

THE PLASTIC RECYCLING INDUSTRY AND ITS RELATIONSHIP TO OIL PRICE

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Abstract

Plastic manufacturers have a choice of purchasing virgin or secondary material for production. Virgin material in plastics production is oil, and secondary material is recycled plastic. Both can be used to make resin used in plastic production. This substitute relationship means that the material plastic recycling industry is likely to be impacted by changes to oil prices. If plastic recycling limits the negative externalities caused by virgin resource consumption and provides a viable substitute in the form of secondary material, then understanding the relationship between the two could be key to increasing the recycling rate and usage of secondary material in the future. A finite distributed and autoregressive distributed lag model are used to analyze the constant elasticity relationship between the price of oil and the producer price index of material plastic recyclers, using data from 1996-2016. It is expected that a positive impact between oil price in a previous period and the PPI of material plastic recyclers in the current period will be found.

KEYWORDS: (Oil, Plastics Manufacturing, Autoregressive)

JEL CODES: (Q530, L650, C220)

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Introduction

The price of oil can be volatile. The benchmark price for crude oil produced in the US, West Texas Intermediate (WTI), observed a price fall from \$103.59 per barrel in August of 2013 to just \$44.65 per barrel two years later (“U.S Natural Gas Prices,” 2016). While this drop is celebrated by consumers that spend less at the gas pump, it is devastating to the recycling industry which produces recycled plastic materials to compete directly with the virgin material of oil and its by-products. As oil prices decrease, it becomes cheaper for producers of plastic bottles and packaging materials to use virgin materials derived from oil instead of secondary materials from recycled plastics.

The resulting decrease in demand for recycled plastic material has challenged the industry, with the CEO of Waste Management claiming that “80 percent of its municipal contracts” had been renegotiated in order to decrease recycling collection and increase company revenue and as the drop in demand for recycled products continues to hurt the company’s profitability (Morris, 2016). The New York Times reported in early 2016 that the company had closed about 20% of its recycling facilities and had fired 900 employees since the oil price slump (Gelles, 2016). These struggles are felt by all in the industry, with one recycling plant manager in New Jersey putting it simply: “as profit margins get slimmer, some things just don’t make sense anymore” (Vanek Smith, 2016).

Decreased demand for recycled products not only harms the bottom line of the recycling industry but raises environmental concerns. The practice of recycling began when first person repurposed scrap metal for a new use, making the exercise ancient. Until recent decades the recovery of scarce material was the only motive to recycle, as it could often be more efficient to reuse available material instead of extracting new virgin material (“The

Truth about Recycling,” 2007). In the 1970’s, environmental concerns resulted in more widespread recycling programs. Not only was the conservation of virgin materials now a goal instead of a convenience, but negative externalities associated with virgin material consumption were discovered and widely publicized (“The Truth about Recycling,” 2007). Externalities, or the indirect impacts of production or consumption, are rarely considered in the pricing of goods and services but have widespread consequences, both positive and negative (Helbling, 2012). Reducing the negative externalities associated with virgin material consumption, such as greenhouse gas emissions and habitat destruction, were goals that spurred the recycling movement. Health problems stemming from pollution of the air, land and water also contributed to the environmental cause of decreasing landfill usage and increasing recycling rates (“Recycling Basics,” 2016). Recycling programs of today are designed to improve environmental conditions, public health and resource conservation.

If we are to stand by the claim that recycling benefits society, then we must be concerned about what factors influence the recycling industry. If there is a relationship between the price of a secondary material, like recycled plastic, and the price of a substitute virgin material, like crude oil, then further investigation should be undertaken in order to better understand the plastic recycling industry, hopefully leading to reduced negative consumption externalities. In order to expand on previous research regarding the price relationship between virgin oil material and secondary plastic material, this paper will investigate the relationship between the plastic material recycling industry and the price of crude oil. This is in order to more directly understand the relationship between oil prices and the state of the plastic recycling industry, instead of making an inference based on price.

Two time-series models will be used to analyze the relationship between the monthly Producer Price Index index of plastic material recyclers and monthly prices of crude oil, provided respectively by the US Federal Reserve (FED) and Energy Information Administration (EIA). Assuming a substitute relationship for the virgin and secondary materials, expected findings are a positive relationship between material plastic recycler's PPI and the price of oil.

Section II reviews current literature on the subject, with Section III covering theory, data & method. Results & analysis are covered in section IV. The conclusion is section V following by the appendix in section VI.

Literature Review

A number of factors influence why and at what quantities waste material is recycled. An assessment of academic literature indicates large and unaccounted for negative externalities associated with virgin material consumption and traditional waste disposal methods, as well as evidence for the viability of recycled HDPE and PET plastic materials as substitute intermediate goods on the basis of quality and supply. Factors likely to influence the recycling industry are specified as business cycle fluctuations, government intervention and market structure. While the relationships between price, demand and supply of virgin and recycled materials is dynamic, this paper will focus the specific relationship between virgin price and secondary material recyclers.

Consumption Externalities

In an economy with easy access to cheap virgin materials, what drives society's impulse to recycle? The answer lies in a long-term effort to combat negative externalities associated with the two major consequences of resource consumption: material depletion and waste accumulation.

Material depletion. When recycled material is utilized in substitution for virgin material, the negative externalities associated with resource extraction are never incurred. Decreasing the production of greenhouse gasses is vital to environmental health as it has been established that a build up of gasses such as CO₂ will have disastrous effects as they warm planet, increasing weather extremes and sea levels to the detriment of communities worldwide (Hansen & et al., 1981). The production of these greenhouse gasses is linked to the burning of fossil fuels and between oil utilized as material and energy expended in manufacturing the plastics industry consumes about 7-8% of oil and gas produced annually

(Hopewell, Dvorak & Kosior, 2009). Substituting recycled plastic material for virgin plastic material in order to decrease crude oil and natural gas consumption would extend the lifespan of these natural resource stocks as well as decrease the impact of acidification and toxicity caused by plastics production (Ackerman 1997; Molgaard, 1995).

The extent to which increased consumption of recycled materials can limit environmental harm is exemplified by indications that producing plastic water bottles with recycled PET instead of virgin PET “[would reduce] emissions of CO₂ per bottle by 27%,” (Hopewell, Dvorak & Kosior, 2009). Reduction in virgin material extraction and consumption is made possible through substitution with recycled materials to achieve the goal of “waste prevention,” or the theory that best environmental practice is not to counteract the externalities of virgin resources consumption but to reduce and eventually eliminate virgin consumption in the long-run (Ackerman, 1997).

Waste Accumulation. The ‘lifecycle’ assessment of a product measures the environmental impact of an item from manufacture to destruction, so externalities of different production and disposal methods can be compared (Molgaard, 1995). Traditional waste disposal requires the use of landfills and incineration, which are associated with worse health outcomes and a greater lifecycle impact on the environment.

The first disposal method available is dumping waste in landfills, which emit enough greenhouse gases to account for 4% of US emissions by the mid 1990’s (Ackerman, 1997). Not only do landfill emissions contribute to climate change, but acid gasses consisting of “nitrogen dioxide, sulfur dioxide and halides, such as hydrogen chloride and hydrogen fluoride” emitted from landfills can all negatively impact lung health and trigger asthma attacks (“Impact on Health of Emissions from Landfill Sites”, 2011). A report by the UK

Health Protection Agency found a correlation between a mother's increasing proximity to a landfill and increasing rates of birth defects in her children, as well as an estimate that up to 25% of odor complaints, which are associated with nausea, headaches and respiratory problems, come from nearby landfill locations ("Impact on Health of Emissions from Landfill Sites", 2011). "Marine plastic" is created when waste plastic enters a water system where it accumulates high levels of toxins, resulting in animals at the bottom of the food chain sickened hazardous plastics, with bio magnification transferring these health impacts up the food chain to larger animals (Teuten & et al., 2009). Research on plasticizers (additives to make plastic products more flexible) indicate that when these chemicals leech into mollusk, crustacean and amphibian habitats through improper waste disposal or landfill leakages, these animals experience "reproductive and developmental disturbances" unseen in unaffected environments (Oehlmann & et al., 2009). Reduction in landfill utilization can halt the spread of these negative environmental and health externalities.

While biodegradable plastic has the potential to reduce pressure on landfill capacity and eventually resolve some negative landfill externalities, relying on this new technology to limit landfill emissions harmful to both the plant and its inhabitants is unwise, as most landfills lack the necessary air and light for successful biodegradation (Rebeiz & Craft, 1995). More commonly, incineration is proposed as an alternative to recycling and landfill usage.

Burning waste may be encouraged under the justification that energy production is a positive externality, but negative environmental and health externalities negate this benefit (Molgaard, 1995; WRAP 2008; Rebeiz & Craft, 1995). A comparison of lifecycle impacts of recycled and incinerated plastics clearly indicates that disposal of plastic through

recycling means will almost always produce fewer CO₂ emissions and higher net energy savings than incineration (Patel, Jochem & Worrell, 2000). Additionally, ash from incinerated plastic is highly toxic, creating more negative externalities by requiring disposal at specialty landfill locations, furthering ill health outcomes (Ackerman, 1997). While incineration does reduce the volume of landfill trash, it contributes to more toxic landfill waste and conserves less energy than the recycling process.

Summary. The modern drive to recycle stems from an altruistic desire to reduce negative environmental and health externalities associated with natural resource depletion and waste accumulation. This drive is characterized as altruistic because the negative externalities of virgin material consumption are not factored into market prices, resulting in a market failure as more virgin material is consumed than is sustainable (Buvoll, 1998). If the overuse of virgin material is considered a market failure, then the corresponding market correction may be the increased use of recycled material.

Substitutability of Virgin and Recycled Material

If increasing use of recycled material is to replace declining use of virgin material, then the efficacy of these two materials as substitute goods must be established by comparing quality, costs and supply. These characteristics are of most concern, as “decisive factors are price and quality” in buying decisions, with ‘soft’ factors such as environmental friendliness exerting little influence (Jochem, Janzen, & Weimar, 2016).

Quality. Plastic is the newest material to enter to recycling industry, possibly contributing to more technical complications and higher costs as compared to the recycled paper and metal industries which have had considerably more time to develop (Patel, Jochem & Worrell, 2000). While this attitude initially cast doubt on the strength of the

substitution relationship, years of research and development have greatly improved the quality of recycled plastic material in manufacturing (Ambrose & et al., 2002; Hopewell, Dvorak & Kosior, 2009; Jochem, Janzen & Weimar, 2016; Rebeiz & Craft, 1995). Not only do multiple variations of plastic exist, but quality of recycled plastic material is dependent on the purity and cleanliness of the original plastic recycled, so a range of recycled plastic quality exists on the market (Rebeiz & Craft, 1995; Lyons, Rice & Wachal, 2009). The benefit of using HDPE and PET plastic in recycled products is the common forms of these bottles (milk jugs and water bottles) are easily recognizable and separable in waste and recycling streams, so purity of recycled material for these plastic types is high (Hopewell, Dvorak & Kosior, 2009). Specific usage of recycled plastic material is dependent on its quality, with low-quality recyclables used in alternative wood and concrete products and high-quality recyclables used in new plastic products (WRAP, 2008). Both HDPE (high-density polyethylene) and PET (polyethylene terephthalate) are petrochemicals derived from ethylene, a by-product of crude oil (ICIS Flowchart, 2015).

High-quality recycled HDPE plastic material that has been repurposed for use in high-end plastic products passes stress, chemical and mechanical tests used to determine the function and durability of products made from recycled material (Ambrose & et al., 2002). For lower-quality recycled material, wood-plastic composites made of 70% recycled HDPE and 30% recycled waste wood have been effective in replacing wood-plastic composites made solely of virgin material (Sommerhuber, Welling & Krause, 2015).

Recycled PET material has also been found to be a high-quality substitute to virgin material. A study in the UK found only a slight loss in plastic clarity in products made with recycled PET resin and evidence that recycled material can “directly replace

virgin polymer” (Hopewell, Dvorak & Kosior, 2009). Construction material must be resilient under pressure and time, and when PET plastic is recycled into PC plastic it can be combined with pea gravel, sand, and fly ash to produce an alternative to concrete which requires less time set, decreasing construction closures and detours (Rebeiz & Craft, 1995). When recycled PET plastic is evaluated for environmental and health risks, evidence indicates that if washed and decontaminated properly, the recycled material does not pose an additional threat (Bayer, 2001).

Cost. While the technical specifications of recycled plastic material indicate it is a good substitute for virgin plastic, this substitution is limited by cost considerations, as consumers want to avoid higher prices and price volatility (Ackerman, 1997; Patel & et al., 2000; Bruvoll, 1998; Ambrose & et al., 2002). A major determinant to the cost of recycled material production is the expense of collecting recycling waste from homes and businesses, and plastic material is generally considered more expensive to collect because of its incredibly low weight to volume ratio (Ambrose & et al., 2002). Plastic is also a relatively new material, so recycling processes are newer and more expensive compared to paper and most metals (Patel & et al., 2000). A cost-benefit analysis of US recycling programs in the 1990’s found these programs cost an additional \$142 per ton of recyclables per year, even when accounting for revenue from the sale of recycled scrap material (Ackerman, 1997). The flipside of these claims is that technology is always advancing, and as more plastic is recycled over time the costs will decrease to the more competitive levels seen in other recycled materials markets (Patel & et al., 2000; Mansikkassalo, Lundmark & Soderholm, 2014).

Indeed, some more recent research indicates that recycling programs are not the guaranteed budget-busters as they are often portrayed (Hopewell, Dvorak & Kosior, 2009; Lavee, Regev & Zemel, 2007; Lyons, Rice & Wachal, 2009). In addition to negative health and environmental impacts, landfill construction and upkeep are a major cost to the waste management industry, with this effect felt most strongly in highly populated areas (Ackerman, 2007; Lavee, 2007; Lavee, Regev & Zemel 2009; Tonjes & Mallikarjun, 2013). The smaller population density of rural areas is associated with higher collection costs as more miles and labor must be committed per ton of recyclables collected, cheaper land and a population farther from landfill locations, making a switch to recycling programs an expensive proposition (Ackerman, 1997). This contrasts greatly with high population density areas such as New York City where recyclable collection is a less expensive process and nearby landfill locations are expensive, and in areas where geographic characteristics limit where landfills can safely be constructed, as the Netherlands experiences with flooding vulnerabilities and Japan with hard bedrock constraints (Hopewell, Dvorak & Kosior, 2009). It is important to note that in this context the only requirement for a recycling programs to benefit a community is that its “net costs need to be less than the default option,” and with urban populations growing more places will find advantage in recycling programs (Tonjes & Mallikarjun, 2013)

When studies began to analyze recycling programs individually they discovered when areas adopt efficient policies, such as curbside pickup on the same day as garbage collection, recycling programs can be made fiscally responsible by increasing the volume of recycling material collected in an industry with high fixed costs (Folz, 1999). A study found that in half of Israeli municipalities, “it would be efficient to adopt recycling, even

without accounting for externality costs... municipalities would be able to reduce direct costs by an average of 11%” (Lavee, 2007). The recycled scrap market is also a global market, making it possible for “variations in scrap location, demand, price and transportation cost” to incentivize purchases of recycled material (Ackerman & Gallagher, 2002; Lyons, Rice & Wachal, 2009). The recycled plastics market is in direct competition with products derived from the oil and gas industry, so movements in the global price of oil may have a large impact on the outcome of a cost-benefit analysis regarding the purchase virgin or recycled plastic resources (Lyons, Rice & Wachal, 2009).

It is a misconception that recycled plastic material will always be a more expensive alternative to its virgin material counterpart, as this calculation is highly dependent on unpredictable values such as oil price and future advancements in technology. Another fallacy in the discussion of costs surrounding the substitution of recycled resources for virgin resources is the often repeated claim that recycled resource prices are significantly more volatile than virgin resource prices (Ackerman, 1997). Perceptions of instability may dampen new investment in recycling infrastructure and research and development as plastic producers may perceived the risk associated with switching to recycled plastic material as too high (Ackerman & Gallagher, 1997; Stromberg, 2004; Lavee, Regev & Zemel, 2009). There is no denying that price volatility discourages investment, but evidence suggests that the price of recycled and virgin materials is highly correlated and there is not inherently higher volatility in the recycled material market. A study in the US and Sweden found that in the cases of copper, lead and plastic, “prices of recyclables do not appear to be particularly volatile as compared

with their virgin substitutes” (Stromberg, 2004). It is logical for these prices to not be as volatile because recycled and virgin resource prices are often highly correlated, as is the case for recycled PET pellets, aluminum and cardboard and their virgin resource counterparts in the US (Chen & Liu, 2014). The plastics market in the UK experiences a similar correlation, with the identification of “significant relationships between the price of crude oil/ethylene/naphtha and recycled plastics” (Angus, Casado & Fitzsimons, 2012). The strong price correlation casts doubt on the claim that dramatically higher price volatility in the recycled plastics market will increase substitution costs to such a point that the substitution is not considered a viable option.

Supply. The interesting relationship between price volatility in the virgin and recycled resource markets is a consequence of unique market inefficiencies in the recycling industry (Sommerhuber, Welling & Krause, 2015). Studies of own-price elasticity of supply for recycled resources consistently indicate a very low elasticity of supply for recycled products (Ackerman & Gallagher, 2002; Angus, Casado & Fitzsimons, 2012; Mansikkassalo, Lundmark & Soderholm, 2014). All authors indicate that market intervention is the likely source of disconnect between supply, demand and price signals in the recycled resource market.

In theory, when the recycling industry experiences a drop in the price offered for its product it will decrease the quantity supplied in response, but government efforts to increase recycling rates through methods such as taxing excessive garbage disposal and requiring the use of recycled material in some manufactured items has resulted in the breakdown of this dynamic (Brown & Zhang, 2005; Mansikkassalo, Lundmark & Soderholm, 2014). The removal of these regulations would not necessarily benefit the

recycling industry as they are a response to previously discussed high production costs that discourage early investment and stall technological advancement in recycled resource manufacturing, considered by some environmentalists as key to eventually establishing a self-sustaining supply of recycled material (Patel & et al., 2000). When one considers that “the hallmark of [traditional] styles of recycling is that they are motivated primarily by economic considerations,” environmentalist’s desire to develop a market where recycled resources are by default the cheaper consumption option is a smart way to achieve their goals (Ackerman, 1997). However, unintended consequences of policies which decrease own-price elasticity of substitution, such as high price volatility, discourage new expenditures on the recycled resource industry and hinder the development of new technologies necessary for the industry to be cost-competitive without government help (Ackerman & Gallagher, 2002; Angus. Casado & Fitzsimons, 2012; Mansikkasalo, Lundmark & Soderholm, 2014).

Summary. If the planet is to dramatically decrease consumption of virgin resources it must find a substitute with comparable quality and cost that has accessible supply. Recycled paper, metals, and plastics meet all of these requirements. Although price volatility discourages the adoption of recycled resource consumption, price swings are correlated with those in the virgin materials market and future recycling costs are expected to decrease at the same time as growing populations increase landfill and garbage disposal costs. While recycled resources are an acceptable substitute for virgin resources today, their significance as an alternative to natural resource depletion will only increase over time.

Determinants of Resource Price

Discussion on the relationship between virgin material price and the recycling industry would be incomplete without expanding on what elements determine resource prices. Studies designed to examine the own-price elasticity of supply of recycled resources and those designed to examine cross-price elasticity in general have identified a number of factors, beyond that of substitute material price, which determine the state of the recycled plastic industry.

The business cycle. Contraction or expansion of the general economy will greatly impact demand for virgin and recycled resources (Ackerman & Gallagher, 2002; Bils, 1987; Field & Pagoulatos, 1997; Pagoulatos & Sorensen, 1986; Lyons, Rice & Wachal, 2009; Mansikkasalo, Lundmark & Soderhold, 2014.) Companies that cater to mostly repeat customers with high switching costs are likely to experience an increase in the estimated price elasticity of demand magnitude when the economy is in a recession (Bils, 1987). These are characteristics of the recycled plastics industry, where consumers are manufacturing companies that would need to alter production procedure to accommodate new resource material. The assumption is that during boom times substitution-avoidant consumers become less price-sensitive with increasing price to cost margins, but become much more price-sensitive once price to cost margins drop with falling prices, as seen with US manufactured food products (Field & Pagoulatos, 1997). Higher price elasticity of demand estimates during recessions are also found in industries that have a high level of import penetration and therefore competition, as is the case with the scrap materials market (Field & Pagoulatos, 1997; Strauss, 1986).

Other evidence indicates that virgin and recycled resource price elasticity of demand should increase in magnitude during an expansion as consumers “may turn to recycling markets only as a last resort when the suppliers of virgin material face capacity constraints” (Miansikkasalo, Lundmark & Soderholm, 2014). In other words, an expansion in the business cycle may result in such a large spike in demand that consumers of material used in plastic production are forced to purchase an alternative material in the face of limited supply or drastically increased prices. It is only when the economy slows down that plastic producers can again be picky about where their material is sourced. This result supports claims that recycling is still too costly, because in order for manufacturers to increase demand for the less desirable recycled resource there must first be increasing scarcity due to expansion.

It is highly unlikely that fluctuations in the business cycle do not have an impact of the price elasticity of demand for recycled resources, but it is unclear if the effect is procyclical or countercyclical.

Market Structure. The structure of resource markets will also influence measures of cross price elasticity of demand. Industries with little or uneven access to pricing, supply, and demand data will face weak elasticity of demand effects as consumers have little incentive or ability to alter their consumption choices in the face of altered prices (Pagoulatos & Sorensen, 1986). The recycled scrap industry resembles an industry with fairly high information transparency as “scrap is largely marketed on spot basis,” so signals of a changing economic climate are easily identified (Strauss, 1986). Noted market transparency of recycled plastic resources increases the likelihood of finding a significant elasticity effect.

Cross-price elasticity of demand is also influenced by the characterization of goods in the market. Companies that operate large advertising budgets are likely to be competing in an industry with strong product differentiation, where it is possible to influence consumers through branding and loyalty to purchase a more expensive product, resulting in low cross price elasticity of demand (Pagoulatos & Sorensen, 1986). The plastic resin market is not characterized by differentiation or large advertising costs, indicating that recycled resources are likely to have a measureable cross-price elasticity of demand (Strauss, 1986). However, in addition to their role as substitute goods virgin and recycled materials are also complementary goods used together in the manufacturing process (Brown & Zhang, 2005). As producer goods recycled resources have a large number of complementary goods, this may dampen the effect of any cross-price elasticity of demand relationship because any positive elasticity associated with substitute goods may be effectively disguised or counteracted by the negative elasticity of complementary goods (Pagoulatos & Sorenson, 1986).

Transparency in resource markets increases the likelihood of a cross-price elasticity of demand relationship between recycled and virgin materials, but characterizations of these goods as both non-differentiated substitutes and strong complements will to some extent neutralize the strength of the elasticity relationship in both the positive and negative directions.

Government intervention. The recycling industry is well-known for high-levels of government involvement as an effort to induce positive externalities associated with recycling programs, both on a local and national level (Ackerman, 1997; Tonjes & Mallikarjin, 2013). These schemes are often unsuccessful due to design flaws which fail

to target consumption of recycled material, essentially ensuring “the supply of recycled materials will continue to flow onto the market, despite a lack of demand” (Angus, Casado & Fitzsimons, 2012). Most government programs target increasing the amount of waste that is picked up for recycling, such as programs to persuade companies to produce products that can be easily sorted for recycling collection or increasing garbage fees, without ensuring that these scrap materials actually have an end use (Chen & Liu, 2014; Stromberg, 2004).

These are the conditions that contribute to an inefficient market where recycled resources have a very low own-price elasticity of supply (Mansikkasalo, Lundmark & Soderholm, 2014). However, this does not remain true for policies directed at the demand side of the market, such as minimum recycled content laws, which seem effective in increasing the amount of recycled resources producers consume (Brown & Zhang, 2004). While most government intervention in the recycled resource market is characterized as inadequate, it is probable that new laws regulating required minimum consumption of recycled resources will increase demand for these resources in the future.

Estimating Elasticity

Although conventional wisdom suggests a decrease in oil prices will correspond with a decrease in the price demanded by recycled materials, little research has been conducted to estimate the magnitude or existence of this effect. Even as claims are made like “the price of pulp directly affects the market for waste paper: when the price of pulp increases, there should be an increase in the demand and price for inputs into pulp production such as waste paper”, most research focuses on the price relationship between virgin and recycled material, not the demand relationship (Ackerman & Gallagher, 2002).

Studies may detail low own-price elasticity of supply in the recycled paper and metal materials markets but do not go further in exploration of cross-price elasticity of demand relationship (Blomberg & Soderholm, 2009; Brown & Zhang, 2005; Angus, Casado & Fitzsimons, 2012; Mansikkasalo, Lundmark & Soderholm, 2014). While a study of cross-price elasticity of demand would be interesting, the lack of data on demand for recycled material prevents this analysis. Instead, a different approach to investigating the relationship between virgin and secondary material price will be undertaken by looking at a constant elasticity model of PPI of the secondary material industry and oil price. This is a way to focus on oil price relationship to the industry, instead of solely to the price of the material.

It is well established that elasticity can be estimated using a linear regression, with constant elasticity estimated using a log-log model and semi-elasticity estimated using a log-level model (Woolridge, 2013). Of more than 35 studies examining cross-price elasticity of gasoline price and public transport ridership between 1978 and 2008, the majority used log-log regression models to estimate constant elasticity (Nowak & Savage, 2013). Similar models are used in the tobacco and meat industry, indicating widespread usage (Wohlgenant, 1985; Grace, Kivell & Laugesen, 2014).

Estimating an elasticity model is helpful in understanding the relationship between substitute goods, by both confirming the existence of such a relationship and revealing what factors influence movement from one good to another, such as in the case of e-cigarettes and tobacco (Grace, Kivell & Laugesen, 2014). Similar to our case of virgin and recycled resources there are negative externalities associated with the consumption of the traditional good, but price acts as incentive to consume the healthier

option for “if the price of tobacco cigarettes were to increase by 10%, consumption of e-cigarettes would increase by 1.6%” (Grace, Kivell & Laugesen, 2014). Public transport ridership in Chicago, another good with positive externalities, has an elasticity of “0.28-0.30 for city and suburban bus, and 0.37 for commuter rail” when gas prices are above \$4 a gallon, again revealing how high prices might induce consumption of a less harmful substitute (Nowak & Savage, 2013).

Two studies about cross-price elasticity of lumber and related wood products are of note. Both used log-log regression models. An estimation of cross-price elasticity between softwood lumber and substitute building materials in the US found that “a 1 percent increase in the (weighted) price of other types of building materials in the short run leads to between a 0.10 percent and 0.27 percent increase in softwood lumber demanded” (Uri & Boyd, 1990). A recent German study attempted to estimate cross-price elasticity of demand for wood-based materials and their substitutes in the construction industry and identified “the expected positive sign” associated with a substitute good relationship, although the magnitude of the elasticity effect was low (Jochem, Janzen & Weimar, 2016). The consumption of wood-based construction resources is less harmful to the environment when compared to substitute materials such as brick and concrete, and changing substitute prices may correlate with a change in input good demand (Jochem, Janzen & Weimar, 2016). In place of studies directly examining the constant elasticity between virgin materials and recycling industries, these reports on wood construction materials may serve as the closest standard to follow.

Summary. Increasing the production and consumption of recycled plastic resources will limit the negative health and environmental externalities associated with plastic

consumption. While a traditionally more expensive production resource, recycled HDPE and PET plastic are of a comparable quality, will decrease in cost over time and maintain consistent supply levels. Demand for recycled resources is often dictated by changes in the business cycle, characteristics of the plastics market and government intervention, but few studies have explored what impact the price of substitute virgin resources may have on the plastic material recycling industry on the whole.

Method, Data & Model

Method

A constant elasticity demand function can be used to estimate the percentage change in the dependent variable when the independent variable changes by one percent (Woolridge, 2013). Following the methods of the elasticity studies noted in the literature review (Grace, Kivell & Laugesen, 2014; Nowak & Savage, 2013; Wohlgenant, 1985) and the constant elasticity function in Woolridge's textbook, the equation can be generalized in equation (1) where y is the dependent variable, x are independent variables, B are the coefficients, and u is the error term.

$$(1) \log(y) = B_0 + B_1 \log(x_1) + B_2 \log(x_2) + \dots B_n \log(x_n) + u$$

However, further development to the model is required due to the nature of the time series data. Two distributed lag models will be utilized to account for the possibility that a change in oil price will have both an immediate and delayed correlation with the PPI of the plastic recycling industry. Initially a finite distributed lag model (FDL) will be explored, followed by a more complex autoregressive distributed lag model (ARDL).

Due to the complexity of time series modeling, only one explanatory variable will be used in the model. While an analysis of the relationship between the plastic recycling industry and oil prices would ideally include other explanatory variables likely to influence the plastic recycling industry, including these variables increases the complexity of the model and the likelihood of model misinterpretation. Examples of variables that would ideally be included in a more complex model are plastic manufacturer's capacity utilization and inventory to shipment ratio, as well as GDP,

spending on industry research and development, and secondary plastic import and export levels.

The simple model is likely to be inherently flawed due to omitted variable bias, but it may still be a useful tool in understanding the relationship between the plastic recycling industry and oil prices. This strategy is similar to that of a UK study which only identified a significant correlation, not causal relationship, between oil price and recycled plastic price by employing oil price as the single explanatory variable (Angus, Casado, & Fitzsimons 2012). While these authors identified their process as simple when compared to a model that may determine a causal relationship by controlling for outside factors, they also emphasize that identifying a correlation is still valuable to non-academic observers. This is especially true of any individual or group that has a stake in the recycled material industry.

Data

A number of studies identified in the literature review investigated the relationship between virgin material price and secondary material price for metal, wood, and plastic materials (Stromberg, 2004; Angus, Casado & Fitzsimmons, 2012; Chen & Lui, 2014; Mansikkasalo, Lundmark & Solderhold, 2014; Ackerman & Gallagher, 2002). One may infer that oil prices have a relationship to the plastic recycling industry due to the previously established positive correlation between oil prices and secondary plastic prices, but a more direct analysis could be conducted. This research is designed to explore the existence of that more direct relationship between oil price and the plastic recycling industry by using the plastic recycling industry's producer price index as the dependent variable. The producer price index will indicate the changing condition of the

plastic recycling industry by measuring “average changes in prices received by domestic producers for their output,” as the US Bureau of Labor Statistics has define PPI (“Producer Prices”). The BLS also notes that private businesses often use PPI data to compare the costs of the materials they purchase or sell against an industry average, and that advisors use the index for market analysis and econometric modeling. The nature of the producer price index as a representation of average industry output prices suggests that using either the PPI or the price of secondary plastic material would produce similar results. It is important to confirm such a supposition with data. If there does not appear to be a positive relationship between oil price and the PPI of the plastic recycling industry, this would seemingly contradict results that indicate a positive correlation between oil price and secondary plastic price (Stromberg, 2004; Chen & Liu, 2014; Angus, Casado & Fitzsimons, 2012). Further research into the relationship between PPI and oil price would be required in order the understand the nature of such a discrepancy.

This paper will use the producer price index of the plastic recycling industry as the dependent variable (PPIRecyclers). Compiled by the Federal Reserve (FED) under the title *Producer Price Index by Industry: Material Recyclers: Recyclable Plastics*, this value estimates what price plastic material recyclers can demand for secondary plastic material, which may have utility as an indicator of changing trends in the plastic recycling industry. This seasonally adjusted monthly index has a base period of June 1996 and runs through November of 2016. The first quarter of data for 2004 was missing. Using the method set forth by the 13th Release of the Stata Time Series Manual, these four data points were linearly interpolated. The independent variable (WTI) will be the

monthly spot price of Cushing, OK WTI in US dollars from June 1996 to November 2016, as reported by the Energy Information Administration (EIA).

As this is an examination of constant elasticity, these variables will be transformed into their natural log values. Initial examination of the data using a Dickey-Fuller GLS test for a unit root indicated the presence of a time trend for both PPIRecyclers and WTI (see appendix A for more on unit root testing). The first differenced transformation of the two variables was utilized in order to induce stationarity, allowing for a regression analysis using OLS methods (Woolridge, 2013).

It is important to note these data transformations change the interpretation of the coefficients, but this will be discussed later in the model section. The variables as they will be used in the regression are summarized in table T1. A line plot of the two variables at level is displayed in figure F1 and a line plot of the two variables in first differences is displayed in figure F2.

Table T1 Data Summary

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
PPIRecyclers	245	-0.0013013	0.0802793	-0.855188	0.4477805
WTI	245	0.0032845	0.0875598	-0.3319805	0.2138658

There is a visible spike in the line plots provided in figures F1 and F2. Around the 2008 period the value of both WTI and PPIRecyclers drop dramatically, at level and in first differences. It is possible that the nature of the relationship between the two variables changed after this point, and a further developed model would want to explore this potential break in the data and explore methods to account for this break. Additionally, it

is possible that this drop will serve as an outlying point which could result in biased coefficient estimations.

Figure F1 Line plot of Variables at Level

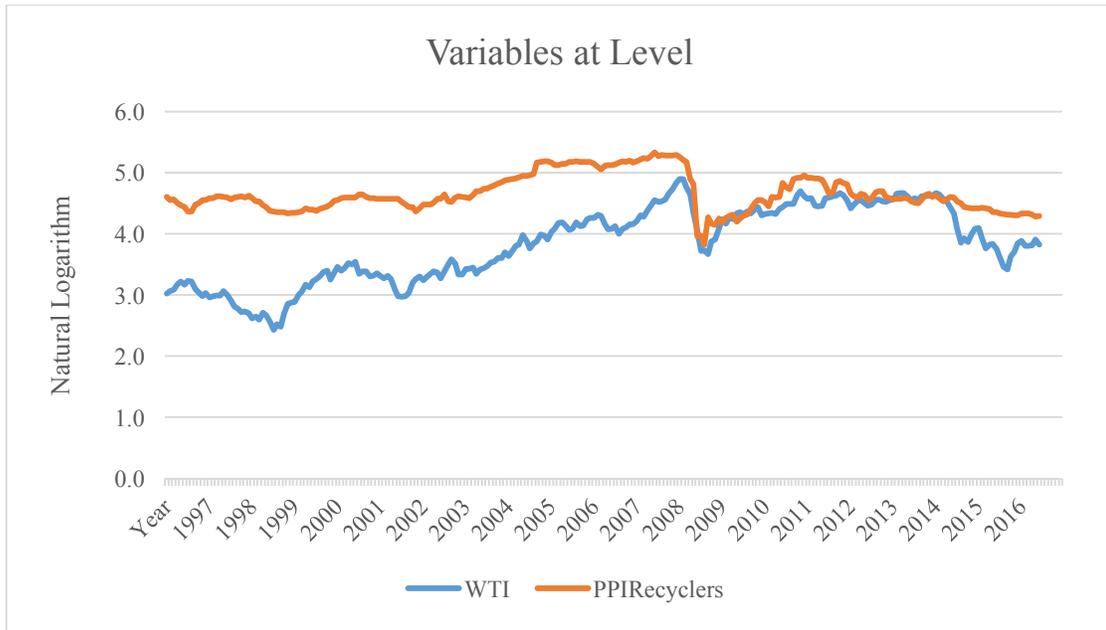
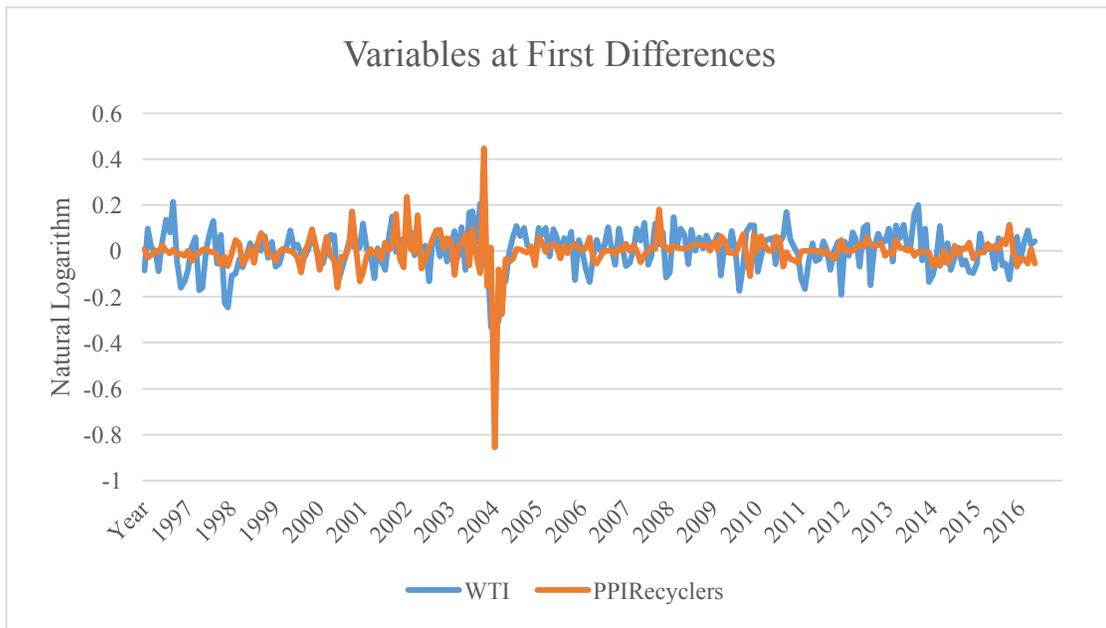


Figure F2 Line plot of Variables in First Differences



Model

The first regression will be a FDL model where PPI Recyclers in the current period is estimated using WTI in the current period and n number of previous periods, as determined by the the cross-correlation of the variables over time. The FDL model is displayed in equation (2).

$$(2) \Delta \log(y_t) = \alpha + \delta_0 \Delta \log x_t + \delta_1 \Delta \log x_{t-1} + \delta_n \Delta \log x_{t-n} + u_t$$

The second regression will be an ARDL model where PPI Recyclers in the current period is estimated using WTI in the current period and n number of previous periods, in addition to the value of PPI Recyclers in the current period and n number of previous periods. This model is considered dynamic because the previous values of the dependent variable are allowed to have feedback on the current value of the dependent variable (Woolridge, 2013). The ARDL model is displayed in equation (3).

$$(3): \Delta \text{Ln}(y)_t = \alpha + \gamma_1 \Delta \text{Ln}(y)_{t-1} + \dots + \gamma_n \Delta \text{Ln}(y)_{t-n} + \delta_0 \Delta \text{Ln}(x)_t + \delta_1 \Delta \text{Ln}(x)_{t-1} + \dots + \delta_n \Delta \text{Ln}(x)_{t-n} + u_t$$

As previously mentioned, data transformations have changed how coefficients need to be interpreted. In equation (1) the B_1 coefficient represented by what percent the dependent variable would change in response to a 1% change in the x_1 variable. However, first differencing of the natural logarithm means the coefficients in models (2) and (3) must be interpreted as the average growth per period, also known as the growth rate (Woolridge, 2013). For example, the δ_1 coefficient in the FDL model represents the expected change in the average monthly growth rate of PPI Recyclers in response to a one percent change in the average monthly growth rate of WTI. However, in the event of

small changes the growth rate can actually be interpreted in a manner similar to percentage change, because for small values $\Delta \ln(y_t) \approx (y_t - y_{t-1})/y_{t-1}$ (Woolridge, 2013). If the value of the coefficient on the differenced-logarithms is less than 20%, this estimation holds and a growth rate is approximately equivalent to a percent change (R Nau, 2017).

Woolridge (2013) identifies the five assumptions that must be met for a model to be considered the best linear unbiased estimator, and as previously discussed these models are unlikely to perfectly uphold all five assumptions. As outline in the data, the variables achieve the first assumption of linear parameters. A pairwise correlation matrix of PPIRecyclers, WTI, and four lags of each variable indicated the distributed lag models would not face issues regarding the second assumption of no perfect collinearity (see appendix C for details).

The third assumption, zero conditional mean, is unlikely to be perfectly upheld, partially due to the previous discussed omitted variable bias caused by the simplicity of the model design. The fourth assumption, homoscedasticity, is likely to be problematic for the reason of extreme values in the 2008 period and the possible change this had to the WTI and PPIRecyclers relationship. Breusch-Pagan testing will be used to identify heteroskedasticity.

Issues regarding serial correlation (auto correlation) will be identified using Alternative Durbin-Watson tests. The possibility that previous values of PPIRecyclers could have a relationship to the current value of PPIRecyclers means the initial FDL model is likely to experience issues regarding serial correlation in the error term. The fifth assumption of no serial correlation is expected to be more closely upheld in the

ARDL model because, as previous discussed, the dynamic quality of the ARDL model allows for previous values of the dependent variable to influence the current value.

Results & Analysis

Results

The regression results of both the FDL and ARDL will now be discussed.

Finite Distributed Lag. The FDL model in equation (2) was used to obtain an initial grasp of the lagged effect of WTI on PPIRecyclers. Only one lag of WTI was selected for use in the model (see Appendix C for more information on lag selection).

The model as specified in the regression is seen in equation (4).

$$(4): \Delta \ln(PPIRecyclers)_t = \alpha + \delta_0 \Delta \ln(WTI)_t + \delta_1 \Delta \ln(WTI)_{t-1} + u_t$$

A Breusch-Pagan test for heteroskedasticity strongly rejected the null hypothesis of constant variance at the 1% level with a chi-square test statistic of 340.43, signifying the existence of problematic heteroskedasticity (see Appendix D for more information on Breusch-Pagan testing). This was not unexpected. A regression was run with robust standard errors, and both regression results are displayed below in figure F3.

An Alternative Durbin-Watson test using three lags was run on the robust regression in order to identify residual autocorrelation. The null hypothesis of no serial correlation could not be rejected at the first lag, but rejection of the null hypothesis occurred at the second lag at the 5% level and the third lag at 1% level (see Appendix E for more information on Alternative Durbin-Watson testing). These results indicate that the FDL model may be improved upon by addressing autocorrelation.

The robust regression greatly increases the variance of the coefficient on both WTI and the first lag of WTI, from 0.0589 to 0.102 and from 0.0590 to 0.111 respectively. Additionally, the only coefficient that is significant in the non-robust

regression is first lag of WTI, and in the robust regression it's significance level decreases from the 1% level to the 5% level.

Figure F3 FDL Regression Results

VARIABLES	(1) FDL	(2) FDL Robust
WTI	0.0795 (0.0589)	0.0795 (0.102)
Lag 1 WTI	0.226*** (0.0590)	0.226** (0.111)
Constant	-0.00215 (0.00496)	-0.00215 (0.00541)
Observations	244	244
R-squared	0.080	0.080

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

Autoregressive Distributed Lag. The ARDL model in equation (3) was developed in order to address problematic autocorrelation identified in the FDL model. An analysis of the autocorrelation of *PPIRecyclers* identified an optimal lag of three (see appendix C for more on lag selection). The model as specified in the regression appears in equation (5).

$$\begin{aligned}
 (5) \Delta \ln(PPIRecyclers)_t &= \alpha + \delta_0 \Delta \ln(WTI)_t + \delta_1 \Delta \ln(WTI)_{t-1} \\
 &+ \gamma_1 \Delta \ln(PPIRecyclers)_{t-1} + \gamma_2 \Delta \ln(PPIRecyclers)_{t-2} \\
 &+ \gamma_3 \Delta \ln(PPIRecyclers)_{t-3} + u_t
 \end{aligned}$$

A Breusch-Pagan test indicated problematic heteroskedasticity in the ARDL model at the 1% level with a chi-square test statistic of 232.31, (see Appendix D for more information on Breusch-Pagan testing). This is a strong indicator of heteroskedasticity,

similar to what was observed in the FDL model. A regression was run with robust standard errors, and both regression results are displayed below in figure F4.

An Alternative Durbin-Watson test using three lags was run on the robust regression in order to identify any residual autocorrelation. The null hypothesis of no serial correlation was unable to be rejected at all three lag levels (see Appendix E for more information on Alternative Durbin-Watson tests). The failure to reject the null hypothesis indicates that the dynamic ARDL model did succeed in elimination of autocorrelation in the residuals.

Figure F4 ARDL Regression Results

VARIABLES	(1) ARDL	(2) ARDL Robust
WTI	0.111* (0.0607)	0.111 (0.104)
Lag 1 WTI	0.181*** (0.0613)	0.181** (0.0815)
Lag 1 PPIRecyclers	-0.0119 (0.0656)	-0.0119 (0.0569)
Lag 2 PPIRecyclers	0.157** (0.0642)	0.157 (0.117)
Lag 3 PPIRecyclers	-0.182*** (0.0621)	-0.182 (0.180)
Constant	-0.00186 (0.00488)	-0.00186 (0.00506)
Observations	242	242
R-squared	0.136	0.136

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

In the non-roust regression all coefficients except the first lag of PPIRecyclers reported statistical significance at minimum level of 10%, reaching into the 1% significance level for the first lag of WTI and the third lag of PPIRecyclers. However, the

non-normality of the variance due to heteroskedasticity indicate that the robust regression will have more reliable results. The robust regression reported larger coefficient standard deviations. The only statistically significant coefficient in the robust regression was the first lag of WTI. This coefficient observed a decrease in its significance level from the 1% level to the 5% level and an increase in the standard deviation from 0.0613 to 0.0815 when the robust regression was run.

Analysis

Interpretation of the model coefficients in a time series regression of constant elasticity provides an opportunity to estimate both the both the immediate and long-term relationship between and independent and dependent variable (Wooldridge, 2013). The impact propensity, or short-run elasticity, is the immediate change in the dependent variable following a one percent change in the independent variable, identified by the δ_0 coefficient on the WTI variable in time period t . The long-run propensity, or long-run elasticity, is the eventual change in the dependent variable following a one percent change in the independent variable, identified by the sum of the δ_0 and δ_1 coefficients on the WTI and first lag of WTI (Wooldridge, 2013).

As previously discussed, use of first differenced natural logarithms in the regression results in coefficients that technically represent changes to the average growth rate. The regression results for all models, displayed below in figure F4, represent small enough changes (below a coefficient value of 0.020) that the coefficient interpretation is essentially the same as a percentage change.

Inference in time series models is dependent on the assumption of normally distributed errors (Wooldridge, 2013). While these models appear to report statistically

significant coefficients, the model t-tests, standard deviations and F-tests are only valid if the residuals are normally distributed and conform to the five previously stated assumptions. While there appears to be statistical significance in the FDL models there is actually an issue of autocorrelation in both the initial FDL and robust FDL models, meaning the both FDL models provides poor inference. Additionally, the initial FDL and ARDL models both experience heteroskedasticity that is only addressed in the robust version of the two models via the employment of robust standard errors. In consideration of these factors, the robust ARDL regression is the model that best conforms to the six assumptions that provide for model inference. As a consequence of the minimized heteroskedasticity and autocorrelation in this version of the model, it provides the best opportunity for inference (see appendix F for more detail on model interpretation).

Figure F5 Complete Regression Results

VARIABLES	(2) FDL	(3) FDL Robust	(4) ARDL	(5) ARDL Robust
WTI	0.0795 (0.0589)	0.0795 (0.102)	0.111* (0.0607)	0.111 (0.104)
Lag 1 WTI	0.226*** (0.0590)	0.226** (0.111)	0.181*** (0.0613)	0.181** (0.0815)
Lag 1 PPIRecyclers			-0.0119 (0.0656)	-0.0119 (0.0569)
Lag 2 PPIRecyclers			0.157** (0.0642)	0.157 (0.117)
Lag 3 PPIRecyclers			-0.182*** (0.0621)	-0.182 (0.180)
Constant	-0.00215 (0.00496)	-0.00215 (0.00541)	-0.00186 (0.00488)	-0.00186 (0.00506)
Observations	244	244	242	242
R-squared	0.080	0.080	0.136	0.136

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

The following analysis refers to the results of the robust ARDL regression.

The short-run elasticity is determined by the δ_0 coefficient on WTI, meaning a 1% change in the oil price corresponds to a 0.11% change in PPIRecyclers. However, this value is not statistically significant under conditions robust to heteroskedasticity, so this study is unable to determine the short-run elasticity of PPIRecyclers in response to WTI. The long-run elasticity is determined by the addition of all statistically significant δ_n coefficients of the WTI and lagged WTI variables. The only statistically significant δ_n coefficient was the δ_1 coefficient on the first lag of WTI, meaning a 1% change in oil price corresponds to an change of 0.18% in PPIRecyclers by the end of the second time period.

While in theory the design of the FDL and ARDL models provided the ability to estimate both short-run and long-run elasticity, only the long-run elasticity estimation was statistically significant under conditions acceptable for inference. It is important to again note that the long-run elasticity is only able to estimate the *correlation* between WTI and PPIRecyclers, *not* a causal relationship. The positive correlation identified in the robust ARDL model does conform to expectations of a positive relationship between the PPI of the plastic recycling industry and oil prices, and supports previous research that indicated a positive correlation exists between the price of secondary plastic material and oil prices.

Conclusion

This study investigated the plastic material recycling industry and its relationship to oil prices. While a positive relationship does appear to exist between the price of oil and the PPI of plastic material recyclers, the result is not significant under conditions robust to heteroskedasticity in an FDL model. However, in an ARDL model a positive long-run elasticity value was identified and significant under robust standard errors. It appears in a simple ARDL model a 1% increase in the average growth rate of WTI correlation to a 0.18% increase in the average growth rate of the PPI of the plastic recycling industry, distributed over a period of two months. While this model does not take into consideration other factors, it is a good place to start for understanding of the industry. With this relationship established, more effort can be put into developing a dynamic model of the relationship between plastic material recycling and oil price in the face of other explanatory variables. This multivariate time series analysis would likely require a VAR or VECM model in order to account for variable endogeneity and cointegration.

Growth in the plastic recycling industry could limit negative externalities caused by plastic production and consumption by decreasing the amount of oil used in the manufacturing process. Understanding the link between this industry and the price of oil, recycled plastic's main substitute, could help leaders make better decisions in the face of current or expected changes to oil prices. Previous research established that virgin and secondary material pricing are often correlated, but it has not been examined how this pricing relationship may transfer through to the plastic recycling industry itself as

measured by industry PPI. This paper indicates that this price relationship is felt by the plastic recycling industry.

With this relationship confirmed, the material plastic recycling industry has even more reason to watch the price of oil. If the recycling industry can better understand both itself and its competitors, it may have a better chance at growth and stability. The long-run propensity of this relationship means changed oil prices do not immediately correlate with lowered industry PPI, meaning recyclers have time to put in place initiatives to support themselves in times of lower oil prices. Increasing replacement of virgin resources with secondary materials reduces negative externalities currently associated with plastic production and consumption, meaning informed decisions by the plastic recycling industry in the face of changing oil prices would not only benefit their bottom line, but benefit society as a whole.

References

- Ackerman, F., & Gallagher, K. (2002). Mixed signals: Market incentives, recycling, and the price spike of 1995. *Resources, Conservation and Recycling*, 35(4), 275-295.
- Ambrose, C. A., Hooper, R., Potter, A. K., & Singh, M. M. (2002). Diversion from landfill: Quality products from valuable plastics. *Resources, Conservation and Recycling*, 36(4), 309-318.
- Angus, A., Casado, M. R., & Fitzsimons, D. (2012). Exploring the usefulness of a simple linear regression model for understanding price movements of selected recycled materials in the UK. *Resources, Conservation & Recycling*, 60, 10-19.
- Ayad, H. (2016). Poverty, inequality and economic growth in Algeria: An ARDL approach. *Journal of Social and Economic Statistics*, 5(1)
- Bils, M. (1987). The cyclical behavior of marginal cost and price. *The American Economic Review*, 77(5), 838-855.
- Blomberg, J., & Söderholm, P. (2009). The economics of secondary aluminum supply: An econometric analysis based on European data. *Resources, Conservation and Recycling*, 53(8), 455-463.
- Brown, R., & Zhang, D. (2005). Estimating supply elasticity for disaggregated paper products: A primal approach. *Forest Science*, 51(6), 570-577.
- Bruvoll, A. (1998). Taxing virgin materials: An approach to waste problems. *Resources, Conservation and Recycling*, 22(1-2), 15-29.
- Chen, C., & Liu, L. Q. (2014). Pricing and quality decisions and financial incentives for sustainable product design with recycled material content under price leadership. *International Journal of Production Economics*, 147, Part C, 666-677.

- Conrad, E. V. L. (1954). The measurement of elasticities of demand. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 3(2), 74-84.
- Gelles, David. *Estimating cross-price elasticity of E-cigarettes using a simulated demand ...*: EBSCOhost Retrieved 10/23/2016, 2016,
from <http://web.a.ebscohost.com/ehost/pdfviewer/pdfviewer?sid=87a59ba7-68e5-4584-8820-80b11fb7666a@sessionmgr4007&vid=1&hid=4209>
- Field, M. K., & Pagoulatos, E. (1997). The cyclical behavior of price elasticity of demand. *Southern Economic Journal*, 64(1), 118-129.
- Finnveden, G., Johansson, J., Lind, P., & Moberg, Å. (2005). Life cycle assessment of energy from solid waste—part 1: General methodology and results *Journal of Cleaner Production*, 13(3), 213 <last_page> 229.
- Folz, D. H. (1999). Municipal recycling performance: A public sector environmental success story. *Public Administration Review*, 59(4), 336-345.
- Graves, P. E., & Sexton, R. L. (2009). Cross price elasticity and income elasticity of demand: Are your students confused? *The American Economist*, 54(2), 107-110.
- Hansen, J., Johnson, D., Cacic, A., Lebedeff, P., Rind, D., & Russel, G. (1981). Climate impact of increasing atmospheric carbon dioxide. *Science*, 213, 957.
- Helbling, T. (2012, March 28). Externalities: Prices Do Not Capture All Costs. Retrieved April 06, 2017, from
<http://www.imf.org/external/pubs/ft/fandd/basics/external.htm>
- Hopewell, J., Dvorak, R., & Kosior, E. (2009; 2009). Plastics recycling: Challenges and opportunities *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1526), 2115 <last_page> 2126.

ICIS petrochemicals flowchart Retrieved 10/17/2016, 2016,

from <http://www.icis.com/resources/content/icis-petrochemicals-flowchart/?intcmp=CHEM-download-flowchart-image>

Impact on health of emissions from Landfill sites - RCE-

18_for_website_with_security.pdf Retrieved 10/17/2016, 2016,

from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/334356/RCE-18_for_website_with_security.pdf

Jochem, D., Janzen, N., & Weimar, H. (2016). Estimation of own and cross price elasticities of demand for wood-based products and associated substitutes in the German construction sector. *Journal of Cleaner Production*, 137, 1216-1227.

Koro, E., & Kelvin, A. (2016). Autoregressive distributed lag (ARDL) cointegration technique: Application and interpretation. *Journal of Statistical and Econometric Methods*, 5(4), 63.

Lavee, D. (2007). Is municipal solid waste recycling economically efficient? *Environmental Management*, 40(6), 926-943.

Lavee, D., Regev, U., & Zemel, A. (2009). The effect of recycling price uncertainty on municipal waste management choices *Journal of Environmental Management*, 90(11), 3599-3606.

LCA of Management Options for Mixed Waste Plastics.pdf(2008). (Final Report No. 2016)WRAP.

Lyons, D., Rice, M., & Wachal, R. (2009). Circuits of scrap: Closed Loop Industrial Ecosystems and the Geography of US international Recyclable Material Flows 1995-2005. *The Geographical Journal*, 175(4), 286-300.

Mansikkasalo, A., Lundmark, R., & Söderholm, P. (2014). Market behavior and policy in the recycled paper industry: A critical survey of price elasticity research. *Forest Policy and Economics*, 38, 17-29.

Microsoft word - Paper_Conference_Berlin_FINAL.doc -

Gurtoo_Antony_Indirect.pdf Retrieved 10/19/2016, 2016, from http://userpage.fu-berlin.de/ffu/akumwelt/bc2006/papers/Gurtoo_Antony_Indirect.pdf

Microsoft word - RPPC.general.outline.!!!.doc - *rppc.pdf* Retrieved 10/19/2016, 2016, from https://www.issa.com/data/moxiestorage/regulatory_education/regulatory-reference-library/rppc/rppc.pdf

Mølgaard, C. (1995). Environmental impacts by disposal of plastic from municipal solid waste. *Resources, Conservation and Recycling*, 15(1), 51-63. doi:[http://0-dx.doi.org.tiger.coloradocollege.edu/10.1016/0921-3449\(95\)00013-9](http://0-dx.doi.org.tiger.coloradocollege.edu/10.1016/0921-3449(95)00013-9)

Morris, M. *City's free ride to recycling success about to end - houston*

chronicle Retrieved 10/6/2016, 2016,

from <http://www.houstonchronicle.com/news/politics/houston/article/City-s-free-ride-to-recycling-success-about-to-end-6850443.php>

Nau, R. (2017,). The logarithm transformation. Retrieved March 15, 2017, from

<https://people.duke.edu/~rnau/411log.htm#changelog>

Website created and operated by Robert Nau of the Fuqua School of Business at Duke University with instruction on regression and time series analysis

Nowak, W. P., & Savage, I. (2013). The cross elasticity between gasoline prices and transit use: Evidence from chicago. *Transport Policy*, 29, 38-45.

Oehlmann, J., Schulte-Oehlmann, U., Kloas, W., Jagnytsch, O., Lutz, I., Kusk, K. O., et al. (2009; 2009). A critical analysis of the biological impacts of plasticizers on wildlife *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1526), 2047 <last_page> 2062.

Pagoulatos, E., & Sorensen, R. (1986). What determines the elasticity of industry demand? *International Journal of Industrial Organization*, 4(3), 237-250.
doi:[http://dx.doi.org/10.1016/0167-7187\(86\)90019-6](http://dx.doi.org/10.1016/0167-7187(86)90019-6)

Patel, M., von Thienen, N., Jochem, E., & Worrell, E. (2000). Recycling of plastics in germany. *Resources, Conservation and Recycling*, 29(1–2), 65-90.

Pesaran, M. H., & Shin, Y. (1995). An autogressive distributed lag modelling approach to cointegration analysis. *Symposium at the Centennial of Ragnar Frisch, the Norwegian Academy of Science and Letters, Oslo, March 3-5, 1995*, Oslo.

Polyethylene terephthalate recycling for food-contact applications: Testing...:

EBSCOhost Retrieved 10/18/2016, 2016,

from <http://web.b.ebscohost.com/ehost/pdfviewer/pdfviewer?vid=1&sid=c80ab987-5ae3-45c1-a164-9b771c689c59@sessionmgr1>

Rebeiz, K. S., & Craft, A. P. (1995). Plastic waste management in construction:

Technological and institutional issues. *Resources, Conservation and*

Recycling, 15(3), 245-257. doi:[http://dx.doi.org/10.1016/0921-3449\(95\)00034-8](http://dx.doi.org/10.1016/0921-3449(95)00034-8)

Recycling basics. (April 7, 2016). , October 6, 2016,

from <https://www.epa.gov/recycle/recycling-basics>

Regulations, rigid plastic packaging containers Retrieved 10/19/2016, 2016,

from <http://www.calrecycle.ca.gov/Laws/Regulations/Title14/ch4a3a.htm>

- Search for FDA guidance documents > guidance for industry: Use of recycled plastics in food packaging: Chemistry considerations* Retrieved 10/19/2016, 2016, from <http://www.fda.gov/RegulatoryInformation/Guidances/ucm120762.htm>
- Sommerhuber, P. F., Welling, J., & Krause, A. (2015). Substitution potentials of recycled HDPE and wood particles from post-consumer packaging waste in Wood–Plastic composites. *Waste Management*, 46, 76-85.
- Stata Time Series Reference Manual Release 13 (2012)*.. Retrieved 2/14/2017 from <http://www.stata.com/manuals13/ts.pdf>
- Strauss, S. D. (1986). Materials markets. *Conservation & Recycling*, 9(2), 159-162. doi:[http://dx.doi.org/10.1016/0361-3658\(86\)90103-7](http://dx.doi.org/10.1016/0361-3658(86)90103-7)
- Stromberg, P. (2004). Market imperfections in recycling markets: Conceptual issues and empirical study of price volatility in plastics. *Resources, Conservation and Recycling*, 41(4), 339-364.
- Teuten, E. L., Saquing, J. M., Knappe, D. R. U., Barlaz, M. A., Jonsson, S., Bjorn, A., et al. (2009; 2009). Transport and release of chemicals from plastics to the environment and to wildlife *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1526), 2027 <last_page> 2045.
- Tonjes, D. J., & Mallikarjun, S. (2013). Cost effectiveness of recycling: A systems model *Waste Management (New York, N.Y.)*, 33(11), 2548-2556.
- The truth about recycling | the economist* (June 7, 2007). Retrieved 10/6/2016, 2016, from <http://www.economist.com/node/9249262>
- Torres-Reyna, O. *Time series.*, February 2017, from <http://dss.princeton.edu/training/TS101.pdf>

U.S. Bureau of Labor Statistics. *Chapter 14 Producer Prices*. Retrieved April 15, 2017,
from <https://www.bls.gov/opub/hom/pdf/homch14.pdf>

U.S. Energy Information Administration (2016). *U.S. Natural Gas Prices*. Retrieved
10/6/2016, from http://www.eia.gov/dnav/ng/ng_pri_sum_dcu_nus_m.htm

[U.S. Federal Reserve](#). *Producer Price Index by Industry: Material Recyclers: Recyclable
Plastic*. Retrieved 1/30/2017, from
<https://fred.stlouisfed.org/series/PCU42993042993042>

Uri, N. D., & Boyd, R. (1990). Estimating the regional demand for softwood lumber in
the United States. *North Central Journal of Agricultural Economics*, 12(1), 137-
147.

Vanek Smith, S. *Low oil prices interfere with what recyclers are paid for plastic :*
NPR Retrieved 10/6/2016, 2016,
from [http://www.npr.org/2016/01/14/463010138/low-oil-prices-interfere-with-
what-recyclers-are-paid-for-plastic](http://www.npr.org/2016/01/14/463010138/low-oil-prices-interfere-with-what-recyclers-are-paid-for-plastic)

Wohlgenant, M. K. (1985). Estimating cross elasticities of demand for Beef. *Western
Journal of Agricultural Economics*, 10(2), 322-329.

Appendix

Appendix A

Unit Root Testing

Failure to reject the null hypothesis of a Dickey-Fuller GLS test indicates the presence of a unit root. A DF-GLS test of PPIRecyclers with four lags failed to reject the null hypothesis at the 1% level for all lags (see table A1 for full test results). After first differencing a DF-GLS test of PPIRecyclers with four lags did reject the null hypothesis at the 1% level for all lags (see table A2 for full test results). A DF-GLS test of WTI with four lags failed to reject the null hypothesis at the 1% level for all lags (see table A3 for full test results). After first differencing a DF-GLS test of WTI with four lags did reject the null hypothesis at the 1% level for all lags (see table A4 for full test results).

Table A1

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
4	-2.155	-3.480	-2.896	-2.610
3	-2.169	-3.480	-2.903	-2.615
2	-2.595	-3.480	-2.909	-2.621
1	-1.996	-3.480	-2.915	-2.626

Table A2

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
4	-5.361	-3.480	-2.897	-2.610
3	-6.573	-3.480	-2.903	-2.616
2	-7.738	-3.480	-2.909	-2.621
1	-7.681	-3.480	-2.915	-2.626

Table A3

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
4	-1.874	-3.480	-2.896	-2.610
3	-1.973	-3.480	-2.903	-2.615
2	-2.156	-3.480	-2.909	-2.621
1	-1.972	-3.480	-2.915	-2.626

Table A4

[lags]	DF-GLS tau Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
4	-6.243	-3.480	-2.897	-2.610
3	-7.295	-3.480	-2.903	-2.616
2	-7.966	-3.480	-2.909	-2.621
1	-8.548	-3.480	-2.915	-2.626

Appendix B

Pairwise Correlation

A pairwise correlation matrix indicates the correlation coefficient between every variable. PPIRecyclers is identified as PPI in the matrix provided in Table B1. PPIRecyclers, WTI and four lags of each variable are included in the matrix. No correlation coefficient has a value greater than 0.5 or less than -0.5, so it appears perfect multicollinearity will not be of issue even with the introduction of lagged variables.

Table B1

	PPI	Lag 1 PPI	Lag 2 PPI	Lag 3 PPI	Lag 4 PPI	WTI	Lag 1 WTI
PPI	1						
Lag 1 PPI	0.0202	1					
Lag 2 PPI	0.2273	0.0203	1				
Lag 3 PPI	-0.1563	0.2274	0.02	1			
Lag 4 PPI	0.0261	-0.1564	0.2275	0.0201	1		
WTI	0.1531	0.3331	0.0563	0.1219	-0.0031	1	
Lag 1 WTI	0.27	0.1539	0.3324	0.0556	0.1223	0.2751	1
Lag 2 WTI	0.0841	0.2701	0.156	0.3341	0.0556	0.1295	0.2809
Lag 3 WTI	0.0479	0.0841	0.2703	0.156	0.3341	-0.0214	0.1301
Lag 4 WTI	-0.0186	0.0479	0.0841	0.2704	0.156	-0.0605	-0.0215
	Lag 2 WTI	Lag 3 WTI	Lag 4 WTI				
Lag 2 WTI	1						
Lag 3 WTI	0.2812	1					
Lag 4 WTI	0.1305	0.2812	1				

Appendix C

Lag Selection

The number of lags of the independent and dependent variables utilized in FDL and ARDL models can be determined through a number of different methods.

Analysis of cross-correlation and significance of additional lags will be used in for determining WTI lag selection. A cross-correlation table of WTI and PPIRecyclers indicated that the significance of the WTI lags dropped off after the first lag (see table C1). A regression run with four lags of WTI indicated that while the first lag of WTI was significant at the 1% level, the second through fourth lags of WTI were insignificant at the 10% level and did not improve the model (see table C2 for regression results). These two criteria indicate one lag of WTI is suitable.

The PPIRecyclers lag selection will be determined by an analysis of a correlogram and the significance of additional lags of PPIRecyclers in a regression model. The correlogram shows a spike only in the second and third lags of PPIRecyclers (see table C3). A regression with PPIRecyclers as the dependent variable with four lags of PPIRecyclers as the independent variables indicated that while the second and third lags of PPIRecyclers were significant at the 1% level, the first and fourth lags were insignificant at the 10% level (see table C4 for regression results). These two criteria indicate that three lags of PPIRecyclers is appropriate in the ARDL model.

Table C1

LAG	CORR	-1	0	1
		[Cross-correlation]		
-6	-0.0508			
-5	-0.0059			
-4	-0.0031			
-3	0.1216			
-2	0.0562			
-1	0.3330			
0	0.1531			
1	0.2692			
2	0.0836			
3	0.0476			
4	-0.0185			
5	-0.0417			
6	-0.0721			

Table C2

VARIABLES	Lag Selection Model 1
WTI	0.0836 (0.0599)
Lag 1 WTI	0.225*** (0.0620)
Lag 2 WTI	0.00115 (0.0623)
Lag 3 WTI	0.0211 (0.0622)
Lag 4 WTI	-0.0133 (0.0602)
Constant	-0.00166 (0.00504)
Observations	241
R-squared	0.083

Table C3

LAG	AC	PAC	0	Prob>Q	-1	1	-1	0	1
					[Autocorrelation]		[Partial Autocor]		
1	0.0201	0.0201	.10062	0.7511					
2	0.2270	0.2268	12.936	0.0016					
3	-0.1560	-0.1733	19.019	0.0003					
4	0.0261	-0.0151	19.19	0.0007					
5	-0.0197	0.0597	19.288	0.0017					
6	0.0108	-0.0230	19.317	0.0037					
7	0.0549	0.0540	20.082	0.0054					
8	-0.1004	-0.1063	22.655	0.0038					

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

Table C4

VARIABLES	Lag Selection Model 2
Lag 1 PPIRecyclers	0.0516 (0.0650)
Lag 2 PPIRecyclers	0.232*** (0.0641)
Lag 3 PPIRecyclers	-0.174*** (0.0641)
Lag 4 PPIRecyclers	-0.0151 (0.0650)
Constant	-0.000633 (0.00503)
Observations	241
R-squared	0.081

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

Appendix D

Breusch-Pagan testing for heteroskedasticity

Regression models that experience heteroskedasticity in the error term will have incorrect estimations of standard deviation and t-statistics. A Breusch-Pagan test can be used to identify heteroskedasticity by rejecting the null hypothesis of constant variance. After the test is completed, a robust regression may be run in order to account for any observed heteroskedasticity, producing regression results with valid standard deviations and t-statistics. The initial FDL model results are in table D1 and the initial ARDL model results are in table D2. Both tests indicated the presence of heteroskedasticity by rejecting the null hypothesis with very large chi-square test values at the 1% significance level.

Table D1 Breusch-Pagan test for FDL

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of PPIRecyclers

chi2(1) = 340.43

Prob > chi2 = 0.0000

Table D2 Breusch-Pagan test for ARDL

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of PPIRecyclers

chi2(1) = 232.31

Prob > chi2 = 0.0000

Appendix E

Alternative Durbin-Watson Testing

An Alternative Durbin-Watson test can be used to identify serial correlation in a time series regression. Rejection of the null hypothesis of no serial correlation is an indication that the model contains a serially correlated error term, meaning the standard deviation and test-statistics are invalid and the model needs further development. The Alternative Durbin-Watson test result for the robust FDL is displayed in figure E1, and the robust ARDL model test result is displayed in figure E2. Both tests utilized three lags, but the robust FDL model rejected the null hypothesis at the 5% level for the second lag and at the 1% level for the third lag. Meanwhile, the robust ARDL model was unable to reject the null hypothesis at any lag value, indicating a lack of autocorrelation.

Figure E1 Alternative Durbin-Watson test for Robust FDL

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	0.711	1	0.3990
2	6.192	2	0.0452
3	15.185	3	0.0017

H0: no serial correlation

Figure E2 Alternative Durbin-Watson test for Robust ARDL

Durbin's alternative test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	1.643	1	0.1999
2	1.636	2	0.4413
3	2.726	3	0.4359

Appendix F

Model Interpretation

In addition to the five assumptions outlined in the methods section of the paper, a final assumption of normally distributed errors must be met in an OLS time series regression in order for the standard deviation, t-statistics, and F-statistic to be unbiased (Wooldridge, 2013). The initial FDL and initial ARDL models face issues regarding heteroskedasticity, as outlined in appendix D. The robust FDL model faces issues regarding autocorrelation, explained in appendix E. The robust ARDL model has managed to minimize heteroskedasticity and autocorrelation, making it the best candidate for inference as the standard deviation and test statistics are more likely to be valid. However, the normality assumption in the robust ARDL model is not fully upheld. Although the distribution is nearly symmetrical, it is too centrally concentrated to be normally distributed. Figure F1 is a histogram of the residuals of the robust ARDL model. One can see that while the histogram only contains a single spike in the middle of the graph, it extends way beyond what the normal distribution line indicates it should reach.

Figure F1 Histogram of robust ARDL model residuals

