SUPPORTING INFORMATION FOR:

Whitefoot, K.S., H.G. Grimes-Casey, C.E. Girata, W.R. Morrow, J.J. Winebrake, G.A. Keoleian, and S.J Skerlos. 2011. Consequential lifecycle assessment with market-driven design: Development and demonstration. *Journal of Industrial Ecology.*

Summary

This supporting information describes the data and submodels used in the demonstration of consequential lifecycle assessment with market-driven design (cLCA-MDD). It details the lifecycle data and modeling characterizing the material and energy flows associated with the lifecycle of a midsize vehicle. It also describes the sources of submodels of consumer demand and production costs and their associated assumptions, as well as the assumptions and formulation of the equilibrium model. Finally, the supporting information describes assumptions of vehicle use used to generate greenhouse gas (GHG) calculations per mile and vehicle miles traveled (VMT) as a function of fuel price.

Life cycle data and modeling used to determine *A* and *B* matrices

The material processing stage of this vehicle analysis includes casting, rolling, forging, and electric arc furnace processes for metals plus glass, PE plastic, and tires production. The economic outputs are forged iron, cast iron, cast aluminum, rolled aluminum, cold rolled steel, EAF steel, hot rolled steel, coated glass, plastics, and tires. Metals chosen contributed the majority of the mass of the USAMP generic vehicle engine (Table S-1) for which specific processing data was available shown in Table S-2 (Smith et al., 2002). All plastic is assumed to be polyethylene (PE). All glass in the vehicle is assumed coated float glass. The material CO_2 burdens are taken from the SimaPro database.

Table S-1. *Lifecycle material flows (kg) for the body, powertrain and suspension of a generic gasoline vehicle. Unpublished data adapted from USAMP (1999).*

Material (kg)		Body	Powertrain	Suspension	Total
Fe:	Iron		26.0		26
	Cast Iron		99	43	142
Steel:	Rolled	48	42	23	113
	EAF	48	72	108	228
	Galvanized	563	43	0.4	606.4
	Hot Rolled	84	5.5	113	202.5
Al:	Cast		63	2.7	65.7
	Rolled		4.8		4.8
Polyethylene:		33	6.8	8	47.8
Tires:				47	47
Total Subsystem		776	362.1	345.1	1483.2

Table S-2. *Mass of processed materials in the base gasoline engine from Smith et al (2002).*

Manufacturing Process	Material (kg)					
	Al	Fe	Steel	Rubber	Plastic	Other
cast	0.20	0.15				
cast, machined	26.7	66.51	7.6			
cast, heat treated			1.43			
rolled, stamped	1.7					
cold rolled			0.367			
cold rolled, stamped			4.3			
forged, machined		22.6				
extruded			2.7			
extruded, machined			2.1			
galvanized, stamped			2.7			
injection molded				0.1	1.2	
no specification	1.23		5.14	0.54		
other			2.7	0.1		0.6
total	29.83	89.26	29.03	0.74	1.20	0.60
fraction	0.20	0.59	0.19	0.00	0.01	0.00
					Total Mass	150.66

The energy and emissions associated with manufacturing the vehicle engine and body change with the rate of change in engine and body weight. For example, the analysis estimates that for every kW of power added, 0.5% of the base engine mass must be added, resulting in gasoline engines ranging from 125 kg to 182 kg. It was therefore assumed that per unit energy inputs and carbon emissions in the engine manufacture model also change at 0.5% per kW change in engine. It is assumed that assembly inputs and emissions do not change significantly with the changes in engine and body called for by the model.

In determining the power-engine mass relationship, several power-displacement models were considered and it was found that a linear regression from Arnold et al. (2005) provided the best fit for the base vehicle data and for 1993 data from Ward's Automotive Yearbook. Displacement-mass data (Messner, 2006) were the only available source of engine weights; data for engines with cast-iron engine blocks were used to best match the base engine-manufacturing model.

The carbon-dioxide emission factors for the use phase depend on the fuel economy performance of the engine (modeled using ADVISOR software) and the age of the vehicle. To account for performance changes arising from age, a modification of the US EPA on-cycle emissions model for carbon monoxide and hydrocarbons incorporates a reduction in fuel economy (and increase in emissions) at various points in the lifetime.

Finally, the end-of-life management model assumes that after each vehicle is driven 15 years and is shredded at the end-of-life with 100% recovery of metals for secondary material. Non-metal materials are assumed to become solid waste, but land filling processes and associated emissions are not modeled.

Consumer choice model to determine vehicle demand in vector *d*

Consumer utility models are commonly used in the economics literature to model consumer choice of products (see Train 2003, Louviere 2003). This modeling approach assumes that consumers choose a product from a set of product choices by maximizing the "utility" or satisfaction they receive from the product. In general, the utility of a product j to a consumer is a function of the product's price p_j, its characteristics, and consumer characteristics (e.g., income). The consumer utility model we choose (Boyd and Mellman 1980) does not account for heterogeneous preferences between consumers, so utility is only a function of product price and characteristics. Because we often do not have data on all of the product characteristics that may influence utility, the observable portion of utility, u_j, is separated from the unobservable portion, ε_j:

$$U_j = u_j + \varepsilon_j \tag{1}$$

where u_j is a function of the product price and observable characteristics, $\mathbf{y}_j$:

$$u_j = f(p_j, \boldsymbol{y}_j) \tag{2}$$

The probability of a consumer choosing product *j* over product *k* is equal to the probability of *j*'s utility being larger than *k*'s utility expressed as follows:

$$P_j = P\left[u_j + \varepsilon_j > u_k + \varepsilon_k\right] = P\left[\varepsilon_k < u_j + \varepsilon_j - u_k\right] \tag{3}$$

which is equivalent to a joint cumulative distribution function with solution:

$$P_j = \int_{-\infty}^{\infty} \int_{-\infty}^{(u_j - u_k + \varepsilon_j)} f(\varepsilon_j, \varepsilon_k)\, d\varepsilon_k\, d\varepsilon_j \tag{4}$$

In the logit consumer utility model, the unobserved utility terms are assumed distributed according to the Type 2 extreme value function so that equation 4 reduces to a logistic function:

$$P_j = \frac{e^{u_j}}{e^{u_j} + e^{u_k}} \tag{5}$$

Considering a larger set of product choices (1,…,J), the probability of a consumer choosing product j is:

$$P_j = \frac{e^{u_j}}{\sum_{j'=1}^{J} e^{u_{j'}}} \tag{6}$$

Given that the logit model treats all consumer preferences as homogeneous, the expected market share of vehicle j is equivalent to P_j. The logit model provides a computationally simple representation of demand, but has some drawbacks. Most notably, the model assumes “independence of irrelevant alternatives” (IIA). For example, if the price of a luxury vehicle was increased, the logit model would indicate that proportional increases in demand occur for both a competing luxury vehicle and a competing compact vehicle. However, we would expect that demand for the competing luxury vehicle would increase disproportionately to the increase in demand for the compact vehicle.

Demand submodel

The empirical vehicle utility model we chose for the case study is from Boyd and Mellman (1980), which was adapted here following Michalek et al. (2004). Observable consumer utility for a given vehicle j is determined by equation 7 where p_j, mpg_j, and $t_{(0-60)j}$ are respectively the purchase price, fuel economy, and 0-60 mph acceleration time of vehicle j, and pgf is the price of (gasoline) fuel. The first term of the equation represents the utility of the cost to purchase and drive the vehicle 50,000 miles. The second term represents the utility of the acceleration performance of the vehicle. Notice that both fuel economy, mpg_j, and acceleration time, $t_{(0-60)j}$, are dependent upon the design decisions (engine horsepower and final drive ratio) considered in the case study, x.

$$u_j = \beta_1 \left(p_j + \frac{50{,}000\, pgf}{mpg_j} \right) + \beta_2 \frac{60}{t_{(0-60)j}} \tag{7}$$

The coefficient terms, β_1 and β_2 are respectively -3.61e-4 (SE: 6.13e-5) and 0.302 (SE: 0.126) as estimated by Boyd and Mellman (1980). The Boyd and Mellman (1980) model also includes characteristics of noise and reliability but are assumed to be constant across vehicles modeled in the case study following Michalek et al. (2004). Further details about this model form and estimation can be found in Boyd and Mellman (1980).

Equilibrium model

The case study uses an oligopolistic model of automotive firms producing mid-size vehicles in partial-equilibrium with respect to vehicle powertrain designs and prices. This model assumes that firms make these decisions in two stages, first choosing powertrain designs and then choosing vehicle prices. The (sub-game perfect) equilibrium is found by modeling these firms as simultaneously maximizing profits. Specifically, each firm solves the following maximization problem:

(8)

where are firm profits, is a vector of design variables (engine power and final drive ratio) of vehicle j, is the marginal production cost of the vehicle, is the (sub-game perfect) equilibrium price of the vehicle as a function of the design variables, and is the demand for the vehicle. The demand is calculated by multiplying the market share, P_j in equation 6, by the size of the market. This scaling of demand, however, does not affect the optimal solution, . Both demand and optimal prices depend on competing firm decisions, , which are taken as given in the optimization problem of equation 8. The joint optimum of all firms is found by sequentially solving for each firm's optimum, given the previous solution of all other firms, until convergence.

Sub-game perfect equilibrium prices in equation 8 are determined by the fixed-point iteration derived in Morrow (2008). Using a logit model of demand, and modeling each firm as producing one vehicle, this fixed point reduces to:

— (8)

where ***p***, ***q***, and ***c*** are (1 x J) vectors of prices, demand, and marginal costs of all vehicles, and is the price parameter of observed utility as in equation 7. The prices in ***p*** represent the profit-maximal prices for all vehicles given the design variables determined in the first stage.

Vehicle manufacturing cost model

Production costs, c, in the case study depend only on the variable costs of manufacturing the engine plus an assumed fixed cost of the "rest of the vehicle". These costs are taken from Michalek et al.'s regression analysis of existing cost and wholesale data as in equation 1. Engine power, x_1, is in units of kW in this equation. Following Michalek et al., capital costs (e.g., for line setup) are assumed to be identical for all considered engine design variables and are excluded from the analysis.

$$c = 670.51e^{0.0063(x_1)} + 7500 \tag{9}$$

Sensitivity of emissions to production cost parameter

Gas vehicles are assumed to have a 'base' manufacturing cost of $7,500 in the original model, derived from the literature and available wholesale data by Michalek et al (2004). This cost was varied by +/- one-third to determine how sensitive market share and overall market burdens are to this assumption.

As the manufacturing cost increases, the price of new vehicles increases, and more consumers continue driving old vehicles (ranging from 4% of car buying population when costs are low, to 13% when costs are high). While the use of more old vehicles increases use phase emissions, this negative effect on market carbon emissions is offset by the reduction in manufacturing and new vehicle use emissions (new vehicles still dominate the market). As a result, increasing manufacturing costs has a slight positive effect on market emissions.

Calculation of per-mile greenhouse gas emissions to determine *B* matrix

Per-mile greenhouse gas emissions, in g CO_2-eq, are determined for each vehicle by equation 10.

$$M_{CO2} = \frac{1}{\alpha_{CO2}}\left(\frac{\alpha_{HC}\rho_{fuel}}{MPG} - \alpha_{CO}M_{CO,vtotal} - \alpha_{HC}M_{HC,vtotal}\right) \tag{10}$$

where:

$$\alpha_{CO2} = \frac{12gC}{44gCO_2}, \quad \alpha_{HC} = 0.86, \quad \alpha_{CO} = \frac{12gC}{28gCO}, \quad \rho_{fuel} = \frac{740g/L}{0.264gal/L},$$

$M_{CO,vtotal}$ and $M_{HC,vtotal}$ are the weighted total emissions of CO and HC over the lifetime of a vehicle, accounting for age deterioration. These values are determined from equation 11, where *e* indexes the emissions from CO or HC.

$$M_{e,vtotal} = \frac{\sum_{i=1}^{n}(42\% * M_{4Kmi,j} + 42\% M_{50Kmi,j} + 16\% M_{100Kmi,j} + malfuction_j + offcycle_j)}{n} \tag{11}$$

M_{mi} in equation 11 is the EPA emissions test rating, $malfuction_j$ and *offcycle* were reported in USAMP(1999) from Ross et al. (1995).

Vehicle use models used to determine demand for vehicle-miles-traveled in vector *d*

The 1980, double-logarithmic VMT model (Figure S-1) depends heavily on fuel costs and fuel economy. Exogenously determined variables influencing VMT, taken from average mid-1990's US data when available, include income levels, road infrastructure, and registered drivers. Urban and rural travel is assumed to contribute equally to a year's driving.

The Goldberg linear regression model (Figure S-1) depends on fuel economy and vehicle purchase price variables determined from the engineering model. Other exogenous variables include household characteristics and regional characteristics:

(13)

where p_{gas} is the price of gasoline, and p and mpg are respectively the price and fuel economy of the vehicle as determined in the partial-equilibrium model. The variable *inc* is the consumer's household income, assumed to be $21,104 (the mean of Goldberg's (1998) data set).

Jones linear regression model (Figure S-1, labeled "Greene") depends much less on fuel economy and associated fuel costs. Income and GDP were exogenous inputs to the VMT model. Jones investigated a range of regression approaches including lagged variables; the model chosen here was a static linear regression:

(14)

where p_{gas} is the price of gasoline and mpg is the fuel economy of the vehicle. The variable *d* is the number of drivers, assumed 176.6 (billions in 1995), VMTmin is 9500 and *GDP* is assumed 8031.7 (billions of USD in 1995).

Travel demand and fuel consumption models often employ fuel-cost elasticity of demand for VMT as a measure of the (in)sensitivity that US consumers may have for changes in fuel prices, or rebound effect (Greene, 1992; Small and Van Dender, 2005). The Jones and Goldberg models produce estimates of 0-5% and 20% short term (negative) elasticity of driving demand, respectively.

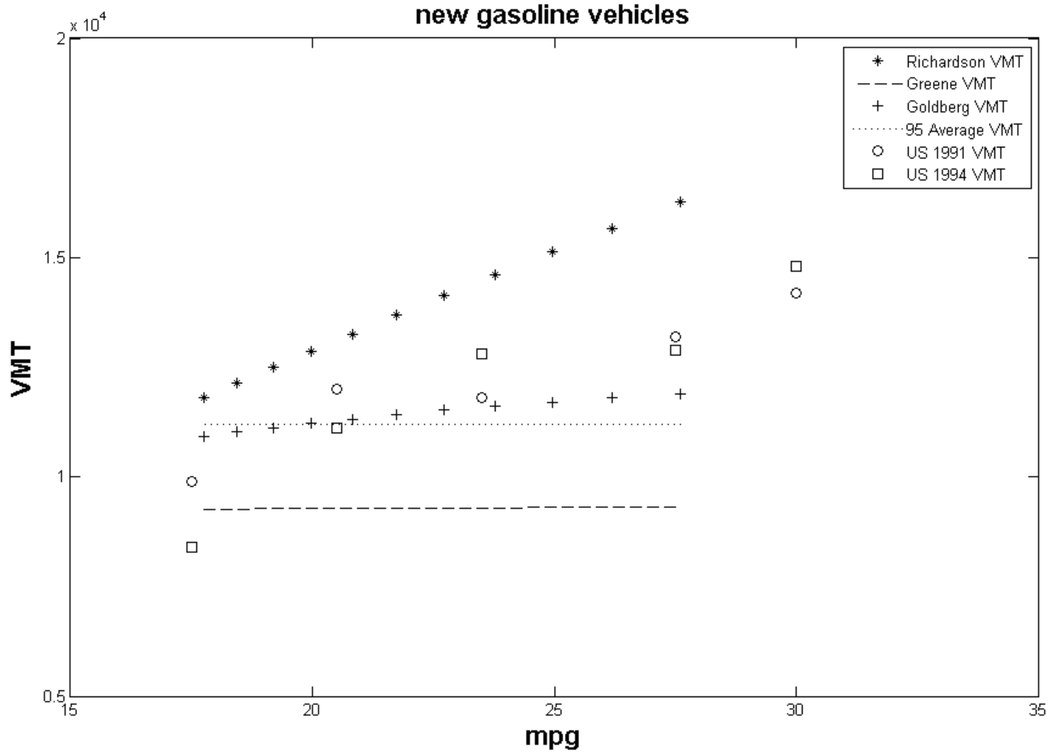

Figure S-1. Annual *VMT according to three driving-demand models and the 1995 U.S. average compared to data from the US Energy Information Administration (US VMT).*

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