase in production volume in the exporting countries. The estimated coefficient of US production ($lnProIm^{k}_{it}$) is positive but not statistically significant. Although the effect is positive, I cannot find supporting evidence of home bias.

Finally, I turn to my main variable of interest, the effect of the LAA on non-coniferous import values. The negative and statistically coefficient estimates of the LAA indicate that implementation of such a trade policy would cause a 42.36[35] decrease in import values of non-coniferous plywood in the US. The estimated coefficient of restriction is positive and statistically significant. Considering both impacts, the LAA created a trade diversion on non-coniferous plywood imports. The results are also consistent with Prestemon (2015). The impact of being a WTO member has a positive but not statistically significant effect on the import values of non-coniferous imports.

3.6 Robustness Checks

Several estimation methods were employed as a robustness check to compare the findings of the previous section for each country and product group. As discussed earlier, zero trade flows and

[35] It is computed as [exp (-0.551)-1]*100.

heteroskedasticity are two main estimation challenges in the traditional gravity model. The omission of zero trade flows might cause issues because it might omit economically useful information in the sample. In addition, heteroscedasticity might lead to biased and inconsistent estimators in the model. Various methods such as ad hoc solutions and other econometric methods have been proposed by the previous literature to avoid the estimation challenges, such as an undefined zero logarithm in the traditional OLS, related to zero trade flows and heteroskedasticity (Gómez-Herrera and Gómez-Herrera, 2013; Martin and Pham, 2020; Silva and Tenreyro, 2006). The success of these approaches, of course, depends on the characteristics of the data and the selected estimation approach. For instance, the existence of high-frequency zero-values flows might be economically informative. Furthermore, truncating them raises additional concerns because doing so might produce unreliable results in international trade policy analysis.

To examine the impact of dropping zero trade flows and heteroskedasticity in my data, I estimated the preferred and alternative specifications by using two different approaches: (1) using a truncated sample that includes only positive import values in the PPML estimator (truncated PPML); and (2) adding an arbitrary number to allow inclusion of zero trade flows in the traditional OLS estimator,[36] hence avoiding the omitted zero trade flows bias in the traditional OLS estimator.

Under these considerations, I first estimated the truncated PPML estimators for the PPML FE and PPML specifications in which only positive trade flows were used as the dependent variable. Second, I run the OLS estimators (OLS FE and OLS) by using *ln(1+imports)* as my dependent variable without truncating the sample. Results of both the truncated PPML estimators and the *ln(1+imports)* OLS estimators for each country and product group are reported in Tables 3.19 through 3.34

Results of estimated coefficients for the truncated PPML estimators (PPML FE and PPML) yield results similar to corresponding parts of Tables 3.3 through 3.18. Although using the truncated PPML reduces the magnitude of coefficients, it yields similar results, in terms of direction and statistical significance, to those obtained from the PPML estimators presented in the previous section. These results are also in line with empirical findings of Martin and Pham (2020) and Silva and Tenreyro (2006). In conclusion, applying the truncated PPML estimators impacts the magnitude of coefficients but not the sign of parameters in the model. However, I do prefer the PPML estimators in my preferred because dependent variables in my data set contain a large share of zero import

[36] I added 1 to import values so that my dependent variable for the traditional OLS estimator becomes *ln(1+imports)* .

values (which is common in forest trade products flows).

Estimation results of the OLS *ln(1+imports)* are presented in columns 3 and 4 of Tables 3.19 through 3.34 . The results are notably different from the truncated OLS estimator reported in columns 3 and 4 of Tables 3.3 through 3.19. The OLS *ln(1+imports)* estimator generates notably smaller and different estimates compared to the truncated OLS estimators displayed. I also apply heteroskedasticity tests for both the OLS *ln(1+imports)* and the truncated (traditional) OLS estimators. Although I found evidence of heteroskedasticity in my sample for both the traditional OLS and the OLS *ln(1+imports)* estimators, the OLS *ln(1+imports)* yields higher test statistics compared with those of the traditional OLS.

3.7 Concluding Remarks

Illegal logging has been a global issue because of its detrimental environmental, economic, and social impacts. Several countries have attempted to take proactive trade measures to address the problem and prevent illegally traded timber from coming to their markets. Trade measures in key consuming countries—Australia, the EU, Japan, and the US—have affected trade patterns of imported wood products. While the purpose of such efforts is the same and enforcement practices are similar in broad sense, the implementation of these policies differs in terms of structure and due diligence process. Previous literature has investigated the impact of various policies either by focusing on only one country or region or by studying certain product groups. To understand current policy structures better and shed light on future policy tools, I explore the impacts of existing trade measures taken by global forest products consumers (Australia, the EU, Japan, and the US) to ban illegal timber trade and point out differences in trade measures taken by those consumers. Using the gravity model, I assess the economic aspects of trade measures on global forest products markets. Overall, I find a negative and significant effect of trade measures implemented by the countries on the importation of wood products. However, my results suggest that the negative impact of trade measures on the imports would vary by countries and product groups.

The enforcement of ILPA has decreased coniferous sawnwood imports by 22.8 percent and coniferous plywood imports by 43.22 percent. I also find significant evidence for trade diversion to the countries where trade measures apply. For instance, my estimates show that coniferous sawnwood imports would be 97 percent higher and non-coniferous sawnwood imports would increase by 60.3 percent if a country imposes a trade measure on illegal logging and related trade. This increase would be even higher (over 100 percent) for coniferous plywood imports because key trading partners of coniferous plywood include highly suspect countries (see Panel A of Fig. 3.6). I find a clear trade pattern change with the ratification of the ILPA in Australia. Australia is the only country where both exporters and domestic producers are subject to compliance with due diligence processes. Australia also makes efforts to form bilateral agreements with key trading partners and prepares guidelines to help them better understand the due diligence processes. Coniferous sawnwood and plywood imports have been on the rise since 2008. Unlike the EU, Australia does not permit CITES as a proof of legality, but it does recognize forest management and chain of custody certification from FSC and PEFC. The government takes action to work closely with states and territories to ensure the protection of high conservation areas and support sustainable practices in forest industry.

The EU's efforts to ban illegal trade imports date to 2003, but the EUTR was not enacted until 2013. The EUTR was designed to be a global trade policy to prohibit illegally traded timber with the purpose of improving domestic legal compliance in its key trading partners. VPAs have been the key component in the EUTR. Therefore, the EUTR implements a more integrated approach compared with other countries evaluated in this study. My results indicate that the implementation of the EUTR reduces coniferous sawnwood and non-coniferous plywood imports. According to my estimates, the implementation of the EUTR reduces coniferous sawnwood by 37.93 percent and decreases non-coniferous plywood by 26.66 percent. One of the interesting results I find is that the EUTR has a positive and statistically significant impact on non-coniferous sawnwood. However, key trading partners of non-coniferous sawnwood imports consist of countries that either ratified VPAs or are in negotiations (see Panel B of Fig. 3.7). Thus, I find that ratification of VPAs has been effective and does not impede trade; rather, it points out that countries make efforts to comply with the requirements of the EUTR. The EUTR's due diligence process is similar to those implemented by the ILPA. One of the key differences is that EUTR accepts CITES requirements as proof of legality, implying that wood included by CITES can be imported without due diligence obligation.

The structure of the JCWA is little different from other policies discussed here. It is a formal voluntary policy scheme aimed at preventing placement of illegally sourced timber in the forest products supply chain. In general, my results indicate a negative and statistically significant impact of the JCWA on imports. In investigating the implementation of the JCWA on coniferous sawnwood imports, I find that the JCWA would lead to a 55.42 percent decrease in coniferous sawnwood imports and Japan would import 25.23 percent more from the countries that have trade measures in place. This finding is not surprising because key trading partners of Japan for coniferous sawnwood include countries such as Finland, Sweden, USA, Austria, etc. for coniferous sawnwood (see Panel A of Fig. 3.9). These countries already enforce policies to prevent illegal logging timber trade from coming into their supply chain. On the other hand, I find that the JCWA would lead to a 40.49 percent decrease in non-coniferous sawnwood imports and would reduce coniferous plywood imports by 43.33 percent. The enactment of the JCWA affects coniferous sawnwood imports more than imports of other product groups because coniferous sawnwood imports account for the highest import values between 1997 and 2017.

The enactment of LAA, as the first demand-side policy model, was set as an example for other countries to develop trade measure that prohibit the importation of illegal forest products. The US approach has been adopted by other countries to develop their own policy agenda for curbing illegal logging. The impacts of the LAA on US imports display mixed results in this study. I find that implementation of the LAA increase coniferous sawnwood imports by 28.53 and that imports from the countries where legal laws are in place decline by 46.42 percent. Although this result is interesting, coniferous sawnwood imports have displayed a sharp increase after 2010, right after the enactment of LAA and Canada has been the major key trading partner since nearly all imports are from Canada (see Panel A of Fig. 3.11).The rest of the countries (Chile, New Zealand, Germany, Brazil etc.) who are the source of coniferous sawnwood are also countries where illegality is not a problem because majority of plantations consist of coniferous trees which assumed to be completely legal. However, results on the impacts of the LAA for non-coniferous sawnwood imports show the opposite direction compared with coniferous sawnwood imports. My results indicate that the LAA decreases importation of non-coniferous sawnwood by 46.9 percent, and I also find supporting evidence of trade diversion with a 68.81 percent increase in imports from countries that impose legal compliances on timber trade. For non-coniferous sawnwood imports, suspected source countries account for a large share of imports (see Panel B of Fig. 3.11). This would be the reason why the effects of LAA are much larger in magnitude for this product group. While I could not find a significant decrease for coniferous plywood, the results on the effects of the LAA are negative and statistically significant. My estimate shows that enactment of the LAA affects the import values, would decrease imports by 42.36 percent for non-coniferous plywood, and would divert trade patterns toward countries with enforcement efforts; in fact, the estimated effect was much higher. In conclusion, I would view the results on coniferous products (sawnwood and plywood) to be not important because the LAA may not affect them as expected.

Overall, the impact of trade measures to remove illegally sourced wood vary by selected product categories and individual countries because of technical and practical differences in policy structures and dynamics of the domestic forest industry in these countries. I find that the extent to which the efforts taken by countries to combat illegal logging have decreased the import values and caused trade diversion depend on product category. In particular, the vast majority of the world's problems with illegal timber sourcing are for non-coniferous wood products not for coniferous. The only country that trades on global markets in large quantities of likely illegally harvested of coniferous wood would be Russia since boreal forest in Russia consists mostly of coniferous wood. Russia's primary export market for illegal wood is China. More specifically, unprocessed logs enter into China's wood market and are being processed in China.

These national efforts by countries also have been setting an example for other countries to take initiatives, maybe not in a similar vein, and develop their own legal governance agenda to curb illegal logging. More recently, South Korea and China have passed new legislation to support international efforts to combat illegal logging, indicating that domestic trade measures taken by consuming countries have stimulated international efforts in processing countries to take actions for importation of legal timbers. These processing countries may not impose the tougher standards mandated by the countries studied in this study, but their efforts show a positive sign on the global forest market. In particular, China has a unique position as being the world's largest importer of both legal and illegal wood.That said, having trade measures in such countries would strengthen efforts made by other countries. To produce meaningful impacts to prevent illegal logging should be a collaborative effort of countries in policy decisions. One of the ways to reduce illegal logging and associated trade might be to encourage increased commitment of forming bilateral agreements with wood-producing countries.

Table 3.1: SITC Product Codes and Descriptions used in Australia Import Values

Product Name	Product Description	SITC Rev.3 Codes
Coniferous Sawnwood	Wood of coniferous species	2482
Non-Coniferous Sawnwood	Wood of non-coniferous species	2484
Coniferous Plywood	Plywood with outer plies of other than tropical or non-coniferous wood	63439
Non-Coniferous Plywood	Plywood of wood sheets with non-coniferous wood	6343 minus 63439

Table 3.2: HTS Product Codes and Descriptions used in the EU, Japan and the US Import Values

Product Type	HTS Code (1996-2006)	HTS Code (2006-2006)	HTS Code (2007-present)
Coniferous Sawnwood	4407.10	4407.10	4407.10
Non-coniferous Sawnwood	4407.24 to 4407.26 and 4407.29	4407.24 to 4407.26 and 4407.29	4407.21 to 4407.22 4407.25 to 4407.29
	4407.91 to 4407.92 and 4407.99	4407.91-4407.92 and 4407.99	4407.91 to 4407.95 and 4407.99
Coniferous Plywood	4412.19	4412.19	4412.39
Non-coniferous Plywood	4412 minus 4412.19	4412 minus 4412.19	4412 minus 4412.39

Table 3.3: Coniferous Sawnwood Estimation Results: Australia

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-9.940***	-1.890***	-6.339*	-1.394
	(3.216)	(0.201)	(3.298)	(1.044)
ComLan	-0.924	0.902**	9.560*	0.217
	(2.798)	(0.357)	(5.291)	(0.850)
Cont	-	-	-	-
	-	-	-	-
lnForEx	0.980***	-0.206	0.763	0.417
	(0.356)	(0.167)	(0.694)	(0.256)
lnForIm	-0.0936	0.319	-0.437	-0.194
	(0.302)	(0.288)	(0.398)	(0.388)
lnGDPEx	0.770	-1.099***	0.538	-0.306
	(0.490)	(0.135)	(1.053)	(0.238)
lnGDPIm	-0.103	1.304***	0.00578	0.884*
	(0.441)	(0.317)	(0.854)	(0.476)
lnExRate	-0.339***	-0.0959	-0.390	-0.138
	(0.113)	(0.0793)	(0.244)	(0.125)
lnProEx	0.923***	1.816***	0.862**	0.913***
	(0.292)	(0.117)	(0.423)	(0.212)
lnProIm	0.154	-0.521	1.278	1.120
	(0.429)	(0.428)	(0.936)	(0.866)
ILPA	-0.259***	-0.383***	-0.399	-0.693**
	(0.0801)	(0.110)	(0.279)	(0.338)
Restriction	0.679***	0.723***	1.114**	1.386**
	(0.218)	(0.242)	(0.442)	(0.547)
Member_WTO	2.155***	4.096***	1.049	2.013***
	(0.726)	(0.558)	(0.864)	(0.624)
Constant	80.67***	1.038	31.11	-9.696
	(31.15)	(3.265)	(28.89)	(11.80)
Observations	1,078	1,860	543	543
R-squared	0.940	0.905	0.790	0.422
Reset (p-value)	0.0151	0	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4: Non-coniferous Sawnwood Estimation Results: Australia

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-2.860***	-3.313***	-0.374	-2.360***
	(0.774)	(0.433)	(0.902)	(0.467)
ComLan	0.287	-0.304	1.865***	0.297
	(1.772)	(0.761)	(0.425)	(0.454)
Cont	-	-	-	-
	-	-	-	-
lnForEx	-0.00603	0.732***	0.184	0.224**
	(0.255)	(0.180)	(0.273)	(0.112)
lnForIm	-0.136	-0.717***	-0.214	-0.191
	(0.169)	(0.222)	(0.302)	(0.300)
lnGDPEx	0.151	0.600***	0.408	0.211
	(0.262)	(0.152)	(0.474)	(0.135)
lnGDPIm	0.598*	0.102	0.449	0.688**
	(0.343)	(0.359)	(0.458)	(0.327)
lnExRate	0.0230	-0.0338	-0.128*	-0.230**
	(0.106)	(0.0627)	(0.0656)	(0.0935)
lnProEx	0.191	0.489***	0.432**	0.362**
	(0.240)	(0.108)	(0.168)	(0.140)
lnProIm	1.149***	1.322**	1.638***	1.510***
	(0.347)	(0.537)	(0.448)	(0.565)
ILPA	-0.262	-0.382	0.218	0.0583
	(0.218)	(0.247)	(0.240)	(0.269)
Restriction	0.472**	2.167***	0.434	0.486
	(0.194)	(0.623)	(0.389)	(0.478)
Member_WTO	1.553***	2.684***	0.390	1.020*
	(0.436)	(0.717)	(0.474)	(0.569)
Constant	8.001	10.25*	-16.77**	0.783
	(8.405)	(6.012)	(8.156)	(6.920)
Observations	1,977	2,159	911	911
R-squared	0.920	0.724	0.826	0.435
Reset(p-value)	0.097	0.001	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5: Coniferous Plywood Estimation Results: Australia

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-6.661***	-1.837***	-6.114***	-1.592*
	(1.931)	(0.512)	(1.406)	(0.841)
ComLan	-4.239	1.928**	1.168	0.867
	(4.326)	(0.840)	(1.364)	(0.738)
Cont	-	-	-	-
	-	-	-	-
lnForEx	0.409	0.325*	0.949*	0.406**
	(0.429)	(0.171)	(0.538)	(0.200)
lnForIm	-0.798***	-0.510***	-0.0377	0.554
	(0.267)	(0.116)	(0.434)	(0.402)
lnGDPEx	1.070	-0.527	1.035*	0.0682
	(0.679)	(0.547)	(0.516)	(0.345)
lnGDPIm	-0.402	0.920*	0.164	1.395***
	(0.651)	(0.520)	(0.589)	(0.447)
lnExRate	-0.113	-0.0709	-0.488***	-0.0910
	(0.214)	(0.0811)	(0.103)	(0.120)
lnProEx	0.465	0.866**	0.460	0.295
	(0.306)	(0.358)	(0.275)	(0.203)
lnProIm	0.00116	-0.227	-0.103	0.363
	(0.321)	(0.301)	(0.496)	(0.489)
ILPA	-0.566***	-0.383***	-0.386	-0.302
	(0.200)	(0.141)	(0.256)	(0.269)
Restriction	2.062***	0.396	1.458**	0.448
	(0.667)	(0.451)	(0.706)	(0.544)
Member_WTO	3.109***	3.655***	3.143***	2.093*
	(0.441)	(1.020)	(0.738)	(1.051)
Constant	50.69***	3.525	39.65***	-0.769
	(19.51)	(7.644)	(11.56)	(9.642)
Observations	820	1,483	385	385
R-squared	0.832	0.634	0.783	0.450
Reset (p-value)	0.9689	0.5026	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.6: Non-coniferous Plywood Estimation Results: Australia

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-2.836***	-2.842***	-3.283	-1.556***
	(0.661)	(0.581)	(2.982)	(0.429)
ComLan	-1.295	0.558	-1.024	0.0728
	(2.200)	(0.880)	(5.906)	(0.533)
Cont	-	-	-	-
	-	-	-	-
lnForEx	-0.475***	0.143	0.00713	-0.0440
	(0.133)	(0.260)	(0.746)	(0.129)
lnForIm	0.358*	0.00390	-0.327	-0.0626
	(0.183)	(0.247)	(0.673)	(0.458)
lnGDPEx	-0.622	-0.123	0.296	-0.242
	(0.418)	(0.316)	(0.941)	(0.225)
lnGDPIm	1.741***	1.127**	0.338	0.961
	(0.515)	(0.443)	(1.164)	(0.589)
lnExRate	-0.306*	0.0582**	-0.233	0.124
	(0.183)	(0.0271)	(0.271)	(0.114)
lnProEx	0.602***	0.847***	0.0928	0.604***
	(0.219)	(0.185)	(0.280)	(0.152)
lnProIm	0.0994***	0.164***	0.623*	0.586*
	(0.0327)	(0.0541)	(0.359)	(0.329)
ILPA	-0.148	-0.203	-0.397	-0.383
	(0.0907)	(0.187)	(0.334)	(0.499)
Restriction	0.0715	0.844	0.924	-0.105
	(0.355)	(0.639)	(0.555)	(0.611)
Member_WTO	1.634***	1.621**	1.933***	2.335**
	(0.351)	(0.770)	(0.705)	(1.017)
Constant	13.77***	10.14*	18.95	0.565
	(4.686)	(5.947)	(31.32)	(5.616)
Observations	641	1,755	274	274
R-squared	0.848	0.835	0.763	0.527
Reset(p-value)	0.1382	0	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.7: Coniferous Sawnwood Estimation Results: the EU

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-1.035***	-1.511***	-2.235***	-0.897***
	(0.363)	(0.164)	(0.232)	(0.121)
ComLan	0.662**	0.109	0.441**	0.131
	(0.263)	(0.251)	(0.200)	(0.234)
Cont	0.611	0.201	1.562***	2.131***
	(0.415)	(0.325)	(0.416)	(0.350)
lnForEx	0.378**	0.442***	0.196	0.422***
	(0.157)	(0.159)	(0.124)	(0.0837)
lnForIm	-0.716***	-0.626***	-0.425***	-0.486***
	(0.177)	(0.178)	(0.128)	(0.162)
lnGDPEx	0.125	-0.195*	-0.0784	-0.114
	(0.154)	(0.113)	(0.124)	(0.0813)
lnGDPIm	0.377**	0.565***	0.808***	0.441***
	(0.177)	(0.126)	(0.135)	(0.146)
lnExRate	-0.126	-0.0409	0.0857*	-0.0108
	(0.0988)	(0.0566)	(0.0487)	(0.0443)
lnProEx	0.264	1.443***	0.0891	0.775***
	(0.211)	(0.114)	(0.112)	(0.0523)
lnProIm	0.328**	0.224**	0.0699	0.183
	(0.131)	(0.113)	(0.103)	(0.123)
EUTR	-0.477***	-0.812***	0.00959	-0.254*
	(0.182)	(0.227)	(0.111)	(0.147)
Restriction	-0.0220	0.244	0.0411	0.530**
	(0.265)	(0.284)	(0.148)	(0.219)
Member_WTO	-0.150	0.0112	-0.192	0.330
	(0.197)	(0.203)	(0.199)	(0.301)
Constant	-5.942	-4.950***	4.286*	-4.635***
	(3.810)	(1.541)	(2.281)	(1.353)
Observations	17,780	19,510	5,139	5,139
R-squared	0.720	0.645	0.722	0.449
Reset(p-value)	0.861	0.0004	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.8: Non-coniferous Sawnwood Estimation Results: the EU

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-2.068***	-0.747***	-1.372***	-0.323***
	(0.339)	(0.127)	(0.143)	(0.0710)
ComLan	0.177	0.782***	0.434***	0.708***
	(0.209)	(0.260)	(0.112)	(0.161)
Cont	0.260	0.772	0.216	0.348
	(0.288)	(0.557)	(0.256)	(0.359)
lnForEx	0.414**	0.832***	0.276**	0.269***
	(0.189)	(0.127)	(0.118)	(0.0527)
lnForIm	-0.552***	-0.571***	-0.378***	-0.159**
	(0.131)	(0.167)	(0.0587)	(0.0786)
lnGDPEx	0.259	0.0875	0.467***	-0.0384
	(0.166)	(0.0763)	(0.0847)	(0.0458)
lnGDPIm	0.0505	0.0533	0.319***	0.311***
	(0.168)	(0.160)	(0.0685)	(0.0936)
lnExRate	0.0891	0.00719	-0.202***	-0.0223
	(0.0801)	(0.0365)	(0.0476)	(0.0279)
lnProEx	0.314***	0.947***	0.148**	0.482***
	(0.108)	(0.0810)	(0.0632)	(0.0425)
lnProIm	0.294***	0.364***	0.217***	0.0463
	(0.0838)	(0.0953)	(0.0498)	(0.0692)
EUTR	0.0774	0.0924	0.156**	0.497***
	(0.0859)	(0.131)	(0.0782)	(0.0886)
Restriction	1.258***	1.403***	1.096***	0.665***
	(0.150)	(0.251)	(0.142)	(0.166)
Member_WTO	1.450***	1.389***	1.485***	0.393**
	(0.224)	(0.270)	(0.251)	(0.198)
Constant	10.04***	-6.352***	2.188*	-4.927***
	(3.492)	(1.377)	(1.307)	(0.740)
Observations	23,220	24,300	7,842	7,842
R-squared	0.455	0.204	0.525	0.234
Reset(p-value)	0.687	0.0609	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.9: Coniferous Plywood Estimation Results: the EU

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-1.472***	-1.783***	-1.499***	-0.795***
	(0.426)	(0.241)	(0.256)	(0.142)
ComLan	0.927**	2.128***	0.0813	0.686**
	(0.377)	(0.392)	(0.246)	(0.314)
Cont	-0.278	-1.371**	0.426	0.415
	(0.455)	(0.667)	(0.412)	(0.360)
lnForEx	0.591***	1.390***	0.304	0.520***
	(0.221)	(0.193)	(0.248)	(0.122)
lnForIm	-0.0299	0.0715	-0.301**	-0.208
	(0.197)	(0.240)	(0.134)	(0.161)
lnGDPEx	0.00335	0.204	-0.0126	0.0353
	(0.208)	(0.193)	(0.170)	(0.123)
lnGDPIm	0.984***	0.993***	0.666***	0.589***
	(0.305)	(0.261)	(0.127)	(0.165)
lnExRate	-0.334	-0.116*	-0.0955	-0.0402
	(0.337)	(0.0623)	(0.0653)	(0.0416)
lnProEx	0.424***	1.003***	0.291***	0.612***
	(0.0859)	(0.123)	(0.102)	(0.0682)
lnProIm	-0.228**	-0.222*	-0.126*	-0.120
	(0.0986)	(0.121)	(0.0695)	(0.0778)
EUTR	-0.204	-0.578***	-0.357**	-0.159
	(0.160)	(0.196)	(0.165)	(0.213)
Restriction	-0.890***	-0.660**	-0.532***	-0.788**
	(0.204)	(0.287)	(0.203)	(0.335)
Member_WTO	-0.157	-0.831**	0.280	0.0362
	(0.344)	(0.420)	(0.329)	(0.328)
Constant	7.728**	3.678*	0.510	-2.260*
	(3.613)	(2.088)	(2.416)	(1.217)
Observations	8,088	10,153	2,239	2,239
R-squared	0.590	0.361	0.549	0.323
Reset(p-value)	0.6709	0.7876	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.10: Non-coniferous Plywood Estimation Results: the EU

Estimation Methods	PPML FE	PPML	OLS FE	OLS
lnDist	-1.052***	-1.513***	-0.963***	-1.289***
	(0.338)	(0.167)	(0.292)	(0.138)
ComLan	1.513***	0.711*	0.723**	0.513*
	(0.519)	(0.374)	(0.290)	(0.271)
Cont	0.338	0.478	0.630*	0.687**
	(0.313)	(0.337)	(0.350)	(0.349)
lnForEx	-0.269	0.253*	0.0949	0.293**
	(0.188)	(0.140)	(0.181)	(0.126)
lnForIm	0.0214	-0.0898	-0.162*	-0.157
	(0.104)	(0.133)	(0.0959)	(0.122)
lnGDPEx	-0.312*	0.0382	-0.119	-0.126
	(0.178)	(0.145)	(0.167)	(0.110)
lnGDPIm	0.937***	0.820***	0.965***	0.912***
	(0.179)	(0.200)	(0.125)	(0.138)
lnExRate	-0.0634	0.0412	-0.0759	0.0192
	(0.114)	(0.0701)	(0.0861)	(0.0455)
lnProEx	0.664***	1.008***	0.427***	0.828***
	(0.108)	(0.104)	(0.0900)	(0.0816)
lnProIm	-0.143*	-0.179**	-0.127**	-0.143*
	(0.0739)	(0.0860)	(0.0599)	(0.0776)
EUTR	-0.302***	-0.586***	-0.197	-0.0957
	(0.111)	(0.122)	(0.137)	(0.186)
Restriction	0.298	0.543**	0.357*	-0.0125
	(0.206)	(0.257)	(0.207)	(0.322)
Member_WTO	0.518***	0.276	0.581**	0.165
	(0.168)	(0.242)	(0.225)	(0.249)
Constant	-2.250	1.421	0.130	0.242
	(2.984)	(1.124)	(2.702)	(1.169)
Observations	7,764	12,745	2,021	2,021
R-squared	0.592	0.294	0.619	0.406
Reset (p-value)	0.7908	0.0041	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.11: Coniferous Sawnwood Estimation Results: Japan

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-1.645	-0.270*	1.228	-0.937**
	(1.276)	(0.156)	(1.625)	(0.464)
ComLan	0.893	-2.655***	-6.290	-3.146***
	(3.654)	(0.424)	(4.719)	(0.814)
Cont	-	-	-	-
	-	-	-	-
lnForEx	0.546***	0.0472	-0.0366	0.809***
	(0.205)	(0.158)	(0.319)	(0.293)
lnForIm	0.0471	0.723***	-0.864***	-0.418
	(0.234)	(0.244)	(0.290)	(0.296)
lnGDPEx	0.621**	-0.729***	0.799*	0.346
	(0.295)	(0.141)	(0.472)	(0.224)
lnGDPIm	0.901**	2.541***	0.0166	0.699
	(0.445)	(0.410)	(0.546)	(0.783)
lnExRate	-0.0340	0.0333	-0.0588	0.150
	(0.154)	(0.0480)	(0.0889)	(0.108)
lnProEx	0.345	2.065***	0.550**	0.962***
	(0.384)	(0.180)	(0.221)	(0.185)
lnProIm	0.866***	0.147	1.672***	0.185
	(0.265)	(0.214)	(0.518)	(0.505)
JCWA	-0.808***	-1.216***	-0.230	-0.344
	(0.0741)	(0.0857)	(0.213)	(0.228)
Restriction	0.225**	5.54e-05	0.644**	-0.0126
	(0.0931)	(0.123)	(0.321)	(0.477)
Member_WTO	0.306	0.635**	0.661	0.887
	(0.225)	(0.256)	(0.646)	(0.751)
Constant	-7.577	-27.82***	-37.24**	-8.247
	(14.28)	(4.125)	(18.39)	(9.300)
Observations	1,240	2,064	763	763
R-squared	0.949	0.923	0.895	0.492
Reset (p-value)	0.0921	0	0.006	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.12: Non-coniferous Sawnwood Estimation Results: Japan

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-1.634***	-0.600***	-0.606**	-0.930**
	(0.167)	(0.147)	(0.272)	(0.410)
ComLan	8.119***	-1.369***	5.978***	1.293**
	(0.935)	(0.322)	(1.092)	(0.627)
Cont	-	-	-	-
	-	-	-	-
lnForEx	-0.212	0.815***	-0.263	0.155
	(0.234)	(0.244)	(0.277)	(0.129)
lnForIm	0.475***	-1.439***	0.306	-0.253
	(0.115)	(0.467)	(0.295)	(0.234)
lnGDPEx	-1.014***	0.502***	-0.422*	0.153
	(0.175)	(0.180)	(0.236)	(0.121)
lnGDPIm	1.275***	-2.890***	0.894**	-0.221
	(0.222)	(0.945)	(0.422)	(0.523)
lnExRate	-0.104	-0.0138	-0.000884	-0.0624
	(0.118)	(0.111)	(0.0941)	(0.0745)
lnProEx	0.182	0.754***	0.293*	0.590***
	(0.161)	(0.206)	(0.150)	(0.106)
lnProIm	0.196***	0.462***	0.0970	0.142
	(0.0404)	(0.0785)	(0.0723)	(0.0887)
JCWA	-0.340***	-0.868***	-0.167	-0.450***
	(0.111)	(0.242)	(0.121)	(0.164)
Restriction	-0.0418	1.176***	-0.00706	0.197
	(0.0917)	(0.417)	(0.267)	(0.427)
Member_WTO	0.189**	-0.0131	0.0575	-0.233
	(0.0890)	(0.618)	(0.478)	(0.482)
Constant	4.710**	14.27**	-4.917	3.147
	(2.313)	(6.287)	(3.539)	(5.751)
Observations	2,472	2,507	1,434	1,434
R-squared	0.933	0.535	0.801	0.401
Reset (p-value)	0.0013	0.3695	0.0039	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.13: Coniferous Plywood Estimation Results: Japan

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-0.794	0.435	-2.147*	-0.0564
	(0.770)	(0.670)	(1.131)	(0.450)
ComLan	-4.671***	-4.930***	0.376	-3.530***
	(1.169)	(0.926)	(1.598)	(0.693)
Cont				
lnForEx	1.941***	0.0900	0.914	0.323
	(0.439)	(0.198)	(0.785)	(0.332)
lnForIm	0.0419	0.100	-1.503*	0.0164
	(0.192)	(0.297)	(0.808)	(0.594)
lnGDPEx	0.410	-0.601	1.033	-0.514
	(0.283)	(0.414)	(0.629)	(0.373)
lnGDPIm	1.165**	1.771*	0.518	2.755**
	(0.538)	(0.915)	(1.536)	(1.265)
lnExRate	0.496*	-0.188	-0.102	-0.0299
	(0.278)	(0.124)	(0.122)	(0.106)
lnProEx	0.944***	1.027**	0.627***	0.696***
	(0.244)	(0.399)	(0.194)	(0.228)
lnProIm	-0.531**	-1.334***	-1.403**	0.0976
	(0.263)	(0.515)	(0.625)	(0.569)
JCWA	-0.568***	-0.599***	-0.180	-0.0936
	(0.130)	(0.136)	(0.325)	(0.317)
Restriction	0.709**	-1.355***	1.272**	-0.436
	(0.300)	(0.520)	(0.485)	(0.582)
Member_WTO	0.500	2.695***	0.0919	2.323**
	(0.620)	(1.024)	(0.768)	(1.038)
Constant	-3.317	-13.45	4.900	-26.91***
	(7.813)	(9.619)	(17.95)	(9.411)
Observations	615	1,553	363	363
R-squared	0.901	0.201	0.759	0.409
Reset(p-value)	0.031	0.3075	0.0127	0.0103
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.14: Non-coniferous Plywood Estimation Results: Japan

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-1.152**	-0.253	-0.939	-0.382
	(0.525)	(0.548)	(0.903)	(0.516)
ComLan	0.895*	-1.377	0.263	-2.529***
	(0.498)	(1.192)	(1.486)	(0.634)
Cont				
lnForEx	0.224	1.471***	0.348	0.445**
	(0.150)	(0.189)	(0.577)	(0.175)
lnForIm	-0.508***	-0.634***	-0.697	-0.513
	(0.174)	(0.133)	(0.613)	(0.451)
lnGDPEx	0.545***	0.502	0.576	-0.286
	(0.137)	(0.318)	(0.613)	(0.211)
lnGDPIm	-0.0640	0.905*	-0.437	0.611
	(0.195)	(0.514)	(0.835)	(0.858)
lnExRate	-0.202*	0.280***	-0.128	0.0460
	(0.103)	(0.0369)	(0.132)	(0.110)
lnProEx	0.620***	1.223***	0.201	0.997***
	(0.115)	(0.157)	(0.302)	(0.160)
lnProIm	0.160***	-0.112	0.514*	0.0825
	(0.0547)	(0.196)	(0.271)	(0.198)
JCWA	-0.548	-0.452	-0.0929	-0.485
	(0.365)	(0.358)	(0.313)	(0.411)
Restriction	-0.103	0.839	0.680	0.0660
	(0.711)	(1.144)	(0.540)	(0.849)
Member_WTO	0.808***	1.514**	3.882**	2.462***
	(0.268)	(0.719)	(1.664)	(0.724)
Constant	-1.409	-16.59*	-4.201	-8.906
	(4.351)	(8.543)	(6.587)	(7.927)
Observations	618	1,947	323	323
R-squared	0.932	0.796	0.899	0.733
Reset (p-value)	0.4641	0.4995	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.15: Coniferous Sawnwood Estimation Results: the U.S

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	3.093**	-0.425	-0.109	-0.458
	(1.207)	(0.497)	(0.941)	(0.713)
ComLan	1.747	2.381***	6.519***	0.663
	(2.385)	(0.331)	(1.998)	(0.708)
Cont	9.526**	-0.293	5.089	3.281*
	(3.854)	(0.840)	(3.900)	(1.813)
lnForEx	-0.0343	-0.0966	0.231	0.518**
	(0.164)	(0.119)	(0.300)	(0.203)
lnForIm	0.648***	0.798***	-0.576	-0.0958
	(0.196)	(0.126)	(0.505)	(0.460)
lnGDPEx	-0.957***	-0.613***	0.208	-0.0139
	(0.177)	(0.125)	(0.493)	(0.244)
lnGDPIm	1.495***	0.912***	0.531	1.647*
	(0.291)	(0.299)	(1.197)	(0.873)
lnExRate	-0.367*	-0.114**	-0.162*	-0.0766
	(0.191)	(0.0539)	(0.0900)	(0.119)
lnProEx	0.696**	1.914***	0.472	0.719***
	(0.347)	(0.143)	(0.291)	(0.158)
lnProIm	1.592***	0.718***	1.831**	0.519
	(0.259)	(0.262)	(0.878)	(1.011)
LAA	0.251**	0.405**	-1.017***	-1.112***
	(0.124)	(0.163)	(0.325)	(0.376)
Restriction	-0.624**	-0.694***	0.396	0.0623
	(0.245)	(0.232)	(0.351)	(0.434)
Member_WTO	1.229**	1.732***	1.012	1.711**
	(0.572)	(0.374)	(0.919)	(0.768)
Constant	-58.22***	-22.83***	-35.58***	-23.21**
	(11.19)	(5.171)	(12.39)	(11.17)
Observations	1,699	2,277	955	955
R-squared	0.990	0.981	0.832	0.431
Reset(p-value)	0.0201	0.2442	0	0
Exporter FE	.	No	No	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.16: Non-coniferous Sawnwood Estimation Results: the U.S

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	1.273***	-1.332***	-2.695***	-0.370
	(0.355)	(0.318)	(0.596)	(0.424)
ComLan	9.996***	1.013***	8.192***	1.281***
	(1.081)	(0.376)	(1.004)	(0.360)
Cont	-1.946	0.912*	-2.629*	2.045
	(1.503)	(0.536)	(1.339)	(1.301)
lnForEx	0.754***	0.403**	0.305	0.202*
	(0.209)	(0.166)	(0.189)	(0.118)
lnForIm	-0.0939	-0.0459	0.390	0.139
	(0.414)	(0.336)	(0.290)	(0.281)
lnGDPEx	0.200	0.0746	-0.146	-0.0129
	(0.193)	(0.208)	(0.282)	(0.132)
lnGDPIm	1.424**	1.343*	2.570***	1.583***
	(0.615)	(0.755)	(0.788)	(0.485)
lnExRate	-0.132**	-0.200***	-0.0916	-0.154**
	(0.0597)	(0.0677)	(0.0643)	(0.0628)
lnProEx	0.200**	0.746***	0.371***	0.602***
	(0.0995)	(0.157)	(0.126)	(0.112)
lnProIm	0.411	0.585	-1.570***	-0.813
	(0.350)	(0.438)	(0.465)	(0.563)
LAA	-0.633***	-0.435***	-1.006***	-0.545**
	(0.101)	(0.133)	(0.202)	(0.253)
Restriction	0.524***	0.139	0.336	-0.142
	(0.203)	(0.532)	(0.217)	(0.330)
Member_WTO	1.410***	2.186***	0.926***	1.706***
	(0.353)	(0.601)	(0.293)	(0.395)
Constant	-36.66***	-12.47**	8.104	-8.611
	(3.836)	(6.151)	(9.160)	(8.024)
Observations	2,581	2,726	1,667	1,667
R-squared	0.941	0.822	0.807	0.369
Reset (P-value)	0.0019	0.2666	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.17: Coniferous Plywood Estimation Results: The U.S

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	-1.388***	-3.174***	-2.457	-3.120**
	(0.198)	(0.836)	(2.600)	(1.372)
ComLan	8.207**	6.185***	5.119**	1.524
	(4.109)	(0.681)	(1.931)	(0.944)
Cont		-3.590***		-2.117
		(1.175)		(2.459)
lnForEx	-0.205	0.166	0.931*	0.370
	(0.232)	(0.192)	(0.543)	(0.315)
lnForIm	0.279	-0.210	-0.608	-0.861
	(0.657)	(0.314)	(0.687)	(0.893)
lnGDPEx	-1.267***	-0.723**	-0.00369	0.197
	(0.181)	(0.284)	(0.684)	(0.397)
lnGDPIm	4.886***	4.116***	2.427	2.986*
	(0.862)	(0.963)	(2.399)	(1.504)
lnExRate	0.295	0.117	0.0224	0.0673
	(0.761)	(0.0802)	(0.298)	(0.134)
lnProEx	1.942***	2.332***	0.833**	0.698***
	(0.249)	(0.300)	(0.355)	(0.210)
lnProIm	1.875**	2.079***	2.447*	2.512
	(0.823)	(0.589)	(1.225)	(1.604)
LAA	-0.280	-0.505***	-0.0528	0.0134
	(0.212)	(0.122)	(0.683)	(0.675)
Restriction	-1.199	0.310	-0.127	-1.603
	(1.015)	(1.073)	(0.830)	(0.993)
Member_WTO	0.297	-1.309	1.519	0.726
	(1.112)	(1.447)	(2.971)	(0.973)
Constant	-62.54***	-43.50**	-35.25	-32.99
	(14.71)	(17.64)	(24.16)	(28.89)
Observations	894	1,634	350	350
R-squared	0.926	0.911	0.817	0.528
Reset (p-value)	0.0003	0	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.18: Non-coniferous Plywood Estimation Results: the U.S

Estimation Method	PPML FE	PPML	OLS FE	OLS
lnDist	2.463***	-1.859***	3.438***	-0.432
	(0.491)	(0.491)	(1.020)	(0.645)
ComLan	-3.197***	-0.00728	-3.327	0.177
	(1.139)	(0.355)	(2.064)	(0.642)
Cont	5.481***	0.791	7.112**	2.369**
	(1.171)	(0.770)	(2.773)	(1.154)
lnForEx	0.124	0.506***	0.467	0.102
	(0.182)	(0.136)	(0.285)	(0.175)
lnForIm	0.334*	0.190	0.0772	0.211
	(0.195)	(0.184)	(0.394)	(0.438)
lnGDPEx	0.0433	0.361**	-0.259	-0.0681
	(0.217)	(0.153)	(0.444)	(0.202)
lnGDPIm	1.430***	1.156***	2.498**	1.969**
	(0.399)	(0.304)	(0.977)	(0.843)
lnExRate	-0.0145	0.124***	-0.194	-0.0569
	(0.126)	(0.0261)	(0.125)	(0.101)
lnProEx	0.865***	1.071***	0.572***	0.878***
	(0.115)	(0.0942)	(0.143)	(0.150)
lnProIm	0.0955	0.352	0.112	0.888
	(0.779)	(0.543)	(0.749)	(0.816)
LAA	-0.551***	-0.712***	-0.779***	-0.525**
	(0.0938)	(0.169)	(0.208)	(0.258)
Restriction	0.888**	0.760*	0.773**	0.492
	(0.373)	(0.388)	(0.327)	(0.511)
Member_WTO	0.601	0.207	1.778**	-0.364
	(0.421)	(0.378)	(0.672)	(1.050)
Constant	-36.62***	-1.828	-54.06***	-23.22**
	(7.556)	(5.057)	(14.62)	(10.79)
Observations	1,028	2,000	780	780
R-squared	0.945	0.910	0.844	0.456
Reset (p-value)	0.9107	0.8487	0.1515	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 3.19: Robustness Checks for Coniferous Sawnwood: Australia

Estimation Method	Truncated PPML FE	Truncated PPML	OLS(1+imports) FE	OLS(1+imports)
lnDist	-6.413***	-1.674***	-0.268	-0.365
	(1.572)	(0.238)	(0.220)	(0.454)
ComLan	10.47***	0.937**	-0.283*	0.0857
	(2.938)	(0.387)	(0.150)	(0.157)
Cont	-	-	-	-
	-	-	-	-
lnForEx	0.979***	-0.289	0.0159	0.0560
	(0.354)	(0.201)	(0.0778)	(0.0368)
lnForIm	-0.0374	0.297	-0.0572	-0.0386
	(0.310)	(0.296)	(0.0391)	(0.0412)
lnGDPEx	0.643	-1.013***	0.0637	-0.0390
	(0.418)	(0.132)	(0.100)	(0.0459)
lnGDPIm	0.00162	1.203***	0.0256	0.124*
	(0.431)	(0.339)	(0.101)	(0.0721)
lnExRate	-0.315***	-0.0891	-0.0211	-0.0164
	(0.100)	(0.0948)	(0.0151)	(0.0224)
lnProEx	0.904***	1.520***	0.0411	0.150***
	(0.285)	(0.151)	(0.0266)	(0.0437)
lnProIm	0.117	-0.552	0.0766	0.0562
	(0.434)	(0.480)	(0.121)	(0.111)
ILPA	-0.233***	-0.350***	-0.0550*	-0.0708
	(0.0819)	(0.0975)	(0.0281)	(0.0542)
Restriction	0.601***	0.564**	0.318***	0.358*
	(0.211)	(0.272)	(0.0970)	(0.187)
Member_WTO	2.042***	3.707***	0.161	0.226
	(0.708)	(0.410)	(0.132)	(0.160)
Constant	40.54***	2.548	1.892	1.612
	(12.95)	(3.263)	(2.458)	(4.351)
Observations	543	543	1,860	1,860
R-squared	0.939	0.896	0.858	0.254
Reset(p-value)	0.0164	0	0	0
Exporter FE	Yes	No	Yes	Yes

Robust standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 3.20: Robustness Checks for Non-coniferous Sawnwood: Australia

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-1.281*	-2.824***	-0.103	-0.516***
	(0.678)	(0.460)	(0.135)	(0.151)
ComLan	1.902***	-0.709	0.649***	0.101
	(0.393)	(0.793)	(0.227)	(0.0765)
Cont	-	-	-	-
	-	-	-	-
lnForEx	0.00889	0.775***	0.0159	0.0756**
	(0.260)	(0.195)	(0.0282)	(0.0302)
lnForIm	-0.142	-0.754***	-0.00431	-0.0642*
	(0.169)	(0.232)	(0.0241)	(0.0347)
lnGDPEx	0.157	0.622***	0.0116	0.0811***
	(0.261)	(0.164)	(0.0487)	(0.0295)
lnGDPIm	0.586*	0.0759	0.0676	0.0141
	(0.345)	(0.349)	(0.0481)	(0.0345)
lnExRate	0.0231	-0.00897	-0.00484	-0.0247
	(0.106)	(0.0617)	(0.00575)	(0.0236)
lnProEx	0.171	0.394***	0.0253	0.0510*
	(0.247)	(0.119)	(0.0166)	(0.0269)
lnProIm	1.132***	1.331**	0.130***	0.172***
	(0.347)	(0.528)	(0.0352)	(0.0447)
ILPA	-0.255	-0.339	-0.00162	-0.0386
	(0.221)	(0.257)	(0.0196)	(0.0321)
Restriction	0.457**	1.941***	0.0551**	0.221*
	(0.194)	(0.578)	(0.0267)	(0.128)
Member_WTO	1.717***	2.728***	0.0550	0.108
	(0.412)	(0.735)	(0.0435)	(0.0850)
Constant	-6.084	6.974	-0.506	3.024**
	(6.154)	(6.235)	(1.296)	(1.211)
Observations	911	911	2,159	2,159
R-squared	0.915	0.720	0.931	0.337
Reset (p-value)	0.085	0.0001	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.21: Robustness Checks for Coniferous Plywood: Australia

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-7.347***	-1.324**	-0.0977	-0.500*
	(1.888)	(0.567)	(0.154)	(0.256)
ComLan	5.491***	1.381	0.513	0.128*
	(2.075)	(0.913)	(0.359)	(0.0769)
Cont	-	-	-	-
	-	-	-	-
lnForEx	0.140	0.232	0.0280	0.0397*
	(0.478)	(0.194)	(0.0414)	(0.0211)
lnForIm	-0.199	0.0467	-0.118**	-0.0707**
	(0.305)	(0.208)	(0.0513)	(0.0331)
lnGDPEx	1.270*	-0.626	0.125	0.00581
	(0.676)	(0.513)	(0.0767)	(0.0291)
lnGDPIm	-0.355	1.302**	-0.0339	0.0973*
	(0.681)	(0.552)	(0.0696)	(0.0535)
lnExRate	0.0620	-0.0610	-0.00166	-0.0259
	(0.270)	(0.0657)	(0.00574)	(0.0184)
lnProEx	0.366	0.806**	0.0486	0.0756**
	(0.310)	(0.350)	(0.0339)	(0.0313)
lnProIm	0.386*	0.135	-0.0120	-0.0100
	(0.214)	(0.204)	(0.0313)	(0.0268)
ILPA	-0.440**	-0.258*	-0.0781**	-0.0459
	(0.176)	(0.153)	(0.0371)	(0.0296)
Restriction	2.031***	0.289	0.0849	-0.0605
	(0.601)	(0.648)	(0.0559)	(0.0766)
Member_WTO	2.190***	2.679**	0.117	0.0589
	(0.619)	(1.127)	(0.140)	(0.0619)
Constant	45.72***	-1.610	0.405	3.854
	(14.62)	(7.809)	(1.605)	(2.512)
Observations	385	385	1,483	1,483
R-squared	0.877	0.624	0.761	0.368
Reset(p-value)	0.3395	0.0088	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 3.22: Robustness Checks for Non-coniferous Plywood: Australia

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-4.748**	-1.361***	-0.245**	-0.383**
	(1.863)	(0.450)	(0.119)	(0.153)
ComLan	1.587	0.485	0.178	0.0330
	(3.026)	(0.512)	(0.296)	(0.0521)
Cont				
lnForEx	-0.978***	-0.0525	-0.0132	0.0222
	(0.171)	(0.148)	(0.0254)	(0.0183)
lnForIm	1.125***	0.593**	-0.0501	-0.0483
	(0.244)	(0.256)	(0.0379)	(0.0301)
lnGDPEx	-0.635	-0.340	0.0290	0.0102
	(0.449)	(0.223)	(0.0586)	(0.0183)
lnGDPIm	1.813***	1.449***	0.0203	0.0502
	(0.508)	(0.368)	(0.0646)	(0.0399)
lnExRate	-0.165	0.0895***	-0.00427	0.00153
	(0.171)	(0.0241)	(0.00435)	(0.0212)
lnProEx	0.718***	0.689***	0.0180	0.0834**
	(0.228)	(0.132)	(0.0184)	(0.0352)
lnProIm	0.0145	0.140**	0.0127	0.00364
	(0.0507)	(0.0566)	(0.00781)	(0.00899)
ILPA	0.0834	0.0627	-0.0568**	-0.0680*
	(0.0622)	(0.201)	(0.0264)	(0.0345)
Restriction	0.455**	-0.0603	0.0344	0.0297
	(0.178)	(0.555)	(0.0243)	(0.0726)
Member_WTO	0.696*	1.075*	0.124	0.0753
	(0.423)	(0.574)	(0.104)	(0.0732)
Constant	27.89	-0.492	1.819	2.870**
	(18.46)	(4.699)	(1.271)	(1.307)
Observations	274	274	1,755	1,755
R-squared	0.935	0.891	0.811	0.301
Reset(p-value)	0.0008	0	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 3.23: Robustness Checks for Coniferous Sawnwood: the EU

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-1.311***	-1.508***	-0.379***	-0.264***
	(0.344)	(0.179)	(0.111)	(0.0330)
ComLan	0.461*	0.0536	0.0358	-0.0212
	(0.251)	(0.252)	(0.0328)	(0.0467)
Cont	1.077***	0.567	0.719**	0.765***
	(0.366)	(0.371)	(0.343)	(0.265)
lnForEx	0.295***	0.501***	0.0279**	0.0625***
	(0.108)	(0.165)	(0.0131)	(0.00829)
lnForIm	-0.690***	-0.648***	-0.0801***	-0.0917***
	(0.170)	(0.173)	(0.0222)	(0.0315)
lnGDPEx	0.0334	-0.140	0.00366	0.00292
	(0.139)	(0.119)	(0.0158)	(0.0118)
lnGDPIm	0.485***	0.593***	0.0689***	0.0595**
	(0.178)	(0.131)	(0.0227)	(0.0299)
lnExRate	-0.0730	-0.0602	-0.0150**	-0.0265***
	(0.0812)	(0.0559)	(0.00746)	(0.00658)
lnProEx	0.569***	1.385***	-0.00716	0.124***
	(0.188)	(0.125)	(0.00572)	(0.0104)
lnProIm	0.275**	0.215*	0.0341*	0.0431*
	(0.126)	(0.112)	(0.0187)	(0.0248)
EUTR	-0.0239	-0.156	-0.0530***	-0.120***
	(0.0897)	(0.125)	(0.0170)	(0.0226)
Restriction	-0.0161	0.110	-0.249***	0.0447
	(0.103)	(0.151)	(0.0781)	(0.0773)
Member_WTO	-0.131	-0.0120	-0.102	-0.0687
	(0.104)	(0.189)	(0.0716)	(0.0637)
Constant	-5.524*	-4.845***	2.111**	1.131***
	(3.090)	(1.474)	(0.948)	(0.329)
Observations	5,139	5,139	19,510	19,510
R-squared	0.773	0.704	0.706	0.337
Reset(p-value)	0.5294	0	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 3.24: Robustness Checks for Non-coniferous Sawnwood: The EU

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-1.872***	-0.593***	-0.289***	-0.0424***
	(0.330)	(0.131)	(0.0357)	(0.0139)
ComLan	0.166	0.657***	0.0726***	0.155***
	(0.206)	(0.239)	(0.0257)	(0.0405)
Cont	0.143	0.647	0.183**	0.180
	(0.290)	(0.496)	(0.0856)	(0.112)
lnForEx	0.359*	0.650***	0.0106	0.0280***
	(0.196)	(0.130)	(0.0101)	(0.00560)
lnForIm	-0.525***	-0.494***	-0.0468***	-0.0382**
	(0.132)	(0.166)	(0.0105)	(0.0148)
lnGDPEx	0.216	-0.00801	0.0293***	0.0107
	(0.165)	(0.0763)	(0.0113)	(0.00701)
lnGDPIm	0.0219	0.0478	0.0392***	0.0354*
	(0.165)	(0.153)	(0.0121)	(0.0188)
lnExRate	0.107	0.0277	-0.00938	-0.00407
	(0.0822)	(0.0336)	(0.00662)	(0.00549)
lnProEx	0.298***	0.805***	0.0107*	0.0820***
	(0.108)	(0.0780)	(0.00586)	(0.00708)
lnProIm	0.278***	0.283***	0.0324***	0.0341**
	(0.0839)	(0.0882)	(0.00947)	(0.0150)
EUTR	0.0248	0.0854	0.0293***	0.0486***
	(0.0831)	(0.126)	(0.0104)	(0.0157)
Restriction	1.038***	1.104***	0.392***	0.370***
	(0.146)	(0.275)	(0.0427)	(0.0614)
Member_WTO	0.455*	0.565**	0.133***	0.0645***
	(0.244)	(0.239)	(0.0382)	(0.0191)
Constant	8.928***	-4.168***	1.972***	-0.488***
	(2.418)	(1.388)	(0.319)	(0.151)
Observations	7,842	7,842	24,300	24,300
R-squared	0.437	0.198	0.551	0.182
Reset(p-value)	0.1947	0	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 3.25: Robustness Checks for Coniferous Plywood: the EU

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-1.268***	-1.212***	-0.165***	-0.0759***
	(0.450)	(0.271)	(0.0505)	(0.0186)
ComLan	0.856**	1.735***	0.00491	0.0940*
	(0.384)	(0.365)	(0.0299)	(0.0564)
Cont	-0.311	-1.085*	0.00821	0.0389
	(0.433)	(0.577)	(0.116)	(0.0927)
lnForEx	0.561***	1.112***	0.0231*	0.0336***
	(0.207)	(0.193)	(0.0134)	(0.00792)
lnForIm	0.000659	0.166	-0.0257*	-0.0127
	(0.196)	(0.222)	(0.0146)	(0.0197)
lnGDPEx	0.0143	0.166	0.000422	-0.00513
	(0.203)	(0.167)	(0.0126)	(0.0113)
lnGDPIm	0.937***	0.903***	0.0626***	0.0644***
	(0.304)	(0.251)	(0.0156)	(0.0234)
lnExRate	-0.333	-0.117**	-0.0124**	-0.00804*
	(0.335)	(0.0517)	(0.00593)	(0.00480)
lnProEx	0.352***	0.688***	0.0294***	0.0979***
	(0.0833)	(0.124)	(0.00632)	(0.0132)
lnProIm	-0.225**	-0.231**	-0.0130*	-0.0141
	(0.0971)	(0.107)	(0.00759)	(0.00869)
EUTR	-0.177	-0.346*	-0.0245**	-0.0319**
	(0.157)	(0.200)	(0.00965)	(0.0156)
Restriction	-0.835***	-0.659**	-0.103***	-0.129**
	(0.199)	(0.256)	(0.0260)	(0.0532)
Member_WTO	-0.165	-0.646	0.00414	-0.0180
	(0.339)	(0.395)	(0.0420)	(0.0474)
Constant	-1.123	2.292	0.995**	0.140
	(3.604)	(2.093)	(0.415)	(0.182)
Observations	2,239	2,239	10,153	10,153
R-squared	0.568	0.395	0.580	0.215
Reset(p-value)	0.738	0.0015	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.26: Robustness Checks for Non-coniferous Plywood: the EU

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-0.816**	-0.983***	-0.154**	-0.133***
	(0.336)	(0.170)	(0.0652)	(0.0225)
ComLan	1.018**	0.444	0.0443	-0.00326
	(0.458)	(0.314)	(0.0323)	(0.0381)
Cont	0.215	0.149	0.473***	0.547***
	(0.303)	(0.308)	(0.136)	(0.178)
lnForEx	-0.211	0.149	-0.0388***	0.0247***
	(0.158)	(0.158)	(0.0150)	(0.00637)
lnForIm	0.0830	0.0739	-0.0148	-0.0224
	(0.0992)	(0.122)	(0.0150)	(0.0214)
lnGDPEx	-0.172	-0.0784	-0.0259	0.0105
	(0.140)	(0.127)	(0.0180)	(0.00961)
lnGDPIm	0.854***	0.770***	0.0885***	0.0788***
	(0.169)	(0.177)	(0.0197)	(0.0255)
lnExRate	0.0163	0.0495	-0.0157**	-0.0109*
	(0.108)	(0.0524)	(0.00673)	(0.00614)
lnProEx	0.534***	0.718***	0.0505***	0.111***
	(0.105)	(0.0813)	(0.0103)	(0.0132)
lnProIm	-0.183**	-0.216***	-0.00852	-0.00627
	(0.0739)	(0.0761)	(0.00988)	(0.0135)
EUTR	-0.216**	-0.211**	-0.0179*	-0.0458**
	(0.0993)	(0.106)	(0.0107)	(0.0190)
Restriction	0.266	0.217	0.110***	0.153**
	(0.186)	(0.223)	(0.0377)	(0.0679)
Member_WTO	0.460***	0.243	0.140**	-0.00256
	(0.174)	(0.240)	(0.0550)	(0.0392)
Constant	0.969	1.383	0.891	0.379**
	(2.718)	(0.947)	(0.648)	(0.189)
Observations	2,021	2,021	12,745	12,745
R-squared	0.570	0.321	0.566	0.249
Reset(p-value)	0.2328	0.1606	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table 3.27: Robustness Checks for Coniferous Sawnwood: Japan

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-1.338	-0.213	-0.249	-0.306
	(1.284)	(0.157)	(0.229)	(0.228)
ComLan	-0.645	-2.839***	-0.573	-1.331***
	(3.620)	(0.456)	(0.597)	(0.437)
Cont	-	-	-	-
	-	-	-	-
lnForEx	0.662***	0.0510	0.0921	0.142**
	(0.191)	(0.156)	(0.0799)	(0.0558)
lnForIm	-0.00997	0.735***	-0.227***	-0.175**
	(0.196)	(0.231)	(0.0791)	(0.0727)
lnGDPEx	0.781***	-0.694***	0.273**	0.128*
	(0.284)	(0.148)	(0.122)	(0.0754)
lnGDPIm	0.705*	2.439***	-0.113	0.00763
	(0.389)	(0.433)	(0.0876)	(0.150)
lnExRate	-0.0961	0.0186	0.00454	0.0179
	(0.157)	(0.0509)	(0.0119)	(0.0411)
lnProEx	0.116	1.964***	0.0202	0.267***
	(0.303)	(0.202)	(0.0298)	(0.0659)
lnProIm	0.948***	0.145	0.317**	0.225
	(0.272)	(0.214)	(0.152)	(0.161)
JCWA	-0.00552	-0.502***	-0.382***	-0.387***
	(0.0744)	(0.0963)	(0.0929)	(0.0967)
Restriction	0.206**	-0.0725	0.0734	0.139
	(0.0846)	(0.107)	(0.121)	(0.239)
Member_WTO	0.382*	0.556**	0.132	0.199
	(0.209)	(0.216)	(0.150)	(0.376)
Constant	-7.739	-26.57***	-1.458	-1.230
	(13.15)	(4.445)	(3.600)	(3.051)
Observations	763	763	2,064	2,064
R-squared	0.963	0.926	0.906	0.384
Reset(p-value)	0.1596	0	0	0
Exporter FE	Yes	No	Yes	Yes

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.28: Robustness Checks for Non-coniferous Sawnwood: Japan

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-1.571***	-0.536***	1.777***	-0.410**
	(0.339)	(0.144)	(0.109)	(0.200)
ComLan	7.989***	-1.439***	-3.323***	0.882***
	(0.738)	(0.306)	(0.138)	(0.282)
Cont	-	-	-	-
	-	-	-	-
lnForEx	-0.222	0.827***	-0.0239	0.0854*
	(0.235)	(0.245)	(0.0487)	(0.0464)
lnForIm	0.504***	-1.404***	0.0407	-0.186***
	(0.116)	(0.456)	(0.0401)	(0.0664)
lnGDPEx	-1.031***	0.529***	-0.0822	0.134***
	(0.176)	(0.188)	(0.0498)	(0.0460)
lnGDPIm	1.317***	-2.809***	0.112*	-0.322**
	(0.220)	(0.917)	(0.0670)	(0.145)
lnExRate	-0.105	-0.0110	0.00426	-0.0172
	(0.119)	(0.108)	(0.0149)	(0.0282)
lnProEx	0.177	0.658***	0.0237	0.116***
	(0.159)	(0.196)	(0.0260)	(0.0338)
lnProIm	0.195***	0.473***	0.0151	0.0450***
	(0.0409)	(0.0805)	(0.00987)	(0.0159)
JCWA	-0.341***	-0.854***	-0.0516***	-0.117***
	(0.111)	(0.238)	(0.0162)	(0.0415)
Restriction	-0.0567	1.097***	-0.0129	0.0604
	(0.0931)	(0.403)	(0.0580)	(0.189)
Member_WTO	0.217**	-0.0111	0.0103	0.0107
	(0.0858)	(0.627)	(0.124)	(0.134)
Constant	4.135**	13.85**	-12.57***	4.717**
	(1.935)	(6.017)	(0.743)	(2.254)
Observations	1,434	1,434	2,507	2,507
R-squared	0.932	0.556	0.920	0.364
Reset (p-value)	0.0008	0.0178	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.29: Robustness Checks for Coniferous Plywood: Japan

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-0.988	0.351	-0.151	-0.0868
	(0.772)	(0.607)	(0.216)	(0.110)
ComLan	-4.005***	-4.819***	-0.495	-0.665***
	(1.184)	(0.877)	(0.437)	(0.240)
Cont	-	-	-	-
	-	-	-	-
lnForEx	1.871***	0.0583	0.194	0.0129
	(0.467)	(0.293)	(0.158)	(0.0235)
lnForIm	0.00315	0.492	-0.226	0.0151
	(0.194)	(0.321)	(0.167)	(0.0538)
lnGDPEx	0.387	-0.682	0.186	-0.0183
	(0.290)	(0.415)	(0.137)	(0.0316)
lnGDPIm	1.231**	2.283**	-0.136	0.156
	(0.599)	(0.992)	(0.238)	(0.109)
lnExRate	0.395	-0.226**	0.00604	0.00282
	(0.269)	(0.102)	(0.00412)	(0.0145)
lnProEx	0.890***	0.691*	0.0416**	0.139***
	(0.272)	(0.364)	(0.0203)	(0.0428)
lnProIm	-0.599**	-0.996*	-0.180	-0.0582
	(0.271)	(0.553)	(0.144)	(0.0660)
JCWA	-0.537***	-0.466**	-0.0453*	-0.0281
	(0.123)	(0.187)	(0.0272)	(0.0230)
Restriction	0.669**	-1.530***	0.143	-0.188
	(0.294)	(0.302)	(0.0981)	(0.121)
Member_WTO	0.617	2.023***	0.0854**	0.152
	(0.672)	(0.748)	(0.0429)	(0.0930)
Constant	-1.813	-13.91*	1.967	-0.281
	(7.344)	(7.251)	(3.111)	(1.171)
Observations	363	363	1,553	1,553
R-squared	0.895	0.315	0.791	0.253
Reset(p-value)	0.0238	0.0001	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.30: Robustness Checks for Non-coniferous Plywood: Japan

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-0.817*	0.524*	0.961***	-0.542**
	(0.446)	(0.314)	(0.176)	(0.243)
ComLan	0.546	-2.849***	-3.467***	-0.259
	(0.449)	(0.533)	(0.465)	(0.275)
Cont	-	-	-	-
	-	-	-	-
lnForEx	-0.0604	0.744***	0.135	0.0644
	(0.142)	(0.138)	(0.115)	(0.0598)
lnForIm	-0.117	-0.0153	-0.157	-0.0160
	(0.103)	(0.137)	(0.111)	(0.0707)
lnGDPEx	0.0731	-0.00545	0.181*	0.0424
	(0.110)	(0.176)	(0.0993)	(0.0500)
lnGDPIm	0.616***	1.424***	-0.155	0.0166
	(0.237)	(0.331)	(0.132)	(0.118)
lnExRate	-0.362***	0.150***	0.00354	0.0250
	(0.0884)	(0.0232)	(0.00709)	(0.0518)
lnProEx	0.551***	1.027***	0.0697*	0.227**
	(0.0942)	(0.123)	(0.0406)	(0.0899)
lnProIm	-0.0426	-0.227*	0.0860**	0.0471
	(0.0467)	(0.130)	(0.0414)	(0.0334)
JCWA	-0.272***	-0.329**	-0.0398	-0.0550
	(0.0893)	(0.165)	(0.0671)	(0.0625)
Restriction	-0.653	-1.549**	0.106	-0.0641
	(0.706)	(0.679)	(0.109)	(0.150)
Member_WTO	0.962***	1.499**	0.370	0.296
	(0.232)	(0.698)	(0.256)	(0.200)
Constant	-3.718	-19.03***	-7.391***	3.644
	(3.708)	(5.573)	(2.022)	(2.414)
Observations	323	323	1,947	1,947
R-squared	0.979	0.899	0.879	0.343
Reset(p-value)	0.0945	0.3748	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.31: Robustness Checks for Coniferous Sawnwood: the US

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-0.180	-0.373	0.327	-0.168
	(0.653)	(0.491)	(0.282)	(0.157)
ComLan	7.101***	2.280***	0.0604	0.249
	(2.129)	(0.323)	(0.266)	(0.211)
Cont	4.389	-0.0510	1.139	3.669*
	(2.769)	(0.820)	(0.752)	(1.992)
lnForEx	-0.0248	-0.124	0.0254	0.0799**
	(0.163)	(0.117)	(0.0418)	(0.0397)
lnForIm	0.641***	0.784***	-0.312***	-0.292***
	(0.195)	(0.122)	(0.102)	(0.0982)
lnGDPEx	-0.962***	-0.592***	0.0868	0.00780
	(0.176)	(0.116)	(0.103)	(0.0614)
lnGDPIm	1.504***	0.833***	-0.0903	0.118
	(0.288)	(0.289)	(0.275)	(0.163)
lnExRate	-0.379**	-0.102**	-0.0242**	-0.0169
	(0.192)	(0.0493)	(0.0109)	(0.0383)
lnProEx	0.685**	1.805***	0.0842**	0.206***
	(0.347)	(0.119)	(0.0360)	(0.0549)
lnProIm	1.596***	0.827***	0.503***	0.520***
	(0.261)	(0.240)	(0.164)	(0.166)
LAA	0.251**	0.406**	-0.244***	-0.215***
	(0.123)	(0.160)	(0.0734)	(0.0803)
Restriction	-0.643***	-0.724***	0.0919	-0.0742
	(0.241)	(0.241)	(0.109)	(0.171)
Member_WTO	1.244**	1.671***	0.147	0.0333
	(0.570)	(0.345)	(0.151)	(0.172)
Constant	-36.22***	-22.84***	-8.143***	-6.551**
	(7.765)	(4.896)	(2.566)	(2.695)
Observations	955	955	2,277	2,277
R-squared	0.990	0.982	0.901	0.425
Reset (p-value)	0.192	0.571	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.32: Robustness Checks for Non-coniferous Sawnwood: the US

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-4.289***	-1.231***	-0.0549	-0.0723
	(0.645)	(0.340)	(0.0923)	(0.141)
ComLan	8.831***	0.904**	-0.0102	0.394***
	(0.797)	(0.370)	(0.162)	(0.125)
Cont	-4.031***	0.958*	4.180***	1.872
	(1.555)	(0.573)	(0.467)	(1.276)
lnForEx	0.752***	0.381**	0.0755*	0.0653*
	(0.212)	(0.163)	(0.0455)	(0.0336)
lnForIm	-0.0772	-0.0230	0.158**	0.0820
	(0.421)	(0.339)	(0.0675)	(0.0750)
lnGDPEx	0.207	0.0560	-0.0293	0.0107
	(0.191)	(0.200)	(0.0682)	(0.0383)
lnGDPIm	1.422**	1.340*	0.792***	0.621***
	(0.615)	(0.732)	(0.210)	(0.153)
lnExRate	-0.142***	-0.198***	-0.0220	-0.0570**
	(0.0523)	(0.0673)	(0.0180)	(0.0262)
lnProEx	0.203**	0.698***	0.0809**	0.193***
	(0.101)	(0.149)	(0.0324)	(0.0348)
lnProIm	0.415	0.628	-0.276**	-0.111
	(0.345)	(0.419)	(0.125)	(0.139)
LAA	-0.630***	-0.397***	-0.251***	-0.199***
	(0.0992)	(0.121)	(0.0580)	(0.0632)
Restriction	0.517**	-0.00632	0.0320	-0.181
	(0.211)	(0.542)	(0.0648)	(0.127)
Member_WTO	1.393***	1.739***	0.0693	0.248**
	(0.358)	(0.447)	(0.0798)	(0.109)
Constant	10.09	-12.66**	-3.105*	-4.393**
	(6.891)	(6.035)	(1.706)	(2.129)
Observations	1,667	1,667	2,726	2,726
R-squared	0.939	0.816	0.883	0.379
Reset (p-value)	0.0004	0.0492	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.33: Robustness Checks Coniferous Plywood: the US

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	-0.901	-4.009***	0.0973	-0.162
	(1.988)	(0.765)	(0.265)	(0.148)
ComLan	4.543	4.752***	0.704	0.195
	(4.541)	(0.705)	(0.469)	(0.137)
Cont	-	-4.775***	3.067***	1.554
	-	(1.026)	(0.925)	(1.124)
lnForEx	-0.268	0.165	0.144*	0.0435
	(0.249)	(0.180)	(0.0845)	(0.0319)
lnForIm	0.351	-0.275	-0.184**	-0.143
	(0.673)	(0.322)	(0.0774)	(0.0966)
lnGDPEx	-1.215***	-0.656**	0.0589	-0.0126
	(0.152)	(0.281)	(0.108)	(0.0397)
lnGDPIm	4.732***	4.208***	0.345	0.451**
	(0.839)	(1.098)	(0.284)	(0.195)
lnExRate	0.442	0.0932	-0.000384	0.00426
	(0.822)	(0.0570)	(0.00830)	(0.0248)
lnProEx	1.951***	1.941***	0.128**	0.185***
	(0.243)	(0.312)	(0.0552)	(0.0646)
lnProIm	1.802**	2.210***	0.345**	0.391**
	(0.845)	(0.747)	(0.140)	(0.179)
LAA	-0.274	-0.493***	-0.0775*	-0.00486
	(0.212)	(0.136)	(0.0418)	(0.0426)
Restriction	-0.380	-0.228	-0.118	-0.325**
	(1.000)	(1.072)	(0.0792)	(0.132)
Member_WTO	-0.0511	-1.680	0.184	-0.0271
	(1.031)	(1.244)	(0.218)	(0.104)
Constant	-60.52**	-33.89*	-8.473**	-7.195**
	(25.83)	(20.27)	(4.186)	(3.268)
Observations	350	350	1,634	1,634
R-squared	0.921	0.892	0.857	0.396
Reset (p-value)	0.0011	0	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05, *p<0.1

Table 3.34: Robustness Checks Non-coniferous Plywood: the US

Estimation Method	Truncated PPML FE	Truncated PPML	OLS (1+imports) FE	OLS (1+imports)
lnDist	1.713***	-1.891***	2.325***	-0.00237
	(0.352)	(0.463)	(0.375)	(0.203)
ComLan	-2.609**	-0.194	1.123***	0.211
	(1.201)	(0.352)	(0.362)	(0.185)
Cont	4.085***	0.574	5.656***	2.061*
	(1.083)	(0.743)	(0.943)	(1.059)
lnForEx	0.144	0.483***	0.00738	0.0599
	(0.180)	(0.125)	(0.0748)	(0.0544)
lnForIm	0.322	0.252	0.0991	0.0549
	(0.197)	(0.180)	(0.0659)	(0.0762)
lnGDPEx	0.0379	0.271**	-0.0934	0.0688
	(0.217)	(0.132)	(0.122)	(0.0711)
lnGDPIm	1.454***	1.390***	0.526**	0.323*
	(0.342)	(0.293)	(0.221)	(0.194)
lnExRate	-0.0398	0.121***	-0.0110	-0.00890
	(0.0756)	(0.0249)	(0.0286)	(0.0381)
lnProEx	0.868***	1.012***	0.147**	0.365***
	(0.118)	(0.0929)	(0.0575)	(0.0754)
lnProIm	0.0561	0.338	0.0974	0.189
	(0.769)	(0.527)	(0.176)	(0.199)
LAA	-0.553***	-0.653***	-0.0646	-0.0808
	(0.0952)	(0.153)	(0.0516)	(0.0572)
Restriction	0.847**	0.651*	0.286**	0.262
	(0.343)	(0.354)	(0.118)	(0.212)
Member_WTO	0.552	0.374	0.662**	-0.105
	(0.418)	(0.369)	(0.288)	(0.288)
Constant	-29.73***	-2.391	-25.64***	-5.067*
	(5.985)	(4.756)	(3.607)	(2.842)
Observations	780	780	2,000	2,000
R-squared	0.945	0.916	0.893	0.463
Reset(p-value)	0.8652	0.2451	0	0
Exporter FE	Yes	No	Yes	No

Robust standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

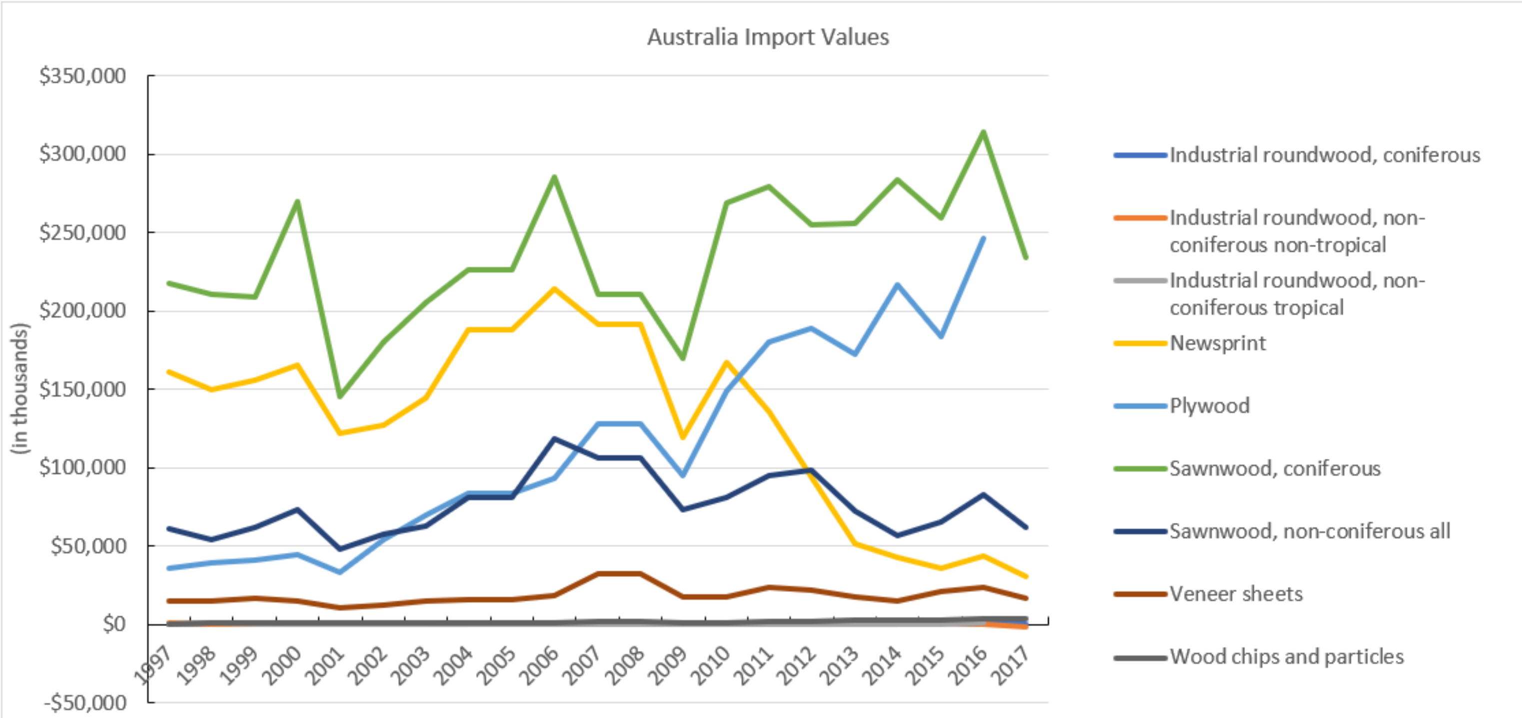


Figure 3.1: Australia Import Values by Product Group,1997-2017 Source: FAO (2017)

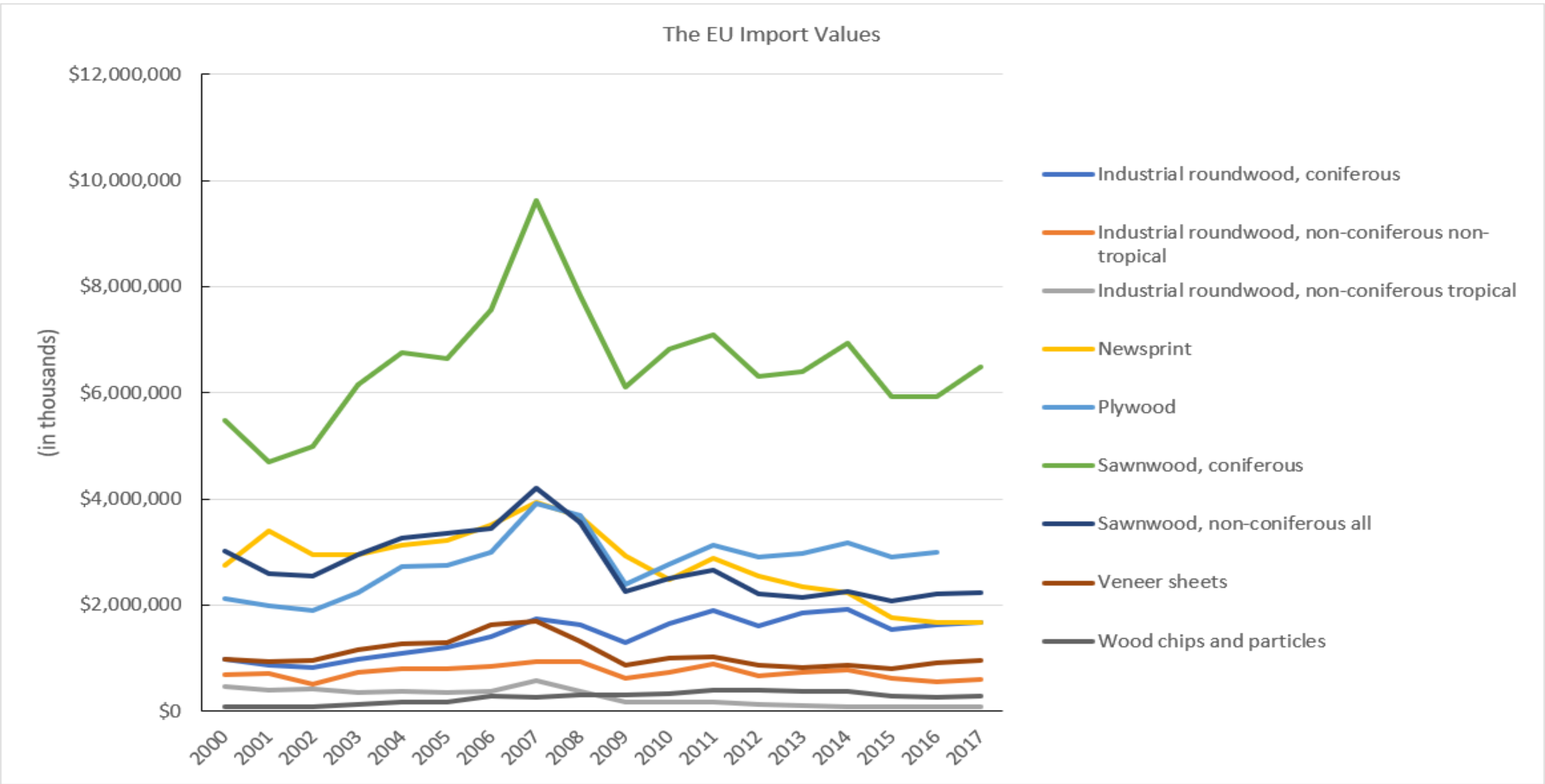


Figure 3.2: The EU Import Values by Product Group ,2000-2017 Source: FAO (2017)

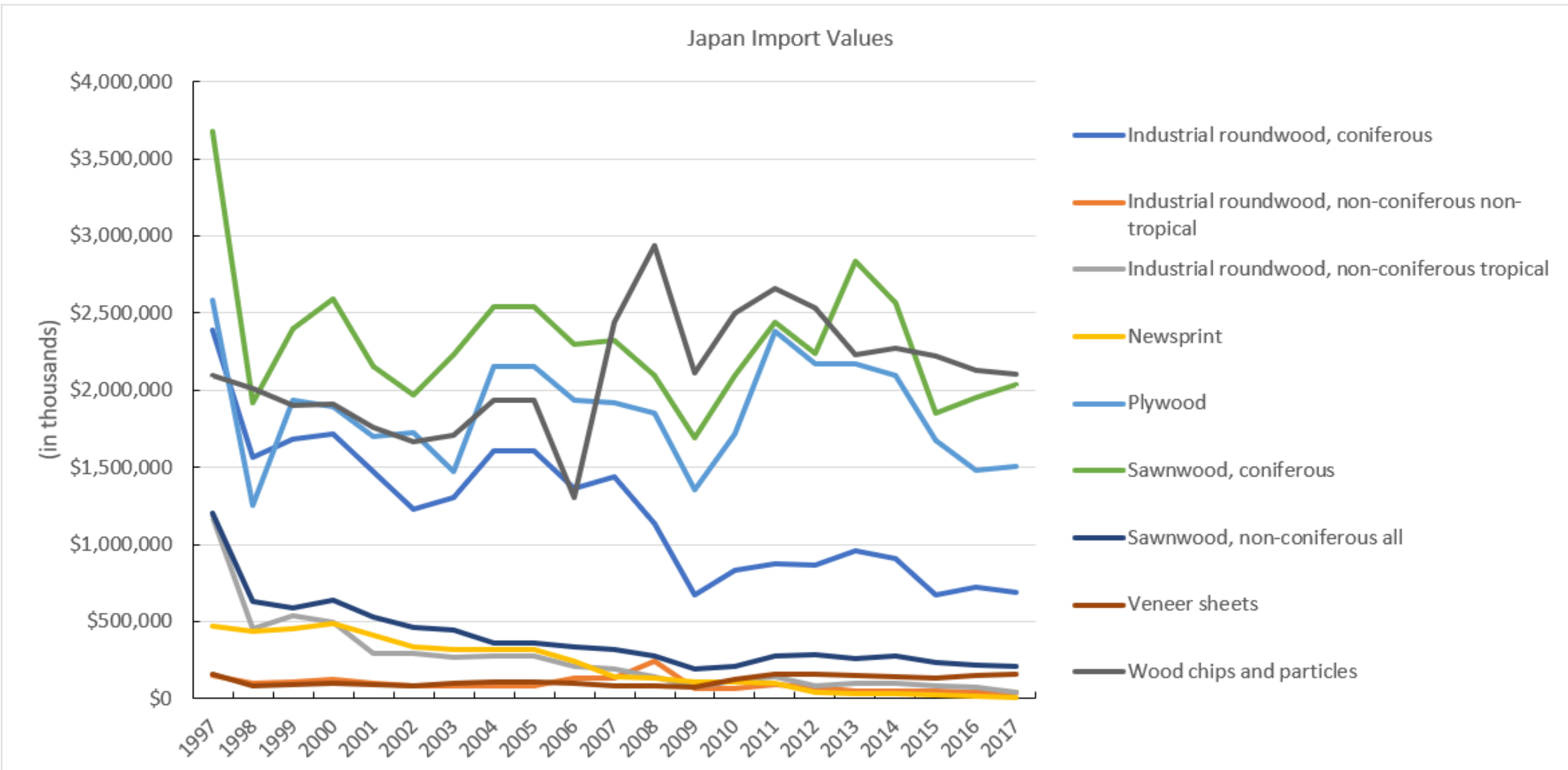


Figure 3.3: Japan Import Values by Product Group,1997-2017 Source: FAO (2017)

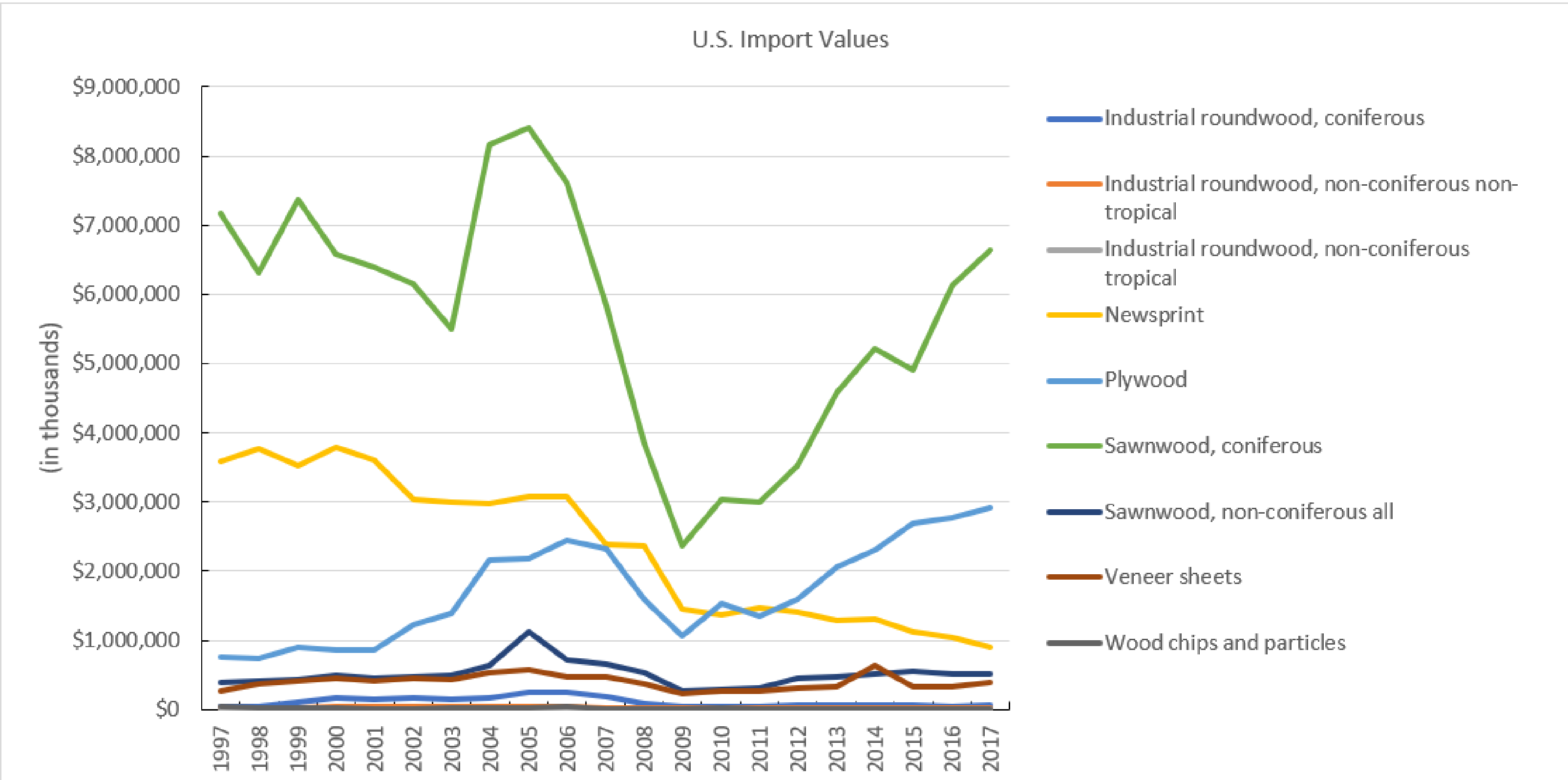
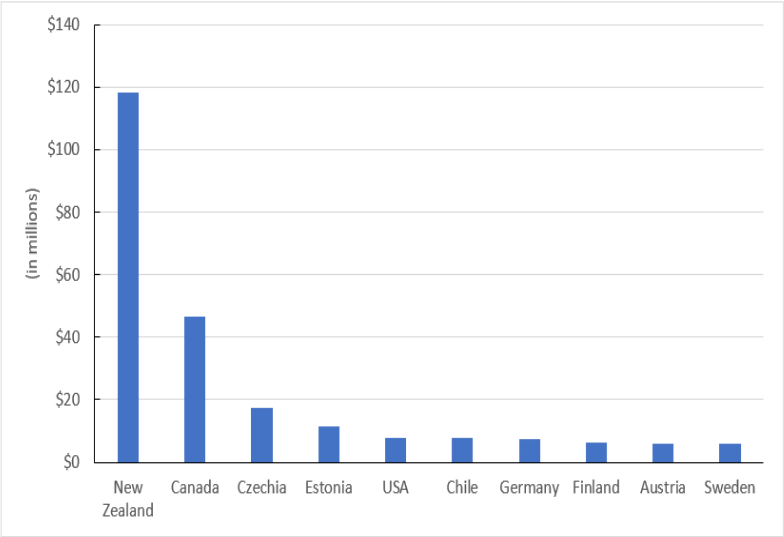
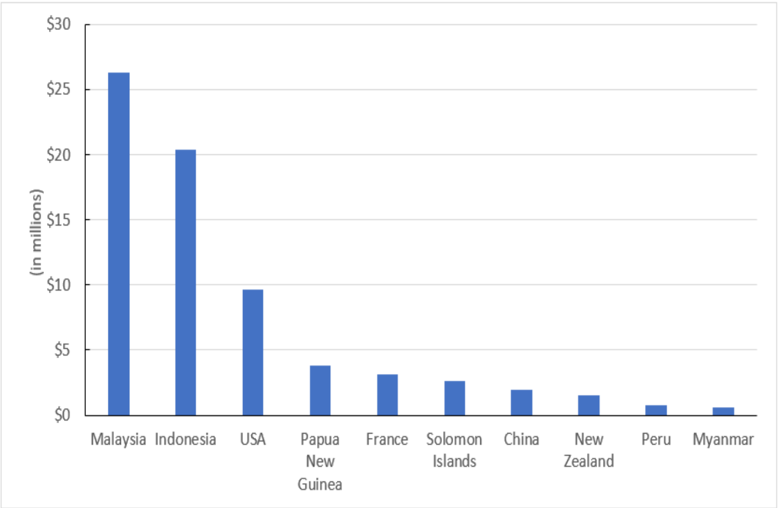


Figure 3.4: The US Import Values by Product Group,1997-2017 Source: FAO (2017)

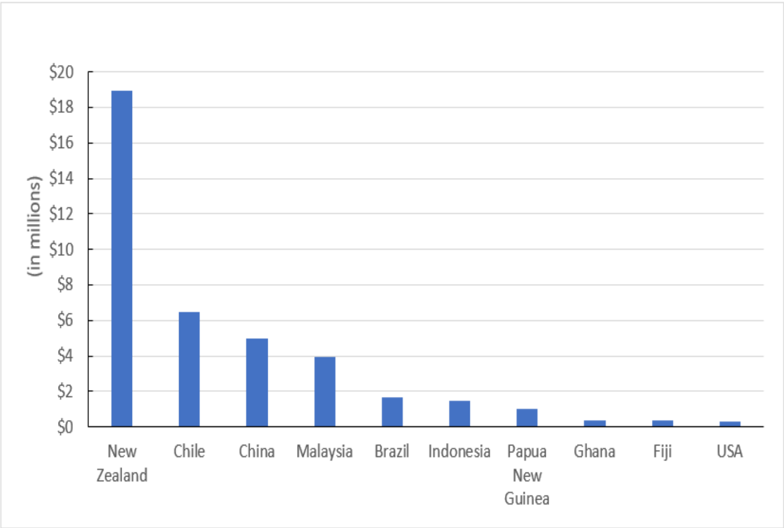


(a) Panel A:Key Trading Partners for Coniferous Sawnwood

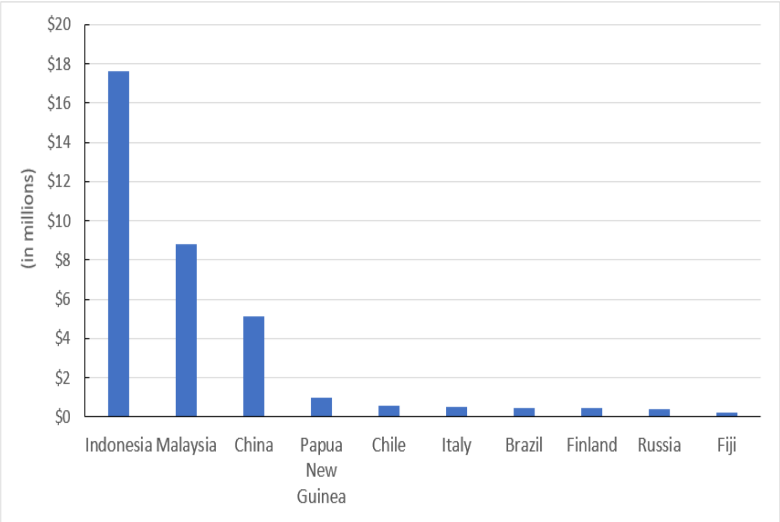


(b) Panel B:Key Trading Partners for Non-coniferous Sawnwood

Figure 3.5: Key Trading Partners of Australia for Coniferous and Non-coniferous Sawnwood by Import Values,1997-2019

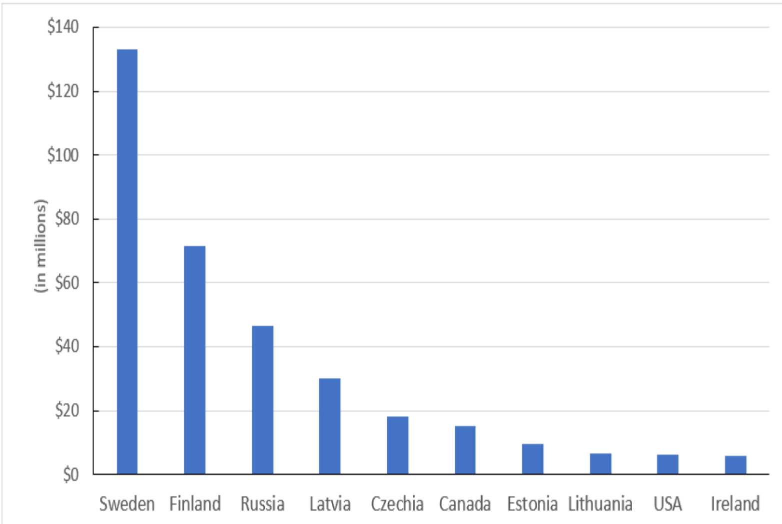


(a) Panel A:Key Trading Partners for Coniferous Plywood

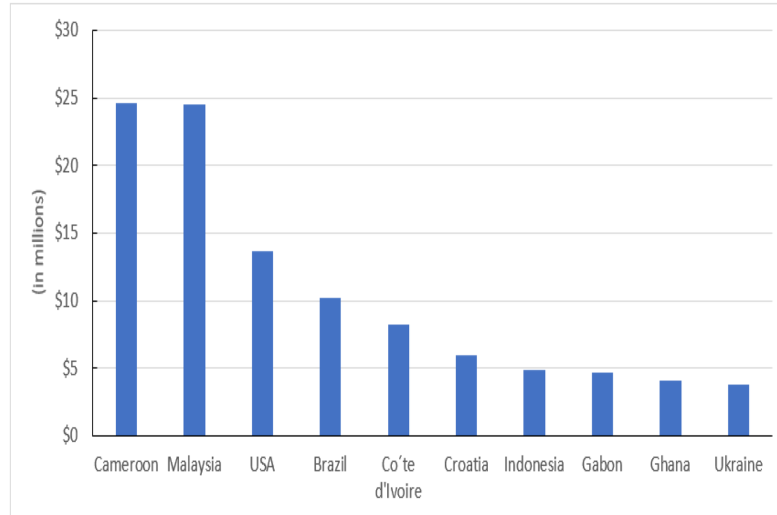


(b) Panel B:Key Trading Partners for Non-coniferous Plywood

Figure 3.6: Key Trading Partners of Australia for Coniferous and Non-coniferous Plywood by Import Values,1997-2019

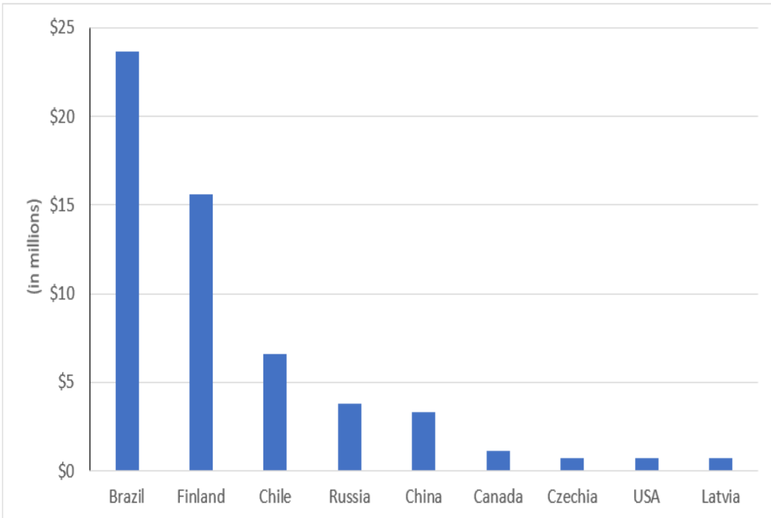


(a) Panel A:Key Trading Partners for Coniferous Sawnwood

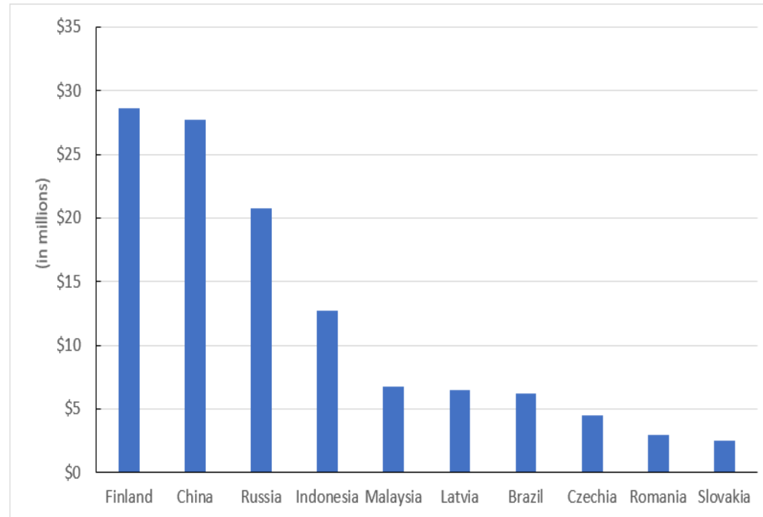


(b) Panel B:Key Trading Partners for Non-coniferous Sawnwood

Figure 3.7: Key Trading Partners of the EU for Coniferous and Non-coniferous Sawnwood by Import Values,2000-2019

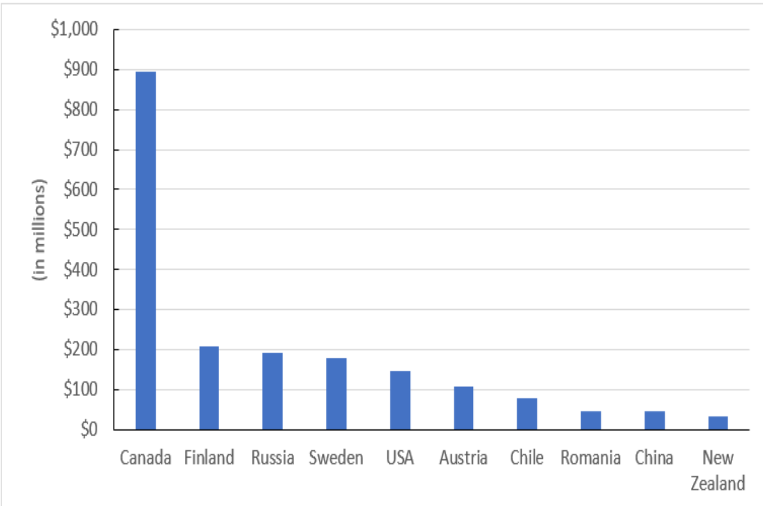


(a) Panel A:Key Trading Partners for Coniferous Plywood

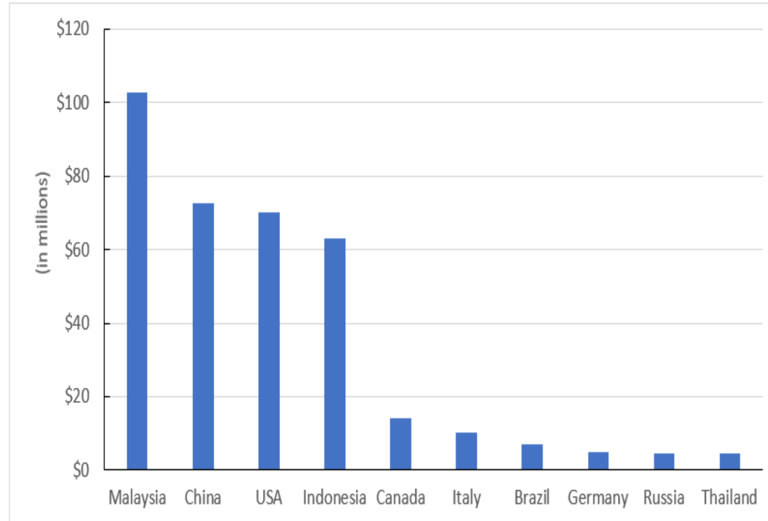


(b) Panel B:Key Trading Partners for Non-coniferous Plywood

Figure 3.8: Key Trading Partners of the EU for Coniferous and Non-coniferous Plywood by Import Values,2000-2019

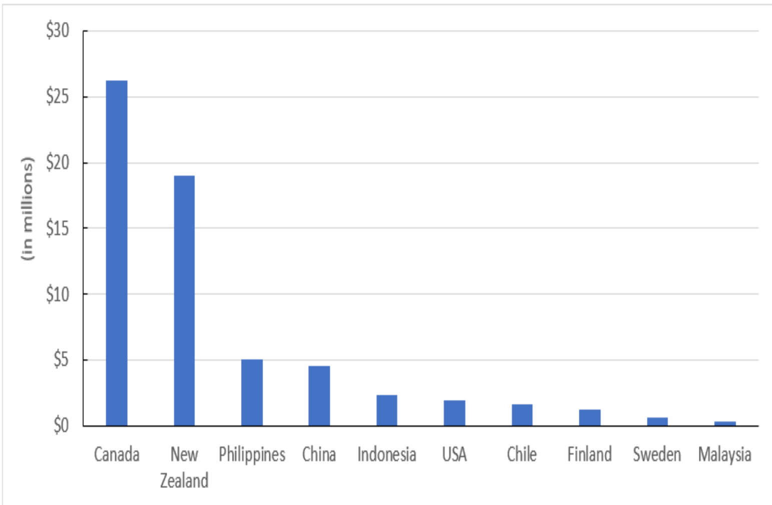


(a) Panel A:Key Trading Partners for Coniferous Sawnwood

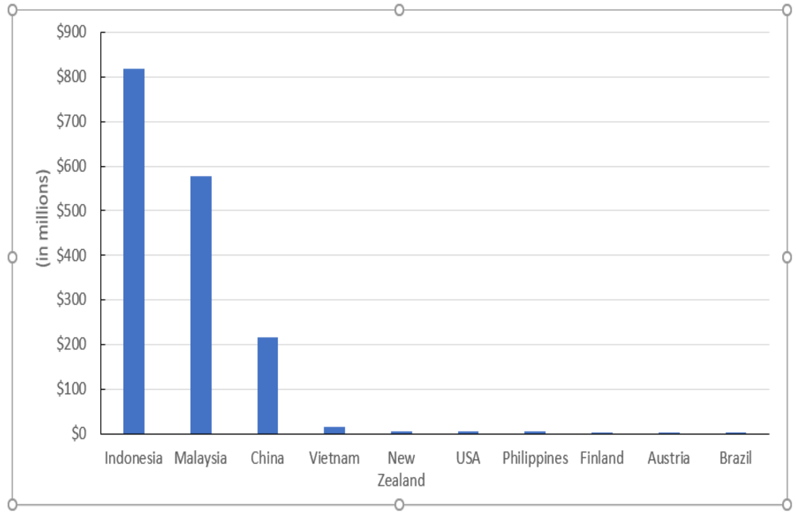


(b) Panel B:Key Trading Partners for Non-coniferous Sawnwood

Figure 3.9: Key Trading Partners of Japan for Coniferous and Non-coniferous Sawnwood by Import Values,1997-2019

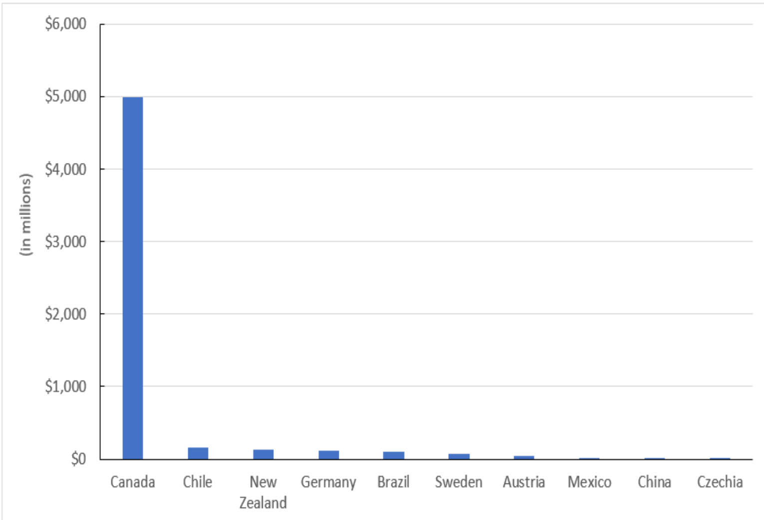


(a) Panel A:Key Trading Partners for Coniferous Plywood

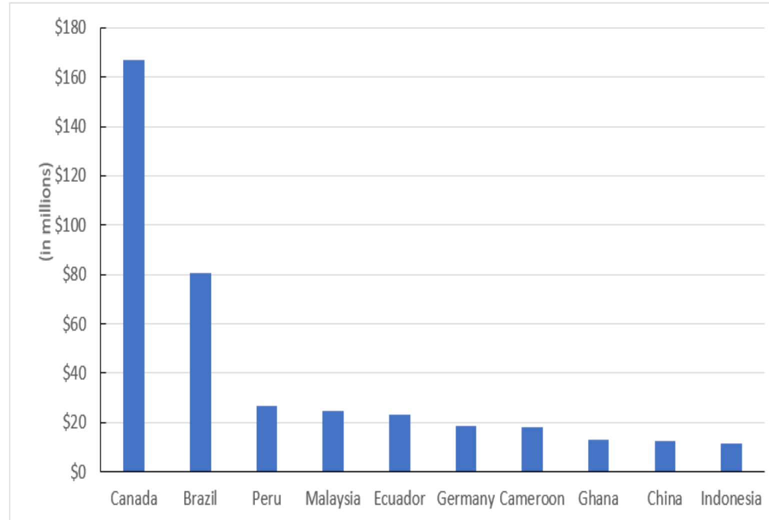


(b) Panel B:Key Trading Partners for Non-coniferous Plywood

Figure 3.10: Key Trading Partners of Japan for Coniferous and Non-coniferous Plywood by Import Values,1997-2019

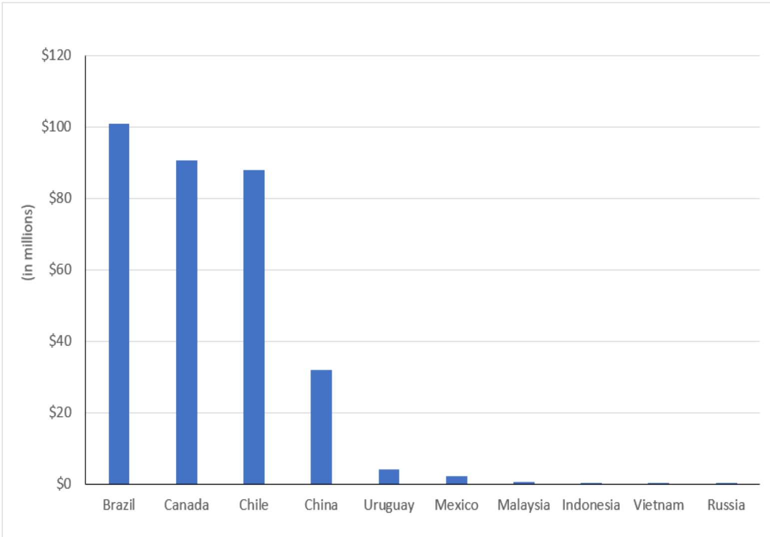


(a) Panel A:Key Trading Partners for Coniferous Sawnwood

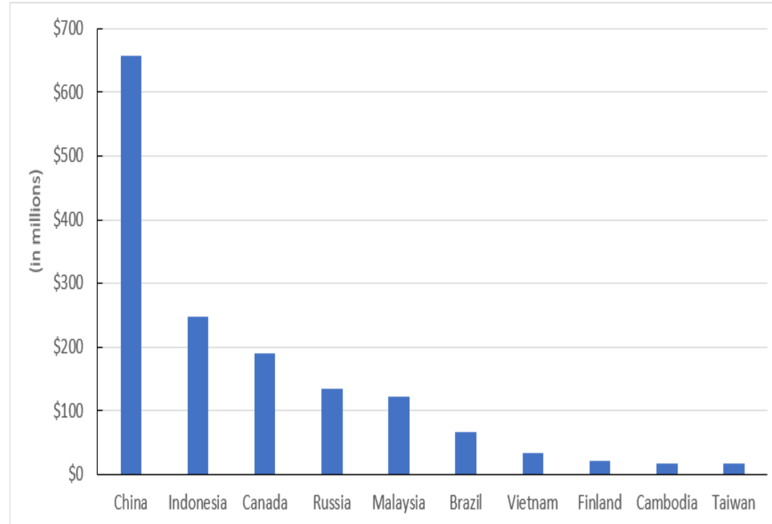


(b) Panel B:Key Trading Partners for Non-coniferous Sawnwood

Figure 3.11: Key Trading Partners of the US for Coniferous and Non-coniferous Sawnwood by Import Values,1997-2019



(a) Panel A:Key Trading Partners for Coniferous Plywood



(b) Panel B:Key Trading Partners for Non-coniferous Plywood

Figure 3.12: Key Trading Partners of the US for Coniferous and Non-coniferous Plywood by Import Values,1997-2019

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APPENDICES

APPENDIX

A

ROBUSTNESS CHECK FOR REGIONAL ESTIMATES

Table A.1: Robustness Check: Parameter Estimates of Alternative Models for Appalachian Region

Variables	Random Effects Probit	CRE Probit
$P_{pulpwood}$	0.0942**	0.0749
	(0.0435)	(0.0527)
$P_{sawtimber}$	-0.0787***	-0.0644***
	(0.0121)	(0.0131)
ConserPay	0.6048***	0.488
	(0.1289)	(0.354)
GovPay	0.0056	0.00572
	(0.0042)	(0.00482)
EstabCost	-0.0102**	-0.0167***
	(0.0047)	(0.0063)
CropP	0.0002	0.0008
	(0.0003)	(0.0006)
LCC1&2	-0.5168	3.009**
	(1.2122)	(1.438)
Pop	-0.0003	0.00803
	(0.0015)	(0.0158)
PerCap	0.0090	0.0244
	(0.0184)	(0.0662)
T-Factor	0.0736	0.187
	(0.1455)	(0.170)
$\overline{P_{pulpwood}}$		0.00651
		(0.177)
$\overline{P_{sawtimber}}$		0.00201
		(0.0579)
$\overline{ConserPay}$		0.618
		(0.388)
$\overline{GovPay}$		-0.00253
		(0.0115)

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table A.1: (Continued) Robustness Check: Parameter Estimates of Alternative Models for Appalachian Region

Variables	Random Effects Probit	CRE Probit
$\overline{CropP}$		-0.0006
		(0.0012)
$\overline{Pop}$		-0.0089
		(0.0167)
$\overline{PerCap}$		-0.0474
		(0.0728)
Intercept	-10.2239***	-10.9020***
	(1.2188)	(2.4442)
Log-Likelihood	-450.98159	-456.00245
χ^2	161.57***	242.37***
AIC	925.96	950.00
BIC	1037.54	1126.67
LR test (H_0:c_i=0) $\overline{\chi}^2$	-10.54	
$pr \geq \overline{\chi}^2$	0.2878	
Observations	80,699	80,699

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table A.2: Robustness Check: Parameter Estimates of Alternative Models for Delta Region

Variables	Random Effects Probit	CRE Probit
$P_{pulpwood}$	0.0218	0.0007
	(0.0473)	(0.0477)
$P_{sawtimber}$	-0.127***	-0.1212***
	(0.0145)	(0.0144)
ConserPay	0.160***	0.3278**
	(0.0611)	(0.1398)
GovPay	0.00520	0.0072
	(0.00459)	(0.0052)
EstabCost	-0.0108***	-0.0071**
	(0.00318)	(0.0031)
CropP	-0.00148***	-0.0014
	(0.000562)	(0.0009)
LCC1&2	-1.229	-0.0426
	(1.261)	(1.2499)
Pop	-0.00177	0.1044***
	(0.00312)	(0.0366)
PerCap	-0.0246	-0.0189
	(0.0243)	(0.0409)
T-Factor	0.132	0.1756
	(0.272)	(0.2556)
$\overline{P_{pulpwood}}$		0.1988
		(0.1397)
$\overline{P_{sawtimber}}$		-0.0167
		(0.0671)
$\overline{ConserPay}$		-0.2582*
		(0.1563)
$\overline{GovPay}$		0.0039
		(0.0128)

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table A.2: (Continued) Robustness Check: Parameter Estimates of Alternative Models for Delta Region

Variables	Random Effects Probit	CRE Probit
$\overline{CropP}$		-0.00002
		(0.0017)
$\overline{Pop}$		-0.1127***
		(0.0384)
$\overline{PerCap}$		-0.0190
		(0.0409)
Intercept	-11.3416***	-12.5522***
	(1.739)	(2.1931)
Log-Likelihood	-684.64	-684.33
χ^2	305.1***	177.70***
AIC	1393.28	1406.67
BIC	1504.84	1583.31
LR test (H_0:c_i=0) $\overline{\chi}^2$	0.61	
$pr \geq \overline{\chi}^2$	0.9	
Observations	80,599	80,599

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table A.3: Robustness Check: Parameter Estimates of Alternative Models for Southeast Region

Variables	Random Effects Probit	CRE Probit
$P_{pulpwood}$	0.0892**	0.0863**
	(0.0369)	(0.0439)
$P_{sawtimber}$	-0.0998***	-0.1096***
	(0.0132)	(0.0159)
ConserPay	0.1695	1.0509***
	(0.1351)	(0.3987)
GovPay	0.0079	0.0079
	(0.0113)	(0.0127)
EstabCost	0.00008	0.0004
	(0.00273)	(0.0026)
CropP	0.00002	-0.00005
	(0.00049)	(0.00102)
LCC1&2	-0.9718	-0.4687
	(1.2065)	(1.7426)
Pop	0.0002	-0.0182
	(0.0025)	(0.0367)
PerCap	-0.0855**	-0.1349
	(0.0417)	(0.0870)
T-Factor	0.0984	0.1212
	(0.2898)	(0.2990)
$\overline{P_{pulpwood}}$		-0.0536
		(0.1199)
$\overline{P_{sawtimber}}$		0.0202
		(0.0469)
$\overline{ConserPay}$		-0.9358**
		(0.4479)
$\overline{GovPay}$		0.0014
		(0.0230)

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

Table A.3: (Continued) Robustness Check: Parameter Estimates of Alternative Models for Southeast Region

Variables	Random Effects Probit	CRE Probit
$\overline{CropP}$		0.0002
		(0.0011)
$\overline{Pop}$		0.0158
		(0.0376)
$\overline{PerCap}$		0.0970
		(0.104)
Intercept	-8.5345***	-9.7590***
	(1.9159)	(2.4060)
Log-Likelihood	-383.31	-380.23
χ^2	165.77***	103.92***
AIC	790.63	798.47
BIC	897.05	966.97
LR test (H_0:c_i=0) $\underline{\chi}^2$	6.16	
$pr \geq \underline{\chi}^2$	0.52	
Observations	52,487	52,487

Standard errors are in parentheses. ***p<0.01, **p<0.05,*p<0.1

APPENDIX

B

VARIABLE DESCRIPTIONS AND SUMMARY STATISTICS OF VARIABLES INCLUDED IN THE ANALYSIS OF THE COUNTRIES

Table B.1: Variable Descriptions and Data Sources for Australia

Variables	Definitions	Data Source
X_{ijt}^{k}	Nominal import value of selected forest products (in millions of US dollars)	UN-Comtrade
$lnDist_{ij}$	Population weighted distance between the exporter and Australia countries (in km).	USITC-Gravity Data
$ComLan_{ij}$	Dummy variable whether the exporter and Australia speak the same language.	USITC-Gravity Data
$Cont_{ij}$	Dummy variable whether the exporter shares a common border with Australia.	USITC-Gravity Data
$lnForEx_{jt}$	Exporter's forest rent (% of GDP).	WDI
$lnForIm_{it}$	Australia's forest rent (% of GDP).	WDI
$lnGDPEx_{jt}$	Nominal GDP of exporter (in billions).	WDI
$lnGDPIm_{it}$	Nominal GDP of Australia (in billions).	WDI
$lnExRate_{ijt}$	Nominal exchange rate.	WDI
$lnProEx_{jt}^{k}$	The quantity of timber production for selected product k in the exporting country (1000 m3).	ITTO
$lnProIm_{it}^{k}$	The quantity of timber production for selected product k in Australia (1000 m3).	ITTO
ILPA	Dummy variable equals to 1 after the implementation of the ILPA.	
Restriction	Dummy variable indicating whether the exporter has a trade measure that forbids illegal logging at time.	
Member_WTO	Dummy variable indicating whether the exporting country has a WTO membership.	USITC-Gravity Data

Table B.2: Variable Descriptions and Data Sources for the EU

Variables	Definitions	Data Source
X_{ijt}^{k}	Nominal import value of selected forest product k (in millions of US dollars).	UN-Comtrade
$lnDist_{ij}$	Population weighted distance between the exporter and the EU (in km).	USITC-Gravity Data
$ComLan_{ij}$	A dummy variable whether the exporter and the EU speak the same language.	USITC-Gravity Data
$Cont_{ij}$	Dummy variable whether the exporter shares a common border with the EU.	USITC-Gravity Data
$lnForEx_{jt}$	Exporter's forest (% of GDP).	WDI
$lnForIm_{it}$	EU's forest rent (% of GDP).	WDI
$lnGDPEx_{jt}$	Nominal GDP of exporter (in billions).	WDI
$lnGDPIm_{it}$	Nominal GDP of the EU (in billions).	WDI
$lnExRate_{ijt}$	Nominal exchange rate.	WDI
$lnProEx_{jt}^{k}$	The quantity of timber production for selected product k in the exporting country (1000 m3).	ITTO
$lnProIm_{it}^{k}$	The quantity of timber production for selected product k in the EU (1000 m3).	ITTO
EUTR	Dummy variable equals to 1 after the implementation of the EUTR.	
Restriction	Dummy variable indicating whether the exporter has a trade measure that forbids illegal logging at time t.	
Member_WTO	Dummy variable indicating whether the exporting country has a WTO membership.	USITC-Gravity Data

Table B.3: Variable Descriptions and Data Sources for Japan

Variables	Definitions	Data Source
X_{ijt}^{k}	Nominal import value of selected forest product k (in US dollars).	UN-Comtrade
$lnDist_{ij}$	Population weighted distance between the exporter and Japan (in km).	USITC-Gravity Data
$ComLan_{ij}$	Dummy variable whether the exporter and Japan speak the same language.	USITC-Gravity Data
$Cont_{ij}$	Dummy variable whether the exporter shares a common border with Japan.	USITC-Gravity Data
$lnForEx_{jt}$	Exporter's forest (% of GDP)	WDI
$lnForIm_{it}$	Japan's forest rent (% of GDP)	WDI
$lnGDPEx_{jt}$	Nominal GDP of exporter (in billions).	WDI
$lnGDPIm_{it}$	Nominal GDP of Japan (in billions).	WDI
$lnExRate_{ijt}$	Nominal exchange rate.	WDI
$lnProEx_{jt}^{k}$	The quantity of timber production for selected product k in the exporting country (1000 m3).	ITTO
$lnProIm_{it}^{k}$	The quantity of timber production for selected product k in Japan (1000 m3).	ITTO
JCWA	Dummy variable equals to 1 after the implementation of the JCWA.	
Restriction	Dummy variable indicating whether the exporting country has a trade measure that forbids illegal logging at time t.	
Member_WTO	Dummy variable indicating that whether the exporting country has a WTO membership.	USITC-Gravity Data

Table B.4: Variable Descriptions and Data Sources for the US

Variables	Definitions	Data Source
X_{ijt}^{k}	Nominal import value of selected forest product k (in millions of US dollars)	UN-Comtrade
$lnDist_{ij}$	Population weighted distance between the exporter and the US (in km.	USITC-Gravity Data
$ComLan_{ij}$	Dummy variable whether the exporter and the US speak the same language.	USITC-Gravity Data
$Cont_{ij}$	Dummy variable whether the exporter shares a common border with the US.	USITC-Gravity Data
$lnForEx_{jt}$	Exporter's forest (% of GDP).	WDI
$lnForIm_{it}$	US's forest rent (% of GDP).	WDI
$lnGDPEx_{jt}$	Nominal GDP of exporter (in billions).	WDI
$lnGDPIm_{it}$	Nominal GDP of the US (in billions).	WDI
$lnExRate_{ijt}$	Nominal exchange rate.	WDI
$lnProEx_{jt}^{k}$	The quantity of timber production for selected product group in the exporting country (1000 m3).	ITTO
$lnProIm_{it}^{k}$	The quantity of timber production for selected product k in the US (1000 m3).	ITTO
LAA	Dummy variable equals to 1 after the implementation of the LAA.	
Restriction	Dummy variable indicating whether the exporting country has a legal law that forbids illegal logging at time t.	
Member_WTO	A dummy variable that takes the value of 1 if the exporting country has a WTO membership.	USITC-Gravity Data

Table B.5: Summary Statistics of Variables Included in the Analysis of Australia

Variable	Observations	Mean	Std. Dev.	Min	Max
X_{ijt}^{k}	10,848	0.881	6.803	0	167.7
$lnDist_{ij}$	10,848	9.286	0.656	4.548	9.774
$ComLan_{ij}$	10,848	0.549	0.498	0	1
$Cont_{ij}$	10,848	0	0	0	0
$lnForEx_{jt}$	9,260	-1.377	2.541	-9.330	3.521
$lnForIm_{it}$	9,944	-1.904	0.258	-2.478	-1.492
$lnGDPEx_{jt}$	9,840	3.994	2.252	-1.459	9.928
$lnGDPIm_{it}$	10,396	6.664	0.535	5.935	7.365
$lnExRate_{ijt}$	10,344	2.579	2.928	-6.873	22.45
$lnProEx_{jt}^{k}$	8,101	4.391	2.590	-3.219	11.27
$lnProIm_{it}^{k}$	10,848	5.636	2.126	1.609	8.402
ILPA	10,848	0.292	0.455	0	1
Restriction	10,848	0.0653	0.247	0	1
Member_WTO	10,848	0.839	0.367	0	1

Table B.6: Summary Statistics of Variables Included in the Analysis of the EU

Variable	Observations	Mean	Std. Dev.	Min	Max
X_{ijt}^{k}	152,880	0.977	11.03	0	868.3
$lnDist_{ij}$	152,880	8.452	0.961	1.384	9.876
$ComLan_{ij}$	152,880	0.198	0.399	0	1
$Cont_{ij}$	152,880	0.0170	0.129	0	1
$lnForEx_{jt}$	117,040	-1.445	2.803	-9.528	3.699
$lnForIm_{it}$	138,320	-3.893	1.191	-6.307	-1.450
$lnGDPEx_{jt}$	132,320	3.127	2.159	-3.890	9.928
$lnGDPIm_{it}$	145,600	6.801	0.924	5.100	8.281
$lnExRate_{ijt}$	137,120	2.998	2.852	-5.634	23.24
$lnProEx_{jt}^{k}$	85,610	3.763	2.606	-5.067	11.27
$lnProIm_{it}^{k}$	132,860	5.588	2.061	-0.693	10.08
EUTR	152,880	0.286	0.452	0	1
Restriction	152,880	0.0340	0.181	0	1
Member_WTO	152,880	0.722	0.448	0	1

Table B.7: Summary Statistics Variables Included in the Analysis of Japan

Variable	Observations	Mean	Std. Dev.	Min	Max
X_{ijt}^{k}	12,384	8.041	70.44	0	2,093
$lnDist_{ij}$	12,384	9.063	0.670	4.056	9.837
$ComLan_{ij}$	12,384	0.00775	0.0877	0	1
$Cont_{ij}$	12,384	0	0	0	0
$lnForEx_{jt}$	10,564	-1.109	2.402	-9.330	3.532
$lnForIm_{it}$	11,352	-4.566	0.275	-5.144	-4.154
$lnGDPEx_{jt}$	11,456	3.612	2.288	-3.890	9.928
$lnGDPIm_{it}$	11,868	8.482	0.108	8.302	8.732
$lnExRate_{ijt}$	11,904	-1.729	2.872	-11.32	17.99
$lnProEx_{jt}^{k}$	12,384	7.380	1.436	4.898	10.03
$lnProIm_{it}^{k}$	9,010	4.130	2.621	-5.067	11.27
JCWA	12,384	0.167	0.373	0	1
Restriction	12,384	0.0601	0.238	0	1
Member_WTO	12,384	0.853	0.354	0	1

Table B.8: Summary Statistics of Variables Included in the Analysis of the US

Variable	Observations	Mean	Std. Dev.	Min	Max
X_{ijt}^{k}	16,224	12.11	206.8	0	7,073
$lnDist_{ij}$	16,224	9.034	0.606	3.994	9.776
$ComLan_{ij}$	16,224	0.609	0.488	0	1
$Cont_{ij}$	16,224	0.0118	0.108	0	1
$lnForEx_{jt}$	12,172	-1.421	2.607	-9.330	3.532
$lnForIm_{it}$	14,872	-2.916	0.325	-3.555	-2.234
$lnGDPEx_{jt}$	13,544	3.373	2.293	-3.890	9.518
$lnGDPIm_{it}$	15,548	9.503	0.268	8.996	9.928
$lnExRate_{ijt}$	14,248	2.774	2.739	-6.628	22.63
$lnProEx_{jt}^{k}$	16,224	9.381	1.415	5.455	11.14
$lnProIm_{it}^{k}$	9,818	3.915	2.619	-5.067	11.27
LAA	16,224	0.458	0.498	0	1
Restriction	16,224	0.0441	0.205	0	1
Member_WTO	16,224	0.718	0.450	0	1

Table B.9: Selected Country List Included in the Analysis of Australia

Albania	Croatia	Kenya	Portugal	United Rep. of Tanzania
Argentina	Czechia	Lao People's Dem. Rep.	Rep. of Korea	Uruguay
Armenia	Dem. Rep. of the Congo	Latvia	Romania	USA
Austria	Denmark	Lithuania	Russian Federation	Vanuatu
Bahamas	Ecuador	Luxembourg	Samoa	Venezuela
Bahrain	Equatorial Guinea	Malawi	Saudi Arabia	Viet Nam
Belarus	Estonia	Malaysia	Serbia	Zimbabwe
Belgium	Eswatini	Mali	Serbia and Montenegro	
Belgium-Luxembourg	Fiji	Malta	Sierra Leone	
Belize	Finland	Mexico	Singapore	
Bolivia	France	Morocco	Slovakia	
Bosnia Herzegovina	Gabon	Mozambique	Slovenia	
British Virgin Islands	Georgia	Myanmar	So. African Customs Union	
Brazil	Germany	Netherlands	Solomon Islands	
Brunei Darussalam	Ghana	New Caledonia	Somalia	
Bulgaria	Greece	New Zealand	South Africa	
Cote d'Ivoire	Guatemala	Nigeria	Spain	
Cambodia	Guinea	Norfolk Islands	Sri Lanka	

Table B.9: (Continued) Selected Country List Included in the Analysis of Australia

Cameroon	Guyana	North Macedonia	Sweden
Canada	Hungary	Norway	Switzerland
Central African Rep.	India	Pakistan	Thailand
Chile	Indonesia	Papua New Guinea	Timor-Leste
China	Ireland	Paraguay	Turkey
China	Israel	Peru	Uganda
Colombia	Italy	Philippines	Ukraine
Congo	Jamaica	Pitcairn	United Arab Emirates
Costa Rica	Japan	Poland	United Kingdom

Table B.10: Selected Country List Included in the Analysis of the EU

Afghanistan	Cabo Verde	Ethiopia	Jamaica	Nauru
Albania	Cambodia	Faeroe Islands	Japan	Namibia
Algeria	Cameroon	Fiji	Jordan	Nepal
Andorra	Canada	Finland	Kazakhstan	New Caledonia
Angola	Central African Rep.	Former Sudan	Kenya	New Zealand
Anguilla	Chile	French Polynesia	Kyrgyzstan	Nicaragua
Antigua and Barbuda	China	Gabon	Lao People's Dem. Rep.	Niger
Argentina	China,Hong Kong SAR	Gambia	Latvia	Norway
Armenia	China,Macao SAR	Georgia	Lebanon	North Macedonia
Aruba	Cocos Islands	Ghana	Lesotho	Oman
Australia	Colombia	Gibraltar	Liberia	Pakistan
Azerbaijan	Comoros	Greece	Libya	Panama
Bahamas	Congo	Grenada	Lithuania	Papua New Guinea
Bahrain	Costa Rica	Guam	Luxembourg	Paraguay
Bangladesh	Croatia	Guatemala	Madagascar	Peru
Barbados	Cuba	Guinea	Malawi	Philippines
Belarus	Cyprus	Guinea-Bissau	Malaysia	Pitcairn
Belize	Czechia	Guyana	Mali	Portugal
Benin	Dem. People's Rep. of Korea	Haiti	Mali	Qatar
Bermuda	Dem. Rep. of the Congo	Holy See (Vatican City State)	Malta	Rep. of Korea
Bhutan	Djibouti	Honduras	Marshall Islands	Rep. of Moldova
British Virgin Islands	Dominica	Hungary	Mauritania	Romania
Brazil	Dominican Rep.	Iceland	Mauritius	Russian Federation
BruneiDarussalam	Ecuador	India	Mexico	Rwanda
Bulgaria	Egypt	Indonesia	Mongolia	Saint Barthelemy
Burkina Faso	El Salvador	Iran	Montenegro	Saint Lucia

Table B.10: (Continued) Selected Country List Included in the Analysis of the EU

Burundi	Equatorial Guinea	Iraq	Montserrat	Saint Pierre and Miquelon
Bolivia	Eritrea	Ireland	Morocco	San Marino
Bosnia Herze-govina	Estonia	Israel	Mozambique	Saudi Arabia
Serbia	Serbia and Montenegro	Seychelles	Sierra Leone	Singapore
Slovakia	Slovenia	Sudan	Suriname	Sweden
Switzerland	Syria	Tajikistan	Thailand	Togo
Trinidad and Tobago	Tunisia	Turkey	Uganda	Ukraine
United Arab Emirates	United Kingdom	United Rep. of Tanzania	Uruguay	USA
Venezuela	Vietnam	Zambia	Zimbabwe	

Table B.11: Selected Country List Included in the Analysis of Japan

Albania	Croatia	Italy	Papua New Guinea	Ukraine
American Samoa	Cyprus	Kenya	Paraguay	United Arab Emirates
Angola	Czechia	Kyrgyzstan	Peru	United Kingdom
Argentina	Dem. People's Rep. of Korea	Lao People's Dem. Rep.	Philippines	United Rep. of Tanzania
Australia	Dem. Rep. of the Congo	Latvia	Poland	Uruguay
Austria	Denmark	Liberia	Portugal	USA
Bangladesh	Ecuador	Lithuania	Rep. of Korea	Vanuatu
Belarus	Equatorial Guinea	Luxembourg	Romania	Venezuela
Belgium	Estonia	Madagascar	Russian Federation	Viet Nam
Belgium-Luxembourg	Eswatini	Malawi	Saint Lucia	Zambia
Belize	Fiji	Malaysia	Samoa	Zimbabwe
Bolivia	Finland	Mali	Senegal	
Bosnia Herzegovina	Former Sudan	Malta	Serbia	
Brazil	France	Mauritania	Serbia and Montenegro	
Brunei Darussalam	Gabon	Mauritius	Sierra Leone	
Bulgaria	Gambia	Mexico	Singapore	
Cote d'Ivoire	Georgia	Mongolia	Slovakia	
Cabo Verde	Germany	Montenegro	Slovenia	
Cambodia	Ghana	Morocco	So. African Customs Union	
Cameroon	Greece	Mozambique	Solomon Islands	
Canada	Guatemala	Myanmar	South Africa	
Central African Rep.	Guinea	Nauru	Spain	

Table B.11: (Continued) Selected Country List Included in the Analysis of Japan

Chad	Guyana	Nepal	Sri Lanka
Chile	Honduras	Netherlands	Suriname
China	Hungary	New Zealand	Sweden
China, Hong Kong SAR	Iceland	Nicaragua	Switzerland
Colombia	India	Nigeria	Thailand
Congo	Indonesia	North Macedonia	Trinidad and Tobago
Cook Islands	Iran	Norway	Turkey
Costa Rica	Ireland	Panama	Uganda

Table B.12: Selected Country List Included in the Analysis of the US

Afghanistan	Cambodia	El Salvador	Iceland
Antigua and Barbuda	Cameroon	Equatorial Guinea	India
Argentina	Canada	Eritrea	Indonesia
Armenia	Cape Verde	Estonia	Iran
Australia	Cayman Islands	Fiji	Iraq
Austria	Central African Rep.	Finland	Ireland
Azerbaijan	Ceylon	France	Israel
Bahamas	Chad	French Polynesia	Italy
Bahrain	Chile	Gabon	Jamaica
Bangladesh	China	Gambia	Japan
Belarus	Christmas Island	Gaza Strip	Kenya
Belgium	Colombia	Georgia	Kosova
Belize	Congo ,Rep.	Germany	Latvia
Benin	Cook Islands	Ghana	Lebanon
Bermuda	Costa Rica	Gibraltar	Liberia
Bhutan	Cote d'Ivoire	Greece	Libya
Brazil	Croatia	Guatemala	Liechtenstein
British Indian Ocean Ter.	Cyprus	Guinea	Lithuania
British Virgin Islands	Czechia	Guyana	Luxembourg
Bhutan	Dem. Rep. of the Congo	Haiti	Macao
Brunei	Denmark	Heard Island McDonald Islds.	Macedonia
Bulgaria	Dominican Republic	Honduras	Malagasy Republic
Bolivia	Ecuador	Hong Kong	Malaya
Bosnia and Herzegovina	Egypt	Hungary	Malta

Table B.12: (Continued) Selected Country List Included in the Analysis of the US

Mauritius	Peru	Sudan	Western Samoa
Mexico	Philippines	Suriname	Zambia
Moldova	Pitcairn	Swaziland	Zimbabwe
Monaco	Poland	Sweden	
Mongolia	Portugal	Switzerland	
Montenegro	Reunion	Syria	
Morocco	Romania	Taiwan	
Mozambique	Russia	Tanzania	
Myanmar	Saint Helena, Ascension, and Tristan da Cunha	Thailand	
Namibia	Sao Tome and Principe	Togo	
Nauru	Saudi Arabia	Tonga	
Netherlands	Senegal	Trinidad and Tobago	
Netherlands Antilles	Serbia	Tunisia	
New Caledonia	Serbia and Montenegro	Turkey	
New Zealand	Seychelles	Turks and Caicos Islds.	
Nicaragua	Sierra Leone	Uganda	
Nigeria	Singapore	Ukraine	
Norfolk Island	Slovakia	United Arab Emirates	
Norway	Slovenia	United Kingdom	
Pakistan	Solomon Islands	Uruguay	
Palau	South Africa	Vanuatu	
Panama	South Korea	Vatican City	
Papua New Guinea	South Sudan	Venezuela	
Paraguay	Spain	Vietnam	