Causal Inference for Quantifying Displaced Primary Production from Recycling

To be submitted to Environmental Research Letters

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Abstract

Recycling only creates environmental benefits when it displaces other material production. It is therefore critically important that we improve our understanding of the causality between the two. This research focuses on estimation of the causal link between an increase in recycling and a reduction in primary production. We first review how structural models of supply and demand, for both the primary material and the recycled material, can be used to identify a causal link. The supply and demand approach suffers from issues of endogeneity, which require the use of advanced regression techniques. These techniques, in turn, require detailed and large datasets, which are often hard to obtain. We present the Difference-in-Differences (DID) estimator as an alternative approach. The DID estimator is based on a quasi-experimental approach, in that it classifies data into treatment and control groups. We introduce the new method, analyze the data structures and assumptions needed for identification of causal effects, and discuss the advantages relative to the supply and demand framework. A hypothetical application of each method to aluminum recycling is provided. Our proposed method will help to better understand, measure, and promote the conditions under which recycling creates environmental benefits.

1. Introduction

Recycling is the process of converting what would otherwise be waste into secondary resources to be used again in the economy. In public environmental policy, recycling is seen as a way to keep solid waste out of landfill. Recycling, or secondary material production, is also a topic that has received intense attention throughout the history of the field of industrial ecology. It turns out that the sole environmental benefit of secondary production is that it can displace, or avoid, other material production processes (Zink *et al* 2015, Geyer *et al* 2015, Yang 2016). Such displacement leads to all other perceived benefits of recycling such as landfill reduction, energy savings, and reductions in raw material usage (Geyer *et al* 2015). Unfortunately, the actual mechanisms of displacement have not been studied until recently.

From early to recent times, displacement has simply been assumed to happen on a 100% basis, which means that each unit of recycled material displaces one unit of primary material. In environmental life cycle assessment (LCA), this assumption is used in the so-called “avoided burden approach”, which serves to allocate the benefits of recycling between the two product systems connected through the recycling activity (Atherton 2007, Weidema 2001, Frischknecht 2010). While authors have acknowledged that quantifying displacement precisely is important (Mcmillan *et al* 2012, Weidema 2003, Geyer *et al* 2015, Geyer 2008, Ekvall 2000, Vadenbo *et al* 2017), only one comprehensive statistical analysis of displacement exists in the industrial ecology literature (Zink *et al* 2017).

The extent to which more scrap and waste collection leads to additional secondary production, and then to displacement, has predominantly been treated as a market equilibrium problem in the literature and approached by assuming or calculating price elasticities (Ekvall 2000, Zink *et al* 2015, 2017, Weidema 2003, Ekvall and Andrae 2006). Displacement has also been identified as a key issue in the methodological development of consequential life cycle assessment (CLCA), which strives to model the net environmental impacts of a change to an industrial system considering all physical and social processes affected (Weidema 2003, Zamagni *et al* 2012, Brander *et al* 2009, Ekvall *et al* 2016, Koffler and Finkbeiner 2017). In general, much of the industrial ecology literature has equated social processes with markets and their equilibria (Earles and Halog 2011, Weidema 2003, Weidema *et al* 2009, Zamagni *et al* 2012, Rajagopal 2016).

Structural market models of primary and secondary variants of one material in isolation from the rest of the economy have been the primary tool proposed and applied to calculating displacement (Ekvall and Andrae 2006, Zink *et al* 2015, 2017, Ekvall 2000). It has been shown that this can be used to assess the displacement of primary aluminum due to aluminum recycling in North America (Zink *et al* 2017). However, supply and demand models are only one avenue to study cause-and-effect mechanisms using observational data.

In this paper, we generalize displacement as a question of the cause-and-effect relationship between secondary production and primary material and show that structural market equilibrium models are not the only possible approach. We identify and investigate the use of an alternative method for causal inference, Difference-in-differences (DID), for quantifying the causal relationship between recycling and primary production. We thoroughly examine the statistical problems and assumptions, causal mechanisms, and operationalization of the two approaches without loss of generality. Idealized case studies for the two methods are hypothesized using aluminum as a platform. Finally, we discuss applying these methods to other displacement problems and the significance of this research in environmental policy and the field of industrial ecology.

2. Generalized displacement

Figure 1 shows a generalized displacement problem. The solid green line represents secondary aluminum production Q_{sec} over time for a regional aluminum market. Prior to the year 2000, secondary aluminum was not produced in this particular market. In the year 2000, an exogenous shock occurs, i.e. a shock that did not affect demand for aluminum directly, hence the dashed lines have the same slope before and after the year 2000. This shock leads to the production of 150 tons of secondary aluminum per year going forward. One example of such a shock would be a legislative act suddenly mandating aluminum producers to increase secondary production. We ask the following question: does additional secondary production cause a decrease in primary production? This question is critical because such an outcome reduces our reliance on raw natural resources and typically reduces the total impact of production. This impact reduction dynamic may affect the environmental assessment of policy-driven changes to product systems. One example is material substitution in vehicles, where lack of displaced production through recycling would affect the environmental performance of light-weight materials (Løvik *et al* 2014, Geyer 2008, Modaresi and Müller 2012, Modaresi *et al* 2014). The dotted lines in Figure 1 (a) are the trends in primary aluminum production Q_{prim} over time, and in Figure 1 (b) they represent the trends in total aluminum production $Q_{tot} = Q_{sec} + Q_{prim}$.

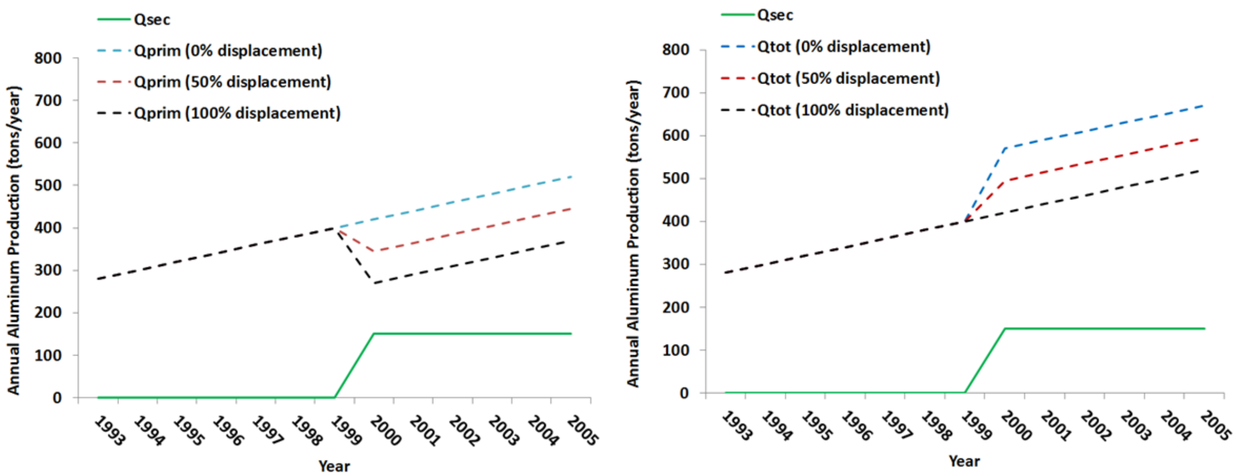

Figure 1: Total quantity of material produced as a function of time with an exogenous shock leading to additional secondary production in the year 2000. Displacement is a research question about what happens after this influx of secondary material. The question can be answered by observing what happens to the primary quantity produced after the shock. Panel (a) shows what happens to primary production for 0%, 50% and 100% displacement. Panel (b) shows the same for total production.

Consider the case where this influx of secondary material goes onto the regional market for automotive materials. In the scenario represented by the black line in Figure 1, all of the secondary aluminum is used to replace primary aluminum (i.e. 150 tons per year), which is 100% displacement. The red line represents the scenario where only 75 tons of the secondary aluminum is used to replace primary aluminum, which is 50% displacement. In a third scenario represented by the blue line, none of the secondary aluminum is used to replace primary aluminum, which is 0% displacement. These examples illustrate the definition of displacement: $d = 1 - \frac{\Delta Q_{tot}}{\Delta Q_{sec}} = \frac{-\Delta Q_{prim}}{\Delta Q_{sec}}$.

In general, there are numerous forces affecting the regional demand for aluminum such as GDP, incomes, and the prices of substitute materials. These other forces will affect how much aluminum is used in automobile manufacturing. In consequence, one cannot estimate the displacement rate simply by computing the observed change in primary and secondary production. To control for these other forces, one could specify a linear regression model with the functional form

$$Q_{prim} = \alpha + \beta_1 Q_{sec} + \beta_2 X_2 + \cdots + \beta_k X_k + \varepsilon \quad (1),$$

where $\sum_{i=2}^{k} \beta_i X_i$ capture the effect of these forces, and ε is the regression error term. Unfortunately, Ordinary Least Squares (OLS) estimates of the effect of Q_{sec} on Q_{prim} (β_1) are likely to be biased and inconsistent due to endogeneity. This presents itself when the explanatory variable of interest is correlated with the regression error term. It also threatens the identification of causal effects from the regression coefficients. Endogeneity arises for a number of reasons, but is frequently due to simultaneous causality between the dependent variable and the explanatory variable. While we expect secondary production to have an effect on primary production, we equally expect that changes in primary production affect secondary production; thus, simultaneous causality is a significant concern in the estimation of Equation 1.

3. Previous approach: Supply and Demand

3.1. Framework

A classical approach to address endogeneity is to estimate a structural model of supply and demand for primary and secondary aluminum using instrumental variable methods rather than OLS (also known as Partial Equilibrium Analysis). This approach has been used historically and frames displacement micro-econometrically, meaning that price responses of supply and demand are assumed to drive the causal relationship between secondary production and primary production (Zink *et al* 2015, 2017, Ekvall 2000, Ekvall and Andrae 2006). One would estimate functional relationships between supply and demand of primary and secondary material and their explanatory variables, which include endogenous prices and exogenous shifters. Equation 2 shows a simplified set of simultaneous equations of supply and demand for primary and secondary material (QS_{prim}, QS_{sec}, QD_{prim} and QD_{sec}) along with equilibrium conditions.

$$QS_{prim} = \alpha_1 + \beta_1 P_{prim} + \pi_1 SHIFTS_{prim} + \varepsilon_1$$

$$QD_{prim} = \alpha_2 + \gamma_1 P_{prim} + \mu_1 (P_{sec} - P_{prim}) + \pi_2 SHIFTD_{prim} + \varepsilon_2$$

$$QS_{sec} = \alpha_3 + \beta_2 P_{sec} + \pi_3 SHIFTS_{sec} + \varepsilon_3$$

$$QD_{sec} = \alpha_4 + \gamma_2 P_{sec} + \mu_2 (P_{prim} - P_{sec}) + \pi_4 SHIFTD_{sec} + \varepsilon_4$$

$QS_{prim} = QD_{prim}$

$QS_{sec} = QD_{sec}$ (2)

In this system, α_n are intercepts, β_n are own-price responses of supply, $\gamma_n - \mu_n$ are own-price responses of demand, μ_n are cross-price responses of demand, $SHIFTX$ are the exogenous shifters, P_x are price variables and ε_n are unobserved error terms. Observations of quantities, prices, and shifters are gathered empirically and used to estimate a set of four regressions. After the coefficients on the equations are estimated, a shock is introduced to α_1, or to the supply of secondary material. Solving the system again after introducing a shock simulates how primary supply would respond to the change in the secondary supply. The algebra behind this is detailed in Zink et. al, 2015. We note that in practice, prices of substitutes and additional control variables are likely to come into play and complicate the algebra even further.

Estimating four simultaneous equations bypasses the particular statistical issue posed in the OLS estimation of Equation 1. However, price is endogenous in the vast majority of markets, leaving us with a new statistical issue. Prices cause supply and demand to change, but changes in supply and demand also affect price, which clearly constitutes simultaneous causality (Wooldridge 2012). The supply and demand framework approach restores the causal interpretation of price-response parameters by estimating four two-stage least squares (2SLS) equations with instrumental variables. The first stage of 2SLS consists of estimating a regression with the endogenous variable as the dependent variable, and the instrument(s) as well as all other exogenous covariates on the right hand side. This generates an estimate for the value of the problem (endogenous) variable that corrects for endogeneity bias, which is substituted into the original regression equation. The second stage is estimating the original regression using the values of the endogenous variable estimated from the first stage. In practice, 2SLS software commands avoid the need for two separate regressions and ensure correct estimates of standard errors.

Consider the first two components of Equation 2. In the case of primary supply, the price of primary material is the endogenous variable. For primary demand, both the price of primary material and the price difference between primary and secondary material are endogenous. Estimating 2SLS requires that there are at least as many instruments as endogenous variables for each equation. The instruments for the primary supply equation are exogenous shifters of primary demand, secondary supply, and secondary demand. The instruments for the primary demand equation are exogenous shifters of primary supply, secondary supply, and secondary demand. Thus, there are at least three instruments for each equation, assuming that we are able to find unique and exogenous shifters for primary supply, primary demand, secondary supply, and secondary demand. Equation 3 provides an example of a first stage regression for the primary supply equation, which generates $\widehat{P_{prim}}$, the estimate for P_{prim} that corrects for endogeneity. We must replace all price variables in (2) with their corrected versions.

$$P_{prim} = \delta_1 + \tau_1 SHIFTD_{prim} + \tau_2 SHIFTS_{sec} + \tau_3 SHIFTD_{sec} + \tau_4 SHIFTS_{prim} + \omega_1$$

$$\widehat{P_{prim}} = \widehat{\delta_1} + \widehat{\tau_1} SHIFTD_{prim} + \widehat{\tau_2} SHIFTS_{sec} + \widehat{\tau_3} SHIFTD_{sec} + \widehat{\tau_4} SHIFTS_{prim} + \widehat{\omega_1} \qquad (3)$$

It turns out that identifying these unique shifters is not so straightforward. In practical applications, the exogeneity of shifters is frequently debatable, which threatens the identification of causal effects. The following discussion illustrates ideal, but hypothetical shifters for all four equations in the case of aluminum.

A truly unique and exogenous shifter of primary aluminum supply would be a measure of political unrest in countries that are primary bauxite suppliers, as bauxite is the key raw material input for aluminum production. One could create a variable indicating how many bauxite-producing countries experience unrest in a given year, for example. Of course, there must be variation in unrest over time. In the case of primary aluminum demand, consider increased costs of shipping for iron ore that increase the cost of steel, making steel sheet for automotive body parts prohibitively expensive. Primary aluminum is the best-known substitute, thus demand for primary aluminum is shifted exogenously by the variation in iron ore shipping costs.

Legislation aimed at increasing recycling rates, such as the “bottle bills” offering deposits for recycling aluminum cans throughout the United States (State of Oregon 1971, State of Hawai’i 2002), have been shown to be exogenous shifters of secondary aluminum supply (Container Recycling Institute 2005). For use in the structural market model, it is required that such policies vary over time, for example by gradually increasing in geographic scope. Finally, an exogenous shifter of secondary aluminum demand would be the purity of recycled aluminum over time, which may increase due to technological improvements. This would exogenously increase the amount of applications where recycled aluminum is a viable substitute.

Figure 2 illustrates the causal pathways of the supply and demand framework via price-quantity relationships, showing how the supply and demand curves for primary aluminum are shifted by the instrumental variables. Shifting the primary demand curve traces out the primary supply curve, and vice versa. This is the key concept in restoring the causal relationship between quantity and price (Stock 2001).

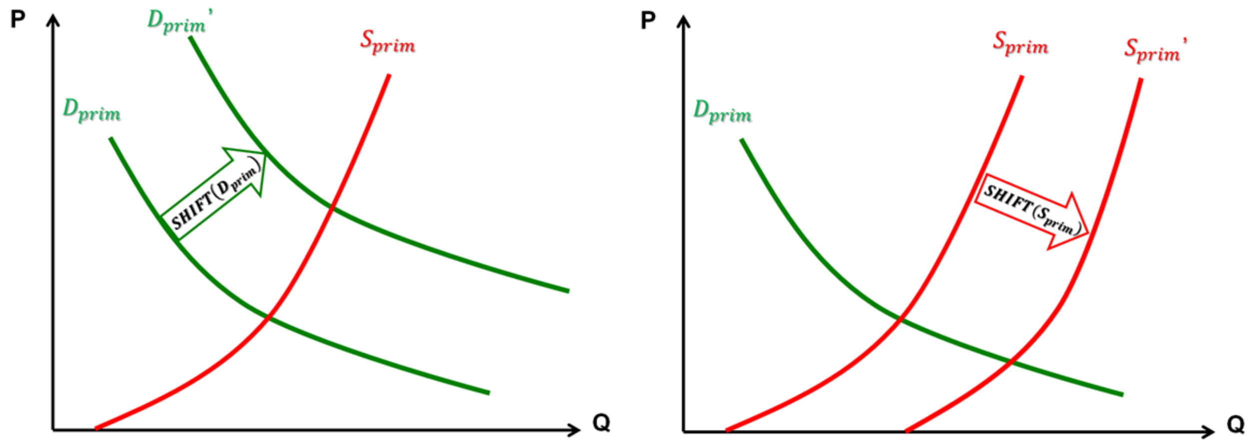

Figure 2: Causal pathways in the supply and demand framework illustrated via price-quantity (P-Q) relationships. Panel (a) shows that one instruments for the primary supply equation shifts the primary demand curve from D to D', while panel (b) shows that one instrument for the primary demand equation shifts the primary supply curve from S to S'.

3.2.Case Study

The lone case study using this methodology explores the question of whether or not aluminum recycling in the U.S. displaces primary production between 1971 and 2013 (Zink *et al* 2017). The exogenous shifters are prices of substitutes as well as a series of process inputs and economic factors (Blomberg and Hellmer 2000, Blomberg and Söderholm 2009), which are not as strong as the idealized shifters we propose above. This is a ubiquitous issue in the identification of causal effects using structural market models. The authors use 43 annual observations of all variables on the national level. The small number of observations contributed to a high level of uncertainty in the results. In fact, in the initial year following a 5% shock to secondary supply, displacement estimated via Monte Carlo simulations has a 5^{th} to 95^{th} percentile range of approximately [-50%, 100%] (Zink *et al* 2017).

3.3.Advantages & Disadvantages

Structural supply and demand models offer a methodology for estimating displacement in competitive markets based on classical economic theory. The structural equations for supply and demand determine the instruments, which are the unique exogenous shifters used in the 2SLS regressions. Thus, setting up the structural equations implicitly provides a solution to price endogeneity and establishes identification of causal effects.

On the other hand, the causal interpretation of supply and demand models requires that the market in question be competitive, in that no individual agent or small group of agents can determine how that market operates. A model of the form of Equation 2 further requires that the effect of price is linear and homogenous. Identifying four unique and exogenous shifters of supply and demand is challenging, and failure to do so introduces bias to the estimation and complicates interpretation of the model. The challenge is amplified in settings where we seek to observe multiple market segments, where shifters are needed for each segment. To overcome these challenges we developed the following framework for quantifying displacement.

4. Novel Approach: Quasi-experimental

4.1.Framework

Rather than construct a structural supply and demand model for the two markets, one could approach endogeneity directly through observations of the quantity of primary and secondary material by seeking out natural experiments in observational data. This quasi-experimental design could be achieved through the gathering of public data, or via primary data collection. A quasi-experiment is a situation where endogeneity is addressed by dividing observations into treatment and control groups based on explanatory characteristics of their values for an outcome variable of interest over time. Observations could be grouped by firms, industries, or geographic regions that may use primary and secondary variants of a material, for example. After some time, an exogenous change to the quantity of secondary material occurs in the treatment group, and the quantity of primary material in the treatment and control groups are compared before and after the exogenous change. Several statistical methods may be applied to a quasi-experiment. Selection of the method depends on the problem at hand and the structure of the data available. Examples include difference-in-differences (DID), regression discontinuity analysis, and propensity score matching (Lee and Lemieux 2010, Imbens and Lemieux 2007, Angrist and Pischke 2009, Caliendo and Kopeinig 2005). We explore the quasi-experimental approach to displacement through the lens of DID estimation.

Consider the simplified DID example of Figure 3, where there is an exogenous increase in the secondary quantity of a material in a subset of market segments ($i = TREAT$) at time t^*=100. The exogenous increase originates from a source uncorrelated with factors that explain the underlying trend in the material quantity on the market. There is a control group of market segments, which do not see any change in secondary material at t^*=100. In the period after the exogenous change at t^*=100 ($t > t^*$), observations of the quantity of primary material in both the treatment and control groups continue to be collected. At time t=300, the difference in primary material in each market segment between t^*=100 and t=300 is measured for both treatment and control groups. If the additional recycling had no effect on primary material, the difference in primary material between t^*=100 and t=300 would be the same in both groups. In Figure 3, the treatment group had a lesser difference in primary material from pre-to post-treatment compared with the control group, thus there is a "difference in the differences", which is reflected by θ. This coefficient is interpreted as the increase in secondary material causing a decrease in primary material given that the identification restrictions outlined in Section 4.2 are satisfied. One would determine θ using a regression with form of Equation 4:

$$Q_{it}^{prim} = \mu + \delta\{i = TREAT\} + \rho\{t > t^*\} + \theta\{i = TREAT\} * \{t > t^*\} + \varepsilon_{it} \qquad (4),$$

where Q_{it}^{prim} is the observation of primary material in market segment i (treatment or control) in period t (pre- or post-treatment), $\{i = TREAT\}$ takes the value 1 for treated observations and 0 for controls, $\{t > t^*\}$ takes the value 1 in the post treatment period and 0 in the pre-treatment period, and ε_{it} is the error term (Angrist and Pischke 2009). The effect of interest is identified by θ, the coefficient on $\{i = TREAT\} * \{t > t^*\}$, which has a value of 1 for observations of the treatment group in the post-treatment period. The change in primary material θ reflected in the regression is converted into displacement by observing the change in secondary material and applying the identity $d = -\frac{\Delta Q_{prim}}{\Delta Q_{sec}} = -\frac{\theta}{\Delta Q_{sec}}$, where ΔQ_{sec} is the increase in recycling that occurs at t^*.

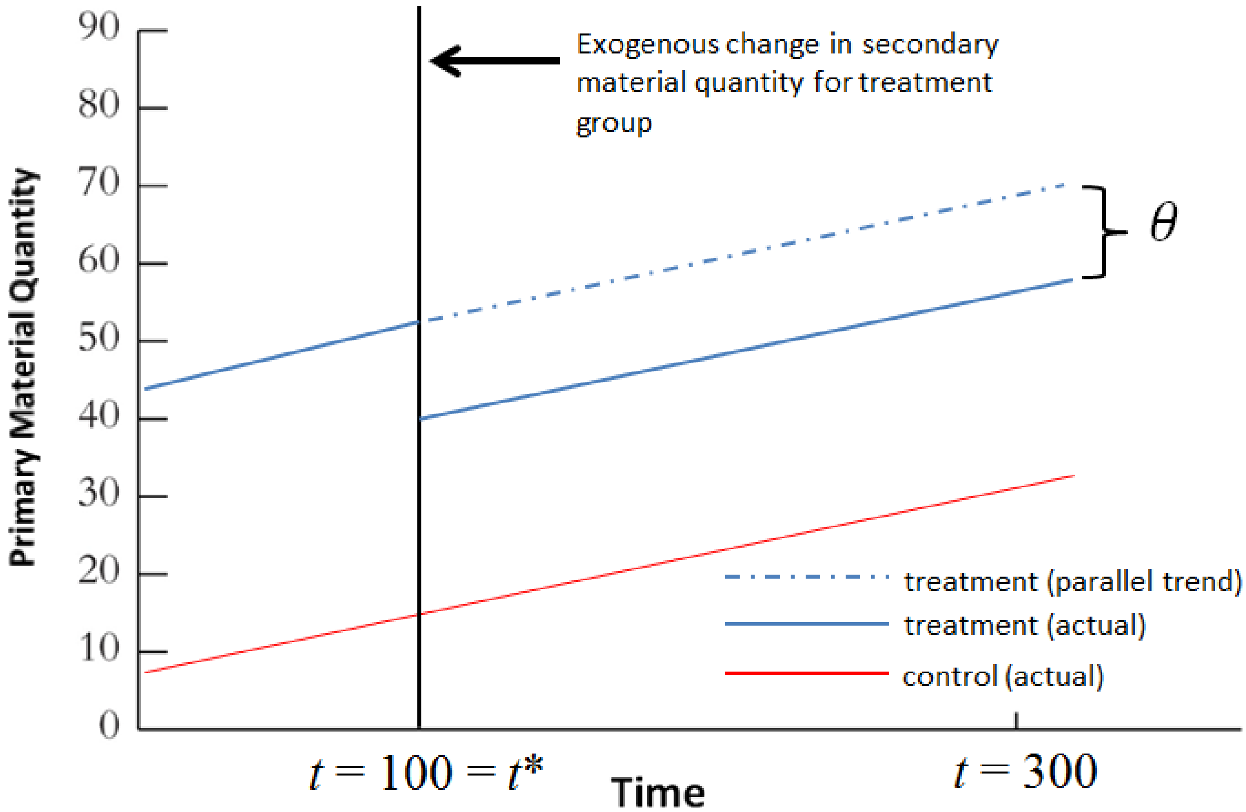

Figure 3: Difference-in-differences estimation of displacement due to increases in recycling. The treatment group of market segments experiences a sudden increase in recycling at t=100. The quantity of primary material is measured in each period, and θ gives the DID estimate of the change in the quantity of primary material caused by exogenous shift in recycling activity.*

4.2. Firm-Level Case Study

We return to the example of automobile manufacturing from the generalized displacement discussion in Section 2. Consider the scenario where groups of treatment and control firms operating in similar markets both use primary aluminum. The treatment firms absorb additional secondary aluminum generated from an exogenous, policy-driven shock. The control firms do not pursue use of the additional secondary aluminum provided by the shock. Selection into the treatment group is random conditional on observable characteristics of the firms. In this hypothetical system, we gather monthly statistics on primary and secondary aluminum used in each firm i on a per vehicle basis. At $t^*=100$, an exogenous, policy-driven shock to the quantity of secondary aluminum occurs and is absorbed by the treatment group of firms. We continue to measure primary aluminum used per vehicle by the treatment and control firms until t=300.

In this application, use of DID requires that the trends in primary aluminum consumption by the treatment and control firms were parallel prior to t^*=100 or that any differences in the trends could be accounted for by observable quantities. For example, the trend in primary aluminum quantity may look different for firms that produce economy class vehicles versus those that produce luxury class vehicles. This is one example of a factor that needs to be included in the DID regression as a control, ensuring that treatment is random conditional on what we observe. With the appropriate controls in place, one could estimate a regression with the form of Equation 5, where Q_{it}^{prim} is the per-vehicle quantity of primary aluminum used in firm i during month t.

$$Q_{it}^{prim} = \mu + \delta\{i = TREAT\} + \rho\{t > t^*\} + \theta\{i = TREAT\} * \{t > t^*\} + \gamma_1 CLASS_{it} + \cdots + \sum_{k=2}^{K} \gamma_k CONTROL_{it} + \varepsilon_{it} \tag{5}$$

The displacement effect is given by $d = -\frac{\Delta Q_{prim}}{\Delta Q_{sec}} = -\frac{\theta}{\Delta Q_{sec}}$.

The first identifying assumption of the DID causal effect is referred to as the parallel trends assumption, and means that we assume the post-treatment trend in per vehicle primary aluminum use would be the same between the treatment and control firms in the absence of treatment (Angrist and Pischke 2009). The robustness of this assumption can be examined, for example, by comparing the trends in per vehicle primary aluminum use between treatment and control groups for the period prior to t^*=100 and verifying they were actually parallel. The second necessary condition is that the treatment, or sudden increase in recycling, did not coincide with another exogenous shock affecting primary aluminum use differently in the treatment and control groups. The causal interpretation of the result is threatened if, for example, a policy requiring improved fuel economy emerges at the same time as the exogenous shock to recycled aluminum, and the treatment and control firms respond by decreasing the mass of their vehicle fleets in ways that affect their primary aluminum use differently. Lastly, the causal interpretation requires that the additional secondary aluminum in the treatment group does not interact with the control group. In other words, the additional secondary aluminum cannot be sold by treatment firms to control firms. The trade of secondary aluminum across groups threatens identification because the treatment will have an effect on outcomes in the control group.

We must also consider the estimation of standard errors, which is influenced by assumptions regarding the correlations between values of ε_{it}. Classic standard errors are not sufficient, as they assume the error terms are uncorrelated and of constant variance, something that is highly unlikely in practice. The correct standard error estimator depends on the structure of the data. One general alternative, that adjusts for arbitrary temporal correlation, is to use the Newey-West estimator (Newey and West 1987, Petersen 2009). In the case of Equation 5, we could also account for the likely scenario that unobserved sources of variance in primary production are clustered by firm, in which case it is more appropriate to use a cluster-robust estimator. These strategies alleviate the risk of constructing standard error estimates that are systematically too small, which would lead to over-rejection of the null hypothesis that $\theta_1 = 0$ (Cameron and Miller 2015). One must also pay attention to the number of firms and the evenness of the distribution of observations across clusters, as cluster heterogeneity may present issues in hypothesis testing (Lee and Steigerwald 2017, Carter *et al* 2016).

4.3. Advantages & Disadvantages

DID uses a simpler regression framework with reduced data requirements compared to structural supply and demand models for estimating displacement. It avoids the need for exogenous shifters of supply and demand in two markets, and the aforementioned complications that go with them. However, unlike the supply-demand framework, DID requires careful balancing of treatment and control observations to avoid biased results due to confounding factors. DID treatment interventions are generally easier to defend as plausibly exogenous than the four shifters in the supply-demand framework. This is because the treatment is sharply defined and pre-treatment parallel trends imply quasi-random assignment of treatment.

DID studies also present inherent limitations. The most critical challenge with DID is that the parallel trends assumption is dependent on a counterfactual trend in the treated observations, which cannot be verified, although the testing of pre-treatment trends helps to mitigate this problem. Another key disadvantage of DID is that the parallel trend assumption is dependent on the way in which the parameter is measured (Lechner 2011, Bertrand *et al* 2002). For example, the parallel trends in primary aluminum production from Figure 3 may not hold for elementary transformations of this variable (i.e. log material production). Underestimation of standard errors due to serial correlation of the treatment and outcome variables is also a known problem leading to misleading conclusions in DID studies (Bertrand *et al* 2002).

It is also important to recognize the difference in scope between structural supply and demand models and a firm-level DID approach. Zink and Geyer (2017) compared partial displacement of recycling to the so-called rebound effect of increases in energy efficiency and thus called it ‘circular economy rebound’. Energy efficiency rebound literature typically distinguishes between direct and indirect effects. For example, if a household acquires a more energy-efficient car, it could use the fuel cost savings to a) drive more (direct rebound) or b) purchase other goods and services (indirect rebound). In an analogous way, increased use of secondary automotive material could lead to increased total material use in the automotive sector, or increased use in other sectors, such as packaging. A structural supply and demand model would capture direct and indirect effects, while the firm-level DID approach outlined in section 4.2 would measure only the direct effect.

5. Outlook

We have framed the discussion of displacement in terms of primary and secondary production of a given material, say aluminum, but there are many other related questions of interest. For example, it is possible that aluminum recycling leads to less use of both primary and secondary plastics, as aluminum is used in many packaging applications. Displacement may also be an issue in generalized material substitution, regardless of whether or not the substitute material originates from recycling. Consider the case where primary aluminum is substituted for primary steel in vehicles. Displaced production of primary steel by additional primary aluminum production may not be solely determined by physical parameters in the product system. Tangential effects, driven by price disturbances or other social parameters, could influence the production volumes of both materials in significant ways. For example, losing sales in one sector might lead to efforts to increase sales in other sectors rather than simply reduce production.

Understanding the net environmental consequences of changes to product systems requires a deep understanding of the physical *and* social processes that cause the systems to evolve over time. This notion is at the core of studies of displacement and of CLCAs in which displacement is a key parameter. Thus, we emphasize the importance of frameworks other than structural models of supply and demand in quantifying the social impacts of changes to product systems.

The use of quasi-experimental methods offers an avenue to advance our knowledge of how social processes translate into physical outcomes, a concept that remains in its infancy in LCA and industrial ecology. This undertaking is essential in order to strengthen the relevance of sustainability assessments for decision-making.

6. Acknowledgements

The first three authors are supported by National Science Foundation (NSF) Chemical, Bioengineering, Environmental and Transport Systems (CBET) grant #1335478.

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