What Affects the Secondhand Value of Smartphones

Evidence from eBay

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Summary

Reuse via secondhand markets can extend the use phase of products, thereby reducing environmental impacts. Analyzing 500,000 listings of used Apple and Samsung smartphones sold in 2015 and 2016 via eBay, we examine which product properties affect how long smartphones retain market value and facilitate market-based reuse. Our results suggest that although repairability and large memory size are typically thought to be "life extending," in practice they have limited impact on the current economic life span of smartphones and their market-based reuse. In contrast, we show that brand, an intangible product property, can extend smartphones' economic life span by 12.5 months. Because longer economic life spans imply extended use phases and longer life spans overall, these results illustrate the potential of harnessing the intangible properties of products to promote sustainable consumption.

Introduction

With penetration rates nearing 90% in developed countries, mobile phones today are almost ubiquitous devices (Broadband Commission for Digital Development 2016). Yet alongside the evident social and economic benefits gained via increased connectivity and access to services (Corbett 2008; Aker and Mbiti 2010), the so-called mobile revolution has come at great environmental cost. For example, modern mobile phones contain over 50 different elements (O'Connor et al. 2016). These elements include conflict minerals linked to civic unrest (Moran et al. 2015; OECD 2010), rare earths subject to supply constraints and depletion (Sprecher et al. 2015, 2017), and various toxic materials (e.g., lead, arsenic) whose leakage into the natural environment has been linked to serious environmental and public health challenges (Grant et al. 2013; Chen et al. 2011; Zhang et al. 2012). Furthermore, although the climate change impacts of a single device are relatively small (e.g., 95 kilograms of carbon dioxide equivalent [$kgCO_2e$] for the iPhone 6) (Apple Inc. 2014), in aggregate, the 1.5 billion devices sold in 2016 alone could amount to over 140 billion $kgCO_2e$ (Gartner 2017).

These environmental costs are intensified as mobile phones have relatively short life spans (defined here as the time between initial purchase and disposal at end of life [EoL]), with recent estimates suggesting a use phase of less than 2 years (Geyer and Blass 2010; Wilson et al. 2017; Wieser and Tröger 2017). Some argue that products that are easy to repair may ease environmental burdens and improve resource productivity by prolonging the active use period (Felton and Bird 2006; van Nes and Cramer 2005; Yu et al. 2011; Go et al. 2015; Cooper 2016; Wieser and Tröger 2017). The basic idea is that because the production, transportation, and EoL management of each product requires a "fixed" investment of resources and energy,

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using products longer would mean gaining more utility from the same fixed investment (Skelton and Allwood 2013). Although longer life spans are not always environmentally beneficial, for products such as smartphones that require many resources up front (i.e., the fixed investment) and few resources during use (i.e., operational inputs), longer use times usually mean more efficient utilization of resources overall (Allwood et al. 2012; Frey et al. 2006; Wieser and Tröger 2017; Cooper and Gutowski 2017).

As one of the three R's (reduce, reuse, recycle), reuse is commonly seen as a basic sustainability practice that can be used to prolong a product's use phase and lower its environmental impacts. While reuse has existed as a market phenomenon for centuries, in recent years, the Internet has revolutionized the trade in preowned goods. Lowering the transaction costs of exchange and expanding the geographic boundaries of the trade, online platforms such as eBay allow consumers to find secondary buyers for their unwanted used possessions and extend their use phases (Davies and Cunningham 2012; Thomas 2011; Lee and Liao 2015; Ghose et al. 2006).

Over the past few years, trade in used smartphones has seen tremendous growth. Estimates suggest that roughly 120 million used smartphones were sold worldwide in 2016, at a total value of $17 billion (Deloitte 2016). Growing at a rate of four to five times higher than that of the overall smartphone market, reuse through the secondhand market plays an increasingly important role in extending smartphone life spans.

While sales of used smartphones could in theory cannibalize sales of new smartphones, research suggests that consumers clearly differentiate between new and used products (Abbey et al. 2017; Abbey et al. 2015) and that it is unlikely that displacement of new phones by used ones accrues on a 1:1 basis (Geyer and Blass 2010; Zink et al. 2014). As such, in some cases smartphone reuse could lead to surplus consumption and increase environmental impacts (Ovchinnikov et al. 2014; Makov and Font Vivanco 2018). Nonetheless, even though reuse could potentially backfire under certain economic conditions, the benefits of a longer use phase are not likely to be completely offset by such "rebound" effects. Furthermore, we argue that when consumers pay money out of pocket to purchase used devices, this purchase is offsetting some other expenditure whose environmental impacts are thus avoided (Zink et al. 2014; Makov and Font Vivanco 2018).

In their comprehensive review of the environmental implications of reuse, Cooper and Gutowski (2017) conclude that the environmental consequences of products that can be directly reused are likely beneficial. Similarly, according to the Ellen MacArthur Foundation, reuse that involves little repair, remanufacturing, or alteration of products represents one of the most environmentally beneficial paths of the circular economy (MacArthur 2013). In addition, much like other used products, smartphone reuse (via access to communications) likely has a positive impact on welfare, especially for households with lower economic power (Gavazza et al. 2014; Raz et al. 2017). It follows that products with longer economic life spans (defined here as the time during which a product can be resold "as is" via secondhand markets) are generally more sustainable than products that lose their value faster and have shorter economic life spans.

Repairability and Intangibles

Smartphones are known to have fast innovation cycles. Because new model releases are frequent, technological progress and consumers' desire for advanced functionality are commonly viewed as the main drivers behind rapid product replacement and short use-phase duration (Wilson et al. 2017; Wieser and Tröger 2017). As a result, several have argued that making phones easier to repair and update, thereby slowing their technical obsolescence, would increase their potential for reuse and extend their use phase (Wilhelm et al. 2011; van Nes and Cramer 2005; Benton et al. 2015).

Yet despite consumers' proclaimed interest in repairability (Wilhelm et al. 2011; Wieser et al. 2015; Cooper 2016), evidence suggests that they might be content with product life spans (Gnanapragasam 2017), and not genuinely interested in fixing their devices. For example, Jacoby and colleagues (1977) showed that consumers use minor malfunctions or physical imperfections as justification for replacing working products. Bellezza et al. (2017) found that consumers are more careless with their possessions if they know an upgrade is available. Relatedly, the limited market success of modular phones or phones that are specifically optimized to allow unlimited repair and upgrades (e.g., Fairphone) challenges the notion that repairability is a highly sought-after feature in smartphones (Lowe 2016; Agrawal et al. 2016; Hill 2017). Thus, despite growing advocacy and pending legislation affirming consumers' "right to repair" (The Repair Association 2017; Koebler 2017; Bloomberg 2017), it remains unclear whether consumers truly value the ability to repair and upgrade devices and to what extent such enhanced functional durability (defined here as the duration of time products remain functionally up to date) extends the use phase in smartphones.

In addition, past work demonstrates that qualities that go beyond functional aspects can increase the utility a product provides. For example, displaying a luxury branded shirt can increase a job applicant's chances of securing a position or a charity representative's ability to solicit donations from strangers (Nelissen and Meijers 2011). In such cases, the benefit of wearing the shirt does not stem from its function as a clothing garment but rather from the social context it provides about the wearer's social status and/or character.

Such nonfunctional utility could also impact prices and demand for products in secondary markets. Hendel and Lizzeri (1999) for example, found that depreciation trends of used cars were based on perceived brand quality and not based on differences in physical durability. Sullivan (1998) compared resale prices of twin automobile pairs to examine the impact of brand name on deprecation. Twin automobiles are typically made at the same plant and have the same functional and physical properties but different brand names (e.g., Ford Thunderbird and Mercury Cougar). Even though twin models are essentially the same, Sullivan found that vehicles sold under the stronger parent brand maintained value better than their twin counterpart sold under the weaker brand name. These findings speak to the role brand name can play in curbing depreciation. Much like cars, perceptions of brand quality could also affect depreciation trends of used smartphones. Moreover, similar to cars, smartphones also act as items of conspicuous consumption, allowing consumers to convey their wealth, status, and identity to others (Thompson and Norton 2011; Goodman and Irmak 2013; Katz and Sugiyama 2006).

In the United States, the two largest manufacturers of smartphones, Apple and Samsung, together commanded roughly 70% of the smartphone market, each capturing a similar market share (35% in 2017; Haselton, 2017). Yet while Apple is repeatedly ranked at the top of the list of the world's most valuable brands, Samsung usually falls just outside of the top ten (Badenhausen 2017). Thus, even though the devices produced by the two manufacturers are similar enough to justify an ongoing patent infringement lawsuit (Pepitone 2013), they clearly differ with respect to brand equity.

In addition to other components of the marketing mix such as advertising and store presence, pricing strategy plays a major role in shaping brand equity and perception (Yoo et al. 2000). Specifically, aggressive pricing and sales promotions tend to have a negative impact on consumer perceptions of brand quality (Rao and Monroe 1989). As such, Samsung's aggressive pricing strategies and the discounts it offers on new smartphones likely reinforce its lower brand positioning compared to Apple, which tightly controls retail prices of its products and keeps price drops of new smartphones limited and predictable. Such differences in brand equity (as well as other intangible qualities) could affect how long it takes smartphones to reach the end of their economic life span, namely, the point at which they lose all value in secondhand markets.

Because longer economic life spans imply longer use phases and greater resource efficiency, despite relative functional similarities (Pepitone 2013), Samsung and Apple smartphones could have different environmental consequences. Here, we use market data to examine whether and how intangible qualities such as brand and newness (i.e., whether the phone is the newest model available) affect the economic life span of smartphones, and compare their relative importance of such intangible properties to that of features such as repairability and memory size, which presumably prolong functional durability (see table 1 for detailed definitions).

Methods and Data

To examine the role different product properties play in shaping the economic life span of smartphones, we collected detailed information on nearly 500,000 listings of used Apple and Samsung smartphones sold via eBay.com in the first quarters of 2015 and 2016. Extracting resale price and detailed device information for each listing, we calculated the percentage of overall value each device had lost by the time it was resold in comparison to its original retail price at the time of launch (hereafter market depreciation). We then used ordinary least squares (OLS) regression to formulate market depreciation as a function of intangible qualities, functional features, and control variables and estimate the economic life span of Apple and Samsung smartphones.

We specifically chose to focus on Apple and Samsung smartphones for several reasons. First, together the two brands dominate the U.S. market, accounting for 70% of all new smartphone sales (Haselton 2017). Second, even though neither brand is particularly well known for its efforts to extend product life spans, they each produce both models that are relatively easy

Table 1 Predicting variables: Model 1 and model 2

Predictors	*Description*
Brand	Binary dummy, Apple/Samsung (1 = Apple; 0 = Samsung)
Newness	Binary dummy (yes/no); Is this the newest model on the market from this series? (1 = Yes; 0 = No)
Repairability	Composite indicator for random access memory (RAM) and iFixit Repair score (see section 4 in the supporting information on the Web)
Capacity	Capacity (in gigabytes [GB])
Condition	Ordinal—on a scale of 1 to 3, when 1 = excellent, and 3 = bad
Control	*Description*
Log-transformed age	The natural log of phone age in months Age: number of months between launch and resale date
Screen	Screen size (inches)
Camera	Megapixel (MP)
Weight	Device weight in grams
Carrier	A set of five binary (dummy) variables for each carrier (AT&T, Sprint, T-Mobile, unlocked, and other carriers), Verizon as the baseline
Free shipping	Binary (1 = Yes; 0 = No); based on shipping cost
Seller ranking	Binary (1 = Yes; 0 = No); top-rated seller ranking by eBay
Sale type	Binary (1 = bid; regular sale = 0)

to repair and those that are harder to repair (see table S6 in the supporting information available on the Journal's website). Finally, while both manufacturers sell a similar number of new smartphone devices in the United States, they differ with regard to brand equity (Badenhausen 2017). As such, by analyzing sales of used Apple and Samsung, we could empirically examine and compare the effect repairability and brand have on the economic life span of smartphones in the United States.

The following sections provide a detailed description of data collection, case selection, variable definitions, and the regression models employed in our analysis.

Market Depreciation and Economic Life Span

In economics, the equilibrium price of a good is thought to reflect the good's overall value. As such, when consumers lose interest in reusing a product, secondhand market prices should directly reflect such judgment, and the product is expected to lose most or all of its economic value. Because eBay is not a traditional retailer but a diverse marketplace with numerous independent sellers and buyers, many view it as a close approximation of the central marketplace discussed in classic economics theory. Subsequently, market prices of goods traded on eBay are thought to reflect equilibrium prices (Hasker and Sickles 2010).

Therefore, when a product approaches full market depreciation on eBay and reaches the end of its economic life span, it is an indication that consumers no longer view it as useful, and thus it has reached the end of its use phase. This suggests that, generally, products that depreciate faster have shorter use phases and shorter life spans compared to products that depreciate at a slower rate and maintain their market value longer.

Data Collection and Assembly

Data were collected over two 10-day periods in April 2015 and April 2016, directly from the eBay.com website using a software agent. The collection included data on all completed listings of smartphones described as in "used" condition by sellers, sold within the United States. eBay routinely allows users to view completed listings (both sold and unsold) that date back approximately 90 days; thus, our dataset included listings that appeared on the website during the first quarters of 2015 and 2016.

Resale price (for sold items), shipping, seller rankings (top rated yes/no), and sale type (auction/regular sale) were retrieved by a computer agent directly from the relevant rubric on the eBay website. Specific model and capacity, condition, and cellular provider (e.g., unlocked, AT&T, Verizon) were extracted from the listing title and accompanying description. Once the specific phone model was cataloged, U.S. launch date and technical specifications were added to each listing based on official product specification descriptions available online (see the *Variable Selection* section below for more). Crossing model and capacity (e.g., iPhone 4s 16GB), original sales prices were assigned and adjusted for inflation based on sale date using the Consumer Price Index (CPI) calculator (Bureau of Labor Statistics 2017). Phone age (in months) was calculated based on the time between launch and resale date on eBay. Because phone age presents time between launch date and resale, it does not capture intermodel differences in use duration. For example, an iPhone 6 originally bought from Apple in September 2015 is in use 6 months longer than an identical device bought in March 2016. However, because most secondary buyers cannot tell whether a specific device was originally purchased in September or March, they can only estimate phone age based on the model's launch date. As such, we believe that our indicator for phone age reflects the information consumers rely on when making purchasing decision.

For Apple phones, launch dates and prices were based on information provided on the company's official website (Apple Inc. 2016). For Samsung, prices and dates of release were retrieved using a historical Google search for official launch notices published. For both brands, when unlocked phone prices were unavailable, the net cost of a phone purchase was calculated by subtracting the price of a cellular service package from the price of a combined service + phone package offered by AT&T. General statistics and frequencies are presented in table S5 and section 6 in the supporting information on the Web.

Case Selection

Once all data were compiled, we manually examined and corrected inconsistencies (e.g., a mismatch between device brand and model) and randomly cross-checked cases to verify that the information retrieved matched the full item description. Of the 784,927 listings retrieved from the website that resulted in financial transactions (i.e., items that were sold), all listings were excluded that contained products other than smartphones, multiple products (several phones), or those for which we were unable to determine the exact model or memory capacity ($N = 157{,}044$). Of the remaining listings, roughly 86% were phones by the top two manufacturers, Apple and Samsung, suggesting that these brands dominated the secondhand market as well as the retail market for smartphones (Haselton 2017). Given our specific interest in Apple and Samsung, we chose to exclusively focus on these two brands in our analysis, limiting the sample to phone models that included at least 1,000 listings. Finally, devices that were sold for more than 120% of the original retail price ($N = 1{,}853$) were excluded from the analysis (see below for calculation of value maintained), leaving a total of 494,094 cases in total.

Variable Selection

Dependent Variable—Market Depreciation

Table 1 presents the full list of regression variables and their operationalization for both regression models 1 and 2. The dependent variable, market depreciation (overall share of value lost), was calculated for each listed device by dividing the eBay resale price—the full cost to the consumer calculated as price paid with shipping—by the U.S. launch retail price (adjusted for inflation) of the specific phone model and capacity. Because most of the smartphone models included in our analysis were older models that were no longer sold new by the manufacturers in 2015–2016, we chose to use official retail prices at the time of launch as our benchmark for depreciation.

$$MARKET\ DEPRECIATION = 100\% \times \left(1 - \frac{eBay\ resale\ price}{U.S.\ retail\ launch\ price}\right) \quad (1)$$

As mentioned previously, the value of a durable good declines over time. Therefore, we expected that smartphone age would have a significant impact on its market value. Curve estimation fit indicated that the relationship between smartphone age and its secondhand value follows an exponential curve ($R^2 = 0.91$). To allow for easier interpretation, we use log-transformed age instead of actual age in our analysis.

Predictors and Control Variables

Because many factors could potentially affect market depreciation and useful life span of smartphones (Kwak et al. 2012), in addition to phone age, a long list of possible phone properties was considered (including central processing unit [CPU], battery size, screen size, camera resolution, weight, talk time, capacity, and more; see section 2 in the supporting information on the Web).

Given our specific interest in functional adaptation, memory size (capacity) and repairability were included in the regression. Because the ability to maintain, repair, and upgrade a used device is dependent on several factors, we compiled a composite repairability indicator, giving equal weight to random access memory (RAM), and an external repairability score calculated by iFixit, a company specializing in consumer electronic repair (see section 2 in the supporting information on the Web for more). Since neither Apple nor Samsung is particularly well known for being easy to repair, we first confirmed that there was variance in repairability scores between the different phone models both within brands and between brands (see figure S2 in the supporting information on the Web). Cosmetic condition (as defined by the seller) was included to account for the phones' physical wear and tear and brand (Apple or Samsung) and newness (whether the device was the newest model available on the market) were added as dummy variables to account for the impact of intangible properties.

Next, we sought to control for external factors related to the eBay platform (i.e., seller reputation, free shipping, and sale type) and cellular network (i.e., carrier) as well as additional technical product specifications that might affect market deprecation of smartphones (e.g., screen size). Since each new phone model incorporated technological improvements over its predecessors (e.g., larger screen size and enhanced camera resolution), several potential predictors were found to be highly correlated with one another (see table S2 in the supporting information on the Web), introducing the challenge of collinearity. While collinearity does not reduce the overall predictive capabilities of the model, it can invalidate results for individual predictors and produce inflated coefficient and error terms.

Partial least squares (PLS) is a statistical method often used to overcome collinearity. However, PLS and similar statistical methods are typically not considered suitable for evaluating the relative importance of different predictors (Kwak et al. 2012). Because our main goal was to assess the relative impact of each predictor and not to find the formula with the best predictive powers, we chose OLS regression and excluded some collinear predictors to bypass challenges of collinearity. To determine which predictors to exclude we relied on theory and gave preference to predictors that are typically salient at point of sale, as they were expected to involve lower information asymmetry.

To verify that our main findings were robust to the inclusion of other predicting variables and different variable definitions (e.g., seller reputation, see Subramanian and Subramanyam (2012)), we repeated the analysis using alternative regression models (see table S3.1 and section 3 in the supporting information on the Web). However, we acknowledge that other technical properties not included in our regression model could also affect smartphone depreciation, as we have no reason to believe that they would not be highly correlated with the salient technical specifications that are included. Hence, we believe that the unique impact of technical properties that are missing from our current model is captured by the technical properties that are included.

Regression Models

Model 1

Using OLS regression, we first formulated market depreciation as a function of intangible qualities, functional features, and control variables (Model 1; see equation (2)) as outlined in table 2. Specifically, in model 1, we focused on features that pertain to functional durability (operationalized as repairability and capacity) and physical wear and tear (condition), versus intangible properties (e.g., brand, newness), while controlling for device age, other technical specifications (e.g., screen size, camera, weight), and external factors (e.g., carrier, seller reputation) that could also affect resale value.

$$DEPRECIATION = \Sigma_i\ (\beta_i \times PREDICTOR_i) + \Sigma_j\ (\beta_j \times CONTROL_j) + \varepsilon \quad (2)$$

where predictors are the variables of interest, and control variables represent other factors that might influence depreciation (see table 2 for full description). Nominal variables were assigned dummy variables (Apple, carrier, free shipping, top-rated seller, sale type).

Because only 27% of our dataset contained information on cosmetic condition and cellular carrier, we performed this regression on the subset of full information cases (roughly 134,500 devices), using the Stata program (version 14). White's test revealed heteroscedasticity (chi-square (147) = 4791.6; $p < 0.000$), suggesting a strong correlation between explanatory variables and the variance in the error term, with larger variability in error for newer models compared to older ones. Therefore, we report robust/white errors for this regression analysis.

The relative explanatory power of each individual predictor (i.e., R^2 change) was assessed using a hierarchal additive regression model, where variables were added, stepwise, to the regression model based on their expected importance. While a different order might alter the relative contribution (in terms of R^2) of each model step, it would not affect the final coefficients and error statistics for the complete model.

Model 2

Confirming that brand affects market depreciation even when technical differences are controlled for, we then constructed a simpler model predicting market depreciation based solely on phone brand and age (model 2). To reduce collinearity resulting from inclusion of an interaction term, we used centered variables to create the interaction between brand and age.

$$DEPRECIATION = \beta_1 \times BRAND + \beta_2 \times \log(AGE) + \beta_3 \times (\text{centered\_}\log(AGE) \times BRAND) + \varepsilon \quad (3)$$

where brand is a dummy variable (Apple = 1, Samsung = 0), age is the number of months since appearance on the market, the β variables are the coefficients fitted using OLS, and ε the error term.

This simplified model offered two important advantages. First, because information regarding cosmetic condition and carrier were not required, we were able to expand our database and include more cases (N = 494,094). Second, it allowed us to isolate the impact of brand and quantify its impacts on market depreciation and, subsequently, economic life span in terms of months. Such quantification could not be performed based on model 1 because no Samsung and Apple phones have the exact same configuration that permitted keeping all variables other than brand constant.

Considering the factors described above, therefore, we used model 2 to calculate at which age Apple and Samsung smartphones approach full depreciation, measured by the loss of 95% of their original value.

Results

Model 1

Table 2 presents regression results for model 1. Analyzing all sold listings (i.e., listings that resulted in ownership change) containing full information on physical condition and cellular carrier (model 1; N = 134,569), we find that intangibles (i.e., brand and newness) are at least as important as determinants of market depreciation such as physical wear and tear

Table 2 Market depreciation (as percentage of retail launch price lost) by product properties

	Coef.	*Robust Std. Err.*	*Standardized coef.*	*Cumulative adj. R^2*	*R^2 change*
Model 1					
Dependent variable: % Depreciation					
Brand (Apple)	–12.15*	0.11	–0.25	0.002*	
Newness	–4.60*	0.13	–0.07	0.374*	0.373
Repairability	1.63*	0.06	0.05	0.421*	0.047
Capacity	–0.02	0.00	–0.02	0.488*	0.067
Condition	4.37*	0.03	0.14	0.520*	0.032
Control variables					
ln(age), screen size, camera (MP), weight, cellular carrier, seller ratings, free shipping, sale type, regression constant				0.868*	0.348
N = 134,569; F (17, 134551) = 41940; Root MSE = 7.20					
Model 2					
Dependent variable: % Depreciation					
Brand (Apple)	–8.57*	0.02	–0.20	0.002*	
Log-transformed age (centered)	28.76*	0.04	0.85	0.802*	0.800
Interaction term	2.84*	0.06	0.07	0.804*	0.002
Regression constant	74.16*	0.02			
N = 494,094; F(3, 494090) = 99999; Root MSE = 8.56					

Notes: *p < .001; cumulative R^2 change is the change in adjusted R^2 resulting from the addition of the variable or set of variables to the model. MP = megapixel; MSE = mean squared error.

(condition) or features related to functional durability (repairability, capacity). Specifically, we find that brand significantly impacts depreciation, with Samsung phones losing 12.3 ± 0.2% more of their original value compared to otherwise equivalent age and technically equivalent Apple phones.

Newness is also statistically significant, with new models losing 4.5 ± 0.3% less of their original value compared to otherwise equivalent yet "older" models. Although it can be argued that there are functional benefits for carrying the most up-to-date model, we maintain that even if not specifically represented in our models as predictors, given that all technical features examined were highly correlated (see S2 in the supporting information on the Web), such benefits should be captured by the technical features already included in model 1 (e.g., screen size, capacity, camera resolution). Newness, however, reflects the added value that is not strictly functional, for example, the hedonic pleasure of owning the latest gadget or the opportunity to publicly display one's technological sophistication.

In contrast, all else being equal, phones with the highest repairability scores and largest memory capacity in our dataset (128 gigabytes [GB]) lose 2.7 ± 0.3% more of their original value compared to phones with the lowest repairability scores and smallest capacity possible (8 GB). Hence, our second finding is that functional durability does not curb depreciation and might be of lower importance for extending product use phase compared to brand and other intangible properties. Physical wear and tear (condition) has a larger impact, with devices described by sellers as in "bad" condition losing 8.8 ± 0.1% more of their original value compared to equivalent devices described as in "excellent" condition. A post hoc analysis revealed no interaction between brand and condition ($p = 0.2$; see section 4 in the supporting information on the Web), suggesting that, in this case, wear and tear reflect user behavior and use intensity more than any deliberate design or manufacturing choice. Although our model includes some collinear variables, given the large data sample we use, the high adjusted R^2 value of our model, and the fact that all variables were statistically significant despite collinearity, we believe our results are still statistically valid (O'brien 2007).

Our results demonstrate that phone brand has a significant and meaningful impact on market deprecation. In line with this finding, all alternative regression models examined led to similar results (see tables S3.1 through S3.3 in the supporting information on the Web). Because full market depreciation signals that a product has reached the end of its economic life, in theory, model 1 could be used to isolate the effect of brand and estimate the age at which Samsung and Apple phones are no longer viable for reuse via secondary markets. Phone models, however, are not available in all possible configurations (e.g., no iPhone has an 18-megapixel [MP] camera). As a result, it is not possible to keep all of the other predictors constant while brand is isolated because it would violate the *ceteris paribus* assumption of our regression. Therefore, to estimate the economic life and use-phase duration for each brand, we constructed a simpler model that predicts depreciation as a function of brand and phone age only (model 2).

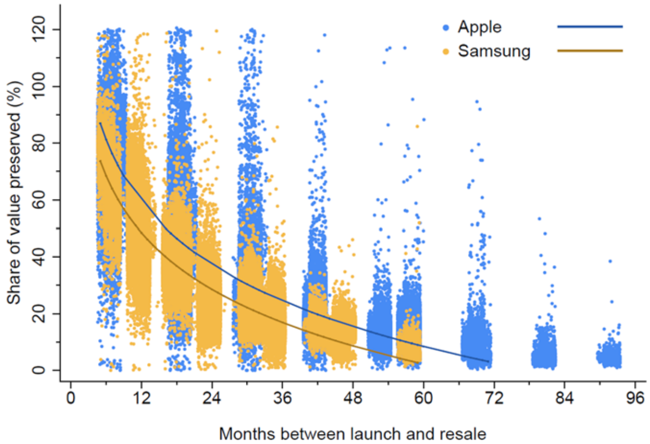

Figure 1 Market depreciation per brand by age. Blue dots represent Apple smartphones, and yellow dots Samsung phones. Yellow (Samsung) and blue (Apple) trendlines represent market depreciation as calculated for each brand based on model 2.

Model 2

Results of model 2 (N = 498,326) are presented in table 2. Consistent with the results of model 1, we find a negative linear relationship between market depreciation and log-transformed age, with a significant impact for brand and an interaction between the two predictors. In this case, market prices indicate that Samsung smartphones lose value faster and reach the end of their reuse life span after 54.5 ± 0.2 months, while Apple smartphones reach it after 66.9 ± 0.6 months (see figure 1). Hence, our third finding is that brand, an intangible quality, can have a meaningful impact on prolonging the economic life span of smartphones, which, in this case, takes the form, on average, of 12.5 months being added to the use phase. In summary, because Apple phones are shown to have a longer use phase than Samsung phones, then for every Apple phone, one would need roughly 1.23 Samsung phones of similar age, size, and functional capabilities to deliver the same amount of utility.

Discussion and Conclusions

This work provides evidence that, despite wide advocacy for repairability, currently functional durability has, at best, a marginal impact on the economic life span and use-phase duration of smartphones. Though the importance consumers place on repairability might change over time, we found no evidence for change between the two time periods examined. In contrast, intangible product properties can affect economic life spans and therefore the environmental impacts products bear. Specifically, we find that in the case of smartphones, brand equity can lead to a 1-year difference in economic life span, which suggests that phones from stronger brands remain in use for a longer period of time. Because most of the environmental impacts associated with smartphones accrue during production, transport, and EoL, this longer use period means more efficient use of resources and energy.

Our findings illustrate that, in general, intangibles might be better predictors of sustainability in consumer electronics than repairability, even if the latter seems to fully align with consumers' professed attitudes, and provide relevant tools to overcome product obsolescence. As our findings are based on nearly half a million sales of used smartphones concluded in a free market setting over two time periods, we argue that they more genuinely reflect real-life consumer choices than does previous work, which was based mostly on consumer surveys or replacement cycles of new products (Wilhelm et al. 2011; Wieser et al. 2015; Cooper 2016; Miller et al. 2016). Although we focus on Apple and Samsung smartphones, given that these are the clear market leaders in the United States and globally, we believe our result are representative of the average consumer's preferences (Kantar Worldpanel 2017; Gartner 2017). Although other functional features not included in our regression models could potentially affect depreciation, because functional features tend to be highly correlated with one another and all alternative models examined led to similar conclusions (see supporting information on the Web), we expect our main findings—that repairability is of low importance while brand plays a key role in depreciation—to hold.

As intangibles play a pivotal role in shaping consumption, a more accurate attribution of their environmental consequences could help identify leverage points for enhancing product sustainability. In particular, intangibles might be especially important for consumers in secondary markets, which have already become major venues for product reuse (Deloitte 2016). Past work suggests that lower socioeconomic agents tend to place higher importance on status signaling when shopping compared to agents that are better off economically (Vanden Abeele and Roe 2013; Charles et al. 2009). Because price is one of the major motivators for purchasing electronics secondhand (Guide and Li 2010), the impact of intangibles might be especially prominent in identifying consumption patterns of used goods. In particular, the relationship between brand quality and price and how it might affect consumer perceptions of purchase risk in secondary markets might be of particular interest for better understanding the implications of brand on product reuse. As the popularity of secondary online markets continues to expand, the importance of branding and other social status signals for enhancing reuse and resource efficiency could also increase.

Although the knowledge that brand can affect the economic life span of products intuitively makes sense, we are unaware of previous work that has empirically quantified a similar effect in consumer electronics. These findings put into question the common practice in life cycle assessment (LCA) of assuming that all products in the same product category (i.e., phones, cars) have identical life spans. Recent years have brought about great improvements in use-phase efficiency of products (e.g., smartphones, household appliances, cars). As this trend increases across product categories, LCA results will become more sensitive to assumptions regarding life span duration, and the importance of accounting for the impact intangibles can have on product life span will increase. We suggest that market depreciation and economic life spans might provide a practical way to examine variance in product life spans and improve estimate accuracy.

This work has several limitations. First, our analysis draws on sales of used phones executed via eBay, within the United States. Even though eBay is the largest online market for secondhand goods, it may not be representative of the market as a whole. In addition, we include only transactions completed during the first quarters of 2015 and 2016. Although post hoc analysis did not reveal any meaningful difference between the two years, it remains to be seen whether they are representative of other time periods as well. Moreover, the current analysis does not differentiate among the different components of the marketing mix (e.g., advertising, retail prices and promotions, new model launch) and the impacts of brand as a whole. Specifically, because retail prices of smartphones are not static but change over time, it is possible that differences in pricing strategies (e.g., discounts, rebates) are also reflected in price changes in secondary markets. Given that the aim of this work was to examine whether repairability and functional durability affects reuse via secondary markets, disentangling the various components of brand positioning is beyond the scope of this work. Although a post hoc analysis indicated that depreciation of used smartphones is not mediated by retail price changes in primary markets (see section 5 in the supporting information on the Web), future work should specifically examine whether and how pricing strategy and the frequency of new model releases affects supply and demand in secondary markets. In addition, we could not isolate the impact of operating system usability and consumer satisfaction from brand (because they were fully correlated). Although these can fall under intangibles (Joshi and Hanssens 2010), future work could control for the impact of operating systems by, for example, comparing depreciation of different smartphone brands that have an Android operating system.

Furthermore, relying on cases of sold smartphones does not account for the share of older devices that were retired and never offered for resale on eBay. Because the effective market value of retired devices is zero, this introduces selection bias into our analysis that likely leads to lower deprecation estimates for older models. Alternatively, it is possible that the best phones are seldom offered for sale in secondary markets such as eBay because owners never see the need to replace them. For example, it is possible that owners of modular phones, that have the ability to endlessly update the functional capabilities and cosmetic appearance of their devices, do not replace their smartphones before they reach their physical end of life, at which point they have no market value. Here, we focused solely on smartphone models with high resales volumes, so it is possible that our data sample does not contain the smartphone models that preserve value best. Therefore, it could be argued that our data represent a "market for lemons," where sellers are interested only in passing on lower-quality goods (Akerlof 1970) to others. Nonetheless, if indeed secondary markets are full of lemons, it is reasonable to assume that repairability would be highly valued in this market, as it would somewhat mitigate the risk of purchasing a useless device. However, because all smartphone models sold by the two brands were represented in our dataset, there is no reason to assume that the market for lemons hypothesis would affect one brand more than the other. Future work could examine the ratio between sold and unsold listings using market demand to estimate the real EoL.

In addition, our results regarding repairability are sensitive to the way we chose to operationalize it based on iFixit scores and internal memory. It is possible that a different definition of repairability would have led to different results. Furthermore, neither Apple nor Samsung are particularly well known for their efforts to enhance smartphone life span. Thus, although repairability scores varied among the different phone models examined (see figure S2 in the supporting information on the Web), it is possible that consumers were unaware of the fact that some phones are easier to repair than others. Because repairability scores are not commonly advertised, it remains unclear whether given sufficient information regarding product repairability and functional durability in general, economic life span of more functionally durable models would increase. Future work should examine the effect of making repairability information more salient to consumers.

Moreover, consumers that have a special interest in repairability and know about repairability scores of different models might choose to purchase devices that are designed (and marketed) to address these issues. Because we focus only on the two big brands, our dataset does not include the manufacturers that cater specifically to environmentally conscious consumers, such as Fairphone. Nonetheless, as sustainability-focused smartphones are still a niche market—for example, total Fairphone devices sold amounts to less than 0.01% of smartphone sales in the United States (Hill 2017)—they are likely not as representative of general consumer preferences as Apple and Samsung, who jointly command over 70% of the U.S. market (Kantar Worldpanel 2017). Finally, although smartphones are ubiquitous, research suggests that consumers might have especially strong emotions toward their devices (Melumad and Pham 2018) and thus the extent to which smartphones are representative of other consumer products should be explicitly tested.

Our findings underscore that a narrow focus on technical aspects such as repairability is likely to fall short of achieving the desired outcome of longer life spans for smartphones and consumer electronics in general. Furthermore, these findings highlight the importance of considering the consequences of intangibles when assessing the environmental impacts of consumer products. Although we focus on the case study of smartphones, our approach is generally applicable and could be selected to examine other consumer products and different intangibles beyond brand and newness. Future work should focus on products that have a strong secondary market and a wider range of possible configurations such as automobiles, which might prove a good fit for estimations based on regression results. While more work is needed to pinpoint under what circumstances brand and other intangibles could be harnessed to promote sustainable consumption, strategies aimed at slowing down obsolescence rates of consumer-facing products would likely benefit from considering creative ways to incorporate them.

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References

Abbey, J. D., M. G. Meloy, V. D. R. Guide, and S. Atalay. 2015. Remanufactured products in closed-loop supply chains for consumer goods. *Production and Operations Management* 24(3): 488–503.

Abbey, J. D., R. Kleber, G. C. Souza, and G. Voigt. 2017. The role of perceived quality risk in pricing remanufactured products. *Production and Operations Management* 26(1): 100–115.

Agrawal, V. V., A. Atasu, and S. Ülkü. 2016. Modular upgradability in consumer electronics: Economic and environmental implications. *Journal of Industrial Ecology* 20(5): 1018–1024.

Aker, J. C. and I. M. Mbiti. 2010. Mobile phones and economic development in Africa. *Journal of Economic Perspectives* 24(3): 207–232.

Akerlof, G. A. 1970. The market for "lemons": Quality uncertainty and the market mechanism. *Quarterly Journal of Economics*. 84(3): 488–500.

Allwood, J. M., J. M. Cullen, M. A. Carruth, D. R. Cooper, M. McBrien, R. L. Milford, M. C. Moynihan, and A. C. Patel. 2012. *Sustainable materials: With both eyes open*. Cambridge: UIT Cambridge.

Apple Inc. 2014. iPhone 6 Enviromental Report. Official Apple website. www.apple.com/environment/reports/docs/iPhone6_PER_Sept2014.pdf. Accessed July 9, 2018.

Apple Inc. 2016. Timeline of iPhone models. Apple.com: Press Release Library. www.apple.com/newsroom/archive/iphone/. Accessed June 7, 2018.

Badenhausen, K. 2017. Apple heads the world's most valuable brands of 2017 at $170 billion. *Forbes*, May 23. www.forbes.com/sites/kurtbadenhausen/2017/05/23/apple-heads-the-worlds-most-valuable-brands-of-2017-at-170-billion/#1adf0f0f384b. Accessed July 30, 2018.

Bellezza, S., J. M. Ackerman, and F. Gino. 2017. "Be careless with that!" Availability of product upgrades increases cavalier behavior toward possessions. *Journal of Marketing Research* 54(5): 768–784.

Benton, D., E. Coats, and J. Hazell. 2015. *A circular economy for smart devices: Opportunities in the US, UK and India*. Report by Green Alliance, London. London, UK: Green Alliance.

Bloomberg, J. 2017. John Deere's digital transformation runs afoul of right-to-repair movement. Forbes. www.forbes.com/sites/jasonbloomberg/2017/04/30/john-deeres-digital-transformation-runs-afoul-of-right-to-repair-movement/#3140a28a5ab9. Accessed July 30, 2018.

Broadband Commission for Digital Development. 2016. *The state of broadband 2016: Broadband catalyzing sustainable development*. Geneva, Switzerland: United Nations Educational, Scientific and cultural Organization.

Bureau of Labor Statistics. 2017. CPI inflation calculator. https://data.bls.gov/cgi.bin/cpicalc.pl. Accessed September 6, 2017.

Charles, K. K., E. Hurst, and N. Roussanov. 2009. Conspicuous consumption and race. *Quarterly Journal of Economics* 124(2): 425–467.

Chen, A. M., K. N. Dietrich, X. Huo, and S. M. Ho. 2011. Developmental neurotoxicants in e-waste: An emerging health concern. *Environmental Health Perspectives* 119(4): 431–438.

Cooper, D. R. and T. G. Gutowski. 2017. The environmental impacts of reuse: A review. *Journal of Industrial Ecology* 21(1): 38–56.

Cooper, T. 2016. *Longer lasting products: Alternatives to the throwaway society*. New York, NY: CRC Press.

Corbett, S. 2008. Can the cellphone help end global poverty. *The New York Times*, April 13, MM34.

Davies, R. and S. Cunningham. 2012. A review of online trading and user perceptions of usability & trust. *Journal of Advanced Internet of Things* 1(1): 1–23.

Deloitte. 2016. Technology, media and telecommunications predictions. In *Used smartphones: The $17 billion market you may never have heard of*. Produced by The Creative Studio at Deloitte, London. https://www2.deloitte.com/gi/en/pages/technology-media-and-telecommunications/articles/tmt-predictions.html. Accessed July 30, 2018.

Felton, A. and E. Bird. 2006. Design for recyclability: Product function, failure, repairability, recyclability and disposability. Paper presented at Geotechnical and Environmental Aspects of Waste Disposal Sites: Proceedings of the 4th International Symposium on Geotechnics Related to the Environment-GREEN 4, Wolverhampton, UK, 28 June–1 July 2004.

Frey, S. D., D. J. Harrison, and E. H. Billett. 2006. Ecological footprint analysis applied to mobile phones. *Journal of Industrial Ecology* 10(1–2): 199–216.

Gartner, I. 2017. *Gartner says worldwide sales of smartphones grew 7 percent in the fourth quarter of 2016*. Egham, UK: Gartner, Inc.

Gavazza, A., A. Lizzeri, and N. Roketskiy. 2014. A quantitative analysis of the used-car market. *American Economic Review* 104(11): 3668–3700.

Geyer, R. and V. D. Blass. 2010. The economics of cell phone reuse and recycling. *International Journal of Advanced Manufacturing Technology* 47(5–8): 515–525.

Ghose, A., M. D. Smith, and R. Telang. 2006. Internet exchanges for used books: An empirical analysis of product cannibalization and welfare impact. *Information Systems Research* 17(1): 3–19.

Gnanapragasam, A., M. Oguchi, C. Cole, and T., Cooper. 2017. Consumer expectations of product lifetimes around the world: A review of global research findings and methods. In *Product Lifetimes and the Environment 2017 – Conference Proceedings*, edited by C. Bakker and R. Mugge, 464–469. Delft University of Technoloy and IOS Press.

Go, T. F., D. A. Wahab, and H. Hishamuddin. 2015. Multiple generation life-cycles for product sustainability: The way forward. *Journal of Cleaner Production* 95: 16–29.

Grant, K., F. C. Goldizen, P. D. Sly, M. N. Brune, M. Neira, M. van den Berg, and R. E. Norman. 2013. Health consequences of exposure to e-waste: A systematic review. *Lancet Global Health* 1(6): E350–E361.

Guide, J. V. D. R. and J. Li. 2010. The potential for cannibalization of new products sales by remanufactured products. *Decision Sciences* 41(3): 547–572.

Haselton, T. 2017. Samsung retakes top spot from Apple in US smartphone market, Kantar says. CNBC. www.cnbc.com/2017/08/09/samsung-retakes-top-spot-from-apple-in-us-smartphones-kantar-says.html. Accessed July 30, 2018.

Hasker, K. and R. Sickles. 2010. eBay in the economic literature: Analysis of an auction marketplace. *Review of Industrial Organization* 37(1): 3–42.

Hendel, I. and A. Lizzeri. 1999. Adverse selection in durable goods markets. *American Economic Review* 89(5): 1097–1115.

Hill, S. 2017. Fairphone has sold 125,000 modular phones and is rolling out Android 6.0. Digital Trends: Designtechnica Corporation. www.digitaltrends.com/mobile/fairphone-mwc17/. Accessed July 30, 2018.

Jacoby, J., C. K. Berning, and T. F. Dietvorst. 1977. What about disposition? *Journal of Marketing* 41(2): 22–28.

Goodman, J. K. and C. Irmak. 2013. Having versus consuming: Failure to estimate usage frequency makes consumers prefer multifeature products. *Journal of Marketing Research* 50(1): 44–54.

Joshi, A. and D. M. Hanssens. 2010. The direct and indirect effects of advertising spending on firm value. *Journal of Marketing* 74(1): 20–33.

Kantar Worldpanel. 2017. Samsung back to #1 in the US, but share is down. Kantar Worldpanel. www.kantarworldpanel.com/global/News/Samsung-back-to-1-in-the-US-but-share-is-down. Accessed February 28, 2018.

Katz, J. E. and S. Sugiyama. 2006. Mobile phones as fashion statements: Evidence from student surveys in the US and Japan. *New Media and Society* 8(2): 321–337.

Koebler, J. 2017. Five states are considering bills to legalize the "right to repair" electronics. https://motherboard.vice.com/en_us/article/mg7nbv/five-states-are-considering-bills-to-legalize-the-right-to-repair-electronics. Accessed May 22, 2017.

Kwak, M., H. Kim, and D. Thurston. 2012. Formulating second-hand market value as a function of product specifications, age, and conditions. *Journal of Mechanical Design* 134(3): 032001–032001.

Lee, T. and S. Liao. 2015. Mental account matters in planning C2C on-line resale: The influnece of endowment effect. In *Proceedings of the 2010 Academy of Marketing Science (AMS) Annual Conference*, edited by D. R. Deeter-Schmelz. Basel, Switzerland: Springer International Publishing.

Lowe, M. 2016. Are modular phones the shape of things to come? theguardian.com. The Guardian. www.theguardian.com/technology/2016/jul/10/modular-smartphones-future. Accessed July 30, 2018.

MacArthur, E. 2013. *Towards the circular economy: economic and business rationale for an accelerated transition*. Cowes, UK: Ellen MacArthur Foundation.

Makov, T. and D. Font Vivanco. 2018. Does the circular economy grow the pie? The case of rebound effects from smartphone reuse. *Frontiers in Energy Research* 6(39).

Melumad, S. and M. T. Pham. 2018. Understanding the psychology of smartphone use: The adult pacifier hypothesis. Columbia University working paper.

Miller, T. R., H. Duan, J. Gregory, R. Kahhat, and R. Kirchain. 2016. Quantifying domestic used electronics flows using a combination of material flow methodologies: A US case study. *Environmental Science & Technology* 50(11): 5711–5719.

Moran, D., D. McBain, K. Kanemoto, M. Lenzen, and A. Geschke. 2015. Global supply chains of coltan. *Journal of Industrial Ecology* 19(3): 357–365.

Nelissen, R. M. A. and M. H. C. Meijers. 2011. Social benefits of luxury brands as costly signals of wealth and status. *Evolution and Human Behavior* 32(5): 343–355.

O'brien, R. M. 2007. A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity* 41(5): 673–690.

O'Connor, M. P., J. B. Zimmerman, P. T. Anastas, and D. L. Plata. 2016. A strategy for material supply chain sustainability: Enabling a circular economy in the electronics industry through green engineering. *ACS Sustainable Chemistry & Engineering* 4(11): 5879–5888.

OECD. 2010. Materials case study 1: Critical metals and mobile devices: OECD Environment Directorate. Paris, France: OECD Publishing.

Ovchinnikov, A., V. Blass, and G. Raz. 2014. Economic and environmental assessment of remanufacturing strategies for product + service firms. *Production and Operations Management* 23(5): 744–761.

Pepitone, J. 2013. Apple vs. Samsung scorecard. In *Apple and Samsung's fiercest battle isn't playing out in the smartphone market*. money.cnn.com: CNN. https://money.cnn.com/2013/08/08/technology/mobile/apple-samsung-timeline/index.html. Accessed July 30, 2018.

Rao, A. R. and K. B. Monroe. 1989. The effect of price, brand name, and store name on buyers' perceptions of product quality: An integrative review. *Journal of Marketing Research* 26(3): 351–357.

Raz, G., A. Ovchinnikov, and V. Blass. 2017. Economic, environmental, and social impact of remanufacturing in a competitive setting. *IEEE Transactions on Engineering Management* 64(4): 476–490.

The Repair Association . 2017. https://repair.org/. Accessed May 22 2017.

Skelton, A. C. and J. M. Allwood. 2013. Product life trade-offs: What if products fail early? *Environmental Science & Technology* 47(3): 1719–1728.

Sprecher, B., I. Daigo, S. Murakami, R. Kleijn, M. Vos, and G. J. Kramer. 2015. Framework for resilience in material supply chains, with a case study from the 2010 rare earth crisis. *Environmental Science & Technology* 49(11): 6740–6750.

Sprecher, B., I. Daigo, W. Spekkink, M. Vos, R. Kleijn, S. Murakami, and G. J. Kramer. 2017. Novel indicators for the quantification of resilience in critical material supply chains, with a 2010 rare earth crisis case study. *Environmental Science & Technology* 51(7): 3860–3870.

Subramanian, R. and R. Subramanyam. 2012. Key factors in the market for remanufactured products. *Manufacturing & Service Operations Management* 14(2): 315–326.

Sullivan, M. W. 1998. How brand names affect the demand for twin automobiles. *Journal of Marketing Research* 35(2): 154–165.

Thomas, V. M. 2011. The environmental potential of reuse: An application to used books. *Sustainability Science* 6(1): 109–116.

Thompson, D. V. and M. I. Norton. 2011. The social utility of feature creep. *Journal of Marketing Research* 48(3): 555–565.

van Nes, N. and J. Cramer. 2005. Influencing product lifetime through product design. *Business Strategy and the Environment* 14(5): 286–299.

Vanden Abeele, M. and K. Roe. 2013. Adolescents' school experience and the importance of having a "cool" mobile phone: Conformity, compensation and resistance? *Poetics* 41(3): 265–293.

Wieser, H. and N. Tröger. 2017. Exploring the inner loops of the circular economy: Replacement, repair, and reuse of mobile phones in Austria. *Journal of Cleaner Production* 172: 3042–3055.

Wieser, H., N. Tröger, and R. Hübner. 2015. The consumers' desired and expected product lifetimes. Paper presented at Product Lifetimes and the Environment, Conference Proceedings Nottingham, PLATE Conference.

Wilhelm, W., A. Yankov, and P. Magee. 2011. Mobile phone consumption behavior and the need for sustainability innovations. *Journal of Strategic Innovation and Sustainability* 7(2): 20–40.

Wilson, G. T., G. Smalley, J. R. Suckling, D. Lilley, J. Lee, and R. Mawle. 2017. The hibernating mobile phone: Dead storage as a barrier to efficient electronic waste recovery. *Waste Management* 60: 521–533.

Yoo, B., N. Donthu, and S. Lee. 2000. An examination of selected marketing mix elements and brand equity. *Journal of the Academy of Marketing Science* 28(2): 195.

Yu, S., Q. Yang, J. Tao, X. Tian, and F. Yin. 2011. Product modular design incorporating life cycle issues: Group Genetic Algorithm (GGA) based method. *Journal of Cleaner Production* 19(9–10): 1016–1032.

Zhang, W. H., Y. X. Wu, and M. O. Simonnot. 2012. Soil contamination due to e-waste disposal and recycling activities: A review with special focus on China. *Pedosphere* 22(4): 434–455.

Zink, T., F. Maker, R. Geyer, R. Amirtharajah, and V. Akella. 2014. Comparative life cycle assessment of smartphone reuse: Repurposing vs. refurbishment. *International Journal of Life Cycle Assessment* 19(5): 1099–1109.

Supporting Information

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

Supporting Information S1: This supporting information provides sections on smartphone market share, variable specifications, alternative regression models, moderation analysis for condition, retail price changes and depreciation in secondary markets, and data summary.