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A framework for modeling fraud in E-waste management

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ABSTRACT

Despite the adoption of electronic waste recycler certification schemes in the United States, there remain notable instances in which recyclers might engage in dishonest practices. To better understand mechanisms that may encourage honest electronics end-of-life management, we develop a framework to analyze the decision calculus of electronic waste recyclers facing a decision between an honest choice that might be more expensive or a dishonest choice that saves money but has some probability of being caught. Building an analytical decision tree model under which a recycler maximizes expected returns, we explore the influence of supervision on the choices a recycler faces and provide an analytical solution that describes the boundaries that separate those choices. Using our framework, we systematically catalog which interventions may help and which may not. The model suggests that direct unqualified subsidies to recyclers may not be particularly effective, although properly targeted subsidies have promise. We also find that there are substitution effects between increasing the cost of fraud and decreasing the costs of proper electronic waste recycling. That is, increasing the cost of fraud can serve as a policy instrument to produce effects similar to decreasing a recycler's costs from engaging in honest behavior. We also discuss the role of digital fraud prevention technologies such as blockchain as another mechanism to help achieve sustainability outcomes in e-waste management while lowering the costs of third-party supervision.

1. Introduction

Electronic waste (e-waste) presents a complex challenge to the growing field of circular economy (CE). Electronic products have become integral to modern society, and their use can provide sustainability benefits, particularly if they provide digital alternatives to resource-intense goods and services (Coroama et al., 2015). However, electronics are also responsible for significant impacts across their life cycle. This starts with the extraction of a diverse mix of valuable, scarce, and hazardous raw materials (Greenfield and Graedel, 2013); continues with the energy-intense manufacturing of components (Deng et al., 2011; Williams, 2004); and ultimately ends with a complex, continuously evolving e-waste stream (Althaf et al., 2020). CE strategies such as reuse and re-manufacturing offer the potential to mitigate these impacts. For example, these strategies might extend product lifespan, reduce demand for new products, or provide broader access to essential technology. Recycling also provides an opportunity to keep valuable materials in productive use, minimize future demand for primary material extraction, and reduce the release of hazardous materials into the environment.

However, numerous barriers exist to achieving CE aims in the electronics sector, and less than 40% of e-waste is currently estimated to be reused or recycled (United States Environmental Protection Agency, 2020a). Electronics are typically not designed to be easily disassembled, increasing the labor costs associated with product repair and component recovery (Tansel, 2017). Volatility in commodity markets leads to unpredictable shifts in the economic incentives driving material recovery (Bangs et al., 2016). Consumer awareness and participation in e-waste recycling programs are variable, making it more challenging for recycling businesses to effectively forecast the timing, composition, and magnitude of products requiring management (Brown-West et al., 2010). Even under the best circumstances, current recycling methods are not perfect and lead to the loss of critical materials present in low concentrations (Graedel et al., 2011; Reck and Graedel, 2012). While policy interventions could potentially help overcome some of these challenges, the U.S. currently lacks a federal e-waste policy. The current patchwork of 25 state e-waste laws have inconsistent product coverage, compliance mechanisms, and recycling targets (Schumacher and

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Agbemabiese, 2020).

These challenges may also give rise to situations where dishonest actors try to circumvent economic and policy constraints by engaging in fraudulent practices. Notable recent examples of fraud center on management of legacy cathode ray tube (CRT) devices, which have high costs of recycling and low resale or commodity market value (Kang and Schoenung, 2006; United States Environmental Protection Agency, 2020b; Xu et al., 2013). Some US firms who touted safe, ethical, and green recycling practices to gain business actually engaged in illegal stockpiling, abandoning, or exporting waste CRTs (Paben, 2019; 2020). The primary threat of stockpiling, or speculative accumulation, is that it increases the risk of mismanagement or abandonment of CRTs, which contain leaded glass and other potentially harmful materials (United States Environmental Protection Agency, 2020b). The EPA notes that in order to demonstrate that used CRTs and CRT glass are not being speculatively accumulated, both parts of the provision must be met — that is, (1) the person accumulating the used CRTs and CRT glass can show that the material is potentially recyclable and has a feasible means of being recycled and (2) that during the calendar year the amount of material that is recycled, or transferred to a different site for recycling, equals at least 75 percent by weight or volume of the amount of that material accumulated at the beginning of the period (see title 40 of the Code of Federal Regulations section 261.1(c)(8) (Office of the Federal Register, 2021)). When caught, firms have faced lawsuits, criminal charges, and stiff financial penalties. Another widely studied issue is export of used electronics to developing countries where some products may be recycled via unregulated and harmful methods (Williams et al., 2008). New examples of fraud or dishonest practices include lapses in personal data security when used electronics are resold (Qu et al., 2019; Tan et al., 2018), non-functioning products included in trans-boundary shipments under the guise of reuse (Wong et al., 2012), buyer or seller fraud during online resale or product auctions (Dong et al., 2009; Esenduran et al., 2020), and electronics repair with counterfeit components (Pecht and Tiku, 2006).

A variety of policy and market solutions have been deployed to prevent or reduce harm from fraudulent electronics management, with varied degrees of success. For example, the Basel Convention was drafted to limit off-shoring e-waste to developing countries, and all OECD countries but the United States ratified this treaty (United Nations Environment Programme, 2020). The U.S. lacks a federal e-waste policy and has favored voluntary mechanisms, such as recycler certification programs, with e-Stewards (Basel Action Network, 2020) and R2 (Sustainable Electronics Recycling International, 2020) serving as examples. These programs designate participating recyclers as compliant with best practices concerning worker health and safety, data security, and proper management of discarded electronics through the entire recycling system. The United States Environmental Protection Agency (EPA) studied the implementation of these standards and concluded that these programs have brought order and a growing understanding of regulations and best practices to electronics recyclers and related stakeholders (United States Environmental Protection Agency, 2016). However, the EPA also notes in its report that opportunities for improvement are apparent across all dimensions it assessed in the study.

While recycler certification has helped move the field toward more transparent practices, it is not a universal fail-safe against fraud and does not necessarily guarantee sustainable outcomes. One particular challenge is that detecting fraud is costly and labor-intense when considered against the complex global scale of used electronics flows (Lee et al., 2018). Some organizations have sought to use lower-cost technology solutions to identify dishonest practices. For example, between 2014 and 2016, BAN implanted GPS trackers in electronics delivered to a set of U.S. recyclers and then used the resulting data to show that about 30% of the products ended up overseas (Basel Action Network, 2016). While this initiative received much public attention, and recyclers and manufacturers pledged to improve operations, fraudulent activities have continued, as evidenced by recent lawsuits, criminal charges, and stiff financial penalties to firms, including the notable example of Total Reclaim (Staub, 2019). Further, such strategies can potentially erode public trust and participation in electronics recycling or eliminate legitimate product reuse pathways, which offer significant potential to reduce life cycle impacts of consumer electronics (Deng et al., 2011). In addition, without trust, shared decision making, and meaningful engagement of global partners, strategies aimed at accountability can actually limit partnerships that effectively link formal and informal electronics reuse and recycling sectors (Lepawsky et al., 2017; Williams et al., 2013).

There is a clear need to better understand mechanisms that can foster reuse and recycling practices that maximize the social, economic, and environmental outcomes for electronics while minimizing social and health risks. Recent studies have looked at the complex interactions between consumers, governments and recyclers using game-theoretic reasoning. For example, it has been observed that consumers sometimes store used electronic devices for a relatively long time. Subsequently, game theory has been used to estimate the optimal monetary incentive for take-back programs to encourage consumers to return their used electronics (Sabbaghi et al., 2016; 2015). A related study by Li et al. has modeled the efficacy of various subsidy schemes, where they found that the deposit-refund subsidy pioneered in Shenzhen, China can increase the collection rate of batteries used in electric vehicles (Li et al., 2020). In similar spirit, Ma and Zhang have applied an evolutionary game model to China's construction space and found that government subsidies to construction enterprises are essential for recycling. Interestingly, in this last model the authors discovered that subsidizing recyclers is not generally necessary since the recyclers' behaviors tend to be coupled to those of the construction enterprises (Ma and Zhang, 2020). However, some studies suggest that, in developing countries like China, regulations are less effective due to the "pull" of informal recycling enterprises (Zhang et al., 2020). Consequently, official recovery rates of electronics have not followed suit. This is not unlike the demand-side pull of electronics at the international scale, where used electronics and e-waste often flow from developed to developing countries where there is strong demand for reuse and recoverable materials (Chika et al., 2012; Kahhat and Williams, 2009; Zhang et al., 2012). Indeed, the import of electronics has many social and economic benefits in developing countries, albeit with the potential of negative environmental externalities (Williams et al., 2008).

Closely related work by Wang et al. has considered the role illegal or unqualified disposal plays in the equilibrium strategies of governments, consumers and recyclers (Wang et al., 2020b). This work acknowledges the important role the informal sector plays in developing countries and uses evolutionary game theory to study the conditions under which compliance among recyclers can be achieved. This analysis suggests government intervention through a "reward-penalty-supervision" mechanism may help the e-waste recycling space mature to broader compliance. For this mechanism to be effective, government supervision must be effective and always "catch" recyclers that do not comply with environmental law. However, the methods by which a government or regulator can efficiently and effectively supervise recyclers is not clear. Therefore, the goal of this study is to model decision making and fraud in electronics management to identify means of more efficient and effective supervision.

1.1. Research approach

Here we present a model framework that analyzes dishonest end-of-life electronics management in the presence of *probabilistic* supervision. Such dishonest activity could take many forms, such as improper handling or storage of e-waste, illegal exports, or product resale for reuse without adequate data security measures. Similarly, supervision could also take many forms relevant to the nature of fraud, such as facility inspection, verification of shipment manifests, or the use of a GPS location tracker (Lee et al., 2018). The decision model includes conditions that may lead recyclers to pursue fraudulent activities: cheap dishonest alternatives combined with high costs and low short-term returns of honest recycling or reuse alternatives. Our model also considers the effects of subsidies to recyclers that would incentivize honest practices. Here we also develop an analytical framework that describes the boundary conditions between alternate decisions in scenarios with varying degrees (i.e., probabilities) of third party supervision.

To this end, we begin by constructing a simplified, binary model in which a recycler must choose between honest or dishonest management practices, broadly construed. We then enrich the model to describe the role of supervision in altering a recycler's choice set. By maximizing expected utility, we obtain a formula delineating the boundary between a recycler's choices. Using this formula we can then analyze the connection between the choice of honest management and the underlying structural parameters. Notably, we look at the implications this model has for fraud prevention and apply the principles in a brief case study. Our discussion is primarily focused on those consumer electronics widely owned in US households and covered by existing state laws, and which tend to have mature markets where material opportunities and risks are known. Such products typically include cathode ray tube (CRT) monitors and televisions, printers, laptop and desktop computers, and exclude large household appliances, which are managed separately in the US (Althaf et al. (2019); Electronics TakeBack Coalition (2015)).

However, model applicability is not limited to electronics. An analysis similar to the one we conduct here could be adopted for any scenario in which there are two players R and G and

(a) R has a choice among two or more actions, with each action having different returns;
(b) G has a preference over which action R chooses and this preference is codified in policy or market mechanisms;
(c) The action of R that G prefers most has lower returns for R, at least in some cases;
(d) G has some (not necessarily perfect) mechanism for monitoring R's actions and subsequently punishing R for any wrongdoing.

Requirement (c) is necessary, for otherwise the situation would be trivial: R's preferences would align with G's preferences and we would not have a problem. Requirement (d) is necessary for player G to put *downward pressure* on the actions of R; if there were no repercussions for R, then there would be little we could do to influence R's choice outside of making G's preferred action more profitable for R. It is important to note that in the absence of a player G who can monitor R, then our model cannot be applied. Thus the strategies we develop cannot be used to study fraud in the absence of supervision.

Our study of electronics in the United States satisfies these criteria, where the e-waste recycler plays the role of R and a regulator plays the role of G. In fact, most regulatory situations satisfy these criteria, and we discuss possible extensions of this model along these dimensions in Section 4.3. Now, although in the United States there does not exist a unified, federal e-waste policy, that does not violate assumptions of the model. State regulators still administer supervision in the 25 states that have an e-waste policy (NCER, 2021), and furthermore third party organizations also engage in supervision through market mechanisms and voluntary certification programs. The lack of federal e-waste policy in the United States is arguably more reason to systematically analyze fraudulent recycling practices to look for novel solutions.

2. A two-choice model

We begin by first considering a recycler R. We assume there is only one type of electronic product requiring management and R is a passive receiver of this product. It is also assumed that external organizations are unable to directly observe R's business operations.

Figure 1 shows the two options facing R: H engage in honest management; and D engage in dishonest management. Dishonest management has a payoff, ψ, defined by a single marginal cost parameter, $\psi(\chi) = -\chi$. On the other hand, honest recycling has a payoff of $\pi(\alpha, \phi, \gamma)$, where γ is the marginal cost of recycling (e.g. labor), α is the downstream revenue potential, and $\phi \in [0,1]$ tells us the *fraction* of electronics that can be harvested for downstream resale. Examples of downstream revenue sources for electronics include the resale of products for reuse as well as the resale of components to brokers for the purposes of recycling in commodity markets. Choosing a functional form, the payoff per unit of recycled e-waste is

$$\pi(\alpha, \phi, \gamma) = \phi\alpha - \gamma. \tag{1}$$

For convenience, Table 1 summarizes the parameters discussed so far in addition to more parameters we will soon discuss.

We make the following additional assumptions: R is paid some amount for every unit of product that is delivered; R does not influence the price level on downstream markets (e.g., the price of raw scrap materials, products or components on the resale market); and R's fixed costs do not enter into its calculus at the margin. Note that with the first assumption, we can normalize all returns by whatever that purchase price may be since both actions H and D would increase by the same amount. That is, although we could explicitly include the revenue obtained by R upon receipt of a unit of e-waste, this would increase both π and ψ by the same amount. Thus in any direct comparison between π and ψ, the returns of H and D, this revenue term will cancel. Therefore, since we are most interested in a comparison of π and ψ to determine a threshold condition for the decision of R, we do not make explicit the dependence on any payments R receives for conducting business.

R will choose H for a unit of the product when

$$\pi(\alpha, \phi, \gamma) \geq \psi(\chi) \tag{2}$$

Although the right hand side of Equation (2) is strictly negative, it should be unsurprising that e-waste recyclers may "play" D on occasion, and as discussed in Section 1, recyclers have indeed been observed engaging in fraudulent management practices. According to our model, if the marginal cost of honest recycling is too high or downstream markets do not afford lucrative revenues, dishonest management becomes alluring. Combining Equations (2) and (1), we can assert that R will engage in honest management precisely when

$$\gamma \leq \phi\alpha + \chi. \tag{3}$$

In other words, R will engage in honest management only when its marginal costs are sufficiently small.

Although this conclusion is straightforward, it is nevertheless important to emphasize here. High relative costs of recycling may lead e-waste recyclers to engage in socially suboptimal behavior. Moreover, simply increasing the price paid to R will not influence their behavior, and so a direct unqualified subsidy may *not* be sufficient to encourage honest recycling. However, this simplified model does suggest one

Table 1
Summary of model parameters

Parameter	Definition	Example
χ	Cost of dishonest management	Purchasing a warehouse for speculative accumulation
γ	Cost of honest management	Wages for labor to disassemble a CRT TV
α	Downstream revenue potential	Price received for selling harvested copper wire
ϕ	Fraction of e-waste recoverable	Fraction of gold recoverable from a circuit board
ζ	Benefits of "provable" honesty	Increased business from green certification
κ	Court costs	Legal fees
ρ	Cost of punishment	Fines
λ	Cost of lying	Difficulty of forging evidence

possible mechanism through which to leverage subsidies. We can decompose α into

$$\alpha = \alpha_m + \alpha_s, \tag{4}$$

where α_m is the per-unit revenue available via downstream channels and α_s is some *subsidy* afforded to R along those same channels. Under these circumstances, provided that

$$\alpha_s > \frac{\gamma - \chi}{\phi} - \alpha_m, \tag{5}$$

the inequality in Equation (2) will be satisfied, and R will find it favorable to choose H instead of D. We frame downstream revenues α in the abstract to aid in generalizing this reasoning: α can represent *any* positive return afforded by honest recycling. In our model, branch H separates honest recycling from dishonest recycling. By subsidizing only along channels reachable through branch H, we can unambiguously benefit and encourage desired behavior. An unqualified subsidy would not differentiate between behaviors and, at least in this simplified model, would not change a recycler's decision at the margin. This refinement to the subsidy scheme could increase the efficacy of the "reward" component of the policy mechanism outlined by Wang et al. and described in Section 1 (Wang et al., 2020b).

3. The role of supervision

Here we extend the model to include supervision. Let G be a government or third-party organization that takes on the role of supervision. Suppose G applies supervision to R with frequency σ, and that the outcome of supervision can later bring R's actions under scrutiny based on the ability to observe the means through which the product was ultimately transported, stored, reused, recycled, or disposed.

Figure 2 shows a decision tree representing R's possible actions in this context. At stage 0, G applies supervision to the recycler with probability σ. At stage 1 when R receives the product, they do not know if they are being supervised. The left half of the tree represents the subsequent outcomes when no supervision is present. In this version of events, R's choices and subsequent payoffs are the same as those discussed in Section 2.

The right half of the tree in Figure 2 differs slightly and represents a sequence of events occurring when R's management is supervised. In this scenario, if R engages in honest management, they achieve a return

$$\pi' = \pi + \zeta = \phi\alpha - \gamma + \zeta, \tag{6}$$

where we use π as defined earlier in Equation (1) and we use ζ to account for additional benefits R may reap from having been observed to be honest. Such benefits may, for example, come in the form of subsidies or greater market share due to third party certification or increased consumer confidence.

However, should R take part in dishonest management, we reach decision node 2 at which R faces consequences from evidence suggesting dishonest behavior. Such consequences may include litigation by environmental regulators or a negative public opinion that decreases business or their ability to secure future contracts. At this stage, R faces two choices: A, accept its fate, or L, craft a defense to contradict G's claims. We denote R's returns from A by

$$\psi'_A = -\rho - \kappa - \chi, \tag{7}$$

where ρ is a measure of "punishment" rendered against R; κ is litigation costs, the costs of "going to court", should the consequences entail litigation; and χ remains as before, the marginal cost of dishonest management.

We similarly denote R's returns from mounting a defense by

$$\psi'_L = -\lambda - \kappa - \chi. \tag{8}$$

The parameters κ and χ are the same as those in the payoffs to A, while λ represents the costs of mounting a defense. There may be some probability that the defense fails and so λ represents the expected return from L net the fixed costs κ and χ. We refer to λ as the "cost of lying" because it represents R's return from arguing they had not engaged in dishonest management when indeed they have. Possible behaviors encompassed by λ include bribery, forgery, and intimidation.

Given σ, we want to know whether R will engage in dishonest management. We denote R's optimal share of dishonest behavior by $\delta \in [0,1]$. Figure 3a plots the correspondence between δ and σ. The vertical segment denoted by σ^* traverses the entire interval $[0,1]$ and tells us the level of monitoring at which R is indifferent between actions H and D. Indifference is met when expected returns from either action are equivalent, that is when $E[H|\sigma] = E[D|\sigma]$. Were we to consider a game theoretic model in which the strategy of G is determined by a host of tradeoffs, we would find that the intersection of G's decision correspondence with that of R shown in Figure 3a would determine the level at which R would engage in dishonest management. A value of δ between 0 and 1 in this context would represent the probability that R will dishonestly manage a given unit of the product.

R's expected returns from playing H in this context are simply

$$E[H|\sigma] = (1-\sigma)\pi + \sigma\pi'. \tag{9}$$

To calculate $E[D|\sigma]$ we need one additional piece of information, namely R's return at stage 2. Since R will choose whichever of L or A has a higher return we define

$$\psi' := \max\{\psi'_L, \psi'_A\}, \tag{10}$$

through which we have

$$E[D|\sigma] = (1-\sigma)\psi + \sigma\psi'. \tag{11}$$

This gives us R's decision point:

$$\sigma^* = \frac{\psi - \pi}{\Delta\pi - \Delta\psi}, \tag{12}$$

where we've defined $\Delta\pi := \pi' - \pi$ and $\Delta\psi := \psi' - \psi$.

Again, σ^* tells us the level of supervision at which R is indifferent between honest and dishonest management practices; σ^* delineates the boundary between R's decision. For values of σ *less* than σ^*, R finds it optimal to behave dishonestly when handling all products it receives, yet for values above σ^* the likelihood of facing negative consequences is a sufficient deterrent and so R engages in honest management.

3.1. Shift effects

Figure 3 b illustrates how changes in underlying parameters produce a *shift* in the decision boundary σ^*. The figure considers a *decrease* from σ^*_A to σ^*_B and provides geometric intuition for why such a shift is desirable: The closer σ^* is to zero, the smaller the region over which dishonest

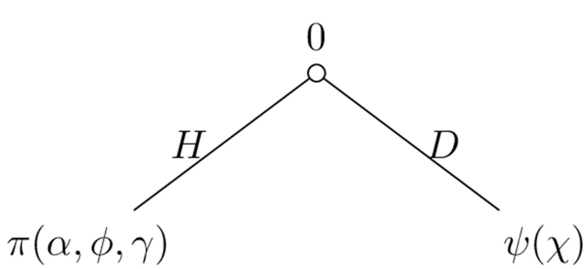

Fig. 1. A recycler R's core decision tree. Upon receipt of a product at decision node 0, R has two choices: H engage in honest management, or D take part in dishonest management. Each choice has a distinct payoff shown at the end of each decision branch.

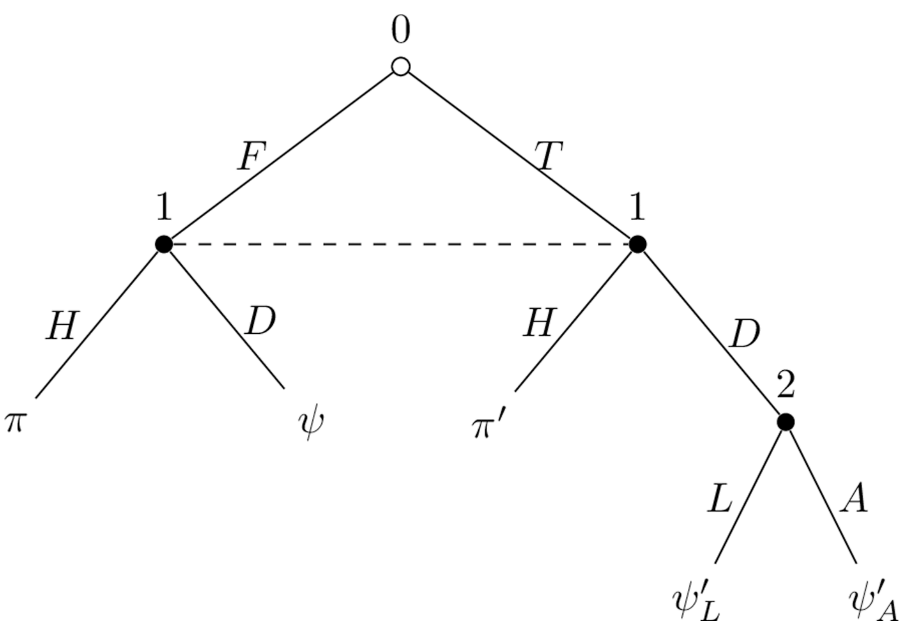

Fig. 2. A recycler R's decision tree within the context of supervision by a third party G. A product is delivered to R at decision node 0, but unlike in Figure 1, there is some probability σ that G is supervising R's management of the product. The left branch F of the tree traces a path in which R is *not* being supervised; the right branch T, on the other hand, represents a sequence of events in which R is being supervised. At decision node 1, R does not know which path it is on, a situation we denote as a dashed line between the two decision nodes.

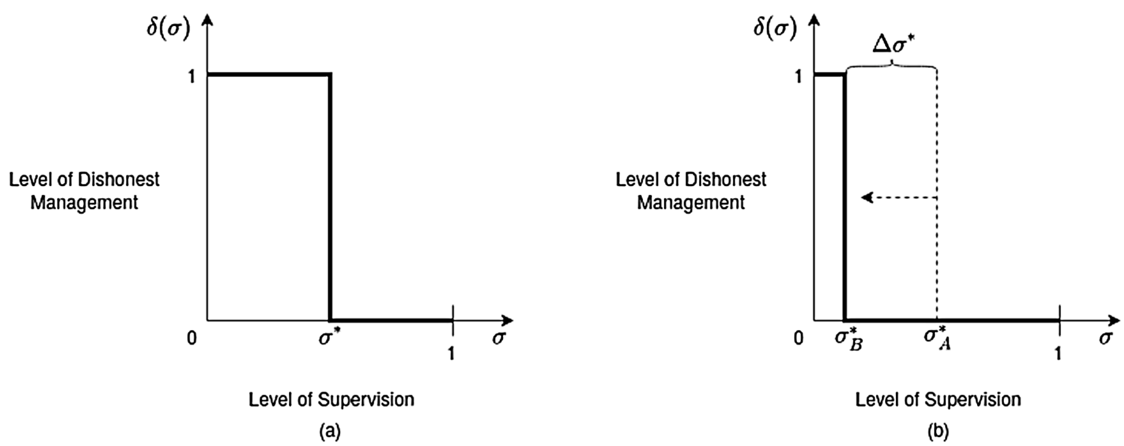

Fig. 3. A recycler R's: 3(a) decision correspondence with a boundary at σ^*; and 3(b) shift in decision boundary from $\sigma^*_A \rightarrow \sigma^*_B$, with $\sigma^*_A > \sigma^*_B$.

management remains an optimal decision.

Ultimately, in the real world, we know that levels of supervision are often *inadequate*, and our model can illustrate this theoretically. We are interested in studying the ways we may be able to influence the underlying parameters of our model to see which interventions may help and in what way. To begin, we rewrite (12) with the parameters explicitly substituted:

$$\sigma^* = \frac{\gamma - \chi - \phi\alpha}{\zeta + \kappa + \min\{\lambda, \rho\}}. \tag{13}$$

Note that R wants to maximize returns at decision node 2, which corresponds to picking whichever of $\{L, A\}$ has a higher payoff. Based on (7) and (8), that means the payoff from decision node 2 will be λ or ρ, whichever is smallest, and so that is why the denominator contains $\min\{\lambda, \rho\}$. An interesting consequence, of course, is that the punishment would need to be sufficiently high to produce useful outcomes. For the purposes of this analysis, we assume that ρ is sufficiently large so that R faces negative consequences that pose an adequate threat. With that assumption, $\min\{\lambda, \rho\} = \lambda$. In theory it should be easy to make ρ arbitrarily large (e.g., adding an extra year on a prison sentence or an additional fine). In practice, however, no punishment can be arbitrarily large and what is important is that ρ be made *sufficiently* large.

We can now write the differential $\mathrm{d}\sigma^*$ as

$$\eta \mathrm{d}\sigma^* = \mathrm{d}\gamma - \mathrm{d}\chi - \mathrm{d}\phi\alpha - \phi\mathrm{d}\alpha - \sigma^*(\mathrm{d}\zeta + \mathrm{d}\kappa + \mathrm{d}\lambda), \tag{14}$$

where $\eta := \zeta + \kappa + \lambda$ is the denominator of σ^* with $\min\{\lambda, \rho\} = \lambda$ substituted appropriately. The variables on the right-hand side of Equation (14) are those over which we have some level of control. Structurally, they represent interventions that can be used to influence R's decision point.

How could one efficiently influence R's choice? The decision boundary σ^* reports the minimum level of supervision necessary to have R choose H. In this context, by *efficient* we mean not supervising more often than σ^*. As illustrated by Figure 3b, σ^* is not necessarily a static variable according to our model. By decreasing σ^* we can require less supervision and still achieve honest recycling on behalf of R. We can use Equation (14) to list off the the parameters we should target: an *increase* in a term that is preceded by a negative sign or a *decrease* in a term that is preceded by a positive sign will produce the desired *decrease* in σ^*.

Such shifts in individual decision boundaries are to be expected when considering real world situations with more than one individual. Many examples in the field of behavioral ecology illustrate the evolution of frequency-dependence with regards to genes that underpin cheating and policing behavior in social groups at all levels of life forms. These

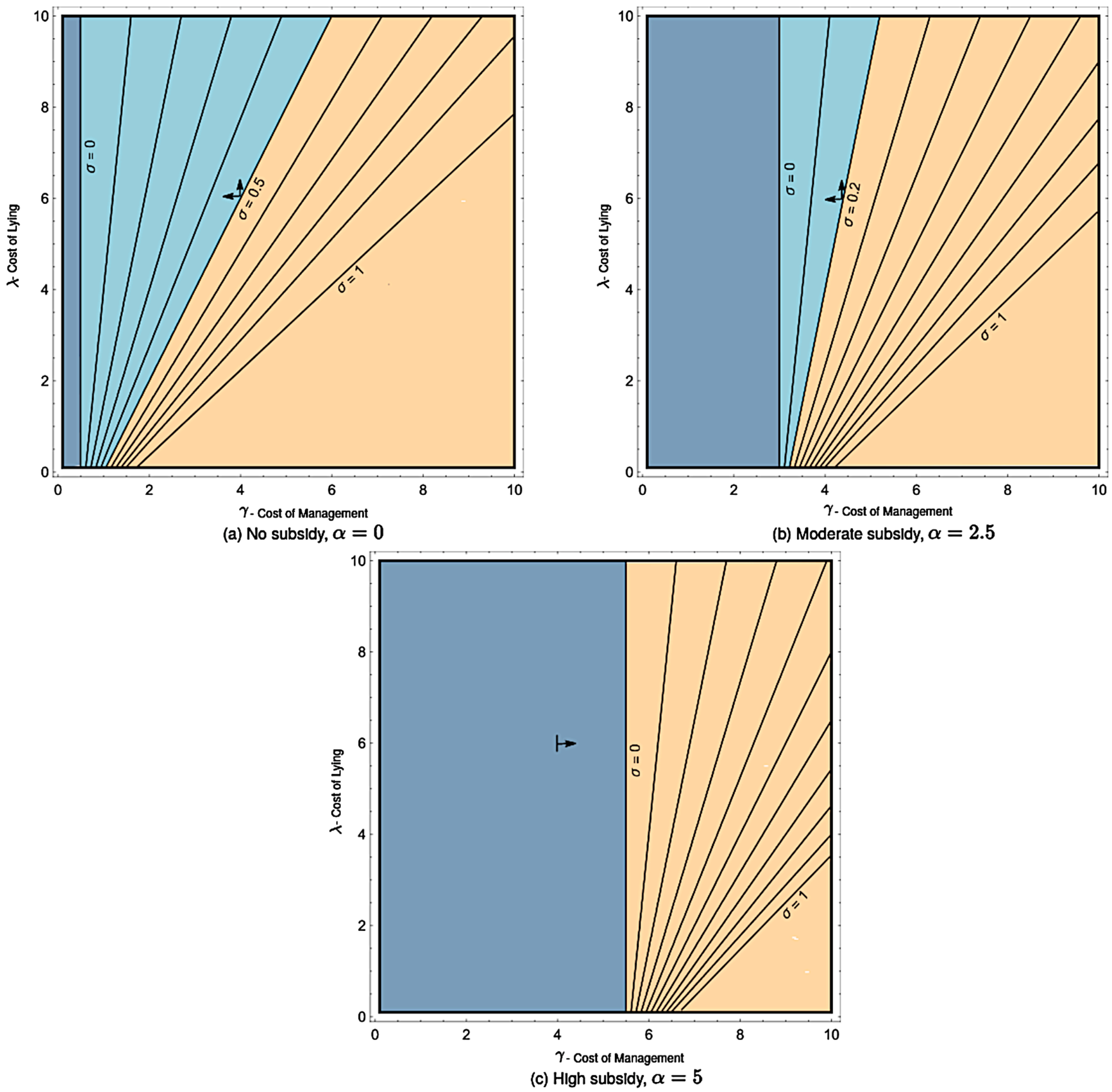

Fig. 4. Contour plots of R's decision boundary as a function of management costs (γ) and costs of lying (λ) for various levels of subsidy (α). Illustrative values for the other parameters were chosen as follows: $\phi = 1$ and $\chi = \zeta = \kappa = 0.5$. The cross hairs in each plot indicate σ^*, the minimum level of supervision required to influence R to choose honest recycling when $\gamma = 4$ (relatively "low") and $\lambda = 6$ (relatively "high"). The positive effects of subsidy are shown for $\alpha = 0$ (4 a), $\alpha = 2.5$ (4 b) and $\alpha = 5$ (4 c). The region in which no supervision is needed is depicted in dark blue. Relative to $\gamma = 4$ and $\lambda = 6$, the region in which relatively less supervision is needed is depicted in light blue; the region in which relatively more supervision is needed is depicted in orange.

dynamics exist because the calculus of individual risk-reward to fitness with respect to policing behavior is a natural function of how much policing is happening at any given time in a population (Hauser, 1992; Ratnieks and Visscher, 1989; Santorelli et al., 2008; Sinervo and Lively, 1996).

Unsurprisingly, the only parameter we should decrease is γ, the marginal cost of honest management; all other parameters should be increased to achieve desired effects. There are various mechanisms to achieve reduced e-waste management costs, such as upstream product design that is optimized for later disassembly to enable repair and reuse (Vanegas et al., 2018) or improved recycling technology (e.g., robots with advanced computer vision (Wang et al., 2020a; 2019; Wegener et al., 2015)). As an added benefit, these mechanisms have positive spillover effects including higher system throughput and increased product and material recovery rates.

4. Analysis of the cost of fraud

According to our model, in a world where it is cheap to improperly manage e-waste, the only way to guarantee that an e-waste recycler will engage in honest practices is to reduce the costs of recycling below the downstream revenue potential of e-waste reuse or recycling. In this case, supervision would not be necessary, regardless of the other parameters. However, for some kinds of e-waste, proper recycling costs may be relatively too high, and so supervision may be necessary. Although ideally we would address the root causes of fraudulent e-waste recycling — through policy, designing for disassembly, and reducing recycling costs — our model offers an opportunity to study ways of mitigating the fraud that may result as a symptom of these deeper problems.

Figure 4 provides three contour plots to summarize our discussion of the parameters. Each plot shows the minimum level of supervision σ^* as a function of γ and λ, the costs of management and lying, respectively. The plots differ in the level of α chosen to show the effects of various levels of subsidy; the first plot shows a scenario with zero subsidy, while the subsequent plots illustrate the effects of larger subsidies. Although levels of α can also be interpreted as levels of downstream revenue potential, we choose to view α as a subsidy in this section since presumably that is something over which policy makers have greater control. The other parameters in our model are given illustrative values of $\phi = 1$ and $\chi = \zeta = \kappa = 0.5$. Since the framework does not rely on specific units for these parameters (e.g., USD), and these parameters are not the focus of our analysis, we will not discuss them further.

Every point in Figure 4 tells us the *minimum* amount of supervision required to achieve honest management. For example, in each plot we focus on the location of the decision boundary when $\gamma = 4$ (relatively "low") and $\lambda = 6$ (relatively "high"), indicated by the arrows (or cross-hairs) in the planes of Figures 4a and 4 b. In Figure 4a where there is zero subsidy, we see that supervision must occur with a frequency of 0.5 — i.e., 50% of e-waste received by R must be supervised — for honest recycling to occur.

The minimum level of necessary supervision can be reduced by decreasing recycling costs or increasing the costs of lying. Graphically, this amounts to moving the crosshairs into either the light or dark blue regions of the contour plots. This shift can also be achieved by increasing the area occupied by the blue regions which is illustrated in Figures 4b and 4 c where the level of α has been increased, resulting in a lower level of minimum supervision required. Once we have reached the relatively high level of subsidy shown in Figure 4c, not only is no supervision required with our example values of $\gamma = 4$ and $\lambda = 6$, the subsidy is perhaps too large: a smaller subsidy, one that would shrink the light and dark blue regions until the orange half of the plot rests on the cross hairs, would have the same outcomes.

Shown in dark blue is the critical strip in which no supervision is necessary. Observe that increasing the level of subsidy increases the size of this region and consequently allows for R to engage in honest recycling even when recycling costs may be high. Note that since the strip lies parallel to lines of constant γ, no variation in λ can help us traverse into the critical strip.

To summarize, when recycling costs are large enough to require high levels of supervision, we can decrease the level of supervision by increasing lying costs, an implication we pursue further in Section 4.2. Another alternative presented by our model is to increase the returns from honest management, perhaps via subsidies.

4.1. Case study

We now use our model to compare recycling of printed circuit boards (PCBs) and cathode-ray tubes (CRTs) found in legacy analog televisions and monitors. Demand for CRTs and CRT glass has collapsed in recent years due to consumer tastes for flat screen monitors (Kasulaitis et al., 2015). Decreased demand for recovered components and added expenses of safe handling and treatment (Singh et al., 2016) have driven some recyclers to export or accumulate the devices indefinitely. As a result, the United States Environmental Protection Agency (EPA) has imposed strict regulations to limit these behaviors, classifying CRTs as hazardous e-waste due to their leaded glass (United States Environmental Protection Agency, 2020b). On the other hand, PCBs continue to be recycled at a high level, due to the value of gold they contain (Zeng et al. (2018)). Recycling PCBs presents fewer technical challenges, as they can be removed during manual disassembly or pre-processed via mechanical shredder prior to recovery in established precious metal smelters. Their high commodity value tends to keep PCBs flowing into material recovery pathways, although they may also be characterized as hazardous depending on material content (legacy PCBs contain lead solder) and state regulations. Thus, mismanagement of PCBs could also pose legal risks for recyclers, although this risk is seldom realized.

To put this in the context of our model, the cost of recycling a CRT is greater than that of a PCB: $\gamma_{CRT} > \gamma_{PCB}$. However, revenues from resale of PCBs exceeds that from CRTs: $\alpha_{CRT} < \alpha_{PCB}$. For the purposes of this simplified comparison, we can say the cost of dishonest management of both types of e-waste is the same, i.e. $\chi_{CRT} = \chi_{PCB} = \chi$. However, mismanagement of CRTs warrants harsher punishment. That is, $\rho_{CRT} > \rho_{PCB}$. It is worth noting that recyclers typically have no reason to mismanage PCBs since they are valuable components in e-waste. Although ρ_{PCB} may not be realized in practice, it is important only that the punishment be a sufficiently credible threat; if not *realized* it must be *realizable*.

In terms of the act of doing the lying (e.g., forging data to suggest waste was received more recently than it actually was) there is no reason to believe a recycler faces differential lying costs for each type of e-waste. Thus, $\lambda = \lambda_{CRT} = \lambda_{PCB}$. Again, λ denotes the cost of lying, not the ramifications from lying. Because punishment from illicit mismanagement of e-waste is much more costly than lying, we can also say that $\lambda < \rho_{PCB} < \rho_{CRT}$, and so the denominator of Equation 13 is the same for both types of e-waste, i.e. $\eta_{CRT} = \eta_{PCB} = \eta$. This gives the comparison

$$\sigma^*_{CRT} - \sigma^*_{PCB} = \frac{1}{\eta}[(\gamma_{CRT} - \gamma_{PCB}) + (\alpha_{PCB} - \alpha_{CRT})]\rangle 0. \tag{15}$$

In other words, the minimum level of supervision required for honest management of CRTs is greater than that required for PCBs.

We can also take the analysis a step further when we consider a change in lying costs. Note that from Equation (14), the first derivative of σ^* with respect to lying costs is

$$\frac{\partial \sigma^*_i}{\partial \lambda} = -\frac{\sigma^*_i}{\eta} \tag{16}$$

where the index i can represent either CRT or PCB. From Equation (15) we have $\sigma^*_{CRT} > \sigma^*_{PCB}$ and so

$$\left|\frac{\partial \sigma^*_{CRT}}{\partial \lambda}\right| > \left|\frac{\partial \sigma^*_{PCB}}{\partial \lambda}\right|. \tag{17}$$

The implications of this are that an increase in the costs of lying in the CRT space have a more significant impact than they would on the PCB space.

The goal with this model is to provide a theoretical framework with which to reason about fraud and ways to prevent it and upon which future case studies can be applied to analyze systems with real data. However, we can give estimates for the case study analysis above to provide a suggestion of how to apply the model as an approximation. As Kang and Schoenung found, the most critical cost driver for an e-waste materials recovery facility is to have CRT glass recycled, and this accounts for 30% of the facility's annual operating costs (Kang and Schoenung, 2006). Without worrying about the precise cost to recycle a PCB, we can then make the conservative estimate that CRTs and PCBs have the same recycling cost profile, i.e., $\gamma_{CRT} = \gamma_{PCB}$. The critical parameters in Equation (15) then reduce to α_{CRT} and α_{PCB}, the revenue potential of CRTs and PCBS, respectively. This assumption underestimates the difference in (15), but preserves the sign.

Continuing, the most valuable components of both a CRT monitor and a PCB are the metals they contain. Recent mass balance analyses of CRT monitors indicate they are 3% copper and 0.005%-0.011% gold by mass (Zeng et al., 2018). Meanwhile a typical PCB is about 10%-20% copper and 0.011%-0.33% gold (Ghosh et al., 2015; Montero et al., 2012). According to the London Metal Exchange for the month of January 2021, the price of copper was 8,000 USD per tonne while the price of gold was 1,800 USD per fine troy ounce (London Metal Exchange, 2021). With these calculations, the downstream revenue potential for one kilogram of CRT is about $\alpha_{CRT} = 6.60$ USD in the *best* case while for one kilogram of PCB it is $\alpha_{PCB} = 7.15$ USD in the *worst* case. Thus the difference, and hence Equation (15), is indeed positive even under the most favorable circumstances for a CRT's material and cost profile. This trend is anticipated to be true for product reuse as well. In one case study, the market values of laptop and desktop computers intended for reuse were observed to be 10-100 times higher than those for CRT monitors, which currently see limited demand in the U.S. (Babbitt et al., 2011). Based on the differences in revenue potential, fraud is more likely to occur while managing CRTs. The model also suggests efforts to prevent fraudulent management of CRTs should have a greater impact on the decisions of a recycler than efforts to prevent mismanagement of PCBs.

4.2. Fraud prevention and substitution effects

We now study the equivalence between an increase in the cost of lying and a decrease in the cost of management. To develop this relation, we use (14) and imagine that we can change only the two parameters γ and λ and that we are constrained at $d\sigma^* = 0$. That is, we ask: Were we to *increase* the difficulty of lying, by how much would we need to *increase* the marginal cost of management to keep R's decision boundary unchanged? From Equation (14) this relation is just

$$d\gamma = \sigma^* d\lambda. \tag{18}$$

Graphically, the situation is illustrated by the contour lines in Figure 4. For interior points, where $\sigma^* \in (0,1)$, we see that a one-unit increase in λ is less powerful in some sense, since the required increase in γ is less than one. Visually this corresponds to the relative steepness of the contour lines with respect to the γ (horizontal) axis in the figures. Indeed, σ^*'s decrease from λ is diminishing since $\frac{\partial^2 \sigma^*}{\partial \lambda^2}$ is positive[1]. Thus on theoretical grounds, increasing the cost of lying has effects proportional to decreasing recycling costs.

We now consider the inputs to both γ and λ. That is, we consider both parameters as functions of other factors that, when combined, lead to the levels assumed by γ and λ. For example, the marginal cost of recycling can implicitly be affected by product design, labor costs and productivity, as well as the technology employed by the recycler. Technology, or technological capital, in this domain can include mechanical shredders, physical and optical separation, and hydrometallurgical and pyrometallurgical material recovery processes. Similarly, the difficulty of lying may be influenced by the strength of institutions and their ability to enforce policy in addition to technology like blockchain that makes it nearly impossible to falsify data.

To formalize, let τ_γ denote the amount of technological capital used by R as input to its recycling practice, and let τ_λ denote the role technology plays in lying costs. That is, we regard γ as a function of τ_γ among other implicit factors (i.e., $\gamma = \gamma(\tau_\gamma)$), and we regard λ as a function of τ_λ among other implicit factors (i.e., $\lambda = \lambda(\tau_\lambda)$). Then using Equation (14) in conjunction with the chain rule we get

$$\frac{d\tau_\gamma}{d\tau_\lambda} = \sigma^* \frac{\partial\lambda/\partial\tau_\lambda}{\partial\gamma/\partial\tau_\gamma}. \tag{19}$$

The right-hand side of the equation represents the marginal rate of substitution between τ_λ and τ_γ. Holding σ^* fixed at a given level, it tells us how much we must decrease τ_γ given a marginal increase in τ_λ. This is useful because given relative prices of inputs τ_λ and τ_γ we can determine if we are achieving σ^* optimally. If we are, then $d\tau_\gamma/d\tau_\lambda = -p_{\tau_\lambda}/p_{\tau_\gamma}$.[2]

Although a similar analysis can be conducted for any of the parameters in our model, there are reasons to focus on λ. Whereas technology to lower the costs of recycling is likely to develop slowly, require high capital costs, depend on recyclers' willingness to adopt, and in some cases faces fundamental limits imposed by material dispersion and thermodynamics (e.g., the minimum energy required to separate a mixture into its component parts (Dahmus and Gutowski, 2007)), technology to increase the cost of lying can both increase rapidly and has no obvious bounds set by physical laws. Notably, recent advances in computing technology may play a role here, such as blockchains, which are immutable, append-only ledgers of data records that make retroactive tampering practically impossible. Thus $\partial\lambda/\partial\tau_\lambda$ may be relatively larger than $\partial\gamma/\partial\tau_\gamma$. If this is indeed the case, we may be able to achieve the same decision boundary σ^* more efficiently by substituting toward technology that is built upon such improvements in data immutability.

We also add that there are spillover effects of technologies such as blockchains. In its report on certification programs, the EPA offered suggestions for improvement, including: control of records, improved tracking, downstream accountability, and export practices (United States Environmental Protection Agency, 2016). Central themes in the report include the need for enhanced material tracking and records management and the inherent complexity of verifying compliance among downstream e-waste processors. Because of the short time span of audits, the EPA notes that it is difficult to conduct a thorough accounting of all transactions into and out of recycling facilities. In practice, there is room for auditors to miss illegal activity at the facility (like CRT stockpiling, for example). The potential benefit of better record keeping technology is that it can allow for accurate and algorithmic mass balance analyses, reducing the time and costs of auditing. In addition, with increasing numbers of recyclers using similar software, it becomes easier to ensure compliance of downstream vendors. This also has implications for the study by Wang et al. in which, as described in Section 1, the authors propose a joint "reward-penalty-supervision" mechanism to achieve universal compliance among recyclers (Wang et al., 2020b). Our discussion suggests blockchain could play a role in reducing both the level and cost of supervision which could make their proposed mechanism more achievable in practice. In the US, where there is no unified e-waste policy, blockchain also has the potential to alleviate pain from differences in state and local policies. There may be other societal benefits from adopting this technology as well. As França et al. found in a study of waste management in small Brazilian municipalities, a blockchain-based system contributed to social inclusion, and, by offering a currency, also contributed to the local economies throughout the communities (França et al., 2020).

4.3. Limitations and extensions

It is worth noting some important considerations that our model does not address. We assume that a recycler's operations are not observable by an outside organization. However, recyclers' behavior is not determined under the assumption that no one can observe their business and that no one internally will report misdeeds. Also, our model allows for recyclers to fraudulently manage *all* of their e-waste (as opposed to just a small fraction), even though in practice that would be an obvious tell that something is amiss, and it would be difficult to conceal such behavior. Recyclers can also alter or modify their level of fraudulence depending upon the frequency of supervision (i.e., in response to frequency-dependent selection acting upon the calculus of risk and reward mentioned earlier). Additionally, there are different types and quality levels of e-waste, each with their own recycling costs and downstream revenue potentials. Recyclers may also actively seek for e-waste that maximizes profit. All of these considerations suggest that recyclers in practice are selective about the electronics they resell or recycle (or choose to fraudulently manage). Furthermore, our model does not study an e-waste recycler in the broader ecosystem of recyclers, and we ignore altruism and reputation effects, which influence both consumer choice as well as recycler behavior.

As described in the Introduction, this model is applicable in other situations, provided the application domain satisfies the criteria enumerated in Section 1.1. The particular consequences of the model will depend on the region in which a policymaker or researcher believes the parameters of the application domain are situated. For example, one possible extension could be to consumer recycling of plastics. In this context the consumer would assume the role of the recycler R. Our model then gives another justification for why bottle deposits encourage consumers to recycle more (Saphores and Nixon, 2014): the bottle

[1] To see this, note that Equation (14) says $\partial\sigma^*/\partial\lambda = -\sigma^*/\eta$, where $\eta = \zeta + \kappa + \lambda$. So then $\partial^2\sigma^*/\partial\lambda^2 = 2\sigma^*/\eta^2$, and recall that all parameters are positive by definition.

[2] Note that $\frac{\partial\gamma}{\partial\tau_\gamma} < 0$ since an increase in technological capital that makes recycling easier means a decrease in the costs of recycling.

deposit functions as a subsidy to the consumer that is achievable only when the consumer recycles a bottle properly through official channels. The model may also find utility in mitigating fraudulent cross-border redemption in Bottle Bill states, where deposit-refund schemes allow consumers to return bottles after use and receive a small refund (Niu, 2017).

The model may also be applicable to comparisons of e-waste policy between the US and the European Union (EU). Validation of the model may come from the space of *consumers* of electronics and not recyclers. As noted by Ongondo et al., stockpiling is a common practice among US households where instead of taking their used products to a recycler where they may have to pay an end-of-life fee, households store used electronics (Ongondo et al., 2011). This is in contrast to the situation in the EU where extended producer responsibility (EPR) policies place the burden of product take-back onto the *producer* (Sachs, 2006). The "qualified subsidy" in this case is to consumers who share the burden of end-of-life fees with producers. Again, because this subsidy is targeted only along honest take-back pathways (i.e., not afforded to consumers who stockpile) this positive difference in the relative rate of consumer take-back between the US and EU aligns with expectations based on our model. Similar differences were also observed in Maine under the introduction of EPR policy in 2006 where the quantity of electronics collected and recycled increased by over 100% during the first three years of the policy (Wagner, 2009). Further research needs to be done to apply the model to understand the differences in the behaviors of *recyclers* between the EU under EPR and the US which lacks unified federal policy on electronics product externalities. It may be that differential rates of illegal e-waste export could be due to EPR, via the subsidy channel suggested by the model, but there may be a variety of other factors at play.

Future work can also extend the approach taken here as a game-theoretic analysis that examines a market with two or more competing recyclers to understand the strategic implications of their decisions. There is also a need to model the motivations of third-party entities to see how the incentives of auditors and certifiers influence the decisions of recyclers. Another natural extension would be the application of a machine learning decision tree model on real data; our model would offer one structural framework to interpret behavior observed in the data. In absence of observational data, agent based modeling could be used to generate output against which a decision tree model could be trained. The dynamics exhibited by recyclers and auditors could then be more readily ascertained, and, in particular, one could directly observe the shifts in the decision boundary under various conditions.

5. Conclusion

In this study, we have formulated the decision calculus of an e-waste recycler facing a trade-off between honest and dishonest e-waste management options. Within this framework we find that the cost of honest recycling is a key determinant of recyclers' choices. Moreover, our decision model illustrates why an unqualified government subsidy to recyclers may not be sufficient to shift the choices of a recycler. Instead our model suggests a more targeted approach that benefits recyclers that engage honestly with downstream material or resale markets.

In addition, our model gives special consideration to the influence of monitoring and supervision. The framework provides theoretical justification for why certain types of supervision that are probabilistic may be effective. It also suggests reasons why supervision may be *inadequate*, including high marginal costs of honest management. In such cases, our model recommends various interventions, such as targeted subsidies and increased costs of fraud, and describes the direction of influence they will have on outcomes.

Ideally we would reduce recycling costs or allow for stronger policies. However, when these are not options, the analysis suggests that an increase in the cost of fraud plays a similar, albeit attenuated, role as would a decrease in the cost of recycling. We regard this relation as a substitution effect between a parameter we would like to target (i.e., the cost of recycling) and another variable over which we believe there is still unexplored potential (i.e., the cost of committing fraud). We posit that immutable record keeping technologies like blockchain may be one solution along this dimension. Thus, as the world becomes increasingly digitized, fraud-prevention technologies like blockchain may be another tool to align behaviors across recyclers and towards a circular economy.

CRediT authorship contribution statement

Daniel Salmon: Methodology, Writing - original draft. **Callie W. Babbitt:** Writing - review & editing. **Gregory A. Babbitt:** Writing - review & editing. **Christopher E. Wilmer:** Wr Editing and overall project guidance & administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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