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1 **Econometric modeling of recycled copper supply**

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10 **Abstract**

11 The supply of recycled material depends on historic consumption, i.e. what constitutes scrap
12 available today originates from previously made products. Analytical tools, such as materials
13 flow analysis, use this observation to estimate scrap metal flows. The supply of recycled
14 metal also depends on changing economic conditions, e.g. metal consumption rates correlate
15 with changes in gross domestic product. We use an autoregressive distributed lag approach to
16 model the supply of recycled copper as a complementary approach to material flow analysis.
17 We find that both industrial activity and world GDP correlate with total scrap supply, with
18 limited dependence on copper price. We also develop independent models for direct remelt
19 (higher quality) and refined (lower quality) scrap. A 1% increase in industrial production
20 leads to a 2.1% increase in higher quality scrap quantity, while a similar increase in world
21 GDP leads to a 1.4% increase in lower quality scrap. Based on this model dependence, we
22 suggest that a recycling policy aimed at increasing recycling through the use of subsidies,
23 taxes or price incentives should be directed towards the low-end segment of the scrap market
24 and there it may still only have limited impact.
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27 **Keywords:** copper, autoregressive distributed lag, recycling, scrap, price elasticity
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39 1. Introduction

40 Approximately 33% of the copper consumed worldwide is derived from secondary sources,
41 i.e. it has either been part of a product or it has been collected as waste from a manufacturing
42 process (Gloser et al. , 2013). While the fraction of secondary versus primary (derived from
43 ore) has stayed between 30 and 40% over the past 40 years; in absolute terms the use of
44 copper from secondary sources has tripled over the same period (ICSG, 2013). The collection
45 of copper scrap is desirable from an environmental perspective for two primary reasons
46 (Gomez et al. , 2007, Northey et al. , 2014, Reck and Graedel, 2012). First, copper is
47 relatively scarce compared to other industrial metals: by one metric, the static depletion
48 index, the time to exhaust current reserves is only about 40 years , while ore grade for copper,
49 is 0.2-5 wt% (recent values less than 0.45 wt%) (Ruth, 1995). Although not accounting for
50 increased demand or improved efficiency from extraction technology, this metric is an order
51 of magnitude lower than that of aluminum and iron (Alonso et al. , 2007). Second, as is
52 typical for metals, copper production from secondary sources requires less energy than that
53 from primary sources: for some grades of copper secondary production reduces energy needs
54 by 85% compared to primary production (Rankin, 2011). There is economic incentive as
55 well: multiplying the year average price of \$3.4/lb by estimates for annual scrap flows
56 (Gloser, Soulier, 2013), the nominal value of the copper in global waste streams in 2010 was
57 \$81 billion.

58
59 As a result of these drivers, much effort has gone into understanding the various technical
60 (Gaustad et al. , 2010, Olivetti et al. , 2011), economic (Achillas et al. , 2013) and life cycle
61 (Rubin et al. , 2014) aspects of improving recycling. To this end, materials flow analysis
62 (MFA) provides a diagnostic modeling tool for analyzing materials systems (Liu and Muller,
63 2013, Muller et al. , 2014). The results of an MFA covering end of life fate of a material
64 describe waste generation flows and identify where dissipative losses occur (Lifset et al. ,
65 2012); furthermore, results may be tracked over time and compared across geographic
66 regions, thereby identifying high leverage opportunities for increased recovery (Wubbeke and
67 Heroth, 2014). MFA models can also provide estimates of metrics that are otherwise not
68 reported directly by recyclers, such as recycling and collection rates for different end-use
69 sectors (Chen, 2013). Information of this sort can be used to inform industry and government
70 strategy aimed at increasing these rates (Gsodam et al. , 2014, Habuer et al. , 2014, Wang et
71 al. , 2014). In an MFA model the material recovered in a year is typically estimated based on
72 historical materials consumption, estimated product lifetimes, and collection rates (Bertram et
73 al. , 2002, Cullen and Allwood, 2013). These models therefore, by design, assume that past
74 patterns of behavior are consistent with those into the future and do not directly incorporate
75 the effect of changing economic conditions. As incentives to use, discard, collect and recycle
76 copper and copper containing products depend on the immediate economic situation for
77 particular agents in the system, a solely MFA-based approach may lead to an incomplete
78 description of scrap supply (McMillan et al. , 2010). Complementary to MFAs, econometric
79 analysis is used to model scrap volumes based on incorporating an array of independent
80 variables describing various facets of the economy (Angus, Casado, 2012, Gomez, Guzman,
81 2007). Many of these variables, such as indices of industrial production (IP), are routinely

82 forecasted with reasonable fidelity. The relative ease with which data can be obtained make
83 econometric modeling an attractive route for projecting future scrap flows. In this paper, we
84 use ordinary least squares to model the supply of recycled copper. Copper was chosen
85 because of data availability and its economic importance, i.e., a combination of significant
86 amounts of global production and relatively high price.

87
88 The economic analysis of metals markets has often been studied from a financial (Baffes and
89 Savescu, 2014) and a resource economics (Slade, 1982, Solow, 1974) point of view. The
90 modeling of metals supply and demand has been developed for the primary industry (Alonso
91 et al. , 2012, Wagenhals, 1984). A few studies have also focused on the supply of secondary
92 metal including copper. For example, economic models have shown that secondary
93 production correlates with price (Blomberg and Soderholm, 2009, Gleich et al. , 2013),
94 production inputs (Slade, 1980) and the available stock of copper scrap not recycled in earlier
95 years (Gomez, Guzman, 2007). Results of this sort are valuable when designing policy
96 strategy intended to influence materials recovery, e.g. fiscal subsidies directed towards
97 material recovery are effective only if scrap flow responds to changes in price (Finnveden et
98 al. , 2013, Mansikkasalo et al. , 2014, Soderholm, 2011, Soderholm and Tilton, 2012).

99 The above studies focus on the refinery sector of the recycling industry, which, in the
100 case of copper, includes only 42% of recycled metal globally, i.e., scrap that can be directly
101 melted without being refined is not counted (ICSG, 2013). The important distinction between
102 the two types of scrap is not necessarily the source (e.g. old versus new scrap), but rather the
103 quality (e.g. end-of-life power cable versus waste electrical and electronic equipment) (Flores
104 et al. , 2014). The focus of previous work on a subset of the recycling industry, i.e. the
105 refinery sector, limits its applicability to relatively lower grade scrap and the products that
106 make up such scrap. They are less useful for improving direct melt scrap recycling because
107 this part of the market consists of different products and different waste collection streams. A
108 large part of this stream is waste from semi-finished goods production. Through econometric
109 modeling of scrap volumes with annual sampling frequency, both globally and regionally, we
110 investigate what might drive availability of different qualities of scrap. We discuss our
111 findings in light of environmental policy strategy towards increasing scrap availability.
112 Specifically, we show whether price and what other forms of economic activity affect
113 different parts of the copper waste stream.

114 **2. Data and Methods**

115 We first study the world consumption of copper scrap with *annual* sampling frequency
116 between 1972 and 2012 from the International Copper Study Group (ICSG) database (ICSG,
117 2013). This dataset is partitioned into scrap that is first refined before use (refined scrap) and
118 scrap that can be directly melted at the time of use (direct melt scrap). The latter category
119 comprises secondary copper that requires minimal processing in order to be used in a new
120 product, i.e. high purity and/or knowledge of chemical composition.

121 The dependent variables are the quantities of copper produced from secondary
122 sources (annual). In the literature, these quantities are sometimes referred to as supply,
123 consumption or flow (Blomberg and Soderholm, 2009, Gloser, Soulier, 2013, Gomez,

124 Guzman, 2007). Henceforth, we will refer to them as copper supply. The independent
125 variables, i.e. the potential drivers for secondary copper supply are captured by indices of
126 industrial activity, prices, and monetary conditions. They were chosen based on a survey of
127 econometric literature pertinent to metals markets and aim to be comprehensive in their
128 coverage of activities that may influence the supply and demand of copper more generally
129 (Azadeh et al. , 2013, Elshkaki et al. , 2005, Finnveden, Ekvall, 2013, Reck and Graedel,
130 2012). The choice of independent variables was also based on our interest in reflecting scrap
131 generation rather than scrap consumption. For example, while China consumes large amounts
132 of copper, most postconsumer scrap is still generated in the major advanced economies
133 (represented by the G7 countries). The price variable is the real price of refined primary
134 copper from the London Metal Exchange (LME). Based on copper-content, scrap is traded at
135 a discount relative to the primary price, but the correlation between primary and secondary
136 prices is very strong (Xiarchos and Fletcher, 2009). The complete list of variables considered
137 is available in Table S1 in the supporting information.

138

139 Prior to performing the regression analysis, we logarithmically transformed all variables that
140 reflect quantity, price and value, in order to stabilize variable variance. Price, futures and
141 world GDP are deflated by world real GDP deflator. In addition, it is common practice in
142 econometrics to consider de-trending data. A linear trend in both the predictors and the
143 response may cause the model to have a high goodness of fit. This leads to a problem called
144 spurious regression, and the model developed this way will not accurately reflect the causal
145 relationships between the variables. Therefore, in order to remove the deterministic (linear)
146 trend of variables, all the variables are regressed against time, which is the year variable in
147 our case. This is equivalent to adding (or forcing) ‘year’ as an independent variable
148 (Hamilton, 1994).

149 We note that de-trending of a time series can also be performed by “differencing” if
150 there is a stochastic trend, and results from the Augmented Dickey-Fuller (ADF) unit root test
151 show that all variables are non-stationary in levels and stationary in first differences except
152 for interest rates. The ADF test speaks to data stationarity, i.e., whether the statistical
153 properties of the time series are constant over time; further detail on this test can be found in
154 the supplementary information. However, here we focus on de-trending the deterministic
155 trend (Hamilton, 1994). By adding the time term in the models we are able to capture
156 unobserved effects that might drive copper supply to increase exponentially, such as
157 technology improvement, population growth, etc. Interested readers can refer to Figure S1 in
158 the supporting information, where we find that the model which starts with differencing does
159 not fit the actual data as well as the model which starts with linear de-trending.

160

161 The relationships between dependent and independent variables were modeled using
162 autoregressive distributed lag (ARDL) model. The modeling method consisted of five basic
163 steps designed to understand which type of independent variable correlates with scrap
164 volumes over time. First, we grouped the hypothesized explanatory variables by identifying
165 those that had strong correlation ($\rho^2 > 0.5$) to end up with candidates from each hypothesis of
166 what may drive scrap availability (this is a modeling assertion to consider possible influence
167 from the hypothesized categories). Once we obtained these groups, we used the correlation

168 coefficient between independent variables and explanatory variables within each group to
 169 decide which variable from each group to move into the next step. In addition to individual
 170 variables, we also included all possible combinations of first-order interaction terms. In this
 171 way, we screened for the most influential variable within a category.

172 Next, in order to further reduce the number of explanatory variables used, we use forward
 173 stepwise regression for variable selection. The variable to include in each step is based on
 174 Bayesian information criterion (BIC). An often used guideline suggests that at most $m/10$ or
 175 even $m/20$ candidate variables should be considered for inclusion in the regression model,
 176 where m is the number of observations (Harrell, 2015). So to be conservative we have
 177 included no more than three direct variables in the model (the inclusion of lag terms may add
 178 more than three). The variables identified in the forward selection serve as a starting point for
 179 ARDL model. An ARDL model, where there are k covariates and the j^{th} covariate has q_j
 180 autoregressive terms, is of the form:

$$181 \quad Y_t = c + \sum_{p=1}^P \gamma_{t-p} Y_{t-p} + \sum_{j=1}^k \sum_{i=0}^{q_j} \alpha_{j,t-i} X_{j,t-i} + \varepsilon_t \quad (1)$$

182 As the ordinary least squares (OLS) model requires that the error terms have no
 183 autocorrelation, we run the OLS model and look at the autocorrelation function (ACF) plot of
 184 the regression residuals. If residuals exhibit significant autocorrelation, then lag terms of
 185 variables should be included.

186 Finally, we determine which lag orders for which terms to include. To do this we first
 187 use BIC of the vector autoregressive model (VAR) to determine the optimal lag order l . The
 188 VAR model is essentially an ARDL model where all q_j 's and p equal to l . Second, we
 189 determine the appropriate lag terms to be included by adding lag terms into the OLS model in
 190 step 3. The OLS model includes one dependent variable and k independent variables, so we
 191 assess all models with different lag terms included, where the q_j 's and p vary from 0 to l .
 192 Goodness-of-fit was evaluated through adjusted r^2 and mean absolute percentage error
 193 (MAPE). In addition, a back-casting MAPE of each of these $((k+1)^{l+1})$ models is compared
 194 and the best model is selected. Models are first trained using only 1972 to 2002 data, and the
 195 MAPE of fitted scrap supply values in the test set 2003 to 2012 is calculated. Then the
 196 training set is moved one year forward (1973 to 2003) and the MAPE is calculated for 2004
 197 to 2012. We repeat this procedure until the training set includes the last year of data, and
 198 calculate the average of the 10 MAPE's as the goodness-of-fit metric for models comparison.
 199 By calculating the MAPE this way, we cross-validated the model performance using different
 200 test sets, and also preserve the time series structure with the continuous annual sequence in
 201 the training set. In this way we aim to have a robust analysis of the economic and physical
 202 variables that are related to supply of copper scrap.

203 **3. Results and Discussion**

204 **3.1 Total Copper Scrap Supply**

205 Based on the method described above, we first explore the relationship between the variables
 206 of interest and **total** copper scrap supply. In the first step, 29 explanatory variables are
 207 partitioned into 11 groups, and within each group the variable that shows the strongest

208 correlation with total scrap quantity is carried to the next step (see supporting information for
 209 grouping results). Via forward stepwise variable selection we then include three explanatory
 210 variables: OECD Industrial Production Index (OECDIP), the difference between price and 5
 211 year trailing average (DTA5) and an Electrical Equipment, Appliance, and Component Index
 212 (EEAC). Time is also forced in the model as described above.

213 As shown in supporting information, the ACF plot of the OLS regression residuals
 214 does show significant autocorrelation, so lag terms of the dependent and the independent
 215 variables need to be included. BIC of the VAR model shows that at most the first lags should
 216 be included and the higher order lags are unnecessary. Now that the optimal lag order $l=1$
 217 and $k=3$ independent variables are included in the model, $(k+1)^{l+1} = 16$ are compared. The
 218 back-casting MAPE shows that the highest performing model for total scrap supply can be
 219 expressed via Equation 2 and the coefficients provided in Table 1.

$$220 \quad Total_t = c + \alpha t + \gamma Total_{t-1} + \beta_1 OECDIP_t + \beta_2 DTA5_t + \beta_3 DTA5_{t-1} + \beta_4 EEAC_t$$

$$221 \quad + \varepsilon_t \quad (2)$$

222 The ARDL model residuals also do not show significant autocorrelation for the first few
 223 terms as shown in the supporting information.

<i>Dependent variable:</i>	
Total	
Constant	-18.376*** (6.388)
Year	0.012*** (0.003)
1st lag of dep var	0.332*** (0.100)
OECD IP	0.003 (0.002)
DTA5	0.001*** (0.0001)
1st lag of DTA5	-0.0004*** (0.0001)
EEAC	0.003*** (0.001)
Observations	40
R ²	0.992
Adjusted R ²	0.990
Residual Std. Error	0.034 (df = 33)
F Statistic	661.784*** (df = 6; 33)

224 *Note:* *p<0.1; **p<0.05; ***p<0.01

225 **Table 1. Summary of the highest performing ARDL model for total scrap supply**

226 Assuming the variables in the model are stable in the long run², the long run effect from
 227 OECDIP, DTA5 and EEAC is $\frac{\beta_1}{1-\gamma}$, $\frac{\beta_2 + \beta_3}{1-\gamma}$, $\frac{\beta_4}{1-\gamma}$ respectively, and the values are 5.2×10^{-3} ,
 228 2.5×10^{-4} , 4.9×10^{-3} . Since the values of all three explanatory variables are around 100,
 229 this means that +1% change in OECDIP and EEAC would lead to approximately +0.5%
 230 change in copper scrap supply, while +1% in DTA5 would only lead to about +0.025%
 231 change. Therefore, we interpret that OECDIP and EEAC are the two main drivers of total
 232 copper scrap supply. In market equilibrium models, the equilibrium quantity we observe is
 233 influenced by supply shifters and demand shifters simultaneously (Mankiw, 2006). Our
 234 model reflects this theory as OECDIP is a supply shifter for the level of industrial production
 235 in developed countries, while EEAC reflects the level of manufacturing (and therefore
 236 demand) for electrical products, an end use that accounted for more than 20% of copper
 237 demand in 2012 (Kelly et al. , 2010).

238 The regression coefficients for OECDIP and EEAC are positive, i.e. everything else
 239 equal, an increase in either independent variable correlates with an increase in scrap supply.
 240 This follows our intuition for the behavior of scrap availability as a function of changes in IP
 241 index where increased industrial activity is likely to boost both the source of scrap (e.g.
 242 increased demolition and manufacturing) as well as processed scrap demand (e.g. from brass
 243 mills). A positive relationship between materials supply and industrial activity has also been
 244 found for primary metal (Binder et al. , 2006). We also observe that the regression coefficient
 245 for the lagged dependent variable is positive and less than one. This means that an increase in
 246 scrap supply is likely to be followed by further increase in succeeding years, everything else
 247 equal. Conversely, a decrease in scrap volume is more likely succeeded by further decrease
 248 than an increase. This may suggest that scrap which is not collected in year t (because of
 249 factors such as price and industrial activity) may not necessarily be available in year $t+1$. In
 250 line with this, others have found that old scrap stocks, the stock of copper having reached its
 251 end-of-life without being recycled, have a very modest impact on the production of
 252 secondary copper (Gomez, Guzman, 2007). At least to some degree this correlation suggests
 253 whether or not the metal may be recycled at all. Metal products reaching their end-of-life in a
 254 year with falling industrial production may not simply be set aside for recycling in more
 255 prosperous years – they may never be recycled (Blomberg and Soderholm, 2009).

256 Lastly, we note that we found no significant correlation between secondary and
 257 primary copper supply even when not correcting for IP and price. While links between
 258 primary and secondary metal markets exist, especially in terms of price and volatility
 259 (Xiarchos and Fletcher, 2009), our results suggest that the supply of secondary copper is not
 260 strongly correlated with the supply of primary copper.

261 In this first result, we treated different categories of copper scrap supply together.
 262 However, since the dataset (and metallurgical reality) of copper scrap is partitioned into high
 263 quality scrap (direct melt scrap) and low quality scrap (refined scrap), we also investigate

² In the ARDL model, the short run effect of an explanatory variable is directly represented by the estimated regression coefficient, while the long run effect is estimated assuming that the variable of interest is stable in time. For example, we assume that scrap supply is stable, therefore $Total_t = Total_{t-1} = \widehat{Total}$, the long run effect of *OECDIP* is $\frac{\partial Total}{\partial OECDIP} = \frac{\beta_1}{1-\gamma}$.

264 these two scrap populations independently to understand whether the drivers behind them are
 265 different.

266

267 **3.2 Direct Melt Scrap**

268 We now focus on models for which **direct melt scrap** volumes are the dependent variable. In
 269 this case variable grouping and forward stepwise variable selection yields three explanatory
 270 variables: United States Industrial Production Index (USIP), HVAC, metalworking, and
 271 power transmission machinery Index (IPDG) and EEAC. Time is again forced in the model.
 272 The ACF plot of the OLS model exhibits significant autocorrelation, and the highest
 273 performing back-casting MAPE ARDL model is summarized in Table 2 (with details in the
 274 supporting information).

	<i>Dependent variable:</i>
	Direct Melt
Constant	13.553 (8.403)
Year	-0.005 (0.004)
1st lag of dep var	0.409** (0.159)
USIP	0.013*** (0.004)
IPDG	-0.002 (0.001)
EEAC	0.007*** (0.002)
1st lag of EEAC	-0.004* (0.002)
Observations	40
R ²	0.986
Adjusted R ²	0.983
Residual Std. Error	0.046 (df = 33)
F Statistic	382.408*** (df = 6; 33)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

275

276 **Table 2. Summary of the best ARDL model for direct melt scrap supply, termed DM**
 277 **FSVS (direct melt forward stepwise variable selection)**

278

279 The long run effects from USIP, IPDG and EEAC are 2.2×10^{-2} , -3.3×10^{-3} , 4.0×10^{-3}
 280 respectively. All three indicators are normalized to a scale of 100, so with +1% change in the
 281 three variables, direct melt copper scrap supply would change approximately 2.2%, -0.33%
 282 and 0.4% respectively. It is clear that among the three variables, USIP is the main driver of
 283 scrap supply. Although the USIP index is calculated only for US, its time series is very
 284 similar to OECDIP ($\rho = 0.99$). Therefore, we interpret from the estimated regression

285 coefficients that direct melt copper scrap supply is driven by level of industrial production
 286 activity for developed countries.

287
 288 The complexity of this model (which we will refer to as DM FSVS – direct melt forward
 289 stepwise variable selection) lies on the edge of Harrell’s rule of thumb which requires that a
 290 minimum of 10 observations are required per each explanatory variable). Therefore, in order
 291 to further reduce the risk of over-fitting, we test (based on our cross-validated back casting
 292 MAPE) a simpler ARDL model (DM simplified) where we start with an OLS model that only
 293 includes year and USIP (based on the strength of the correlation with USIP described above).
 294 This DM simplified model is summarized in Table 3 and does not show significant
 295 autocorrelation.

<i>Dependent variable:</i>	
Direct Melt	
Constant	9.633 (5.762)
Year	-0.003 (0.003)
1st lag of dep var	0.485*** (0.174)
USIP	0.021*** (0.003)
1st lag of USIP	-0.010** (0.005)
Observations	40
R ²	0.981
Adjusted R ²	0.979
Residual Std. Error	0.051 (df = 35)
F Statistic	455.322*** (df = 4; 35)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

296
 297 **Table 3. Summary of the best performing simplified model for direct melt scrap supply,**
 298 **termed DM simplified**
 299

300 The long run effect from USIP is 0.021, which means that everything else being equal, a +1%
 301 change in USIP would lead to approximately +2.1% change in direct melt copper scrap
 302 supply. We find that the performance of the DM simplified model developed by choosing the
 303 variable with strongest dependence is similar to our more complex model found through
 304 forward stepwise variable selection. DM FSVS and DM simplified exhibit similar adjusted r²,
 305 and MAPE values. We summarize this DM model comparison along with the model for
 306 refined scrap found in the next section in Table 6 (and section 3.4). The **Test MAPE** shown
 307 in the table is the back-casting MAPE using 1972~2002 data as the training set and
 308 2003~2012 data as the test set.

309

310 **3.3 Refined Scrap**

311 We then use **refined scrap** volumes as the dependent variable and perform the regression
 312 analysis, following the same procedure. After variable grouping and forward stepwise
 313 variable selection, three explanatory variables are included in the refined (R FSVS) model:
 314 world GDP (WGDP), Mining Index (MI) and real refined copper price, and a year variable is
 315 again forced in the model. ACF plot of the OLS model exhibits significant autocorrelation
 316 (Figure S2), and the best performing R FSVS ARDL model selected is summarized in Table
 317 4.

<i>Dependent variable:</i>	
	Refined
Constant	-0.325 (7.405)
Year	-0.005 (0.006)
1st lag of dep var	0.731*** (0.120)
WGDP	-0.103 (0.248)
1st lag of WGDP	0.465* (0.241)
MI	0.003 (0.002)
Price	0.292*** (0.055)
1st lag of Price	-0.270*** (0.058)
Observations	40
R ²	0.978
Adjusted R ²	0.974
Residual Std. Error	0.055 (df = 32)
F Statistic	207.784*** (df = 7; 32)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

318 **Table 4. Summary of the best performing model for refined scrap supply, termed R**
 319 **FSVS**
 320
 321

322 The long run effects from WGDP, MI and price are 1.35, 0.011 and 0.082 respectively. Since
 323 WGDP and price are already log transformed, the estimated regression coefficients can be
 324 directly interpreted as supply elasticities (Blomberg and Soderholm, 2009). This means that
 325 +1% change in world GDP and copper price would lead to +1.35% change and 0.08% change
 326 in refined copper scrap supply, respectively. Given that values of MI are normalized to a
 327 scale of 100, +1% change in MI would lead to about +1.1% change in refined copper scrap
 328 supply.

329 Previous work has shown that steel is price inelastic and the demand elasticity is in
 330 the range of -0.2 to -0.3 (Malanichev and Vorobyev, 2011). Therefore, based on the estimated
 331 price elasticity, we argue that refined copper scrap supply is price inelastic, and its main
 332 drivers are world GDP and level of mining activity. MI on the other hand, reflects the

333 manufacturing output of the entire mining industry in US, and therefore can be seen as a
 334 supply shifter that affects copper supply in a general way.

335 World GDP is an approximation of global income growth rate and reflects demand of
 336 products in general. It can, therefore, be considered as a demand shifter in general accordance
 337 with economic theory. Since the long run effects from world GDP is the greatest among three
 338 variables, we also explore a simpler ARDL model (R simplified) similar to the one we
 339 develop for direct melt copper scrap. We start with an OLS model that only includes year and
 340 WGDP, and select the best back-casting MAPE ARDL model, which is summarized in Table
 341 5.

<i>Dependent variable:</i>	
	Refined
Constant	-1.822 (6.498)
Year	-0.007 (0.005)
1st lag of dep var	0.504*** (0.120)
WGDP	0.610*** (0.169)
Observations	40
R ²	0.956
Adjusted R ²	0.952
Residual Std. Error	0.075 (df = 36)
F Statistic	259.567*** (df = 3; 36)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

342
 343 **Table 5. Summary of the best performing simple model for refined scrap supply,**
 344 **termed R simplified**
 345

346 We find that the complex model slightly outperforms the simple model in terms of adjusted r^2
 347 and MAPE, but the simple model has a significantly lower back-casting MAPE shown in
 348 Table 6. We compare the performance of each of the FSVS and simplified models for direct
 349 melt and refined in the next section.

350 We have shown that direct melt copper scrap supply is driven mainly by the level of
 351 industrial production in developed countries, while refined copper scrap supply is driven
 352 mainly by income growth rate and level of mining activities. In addition, the simplified
 353 ARDL models for direct melt and refined scrap, which include only one explanatory variable,
 354 offer similar or better performance compared to the complex models.

355 We see limited dependence of copper supply on price. Refined scrap, the lower
 356 quality portion of the two, correlates in a limited way with price (and indirectly through
 357 GDP), but not with industrial activity. Direct melt scrap, the higher quality portion of the two,
 358 correlates with industrial activity, but not with price. The low own-price elasticity of
 359 secondary refined copper production of 0.08 is comparable to previous findings from

360 secondary materials, such as copper (0.25 to 0.29), aluminum (0.18 to 0.32) and paper (0.20-
 361 0.30)(Blomberg and Soderholm, 2009, Fisher et al. , 1972, Mansikkasalo, Lundmark, 2014).
 362 The relatively low own-price elasticity of recycled material supply is in part due to its
 363 dependence on past consumption patterns.

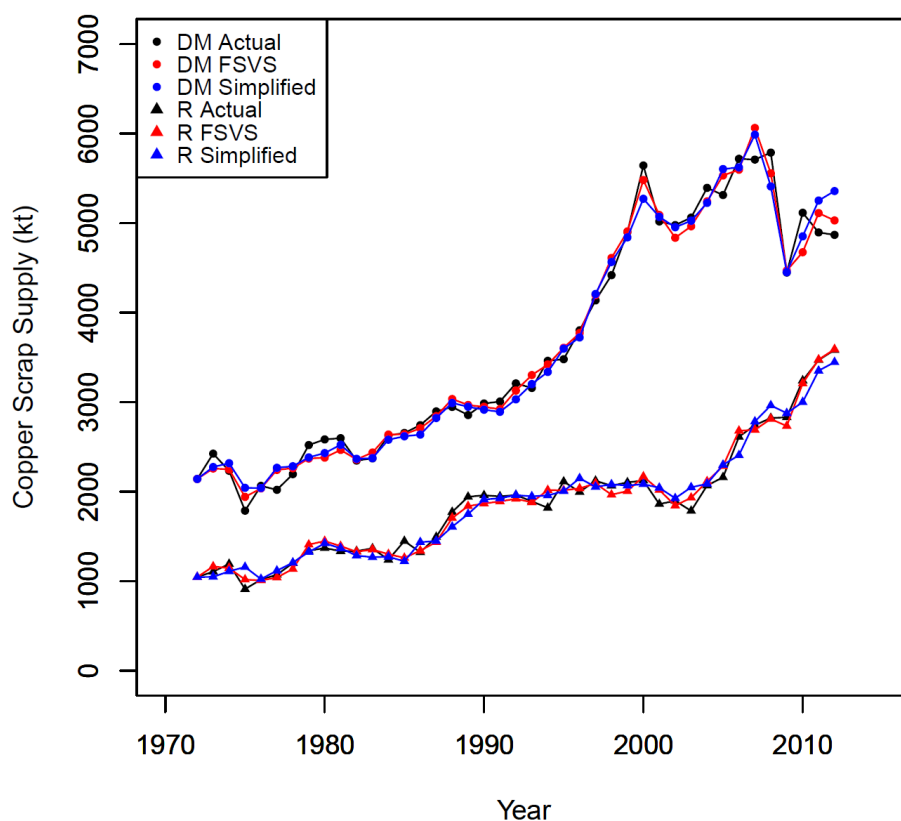
364

365 **3.4 Model performance comparison**

366 In section 3.1, we did not differentiate high quality copper scrap from low quality scrap,
 367 and demonstrated that two main drivers of total scrap supply were OECDIP and EEAC,
 368 which reflect levels of industrial production in developed countries and production of
 369 electrical products. On the other hand, our independent models for direct melt scrap and
 370 refined scrap contained USIP as the most important driver for direct melt scrap and WGDP
 371 for refined scrap. Although these are different variables from the ones in the total scrap
 372 model, they essentially reflect the same categories of drivers of scrap availability: OECDIP
 373 and USIP both reflect how industrial production in developed countries drives supply of
 374 copper scrap, while EEAC reflect drivers for copper demand in a specific end-use sector and
 375 WGDP for copper demand in general.

376 Here we compare model performance to synthesize our findings on what drives
 377 copper scrap availability. First, Figure 1 plots the FSVS (red lines) and simplified (blue lines)
 378 models for direct melt (circles) and refined (triangles) copper along with the actual historic
 379 data on copper scrap supply (black lines). The similarity among the lines for each scrap type
 380 is clear and Table 6 summarizes the quantitative comparison between the FSVS and
 381 simplified models.

382



383

384 Figure 1. Comparison of FSVS (red) and simplified (blue) econometric models for direct
 385 melt (circles) and refined (triangles) scrap with actual historic copper scrap supply (black) in
 386 kilotons.
 387

Model	Equation	Adj. R^2	MAPE	Test MAPE
DM FSVS	$DM_t \sim t + DM_{t-1} + USIP_t + IPDG_t + EEAC_t + EEAC_{t-1}$	0.983	0.41%	0.50%
DM Simplified	$DM_t \sim t + DM_{t-1} + USIP_t + USIP_{t-1}$	0.979	0.47%	0.56%
R FSVS	$R_t \sim t + R_{t-1} + WGDP_t + WGDP_{t-1} + MI_t + Price_t + Price_{t-1}$	0.974	0.53%	1.27%
R Simplified	$R_t \sim t + R_{t-1} + WGDP_t$	0.952	0.70%	0.81%

388
 389 **Table 6. Comparison of simplified and FSVS models for direct melt and refined scrap**
 390 **supply**
 391

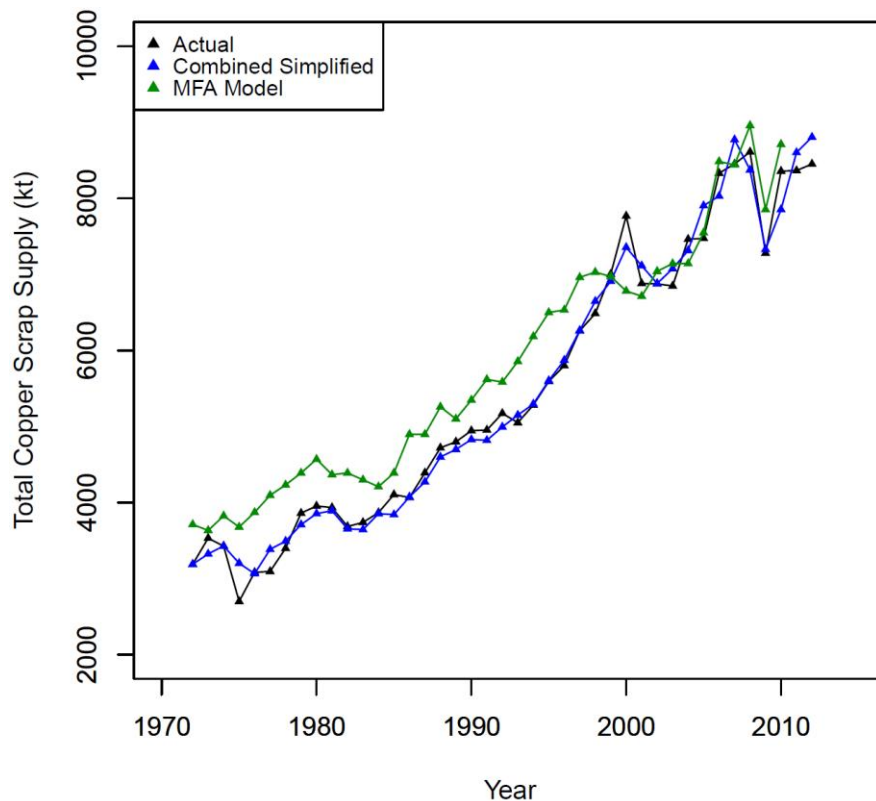
392 Now that we have independent models for direct melt scrap and refined scrap, we develop
 393 two additional models for **total** copper scrap supply and compare model performance. The
 394 first additional model adds up the fitted variables of direct melt scrap and refined scrap from
 395 the simple ARDL models (combined simplified). The second model performs an independent
 396 regression including the variables used in the two independent simple ARDL models
 397 (simplified). In order to demonstrate that the variables included are important, we also add
 398 two other models for comparison. The first is a model that only includes lead terms USIP
 399 (Optional model 1), and the second includes two less significant variables which are 10 year
 400 interest rate (Constant Maturity Rate) and price (Optional model 2). The performance of
 401 these four models compared with the total FSVS model developed in section 3.1 is
 402 summarized in Table 7.
 403

Model for Total	Equation	Adj. R^2	MAPE	Test MAPE
FSVS	$Total_t \sim t + Total_{t-1} + OECDIP_t + DTA5_t + DTA5_{t-1} + EEAC_t$	0.990	0.28%	0.44%
Combined Simplified	Addup the fitted values from DM simplified and R simplified	0.980	0.36%	0.41%
Simplified	$Total_t \sim t + Total_{t-1} + WGDIP_t + USIP_t + USIP_{t-1}$	0.982	0.37%	0.51%
Optional Model 1	$Total_t \sim USIP_t$	0.965	0.58%	0.60%
Optional Model 2	$Total_t \sim t + Interest_t + Price_t$	0.965	0.58%	0.60%

Table 7. Comparison of different econometric models for total scrap supply

We find that the first three models in Table 7 perform similarly. The FSVS model, our ‘complex’ model for total scrap supply, is the best model in terms of fitting. Combined simplified, the add-up of two simplified ARDL models, is the best in terms of predictive power. All three have improved performance over the other models in Table 7.

One of our motivations for this econometric study of copper scrap supply was as a complementary approach to material flow analysis (MFA) to quantify copper scrap supply (or potential supply). An example of the differences between these approaches is shown in Figure 2, where we’ve plotted MFA results by Gloser et al. (Gloser, Soulier, 2013), along with the fitted values from the combined simplified model, which we have chosen based on its predictive performance. We see improved performance for the econometric model over the MFA model for certain time periods. In addition, the MAPE of the combined simplified model is 0.36%, while the MAPE of MFA is 1.27%. This observation, in addition to the relatively lower effort and data requirements of econometric modeling make it an attractive route for short term estimation. In addition to the estimates shown in Figure 2, however, the two methods produce an array of useful information and are complementary. For example, while the MFA model yields collection rates of waste types, econometric models may shed light on how efficient incentives can be at improving those rates.



425
 426 Figure 2. Comparison of econometric “combined simplified” model, MFA results (Gloser,
 427 Soulier, 2013) and historic copper scrap supply in kilotons
 428

429 **4. Conclusion**

430 We have adopted and modified an approach to develop a set of econometric models
 431 for quantifying secondary copper supply. Our investigation of econometric drivers of scrap
 432 availability led to several conclusions that we summarize here. Total scrap is most strongly
 433 correlated with variables such as the OECD Industrial Production and production indices of
 434 copper-containing products, such as electrical equipment and appliances. We found that an
 435 increase in either of these variables corresponds to an increase in scrap supply. Based on
 436 incorporation of a lagged term on scrap supply, our model on total scrap supply also suggests
 437 that scrap which is not collected in one year may not necessarily be available for collection in
 438 subsequent years. Previous work has commented on potential availability of these so called
 439 hibernating stocks (Daigo et al. , 2015). This potential for scrap hibernation indicates that
 440 incentives should focus on capturing material as soon as scrap is generated or focus on
 441 reduction of collection costs.

442 The models that we developed independently for direct melt (higher quality) and
 443 refined scrap demonstrated complementary correlations. Our model of direct melt scrap
 444 correlates most strongly with the Industrial Production index for the US, while for refined
 445 scrap the dependence is dominated by world GDP and mining activity, with a limited
 446 correlation with price. More generally, direct melt scrap availability demonstrates stronger
 447 dependence on so-called supply shifting variables, while refined scrap depends more on
 448 demand shifting variables. Finally, we have shown that the performance of these econometric
 449 models performs as well or better than an MFA-derived model of historic scrap supply, and,

450 therefore, provides an opportunity for a complementary approach to understand flows of
451 recycled material.

452 The results above suggest that as long as scrap is generated (e.g. through demolition
453 and manufacturing waste) higher quality scrap will be collected and used to produce copper
454 products almost regardless of price. This follows intuition that the collection of lower grade
455 scrap would be more related to the economics of the collectors. The cost of collection (and
456 processing for market) are on the order of the price for this grade of copper meaning that
457 price fluctuations make some forms of collection and processing less attractive, although with
458 *limited* influence. This is in contrast to the higher value material, where its higher price is
459 effectively always above the threshold that triggers willingness to collect and process. It
460 could be that further processing steps on the lower grade material add a cost to the production
461 of secondary copper cathode that make the industry margins more sensitive to price changes.

462 The relationship between secondary material supply and explanatory variables has
463 previously been discussed in light of price and quantity based policy strategies (Sigman,
464 1995). For example, a necessary condition for price-based policies to be effective is some
465 correlation between material supply and price (Blomberg and Soderholm, 2009). By
466 accounting for the quality of the scrap, the present study takes this discussion one step
467 further: the lower the quality of scrap, the higher the potential impact of price.

468 Now that we have explored potential drivers of scrap availability, we comment briefly
469 on relevant policy instruments that have been used to influence scrap availability (or to drive
470 increased recycling). Generally market-based policy instruments include tax-subsidy
471 combinations with a disposal fee, deposit-refund (combined output tax and recycling subsidy)
472 and tradeable permit schemes. Research has found that these fees should be matched as
473 closely as possible to the cost of waste disposal or the potential for damage (Calcott and
474 Walls, 2005), but these combined approaches have been found to be more effective than only
475 taxing waste or use of virgin materials (Kinnaman, 2016). These policy instruments can be
476 contrasted with end-of-pipe or more general emissions monitoring on primary alternatives,
477 which act more indirectly to increase recycling and are generally more costly (Soderholm,
478 2011). We therefore hypothesize that any policy instruments based on price should be
479 directed towards the low-end segment of the scrap market where they may have more impact.
480 This analysis has focused on primary copper price, which may not be as effective a proxy for
481 lower grade scrap. In other words, low quality scrap may have a stronger correlation with
482 primary copper price but is still inelastic to secondary copper prices. Materials that
483 demonstrate own-price inelasticity (as we have demonstrated here) should likely be taxed
484 higher than those which exhibit greater price sensitivity (or these policies may have little
485 impact on recycling rates). Alternatively, we hypothesize that measures directed at demand-
486 side behavior may have stronger impact or policies that facilitate willingness to invest in
487 collection and recycling infrastructure, such as forward contracts. Others have proposed
488 tighter coupling or cooperation between primary and secondary producers (Løvik et al. ,
489 2014), so our findings also show this may be a promising strategy, both in terms of cost
490 effectiveness and potential for increasing scrap availability.

491

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497

498 REFERENCES

- 499 Achillas C, Aidonis D, Vlachokostas C, Karagiannidis A, Moussiopoulos N, Loulos V. Depth
500 of manual dismantling analysis: A cost-benefit approach. *Waste Manage.* 2013;33:948-56.
501 Alonso E, Field FR, Kirchain RE. Platinum Availability for Future Automotive
502 Technologies. *Environ Sci Technol.* 2012;46:12986-93.
503 Alonso E, Gregory J, Field F, Kirchain R. Material availability and the supply chain: Risks,
504 effects, and responses. *Environ Sci Technol.* 2007;41:6649-56.
505 Angus A, Casado MR, Fitzsimons D. Exploring the usefulness of a simple linear regression
506 model for understanding price movements of selected recycled materials in the UK.
507 *Resources Conservation and Recycling.* 2012;60:10-9.
508 Azadeh A, Neshat N, Mardan E, Saberi M. Optimization of steel demand forecasting with
509 complex and uncertain economic inputs by an integrated neural network-fuzzy mathematical
510 programming approach. *Int J Adv Manuf Tech.* 2013;65:833-41.
511 Baffes J, Savescu C. Monetary conditions and metal prices. *Appl Econ Lett.* 2014;21:447-52.
512 Bertram M, Graedel TE, Rechberger H, Spatari S. The contemporary European copper cycle:
513 waste management subsystem. *Ecological Economics.* 2002;42:43-57.
514 Binder CR, Graedel TE, Reck B. Explanatory variables for per capita stocks and flows of
515 copper and zinc - A comparative statistical analysis. *J Ind Ecol.* 2006;10:111-32.
516 Blomberg J, Soderholm P. The economics of secondary aluminium supply: An econometric
517 analysis based on European data. *Resources Conservation and Recycling.* 2009;53:455-63.
518 Calcott P, Walls M. Waste, Recycling, and Design for Environment. *Resource and Energy*
519 *Economics.* 2005;27:287-305.
520 Chen WQ. Recycling Rates of Aluminum in the United States. *J Ind Ecol.* 2013;17:926-38.
521 Cullen JM, Allwood JM. Mapping the Global Flow of Aluminum: From Liquid Aluminum to
522 End-Use Goods. *Environ Sci Technol.* 2013;47:3057-64.
523 Daigo I, Iwata K, Ohkata I, Goto Y. Macroscopic evidence for the hibernating behavior of
524 materials stock. *Environ Sci Technol.* 2015;49:8691-6.
525 Elshkaki A, van der Voet E, Timmermans V, Van Holderbeke M. Dynamic stock modelling:
526 A method for the identification and estimation of future waste streams and emissions based
527 on past production and product stock characteristics. *Energy.* 2005;30:1353-63.
528 Finnveden G, Ekvall T, Arushanyan Y, Bisailon M, Henriksson G, Ostling UG, et al. Policy
529 Instruments towards a Sustainable Waste Management. *Sustainability-Basel.* 2013;5:841-81.
530 Fisher FM, Cootner PH, Bailey MN. Econometric Model of World Copper Industry. *Bell J*
531 *Econ.* 1972;3:568-609.
532 Flores GRFA, Nikolic S, Mackey PJ. ISASMELT (TM) for the Recycling of E-Scrap and
533 Copper in the U.S. Case Study Example of a New Compact Recycling Plant. *Jom-U.S.*
534 2014;66:823-32.
535 Gaustad G, Olivetti E, Kirchain R. Design for Recycling. *J Ind Ecol.* 2010;14:286-308.
536 Gleich B, Achzet B, Mayer H, Rathgeber A. An empirical approach to determine specific
537 weights of driving factors for the price of commodities-A contribution to the measurement of
538 the economic scarcity of minerals and metals. *Resour Policy.* 2013;38:350-62.
539 Gloser S, Soulier M, Espinoza LAT. Dynamic Analysis of Global Copper Flows. *Global*
540 *Stocks, Postconsumer Material Flows, Recycling Indicators, and Uncertainty Evaluation.*
541 *Environ Sci Technol.* 2013;47:6564-72.

542 Gomez F, Guzman JI, Tilton JE. Copper recycling and scrap availability. *Resour Policy*.
543 2007;32:183-90.

544 Gsodam P, Lassnig M, Kreuzeder A, Mrotzek M. The Austrian silver cycle: A material flow
545 analysis. *Resources Conservation and Recycling*. 2014;88:76-84.

546 Habuer, Nakatani J, Moriguchi Y. Time-series product and substance flow analyses of end-
547 of-life electrical and electronic equipment in China. *Waste Manage*. 2014;34:489-97.

548 Hamilton JD. *Time series analysis*: Princeton university press Princeton; 1994.

549 Harrell F. *Regression modeling strategies: with applications to linear models, logistic and
550 ordinal regression, and survival analysis*: Springer; 2015.

551 ICSG. *The World Copper Factbook*. 2013.

552 Kelly TD, Matos GR, Buckingham D, DiFrancesco C, Porter K, Berry C, et al. Historical
553 statistics for mineral and material commodities in the United States. *US Geological Survey
554 data series*. 2010;140.

555 Kinnaman TC. Understanding the Economics of Waste: Drivers, Policies, and External Costs.
556 *International Review of Environmental and Resource Economics*. 2016;8:281-320.

557 Lifset RJ, Eckelman MJ, Harper EM, Hausfather Z, Urbina G. Metal lost and found:
558 Dissipative uses and releases of copper in the United States 1975-2000. *Sci Total Environ*.
559 2012;417:138-47.

560 Liu G, Muller DB. Centennial Evolution of Aluminum In-Use Stocks on Our Aluminized
561 Planet. *Environ Sci Technol*. 2013;47:4882-8.

562 Løvik AN, Modaresi R, Müller DB. Long-Term Strategies for Increased Recycling of
563 Automotive Aluminum and Its Alloying Elements. *Environ Sci Technol*. 2014;48:4257-65.

564 Malanichev A, Vorobyev P. Forecast of global steel prices. *Studies on Russian Economic
565 Development*. 2011;22:304-11.

566 Mankiw N. *Principles of microeconomics*: Cengage Learning; 2006.

567 Mansikkasalo A, Lundmark R, Soderholm P. Market behavior and policy in the recycled
568 paper industry: A critical survey of price elasticity research. *Forest Policy Econ*. 2014;38:17-
569 29.

570 McMillan CA, Moore MR, Keoleian GA, Bulkley JW. Quantifying US aluminum in-use
571 stocks and their relationship with economic output. *Ecological Economics*. 2010;69:2606-13.

572 Muller E, Hilty LM, Widmer R, Schluep M, Faulstich M. Modeling Metal Stocks and Flows:
573 A Review of Dynamic Material Flow Analysis Methods. *Environ Sci Technol*.
574 2014;48:2102-13.

575 Northey S, Mohr S, Mudd GM, Weng Z, Giurco D. Modelling future copper ore grade
576 decline based on a detailed assessment of copper resources and mining. *Resources
577 Conservation and Recycling*. 2014;83:190-201.

578 Olivetti EA, Gaustad GG, Field FR, Kirchain RE. Increasing Secondary and Renewable
579 Material Use: A Chance Constrained Modeling Approach To Manage Feedstock Quality
580 Variation. *Environ Sci Technol*. 2011;45:4118-26.

581 Rankin WJ. Minerals, Metals and Sustainability Meeting Future Material Needs An
582 introduction to sustainability. *Minerals, Metals and Sustainability: Meeting Future Material
583 Needs*. 2011:41-61.

584 Reck BK, Graedel TE. Challenges in Metal Recycling. *Science*. 2012;337:690-5.

585 Rubin RS, de Castro MAS, Brandao D, Schalch V, Ometto AR. Utilization of Life Cycle
586 Assessment methodology to compare two strategies for recovery of copper from printed
587 circuit board scrap. *J Clean Prod*. 2014;64:297-305.

588 Ruth M. Thermodynamic constraints on optimal depletion of copper and aluminum in the
589 United States: A dynamic model of substitution and technical change. *Ecological Economics*.
590 1995;15:197-213.

591 Sigman HA. A Comparison of Public Policies for Lead Recycling. *Rand J Econ.*
592 1995;26:452-78.

593 Slade ME. An Econometric-Model of the United-States Secondary Copper-Industry -
594 Recycling Versus Disposal. *Journal of Environmental Economics and Management.*
595 1980;7:123-41.

596 Slade ME. Trends in natural-resource commodity prices: An analysis of the time domain.
597 *Journal of Environmental Economics and Management.* 1982;9:122-37.

598 Soderholm P. Taxing virgin natural resources: Lessons from aggregates taxation in Europe.
599 *Resources Conservation and Recycling.* 2011;55:911-22.

600 Soderholm P, Tilton JE. Material efficiency: An economic perspective. *Resources*
601 *Conservation and Recycling.* 2012;61:75-82.

602 Solow RM. Economics of Resources or Resources of Economics. *Am Econ Rev.* 1974;64:1-
603 14.

604 Wagenhals G. The World Copper Market - Structure and Econometric-Model. *Lect Notes*
605 *Econ Math.* 1984;233:R3-+.

606 Wang P, Jiang ZY, Geng XY, Hao SY, Zhang XX. Quantification of Chinese steel cycle
607 flow: Historical status and future options. *Resources Conservation and Recycling.*
608 2014;87:191-9.

609 Wubbeke J, Heroth T. Challenges and political solutions for steel recycling in China.
610 *Resources Conservation and Recycling.* 2014;87:1-7.

611 Xiarchos IM, Fletcher JJ. Price and volatility transmission between primary and scrap metal
612 markets. *Resources Conservation and Recycling.* 2009;53:664-73.

613