



SUPPORTING INFORMATION FOR:

Tsai, A., Zhu, Y., Heidari, M. & Cooper, D.R. (2026) Cross life cycle opportunities for increasing the post-consumer recycled content of automotive aluminum body sheet in the United States. *Journal of Industrial Ecology*.

Summary

This supporting information document provides additional methodological details and supplementary result figures for the linear optimization model. The Python code for the model can be found at the Github repository: <https://github.com/alitsai6/ReMaDe-Al-ABS-LP>

SUPPLEMENTARY INFORMATION

S1 DEFINITIONS OF PCRC AND PCRR

The outputs of the LP model include, for a given year, the material flows, $R_{s,d}$ and $P_{s,d}$, that result in the minimum virgin metal use in making the ABS ingots and, therefore, the maximum scrap content. Below, the maximum closed-loop post-consumer ABS recycling rate (PCRR) and the maximum closed-loop post-consumer ABS recycled content (PCRC) are defined in terms of $R_{s,d}$ and $P_{s,d}$ and the total quantity of post-consumer (PC) ABS scrap arising from ELVs. For PCRC (S1), the numerator is the total quantity of ABS PC scrap in ABS ingots while the denominator is the total quantity of metal in the ingots. Meanwhile for PCRR (S2), the numerator is the total quantity of ABS PC scrap added to furnaces to make ABS ingots while the denominator is the total quantity of ABS PC scrap arising from U.S. ELVs (i.e., scrap generated, not collected). In both cases, the numerator reflects the total quantity of ABS PC scrap used—the main difference is the PCRC accounts for melt losses that occur in the furnace.

$$PCRC = \frac{0.95 \times \sum_{s=23:22+|T|} \sum_D R_{s,d}}{Ingot\ Demand} \quad (S1)$$

$$PCRR = \frac{\sum_{s=23:22+|T|} \sum_D R_{s,d}}{ABS\ PC\ Scrap\ Arising} \quad (S2)$$

This analysis examines the recycling of U.S.-generated ELV ABS scrap into ABS ingots used to produce components for vehicles consumed (sold) in the U.S. While some ingot production and generation of production scrap may occur abroad, it is assumed that producers serving U.S. demand have access to the modeled scrap streams. This is reasonable given the global trade in ELV aluminum scrap and the integration of the North American market: U.S. OEMs primarily source ABS coils from domestic and Canadian producers (Hua et al., 2022), and up to half of imported vehicles originate from Canada and Mexico (International Trade Administration).

S2 SUMMARY OF OPTIMIZATION FRAMEWORK CROSS LIFE CYCLE STRATEGIES

Table S1 accompanies Figure 1 in the main text, providing an overview of how cross life cycle strategies for increasing ABS PCRC (discussed in Section 2.3) change the LP model inputs. Input changes propagate through the DMFA and composition modules, then the linear programming model via the corresponding constraints.

Table S1. Mapping cross life cycle strategies to the affected model inputs, relative to the baseline analysis ①.

Sensitivity and intervention strategy simulated	Affected LP model inputs and parameters					
	<i>Ingot demand</i>	<i>Scrap availability</i>	<i>Virgin metal compositions</i>	<i>Ingot composition tolerances</i>	<i>Scrap compositions</i>	<i>Furnace charge constraint (FCC)</i>
ABS demand growth rate and vehicle lifespan sensitivities						
Varying ABS demand growth rate	■	■			■	
Alternative vehicle lifespans		■			■	
Sheet mill strategies						
Using purer primary Al diluent			■			
Designing HRC ABS alloys				■	■	
Increasing dilution with primary Al						■
OEM design and manufacturing strategies						
Segregating production scrap					■	
Shifting ABS demand to 6xxx	■				■	
Reducing ABS ferrous fasteners					■	
ABS recycler strategies						
Isolated shredding of AIVs					■	
Castings removal from Twitch					■	
Sorting Twitch by alloy series					■	
Zorba size-segregated → Twitch					■	
Pre-shredding vehicle disassembly					■	

S3 MINIMAL WORKING EXAMPLE OF LINEAR PROGRAMMING MODEL

A minimal working example of the linear programming model presented in this study can demonstrate the fundamental logic behind the full LP model. This simplified version of the formulation discussed in Section 2.1 calculates the theoretical maximum amount of a Al-Si binary alloy that can be recycled and mixed with virgin aluminum and silicon to produce two other Al-Si binary alloys of different compositions. The sets, decision variables, and parameters are listed below for the minimal working example, following the notations used in Section 2.1. Accompanying notes highlight the simplifications made between the simplified and full model. Sets are defined as follows:

- $D = \{1, 2, \dots, i\}$: set of i demanded alloys (for this Al-Si binary system, $i = 2$)
- $V = \{1, 2, \dots, j\}$: set of j different virgin sources, i.e., primary aluminum and alloying elements (for Al-Si binary system, $V = \{prim_{Al}, prim_{Si}\}$)
- $M = \{1, 2, \dots, k\}$: set of k different production scrap sources (for this Al-Si binary system, $M = \{\}$ —no production scrap sources included for simplicity)
- $T = \{1, 2, \dots, l\}$: set of l different post-consumer scrap sources (for this Al-Si binary system, $l = 1$ —treat initial Al-Si binary alloy as a "scrap" alloy)
- $S = \{1, 2, \dots, n\}$: set of n different metal sources, including virgin and scrap (for this Al-Si binary system $n = 3$, where $S = \{prim_{Al}, prim_{Si}, Al - Si \text{ scrap}\}$)

Decision variables are defined as follows:

- $R_{s,d}, \forall s \in S, \forall d \in D$: non-negative mass of metal flowing from source s for use in producing ingots of product d
- $P_{s,d}, \forall s \in S, \forall d \in D$: flow of metal direct from primary production used to produce ABS ingots (for the Al-Si binary system, this is not needed as the simplified model assumes the "scrap" is always used for production)

Parameters are defined as follows:

- *Ingot demand_d*: ingot demand for product d
- *Metal availability_s*: amount of metal source s available for use in furnace (virgin metal is assumed unlimited)
- *chemistry lower bound_{d,e}*: lower composition bound of element e in product d
- *chemistry upper bound_{d,e}*: upper composition bound of element e in product d
- $E_{e,s}, \forall e \in E, \forall s \in S$: composition of each element e in each scrap source s (e.g., $E_{Al,1}$ indicates the composition of aluminum in scrap source 1)
- α : furnace charge constraint (in Al-Si binary model, this constraint is removed for simplicity)

The simplified LP model formulation is defined below in **SI—P.1**

$$\text{Minimize:} \quad \sum_{V; s=prim_{Al}, prim_{Si}} \sum_D R_{s,d} \quad (S3)$$

$$\text{Subject to:} \quad 0.95 \cdot \sum_S R_{s,d} \geq \text{Ingot demand}_d \quad (S4)$$

$$(SI—P.1) \quad \sum_D R_{s=scrap,d} \leq \text{Metal availability}_{s=scrap} \quad (S5)$$

$$\text{chemistry lower bound}_{d,e} \leq \frac{\sum_S (R_{s,d} \cdot E_{e,s})}{\sum_S R_{s,d}} \leq \text{chemistry upper bound}_{d,e} \quad (S6)$$

In model **SI—P.1** the objective function Equation **S3** minimizes the total quantity of virgin material used. Since the set V represents the different elements as primary metal sources present in the alloy, $R_{s,d}$ (where $s \in V$) represents the amount of material from virgin material v that needs to be used to create product d . The first constraint Equation **S4** is the demand constraint, which ensures demand for each alloy product *Ingot demand_d* is met. The second constraint Equation **S5** is the supply constraint, which ensures the total amount of each scrap supply source s used in all alloy products doesn't exceed the amount of scrap available *Metal availability_{s=scrap}*. Finally, the third constraint Equation **S6** is the composition constraint, which outlines that the composition of the combination of scrap and virgin material used must fall within the lower *chemistry lower bound_{d,e}* and upper *chemistry upper bound_{d,e}* bounds of the alloy demand. For example, product 1 could have composition bounds of 95% - 100% Al and 0% - 5% Si. This means composition of virgin Al and virgin Si mixed with scrap needs to fall within these composition bounds. For this constraint, the numerator sums the total amount of element e in product d , while the denominator sums the total amount of material in product d .

With variables fully expanded, the model **SI—P.1** can be alternatively expressed as:

$$\text{Minimize:} \quad R_{prim_{Al},prod_1} + R_{prim_{Si},prod_1} + R_{prim_{Al},prod_2} + R_{prim_{Si},prod_2} \quad (S7)$$

$$\text{Subject to:} \quad 0.95 \cdot (R_{prim_{Al},prod_1} + R_{prim_{Si},prod_1} + R_{scrap,prod_1}) \geq \text{Ingot demand}_{prod_1} \quad (S8)$$

$$0.95 \cdot (R_{prim_{Al},prod_2} + R_{prim_{Si},prod_2} + R_{scrap,prod_2}) \geq \text{Ingot demand}_{prod_2} \quad (S9)$$

$$R_{scrap,prod_1} + R_{scrap,prod_2} \leq \text{Metal availability}_{scrap} \quad (S10)$$

$$\text{chemistry lower bound}_{prod_1,Al} \leq \frac{(R_{prim_{Al},prod_1} \cdot E_{Al,prim_{Al}}) + (R_{prim_{Si},prod_1} \cdot E_{Al,prim_{Si}}) + (R_{scrap,prod_1} \cdot E_{Al,scrap})}{R_{prim_{Al},prod_1} + R_{prim_{Si},prod_1} + R_{scrap,prod_1}} \leq \text{chemistry upper bound}_{prod_1,Al} \quad (S11)$$

$$\text{chemistry lower bound}_{prod_1,Si} \leq \frac{(R_{prim_{Al},prod_1} \cdot E_{Si,prim_{Al}}) + (R_{prim_{Si},prod_1} \cdot E_{Si,prim_{Si}}) + (R_{scrap,prod_1} \cdot E_{Si,scrap})}{R_{prim_{Al},prod_1} + R_{prim_{Si},prod_1} + R_{scrap,prod_1}} \leq \text{chemistry upper bound}_{prod_1,Si} \quad (S12)$$

$$\text{chemistry lower bound}_{prod_2,Al} \leq \frac{(R_{prim_{Al},prod_2} \cdot E_{Al,prim_{Al}}) + (R_{prim_{Si},prod_2} \cdot E_{Al,prim_{Si}}) + (R_{scrap,prod_2} \cdot E_{Al,scrap})}{R_{prim_{Al},prod_2} + R_{prim_{Si},prod_2} + R_{scrap,prod_2}} \leq \text{chemistry upper bound}_{prod_2,Al} \quad (S13)$$

$$\text{chemistry lower bound}_{prod_2,Si} \leq \frac{(R_{prim_{Al},prod_2} \cdot E_{Si,prim_{Al}}) + (R_{prim_{Si},prod_2} \cdot E_{Si,prim_{Si}}) + (R_{scrap,prod_2} \cdot E_{Si,scrap})}{R_{prim_{Al},prod_2} + R_{prim_{Si},prod_2} + R_{scrap,prod_2}} \leq \text{chemistry upper bound}_{prod_2,Si} \quad (S14)$$

The objective expression (Equation S7) minimizes the sum of primary Al and primary Si (all virgin sources for this system) needed to manufacture products 1 and 2. The ingot demand constraints (Equations S8-S9) denote the total amount of material from each metal source ($prim_{Al}$, $prim_{Si}$, and $scrap$) used to manufacture products 1 and 2 must meet the ingot demand for each product. Next, the scrap availability constraint (Equation S10) states the total amount of metal from source $scrap$ used in both products 1 and 2 must not exceed the total amount of $scrap$ available. Finally, the composition constraints (Equations S11-S14) ensure the final compositions of the product alloys fall within the acceptable composition ranges. Each expression in the numerator ($R_{s,d} \cdot E_{e,s}$) represents amount of a certain element in the source metal used to produce a given product. For example in Equation S11 ($R_{prim_{Al},prod_1} \cdot E_{Al,prim_{Al}}$) calculates the amount of aluminum in primary aluminum used in product 1, ($R_{prim_{Si},prod_1} \cdot E_{Al,prim_{Si}}$) calculates the amount of aluminum in primary Si used in product 1, and ($R_{scrap,prod_1} \cdot E_{Al,scrap}$) calculates the amount of aluminum in scrap used in product 1. Summed together, the numerator represents the total amount of aluminum (from all source metals) used in the manufacturing of product 1. Then, the denominator is simply the sum of all source metals used for the product. Thus, the fraction as a whole is the concentration of a specific element in a specific product. Each combination of one element and one product requires a separate composition constraint. For this simplified model, 2 products $\times$ 2 elements yields 4 separate composition constraints. As the number of products and alloying elements grow, the number of composition constraints increases rapidly.

For each recycling strategy, influential compositional constraints were identified by estimating how much the objective function (virgin metal use) would decrease if a constraint were relaxed, calculated as the product of its shadow price and allowable increase. Although linear optimization guarantees a global optimum, it may not produce a unique set of decision-variable values (i.e., scrap and virgin metal flows). To assess uniqueness, the system of binding constraints was examined to determine whether the solution corresponded to a single point or a hyperplane of feasible solutions.

S3.1 Numerical example of minimal working LP model

To demonstrate the minimal working LP model, a numerical example is presented.

Table S2 lists the parameter values used in this numerical example. The scrap alloy has a composition of 90 wt.% Al and 10 wt.% Si, primary aluminum is taken as 100 wt.% Al (0 wt.% Si), and primary silicon as 100 wt.% Si (0 wt.% Al). Product 1 represents a low-silicon alloy with 0-5 wt.% Si, while Product 2 is a higher-silicon alloy with 10-15 wt.%.

Table S2. Parameter values for the numerical example.

Parameter	Description	Value
Source compositions: $E_{e,s}$ [wt%, as a decimal]		
$E_{Al, primAl}$	Al content of primary Al	1.00
$E_{Si, primAl}$	Si content of primary Al	0.00
$E_{Al, primSi}$	Al content of primary Si	0.00
$E_{Si, primSi}$	Si content of primary Si	1.00
$E_{Al, scrap}$	Al content of Al-Si scrap	0.90
$E_{Si, scrap}$	Si content of Al-Si scrap	0.10
Ingot demand: $Ingot\ demand_d$ [kg]		
$Ingot\ demand_{prod_1}$	Demand for Product 1	76
$Ingot\ demand_{prod_2}$	Demand for Product 2	57
Scrap availability: $Metal\ availability_s$ [kg]		
$Metal\ availability_{scrap}$	Al-Si scrap available	100
Composition bounds [wt%, as a decimal]		
$chemistry\ lower\ bound_{prod_1, Al}$	Lower composition bound on Al in product 1	0.95
$chemistry\ upper\ bound_{prod_1, Al}$	Upper composition bound on Al in product 1	1.00
$chemistry\ lower\ bound_{prod_1, Si}$	Lower composition bound on Si in product 1	0.00
$chemistry\ upper\ bound_{prod_1, Si}$	Upper composition bound on Si in product 1	0.05
$chemistry\ lower\ bound_{prod_2, Al}$	Lower composition bound on Al in product 2	0.85
$chemistry\ upper\ bound_{prod_2, Al}$	Upper composition bound on Al in product 2	0.90
$chemistry\ lower\ bound_{prod_2, Si}$	Lower composition bound on Si in product 2	0.10
$chemistry\ upper\ bound_{prod_2, Si}$	Upper composition bound on Si in product 2	0.15

Substituting the values from Table S2 into model SI—P.2 yields the following fully numerical formulation SI—P.3

$$\text{Minimize:} \quad R_{primAl, prod_1} + R_{primSi, prod_1} + R_{primAl, prod_2} + R_{primSi, prod_2} \quad (S15)$$

$$\text{Subject to:} \quad 0.95 \cdot (R_{primAl, prod_1} + R_{primSi, prod_1} + R_{scrap, prod_1}) \geq 76 \quad (S16)$$

$$0.95 \cdot (R_{primAl, prod_2} + R_{primSi, prod_2} + R_{scrap, prod_2}) \geq 57 \quad (S17)$$

$$R_{scrap, prod_1} + R_{scrap, prod_2} \leq 100 \quad (S18)$$

$$0.95 \leq \frac{1.00R_{primAl, prod_1} + 0.00R_{primSi, prod_1} + 0.90R_{scrap, prod_1}}{R_{primAl, prod_1} + R_{primSi, prod_1} + R_{scrap, prod_1}} \leq 1.00 \quad (S19)$$

$$0.00 \leq \frac{0.00R_{primAl, prod_1} + 1.00R_{primSi, prod_1} + 0.10R_{scrap, prod_1}}{R_{primAl, prod_1} + R_{primSi, prod_1} + R_{scrap, prod_1}} \leq 0.05 \quad (S20)$$

$$0.85 \leq \frac{1.00R_{primAl, prod_2} + 0.00R_{primSi, prod_2} + 0.90R_{scrap, prod_2}}{R_{primAl, prod_2} + R_{primSi, prod_2} + R_{scrap, prod_2}} \leq 0.90 \quad (S21)$$

$$0.10 \leq \frac{0.00R_{primAl, prod_2} + 1.00R_{primSi, prod_2} + 0.10R_{scrap, prod_2}}{R_{primAl, prod_2} + R_{primSi, prod_2} + R_{scrap, prod_2}} \leq 0.15 \quad (S22)$$

The optimal solution to model SI—P.3 is:

$$R_{primAl, prod_1} = 40 \text{ kg}, \quad R_{primSi, prod_1} = 0 \text{ kg}, \quad R_{scrap, prod_1} = 40 \text{ kg}$$

$$R_{primAl, prod_2} = 0 \text{ kg}, \quad R_{primSi, prod_2} = 0 \text{ kg}, \quad R_{scrap, prod_2} = 60 \text{ kg}$$

resulting in an objective value of $40 + 0 + 0 + 0 = 40$ kg of virgin material.

Now, each constraint is verified:

Demand constraints (Equations S16-S17).

$$0.95 \cdot (40 + 0 + 40) = 0.95 \times 80 = 76 \text{ kg} \geq 76 \text{ kg} \quad \checkmark$$

$$0.95 \cdot (0 + 0 + 60) = 0.95 \times 60 = 57 \text{ kg} \geq 57 \text{ kg} \quad \checkmark$$

Both demand constraints are exactly binding, meaning no excess material is produced.

Scrap availability constraint (Equation S18).

$$40 + 60 = 100 \text{ kg} \leq 100 \text{ kg} \quad \checkmark$$

This constraint is also exactly binding: all available scrap is fully consumed, which is consistent with the objective of minimizing virgin material use.

Composition constraints for Product 1 (Equations S19-S20).

The total charge for Product 1 is $40 + 0 + 40 = 80 \text{ kg}$.

$$\text{Al: } \frac{1.00 \times 40 + 0.00 \times 0 + 0.90 \times 40}{80} = \frac{40 + 0 + 36}{80} = \frac{76}{80} = 0.950 \quad (95.0 \text{ wt\%})$$

$$0.95 \leq 0.950 \leq 1.00 \quad \checkmark \text{ (binding at lower bound)}$$

$$\text{Si: } \frac{0.00 \times 40 + 1.00 \times 0 + 0.10 \times 40}{80} = \frac{0 + 0 + 4}{80} = \frac{4}{80} = 0.050 \quad (5.0 \text{ wt\%})$$

$$0.00 \leq 0.050 \leq 0.05 \quad \checkmark \text{ (binding at upper bound)}$$

Both composition constraints for Product 1 are exactly binding: the Al content sits precisely at its 95 wt.% lower bound and the Si content sits precisely at its 5 wt.% upper bound. This means equal parts scrap and primary Al must be charged — adding any more scrap would push Si above 5 wt.%, and adding any less scrap would require even more virgin Al to meet demand, both of which would worsen or not improve the objective.

Composition constraints for Product 2 (Equations S21-S22).

The total charge for Product 2 is $0 + 0 + 60 = 60 \text{ kg}$.

$$\text{Al: } \frac{1.00 \times 0 + 0.00 \times 0 + 0.90 \times 60}{60} = \frac{0 + 0 + 54}{60} = \frac{54}{60} = 0.900 \quad (90.0 \text{ wt\%})$$

$$0.85 \leq 0.900 \leq 0.90 \quad \checkmark \text{ (binding at upper bound)}$$

$$\text{Si: } \frac{0.00 \times 0 + 1.00 \times 0 + 0.10 \times 60}{60} = \frac{0 + 0 + 6}{60} = \frac{6}{60} = 0.100 \quad (10.0 \text{ wt\%})$$

$$0.10 \leq 0.100 \leq 0.15 \quad \checkmark \text{ (binding at lower bound)}$$

The scrap composition (90 wt% Al, 10 wt% Si) lies exactly on the upper Al / lower Si bound of Product 2, so Product 2 can be charged with scrap only—no virgin material is required.

The example illustrates a key tension the LP resolves. The scrap (90/10 Al-Si) is too silicon-rich to be used alone for the low-Si Product 1, yet its composition coincides exactly with the upper Al / lower Si limit of the higher-Si Product 2. Thus, the optimization preferentially assigns scrap to Product 2 (where it needs no virgin dilution), and uses the remainder of the scrap for Product 1 supplemented with enough primary Al to bring the blend within the 95-100 wt.% Al composition range. The scrap availability constraint is binding, confirming that the recycled material is the limiting resource and that the objective (virgin metal use) would decrease further if more scrap were available. All five constraints are exactly binding, making this example sensitive to changes in scrap supplied and composition ranges. Several alternative scenarios are explored where Si tolerance is altered in products 1 and 2:

Widening the Si upper bound of Product 1: Although the Si upper bound for Product 1 is binding at 5 wt%, relaxing it does not reduce virgin material consumption under the current parameters. The reason is that the scrap availability constraint is simultaneously binding: all 100 kg of scrap is already fully allocated (40 kg to each product). There is no additional scrap to absorb even if the Si tolerance were opened up — Product 1 cannot receive more scrap without Product 2 receiving less, and Product 2's charge is fixed by its demand constraint. However, if more scrap becomes available, the scrap availability constraint is no longer binding. For instance, with 120 kg of scrap and the current 5 wt.% Si ceiling, Product 1 is still limited to 40 kg of scrap (the Si constraint binds before the extra 20 kg can be used), leaving 20 kg wasted and the objective unchanged. Relaxing the ceiling to 8 wt.% Si allows Product 1 to absorb all 60 kg of remaining scrap, reducing the required primary Al from 40 kg to 20 kg. This illustrates that the value of widening a binding composition tolerance is conditional on scrap availability.

Narrowing the Si upper bound of Product 1: Since the Si upper bound is already binding, tightening it forces a lower scrap fraction in Product 1's charge and leaves scrap unused. The composition constraint $0.10 \cdot R_{scrap,1} / (R_{scrap,1} + R_{primAl,1}) \leq x$ combined with the demand constraint $(R_{scrap,1} + R_{primAl,1}) = 80$ gives $R_{scrap,1} = 800x$ kg. Each 1 wt.% reduction in the Si ceiling therefore reduces usable scrap in Product 1 by 8 kg, wastes that scrap, and requires 8 kg more primary Al. For example, tightening to 4 wt.% Si means only 32 kg of scrap can be used in Product 1 (down from 40 kg), 8 kg of scrap goes to waste, and virgin Al consumption rises to 48 kg. At 2 wt.% Si, 24 kg of scrap is wasted and virgin consumption rises to 64 kg.

Raising the Si lower bound of Product 2: If the Si lower bound for Product 2 is raised above 10 wt%, the scrap alone can no longer satisfy the specification and primary Si must be added. Unlike in a scenario where the Product 1 composition constraints are not binding (where this perturbation would leave the total virgin mass unchanged), here the binding Si upper bound for Product 1 causes the objective to increase. Adding primary Si to Product 2 reduces its scrap charge by a small amount, freeing that scrap for Product 1. However, because Product 1's Si upper bound is binding ($R_{scrap,1} = R_{primAl,1}$), absorbing the extra scrap requires an equal additional quantity of primary Al to maintain the 1:1 ratio. The increase in primary Al for Product 1 exceeds the primary Si added to Product 2, so the total virgin consumption rises. Algebraically, the objective increases at a rate of $\frac{4}{3}$ kg of additional virgin material per 1 wt.% increase in the Si lower bound of Product 2. For instance, raising the bound to 13 wt.% Si increases total virgin consumption from 40 kg to 44 kg.

S4 ECONOMIC SCRAP CHARGE CONSTRAINT ON SECONDARY FURNACES

The furnace scrap constraint reflects the reality that recycling becomes economically and environmentally unviable when the scrap fraction in the furnace charge is too low. As the scrap charge decreases, the cost and greenhouse gas (GHG) emissions from purchasing and remelting primary aluminum begin to outweigh the benefits of displacing only a small portion of primary material. For recycling—using a furnace charge that blends scrap with primary aluminum—to result in lower emissions than direct alloying with 100% primary aluminum, the scrap charge α must exceed a certain threshold. This can be approximated by modeling scrap as emissions-free, highlighting the minimum scrap fraction required for net environmental benefit.

$$Emissions_{primary} \times (1 - \alpha) + Emissions_{remelting} < Emissions_{primary} \quad (S23)$$

Using $Emissions_{primary} = 8.072 \text{ kgCO}_2\text{e/kg}_{\text{ingot}}$ and $Emissions_{remelting} = 0.513 \text{ kgCO}_2\text{e/kg}_{\text{ingot}}$, the minimum scrap furnace charge for recycling to be competitive from an emissions perspective is $\alpha = 0.064$

The equivalent equation for the economics of recycling is:

$$Cost_{primary} \times (1 - \alpha) + Cost_{remelting} < Cost_{primary} \quad (S24)$$

Figure S1 shows the minimum scrap charge fraction required for economically viable recycling, plotted as a function of scrap price and melting cost. Sensible values for these costs—based on energy requirements for remelting and scrap prices relative to primary aluminum, as reported by Schlesinger (2006)—highlight how economic feasibility depends on the scrap type. If the scrap input consists entirely of Twitch (the relatively inexpensive, aluminum-rich stream from ELV recycling), the required scrap charge can be as low as 20%. In contrast, if the input is exclusively Tooth (higher-cost, segregated alloy clippings and solids), the minimum viable scrap charge may be as large as 52%. Given that today's scrap stream is primarily production scrap and future streams will likely include a mix of production and post-consumer scrap, a baseline scrap charge fraction (α) of 0.35 is used as a reasonable assumption in the model, which was vetted by an ABS sheet mill industrial collaborator.

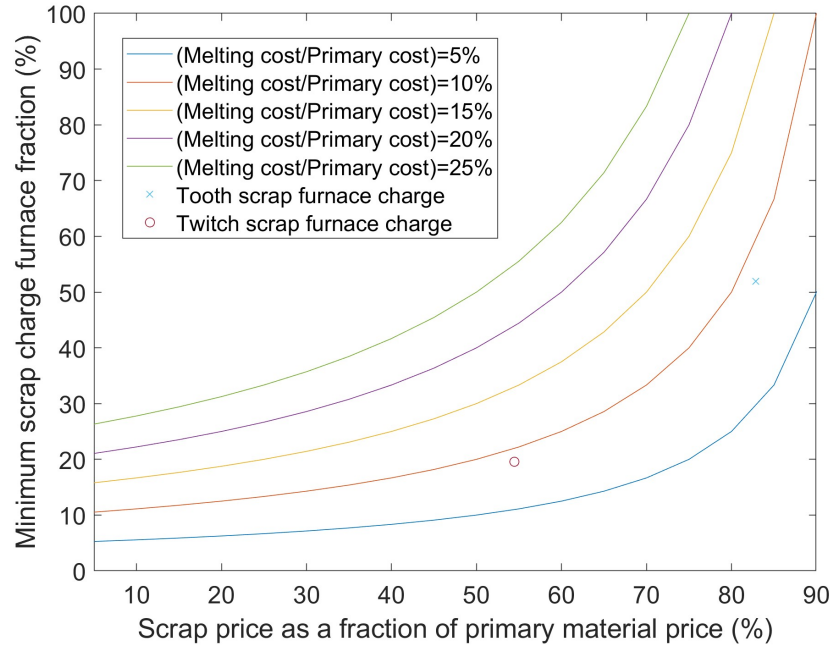
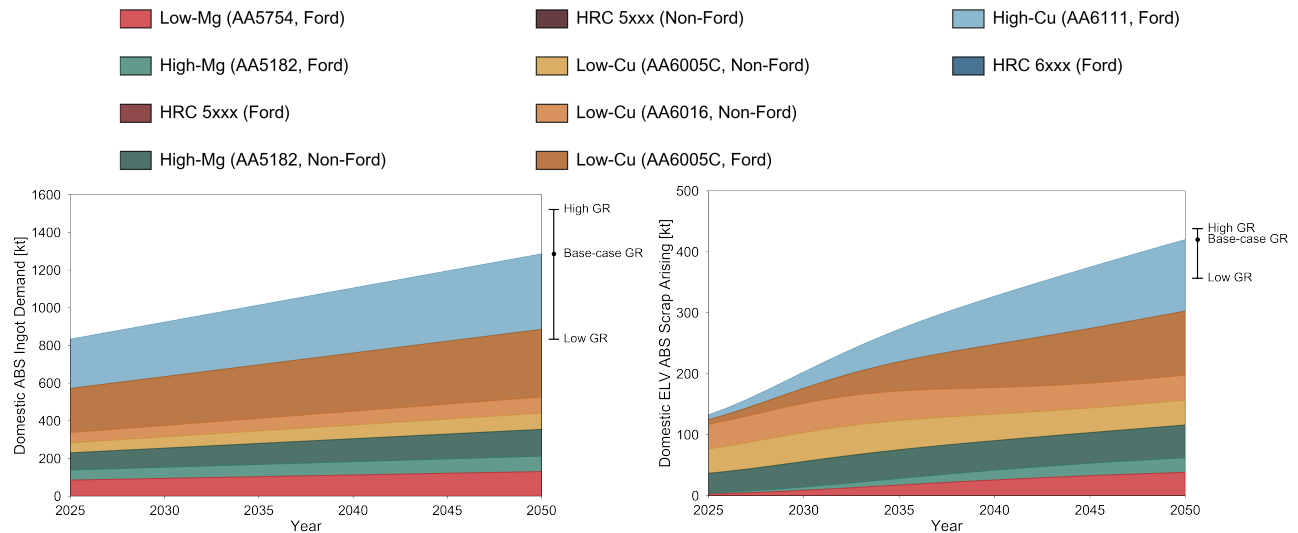


Figure S1. Minimum fraction of scrap charge in secondary furnace (α) required for economically viable recycling

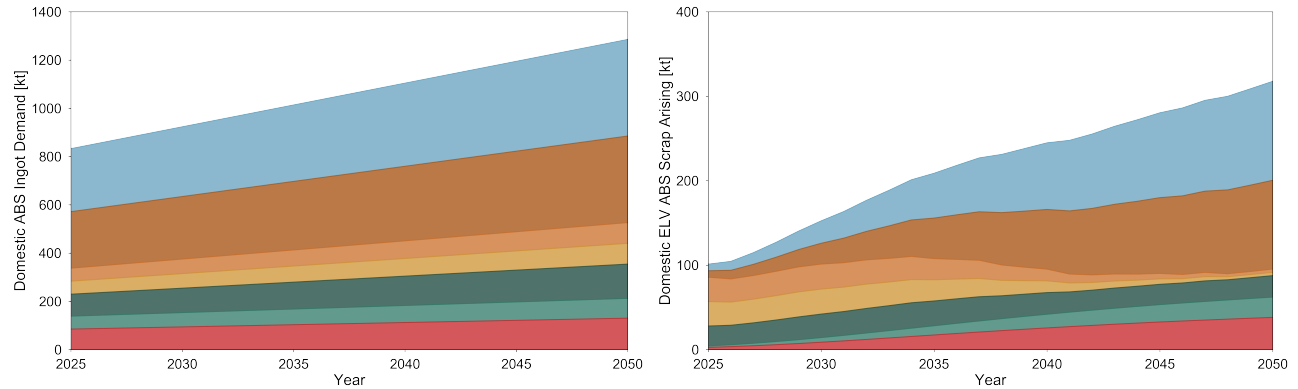
S5 PROJECTING ABS INGOT DEMAND AND SCRAP AVAILABILITY FOR VARIOUS RECYCLING STRATEGIES

For most recycling strategies considered in this study, base-case demand growth rates are assumed across the 7 key ABS alloys of interest: low-Mg (Ford), high-Mg (Ford), high-Mg (non-Ford), low-Cu (Ford), two low-Cu (non-Ford) alloys, and high-Cu (Ford). However, several strategies deviate from this baseline. Figure S2 presents all the potential variations on annual ABS ingot demand and ELV ABS scrap arising in this study. The tick marks on the right-hand side of the two subfigures in Figure S2a indicate the maximum total ingot and ABS scrap volumes in 2050 for low and high demand growth rate assumptions. All material flows scale proportionally to these final totals. Figure S2b presents the annual ingot demand and ABS scrap under the vehicle lifespans from Greene and Leard (2024). As different vehicle lifespans impact the DMFA calculations on vehicle stock and scrap, ingot demand remains the same, but total ELV ABS scrap volumes calculated from the Greene and Leard (2024) vehicle lifespans are lower than those in the baseline, calculated from the Liao (2025) vehicle lifespans. For scenarios where ABS alloys are substituted for HRC alloys, ingot demand for all 5xxx and high-Cu alloys are replaced by HRC 5xxx and HRC 6xxx alloys, respectively, starting in 2030. This change is reflected in Figure S2c, where only the demand for low-Cu alloys remains the same across all years. The corresponding ELV ABS scrap subfigure shows the gradual rise of HRC scrap in ELVs—by 2050, ABS scrap from HRC alloys comprises nearly 40% of all ABS scrap. Similarly, shifting demand for 5xxx ABS alloys to 6xxx manifests in Figure S2d, where ingot demand for all 5xxx alloys are replaced by increased demand for low-Cu alloys in 2030. In the ELV ABS scrap subfigure, scrap volumes for 5xxx ABS alloys slowly taper off in favor of increased 6xxx alloy scrap. Finally, Figure S2e presents the ingot demand and ABS scrap volumes used in scenarios where HRC alloy substitution and shifting 5xxx demand to 6xxx strategies are combined. Thus, Figure S2e merges the trends of high-Cu substitution with HRC 6xxx from Figure S2c with those of 5xxx replacement with low-Cu from Figure S2d.

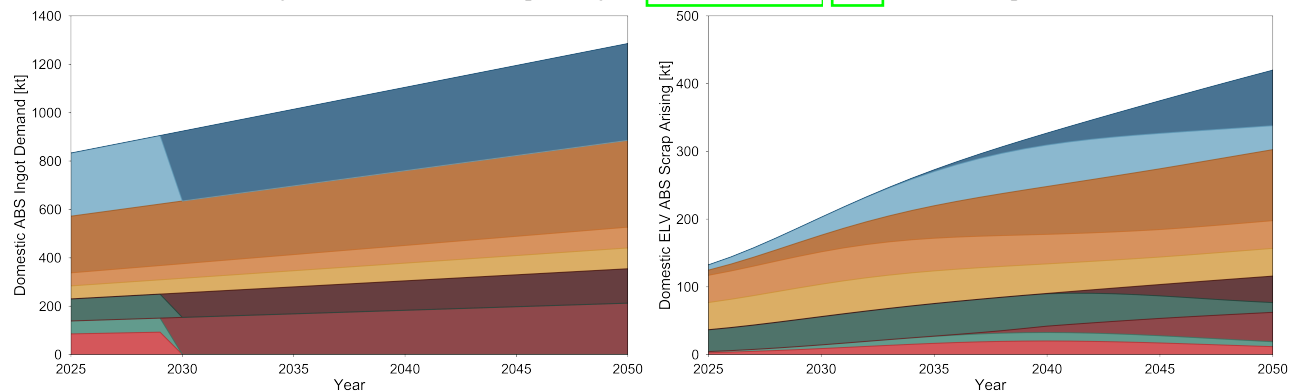
With the exception of ingot demand and scrap volumes calculated from Greene and Leard (2024) vehicle lifespans (Figure S2b), total ingot demand and total ELV ABS scrap volumes of all alternative DMFAs match those of the base-case growth rate calculated from Liao (2025) vehicle lifespans.



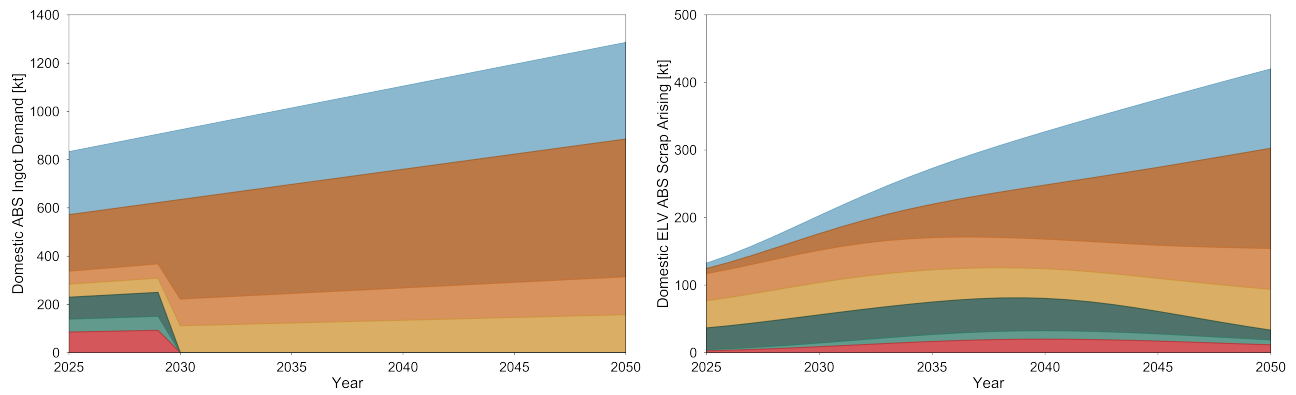
(a) Annual ABS ingot demand and ELV scrap arising for base-case, low demand growth rates, and high demand growth rates scenarios



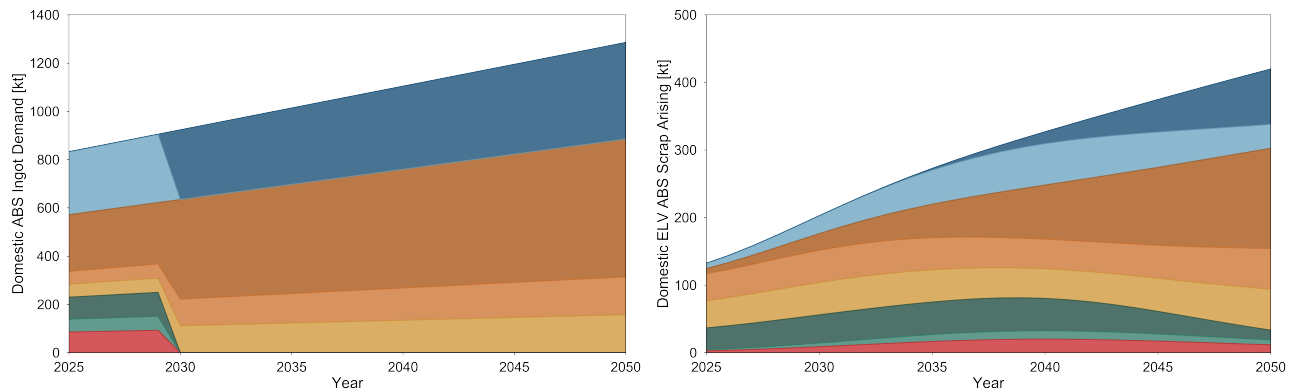
(b) Annual ABS ingot demand and ELV scrap arising for **Greene and Leard (2024)** vehicle lifespans (base-case GR)



(c) Annual ABS ingot demand and ELV scrap arising when ABS alloys are substituted for HRC alloys in 2030 (base-case GR)



(d) Annual ABS ingot demand and ELV scrap arising when demand for 5xxx ABS alloys shifted to 6xxx in 2030 (base-case GR)



(e) Annual ABS ingot demand and ELV scrap arising when demand for 5xxx ABS alloys shifted to 6xxx and Ford high-Cu ABS alloys are substituted for HRC alloys in 2030 (base-case GR). Note: Both HRC 5xxx alloys (Ford and Non-Ford) share the same composition.

Figure S2. Annual ABS ingot demand and ELV scrap arising for different recycling strategies.

S6 U.S. AUTOMOTIVE SCRAP FLOWS AND COMPOSITIONS DERIVATIONS

The input scrap flows for the optimization model in this study are restricted to only those generated from the 7-9 ABS alloys that generate ELV ABS scrap throughout the various strategies: Non-Ford 5xxx, Ford Low-Mg, Ford High-Mg, Non-Ford 6xxx (split into 6005C and 6016), Ford Low-Cu, Ford High-Cu, HRC 5xxx, and HRX 6xxx. In other words, the amount of available ELV scrap that is passed into the supply constraint of the LP model is always the sum of only the ABS scrap alloys. However, the Twitch compositions are calculated from all U.S. ELV scrap generated. For each iteration of the optimization model, Twitch scrap compositions are dynamically calculated from the weighted average of ELV aluminum scrap. The U.S. automotive DMFA (adapted with updated automotive growth rates from [Zhu et al. \(2025a\)](#), as described in Section 2.2.1 of the main article) projects the ELV scrap by alloy family and type (i.e., 1xxx sheet, 6xxx extrusions, A356 castings, etc.). Figure [S3](#) depicts the annual U.S. ELV scrap volumes by alloy type (sheet, extrusion, forgings, or castings) and family (1xxx, 6xxx, etc.). For wrought non-ABS alloys (except for Ford alloys), a representative alloy is selected for the Twitch composition derivation. These representative alloys (summarized in Table [S3](#)) were chosen through a literature review and interviews with aluminum industry experts. Through discussions with ELV recyclers, it was also determined that cast wheels are often removed from vehicles prior to shredding. Thus, the weighted average Twitch composition calculation excludes A356 castings. The midpoint chemistry of the Teal Sheet composition ranges for the representative non-ABS wrought alloys, together with the midpoints of the non-A356 castings Pink Sheet composition ranges (castings equivalent of Teal Sheets) and the ABS alloy chemistries described in Table 1, are used to calculate the weighted average Twitch compositions.

S6.1 Baseline DMFA-to-Twitch adjustment factors

As discussed in Section 2.2.2, the weighted average Twitch compositions are balanced against an experimentally measured Twitch composition from [Kelly \(2018\)](#). These adjustments are made to counteract potential inaccuracies in representative alloy choices—for instance, AA3103 may not account for 100% of all 3xxx series sheet used in vehicles. In addition, U.S. recyclers often process non-automotive products such as refrigerators and washing machines alongside ELVs. DMFA-to-Twitch

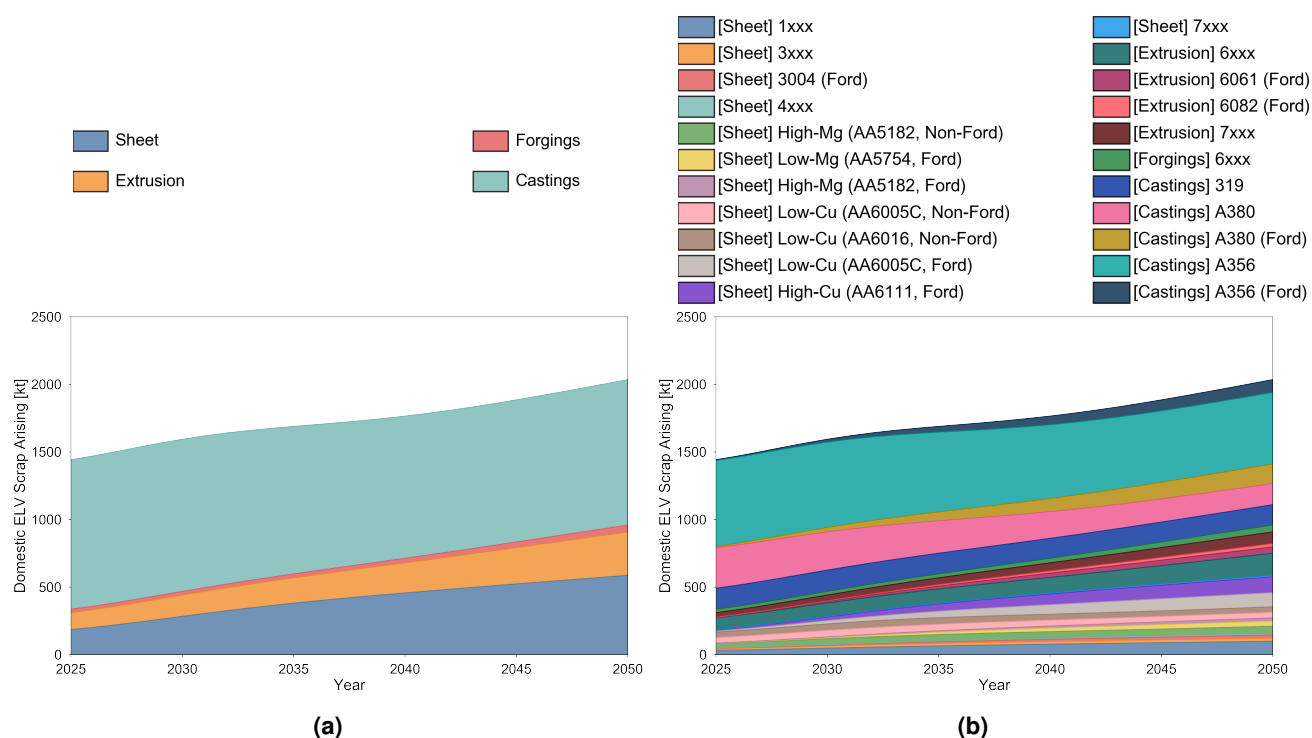


Figure S3. Distribution of projected U.S. ELV aluminum scrap in 2025-2050 by (a) alloy type and (b) alloy family and type

Table S3. Representative alloys for each wrought non-ABS alloy for the calculation of the weighted average Twitch

Wrought non-ABS alloy	Representative alloy
[Sheet] 1xxx	1070A
[Sheet] 3xxx	3103
[Sheet] 4xxx	4032
[Sheet] 7xxx	7075
[Extrusion] 6xxx	6061
[Extrusion] 7xxx	7003
[Forgings] 6xxx	6061

composition adjustment factors are derived by calculating the percent change in the concentration of each alloying element between the weighted average Twitch composition calculated for 2016 and the Twitch composition reported in [Kelly \(2018\)](#). The year 2016 was selected, as this is the year of analysis for the experimental study. Baseline DMFA-to-Twitch adjustment factors and the compositions used to derive each are summarized in Table [S4](#). Except when otherwise specified, these adjustment factors are applied to the weighted average Twitch composition calculated dynamically for each strategy and year analyzed.

Table S4. Baseline DMFA-to-Twitch adjustment factors

	Weighted average Twitch composition (2016)	Experimental Twitch composition (Kelly, 2018)	Adjustment factor
Si	5.20 wt. %	5.10 wt. %	-2.0%
Fe	0.47 wt. %	0.60 wt. %	+28.4%
Cu	2.33 wt. %	1.60 wt. %	-31.4%
Mn	0.21 wt. %	0.30 wt. %	+41.3%
Mg	0.41 wt. %	1.90 wt. %	+369.2%
Zn	1.00 wt. %	1.00 wt. %	+0.0%

S6.2 Ford DMFA-to-Twitch adjustment factors

Ford DMFA-to-Twitch composition adjustment factors are derived using the same process described in Section [S6.1](#). However, the weighted average Twitch compositions calculated use only the Ford alloys in ELV scrap (see Figure [S3](#)): Ford sheet 3004, Ford sheet Low-Mg, Ford sheet High-Mg, Ford sheet Low-Cu, Ford sheet High-Cu, Ford extrusion 6061, Ford extrusion 6082, and Ford castings A380. As with the full U.S. Twitch calculation, A356 is excluded as it is assumed to be used primarily for cast wheels, which are separated from vehicles prior to shredding. Additionally, the experimental Twitch composition used for comparison is from [Zhu et al. \(2025b\)](#), which uses Twitch scrap data experimentally obtained in 2024. Table [S5](#) lists the weighted average composition, the experimental Twitch composition, and the adjustment factors.

Table S5. Ford DMFA-to-Twitch adjustment factors

	Weighted average Ford Twitch composition (2024)	Experimental Twitch composition (Zhu et al., 2025b)	Adjustment factor
Si	3.39 wt. %	3.67 wt. %	+8.3%
Fe	0.37 wt. %	0.53 wt. %	+42.4%
Cu	1.01 wt. %	1.16 wt. %	+15.1%
Mn	0.25 wt. %	0.33 wt. %	+34.1%
Mg	0.85 wt. %	2.32 wt. %	+173.6%
Zn	0.40 wt. %	0.61 wt. %	+50.9%

S6.3 AIV DMFA-to-Twitch adjustment factors

Another set of DMFA-to-Twitch adjustment factors is used for the “Isolated shredding of AIVs”. In this strategy, as with the calculation of the baseline DMFA-to-Twitch factors, the weighted average Twitch composition is calculated from all automotive scrap. This weighted average, however, is compared against the experimental Twitch composition from [Zhu et al. \(2025b\)](#). Table [S6](#) lists the weighted average composition, the experimental Twitch composition, and the adjustment factors.

S7 VARIATIONS IN LIBS COMPOSITION ESTIMATIONS

In the model, Twitch sortation by alloy series, which represents scrap separation using the LIBS technology, is simulated through a series of calculations to approximate the volumes and compositions of each separated scrap stream. Using DMFA ELV Twitch scrap flow data (as described in Sections 2.2.1 and S1-3) and AA Teal Sheets data, the weighted average composition can be calculated as the annual “expected” Twitch scrap composition. When the Twitch Alloy Sort (AS) strategies are applied, the weighted average of each alloy family is calculated (e.g., all wrought 6xxx alloys are considered when calculating the weighted average 6xxx scrap stream composition). The resulting weighted average compositions and volumes of each separated scrap stream reflect the assumption that the Twitch scrap has been sorted into each respective stream with 100% accuracy. However, this is not a realistic expectation for the technology. As demonstrated in past LIBS experiments ([Werheit et al.](#),

Table S6. Isolated shredding of AIVs DMFA-to-Twitch adjustment factors

	Weighted average Twitch composition (2024)	Experimental Twitch composition (Zhu et al., 2025b)	Adjustment factor
Si	4.74 wt. %	3.67 wt. %	-22.6%
Fe	0.58 wt. %	0.53 wt. %	-8.3%
Cu	1.49 wt. %	1.16 wt. %	-21.9%
Mn	0.29 wt. %	0.33 wt. %	+12.2%
Mg	2.15 wt. %	2.32 wt. %	+8.0%
Zn	0.99 wt. %	0.61 wt. %	-38.2%

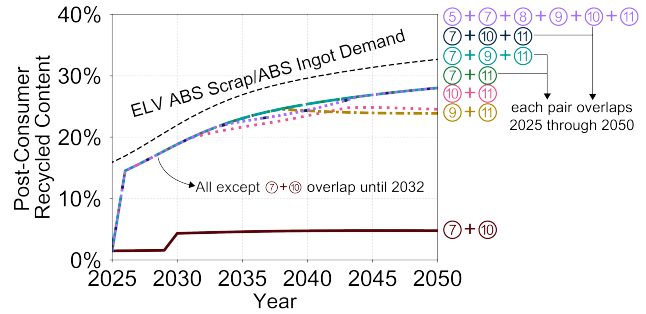
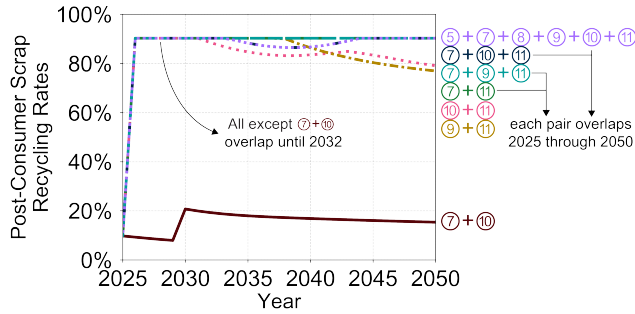
2011), 93% sorting accuracy for LIBS is a reasonable approximation. The model simulates sorting error by splitting 7% of each scrap stream that comes from Twitch among the remaining streams, altering the volumes and compositions of each scrap stream. This methodology forms the basis of two out of the four variations on LIBS simulated in this model. “Twitch-AS-93%” calculates each scrap stream with 93% sorting accuracy for each year of analysis, while “Twitch-AS-100%” uses the weighted average compositions and total volumes of each separated scrap stream. The PCRR and PCRC values presented in Figure 6a (duplicated in Figure S4a for comparison purposes) and discussed in Section 3.1.5, use the “Twitch-AS-93%” Twitch sortation assumption. As shown in Figure S4b, combining “Twitch-AS-100%” with other strategies is a minimal improvement over assuming “Twitch-AS-93%”.

To derive more experimentally-rooted compositions of scrap streams separated from LIBS, results from a LIBS experiment conducted by Kelly (2018) are incorporated. Kelly (2018) collected Twitch samples from two separate recycling facilities, and used a LIBS handheld analyzer to sort the Twitch samples into distinct bins, which included a 5xxx series bin and a 6xxx series bin. Their experimental results show that sorting error is not uniform across all alloy sorting—in particular, the most common misorting is 6xxx into the 5xxx bin. This study uses their experimentally measured compositions of LIBS-sorted 5xxx and 6xxx bins for the “Twitch-AS-Kelly-Fixed” strategy. Figure S4c shows the results of synergizing “Twitch-AS-Kelly-Fixed” with other strategies. By 2050, the three scenarios that combine strategies from all three stages of the ABS supply chain can theoretically use all available ELV ABS scrap maximizing the PCRC at 28%. Combining this LIBS strategy with the use of HRC alloys also shows high potential for improving post-consumer scrap recycling, but starting in 2040, the mixed fabrication scrap stream of the non-Ford alloys (which contains both the non-Ford HRC 5xxx and low-Cu alloys) becomes increasingly compositionally incompatible with the ABS alloy compositions, dropping the PCRC to 25.8% in 2050. Thus, when the “production scrap stream segregation” is added to this pair of strategies, the potential ELV ABS scrap use is maximized. When “Twitch-AS-Kelly-Fixed” is combined with shifting demand from 5xxx alloys to 6xxx, post-consumer scrap use is temporarily increased. By 2050, however, the PCRC of this combined strategy drops to 18.3%, compared to the 13.8% PCRC of “Twitch-AS-Kelly-Fixed” alone. Improvements in PCRC from combining “Twitch-AS-Kelly-Fixed” with “segregated production scrap” are limited by the marginal benefits of segregating production scrap, resulting in a 2050 PCRC of 15.1%.

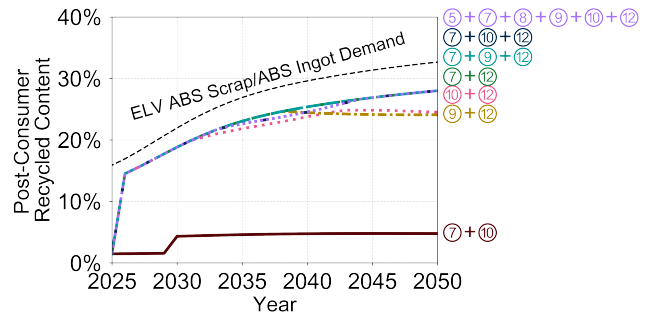
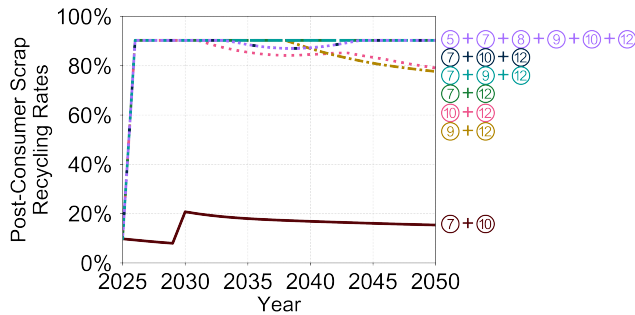
For the final LIBS variant, the compositions of scrap bins collected and separated by Kelly (2018) are compared against the calculated weighted average compositions of scrap streams separated through LIBS with 93% sorting accuracy applied. For the system considered in this study, the scrap streams of interest for ABS closed-loop recycling are the 5xxx series scrap and the 6xxx series scrap. The relative difference in concentration for each alloying element between the theoretical 93% LIBS 5xxx/6xxx streams as calculated for 2016 and the 5xxx/6xxx bins measured by Kelly (2018) are the “LIBS-from-Kelly adjustment factors”. These adjustment factors are then applied to the theoretical 93% LIBS scrap streams to estimate the annual “Twitch-AS-Kelly-Adjusted” compositions of each scrap stream (5xxx and 6xxx streams). Thus, these adjusted scrap stream compositions reflect trends in U.S. ABS scrap generated but are calibrated against experimental LIBS data from Kelly (2018). Figure S4d shows the impact of combining the “Twitch-AS-Kelly-Adjusted” strategy with other key strategies. The effectiveness of each set of strategies combined with “Twitch-AS-Kelly-Adjusted” is similar to the analogous combined strategy with “Twitch-AS-Kelly-Fixed”. One exception is the interaction of “Twitch-AS-Kelly-Adjusted” with “Using HRC alloys”. “Twitch-AS-Kelly-Adjusted” reflects changes to Twitch alloy breakdowns and compositions, so using HRC alloys increases alloying element concentrations in separated Twitch streams. Thus, the compositional mismatch increases as the fraction of HRC alloys increase in Twitch streams separated using “Twitch-AS-Kelly-Adjusted”, lowering the PCRC to 23.9% by 2050. As with the “Twitch-AS-Kelly-Fixed” combined strategies, adding “segregating production scrap” slightly improves post-consumer scrap use, but the compositional mismatch is still too large to overcome.

Although some PCRRs and PCRCs are different in the LIBS variations, the ordinal effectiveness of each combined strategy in 2050 remains the same (see Figure S4e). Combining the strategies of substituting ABS alloys with HRC variants with shifting demand for 5xxx to 6xxx alloys and implementing LIBS has the same effectiveness as when also combined with

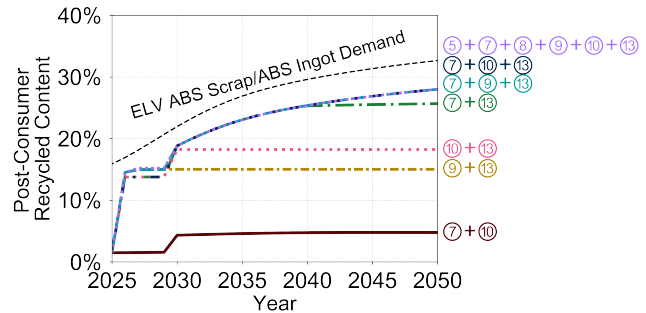
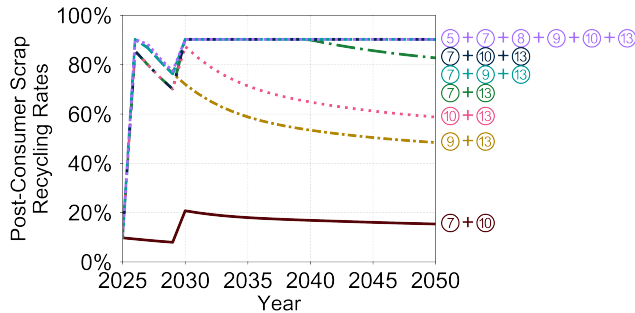
- ① = BAU recycling with base case ABS demand growth
 ② = Low ABS demand growth
 ③ = High ABS demand growth
 ④ = Alternative (Greene and Leard) vehicle lifespans with base case ABS demand growth
 ⑤ = Shifting from P1020 to P0610
 ⑥ = Shifting from P1020 to P0000
 ⑦ = Using High Residual Content (HRC) alloys
 ⑧ = Removing furnace charge constraint (FCC)
 ⑨ = Segregating production scrap by alloy
 ⑩ = Shifting demand for 5xxx to 6xxx series
 ⑪ = Twitch-AS-93%
 ⑫ = Twitch-AS-100%
 ⑬ = Twitch-AS-Kelly-Fixed
 ⑭ = Twitch-AS-Kelly-Adjusted
 ⑮ = Removing castings from Twitch scrap
 ⑯ = Isolating shredding of AIVs



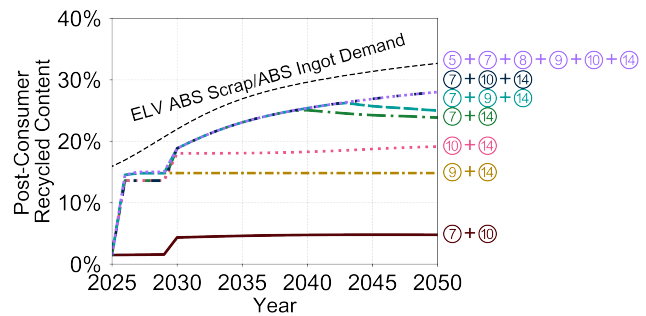
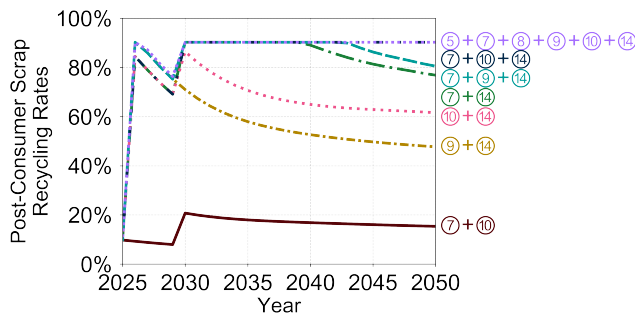
(a) Evolution of PCRR and PCRC over time for combined strategies with LIBS theoretically estimated from weighted averages with 93% separation accuracy applied



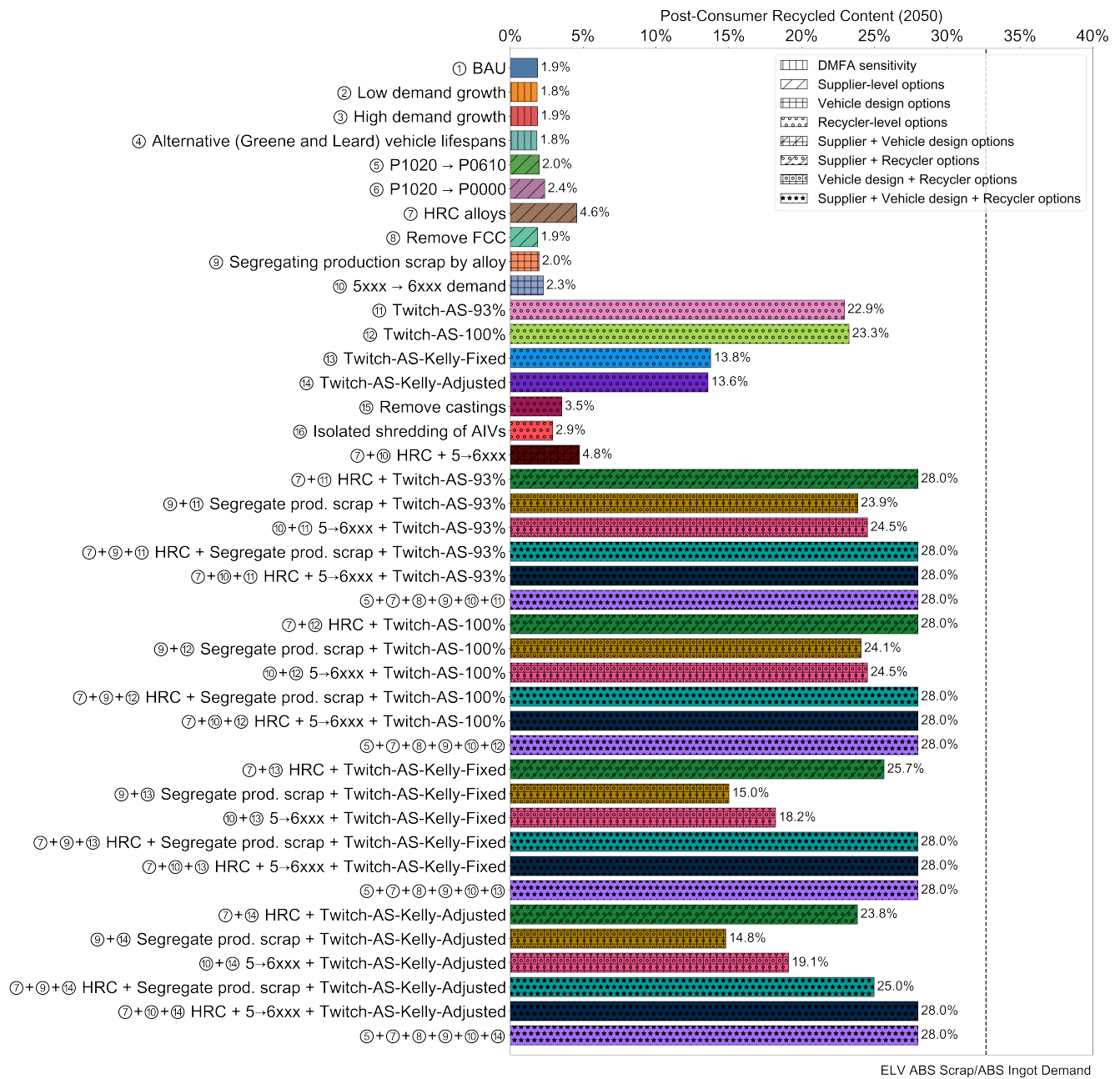
(b) Evolution of PCRR and PCRC over time for combined strategies with LIBS theoretically estimated from weighted averages with 100% separation accuracy applied



(c) Evolution of PCRR and PCRC over time for combined strategies with LIBS compositions set to fixed values from [Kelly \(2018\)](#) LIBS experiments



(d) Evolution of PCRR and PCRC over time for combined strategies with LIBS theoretically estimated with 93% separation, then adjusted using factors derived from [Kelly \(2018\)](#) LIBS experiments



(e) Maximum potential PCRC in 2050

Figure S4. Effect on U.S. ABS closed-loop recycling of combining strategies from across the life cycle designed to boost closed-loop post-consumer ABS scrap recycling. All results correspond to the base-case ABS demand growth rate and the Liao (2025) vehicle lifespan model.

using P0610 instead of P1020, removing the furnace charge constraint, and segregating production scrap by alloy. The pair of strategies that is the most effective is still the substituting ABS alloys with HRC variants combined with sorting Twitch scrap by series, but with the adjusted LIBS compositions, this pair no longer maximizes the potential PCRR/PCRCs. The remaining combined strategies are also less effective than with the theoretically calculated 93% accurate LIBS, but still demonstrate significant improvement over the baseline PCRR/PCRCs.

S7.1 Ford case study LIBS assumptions

For the Twitch sortation by alloy series strategy modeled in the Ford ABS case study, the method of calculating Twitch compositions is most analogous to the method used for “Twitch-AS-93%”. The compositions for the 5xxx and 6xxx bins are theoretically estimated by [Zhu et al. \(2025a\)](#) from weighted average compositions of Ford ELV scrap, with 7% sorting error applied. As a simplifying assumption, fixed compositions for each of the 5xxx and 6xxx bins are used in the optimization model for all years of analysis. This was determined to be a reasonable assumption, as the compositions of the sorted scrap streams are not expected to change significantly when Twitch sortation is applied as an independent strategy (see the compositions of “Twitch-AS-93%” in Table 1).

S8 RESULTS SUMMARY: EFFECT OF EACH STRATEGY ON OPTIMIZATION MODEL CONSTRAINTS

The effect of cross life cycle supply chain strategies (and sensitivities) on the optimization model, relative to the BAU scenario, is summarized in Table S7. Under BAU, binding compositional constraints on the PCRC in 2050 (1.9%) are the tolerance for Si in the 5xxx ABS alloys and for Zn in the 6xxx ABS alloys. Unless stated otherwise, the binding compositional constraints under each strategy in 2050 are still those for the BAU scenario.

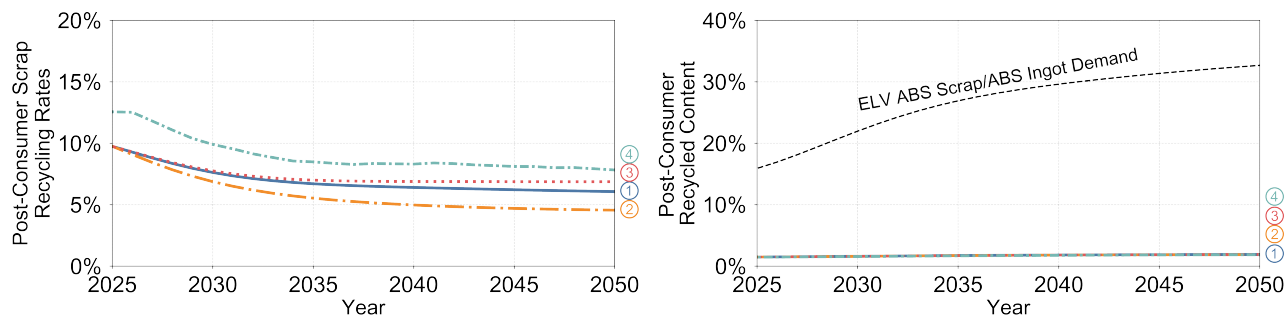
Table S7. Effect of recycling strategies on the linear programming model results

Sensitivity and intervention strategy simulated	Effect on optimization model	Maximum impact on PCRC in 2050 (relative to BAU)
ABS demand growth rate and vehicle lifespan sensitivities		
Low ABS demand growth (2)	Lowers ingot demand and scrap availability. Negligible effect on fraction of ingot demand that can be met using scrap.	Negligible
High ABS demand growth (3)	Raises ingot demand and scrap availability. Negligible effect on fraction of ingot demand that can be met using scrap.	Negligible
Alternative vehicle lifespans (4)	Lowers scrap availability. Negligible effect on fraction of ingot demand that can be met using scrap.	Negligible
Sheet mill strategies		
Using a purer primary aluminum diluent (5) (6)	Increases diluting power of primary aluminum, allowing an increased scrap fraction by lowering the concentrations in $E_{e,primary}$ used in the compositional constraints (Equations 4 and 5).	(5): +0.1% (6): +0.5%
Designing HRC alloys (7)	Increases compositional tolerances for all alloying elements (raises <i>chemistry upper bound_{d,e}</i> in Equations 4 and 5), enabling higher scrap fractions by relaxing the binding compositional constraints of Si in 5xxx and Zn in 6xxx and overall reducing compositional mismatch.	+2.7%
Increasing dilution with primary aluminum (8)	Removes the furnace charge constraint (sets $\alpha = 0$ in Equation 6). Negligible effect on the fraction of ingot demand that can be met using scrap, as production scrap availability enables >35% (nominal α value) scrap in recycling furnaces.	Negligible
OEM design and manufacturing strategies		
Segregated production scrap streams (9)	Improves scrap-to-ingot compatibility and lowers dilution required from virgin metals, as segregated $E_{e,prod, scrap}$ compositions align with respective alloy <i>chemistry lower bound_{d,e}</i> and <i>chemistry upper bound_{d,e}</i> in Equations 4 and 5. Binding compositional constraints on Si in 5xxx and Zn in 6xxx are effectively relaxed as compositional mismatch is reduced.	+0.1%
Shifting ABS demand to 6xxx alloys (10)	Allows increased scrap fractions by switching 5xxx alloy demand to 6xxx alloy demand. Twitch scrap requires less dilution with primary metal to make 6xxx alloys compared to 5xxx alloys (Zhu et al. [2025b]). Dilution required to make 6xxx alloys reduces further over time as the quantity of 5xxx scrap in Twitch scrap reduces, shifting $E_{e,Twitch}$ compositions closer to the <i>chemistry lower bound_{d,e}</i> and <i>chemistry upper bound_{d,e}</i> of 6xxx alloys in Equations 4 and 5. In the absence of 5xxx alloys, the remaining binding composition constraints in 2050 are Zn in 6xxx alloys.	+0.4%
ABS recycler strategies		
Sorting ELV Twitch by alloy series (11) (12) (13) (14)	Allows a significant increase in scrap fractions as the concentrations of Si, Fe, Cu, and Zn are greatly reduced by removing automotive castings. Furthermore, sorting Twitch by alloy series mitigates cross-contamination between wrought alloy families: it prevents elevated Mg levels in 6xxx ABS scrap (otherwise caused by mixing with 5xxx ABS) and limits increases in Cu and Si in 5xxx ABS scrap (otherwise caused by contamination from 6xxx ABS). By splitting $E_{e,Twitch}$ into $E_{e,Twitch-5xxx}$ and $E_{e,Twitch-6xxx}$ in Equations 4 and 5, compositional mismatch is reduced, relaxing the binding compositional constraints of Si in 5xxx and Zn in 6xxx. The 2050 binding constraint remain the upper bound of Si in the 5xxx alloys and Zn 6xxx, with Cu, Mn, and Mg introduced as additional binding constraints in the 6xxx alloys.	(11): +21.1% (12): +21.4% (13): +11.9% (14): +11.7%
Castings removal from Twitch (15)	Allows increased scrap fraction by decreasing the concentrations of the Si, Fe, Cu, and Zn in Twitch scrap, reducing the alloying element concentrations of $E_{e,Twitch}$ in Equations 4 and 5. Binding compositional constraints on Si in 5xxx and Zn in 6xxx are effectively relaxed as compositional mismatch is reduced.	+1.7%
Isolated shredding of AIVs (16)	Higher share of wrought alloys in ELVs reduces residual concentrations associated with castings, reducing concentrations of Si, Fe, Cu, and Zn in Twitch scrap, reducing the alloying element concentrations of $E_{e,Twitch}$ in Equations 4 and 5. Binding compositional constraints on Si in 5xxx and Zn in 6xxx are effectively relaxed as compositional mismatch is reduced.	+1.0%

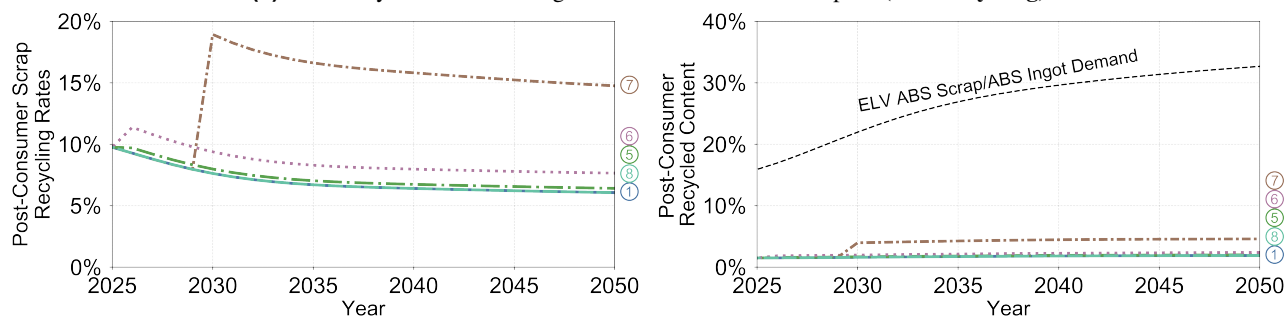
S9 EFFECT OF OMITTING DMFA-TO-TWITCH ADJUSTMENT FACTORS

To evaluate the sensitivity of the results to the DMFA-to-Twitch adjustment factors described in Section S6, a separate set of results was generated using the weighted-average Twitch compositions (omitting the DMFA-to-Twitch adjustment factors). As shown in Figures S5 and S6, omitting the DMFA-to-Twitch adjustment factors has a negligible effect on all PCRR and PCRC values. This is a result of the binding composition constraints, which are consistently Si in 5xxx alloys and Zn in 6xxx alloys. This indicates the concentrations of Si and Zn are the primary barriers to further ELV ABS recycling. Table S4 shows the difference between the weighted average Twitch composition and the experimental Twitch composition, which together are used to derive the DMFA-to-Twitch adjustment factors. For the key alloy elements Si and Zn, the DMFA-to-Twitch adjustment factors are -2% and 0%, respectively. This reflects the minimal difference between the weighted average composition and the experimental composition. Since the concentrations of Si and Zn—the two key binding compositional constraints in the LP model—remain almost the same with or without the DMFA-to-Twitch adjustment factors, PCRR and PCRC values accordingly remain very similar.

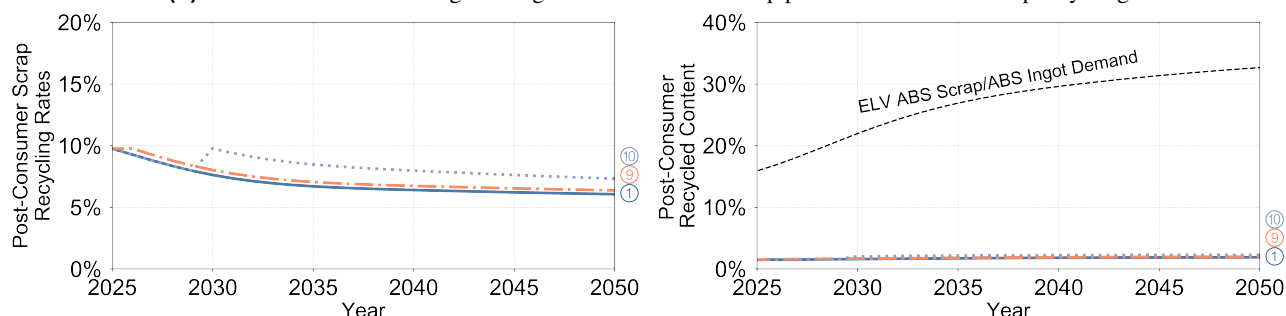
- ① = BAU recycling with base case ABS demand growth
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 ④ = Alternative (Greene and Leard) vehicle lifespans with base case ABS demand growth
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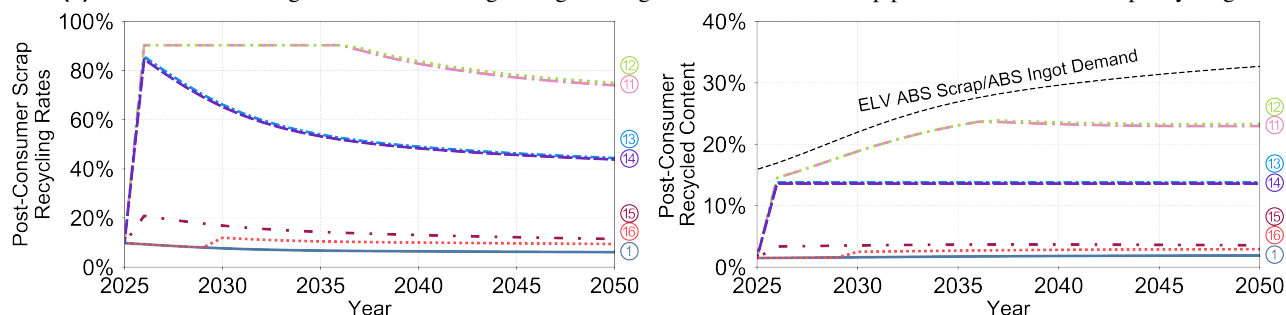
(a) Sensitivity to ABS demand growth rates and vehicle lifespans (BAU recycling)



(b) Effect of sheet mill strategies designed to boost closed-loop post-consumer ABS scrap recycling

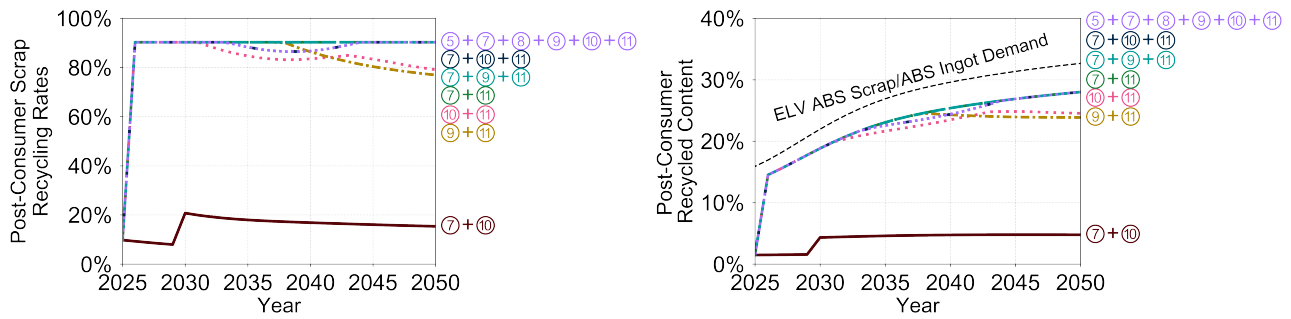


(c) Effect of OEM design and manufacturing strategies designed to boost closed-loop post-consumer ABS scrap recycling

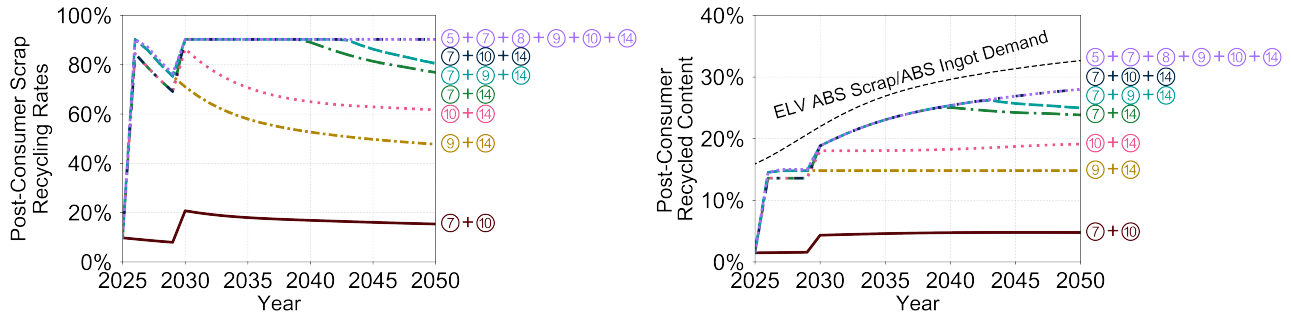


(d) Effect of recycler strategies designed to boost closed-loop post-consumer ABS scrap recycling

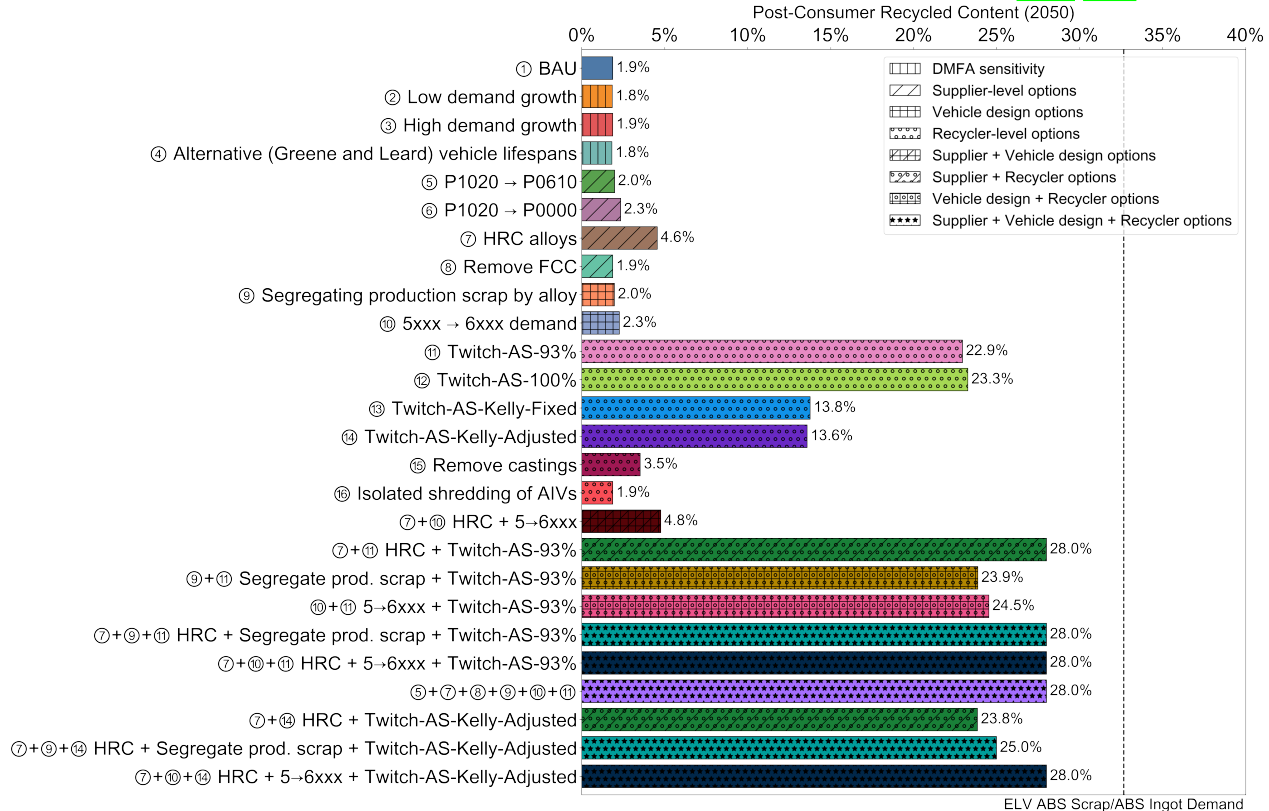
Figure S5. U.S. ABS PCRR and PCRC under different recycling strategies. Twitch compositions are unadjusted weighted averages (DMFA-to-Twitch adjustment factors not included). Except where stated otherwise, all results correspond to the base-case ABS demand growth rate and the [Liao \(2025\)](#) vehicle lifespan model.



(a) Evolution of PCRR and PCRC over time with a focus on LIBS sortation by alloy series with a 93% accuracy (Twitch-AS-93%)



(b) Evolution of PCRR and PCRC over time with a focus on Twitch-AS-Kelly-Adjusted (consistent with Kelly (2018) LIBS experiments)



(c) Maximum potential PCRC in 2050

Figure S6. Effect on U.S. ABS closed-loop recycling of combining strategies from across the life cycle designed to boost closed-loop post-consumer ABS scrap recycling. Twitch compositions are unadjusted weighted averages (DMFA-to-Twitch adjustment factors not included). All results (other than ②-④) correspond to the base-case ABS demand growth rate and the Liao (2025) vehicle lifespan model.

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