Toward Estimating Displaced Primary Production from Recycling

A Case Study of U.S. Aluminum

Trevor Zink,[1] *Roland Geyer,*[2] *and Richard Startz*[3]

[1]*College of Business Administration, Loyola Marymount University, Los Angeles, CA, USA*
[2]*Bren School of Environmental Science & Management, University of California, Santa Barbara, CA, USA*
[3]*Department of Economics, University of California, Santa Barbara, CA, USA*

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Summary

Recycling materials from end-of-life products has the potential to create environmental benefit by displacing more harmful primary material production. However, displacement is governed by market forces and is not guaranteed; if full displacement does not occur, the environmental benefits of recycling are reduced or eliminated. Therefore, quantifying the true "displacement rate" caused by recycling is essential to accurately assess environmental benefits and make optimal environmental management decisions. Our 2016 article proposed a market-based methodology to estimate actual displacement rates following an increase in recycling or reuse. The current article demonstrates the operation, utility, and challenges of that methodology in the context of the U.S. aluminum industry. Sensitivity analyses reveal that displacement estimates are sensitive to uncertainty in price elasticities. Results suggest that 100% displacement is unlikely immediately following a sustained supply-driven increase in aluminum recycling and even less likely in the long term. However, zero and even negative displacement are possible. A variant of the model revealed that demand-driven increases in recycling are less likely than supply-driven changes to result in full displacement. However, model limitations exist and challenges arose in the estimation process, the effects of which are discussed. We suggest implications for environmental assessment, present lessons learned from applying the estimation methodology, and highlight the need for further research in the market dynamics of recycling.

Introduction

Material recycling has remained a focus of environmental management in general and is central to industrial ecology (IE) in particular. Yet, theory and assessment of recycling still suffers from simplistic assumptions and misconceptions (Geyer et al. 2016).

The environmental benefit of recycling comes from preventing, or "displacing," material production with higher environmental impact, for example, the primary version of the material (Geyer 2015). Displacement is governed by market forces and therefore not automatic; the extent to which displacement occurs determines the environmental benefits of recycling. Displacement rate is defined as the proportion (by weight, volume,

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Address correspondence to: Trevor Zink, College of Business Administration, Loyola Marymount University, 1 LMU Drive, Los Angeles, CA 90045, USA. *Email*: trevor.zink@lmu.edu, *Web*: http://cba.lmu.edu/faculty/?expert=trevor.zinkphd

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or functional unit) of material production prevented by recycling (Zink et al. 2016), as shown by equation (1):

$$d_i = -\Delta S_i / \Delta S_{sec} \qquad (1)$$

where d_i is displacement rate and ΔS_i is the change in production of material i caused by ΔS_{sec} , the change in production of secondary material. Displacement rate can be positive, zero, or negative. It is positive if an increase in secondary production leads to a decrease in the production of material i. $d_i > 1$ means that recycling prevents production of more material than is recycled. Negative displacement indicates that recycling stimulates, rather than prevents, material production.

Displacement rates determine the extent to which the added impacts of collection and reprocessing are offset by avoided impacts of displaced production. To illustrate, equation (2) shows the net impact of recycling:

$$E_{net} = E_{sec} - \sum_i d_i \cdot E_i \qquad (2)$$

The unit impacts of displaced production are multiplied by the displacement rates, d_i, and the benefits of recycling or reuse are thus largely determined by these parameters. If displacement rates are high, the benefits of recycling or reuse can be substantial. If they are low, the benefits are reduced or even eliminated; if they are sufficiently low, recycling or reuse can actually *increase* absolute impacts relative to landfill (see Zink et al. [2016] for more detail). There are various examples in IE literature where the environmental preference order for materials, technologies, or end-of-life (EoL) treatments is reversed based on assumptions about displacement rate (Geyer and Doctori Blass 2009; Heijungs and Guinée 2007; Zink et al. 2014). Yet, across life cycle assessments (LCAs) of a wide range of products, assumptions about displacement rate are typically made (often implicitly) without justification or analysis.

For instance, Zabalza Bribiàn and colleagues (2011, 1138) conducted an LCA of building materials that included EoL recycling. They implicitly assume one-to-one displacement, stating that "every kilogramme of secondary steel produced prevents the emission of 1.2 kg CO_2 eq (74%) with respect to the same quantity of primary steel produced," and report similar findings for copper and aluminum. In an LCA of a personal computer, Choi and colleagues (2006, 127) consider various recycling rates, but not different displacement rates; unsurprisingly, they found "a linear relationship between environmental impacts and the recycling rate." Even LCAs that focus explicitly on recycling often do not consider incomplete displacement. For example, Yellishetti and his colleagues (2011, 657) detailed global steel scrap flows, recycling processes, and technical limitations, but never considered the possibility of incomplete displacement attributed to market effects. They concluded that, "Besides conserving mineral and energy resources, the steel recycling also reduces mining and beneficiation activities that disturb ecosystems"—a statement that can only be true under the assumption of displaced primary production. Following similar logic, Dewulf and colleagues (2010) found that battery recycling led to significant material resource, energy, and fossil fuel reductions. The findings of these (and countless other) LCAs are overstated if, and to the extent that, incomplete primary production displacement occurs.

Studying the rate at which recycling displaces production of other materials, in particular, its primary counterpart, is therefore an important research task in IE. In a previous article, we explored the economic underpinnings of the displacement relationship and identified the market forces involved in determining displacement rate. We also proposed a methodology to estimate displacement based in partial-equilibrium modeling (Zink et al. 2016).

In this article, we build off our previous article by applying the proposed methodology to a case study of the U.S. aluminum market. There are two goals for this article. The primary goal is to demonstrate the viability and utility of the proposed methodology. The secondary goal of the article is to estimate the displacement rate of primary aluminum production caused by aluminum recycling in the United States. However, with respect to this second goal, we wish to be explicit that our analysis has significant limitations and our findings are sensitive to important parameters, which we explore in depth in the *Discussion*. Further development of this methodology in the context of aluminum is necessary to arrive at more-robust values, and our results should thus be interpreted as preliminary. Nevertheless, despite the uncertainty, the model does estimate upper and lower bounds for aluminum displacement and, more important, provides a starting place from which future studies can build.

In the following section, we set up a system of equations that models the behavior of producers and users of primary and secondary aluminum. Next, we describe data sources and methodology to estimate the parameters in these equations. We then present estimation results and use the displacement estimation methodology to derive a displacement rate. In the final sections of the article, we spend some time discussing the real-world practicality of the estimation methodology, highlighting both its potential and its limitations for practitioners.

Method

Basic Partial Equilibrium Model

The basic structure of our market model is described by the following system of equations (equation 3):[1]

$$\begin{aligned}
S_{sec} &= f(P_{sec}, W, \alpha_0) \\
S_{prim} &= f(P_{prim}, X) \\
D_{sec} &= f(P_{sec}, P_{prim}, Y) \\
D_{prim} &= f(P_{prim}, P_{sec}, Z) \\
S_{sec} &\equiv D_{sec} \\
S_{prim} &\equiv D_{prim}
\end{aligned} \qquad (3)$$

where S_i, D_i, and P_i represent the supply, demand, and price of aluminum type i, respectively. W, X, Y and Z are vectors of explanatory variables discussed further below. In market-clearing equilibrium, supply of each material is equal to demand. The system of simultaneous equations is solved, and the supply constant α_0 is used to simulate an increase in recycling. The changes to primary and secondary aluminum supply resulting from the increase in recycling are used to calculate the displacement rate, as shown in equation (1).

Aluminum Market Model

As discussed in Zink and colleagues (2016), displacement rate is principally governed by the price response parameters in equation (3). Thus, the first goal in estimating aluminum displacement is to estimate these response parameters. Estimating these parameters is complicated by the fact that supply and demand are determined simultaneously, making ordinary least squares estimates of each of the equations in equation (3) biased (Wooldridge 2010). Rather, estimation requires two-stage least squares (TSLS) using instrumental variables to isolate the slopes of the supply and demand curves.

To get the model ready for regression analysis, we first populate the placeholders W, X, Y, and Z with variables that help explain variance in the supply and demand of each type of aluminum. These include the price of other substitutes (in this case, steel, copper, and magnesium), factors of production (wages, energy costs, the cost of capital, and input prices), production capacity, and indicators of demand (levels of industrial and automotive parts manufacturing and overall gross domestic product [GDP]). See section 1 of the supporting information available on the Journal's website for detail on the aluminum market.

Next, we add lags of the dependent variables. These lagged variables describe the supply and demand of aluminum each year as a function of the supply and demand in the previous year—that is, $Q_t = f(Q_{t-1})$. The lagged variables not only capture any inertia that may exist in the supply or demand of material, but they also make the model dynamic, meaning that shocks to the system take effect over time rather than immediately. Because the model is dynamic, it enables us to determine long-run price responses and therefore the effect of recycling on primary production over time. The optimal number of lagged periods to include depends on specifics of the data and market. Standard time-series diagnostics should be used to aid in lag selection. In this case, a one-period lag was appropriate for all four supply and demand equations.

Finally, we modify the basic model by relaxing the market clearing supply-demand identity to incorporate international trade and stockpiling by suppliers and government. Now, supply and demand are equated according to a stock and flow identity using changes in physical stockpiles ($\Delta Stock$) and levels of imports *IM* and exports *EX* of each material. As a simplification, we treat imports, exports, and stock as exogenous.

The full model is shown in equation (4). Variable names are explained in table 1.

$$
\begin{aligned}
\log(S_{sec}) &= \alpha_0 + \alpha_1 \log(P_{sec}) + W + \alpha_2 \log(S_{sec_{t-1}}) + \varepsilon \\
\log(S_{prim}) &= \beta_0 + \beta_1 \log(P_{prim}) + X + \beta_2 \log(S_{prim_{t-1}}) + \varepsilon \\
\log(D_{sec}) &= \gamma_0 + \gamma_1 \log(P_{sec}) + \gamma_2(\log(P_{prim}) - \log(P_{sec})) \\
&\quad + Y + \gamma_3 \log(D_{sec_{t-1}}) + \varepsilon \qquad (4) \\
\log(D_{sec}) &= \lambda_0 + \lambda_1 \log(P_{prim}) + \lambda_2(\log(P_{sec}) - \log(P_{prim})) \\
&\quad + Z + \lambda_3 \log(D_{prim_{t-1}}) + \varepsilon \\
S_{sec} &\equiv D_{sec} + \Delta Stock_{sec} - IM_{sec} + EX_{sec} \\
S_{prim} &\equiv D_{prim} + \Delta Stock_{prim} - IM_{prim} + EX_{prim}
\end{aligned}
$$

where

$$
\begin{aligned}
W &= \alpha_3(P_{silicon}) + \alpha_4 \log(P_{wages}) + \alpha_5(P_{capital}) \\
&\quad + \alpha_6(P_{energy}) + a_7(P_{scrap}) \\
X &= \beta_3 \log(P_{wages}) + \beta_4 \log(P_{capital}) + \beta_5 \log(P_{energy}) \\
&\quad + \beta_6 \log(Cap) + \beta_7 \log(P_{baux}) \\
Y &= \gamma(\log(P_{steel}) - \log(P_{sec})) + \gamma_5(\log(P_{Cu}) - \log(P_{sec})) \\
&\quad + \gamma_6 \log(A_{auto}) + \gamma_7 \log(A_{rGDP}) \\
Z &= \lambda_4(\log(P_{steel}) - \log(P_{prim})) + \lambda_5 \log(A_{rGDP}) \\
&\quad + \lambda_6 \log(A_{auto})
\end{aligned}
$$

The explanatory regressors that make up W, X, Y and Z are exogenous except in the case of the price differences between substitute metals and aluminum, where only the price of the substitute is exogenous, and in the case of scrap price, which is treated as exogenous in model 1, but endogenous in model 2 (explained further in the *Sensitivity Analysis* section). The subscript $t-1$ denotes a 1-year lag. Specifications for the equations in equation (4) were developed by reviewing previous econometric models of aluminum markets (see table 2 for references) and by investigating the structure and history of the U.S. aluminum market. Various specifications, including competing autoregressive lag structures, were tested. The final specifications were selected based on standard diagnostics, their ability to produce accurate forecasts, and a preference for parsimony. Log-log form is used so that estimated coefficients can be interpreted as elasticities (Wooldridge 2010).

Data Sets and Estimation

We drew annual price and production data from the U.S. Geological Survey (USGS), the U.S. Census Bureau, the U.S. Federal Reserve, the U.S. Energy Information Administration (EIA), The U.S. Federal Reserve Bank (FRED), and the U.S. Bureau of Labor Statistics (BLS). The USGS uses primary aluminum price data from Platts Metals Week and secondary aluminum price data from the American Metal Market. For primary material, we use the single price reported by the USGS. For secondary material prices, we use an average of the prices for alloys reported by the USGS (A380 [3% zinc {Zn}], B380 [1% Zn], A360 [0.6% copper {Cu}], A413 [0.6% Cu], A319 [3% Cu], and A356 [0.2% Cu]). All prices were deflated using

Table 1 Variables and data sources

Variable	*Description*	*Units*	*Source*
Endogenous variables			
Sprim	Production quantity of primary aluminum from bauxite	tonne	USGS
Ssec	Production quantity of secondary aluminum from old and new scrap	tonne	USGS
Pprim	Price of primary aluminum	$/tonne	USGS
Psec	Price of secondary aluminum, average of various aluminum-based alloys	$/tonne	USGS
Dprim	Demand/consumption of primary aluminum	tonne	Identity: $D_i = S_i + IM_i - Ex_i - stockchange_i$
Dsec	Demand/consumption of secondary aluminum	tonne	Identity: $D_i = S_i + IM_i - Ex_i - stockchange_i$
Pscrap	Price of aluminum scrap, weighted average	$/tonne	USGS
Exogenous variables			
Pwages	Average hourly earnings of production and nonsupervisory durable goods employees	$/hr	BLS
Cap	Capacity of primary refineries	thousand tonnes	USGS
Pcapital	Price of capital, approximated by U.S. 10-year constant maturity treasury bill	% yield per annum	FRED
Penergy	Price of West Texas Intermediate crude	$/barrel	EIA
Psilicon	Price of silicon	$/tonne	USGS
Aauto	Value of shipments from automotive manufacturing sectors	million $	U.S. Census
rGDP	Real GDP	billion $	FRED
Pcu	Price of copper	$/tonne	USGS
Psteel	Price of steel	$/tonne	USGS
IMprim	Imports of primary aluminum	tonne	USGS
EXprim	Exports of primary aluminum	tonne	USGS
IMsec	Imports of secondary aluminum	tonne	USGS
EXsec	Exports of secondary aluminum	tonne	USGS
StockPrim	Quantity of primary aluminum in industry and government stockpiles	tonne	USGS
StockSec	Quantity of secondary aluminum in industry and government stockpiles	tonne	USGS

Note: GDP = gross domestic product; USGS = U.S. Geological Survey; BLS = U.S. Bureau of Labor Statistics; EIA = U.S. Energy Information Administration; FRED = Federal Reserve Economic Data.

the U.S. Producer Price Index and wages were deflated using the U.S. Consumer Price Index, both from the BLS. A complete list of variables and associated data sets is provided in table 1. The estimation period was 1971–2013 (N = 43) to maximize the number of observations while also reflecting current market conditions. Before 1970, published prices do not reflect actual selling prices. Regressions were checked for serial correlation using the Cumby–Huizinga general test for autocorrelation, shown at the bottom of table 3.[2]

Model Solution and Calculation of Displacement Rate

After the equations that make up the market model are fully specified and estimated, the model is solved to the reduced form and a shock is introduced. Two factors complicate the model solution and calculation of estimated displacement rate. First, the aluminum model in equation (4) is nonlinear given that the stock-change identity is in levels and the supply and demand equations are in logs. Thus, equation (4) cannot be solved analytically. Rather, we solved the system dynamically using the Broyden method (Broyden 1965) in Stata 13.1, using actual data for the exogenous variables for each year of the estimation period and previous-period solutions for the current-period lagged endogenous variables.

Second, because the model is in log-log form, the solution roughly expresses percentage changes in supply. Because displacement is concerned with absolute, rather than percentage, changes in supply, the percentage changes in supply must be converted to absolute quantity changes by multiplying the percentage change by the actual production quantity of each material. Given that these actual production quantities, as well as the exogenous imports, exports, and stockpiles, vary each year, the model solution also varies each year. Instead of a single value for changes primary and secondary supply, therefore we instead arrive at a set of solutions—one for each year. The initial solution to the system with the parameters as estimated

Table 2 Price elasticity estimates from this study and previous econometric aluminum models

	Price elasticity: Primary		*Price elasticity: Secondary*		*Cross-price demand elasticity*	
Source	*Supply*	*Demand*	*Supply*	*Demand*	*Primary*	*Secondary*
Presented study: Short run	0.40–0.43	−0.22 to −0.20	0.17–0.64	−0.63 to −0.53	0.20–0.47	0.14–0.19
	(0.11–0.16)	(0.34–0.44)	(0.17–0.24)	(0.35–0.57)	(0.34–0.37)	(0.20–0.30)
Presented study: Long run[a]	0.65–0.88	−0.35 to −0.34	0.55–2.50	−1.21 to −1.03	0.34–0.80	0.22–0.37
Deadman and Grace (1979)	0.23					
Carlsen (1980)			0.32			
Slade (1980)	−0.25[b]		0.24			
Hojman (1981)	0.05	−0.17				
Suslow (1986)		−1.93	1.96	−0.88	0.89	1.08
		(0.50)	(0.67)	(0.98)	(0.57)	(1.39)
Gilbert (1995)	0.14	−0.127				
	(1.84)	(2.78)				
US EPA (1998)			2.33	−0.34		
				(0.185)		
Grant (1999)			0.6[c]			
Blomberg and Hellmer (2000)			0.17	0.07[b]		
			(0.085)	(0.036)		
Blomberg (2007)			0.21–0.78			
Blomberg and Soderholm (2009)			0.21			

Note: Standard errors are given in parentheses where provided in the source.
[a]Long-run price elasticities are calculated by dividing the price response coefficient by the quantity one minus the sum of the coefficient on the lagged dependent variable. For instance, the long-run price elasticity for secondary demand is $\gamma_1/(1-\gamma_3)$.
[b]Economic theory predicts coefficient should have the opposite sign.
[c]Elasticity of scrap supply; not equivalent to secondary supply.

and no intervention (i.e., $\alpha_0 = 0$) is referred to as the baseline scenario.

To calculate displacement rates for each solution-year, we introduced a 5% increase to the secondary supply intercept (α_0) beginning in 1995 and persisting through 2013 (i.e., not a one-time intervention, but a *sustained* increase in recycling) and once again solved the system for each year. The solution including the 5% supply shock is referred to as the intervention scenario. The set of solved levels of primary and secondary supply under the baseline scenario were subtracted from those under the intervention scenario to arrive at the change in supply of each material.

Next, the change in supply of primary material between the baseline and intervention scenario was divided by the analogous change in supply of secondary material to obtain the displacement rate, in accord with equation (1). Because the supply changes vary each year, so, too, does the displacement rate; thus, we arrive not at a singular displacement rate, but a time series of estimated displacement rates for each year following the increase in recycling.

Sensitivity Analysis

To assess the effect of the estimation uncertainty on the results, we conducted several sensitivity analyses. First, we estimated two specifications to account for a complication that arises regarding the price of aluminum scrap. Previous studies have used scrap price as an exogenous regressor to estimate secondary supply (Suslow 1986; Blomberg and Hellmer 2000; Blomberg 2007; Blomberg and Söderholm 2009). However, because secondary aluminum supply is the only major industry to utilize aluminum scrap, it is possible that the level of secondary smelting activity also affects the price of scrap: as more secondary aluminum is produced, the demand for scrap increases along with its price. If scrap price is endogenous in the secondary supply equation, including it as an exogenous regressor biases the estimation results.

In model 1 (called exogenous scrap), we follow previous researchers and include scrap price as exogenous. However, we also test for endogeneity of scrap price, using the Durbin–Hausman–Wu test (Hausman 1978) and by using an alternative model specification where scrap price is endogenous. In model 2 (called endogenous scrap), we use an expanded set of instruments that consists of all exogenous variables from all four equations along with one-period lags and one-period lags of all six endogenous outcome variables. The endogenous scrap model can be viewed as a more general model that is less reliant on specific assumptions about the aluminum market.

Second, for both models, we solve the models incorporating coefficient uncertainty using Monte Carlo simulation (>2,000 iterations) to produce a distribution of primary and secondary supply changes and displacement rates. From these distributions, we calculated 5th, 10th, 90th, and 95th percentiles and include them along with graphs of median estimates.[3] We conducted "unrestricted" simulations, where all values from the coefficient distribution are allowed, and "restricted" simulations,

Table 3 Estimation results

	Model 1: Exogenous scrap price				*Model 2: Endogenous scrap price*			
	Primary		*Secondary*		*Primary*		*Secondary*	
	Supply	*Demand*	*Supply*	*Demand*	*Supply*	*Demand*	*Supply*	*Demand*
$\log(P_{prim})$	0.395^{**}	-0.216			0.425^{***}	-0.202		
	(0.170)	(0.435)			(0.109)	(0.340)		
$\log(P_{sec})$			0.642^{***}	-0.626			0.174	-0.532
			(0.240)	(0.567)			(0.147)	(0.350)
$\log(P_{sec}) - \log(P_{prim})$		0.474				0.195		
		(0.386)				(0.340)		
$\log(P_{prim}) - \log(P_{sec})$				0.136				0.191
				(0.302)				(0.201)
$\log(P_{wages})$	-1.301^{*}		-1.945^{***}		-1.318		-1.447^{**}	
	(0.781)		(0.718)		(0.814)		(0.611)	
$\log(P_{capital})$	0.009		-0.100^{**}		0.001		-0.077^{**}	
	(0.095)		(0.040)		(0.085)		(0.035)	
$\log(P_{energy})$	-0.041		0.071		-0.042		0.027	
	(0.045)		(0.048)		(0.045)		(0.040)	
$\log(Cap)$	0.194				0.192			
	(0.211)				(0.209)			
$\log(P_{baux})$	0.222^{**}				0.231^{**}			
	(0.096)				(0.111)			
$\log(rGDP)$		-0.101		-0.409		-0.188		-1.018^{***}
		(0.213)		(0.369)		(0.189)		(0.201)
$\log(A_{auto})$		0.167		0.557^{***}		0.196^{*}		0.826^{***}
		(0.126)		(0.163)		(0.111)		(0.122)
$\log(P_{silicon})$			-0.143				-0.106	
			(0.104)				(0.091)	
$\log(P_{scrap})$			-0.001				0.105	
			(0.079)				(0.065)	
$\log(P_{steel}) - \log(P_{prim})$		-0.411				-0.330		
		(0.364)				(0.277)		
$\log(P_{steel}) - \log(P_{sec})$				-0.457				-0.494^{*}
				(0.452)				(0.300)
$\log(P_{cu}) - \log(P_{sec})$				0.038				0.243^{***}
				(0.095)				(0.057)
$\log(S_{prim})_{t-1}$	0.508^{***}				0.515^{***}			
	(0.178)				(0.163)			
$\log(D_{prim})_{t-1}$		0.406^{**}				0.419^{***}		
		(0.199)				(0.148)		
$\log(S_{sec})_{t-1}$			0.743^{***}				0.683^{***}	
			(0.100)				(0.086)	
$\log(D_{sec})_{t-1}$				0.393^{**}				0.482^{***}
				(0.155)				(0.112)
Intercept	5.806	8.653^{*}	5.440	9.679^{**}	5.524	9.038^{**}	7.575^{***}	9.913^{***}
	(4.590)	(5.182)	(3.366)	(4.581)	(3.948)	(4.073)	(2.881)	(3.008)
R^2	0.87	0.66	0.95	0.95	0.87	0.70	0.96	0.96
C-H χ^2, 1 lag (p)	0.26 (0.61)	1.00 (0.32)	0.58 (0.45)	3.05 (0.08)*	0.33 (0.57)	1.04 (0.31)	0.00 (0.99)	0.01 (0.93)
N	43	43	43	43	43	43	43	43

Note: Robust standard errors in parentheses.
Model 1 instruments: All exogenous variables in the regression including one-period lag of DV, plus exogenous variables from the opposite supply/demand equation. DV = dependent variable.
Model 2 instruments: All exogenous variables from all four regressions, plus one-period lags of all exogenous and outcome variables.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$, two-tailed tests.

where values with signs that contradict basic economic theory are eliminated (see section 2 of the supporting information on the Web).

Third, It has been shown that supply- and demand-side shocks can lead to different results (Kilian 2009). Our initial explorations of a demand-side shock in our previous article (Zink et al. 2016) also indicated that supply and demand shocks may lead to different results. Therefore, we also tested the effect of a shock to secondary aluminum demand rather than supply. This is done by moving the constant α_0 in equation (3) to the secondary demand equation and introducing a 5% shock to this variable. For the demand shock, we use the estimation results from the exogenous scrap model.

Finally, we tested several other variations of the model and intervention, including altering the intervention year and size, and using a one-time, rather than constant, intervention.

Results

Estimation results for the primary and secondary aluminum equations are shown in table 3. Short- and long-run price elasticities are presented alongside others from the literature in table 2. Model fit diagnostics and the model forecast values for supply of both materials are presented in section 3 of the supporting information on the Web. Supply change forecasts and estimated displacement rates are shown in figures 1 to 3, discussed in the following sections.

Exogenous Scrap Model Results

Figure 1 shows the difference between the supply shock scenario and the baseline for supply of both materials using the endogenous scrap model (baseline and intervention series shown in absolute values are presented in section 4 of the supporting information on the Web). After the secondary supply intervention, secondary supply increases and primary supply decreases, as expected given that the materials are substitutes. Because supply of each material in equation (4) is dependent on exogenous factors, the supply changes following the shock are not constant, but vary each year. Figure 1 shows that the increase in secondary supply is larger and grows more over time than the decrease in primary supply.

The time series of displacement rates for the exogenous scrap model is shown in figure 2. The median estimated displacement rate is 12% immediately following the shock, falling to 7% after 15 years.

Exogenous Scrap Model Sensitivity Results

The percentiles plotted in figures 1 and 2 show the uncertainty in supply responses and displacement rate caused by uncertainty in the underlying equation parameter estimates. The inner 90% of the estimated displacement distribution (i.e., the difference between the 5th and 95th percentiles) is 1.2 in the period following the shock and 0.6 after 15 years. The restricted distribution is tighter, with an inner 90% range of only 0.66 in the period after the shock. Both the full and restricted distributions have long, but thin, tails as demonstrated by a much smaller inner 80% range.

Despite the uncertainty, some patterns emerge. First, the overall pattern of declining displacement, despite a constant increase in recycling, holds across the high end of the simulation results. Additionally, for the entire time series, the 95th percentile of the unrestricted distributions is never larger than 100%, meaning the model predicts, at best, less than 5% probability of achieving full displacement; 95% of the displacement rates using the restricted distributions fall below 64%. The 5th and 10th percentiles are below zero for the entire series, indicating that negative displacement is possible. This is a result of uncertainty in the response of primary production, which can be positive, as shown in figure 1 (meaning increased recycling could stimulate rather than prevent primary production).

The year in which the intervention is introduced is inconsequential; a nearly identical pattern emerges no matter when the secondary supply shock is introduced. When modeling a one-time rather than sustained intervention, the initial effect on each material supply is similar, but wears off more quickly, resulting in a more drastic decline in displacement after the intervention period.

Results for the demand-side shock are presented and discussed in section 5 of the supporting information on the Web. In summary, a demand-side shock increases both secondary *and* primary supply, leading to negative displacement. These results support Kilian's (2009) finding and Thomas's (2003) theoretical prediction: A demand-side shock results in different market responses that have drastic implications for displacement and the environmental profile of recycling. Accounting for coefficient uncertainty, 87% of the estimated displacement rates fall below 0%, meaning that increased demand for secondary aluminum is likely to increase supply of both materials and therefore increase environmental impacts.

Endogenous Scrap Model Results

The Hausman test for endogeneity of the price of scrap does not reject the null hypothesis that scrap price is exogenous ($\chi^2(7d.f.) = 6.15$, $p = 0.523$). This means that there is no statistical necessity to treat scrap price as endogenous. Nonetheless, we used the alternative model specification to see whether assumptions about scrap price endogeneity lead to practical differences in displacement.

As seen in table 3, the important differences between exogenous scrap model and the endogenous scrap model are the size of the price elasticities. The difference between the two models is generally small except in the case of the own-price response of secondary supply and the cross-price response of primary demand.

These differences have a small, but noticeable, effect on supply responses and therefore displacement estimates, shown in figure 3 (supply changes are shown in section SI-4 of the supporting information on the Web). The main difference is that secondary supply increases more than under the exogenous scrap

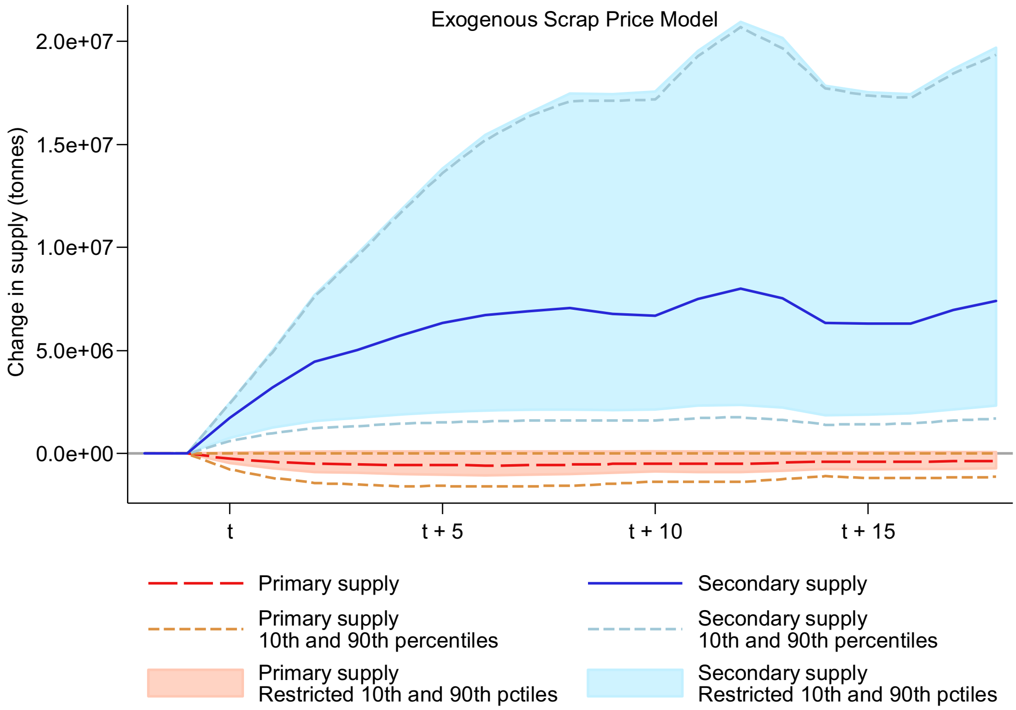

Figure 1 Dynamic response of primary and secondary production to 5% increase in recycling, using estimation results from model 1. Full distributions created from 3,950 Monte Carlo iterations; restricted distributions created from 2,600 iterations.

model, leading to slightly higher displacement rates. Using the endogenous scrap model, 95% of the estimated displacement distribution falls below 102% and 90% of the distribution falls below 70%. Additionally, under the endogenous scrap model, there is a higher chance of negative displacement rates, even using the restricted parameter distributions, a result of the smaller cross-price response of primary demand.

Discussion

Coefficient estimates from previous studies are presented in table 2 alongside those from this study. Overall, the coefficient estimates in table 3 correspond well with economic theory and are generally in line with those in previous studies. Only the cross-price response of secondary demand deviates notably from Suslow's (1986) estimate. However, it is worth pointing out that the literature estimates themselves exhibit considerable variation. The model fit diagnostics (section SI-3 of the supporting information on the Web) build confidence in the models' predictive power.

The main results in figures 2 and 3 show that increased aluminum recycling is very unlikely to displace 100% of its mass in primary aluminum in the first year; it is possible that aluminum recycling stimulates, rather than prevents, primary production. In both models, displacement decreases after the initial shock, even though the increase in secondary supply is sustained.

Increasing secondary aluminum demand appears to lead to negative displacement (i.e., stimulates primary aluminum production). This result is more robust to coefficient uncertainty than the supply-side shocks (87% of estimated displacement rates were negative), though it is not impossible that positive displacement can occur in response to demand-side shocks.

The displacement estimates show considerable coefficient uncertainty. The amount of variability suggests that more work is needed to develop even more advanced econometric models that can provide more tightly estimated elasticity parameters.

Mass Balance: If Not Displaced Primary Production, Then What?

At this point, it would be natural to wonder, "If secondary production doesn't fully displace primary production, where does the 'extra' material go?" The answer is illustrated in figure 4. The common assumption that recycled material displaces primary material of the same type is depicted in the leftmost circles in figure 4. However, two other outcomes are possible that result in partial displacement.

First, as discussed in the introduction, secondary aluminum may displace production of materials other than primary aluminum (the rightmost circles in figure 4). Recycled aluminum may, for instance, displace primary or secondary steel, copper, magnesium, or plastic. Determining the sign of E_{net} in equation (2) requires estimating the displacement rates of all displaced materials. Whereas the framework presented in our methodology article (Zink et al. 2016) can accommodate other-material displacement, such an exploration is beyond the scope of this case study and is left for future research.

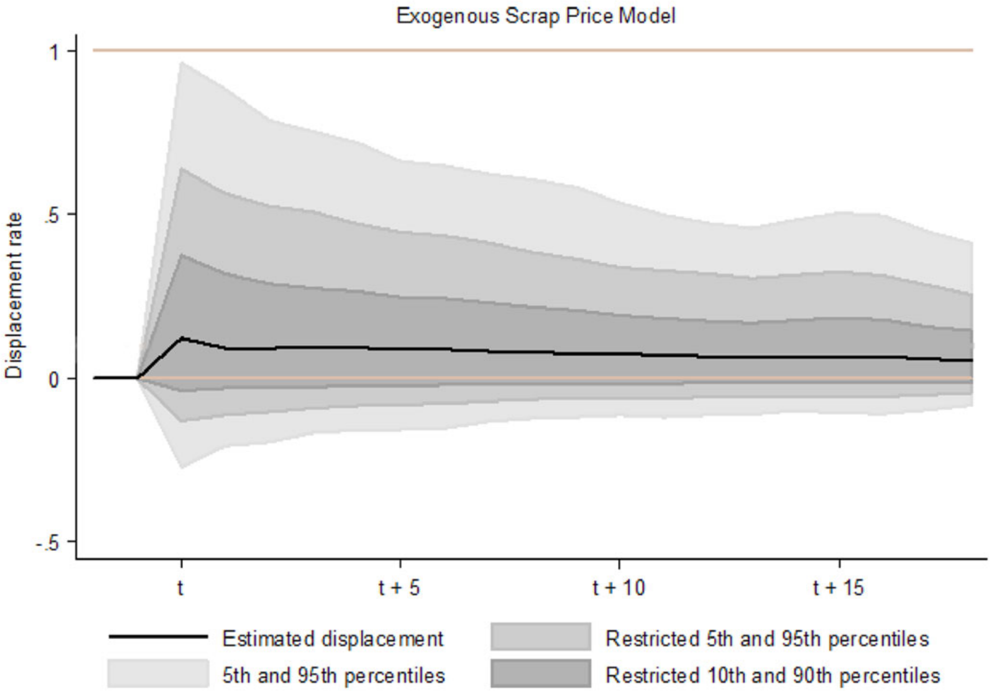

Figure 2 Estimated U.S. aluminum displacement rate following a 5% increase in recycling in period *t*, using the exogenous scrap model. Horizontal lines mark 0% and 100% (full) displacement. Full distributions created from 3,950 iterations; restricted distributions created from 2,600 iterations.

Second, increased aluminum recycling can also affect overall aluminum demand (the center circles in figure 4). For instance, it is possible that increased recycling can lower prices of both primary and secondary material and thus increase demand for aluminum (similar to the energy efficiency "rebound effect"). Note that this market increase is independent of any exogenous growth that may occur simply as a result of global economic forces. Production and consumption data show that both aluminum recycling rates and the size of the aluminum market have been growing rapidly for the last 100 years; it is possible that some of this increase is a result of decreased material prices from increased recycling.

Model Limitations

The aluminum model is simplified in several important ways. First, it does not consider various nonmarket factors, such as government recycling targets, subsidies, and quotas, to the extent that these are not captured in price changes. It also treats all primary aluminum and all secondary aluminum as homogenous products, when, in reality, there are many grades and alloys of both. In the case of secondary material, robustness checks using only prices of single types of secondary material did not qualitatively change the results, given that the various secondary material prices are highly correlated with one another. Therefore, treating secondary material as homogenous does not affect the overall results. Additionally, scrap is treated as homogenous and a single scrap price is used, which is a production quantity-weighted average of mixed low-copper-content clippings, clean dry turnings, old sheet and castings, and used beverage cans. This mix represents both old and new scrap, which is handled by different industrial actors. Home scrap is not sold and therefore has no price, so it was excluded. The model also ignores the fact that not all scrap is suitable for all recycling uses. However, scrap price enters the model only as an input to secondary supply, and these four grades of scrap varied in price by only 10% to 15% during the estimation period; thus, treating scrap as homogenous is justified; sensitivity analysis using only the price of used beverage cans did not change the overall findings.

The aluminum model is geographically limited to the U.S. market. This limitation was necessitated by the considerable data requirements of the study and the limited availability of public data outside the United States. The United States relies heavily on imports of bauxite for aluminum production and relies on exports for refined aluminum and for scrap, primarily to China. An attempt was made to account for these flows by including actual annual data on imports and exports for each type of material, but those flows were kept exogenous in the model. The effect of this limitation is that domestic supply and demand in the model react to price changes without intervention from international markets.

Building dynamic imports and exports into the model would require a significantly more complex global model with similar data demands for six or more major producing and consuming countries. Previous researchers have attempted such models for aluminum-bauxite (Hojman 1981) and copper (Fisher

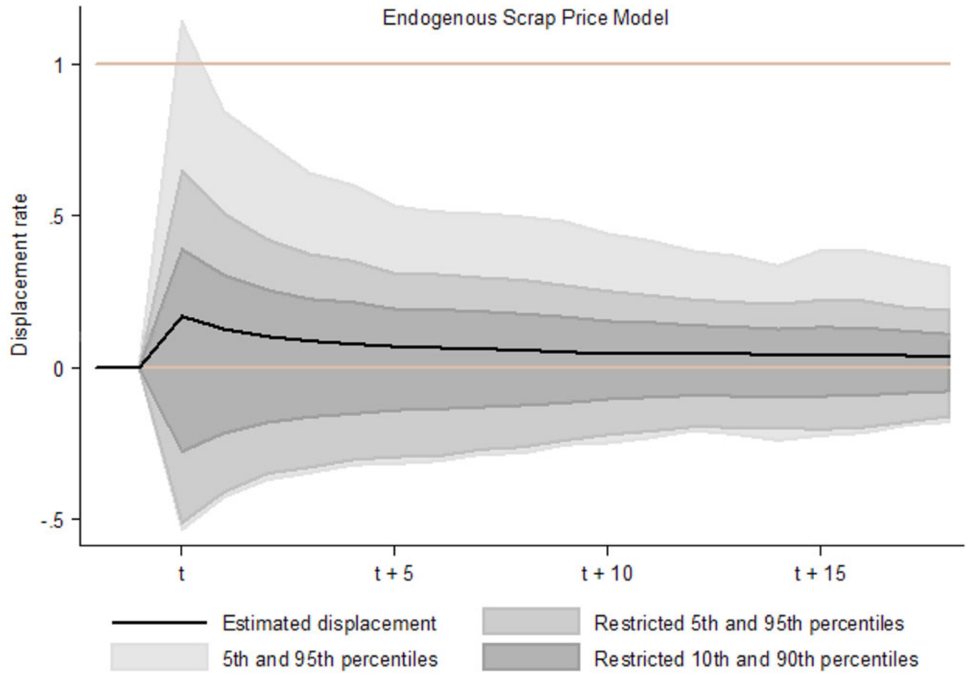

Figure 3 Estimated U.S. aluminum displacement rate following a 5% increase in recycling in period *t*, using the endogenous scrap model. Horizontal lines mark 0% and 100% (full) displacement. Full distributions created from 3,950 iterations; restricted distributions created from 2,600 iterations.

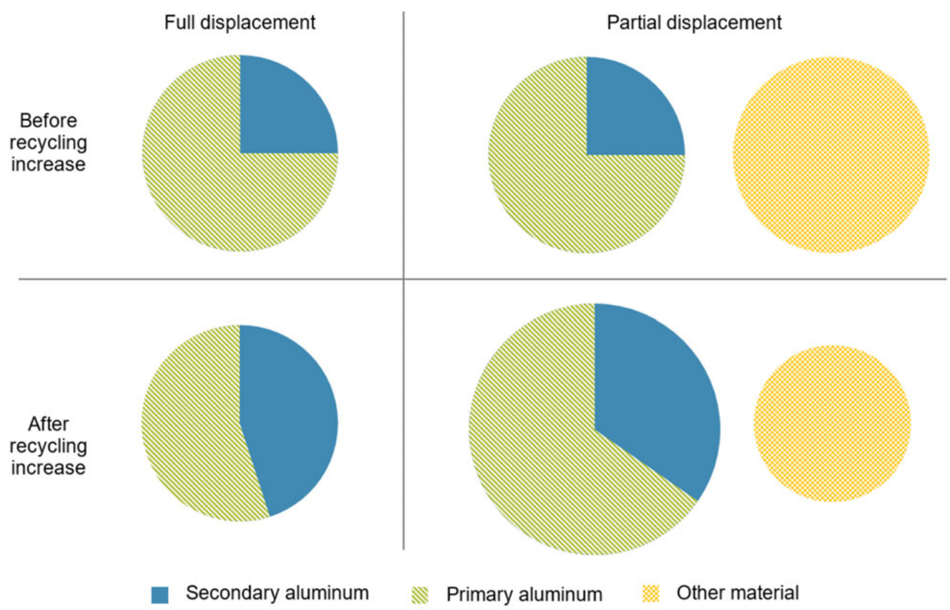

Figure 4 Graphical representation of partial displacement. Shape area represents production quantity. Increased secondary production may fully displace primary material of the same type (left circles), grow overall material demand (middle circles), or displace material of a different type (right circles).

et al. 1972), though they were forced to significantly simplify the control variables used, and ultimately arrived at own-price elasticities roughly in line with those estimated in this study. This suggests that the added complexity may not deliver more-accurate or more-useful model results. Additionally, the availability of data on secondary metals production and prices is significantly worse on a global scale; for instance, neither of the mentioned multicountry models explicitly considers the effect of recycled material on the market, partly attributable to data availability.

Production capacity and measures of demand (levels of industrial manufacturing and aluminum castings) were treated as exogenous. Whereas this is likely to be accurate in the short term, these factors could respond to prices in the long term. However, maintaining these variables as exogenous was necessary to keep the size of the model manageable and has precedent in econometric industry models of copper and aluminum (Hojman 1981; Blomberg and Hellmer 2000; Blomberg and Söderholm 2009).

Additionally, aluminum stock accumulation and depletion is simplified in that we modeled stock as an exogenous variable, whereas, in reality, the level of stock is a function of both random market fluctuations and suppliers' expectations about future demand and preferred stock size. Expanding the model to include intentional fluctuations in stock size would increase the realism of the model, but would require a model to describe suppliers' and buyers' stock-holding behavior, which was outside the scope of this study. A simple exploration that included stock-holding behavior in the model as a function of previous-period stock size and prices did not result in any substantive difference in the results, suggesting the simplification is justified (see section 6 of the supporting information on the Web).

Finally, to model current conditions, we limited the estimation period to the years 1971–2013, resulting in 43 observations per regression. TSLS with instrumental variables produces unbiased estimates only under large samples; there is some possibility that our sample is sufficiently small that the estimates are biased.

Conclusions

Although the environmental benefits of recycling come primarily from their potential to displace more impactful primary production processes, alarmingly little is known about actual rates of displacement. Just like it should not be expected that efficiency improvements translate one to one into energy savings, it should not be expected that recycling activities cause one-to-one displacement of primary production (Geyer et al. 2016). Many studies of the so-called rebound effect in energy efficiency exist, yet a similar effort for displacement is currently missing. Whereas there may be many meaningful and insightful ways to study displacement attributed to recycling, the use of partial equilibrium analysis is one obvious avenue (Zink et al. 2016). However, to derive actual displacement estimates, the parameters of the resulting structural equations need to be quantified first (e.g., through regression analysis).

This study showcases the use of partial equilibrium modeling and econometric regression analysis to estimate the impact of aluminum recycling on primary aluminum production in the United States. Despite good data availability and considerable modeling and regression efforts, the resulting displacement estimates are burdened with significant uncertainty. Yet, even with the uncertainty of the results in mind, there is substantial evidence that displacement does not occur on a one-to-one basis.

Lessons Learned: Application of the Methodology

Our example of estimating displacement through partial equilibrium modeling and regression analysis highlights both the uses and the challenges of this approach. Notably, data requirements are significant and are likely to be even higher if one is to improve the estimation precision. Sufficient time-series data are required to have enough observations for two-stage least-squares estimation.

Even with availability of high-quality data in a relatively long time series, estimating price elasticities is notoriously difficult (Fisher et al. 1972). Seemingly trivial decisions of which years to include, which demand or input variables to use, whether certain variables should be exogenous or endogenous, and which variables to use as instruments can have striking effects on the outcome. Because displacement is a function of all the price response coefficients, uncertainties in each of them combine to create large uncertainty in displacement. It is necessary to have tightly estimated price responses to have a hope of learning anything useful about displacement, but the nature of supply-demand estimation makes this difficult. In the current study we have used 5th and 95th percentiles as a cutoff for reasonable certainty.

Lessons Learned: Assessment and Practice of Recycling

Although this case study is just a first step toward a better understanding of displacement, it does suggest that we are currently systematically overestimating the environmental benefits of recycling. Assessments that include recycling processes should therefore, at a minimum, include the sensitivity of the results with regard to partial displacement. This is different than reporting the sensitivity of the results with regard to the allocation methodology for recycling (e.g., recycled content vs. avoided burden), given that they all assume one-to-one displacement. It is also different than accounting for technical substitutability, as, for example, done in the value-corrected substitution method (e.g., Koffler and Florin 2013). Including sensitivity to incomplete displacement in LCA and other analyses need not take the form of formal Monte Carlo simulation or even partial equilibrium modeling as demonstrated in this case study. Instead, it can mean including a range of potential impact results based on a range of reasonable displacement rates. In the case of studies focused on EoL management, break-even displacement rates for each impact category should be reported.

That the current environmental benefits are lower than we think they are does not mean we should stop recycling. Instead, it tells us that recycling currently does not fulfil its environmental potential, and recycling efforts should therefore focus on maximizing displacement rather than simply maximizing collection, reprocessing, and market development for secondary resources. To know the effectiveness of recycling efforts, we need to be able to measure displacement, which brings us back to this article and its predecessor. We hope that these first steps inspire other researchers to conduct research on displacement so that the circular economy does not simply turn into another vehicle of consumption growth.

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Notes

1. Consult Zink and colleagues (2016) for a detailed explanation of the basic market model.
2. Due to the fact that some of the regressors included in equation (4) are endogenous, the more standard Durbin–Watson test for serial correlation is invalid (Wooldridge 2010). The Cumby–Huizinga test is more general and is valid in small samples, under heteroskedasticity, and with endogenous regressors (Cumby and Huizinga 1992).
3. Due to the occurrence of division by near-zero values, percentiles provide a better indication of model uncertainty than confidence intervals based on standard errors.

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Supporting Information

Supporting information is linked to this article on the *JIE* website:

Supporting Information S1: This supporting information contains information about aluminum production and market structure, restricted coefficient distributions, model diagnostics, supply and demand absolute differences, demand-side shock, and the stock-holding model used in the main article.