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#### The Economics of Recycling Rate: New Insights from Waste Electrical and Electronic Equipment

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#### Abstract

This paper addresses the determinants of metal recycling rates. The literature on recycling flows is scarce and does not directly address the issue of achieving a high recycling rate. In addition, extant literature has not quantified the recycling rate response to metal prices. Therefore, this paper explores factors that affect the recycling rate of different metals embodied in computers. We examine the effects of metal price, metal concentration in products, relative concentration ratio (i.e., primary vs. secondary supply), and embodied metal value on the recycling rate. Although the results reveal a significant effect of metal price on the recycling rate, the marginal response is low across different models (ordinary least squares, generalized linear model, fractional response model with endogenous regressor, and left-censored Tobit). This effect is not surprising and is in line with extant literature on recycling flows. Unfortunately, for most unrecycled metals, achieving a minimum embodied value is unlikely, as it would require a median price increase by one or two order of magnitude. In addition, it seems that the recycling rate is more elastic to other technical factors, such as the metal concentration in products or the relative concentration ratio. While the findings suggest important public policy implications, more data and interdisciplinary research are required to support these preliminary results.

*JEL classification:* C25; C26; Q53; Q57 *Keywords:* Recycling rate; Metal; Price; Circular economy; GLM, WEEE

#### 1. Introduction

Numerous reports and studies indicate that the dynamics of metal consumption and overall natural resource consumption are unsustainable (Ali et al., 2017; UNEP, 2019; 2016). A source of concern is the ability of economic systems to discover, open, and operate new mines with sufficient speed to address the demand surge. Other analyses underscore the vulnerability of strategic sectors (e.g., digital, green energy, military) to the unavailability of specific key metals (Department of Energy, 2011; European Commission, 2010; JRC et al., 2011; Blagoeva et al., 2016; World Bank, 2017). Such concerns motivate the effort to delink primary resource consumption through greater material efficiency and recycling.

From an environmental perspective, solid, air, water, and soil pollutions generated by economic activities are all causes for concern. In this respect, global warming is a prominent issue (IPCC, 2014). However, again, it seems that the waste and pollution problem is strongly linked to natural resource overconsumption (Behrens et al., 2007; Brooks and Andrews, 1974; Schandl and West, 2010; Smil, 2013; UNEP, 2013a). For example, Fizaine and Court (2015) show that metal production absorbs 10% of primary energy production; on a much larger scale, Smil (2013) demonstrates that the production of metals, plastics, construction materials, paper, and fertilizers need 20% of the total energy supply. Naturally, this energy consumption translates into greenhouse gas emissions. A recent UNEP (2019) report argues that global material extraction and processing are responsible for 50% of global greenhouse gas emissions. Solid waste also creates significant environmental and health issues (UNEP, 2013b). Again, the flow of global solid waste (2.01 Gt in  $2016^{1}$ ) is increasing; at best, it is landfilled, or worse, it is dispersed throughout the environment. In this context, the "seventh continent" of plastic in the Pacific Ocean is an astonishing illustration of the significant challenge resulting from poor management of the increasing flow of solid wastes (Lebreton et al., 2018). Moreover, even the flow of solid wastes from sectors often viewed as dematerialized, such as the digital sector, poses major challenges. Indeed, the waste from electric and electronic equipment is also increasing (44.7 Mt in 2016)

<sup>&</sup>lt;sup>1</sup>This figure, which comes from the World Bank, and could grow by 70% by 2050. See : https://www.worldbank.org/en/topic/urbandevelopment/brief/solid-waste-management.

and is generating important health and environmental issues for countries in which metal wastes leak (Baldé et al., 2017; Cui and Roven, 2011).

Given these concerns, recycling and a circular economy are now understood to be promising tools for reducing both primary resource needs on the one hand and waste on the other hand. Increasing the recycling rate involves several co-benefits (Blomberg and Söderholm, 2011; Hagelüken, 2014; UNEP, 2013a):

- Decreasing the environmental impact associated with waste (air, water, and soil pollutant emissions),
- Saving landfill space,
- Substituting the more important energy and environmental costs of primary production (greenhouse gases, water consumption, floor space consumption),
- Improving resources conservation,
- Increasing the geopolitical independence of raw-material-producing countries,
- Creating local alternative substitutes for imported raw materials that may finance armed conflicts,
- Reducing the potential disequilibrium between demand and supply through supply diversification,
- Creating jobs and local infrastructures linked to the activity, and
- Partially decoupling metals subject to byproduction due to an increase of secondary supplies.

Moreover, in contrast with reduction and reuse activities, recycling activities are more closely aligned with the business of traditional throughput economies, sharing economies of scale and cost minimization through international trade specialization (Ghisellini et al., 2016; Stahel, 2013). Unfortunately, despite these important advantages, recycling activities and, in particular, metal recycling suffer from a lack of knowledge on several topics.

First, despite the voluntary goals of international organizations and national governments, metal recycling rates are low and are expected to remain stable in the coming decades (Ali et al., 2017; UNEP,

2013a). To improve, it is necessary to identify the most effective triggers of high recycling rates and avoid potentially useless and expensive public policies. More precisely, with end-of-life recycling rates below 1%, many minor metals do not profit from the opportunities provided by recycling (UNEP, 2011) while several more recent works show that several metals can reach higher levels of recycling rate when analyzed over smaller geographic areas (Blengini et al., 2019). However, the consumption of minor metals has increased substantially given their importance in electric and electronic equipment. Indeed, the information and communication technologies (ICT) sector has experienced significant growth, suggesting many issues associated with resource and energy conservation. For example, a French report from the Shift Project (2018) indicates that total energy consumption for digital technologies is growing at 9% per year. Although the share of the digital sector in the global final energy consumption was low at the beginning of the decade (1.9% in 2013), this share has been substantially increase since then (2.7% in 2017). While many sectors improve their energy efficiency through the decrease of their energy intensity (ratio of energy consumption of the sector on the added value of the sector), the energy intensity of digital sector is increasing. Indeed, compared with the energy intensity of other sectors (-1.8%) per year), the energy intensity of the digital sector has risen at 4% per year. This previous work also underscores that 45% of this energy is devoted to the production of electric and electronic equipment using a variety of energy-intensive metals. In addition, if several metals found in waste electric and electronic equipment (WEEE) are well recycled, this hierarchy does not account for the environmental cost of metals (external costs). Therefore, we find some paradoxes in recycling, such that major metals are more often recycled than minor metals, though the unitary environmental costs of the former are well below that of the latter (Nuss et al., 2014). For example, in considering different well-known environmental indicators such as global warming potential (kg  $CO_2$  eq./kg), terrestrial acidification, and freshwater eutrophication, we observe that the unitary environmental impact of metals such as iron, aluminum, and copper is one, two, and three orders of magnitude lower than those of germanium, gallium, and tantalum (minor metals). Therefore, it is important to understand how recycling activities work for these metals and the best way to achieve high recycling rate targets.

Second, metal recycling is far behind other recycling programs. Metal recycling and other major material recycling differ in major ways. Unlike other materials such as paper, paperboard, or plastic, pure metal allows theoretically infinite recycling opportunities<sup>2</sup> (UNEP, 2013a). In addition, waste containing metals is less homogeneous than paper and plastic waste. The number of elements, the high variety of quality, and the concentration of metals in products involve challenges that are absent from other major recycled wastes. Consequently, WEEE recycling facilities are different from, for example, paper recycling facilities. More precisely, metal recycling requires high capital investments and sophisticated technologies for separating most of the specialty/rare/precious/base metals. For example, \$1 billion has been invested in the Umicore WEEE recycling and refining plant operating in Belgium (Hagelüken and Corti, 2010). This plant extracts 30 tons of gold, 37 tons of platinum group metals, 1000 tons of silver, and 68,500 tons of other metals per year from wastes. That makes it equivalent to the third largest gold mine in the world. For comparison, a standard paper recycling facility requires a base investment of \$30–\$50 million. This is why some scholars advocate embracing the issue of metal recycling separately from other materials (Andersson and von Borgstede, 2010; Lakhan, 2014; Hagelüken, 2014).

Third, previous literature has focused on the household and municipal collection steps but has not deeply analyzed the industrial recycling step. To be more precise, a quick overview of the literature on recycling shows three main streams: (1) studies that examine household and municipal wastes, (2) studies that model the economics of a specific resource industry, and (3) studies that analyze the technical characteristics of wastes.

To begin with, many studies have analyzed the different factors affecting municipal waste recycling rates (Berglund and Söderholm, 2003; Dijkgraaf and Gradus, 2017; Sterner and Bartelings, 1999; Yang and Innes, 2007). A complete survey of these studies is beyond the scope of this paper. Although this literature includes the overview of the impact of many factors (e.g., income, education, age, household size, population density, pay-as-you-throw pricing system), many gaps must be filled. For example, these studies do not quantify the effect of raw material prices on recycling rates. Moreover, most of

<sup>&</sup>lt;sup>2</sup> This does not mean that it is possible to operate at 100% recycling rate efficiency but rather that metal quality does not diminish when recycled.

these studies do not desegregate the different flows of raw materials. This could be problematic because the recovery and recycling rate can differ greatly across different raw materials (Andersson and von Borgstede, 2010; Lakhan, 2014). In addition, metals hold very specific characteristics and thus must be examined separately (Hagelüken, 2014). Other studies have embraced the economics of recycling rates in a more conventional way. This stream of research explicitly models the supply and demand of secondary metal flows (Blomberg and Söderholm, 2009; Edwards and Pearce, 1978). In contrast with the first type of literature, metal prices are taken into account. The studies typically reach the same conclusions: secondary recycled flows are price inelastic (Edgren and Moreland, 1989; Edwards and Pearce, 1978). Though scarce, the estimates do not really change across metals; for example, price elasticity varies for aluminum within a range of 0.18 to 0.32 (Blomberg and Hellmer, 2000; Blomberg and Söderholm, 2009, 2011; Carlsen, 1980; Slade, 1980a), while similar estimates for copper range from 0.1 to 0.29 (Fisher et al., 1972; Fu et al., 2017; Gomez et al., 2007; Slade, 1980a, 1980b) . The outcomes highlighted in these studies are notable, but they cannot be directly applied to recycling rate. In addition, they only document the price impact for copper and aluminum, two metals that are currently well recycled. No conclusion can be established for minor metals, which nevertheless inundate WEEE. Last, other scholars, primarily engineers and geologists, have shown that the dilution of metal in products could affect the incentive to recycle products (Johnson et al., 2007; Rombach, 2006; Vidal, 2017; Vidal et al., 2017). Unfortunately, these studies do not explicitly integrate the effects of metal prices and generally adopt a descriptive approach (e.g., scatter graph, no modeling).

Fourth, understanding how the policies intended to fight global warming interact with recycling and circular economic policies is important. To date, most studies have analyzed these issues separately; however, there is (at least theoretically) the possibility of complementary or substitute effects between them (crowding out).

In short, it is necessary to investigate the topic of metal recycling rates and the stakes associated with the global understanding of metal recycling rates in WEEE facilities. This paper explains the main determinants of metal recycling rates. Is the price (through taxes) a promising tool for achieving a higher recycling rate target? Are there other determinants of the metal recycling rate? Do the policies intended to fight climate change promote recycling by taxing CO<sub>2</sub>?

We show that the effect of metal price on the recycling rate is rather weak. Conversely, the recycling rate seems more elastic to other variables such as the metal concentration in products, embodied metal value, and relative concentration ratio. Given the findings of this study, the internalization of greenhouse gas costs would not lead to a significant increase in the metal recycling rate. Therefore, we stress that no overlap is apparent between climate policies and recycling polices. This paper also reveals that material/technical design policies can be promising and that focusing on economical tools (e.g., taxes) can be disappointing, as Söderholm (2011) also suggests. Finally, we highlight the potential tradeoff between a high material efficiency target and a high recycling rate target (for metals).

Overall, this paper offers a fourfold contribution to the existing literature. First, we assess the economic incentives (price) relative to raw material recycling rates (on the industrial side), as well as the impact of metal concentration. Thus far, the literature has not quantified the effects of these variables. Second, we examine the question of "fringe materials" through the example of minor metals. Third, to the best of our knowledge, this study is the first to explore the determinants of recycling rates from a materials perspective (elements in cross-section) and to focus on the industrial step (i.e., recycling efficiency rate) rather than a monograph or household panel rate studies. Fourth, we build a bridge between economic and technical approaches by using economic and technical determinants of the recycling rate (first use and estimation of relative concentration ratio and embodied metal value). Surprisingly, most of the prospective studies presented previously do not model (or even include) the impact of metal recycling. Some of the articles deliberately ignore the issue (e.g., Moss et al., 2013; Northey et al., 2014; World Bank, 2017), while others introduce an exogenous and arbitrary recycling rate (Blagoeva et al., 2016; Sprecher et al., 2017; Vidal, 2017). Therefore, the results from this study can also help scholars design future studies related to metal availability.

To answer the issues raised in the introduction, we proceed as follows: the next section ("Methodology and data") presents the data and different models used in this paper. The third section ("Results") provides different estimates of the models. The fourth section ("Discussion") introduces robustness and sensitivity analyses. This section also includes a discussion of potential caveats of this study. The final section considers public policy recommendations and future research.

#### 2. Methodology and data

#### 2.1 About the recycling rate

According to the UNEP (2011) report, there are at least four different recycling rates: end-of-life recycling rate, old scrap collection rate, recycling efficiency rate, and recycling content rate. The end-of-life recycling rate describes the share of recycled metal quantities in the total end-of-life waste flow of the metal. The old scrap collection rate describes the share of collected metal waste quantities on the end-of-life waste flow of the metal. The recycling efficiency rate is computed as the share of the recycled metal quantities in the collected metal waste flow. Lastly, the recycling content rate is the share of recycled metal quantities in the total metal consumption (which adds recycled and primary metal quantities). We are also aware of other types of recycling rates, such as the utilization rate and the recovery rate, in the economic literature (see Berglund and Soderholm, 2003). Although useful for analyzing some issues, such as international waste trade, these recycling rates are neither available for fringe elements nor easily computable at the global scale.

Here, we use the recycling efficiency rate and designate it with the general term "recycling rate." The recycling efficiency rate is computed as the ratio of recycled metal to the collected metal. Therefore, this measure focuses on the industrial recycling step rather waste collection at the household level (old scrap collection rate). The multiplication of the old scrap collection rate by the recycling efficiency rate provides the end-of-life recycling rate.

#### 2.2 Data

The data used in this study come from several sources. The recycling rate of different metals found in computers and the average metal concentrations in computers (% of total weight) come from a UNEP report (UNEP, 2013). The price of metals (\$/kg) comes from United States Geological Survey (USGS). Average mining concentration and crustal grade (%) are derived from three primary sources (Craig et

al., 2001; Fizaine and Court, 2015; Valero and Botero, 2002), while the unitary energy consumption of metals (GJ/t) comes from Nuss and Eckelman (2014). Table 1 provides the main descriptive statistics.

Moreover, based on data from UNEP (2013a), Figure 1 shows that the value of metals embodied in printed wired boards of computers per kg of waste is mainly derived from the value of gold (\$0.64), copper (\$0.52), aluminum (\$0.32), tin (\$0.21), nickel, lead and silver (\$0.1–\$0.2), and beryllium, palladium, and zinc (\$0.05–\$0.07) rather than other metals (<\$0.01). Data collected from different studies (see Bizzo et al., 2014; Işıldar et al., 2018; Fizaine and Court, 2015) show that the dilution of different elements in computer is highly variable and not always more important than primary mine dilution (Figure 2). This observation is particularly true for minor metals and runs counter to the idea of urban mine.

#### 2.3 Specification

In line with other studies (Johnson et al., 2007; Vidal, 2017), we explore the impact of different determinants of the metal recycling rate in computers. In a first model, we assume that the recycling rate of metal *i* depends on different factors: the price of metal (thereafter *price*), the concentration of metal in computers (*concentration p*), and the ratio between metal concentration in computers and metal concentration in deposits (hereinafter, relative concentration ratio, or RCR) which also need the concentration of metal in deposits (concentration m):

Recycling rate<sub>i</sub> = 
$$c + \beta_1 price_i + \beta_2 concentration p_i + \beta_3 \frac{concentration p_i}{concentration m_i} + \varepsilon_i.$$
 (1)

Metal *price* increases the revenue of recyclers, *concentration p* decreases the cost of recycling, and *RCR* account for the effect of competition between primary mining and secondary supply (recycling). In a second model, we substitute the RCR variable with a dummy variable (called *threshold*) indicating whether the average metal concentration is higher in products than in primary metal deposits:

Recycling rate<sub>i</sub> = 
$$c + \beta_1 price_i + \beta_2 concentration p_i + \beta_3 threshold_i + \varepsilon_i$$
, (2)

where *threshold* takes the value of 1 if the element concentration of products is higher than the element mining concentration and 0 otherwise. Last, we simply check the impact of price and logarithm of RCR (called lnRCR):

Recycling 
$$rate_i = c + \beta_1 price_i + \beta_2 \ln\left(\frac{concentration p_i}{concentration m_i}\right) + \varepsilon_i.$$
 (3)

Moreover, we check the possibility of the recycling rate being affected by the metal value included in the computer rather than the metal price itself. This variable, *Value*, is computed as

$$Embodied Metal value (\$) = Price \times Concentrationp \times Total Weight$$
(4)

Then, we estimate the following effect of the embodied value on the recycling rate:

$$Recycling \ rate_{i} = c + \beta_{1} Embodied \ Value_{i} + \beta_{2} ln \left(\frac{concentration \ p_{i}}{concentration \ m_{i}}\right) + \varepsilon_{i}.$$
(5)

#### 2.4 Models and issues with estimations

To assess the potential impact of each determinant, we provide a series of graphical (scatterplots) and non-conditional tests of means for the different variables. We sort the sample by increasing the value for each variable (4 variables) and separate the sample into two parts. We then perform a t-test of equality of means (average recycling rate in each subsample). We also represent the average recycling rate for each subsample when the total sample is sorted by increasing the value and separating it into three parts (terciles).

Next, we use econometric methods. More especially, before providing the estimate of equations (1)–(5), we need to address some typical econometric issues raised by our data.

*Small sample size*. We have limited data, and the sample is small (observations = 30). Small sample sizes can be problematic because they generate low statistical power and inflated effect sizes. Although we are aware of these issues, there is no easy way to deal with the small sample size. Moreover, the lack of studies on this topic is likely due to the lack of data. Nonetheless, inflated effect size is not problematic

here because our data show the reverse (i.e., we do not show a more important effect of some variables on recycling rate). In addition, the discussion and originality of our paper is not based on the absence of a detected effect of the variable that could be due to low statistical power. To avoid the loss of degrees of freedom, we introduce a low number of independent variables (a maximum of three variables).

*Heteroskedasticity*. Heteroskedasticity could be problematic because of its effect on statistical inference. We check this issue with the White test. If the test rejects the assumption that the variance of residuals is homoskedastic, we estimate heteroskedasticity-consistent standard errors (White/Hubbert covariance).

*Collinearity*. Collinearity can inflate standard errors and lead to non-significant results. Again, we report the variance inflation factor (VIF) and delete variables with a VIF higher than 10. This does not happen in our model estimations (the VIF statistics are always less than 2).

*Nonlinearity*. The use of ordinary least square (OLS) on fractional dependent variables is highly debated. The use of this kind of model on this form of data can lead to the ignorance of nonlinear effects or the generation of impossible outcomes (a negative percentage or higher than 100%). Here, we report OLS results for illustration and estimate a generalized linear model (GLM). GLMs avoid the generation of impossible outcomes and are recommended for modeling proportions (Baum, 2008; Papke and Wooldridge, 1996). More specifically, we use the binomial family with a logit link:

$$y^* = \ln\left(\frac{y}{1-y}\right) = X\beta + \varepsilon.$$
 (6)

We also use a robust variance estimator in the GLM, as various scholars have recommended (Baum, 2008; Papke and Wooldridge, 1996; Wooldridge, 2011). The use of a probit link does not lead to different results, though the prediction power is less important (see Appendix 1.2).

*Endogeneity*. We could suspect endogeneity between prices and the metal recycling rate. Therefore, we employ the fractional response model with endogenous regressor (FRMER), which uses a similar framework to the GLM but allows for the treatment of endogenous variables (Wooldridge, 2011). Following Jordan and Eggert (2018), we take the primary unit energy consumption for each metal (GJ/t)

and the average grade of metal in the crustal crust as an instrument for price. The primary metal unit energy consumption and the crustal grade of the metal are fixed by physical laws and do not depend on economic parameters, so we cannot suspect them to be endogenous to the recycling rate or price. We have also replicated the process with the average grade in crustal crust and the metal price 5 years before the cross-sectional estimation period as alternative instruments for metal price. The results are similar and appear in Appendix 1.2 (see FRMER 1.1 and 1.2). For illustration purposes only, we report standard post-estimations from traditional two-stage endogenous regression for price in natural logarithm and price in level (see Appendix 1, Instrumental variables). The R-square of the first stage is high (0.92 and 0.98), with an important F-statistic (120 and 789), thus avoiding issues associated with weak instruments. In addition, the Sargan–Basmann tests cannot reject that our instruments are uncorrelated with the error term (p-value associated with Sargan: 0.74/0.28; p-value associated with Basmann: 0.76/0.32), and the Anderson Lagrange-multiplier statistic test rejects the assumption that our model is underidentified., The results associated with the FRMER framework appear in the "Results" section.

#### 3. Results

#### 3.1 Relationship between variables and recycling rate

The different scatterplots in Figure 3 show that all variables are positively correlated with the recycling rate. However, the relationship between the price of metals and the recycling rate is weak, as indicated by the scatterplot and the test of equality of means (Table 2). Conversely, the correlation of the recycling rate with other variables seems more explicit. Figure 4 also supports this first statement.

Tables 3, 4, and 5 provide estimates of specifications (1)–(5) with OLS, GLM, and FRMER models. Most of the time, all the variables are significant at 5% and sometimes at 1% of risk. The signs of the different variable coefficients are identical across the models and are in line with theoretical expectations. In this way, the price is positively correlated with the recycling rate. The higher the metal concentration in the product, the lower is the cost of metal recovery, so the recycling rate is higher. The effect of supply competition is also perceptible through the results. Indeed, the effect of *RCR*, *threshold*, and *logarithm of RCR* are all positive. In this regard, the more important the metal production concentration relative to the metal mining concentration, the more the recycling rate of the metal will be important. This means that the presence of high-concentration (low-cost) mining alternatives disfavors the recycling of metal from low-grade metal products. The effect of embodied value is also observable with a significant coefficient of 0.02. This means that an increase of \$1 of the metal value embodied in a computer is correlated with an increase of two percentage points in the recycling rate.

In addition, as expected, the OLS models generate impossible forecasts. The OLS methods also provide significant estimates of the intercept. The interpretation of these results is problematic because it allows a positive (non-zero) recycling rate with a zero level for price/concentration and RCR variables. This is why it is necessary to use GLM and FRMER models.

All variables are also significant in the GLM and FRMER models. The different coefficients associated with the variables cannot be directly compared with OLS estimations because of the nonlinear transformation. The predictions provided by these models are more adequate. The models reproduce nearly 47% to 70% of the observed variance. The instrumentation of price with unit energy consumption and average crustal grade (but also the price five years before) does not greatly change the results, though the Wald test of exogeneity rejects the assumption that there is no endogeneity for a 5% risk threshold.

#### 3.2 Marginal effects

To make an appropriate interpretation of variable coefficients in the different models, we compute the average marginal effects on recycling rate for the different variables (see Figure 5 and Table 6). Four novel statements can be made about these computations. First, the average marginal effect of metal price, while significant, is low. A metal price increase of \$1,000 per kg leads to an average increase of 1.94 percentage points in the recycling rate. Second, increasing the metal concentration in products greatly enhances the recycling rate. An addition of one percentage point of metal concentration is correlated with a rise in the metal recycling rate of 2.52 percentage points. Third, increasing the RCR by one corresponds to an increase in the recycling rate of 6 percentage points. Fourth, metals that have a concentration in products that is higher than their mining concentration also have a higher recycling rate of approximately 31 percentage points. The effect of the embodied value is significant and close to

0.02, indicating that \$1 of metal value corresponds to an increase in the recycling rate of 2 percentage points. However, the average marginal effect is no longer significant when using GLM models. Conversely, the same specification with the embodied value in logarithm form reaches opposite conclusions for significance. In any event, at best, the value indicates that a one-unit increase<sup>3</sup> of the metal value logarithm is correlated with a rise of 3 percentage points in the recycling rate.

#### 3.3 Predictions

In Figure 6, we report the predicted and actual recycling rate for specification (1-5) with GLM model. The GLM and FRMER models perform better than the OLS models. The OLS forecast is more erratic and has a higher dispersion than the forecast of the GLM and FRMER models. Nonetheless, despite a good overall forecast, all specification fail to correctly predict the recycling rate of different metals such as lead (overestimation) and cobalt (underestimation). This could be due to other variables not being taken into account in our different specifications, such as the effect of Registration, Evaluation, Authorisation and Restriction of Chemicals (REACH) regulations, which are difficult to model.

#### 4. Discussion

In this discussion, we conduct different robustness and sensitivity analyses associated with the outcomes presented in the "Results" section. We also discuss the impact of the different statements described in the "Results" section for public polices and future studies.

#### 4.1 Does metal price really matter? A robustness analysis

The results obtained in this study are important because the effect of metal price on the metal recycling rate appears to be very low<sup>4</sup>. These results are in line with the low price elasticity of metal recycling flows found in the economics literature (see the "Introduction"). Thus, our results are not specific to the

<sup>&</sup>lt;sup>3</sup> This represents an average increase of each embodied metal value of \$3.92 for the sample (Mean = 2.22, Median = 0.17).

<sup>&</sup>lt;sup>4</sup> Here, our paper does not estimate a recycling rate price elasticity but rather a cross price elasticity recycling rate because the variable price denote the primary (mining) metal price. Indeed, due to the absence of recycling most of minor metals do not have secondary metal price thus preventing the use of secondary (recycled) metal price. However as many studies have shown that primary and secondary metal prices are cointegrated and evolve in the same way over the long term, we think that it would not alter our conclusions.

metal recycling efficiency rate. Moreover, another qualitative study related to the recycling of printed wire board in electronics and end of life vehicles reaches the same conclusion about the likelihood of increasing recycling rate for minor metals (Andersson et al., 2019). This observation is confirmed here by the revenues generated by different minor metals in comparison to precious and base metals (see figure 7). The median revenue generated for unrecycled metals is \$0.0004 per kg of wastes while this statics reaches \$0.12 per kg of wastes for recycled metals (a 300-fold increase). We understand that equalizing revenues generated by precious/base metals with minor metals would require unexpected price increases (or alternatively a very high concentration of minor metals). We must remember that the recycler's objective is to cover the cost of co-recycling. This cost is estimated at \$1.35/kg of electronic cards in China according to the study by Zeng et al. (2018) and is indicated by the black line on the figure 7.

Another question is whether this effect comes from our choice to introduce metal price in level rather than in logarithm. This choice does not affect the low level of the marginal effect of metal price (see the alternative robustness analysis presented in Table 7). For example, the highest estimate found in the robustness analysis is 7.9 percentage points of recycling rate per unit of price logarithm (1.2). Recall that at the average observation of the sample (\$28/kg<sup>5</sup>), an increase of one unit of logarithm represents nearly \$50/kg, which is approximately equivalent to tripling the price. Although these large and temporary price variations can occur naturally, it is unlikely that governments can reach this target with the tax lever. In addition, the price effect is not different when considered alone (1.4).

We also conducted a sensitivity analysis (see Appendix 2, Sensitivity analysis). We deleted one metal each time and repeated the estimation of the OLS and GLM models for specification (1), which integrates all the variables. The conclusion for the price effect does not change and is still significant. Nonetheless, we observe that gold and palladium influence the price effect (in level), though the variable remains significant. We find a similar sensitivity for iron with the *concentration* p variable and for copper, selenium, and lead with the RCR variable.

<sup>&</sup>lt;sup>5</sup> Here, we compute the exponential of the mean of price in logarithm. This mean differs from the average price (see the descriptive statistics).

Last, we perform different robustness analyses using a left-censured Tobit model because several metals, while available from printed wire board, are not recycled in our sample (see Appendix 3). The marginal effects for price remain significant, low, and close to the range of other estimates  $(1.4-3.5 \times 10^{-5})$ . Conversely, the marginal effect of other variables increases.

#### 4.2 Internalization of externalities in metal prices

As described previously, the response of the recycling rate to price seems to be very low. In such conditions, the question is whether the internalization of externalities in metal price might lead to a higher metal recycling rate.

At \$100 per ton of  $CO_2$  equivalent, metal price increase remains highly moderate for most of the metals. Except for aluminum (a 35% price increase) and steel (+100%), the impact is low for other base metals: copper (+3.68%), nickel (+3.10%), and zinc (+13.78%). Precious and minor metals show similar results: gold (+3.13%), silver (3.05%), palladium (1.99%), and indium (+2.5%). Therefore, given the low elasticity of metal price to carbon tax and a low elasticity of recycling rate to metal price, increasing metal price due to the internalization of externalities will not help achieve a higher recycling rate target.

Greenhouse gas emissions are not the only externalities associated with primary metal production (e.g., environmental burden of waste disposal). Moreover, we do not discuss here the usefulness of public policies of internalizing the cost of greenhouse gas emissions; we simply show that there is no overlap between climate public policies and resource conservation policy.

#### 4.3 Modification of metal concentration in products (eco-conception)

Increasing metal concentration in products could be more promising as a public policy than using the price channel. This option has already been advocated by the developers of eco-conception (Braungart and McDonough, 2011). Making metals more easily recoverable in products by increasing their concentration could reduce the cost of recycling and thus promote it. Increasing metal concentrations in products could also foster a higher recycling rate through the channel of competition between primary

and secondary production. If urban mining (recycling) is less costly than primary mining, activities will gradually switch to the former.

Unfortunately, by aiming for cost reduction, component miniaturization and nanotechnologies are preventing this effect. Indeed, there is a paradox inherent to the 3R strategy (reduce, reuse, and recycle); different public goals seem in some way incompatible. Indeed, if the term "reduce" refers to material efficiency policies that lead to the development of thinner, more complex, and lighter products and components, this may in turn mean a downward concentration of valued metals. This paradox might lead the first principle (reduce) to compromise the third (recycle). For example, according to Adie et al. (2016) and Cui and Roven (2011), technical progress and cost optimization have led to a downward trend of precious metal content in electronic products, though that is not systematic for all metals. Another phenomenon is the substitution of pure metal with a lower quantity of metal mixture. This can only lead to downward incentives to extract and recycle metals due to less valuable metal content and to increasing technical difficulties to recovery each element.

#### 4.4 Metal depletion and decreasing deposit concentrations

An increasing number of studies show that average metal grade deposits are continuously decreasing. This can be observed at different scales (deposits, country, global) and in different metals (Crowson, 2012; Mudd, 2010; Schodde, 2010). While this phenomenon leads to increasing energy (Fizaine and Court, 2015), water, and acid input consumption (Mudd, 2010; Mudd and Diesendorf, 2008), it might also make recycling more viable and profitable (an increase of RCR). However, this can only happen if (1) metal grade deposits continue to decline, (2) metal concentration in products increase or remain stable, and (3) the effect of technical progress cost reduction is not greater in the mining sector than in the recycling sector. Regarding the overall view, according to Tilton this last assumption did not happen in the "benevolent past" (Tilton, 2003) and that the increase of recycling due to mineral depletion is not likely to occur in the midterm (Tilton, 1999). This optimistic forecast about future primary metal depletion is not shared by other scholars (Kerr, 2014; Northey et al., 2014; Ali et al., 2017), but this debate is beyond the scope of this paper.

#### 4.6 What is lacking? Improving knowledge about price effects on recycling rate

Our models are not perfect and need to be improved in several ways. First, given the lack of data and, more generally, information, we use cross-sectional data. This implies that we do not capture the dynamics of the recycling rate. Although the dynamics of the recycling rate for many metals are flat, the use of panel data may greatly change the results. Second, the economics of the recycling rate involve many complexities not captured in our model. For example, the presence of organic components, the number of product parts and elements (Dahmus and Gutowski, 2007; Greenfield and Graedel, 2013; Gutowski et al., 2013), the dispersion between average metal concentrations, the interaction effect with the concentration of other metals (co-product recycling), metal price volatility, and the diversity of products could all greatly modify the profitability of recycling. Unfortunately, these variables are rarely quantified and even less rarely linked to recycling rate. Therefore, improving knowledge about recycling is equivalent to raising the question about the availability of comprehensive and interdisciplinary data associated with recycling.

#### 5. Conclusion

In this paper, we explore different factors related to the recycling rate of metals in computers. We can explain the recycling rate of metals by their price, their concentration in the product, and the relative metal concentration between products and primary deposits. The marginal response of the recycling rate to price seems to be low, regardless of the specification and the model used. At best, tripling price corresponds to an increase of +7.9 point of percentage of recycling rate. This finding is in line with the sparse literature on metal recycling flow. The observation of revenues generated by unrecycled metals does not modify this assertion (the median required price must increase by one or two order of magnitude in order to provide the equivalent of precious/base metal revenues). Other technical factors (relative to metal concentration) could have a deeper impact on the recycling rate, though their modifications with public policies could be challenging. More precisely, an addition of one percentage point of metal concentration is correlated with a rise in the metal recycling rate of 2.52 percentage points. In addition, metals that have a concentration in products that is higher than their mining concentration also have a

higher recycling rate of approximately 31 percentage points. Moreover, due to both the low elasticity of metal prices to carbon price and the low price elasticity of recycling rate, it is unlikely that internalizing carbon emissions in the metal sector will trigger a higher recycling rate. Last, there may be some crowding-out effects between circular economy levers, especially between dematerialization and recycling activities.

#### Bibliography

Adie, G.U., Sun, L., Zeng, X., Zheng, L., Osibanjo, O., Li, J., 2016. Examining the evolution of metals utilized in printed circuit boards. Environmental Technology 1696–1701.

Ali, S.H., Giurco, D., Arndt, N., Nickless, E., Brown, G., Demetriades, A., Durrheim, R., Enriquez,
M.A., Kinnaird, J., Littleboy, A., Meinert, L.D., Oberhänsli, R., Salem, J., Schodde, R., Schneider, G.,
Vidal, O., Yakovleva, N., 2017. Mineral supply for sustainable development requires resource
governance. Nature 543, 367–372.

Andersson, M., Ljunggren Söderman, M., Sandén, B.A., 2019. Challenges of recycling multiple scarce metals: The case of Swedish ELV and WEEE recycling. Resources Policy 63, 1-12. https://doi.org/10.1016/j.resourpol.2019.101403

Andersson, M., von Borgstede, C., 2010. Differentiation of determinants of low-cost and high-cost recycling. Journal of Environmental Psychology 30, 402–408.

Baldé, C.P., Forti, V., Gray, V., Kuehr, R., Stegmann, P., 2017. The Global E-waste Monitor – 2017. United Nations University (UNU), International Telecommunication Union (ITU) & International Solid Waste Association (ISWA), Bonn/Geneva/Vienna.

Baum, C.F., 2008. Modeling proportions. Stata Journal 299–303.

Behrens, A., Giljum, S., Kovanda, J., Niza, S., 2007. The material basis of the global economy. Worldwide patterns of natural resource extraction and their implication for sustainable resource use policies. Ecological Economics 64, 444–453.

Berglund, C., Söderholm, P., 2003. An Econometric Analysis of Global Waste Paper Recovery and Utilization. Environmental and Resource Economics 26, 429–456.

Bizzo, W.A., Figueiredo, R.A., de Andrade, V.F., 2014. Characterization of Printed Circuit Boards for Metal and Energy Recovery after Milling and Mechanical Separation. Materials 7, 4555–4566.

Blagoeva, D.T., Alves Dias, P., Marmier, A., Pavel, C.C., 2016. Assessment of potential bottlenecks along the materials supply chain for the future deployment of low-carbon energy and transport technologies in the EU;Wind power, photovoltaic and electric vehicles technologies, time frame: 2015-2030 (No. EUR 28192 EN). JRC.

Blengini, G.A., Mathieux, F., Mancini, L., Nyberg, M., Viegas, H.M., Salminen, J., Garbarino, E., Orveillon, G., Saveyn, H., Mateos Aquilino, V., Llorens González, T., García Polonio, F., Horckmans, L., D'Hugues, P., Balomenos, E., Dino, G., de la Feld, M., Mádai, F., Földessy, J., Mucsi, G., Gombkötő, I., Calleja, I., 2019. Recovery of critical and other raw materials from mining waste and landfills: State of play on existing practices (No. EUR 29744 EN). Publications Office of the European Union, Luxembourg.

Blomberg, J., Hellmer, S., 2000. Short-run demand and supply elasticities in the west European market for secondary aluminium. Resources Policy 26, 39–50.

Blomberg, J., Söderholm, P., 2009. The economics of secondary aluminium supply: An econometric analysis based on European data. Resources, Conservation and Recycling 53, 455–463.

Blomberg, J., Söderholm, P., 2011. Factor demand flexibility in the primary aluminium industry: Evidence from stagnating and expanding regions. Resources Policy 36, 238–248.

Braungart, M., McDonough, W., 2011. Cradle to cradle: Créer et recycler à l'infini, Manifestô. Alternatives.

Brooks, D.B., Andrews, P.W., 1974. Mineral Resources, Economic Growth, and World Population. Science 185, 13–19.

Carlsen, E.H., 1980. Aluminium recycling coefficients. Business Economics 15, 41-46.

Craig, J.R., Vaughan, D.J., Skinner, B.J., 2001. Resources of the Earth, Prentice Hall. ed. Pearson Eduction.

Crowson, P., 2012. Some observations on copper yields and ore grades. Resources Policy 59-72.

Cui, J., Roven, H.J., 2011. Chapter 20 - Electronic Waste, in: Waste. Trevor Letcher and Daniel Vallero. Dahmus, J.B., Gutowski, T.G., 2007. What Gets Recycled: An Information Theory Based Model for Product Recycling. Environ. Sci. Technol. 41, 7543–7550.

Department Of Energy, 2011. Critical Material Strategy. USA.

Dijkgraaf, E., Gradus, R., 2017. An EU Recycling Target: What Does the Dutch Evidence Tell Us? Environmental and Resource Economics 68, 501–526.

Edgren, J.A., Moreland, K.W., 1989. An econometric analysis of paper and wastepaper markets. Resources and Energy 11, 299–319.

Edwards, R., Pearce, D., 1978. The effect of prices on the recycling of waste materials. Resources Policy 4, 242–248.

European Commission, 2010. Critical raw materials for the EU.

Fisher, F.M., Cootner, P.H., Baily, M.N., 1972. An econometric model of the world copper industry. The Bell Journal of Economics and Management Science 3, 568–609.

Fizaine, F., Court, V., 2015. Renewable electricity producing technologies and metal depletion: A sensitivity analysis using the EROI. Ecological Economics 110, 106–118.

Fu, X., Ueland, S.M., Olivetti, E., 2017. Econometric modeling of recycled copper supply. Resources, Conservation and Recycling 122, 219–226. https://doi.org/10.1016/j.resconrec.2017.02.012

Ghisellini, P., Cialani, C., Ulgiati, S., 2016. A review on circular economy: the expected transition to a balanced interplay of environmental and economic systems. Journal of Cleaner Production 114, 11–32. Gomez, F., Guzman, J.I., Tilton, J.E., 2007. Copper recycling and scrap availability. Resources Policy 32, 183–190.

Greenfield, A., Graedel, T.E., 2013. The omnivorous diet of modern technology. Resources, Conservation and Recycling 74, 1–7.

Gutowski, T.G., Sahni, S., Allwood, J.M., Ashby, M.F., Worrell, E., 2013. The energy required to produce materials: constraints on energy-intensity improvements, parameters of demand. Phil Trans R Soc A 371.

Hagelüken, C., 2014. Recycling of (critical) metals, in: Critical Metals Handbook. Gus Gunn., pp. 41–69.

Hagelüken, C., Corti, C.W., 2010. Recycling of gold from electronics: Cost-effective use through 'Design for Recycling. Gold Bulletin 43, 209–220.

IPCC, 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Işıldar, A., Rene, E.R., van Hullebusch, E.D., Lens, P.N.L., 2018. Electronic waste as a secondary source of critical metals: Management and recovery technologies. Resources, Conservation and Recycling 135, 296–312. https://doi.org/10.1016/j.resconrec.2017.07.031

Johnson, J., Harper, E.M., Lifset, R., Graedel, T.E., 2007. Dining at the Periodic Table: Metals Concentrations as They Relate to Recycling. Environ. Sci. Technol. 41, 1759–1765.

Jordan, B., Eggert, R., 2018. What can earth abundance really tell us about material prices and availability? Combining physical and economic perspectives. Working paper 15p.

JRC, Moss, R.L., Tzimas, E., Kara, H., Willis, P., Kooroshy, J., 2011. Critical Metals in Strategic Energy Technologies, Assessing Rare Metals as Supply-Chain Bottlenecks in Low-Carbon Energy Technologies.

Kerr, R.A., 2014. The Coming Copper Peak. Science 343.

Lakhan, C., 2014. Exploring the relationship between municipal promotion and education investments and recycling rate performance in Ontario,Canada. Resources, Conservation and Recycling 92, 222–229.

Lebreton, L., Slat, B., Ferrari, F., Sainte-Rose, B., Aitken, J., Marthouse, R., Hajbane, S., Cunsolo, S., Schwarz, A., Levivier, A., Noble, K., Debeljak, P., Maral, H., Schoeneich-Argent, R., Brambini, R.,

Reisser, J., 2018. Evidence that the Great Pacific Garbage Patch is rapidly accumulating plastic. Scientific Reports 8, 4666. https://doi.org/10.1038/s41598-018-22939-w

Moss, R.L., Tzimas, E., Kara, H., Willis, P., Kooroshy, J., 2013. The potential risks from metals bottlenecks to the deployment of Strategic Energy Technologies. Energy Policy 55, 556–564.

Mudd, G.M., 2010. The environmental sustainability of mining in Australia: key mega-trends and looming constraints. Resources Policy 35, 98–115.

Mudd, G.M., Diesendorf, M., 2008. Sustainability of Uranium Mining and Milling: Toward Quantifying Resources and Eco-Efficiency. Environ. Sci. Technol. 42, 2624–2630.

Northey, S., Mohr, S., Mudd, G.M., Weng, Z., Giurco, D., 2014. Modelling future copper ore grade decline based on a detailed assessment of copper resources and mining. Resources, Conservation and Recycling 83, 190–201.

Nuss, P., Eckelman, M.J., 2014. Life Cycle Assessment of Metals: A Scientific Synthesis. PLOS one 9, 1–12.

Papke, L.E., Wooldridge, J., 1996. Econometric methods for fractional response variables with an application to 401(k) plan participation rates. Journal of Applied Econometrics 11, 619–632.

Rombach, G., 2006. Limits of metal recycling, in: Sustainable Metals Management: Securing Our Future - Steps Towards a Closed Loop Economy. Arnim von Gleich, Robert U. Ayres, Stefan G ling-Reisemann, pp. 295–312.

Schandl, H., West, J., 2010. Resource use and resource efficiency in the Asia-Pacific region. Global Environmental Change 20, 636–647.

Schodde, R., 2010. The key drivers behind resource growth: an analysis of the copper industry over the last 100 years.

Shift Project, 2018. Lean ICT – Pour une sobriété numérique, october 2018. Available at: https://theshiftproject.org/wp-content/uploads/2018/11/Rapport-final-v8-WEB.pdf.

Slade, M.E., 1980a. The effects of higher energy prices and declining ore quality—copper–aluminium substitution and recycling in the USA. Resources Policy 6, 223–239.

Slade, M.E., 1980b. An econometric model of the U.S. secondary copper industry: recycling versus disposal. Journal of Environmental Economics and Management 7, 123–141.

Smil, V., 2013. Making the Modern World: Materials and Dematerialization, Wiley. ed.

Söderholm, P., 2011. Taxing virgin natural resources: Lessons from aggregates taxation in Europe. Resources, Conservation and Recycling 55, 911–922.

Sprecher, B., Reemeyer, L., Alonso, E., Kuipers, K., Graedel, T.E., 2017. How "black swan" disruptions impact minor metals. Resources Policy 54, 88–96.

Stahel, W.R., 2013. Policy for material efficiency—sustainable taxation as a departure from the throwaway society. Philos Transact A Math PhysEngSci 371.

Sterner, T., Bartelings, H., 1999. HouseholdWaste Management in a Swedish Municipality: Determinants of Waste Disposal, Recycling and Composting. Environmental and Resource Economics 13, 473–491.

Tilton, J.E., 1999. The future of recycling. Resources Policy 25, 197–204.

Tilton, J.E., 2003. On Borrowed Time? Assessing the Threat of Mineral Depletion, Resources for the Future. ed.

UNEP, 2013a. Metal Recycling: opportunities, Limits, Infrastructure.

UNEP, 2013b. Environmental risks and Challenges of Anthropogenic metals flows and cycles.

UNEP, 2016. Global Material Flows and Resource Productivity.

UNEP, 2019. Global Resources outlook 2019: Natural Resources for the Future We Want.

Valero, A., Botero, E., 2002. Exergetic evaluation of Natural Mineral Capital (2). Application of the methodology to current world reserves.

Vidal, O., 2017. Mineral Resources and Energy: Future Stakes in Energy Transition. ISTE Press - Elsevier.

Vidal, O., Rostom, F., François, C., Giraud, G., 2017. Global Trends in Metal Consumption and Supply: The Raw Material–Energy Nexus. Elements 13, 319–324. Wooldridge, J.M., 2011. Fractional Response Models with Endogenous Explanatory Variables and Heterogeneity.

World Bank, 2017. The Growing Role of Minerals and Metals for a Low Carbon Future.

Yang, H.-L., Innes, R., 2007. Economic Incentives and Residential Waste Management in Taiwan: An Empirical Investigation. Environmental and Resource Economics 37, 489–519.

Zeng, X., Mathews, J.A., Li, J., 2018. Urban Mining of E-Waste is Becoming More Cost-Effective Than Virgin Mining. Environ. Sci. Technol. 52, 4835–4841. https://doi.org/10.1021/acs.est.7b04909

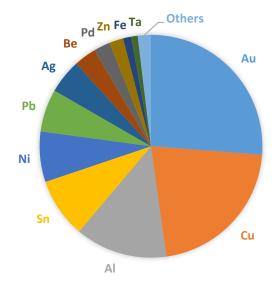


Figure 1 Value share of each metal available in printed wire boards from computer.

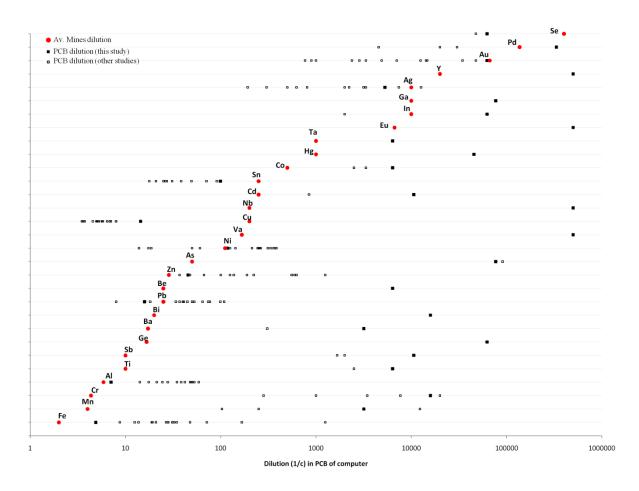


Figure 2 Average dilution of metals in mines and in different Printed circuit board (PCB). Source: various (see text).

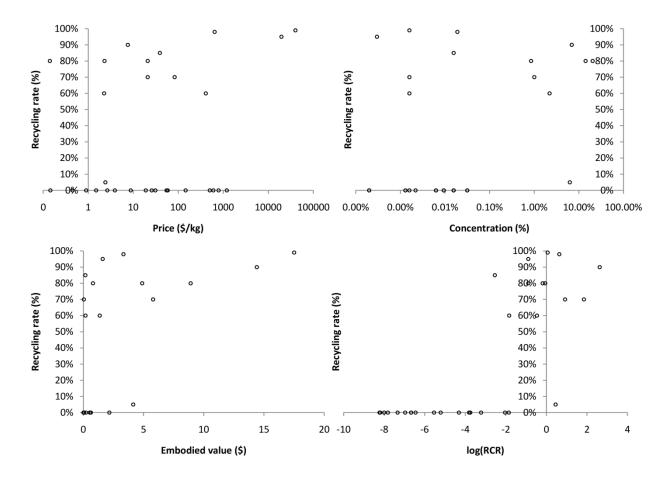


Figure 3 Scatter plots between different variables and recycling rate (%).

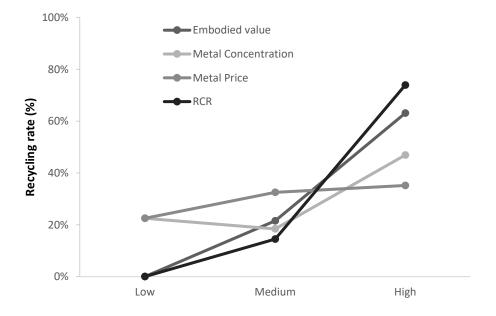


Figure 4 Average recycling rate when data are sorted by tercile of values.

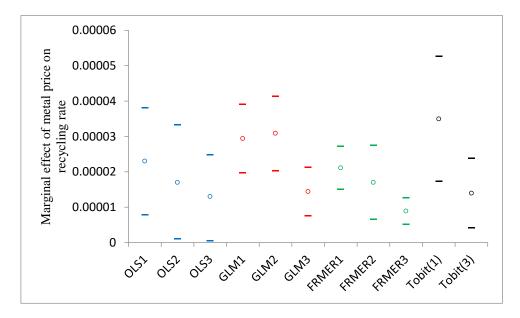


Figure 5 Marginal effects of price on metal recycling rate according to different modelizations. Note: Average marginal effect across models: 0.0000203, standard errors indicate a 5% threshold risk.

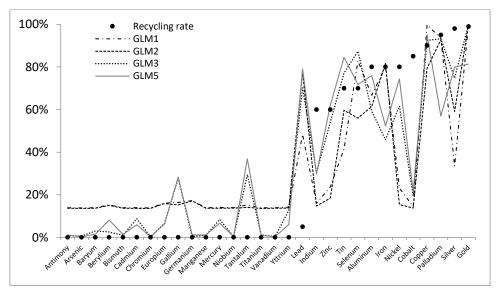


Figure 6 Predictions of recycling rate according to different specifications.

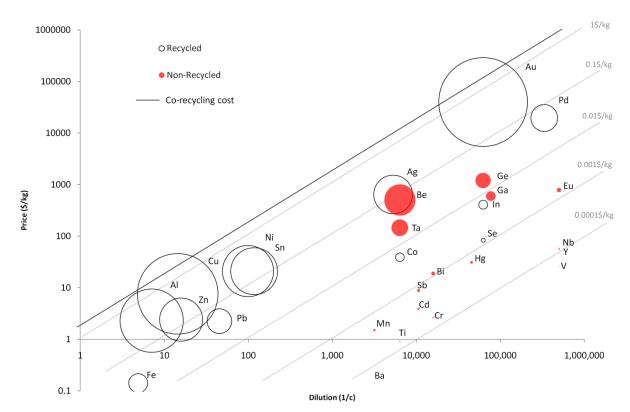


Figure 7 Relationship between dilution, price per kg and element recycling in printed wired board. Reading: the size of bubbles rise proportionally with the embodied value of the element in the computer (see iso-value curves at the right).

	Unity	Mean	Standard deviation	Median	Q1	Q3	Min	Max	n
ConcentrationM	%	5.64%	10.54%	0.55%	0.04%	5.60%	0.00%	50.00%	30
Price	(\$/kg)	2138.99	7844.91	23.30	2.46	342.50	0.14	40000.00	30
ConcentrationP	%	1.74%	4.56%	0.01%	0.00%	0.03%	0.00%	20.47%	30
Recycling rate	%	32.40%	40.20%	0.00%	0.00%	77.50%	0.00%	99.00%	30
RCR	-	1.04	2.69	0.06	0.00	0.78	0.00	13.86	30
Threshold	-	0.20	0.40	0.00	0.00	0.00	0.00	1.00	30
Embod. Value	\$	2.22	4.32	0.17	0.01	2.01	0.00	17.50	30
Unit. Energy Cons.	GJ/t	10286.53	38939.82	156.50	53.18	1720.00	4.00	208000.00	30
Av. grade crust	%	0.49%	1.76%	0.00%	0.00%	0.01%	0.00%	8.23%	30

Table 1 Main descriptive statistics

	Price		Concentration		RCR		Embodied Value	
	Low	High	Low	High	Low	High	Low	High
Average Recycling Rate	31.0%	33.8%	21.6%	43.2%	0.0%	64.8%	10.3%	54.5%
Standard deviation	0.39	0.44	0.38	0.42	0.00	0.35	0.27	0.41
Equality of means*	-0.18 (j	p=0.85)	-1.48 (j	p=0.15)	-7.20 (	(p=0.00)	-3.47 (p:	=0.0017)
Conclusion	Equal	means	Equal	means	Non-Eq	ual means	Non-Equ	al means

Table 2 Tests of mean equality when the sample is sorted by increasing value and breaking down in two part. \*When variances are equals we perform the t-test of egality of means and the Satterthwaite–Welch t-test otherwise (for unequal variances).

OLS - Recycling rate				
(%)	(1)	(2)	(3)	(4)
	0.164627	0.1560699	0.577273	0.525836
Intercept	(0.06642)**	(0.06899)**	(0.0670)***	(0.1056)***
	0.000023	0.000017	0.000013	
Price	(0.00001)***	(0.00001)**	(0.00001)**	-
	2.93432	3.306493		
ConcentrationP	(1.29229)**	(1.29228)**	-	-
	0.05703			
RCR	(0.02182)**	-	-	-
		0.36863		
Threshold	-	(0.15341)**	-	-
			0.087194	0.077951
Ln(RCR)	-	-	(0.0140)***	(0.01469)***
				0.021899
Value	-	-	-	(0.00929)**
F	7.73***	7.20***	25.84***	23.54***
R <sup>2</sup>	0.4714	0.4537	0.6568	0.6355
VIF	[1.01-1.06]	[1.02-1.12]	[1.05]	[2.16]
JB	6.43**	2.07	0.81	0.15
Heteroscedasticity test	1.78	0.65	1.77	3.89**
n	30	30	30	30

Table 3 Estimate of specifications 1-3 with OLS

GLM & FRMER - Recycling rate						
(%)	GLM(1)	GLM(2)	GLM(3)	FRMER(1)	FRMER(2)	FRMER(3)
Intercept	-1.826929 (.4606745)***	-1.845957 (.5039149)***	0.5137347 (0.4513746)	-1.005963 (0.252363)***	-0.99643 (.2662858)***	0.3150084 (0.2411082)
Price	0.0002185 (0.0000343)***	0.0002248 (0.0000397)***	0.0001433 (0.0000299)***	0.0000814 (0.0000119)***	0.000063 (0.000017)***	0.0000491 (0.00001)***
ConcentrationP	14.69676 (3.639253)***	16.31619 (4.46999)***	-	8.437343 (2.00898)***	9.215483 (2.259796)***	-
RCR	0.5288516 (0.2664065)**	-	-	0.2318354 (0.1014585)**	-	-
Threshold	-	2.068012 (0.924391)**	-	-	1.03647 (0.5026551)**	-
Ln(RCR)	-	-	0.7603299 (0.1641071)***	-	-	0.4303107 (0.0821208)***
Wald chi2	45.18***	36.63***	46.79***	53.37***	42.93***	67.58***
R <sup>2</sup>	0.5388	0.5042	0.7054	0.4714	0.4537	0.6568
Wald test of exogeneity	-	-	-	5.53**	6.94***	8.65***
n	30	30	30	30	30	30

Table 4 Main results associated with specifications 1 to 3. Note: Generalized Linear Models (GLM), Fractional Response model with endogenous regressors (FRMER). Energy consumption per unit of metal (GJ/t) and average grade of metal in crustal crust is used as instruments.

<b>OLS/GLM - Recycling</b>				
<b>rate (%)</b>	OLS(4)	OLS(5)	GLM(4)	GLM(5)
	0.525836	0.61849	0.492242	0.688861
Intercept	(0.1056)***	(0.065842)***	(0.628568)	(0.442526)
	0.077051	0.070752	0 712117	0.50(9(9)
	0.077951	0.070753	0.713117	0.596868
Ln(RCR)	(0.01469)***	(0.021253)***	(0.173157)***	(0.120218)***
	0.021899		0.077208	
Value	(0.00929)**	-	(0.067875)	-
		0.032299		0.260828
Ln(Value)	-	(0.022157)	-	(0.110927)**
F	23.54***	22.83***		
Wald chi2			24.21***	26.54***
R <sup>2</sup>	0.6355	0.6284	0.6604	0.6711
n	30	30	30	30

Table 5 Main results associated with specification 5 including embodied metal value.

Upper bound (95%)         5.5907         5.9628         2.6842         3.0398         2.9 2.9           Lower bound (95%)         0.2780         0.6502         1.2712         1.4386         1.4           OLS2         GLM2         FRMER2         5.5907         5.9628         0.2805         5.5907         5.9628         0.2992           Threshold         Mean         0.3686         0.2838         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.2805         5.5907         5.9628         0.0765         0.0768         0.0769         0.0768         0.0769         0.0768         0.0769         0.0768         0.0769         0.0768         0.0769         0.076	911 2.4942
(95%)         5.5907         5.9628         2.6842         3.0398         2.9           Lower bound         (95%)         0.2780         0.6502         1.2712         1.4386         1.4           OLS2         GLM2         FRMER2         Image: constraint of the second of the s	
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	3.3367
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	719 1.6517
Upper bound (95%)         0.6840         0.4520         0.5008            Lower bound	
(95%)         0.6840         0.4520         0.5008           Lower bound         (95%)         0.0533         0.1156         0.0602           (95%)         0.0533         0.156         0.0602         GLM4         GLM           In(RCR)         Mean         0.0872         0.078         0.0765         0.0768         0.0           Upper bound         (95%)         0.1159         0.1081         0.0878         0.0983         0.0           Lower bound         (95%)         0.0585         0.0478         0.0651         0.0554         0.0           Lower bound         (95%)         0.0585         0.0478         0.0651         0.0554         0.0           RCR         Mean         0.0570         0.0712         0.0602         0.0         0.0           Upper bound         (95%)         0.1019         0.0070         0.1077         0.0         0.0           Lower bound         (95%)         0.0122         0.1353         0.0128         0.0         0.0           Lower bound         (95%)         0.0129         0.0083         0.0         0.0         0.0         0.0         0.0         0.0         0.0         0.0         0.0         0.0         0.0	
OLS3         OLS4         GLM3         GLM4         GLM           ln(RCR)         Mean         0.0872         0.078         0.0765         0.0768         0.0           Upper bound         (95%)         0.1159         0.1081         0.0878         0.0983         0.0           Lower bound         (95%)         0.0585         0.0478         0.0651         0.0554         0.0           Very bound         (95%)         0.0585         0.0478         0.0651         0.0554         0.0           RCR         Mean         0.0570         0.0712         0.0602         Upper bound         0.0570         0.1017         0.0602         Upper bound         0.05%)         0.0122         0.1353         0.0128         0.021         Upper bound         0.0584         GLM4         Value         Mean         0.0219         0.0083         0.0128         0.0128         0.021         0.0218         0.021	
In(RCR)         Mean Upper bound (95%)         0.0872         0.078         0.0765         0.0768         0.0 0.0           Lower bound (95%)         0.1159         0.1081         0.0878         0.0983         0.0           Lower bound (95%)         0.0585         0.0478         0.0651         0.0554         0.0           RCR         Mean (95%)         0.1019         0.0712         0.0602         0.1077           Lower bound (95%)         0.1019         0.0070         0.1077         0.1077           Lower bound (95%)         0.0122         0.1353         0.0128           Value         Mean Upper bound (95%)         0.0219         0.0083           Value         Mean (95%)         0.04095         0.021	
Upper bound (95%)       0.1159       0.1081       0.0878       0.0983       0.0         Lower bound (95%)       0.0585       0.0478       0.0651       0.0554       0.0         RCR       Mean       0.0570       0.0712       0.0602       0.0070         Upper bound (95%)       0.1019       0.0070       0.1077       0.0602         Upper bound (95%)       0.0122       0.1353       0.0128       0.0128         Value       Mean Upper bound (95%)       0.0219       0.0083       0.0219	A5 FRMER3
(95%) 0.1159 0.1081 0.0878 0.0983 0.0 Lower bound (95%) 0.0585 0.0478 0.0651 0.0554 0.0 OLS1 GLM1 FRMER1 RCR Mean 0.0570 0.0712 0.0602 Upper bound (95%) 0.1019 0.0070 0.1077 Lower bound (95%) 0.0122 0.1353 0.0128 OLS4 GLM4 Value Mean 0.0219 0.0083 Upper bound (95%) 0.04095 0.021	0631 0.0781
OLS1         GLM1         FRMER1           RCR         Mean         0.0570         0.0712         0.0602           Upper bound         0.0570         0.0712         0.0602           (95%)         0.1019         0.0070         0.1077           Lower bound         0.0122         0.1353         0.0128           Value         Mean         0.0219         0.0083           Upper bound         0.04095         0.021	0.0896
RCR         Mean         0.0570         0.0712         0.0602           Upper bound         (95%)         0.1019         0.0070         0.1077           Lower bound         (95%)         0.0122         0.1353         0.0128           OLS4         GLM4           Value         Mean         0.0219         0.0083           Upper bound         (95%)         0.04095         0.021	0.0665
Upper bound (95%)         0.1019         0.0070         0.1077           Lower bound (95%)         0.0122         0.1353         0.0128           Value         Mean Upper bound (95%)         0.0219         0.0083           Value         Mean (95%)         0.04095         0.021	
(95%)       0.1019       0.0070       0.1077         Lower bound       0.0122       0.1353       0.0128         (95%)       0.0122       0.1353       0.0128         Value       Mean       0.0219       0.0083         Upper bound       0.04095       0.021	
OLS4         GLM4           Value         Mean         0.0219         0.0083           Upper bound         0.04095         0.021	
Value         Mean         0.0219         0.0083           Upper bound         0.04095         0.021	
Upper bound (95%) 0.04095 0.021	
Lower bound	
(95%) 0.00284 -0.005	
OSL5 GLM5	
ln(Value) Mean 0.0323 0.0276 Upper bound	
(95%) 0.0778 0.0433 Lower bound	
(95%) -0.0132 0.0119	

Recycling rate (%) - OLS	(1)	(1.2)	(1.3)	(1.4)
Intercept	0.1646268 (0.06642)**	0.686629 (0.170334)***	0.684212 (0.135858)***	0.279579 (0.071993)***
Price	0.000023 (0.00001)***	-	-	0.000021 (0.000001)**
Ln(Price)	-	0.078853 (0.021525)***	0.035633 (0.023799)	-
ConcentrationP	2.934317 (1.29229)**	-	-	-
Ln(ConcentrationP)	-	0.075673 (0.020497)***	0.028281 (0.024365)	-
RCR	0.0570336 (0.021819)**	0.032890 (0.022386)	-	-
Ln(RCR)	-		0.072373 (0.021908)***	-
F	7.73***	9.25***	14.82***	5.50**
R <sup>2</sup>	0.4714	0.5163	0.6310	0.1642
JB	6.43**	0.73	2.02	4.55
White test	1.78	1.86	0.67	0.80
n	30	30	30	30

Table 6 Average marginal effect of different variable on recycling rate for different models.

Table 7 Robustness analysis. Note: GLM estimations give similar results.

IV - Recycling rate (%)	(IV1.1)	(IV1bis)	(IV1.2)
Intercept	0.1673336 (0.0618967)***	-0.0043171 (0.0985931)	0.1644332 (0.0618433)***
Price	0.0000219 (0.0000069)***	-	0.000023 (0.0000069)***
Ln(Price)	-	0.0594803 (0.020499)***	-
ConcentrationP	2.914621 (1.203681)**	4.262002 (1.361367)***	2.935725 (1.203088)**
RCR	0.0570325 (0.0203215)***	0.0522964 (0.020814)**	0.0570337 (0.0203127)***
Wald-chideu	25.51	23.25	26.78
R <sup>2</sup>	0.4709	0.4483	0.4714
First stage			
F	120	789	1548
R <sup>2</sup>	0.92	0.98	0.99
Instruments for price	Average grade in crust	Average grade in crust	Average grade in crust
	UnitaryEnergyconsumptio n	UnitaryEnergyconsumptio n	Five year lead metal price
Exogeneity of IV			1
Sargan (score)	1.1291 (p = 0.2880)	0.105358 (p = 0.7455)	1.11921 (p=0.2901)
Basmann chi2	0.977713 (p = 0.3228)	0.088107 (p = 0.7666)	0.96882 (p = 0.3250)

Appendix 1.1 - Instrumental variables for metal price

GLM & FRMER - Recycling rate (%)	GLM(1) link = logit	GLM(2) link = probit	FRMER(1.1)	FRMER (1.2)
Intercept	-1.826929 (.4606745)***	-1.059855 (0.2573156)	-1.005963 (0.252363)***	-1.073982 (0.260287)***
Price	0.0002185 (0.0000343)***	0.0001179 (.000022)***	0.0000814 (0.0000119)***	0.0001298 (0.0000274)***
ConcentrationP	14.69676 (3.639253)***	8.816868 (2.048088)***	8.437343 (2.00898)***	8.887523 (2.049361)***
RCR	0.5288516 (0.2664065)**	0.239629 (0.1041614)**	0.2318354 (0.1014585)**	0.24192 (0.1059287)**
Av. Marginal effect Price	0.0000294***	0.000029***	0.0000211***	0.0000314***
Av. Marginal effectConcent.	1.977687***	2.166764***	2.191102***	2.15305***
Av. Marginal effect RCR	0.0711656**	0.0588893**	0.0602055**	.0586064**
Wald chi2	40.51***	37.55***	53.37***	33.23***
R <sup>2</sup>	0.5388	0.5251	0.4714	0.4714
Wald test of exogeneity	-	-	5.53**	0.53

Appendix 1.2 FRMER results with different instrumental variables and models

### Appendix 2 - Sensitivity analysis for specification 1

II.		<b>J</b>		
Price effect	CoeffOLS	t-value	CoeffGLM	z-value
1	0.000023	3.0890218	0.00021853	6.34251718
2	0.000023	3.04609264	0.00021487	6.21682600
3	0.000024	3.52111105	0.00021546	5.8043915
4	0.000023	3.04591681	0.00021483	6.21410215
5	0.000023	3.04602982	0.00021482	6.2141898
6	0.000023	3.0550414	0.00021786	6.39327767
7	0.000023	3.04625958	0.00021493	6.22009535
8	0.000023	3.04603778	0.00021482	6.21537523
9	0.000023	3.04597305	0.00021484	6.21483168
10	0.000024	3.53530878	0.00023777	7.31427405
11	0.000022	3.15633569	0.00022099	6.29704914
12	0.000023	3.21022126	0.00022401	6.34335629
13	0.000023	3.06039178	0.00021996	6.51612613
14	0.000023	3.05918761	0.00021855	6.369077
15	0.000023	3.05744953	0.00021861	6.43846659
16	0.000023	3.0685561	0.00022365	6.74313576
17	0.000023	3.24319429	0.00022278	6.12414062
18	0.000023	3.04604784	0.00021483	6.21460277
19	0.000023	3.04648488	0.00021497	6.22409090
20	0.000024	3.37505485	0.00023158	6.65118172
21	0.000023	3.04691991	0.00021514	6.23276923
22	0.000040	2.41094253	0.00023749	7.1212974
23	0.000019	2.41244395	0.0001527	4.3467726
24	0.000023	3.12381735	0.0002133	6.35020543

25	0.000023	3.11652941	0.00021701	6.2747484
26	0.000023	3.04892375	0.00021549	6.26432933
27	0.000023	3.04597899	0.00021483	6.21432742
28	0.000023	3.04635068	0.00021496	6.2221865
29	0.000023	3.04692754	0.00021508	6.23199923
30	0.000023	3.18664969	0.00022647	6.35286121

Concentration P	Coeff	t-value	Coeffglm	z-value
	2.42216864042598	1.58387502922824	12.5320922527957	3.23934130931676
2	2.89078208070413	2.20151028714727	14.3956778274842	3.94909488772636
3	3.19264251238441	2.69092281957862	16.288835116852	4.47444596636755
4	2.8906489856624	2.20129345701122	14.3951546019954	3.94863244528755
4	2.89119056857711	2.20129345701122	14.3975733426777	3.95018818137783
5	2.88881769561848	2.20204155254858	14.3797556369337	3.95020666083091
7	2.89066320995544	2.2014287214392	14.3949760356367	3.9489156812036
8	2.89023845820261	2.20122429502931	14.3923714146623	3.94824242061719
9	2.89075742890998	2.20143265611757	14.3956576702454	3.9489354327424
10	3.11561541098519	2.61899640675414	16.4018838753441	4.45451849187002
11	3.05579855621419	2.47730795299052	14.8024067882978	3.79182804150268
12	3.02260459756971	2.35369098476442	15.1620269409246	4.04450912379946
13	2.88707098960997	2.20173711281508	14.3668475391282	3.94967881809882
14	2.8343522377023	1.31835732727486	14.7741125252087	2.14495589315144
15	2.88480841952818	2.20012516237624	14.3538692884679	3.94490919777537
16	2.88584325969194	2.20246985934498	14.3548861461914	3.95182144163231
17	3.04694540161827	2.39352550859336	15.6996894613945	4.11686693779484
18	2.891288256893	2.20209383040845	14.3981634748268	3.95034472435824
19	2.89000224747619	2.20106369991295	14.3909601345683	3.94791300001362
20	3.02982595228113	2.45613083490217	15.5813270110787	4.07794302578205
21	2.89038487325529	2.20129661180835	14.3931968745433	3.94863897703307
22	2.99435570162534	2.32777582587576	14.7440792886467	4.04701891569393
23	2.96858532019015	2.30799609501731	14.6198993771628	4.01914597046539
24	3.23497907957478	2.49579257821217	16.9038248722045	5.09563106347375
25	3.06605112400088	2.30908628927694	13.5916361977673	3.63888535413876
26	2.88635778435386	2.19979309052411	14.3668843090673	3.94369174709842
27	2.89093714844656	2.20166661074634	14.3964909300904	3.94942454893813
28	2.89052539551567	2.20128058827878	14.3942693546325	3.94860656205623
29	2.88940153090088	2.20079440386587	14.3871563231464	3.9471431609017
30	2.90560258448703	2.256077303476	14.7433211800502	3.9106594728264

RCR	Coeff	t-value	Coeffglm	z-value
	1 0.0590799938858098	2.64988714969997	0.529073636002518	1.99642339886082
	2 0.0563440541431601	2.54200271617773	0.514472396768426	1.9880819977069
	3 0.0533147806035845	2.66429045943686	0.437148374946569	2.57612546940083
	4 0.0563464564538031	2.54204201747022	0.514503613401108	1.98802461074776
	5 0.0563426810168062	2.54208082683608	0.514508157376046	1.98800419867647

6	0.0562982647255993	2.54204299383644	0.513327675510568	1.99022721580045
7	0.0563439771034554	2.5420345405866	0.514459477365966	1.98810239988094
8	0.0563582361854432	2.54308058762084	0.514786299190712	1.98739432001878
9	0.0563449173537282	2.54199222297193	0.514483747023239	1.98806373002008
10	0.0596050355825796	2.96927698750786	0.603764749022162	1.97187711435645
11	0.130700614375147	2.97173894427902	0.779334685368163	1.57164759084673
12	0.0541514386361695	2.48613396856749	0.457127360708328	2.22816437187564
13	0.0562818468519962	2.54265799085185	0.512788549311952	1.99127903653447
14	0.0574777464052564	2.44637327090344	0.528543306564444	1.98685071767611
15	0.056381451434405	2.54875021944838	0.51515929561859	1.98540710869711
16	0.0562333510550594	2.54206248642116	0.511440200562084	1.99426950402574
17	0.0584335558698592	2.7212324581615	0.567239403091228	1.97128826837846
18	0.0563400286197299	2.54188136515534	0.514449561943511	1.98812965864552
19	0.056356416836162	2.5430488587842	0.514719629083671	1.9875187665212
20	0.0569933007795829	2.73868416182045	0.516062009353362	2.16958216867136
21	0.0563411398881096	2.54202133031237	0.514370387315121	1.98826426109378
22	0.0579972388551178	2.67055410269053	0.530434269790068	1.9836038320276
23	0.0578151864181302	2.66162890465552	0.528873185406358	1.97682614912906
24	0.0569811551493359	2.64607297898309	0.589437350381421	1.66827658804989
25	0.0514283413189071	2.13737402609764	0.858165764727905	1.12827247013069
26	0.0564331809664394	2.5497015657529	0.516478373352298	1.9827171503345
27	0.0563437790379702	2.54199542486446	0.514486313538111	1.98805647743785
28	0.0563441505699101	2.54202679997769	0.514444153462792	1.98813195903912
29	0.0563659066260565	2.54392716336787	0.514919698285861	1.98702985180144
30	0.0578175986655311	2.65798198203425	0.536155438124745	2.04322200044329

Recycling rate (%)	Tobit(1)	Tobit (2)	Tobit (3)	Tobit(4)	Tobit(5)	Tobit(6)
Intercept	2513849 (0.1814775)	-0.3051003 (0.1928403)	0.5635287 (0.0996537)***	-0.2233031 (0.1971879)	0.3537006 (0.1297589)**	0.5912701 (0.095384)***
Price	0.000035 (0.000009)***	0.000024 (0.0000128)*	0.000014 (0.000005)**	-	-	-
ConcentrationP	5.291654 (1.193004)***	5.955068 (1.278419)***	-	-	-	-
Threshold	-	0.7215953 (.2437557)***	-	-	-	-
RCR	0.0934093 (0.0368382)**	-	-	0.0437285 (0.0463913)	-	-
Ln(RCR)	-	-	0.2111639 (0.0352678)***	-	-	0.1697008 (0.0319274)***
Value	-	-	-	0.0778412 (0.0216533)***	-	-
Log(Value)	-	-	-	-	0.2077594 (0.0339973)***	0.0694806 (0.0218846)***
F	8.62***	8.56***	20.17***	8.28***	37.34***	19.83***
R <sup>2</sup>	0.4038	0.3997	0.6580	0.3043	0.4920	0.6333
JB	4.62*	1.43	3.37	3.10	0.41	6.84**

 $Appendix \ 3-Alternative \ models-Left \ Censured \ Tobit$