Do E-Waste Laws Create Behavioral Spillovers? Quasi-Experimental Evidence from California

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To appear in Production and Operations Management Journal.

The citation for the paper is:

Dhanorkar, Suvrat, and Suresh Muthulingam. (2020) "Do E-Waste Laws Create Behavioral Spillovers? Quasi Experimental Evidence from California." *Production and Operations Management*. https://doi.org/10.1111/poms.13182

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Abstract

Many governing bodies have launched efforts to shape the operations of manufacturers, administration of civic entities and behavior of individuals to limit waste generation. Typically, such efforts commence with the enactment of targeted legislations that create operational changes (e.g., recycling fees, collection centers) to the waste collection and disposal processes. For example, over 25 states in the USA have enacted legislations that aim to properly dispose used electronic and electrical goods (i.e., e-waste) and divert such waste away from landfills. We argue that such legislations can have an impact that extends beyond just reducing e-waste. This is because such laws may not only motivate individuals to restrict e-waste but also induce broader behavioral spillovers that can prompt individuals to reduce waste in general. To explore this idea, we exploit a quasi-experimental setup that arises from California's enactment of the Electronic Waste Recycling Act (EWRA). Specifically, a *difference-in-differences* analysis reveals that the introduction and implementation of the EWRA resulted in at least 4.93% reduction of municipal solid waste (MSW). A plausibility analysis illustrates that these MSW reductions are much larger than what can be attributed purely to the decline of e-waste. Furthermore, we show that the effect of e-waste laws is stronger when consumers have increased market access through (i) *online connectivity* and (ii) *offline proximity*. Our study informs policy makers on the effects of e-waste legislation and the critical role of market access in enhancing the impact of such legislation.

Keywords: E-Waste Laws, Behavioral Spillovers, Online Connectivity, Offline Proximity, Quasi-experiment
Received: March 2019; **Accepted:** March 2020 by Nitin Joglekar after two revisions.

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1. Introduction

The Unites States is discarding increasing quantities of used electronic and electrical goods (more commonly known as 'e-waste'). The Environmental Protection Agency (EPA) estimates that from 2000 to 2012, the amount of e-waste in the U.S. Municipal Solid Waste (MSW) increased from 1,900 to 3,420 thousand tons (EPA 2016). The growth in e-waste is not limited to the U.S. only; e-waste is also considered as one of the fastest growing waste streams in the world. E-waste often contains toxins such as lead, cadmium, mercury, beryllium, and brominated flame retardants. When e-waste is sent to landfills or incinerated, it can result in harmful environmental and health consequences because toxins can leach out and contaminate the soil, atmosphere, waterways and groundwater (Lerner 2011). Given the negative consequences, many countries and governing entities have sought to initiate operational changes (e.g., fees, collection, recycling) to curb the improper disposal of e-waste. Typically, legislative mechanisms are used to authorize these operational changes. For example, member countries in the European Union, 25 states in the USA, Japan (to mention a few) have introduced legislation to divert e-waste away from landfills and to properly dispose hazardous materials (Atasu and Subramanian 2012). In the United States, the predominant approach – pioneered by California's Electronic Waste Recycling Act (EWRA) – places the operational responsibilities for overseeing the collection, recycling and disposal of e-waste on counties and related jurisdictions (Lerner 2011). The operations management (OM) literature has recognized the operational challenges of managing e-waste and several papers have provided a deeper theoretical understanding of the design, policy and operational implications of e-waste legislation (Atasu and Van Wassenhove 2012; Ferguson and Toktay 2006).

The general emphasis of the literature, so far, has been to understand the impact of such legislation on managing and reducing e-waste (Gui et al. 2015; Plambeck and Wang 2009). But e-waste legislations can have an impact that extends beyond just reducing e-waste. In other words, the efforts to reduce and manage e-waste can prompt individuals and organizations to undertake a broader review of current practices, which can uncover additional opportunities to restrict waste in general. This notion is consistent with research on behavioral spillovers, which proposes that pro-environmental interventions in one domain can also induce broader pro-environmental behavioral shifts in other domains (e.g., Poortinga, Whitmarsh and Suffolk, 2013; Truelove *et al.*, 2014; Thomas, Poortinga and Sautkina, 2016). While several papers have examined the operational and strategic aspects of e-waste legislation (Atasu, Özdemir, and Van Wassenhove 2013; Atasu, Wassenhove, and Sarvary 2009; Plambeck and Wang 2009), hardly any research explores whether e-waste legislation has an impact that extends beyond merely reducing e-waste. We seek to bridge this gap by exploring whether e-waste legislation leads to lower municipal solid waste (MSW) and by informing that the impact of such waste reduction goes beyond what can be realized by just reducing e-waste. Our research is driven by the general approach adopted in many industry studies that examine the effect of a public policy on operational decisions and consumer choices (e.g., Joglekar, Davies and Anderson, 2016). We analyze longitudinal data on MSW to investigate the impact of a public policy initiative on broader consumer choices and behaviors. In particular, we ask whether e-waste legislation generates broader behavioral spillovers that can be observed through overall MSW reductions.

Next, we explore two mechanisms that can amplify the impact of the behavioral spillovers that emanate from e-waste legislation. To do so, we recognize that individuals play an important role in the disposal of e-waste. Enhancing their access to repair, reuse, or recycling options can support legislative efforts by curtailing the inflow of e-waste to landfills. When individuals get better information on repair, recycling, and reuse options for e-waste, they can not only reduce their e-waste disposals but also explore recycling and reuse options for other used goods, which can further limit other waste inflows to landfills. One mechanism that can improve individuals' access to repair, reuse and recycling options is increased *online connectivity* (i.e., broadband access), which can facilitate the exchange of information and reduce search costs (Bakos 1997; Brynjolfsson and Smith 2000). For example, higher online connectivity can help individuals by enabling them to form large social networks, connecting them with a range of firms, and allowing them to leverage wider sources of information (Firth and Mellor 2005). Another mechanism that can improve individuals' access to repair, reuse and recycling options is *offline proximity* to other users, which provides opportunities for diffusion of information and ideas through local connections (Choi, Hui, and Bell 2010; Forman, Ghose, and Goldfarb 2009). For example, although online channels (e.g., Craigslist, Freecycle) may generate substantial MSW reductions (Dhanorkar 2019; Fremstad 2017), such channels primarily leverage the geographic proximity of users through local markets (Kroft and Pope 2014) to engage in physical exchange of goods and services. Overall, we theorize that *online connectivity* and *offline proximity* provide the necessary infrastructure to promote reuse and recycling options for individuals, thereby reducing the use of landfills. Consequently, we probe whether higher *online connectivity* and *offline proximity* amplify the behavioral impact of e-waste legislation, which contributes to further MSW reductions.

To examine our research questions, we exploit a quasi-experimental setup that arises in 2003, when California (CA) became the first state in the USA to pass an e-waste law – i.e., the Electronic Waste Recycling Act (EWRA, SB 20, Sher, Chapter 526, Statutes of 2003). Broadly, the legislation introduced changes to the collection and disposal of e-waste by imposing recycling fees and initiating payments to collector agencies. Overall, these operational changes sought to reduce the amount of e-waste disposed in landfills. By contrast, Florida (FL) has not adopted any e-waste laws to this day. We utilize this variation across these two states to assess the impact of the state-wide e-waste legislation. If state-level e-waste legislation reduces the total MSW beyond what is expected from e-waste, then we can infer that such legislation provides significant positive externalities. While legislation should provide the motivation and policy guidelines for individuals, in practice, how individuals act might also depend on the implementation of mechanisms at the county-level. Therefore, we assemble data on certified collection centers that were setup in California starting from 2003 to handle and recycle used electronics as per the requirements of the EWRA. To test our hypotheses, we collect annual county-level data on MSW from California and Florida for fourteen years - 1999 to 2012. This information allows us to compare MSW trends for "treated" California counties with those for similar "control" counties in Florida. Specifically, we leverage (i) the state-level policy change (i.e., introduction of e-waste legislation) and (ii) the county-level policy implementation (i.e., implementation of collection centers) to conduct a difference-in-differences analysis. Our analysis reveals that e-waste legislation resulted in at least 4.93% reduction in MSW per capita. Furthermore, a plausibility analysis (see e.g., Dhanorkar 2019, Emrah Aydinonat 2018, Epstein et al. 2014) supported with interviews with government officials reveals that a reduction of this magnitude can only be explained by behavioral spillovers because the 2003 (i.e., pre-legislation) estimates from the California Department of Resources Recycling and Recovery (CalRecycle) suggest that e-waste constituted not more than 1.2% of total MSW.

Next, we utilize the variation in online connectivity and offline proximity to examine whether these mechanisms complement the effect of e-waste legislation. First, we collect data from the Federal Communications Commission (FCC) on the county-level differences in broadband connectivity in California and Florida counties. We find that access to greater broadband services provides at least an additional 2.97% reduction in MSW per capita for each logarithmic unit increase in online connectivity. Second, we collect data from the U.S. Census Bureau on the county-level differences in population density in California and Florida counties. We find that closer offline proximity provides at least an additional 2.10% reduction in MSW per capita for each logarithmic unit increase in offline proximity. For additional validation, we compare propensity score matched counties and find similar effects for the MSW reductions per capita. Furthermore, we use placebo tests and alternative matching methods, to confirm our findings. Finally, we collect and integrate data from two other states – Minnesota (MN) and North Carolina (NC) – that also implemented e-waste laws and find similar results.

We contribute to the OM literature in two ways. First, our paper is one of the earliest to empirically examine the effectiveness of e-waste legislations and to point out that such legislation provides significant behavioral spillovers. While prior OM studies (Gui et al. 2015; Plambeck and Wang 2009) have used analytical models and numerical analysis to explore the environmental benefits of e-waste legislation, we use California's EWRA to provide empirically quantifiable evidence for the spillovers generated by e-waste legislation. By doing so, we complement extant research and inform future work in this area. Second, we show that increased access to markets (through *online connectivity* and *offline proximity*) can enhance the effectiveness of e-waste legislations. The extant literature has explored the role of manufacturers (Plambeck and Wang 2009), consumers (Atasu et al. 2013; Ferguson and Toktay 2006) and regulators (Gui et al. 2015) in curbing e-waste. We add to the literature by highlighting the role informational and market mechanisms play in restricting the flow of not only e-waste but also other solid waste to landfills. Additionally, our results are relevant for policy makers because many states (i.e., more than 20) in the USA and several countries have yet to implement e-waste laws. Specifically, our study (i) confirms the benefits of e-waste legislation under different scenarios (e.g., policy enactment and policy implementation) and policy settings (e.g., CA for main analysis, MN and NC for robustness), (ii) highlights the potential of e-waste legislation to serve as a multiplier mechanism that encourages broader sustainable behaviors and (iii) identifies two mechanisms – online connectivity and offline proximity – that augment the effectiveness of e-waste legislation.

The rest of the paper is organized as follows: In §2, we review the relevant literatures. In §3, we provide the institutional background on public policy context – e-waste legislation and the rationale for the focus on California and Florida. In §4, we develop our hypotheses. In §5, we describe our data collection process and define the key variables. In §6, we detail our methodology. In §7, we present our results and discuss additional robustness analyses. In §8, we discuss the implications of our findings and the limitations of our analysis.

2. Literature Review

Our work draws on and contributes to the literatures on e-waste, policy interventions, behavioral spillovers, and market access. We provide a broad overview of the relevant literature in these areas, discuss key differences in our study, but defer a more detailed discussion to §4.

Several OM scholars have studied the design and policy aspects of e-waste legislation. Atasu and Wassenhove (2012) synthesize the experiences with e-waste laws passed in various countries to cast light on the operational perspectives of e-waste legislation. They point out that the choice of an e-waste policy is merely the first step; effectiveness of legislation also depends on critical decisions taken by manufacturers and consumers. This is because under certain conditions policies that seek to promote e-waste reduction may backfire because incentives of all stakeholders may not be aligned (e.g., Ferguson and Toktay 2006). Along similar lines, Atasu et al. (2013) examine how stakeholders preferences can inform the design of e-waste legislation and determine the success of e-waste laws. The OM literature has also studied the operational challenges of translating e-waste laws into efficiently functioning systems (Atasu and Subramanian 2012; Plambeck and Wang 2009; Toyasaki, Boyacî, and Verter 2011). For instance, Plambeck and Wang (2009) use analytical models to show that "fee-upon-sale" e-waste legislations (e.g., California's EWRA) can induce behavioral changes in manufacturers as well as consumers. We differ from these studies in two ways: first, we adopt an empirical perspective that contrasts with the analytical approach adopted in prior work; and, second, we explore whether the impact of e-waste laws extends to other waste streams, which has thus far remained unexplored.

Several OM studies on e-waste legislation and take-back laws have adopted the social welfare planner's or the policy maker's perspective (Atasu et al. 2013, 2009; Atasu and Van Wassenhove 2012; Esenduran and Kemahlıoğlu-Ziya 2015; Gui et al. 2015; Mazahir et al. 2019). Furthermore, OM scholars have explored issues from a social planner's perspective in several other domains such as municipal water distribution (Dawande et al. 2013; Murali, Lim, and Petruzzi 2015), organ donation (Arora and Subramanian 2019) and tort liability (Serpa and Krishnan 2016). Our paper similarly takes the social welfare planner's perspective and seeks to provide insights to policy makers on e-waste laws. Additionally, from an operational viewpoint, Atasu and Wassenhove (2012) point out that policy instruments may not be effective when they fail to consider implementation choices. Specifically, in the context of e-waste, they call for research that explores the impact of implementation infrastructure on consumer behavior. Our work is aligned with Atasu and Wassenhove (2012) because we highlight the link between the implementation of e-waste collection centers and the concomitant waste reduction.

Several studies have empirically examined the effects of various policy interventions (e.g., Greenstone, 2002; Short and Toffel, 2010; Reed Walker, 2011), such as the Clean Air Act, and environmental initiatives (e.g., King and Lenox, 2000; Barnett and King, 2008; Short, Toffel and Hugill, 2016), such as the Chemical Industry's Responsible Care Program. While these studies mainly explore firm behaviors, we examine the effects of individual behaviors in response to public policy interventions. Our work also relates to the literature that examines spillover effects in the context of environmental policies (e.g., Ambec & Coria, 2018; Hosseini & Kaneko, 2013; Sigman, 2002, 2005). For instance, Sigman (2002, 2005) examines water pollution across state and international boundaries and finds that suboptimal pollution control investments by upstream entities results in more polluted water for downstream entities. Similarly, Hosseini and Kaneko (2013) find a spatial spillover effect that displaces carbon dioxide (CO_2) emissions across neighboring countries. This literature largely explores the adverse environmental effects of spatial spillover and seeks to identify mechanisms to mitigate the negative consequences. By contrast, we examine how a focused policy intervention (i.e., e-waste law) can create behavioral spillovers that have a broader positive impact on reducing solid waste (i.e., MSW).

The concept of behavioral spillover relates to the idea that a public policy intervention which targets increasing one type of behavior (of consumers or users) can simultaneously lead to shifts in other non-targeted behaviors (Truelove et al. 2014). Studies in the environmental economics and psychology domains (Poortinga et al. 2013; Thomas et al. 2016; Truelove et al. 2014) have shown that various pro-environmental behaviors tend to be highly correlated. This phenomenon exists because individuals tend to avoid the cognitive dissonance (Festinger 1962) which may arise when an individual acts pro-environmentally in one domain while neglecting environmental concerns in another area (Thøgersen 1999; Thøgersen and Ölander 2003). We contribute to the literature on environmental behavioral spillovers in two ways. First, we provide empirical evidence that the operational changes brought forth by e-waste laws result in significant environmental spillovers that go beyond just e-waste reduction. Second, we illustrate two mechanisms (*online connectivity* and *offline proximity*) that amplify behavioral spillovers from e-waste legislation. In this way, we respond to the call of Truelove et al. (2014) for research on factors that augment the impact of pro-environmental behaviors. Additionally, previous literature on environmental behavioral spillovers has mainly used either cross-sectional survey methods (Berger 1997; Weber 1999) or restricted samples (Thøgersen and Ölander 2003; Tiefenbeck et al. 2013). Our study adds to the body of evidence by leveraging an external policy event (i.e., the enactment and implementation of e-waste legislation) to illustrate the effect of behavioral spillovers across a large population that spans multiple counties in four states. Finally, some studies have shown the existence of negative behavioral spillovers (Tiefenbeck et al. 2013; Truelove et al. 2014), which if true in our setting, could pose challenges to the value of e-waste laws.

A large stream of literature has explored the impact of market access on a variety of social issues (Chan, Ghose, and Seamans 2016; Greenwood and Agarwal 2015; Greenwood and Wattal 2017; Kolko 2010b). In the environmental domain, scholars have shown that markets can provide new channels for the allocation of goods and services (Keskinocak and Tayur 2001; Netessine and Rudi 2006); and that they can also significantly facilitate product reuse and recycling efforts (Dhanorkar 2019; Fremstad 2017; Subramanian and Subramanyam 2012). Moreover, Dhanorkar et al. (2015) illustrate that market access can relate to geographical proximity, which in turn can facilitate local reuse and recycling. Therefore, it is likely that individuals' access to information and used goods markets through online and offline channels can facilitate the easier exchange of goods. We contribute by showing the role of online and offline channels in amplifying the impact of e-waste laws.

To summarize, we contribute by providing empirical evidence for the impact of behavioral spillovers resulting from e-waste legislation and by highlighting how access to opportunities (both online and offline) can augment the effectiveness of such legislation. We discuss the related literature in more detail as we formulate our hypotheses. Next, we discuss the institutional context pertaining to our study.

3. Public Policy Setting

3.1 E-Waste Legislation

Handling e-waste is challenging because it often contains a variety of toxic substances (Kroepelien 2000) that can create substantial health hazards (Frazzoli et al. 2010). Additionally, e-waste has grown rapidly across the world; from 19.5 million tons in 1990 to over 75 million tons in 2015 (Huisman 2012). This means that many countries face the demanding challenge of handling increasing quantities of e-waste. Although several feasible solutions (e.g., product redesign, cradle-to-cradle technology) have been developed to reduce e-waste, the current rate of e-waste generation has vastly outpaced the deployment of such solutions. As a result, several countries have resorted to legislative approaches to initiate operational changes that can better manage e-waste and reduce its improper disposal.

The European Union (EU) pioneered many legislative efforts to handle e-waste. Notably, the EU enacted the Waste Electronic and Electrical Equipment (WEEE) directive in 2003 that initiated extended producer responsibility (EPR), and the Restriction of Hazardous Substances (RoHS) directive in 2003 that restricted the use of hazardous chemicals. By contrast, the United States has a mixed record on the legislative efforts to handle e-waste. There is no federal law on e-waste, but several states have enacted e-waste laws to curtail the generation and facilitate the recycling of e-waste. California was the first state in the United States to pass an e-waste legislation in 2003. Since then, 25 other states and the District of Columbia have passed e-waste laws. Broadly, e-waste legislations (in the EU and USA) initiate the collection of e-waste by collector agencies, limit the use of hazardous substances by manufacturers and promote reuse and recycling of electronic devices by consumers. These initiatives aim to reduce the amount of e-waste ending in the waste stream.

3.2 Research Context - Rationale for using California and Florida

In this study, we focus on California's EWRA (SB 20, Sher, Chapter 526, Statutes of 2003) that established an overarching system for the collection and recycling of e-waste. Two reasons guide the choice. First, California has been at the forefront of the efforts to curtail e-waste. For example, California was one of the two states (other was Massachusetts) that banned the disposal of Cathode Ray Tubes (i.e., CRT) in landfills. With the enactment of EWRA in 2003, California became the first U.S. state to implement a formal law for curbing e-waste. Second, California's EWRA constituted a broader effort to reduce e-waste because it sets out directives for manufacturers and, more importantly, it addresses key aspects related to the collection and handling of e-waste (Bergner 2004). The act also imposed an "advanced recycling fee" that was collected upon the purchase of various electronic devices. The fee is intended to fund e-waste collectors, recyclers, and other administration costs. Since California's EWRA directly impacted not only manufacturers but also consumers, we expect that this legislation will also have broader implications for solid waste. By contrast, most of the e-waste laws in the other states (e.g., Maine, Michigan) adopt the extended producer responsibility (EPR) model, which makes manufacturers responsible for funding the collection and recycling of the products covered under law. Previous research (Plambeck and Wang 2009) shows that "fee-upon-sale" type of e-waste regulation (e.g., California's EWRA) can be more successful (compared to EPR) in reducing disposal rates by altering consumer behaviors. Since we are interested in understanding spillovers emanating from consumer behaviors, California's EWRA lends itself well to our study.

To examine the impact of e-waste legislation, we use a quasi-experiment – i.e., California's enactment of EWRA in 2003. Additionally, we leverage the fact that Florida has not enacted any e-waste law to date. This allows us to statistically estimate the impact of e-waste laws by comparing MSW trends for California counties with those for Florida counties. We choose to compare CA and FL for the following reasons. First, accurate annual MSW data was available for all counties in CA and FL. For California, we obtained county-level MSW data for 58 counties from the Data Reporting System managed by CalRecycle[1]. For Florida, we collected county-level solid waste data from the Florida Department of Environmental Protection[2] for the 67 counties. Second, CA and FL are both densely populated states with multiple metropolitan counties. In 2000, the population density[3] ranks were CA (11) and FL (8) respectively. This should allow for more comparable pre-treatment MSW trends between CA and FL counties. Third, California and Florida also have fairly comparable weather conditions, in contrast to several other U.S. states. The similarity in weather conditions is an important factor because earlier studies have shown that weather can be a contributing factor in waste generation (Chang and Lin 1997). Fourth, California and Florida are geographically well-separated, which eliminates potential

[1] http://www.calrecycle.ca.gov/LGCentral/DataTools/Reports/ Retrieved November 20, 2016

[2] http://www.dep.state.fl.us/waste/quick_topics/publications/default.htm. Retrieved January 5, 2016

[3] https://www.census.gov/2010census/data/apportionment-dens-text.php. Retrieved October 26, 2017

confounds from cross-border spillovers effects (Dube, Lester, and Reich 2010) of either e-waste legislation or MSW. Finally, MSW comparisons between California and Florida have been made previously in the waste-reduction literature (e.g., Fremstad 2017).

4. Hypotheses

In our hypotheses, we start by exploring the overall behavioral spillover effect of e-waste legislation on reducing MSW. Then, we examine how increased market access, through online connectivity and offline proximity, boosts the impact of e-waste legislation.

4.1 Behavioral Spillovers from E-Waste Legislation

The effect of government policies and initiatives can often be uncertain, which may cause either positive or negative spillover effects (Coates IV 2007). For instance, the effect of minimum wage laws has been debated for decades (Dube et al. 2010; Katz and Krueger 1992; Stigler 1946). Hence, while California's EWRA might be a step in the right direction, our discussions with policy-makers revealed the uncertainty related to whether and to what extent e-waste laws could impact MSW, especially given their unique operational and implementation challenges (Atasu et al. 2009; Atasu and Van Wassenhove 2012). Second, even when certain behavioral and economic effects of policies can be anticipated in advance, the magnitude of such impacts can be uncertain. For example, while conventional wisdom would suggest that safety inspections should improve factory working conditions and therefore reduce workplace injuries, Levine et al. (2012) show that the magnitude of reduction in injuries (up to -9.4%) is substantial to continue investment in such approaches. Similarly, prior work in accounting has also leveraged the passing of various policies and regulations (e.g., Sarbanes-Oxley Act) to examine the magnitude of economic consequences of such policies (Zhang 2007). In a similar vein, we discuss the causal mechanisms through which e-waste laws can have the desired effect on MSW.

E-waste laws mandate administrative entities, such as counties, to develop systems to collect, recycle and dispose used electronics (Lerner 2011). Thus, e-waste legislations initiate important operational changes by supporting the development of infrastructure that is essential for redirecting the flow of e-waste from landfills. In California, these operational changes were largely funded by an "advanced recycling fee" that was collected upon the purchase of new electronic devices. Because such policy interventions can significantly alter consumer purchase and disposal behaviors (Plambeck and Wang 2009), the above mechanism suggests a direct effect where e-waste legislation leads to a reduction in the amount of e-waste generated and disposed. While the first order effect of e-waste reduction is expected, we posit that e-waste legislation influences an overall reduction in municipal solid waste (MSW) that goes beyond what can be realized by just reducing e-waste.

There are two reasons why we expect behavioral spillovers from e-waste legislation. First, we argue that e-waste legislations create general awareness among individuals about the negative consequences of sending not only e-waste but also other used consumer goods to landfills. For example, an ERCC[4] survey found that citizens residing in states with e-waste laws showed more awareness regarding reuse and recycling opportunities in their neighborhood. As a result, e-waste legislation can also influence individuals to engage in repair, reuse and recycling activities that can divert their waste away from landfills. Along these lines, research has shown that consumers may alter behaviors in one domain in response to messages or communication received on unrelated yet similar topics. For example, Evans et al. (2013) illustrate that an unrelated environmental message (e.g., "share a car") can increase pro-environmental behaviors in another dimension (e.g., recycling). With the enactment of the EWRA in 2003, California introduced legislation that mandated counties, manufacturers and consumers to undertake necessary steps to reduce e-waste. As a result, we expect that EWRA increased the awareness among the population on the need to reduce waste, in general.

Second, we expect that pro-environmental actions taken by consumers in one domain (e.g., e-waste recycling) will also lead to broader pro-environmental attitudes and actions. This argument is consistent with research that proposes pro-environmental interventions in one domain can also induce broader pro-environmental behavioral shifts in other domains (e.g., Poortinga, Whitmarsh and Suffolk, 2013; Truelove *et al.*, 2014; Thomas, Poortinga and Sautkina, 2016). For instance, Lanzini and Thøgersen (2014) find a positive spillover from "green" purchasing to other types of pro-environmental behaviors (e.g., travel mode choice, conservation, recycling). The literature suggests that the rationale for such behavior is embedded in cognitive dissonance theory (Festinger 1962), which indicates that people strive to be internally consistent in their behaviors across multiple domains that are connected by a common super-ordinate goal (e.g., environmental conservation) (Thøgersen 2004). Consequently, we expect that EWRA will aid the diversion of not just used electronics but also other consumer goods from the municipal waste. Therefore, we hypothesize:

Hypothesis 1 (H1): *E-Waste Legislation will lower MSW per Capita in the affected counties.*

4.2 Mechanism – Access to Markets

Below, we propose that improving access to information and markets (both *online* and *offline*) could induce individuals to explore recycling and reuse for used consumer goods, which can further restrict the overall waste disposed. In other words, while e-waste legislation serves as the trigger for behavioral spillovers, access to information and markets serve as the catalyst to bring about widespread behavioral changes.

Online Connectivity: Increased internet connectivity plays an important role in economic and social development (Kolko 2012). This is because the internet provides access to information (Sinai and Waldfogel 2004), which can in turn modify users' online and offline behaviors (Kolko 2010b). Although internet access provides several benefits, there are differences in the extent to which internet is available even in states such as California, which is at the forefront of technology and innovation (Chan et al. 2016). Hence, we leverage the

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[4] The Electronics Recycling Coordination Clearinghouse (ERCC) is a forum consisting of state and local government agencies that are tasked with implementing and amending electronics recycling laws across the states in U.S. ERCC Consumer Awareness Survey. http://www.electronicsrecycling.org/wordpress/wp-content/uploads/2016/03/ERCC-Consumer-Awareness-Survey-Summary-Report-FINAL.pdf. Retrieved February 6, 2019

differences in internet access across various regions to examine the complementary impact of online channels (along with e-waste legislation) on MSW reductions.

Admittedly, increased internet access could promote waste generation because it may lead to the use of more internet-enabled devices, which could directly result in greater e-waste. Users in regions with higher internet availability may also engage in more frequent shopping due to increased convenience of online channels (Chiang and Dholakia 2003) or higher instances of impulse purchasing (Jeffrey and Hodge 2007); both behaviors could potentially lead to higher waste in general. However, the link between increased online consumerism and waste is contingent on several factors such as consumer attitudes, presence of reuse markets etc. (Brosius, Fernandez, and Cherrier 2013; Ebreo, Hershey, and Vining 1999). Below, we discuss how such increases in consumerism will be largely mitigated by the reductions facilitated by online connectivity, in conjunction with e-waste legislation.

In particular, we claim that increased access to internet, especially broadband, can amplify the effectiveness of e-waste legislation. Two plausible explanations can account for this effect. First, increased access to the internet opens alternative ways to find buyers and sellers of used goods. For example, internet connectivity may allow increased access to other community-based platforms (e.g., Nextdoor.com, Facebook.com). While the primary purpose of such platforms may or may not be to engage citizens and businesses in reuse or recycling, they could still improve access to such opportunities (e.g., through Facebook Marketplace) by improving the quality and frequency of communication in communities. Additionally, increased internet penetration can mitigate uncertainty on quality and reduce information asymmetry, which can lower the barriers for the trade of used goods (e.g., Rapson and Schiraldi 2013). Second, broadband access may also bring informational benefits (Firth and Mellor 2005). For instance, the Consumers Union indicates that an important step towards reducing waste is enabling "…consumers with information, tools and technical support…" to encourage reuse, repair and recycling (Cairns 2005). Moreover, improved knowledge of waste policies resulting from increased broadband access could lower accidental or unintentional dumping of electronic and other consumer goods from entering the waste stream. Similarly, increased knowledge of recycling and collection center locations could encourage local businesses and individual consumers to participate more actively in recycling. For example, the ERCC[5] finds that citizens commonly use government websites as well as other national websites (e.g., greenergadgets.org, earth911.org) to obtain information on local recycling laws and collection centers. Therefore, we expect that increased broadband connectivity will complement the effect of e-waste legislation on MSW reductions. Based on the above discussion, we hypothesize:

Hypothesis 2 (H2): *Increased Online Connectivity will enhance the impact of e-waste legislation by further lowering MSW per Capita.*

[5] ERCC State Consumer Awareness Surveys, http://www.ecycleclearinghouse.org/contentpage.aspx?pageid=107 Retrieved January 1, 2018

Offline Proximity: So far, we examined the impact of e-waste legislation independently and the moderating effects of online connectivity. Next, we explore the non-technological factors that could influence behavioral spillovers. Specifically, we examine whether the physical proximity of user communities plays an important role in amplifying the behavioral spillover effect from e-waste legislation. Geography has been long acknowledged as a crucial driver of success in traditional markets (Huff 1964). Evidently, geographically clustered communities might allow more convenient access to various opportunities (Evans 2009; Vlahov, Galea, and Freudenberg 2005). In our context, this translates to more convenient access to reuse and recycling centers, markets for exchanging used electronics products and other repair services. Such conditions may also favor the formation of industry and business clusters (Keller 2002), which may further enhance access to reuse and recycling options. Additionally, geographical proximity supports the diffusion of knowledge, innovations and technologies (Bass 1969; Rogers 2010). Recent research indicates that the uptake of policies and technological ideas is also amplified by local conditions and demographic characteristics (Bell and Song 2007; Choi et al. 2010); this phenomenon is referred as the local neighborhood effect, which arises because of social connections and local imitation among people residing within the same neighborhood. The presence of neighborhood effects has been seen across several literatures including: sociology (Sampson, Morenoff, and Gannon-Rowley 2002), public health (Diez Roux 2001), poverty (Kling, Liebman, and Katz 2007) and education (Garner and Raudenbush 2006). Scholars have long debated how federal and state level policies can leverage neighborhood effects to encourage positive behaviors among communities (Brown and Richman 1997). Based on the above discussions, we expect that offline (i.e., geographic) proximity of user communities should play an important role in enhancing the behavioral spillover effects of e-waste legislation. The logic is that users in counties with greater geographic proximity would find it easier to identify and leverage information and markets for repair, reuse and recycling. As a result, behavioral spillovers that emanate from e-waste legislation will amplify MSW reductions in counties with greater offline proximity. Therefore, we hypothesize:

Hypothesis 3 (H3): *Increased Offline Proximity of users will enhance the impact of e-waste legislation by further lowering MSW per Capita.*

5. Data

5.1 Data Sources

We use a county-level panel data set to examine the longitudinal relationship between MSW trends and the interplay between e-waste laws, online connectivity and offline proximity. We constructed our data set using information from multiple sources. First, we collected MSW data from California's and Florida's respective environmental agencies – i.e., CalRecycle and Florida Department of Environmental Protection. Second, we use information from CalRecycle[6] regarding California's e-waste legislation for creating the quasi-experimental

[6] Electronic Waste Recycling Act of 2003, http://www.calrecycle.ca.gov/electronics/act2003/ Retrieved July 10, 2017

setup. Third, we obtained data from the Federal Communications Commission (FCC) on broadband connectivity at the zip code level. Finally, we obtain county-level demographic data on population density as well as other demographic characteristics from Sage Business Statistics compiled by Woods & Poole Economics Inc. Our dataset spans for fourteen years from 1999 to 2012, which provides enough data coverage before and after California's e-waste legislation and allows us to clearly evaluate the long-term impact (up to 8 years) of the policy. We restrict our sample to 2012 because beyond this time span, other confounding factors may lead to spurious effects in our models. This approach is in line with prior studies on environmental policy effects (Greenstone 2002; Innes and Mitra 2015; Reed Walker 2011) that use similar time windows to examine the effects of policy interventions.

Next, we describe the dependent, independent, and control variables used in our analysis.

5.2 Dependent Variable

Ln(MSW per Capita)$_{ist}$: The dependent variables in our analysis are measures of MSW that is generated in county *i*, state *s*, and time *t*. To facilitate comparisons across counties, we normalized the MSW data by population to obtain the MSW per capita. We use the logarithmic transformation of MSW per capita to reduce skew. Our measure of MSW is consistent with previous literature (e.g., Fremstad 2016, Dhanorkar 2019). We use MSW data since it comprises all user-generated waste ending up in municipal waste streams. We expect that lower MSW will be generated in a county if e-waste legislation is effective in diverting waste from landfills. While some part of the MSW reductions will obviously result from lower e-waste in the affected regions, we also expect that additional reductions beyond what can be explained by e-waste will be realized via behavioral spillovers. The Environmental Protection Agency (EPA) defines "Municipal Solid Waste (MSW) — more commonly known as trash or garbage — to consist of everyday items we use and then throw away, such as product packaging, grass clippings, furniture, clothing, bottles, food scraps, newspapers, appliances, paint, and batteries (EPA 2016)." Prior MSW characterization studies and reports from the EPA (EPA 2011, 2013, 2014) validate that MSW is a well-accepted terminology in the United States and that across states (including CA, FL, MN, and NC) MSW information is collected and recorded in a similar manner.

5.3 Independent Variables

E-Waste Legislation$_{ist}$ (EWL$_{ist}$): We measure e-waste legislation in two distinct ways that focus on policy enactment and policy implementation. These distinctions allow us to illustrate the nuances of the impact of e-waste legislation and to enhance the robustness of our analysis. First, we use a state-level 'EWL Policy' treatment variable that identifies whether the county *i* comes under the purview of e-waste legislation in period *t*. It is coded as '1' for all the counties in CA from year 2004 onwards (i.e., after the enactment of EWRA) and is '0' otherwise. The variable is coded '0' for all counties in FL (i.e., control group) throughout our sample period. Second, as an alternate measure for e-waste legislation, we use a county-level 'EWL Implementation' variable that identifies whether the county i received a collection center in period t, after the introduction of the e-waste legislation. The focus on collection centers is important because although e-waste legislation provides motivation for consumers to limit their waste; in practice, the extent of such behaviors will depend on the implementation of supporting mechanisms at the county-level. In California, certified collection centers have the authority for handling and disposing used electronics as per the requirements of the Electronic Waste Recycling Act. We expect that such changes "on-the-ground" could make expectations from consumers more explicit and thus enhance the proposed behavioral spillover effect. We code the 'EWL Implementation' variable as the logarithm of the count of active collection centers operating in a specific county in CA in period *t*. The variable is coded '0' for all counties in FL throughout our sample period. It is important to note that irrespective of the presence of a collection center, people are expected to comply with the specific provisions of the law. For example, the EWRA made dumping of CRTs in waste illegal universally across California. In such situations, people are expected to take these items to a registered collection center for processing. The CalRecycle directory includes a database of collection centers, searchable by county, that is advertised by local governments to facilitate recycling and proper disposal of e-waste. Thus, the proximity of collection centers is bound to not only induce law abiding behaviors but also increase the possibilities of behavioral spillovers.

The two treatment variables (for policy and implementation) enable us to examine H1 – whether e-waste legislation results in MSW reduction. In our regression models (in § 6.2), if the coefficients for these variables are negative and significant, then we can infer that e-waste legislation leads to lower MSW.

Online Connectivity$_{ist}$: We collected data on broadband service providers from the Federal Communications Commission (FCC) form 477 for each year from 1999 to 2012. We focus on the broadband service providers because Kolko (2010a) finds that online connectivity increases with the number of broadband providers even after accounting for the county's demographic characteristics. Moreover, Wallsten and Mallahan (2010) point out that the number of broadband providers is positively correlated with the quality of internet service and negatively correlated with the price. This is important because high quality and low price enhances users' online connectivity and internet use experience. Finally, the number of broadband providers is related with market demand and provider competition. Because of the above-mentioned reasons, several studies in the literature have used the number of broadband providers as a measure of online connectivity to examine various social and economic phenomena. For example, Chan et al. (2016) use this measure to examine the impact of online connectivity on racial crimes. Kolko (2012) uses the same measure to assess the impact of online connectivity on local economic growth. We followed recent studies in information systems by Seamans and Zhu (2013) and Chan et al. (2016) to measure county-level broadband connectivity as the average number of broadband providers in all the zip codes comprising each county at a given time. Since the number of broadband providers in a county can be as high as 30 (e.g., Orange County in 2008, CA), we use a logarithmic transformation to reduce skew. We use this variable to evaluate H2 that seeks to examine whether increased broadband access will augment the effect of e-waste legislation in reducing MSW. Therefore, in our regression models (in § 6.2) we will examine the coefficient of the interaction of this variable with either 'E-Waste Policy' or 'E-Waste

Legislation'. If the coefficient is negative and significant, then we can infer that increased access to the internet enhances the ability of e-waste laws to reduce MSW generation.

Offline Proximity$_{ist}$: To explore whether physical proximity moderates the relationship between e-waste legislation and MSW, we collected annual county-level population data from Sage Business Statistics (as in Dhanorkar 2019). Sage Business Statistics compiles annual population data from the United Census Bureau. We normalized each county's population by its area (square miles) to obtain a measure for population density. We focus on population density because it captures the extent to which communities are geographically collocated. The logic is that users in counties with greater collocation would find it easier to identify opportunities for repair, reuse and recycling. We log transform this variable to reduce skew and use this variable to evaluate H3. In our regression models (in § 6.2) we will examine the coefficient of the interaction of this variable with either 'E-Waste Policy' or 'E-Waste Legislation'. If the coefficient is negative and significant, then we can infer that increased offline proximity (i.e., higher population density) enhances the ability of e-waste laws to reduce MSW generation.

5.4 Control Variables

In our analysis, we control for several time-varying and time-invariant factors that might affect MSW. We collected data on various annual county-level demographic characteristics, which could explain MSW patterns. Studies have shown that consumption patterns are an important time-varying driver of MSW (Beigl, Lebersorger, and Salhofer 2008; Dhanorkar 2019). Therefore, we control for *Income* using data from Sage Business Stats, which compiles annual data obtained from the U.S. Census Bureau, and we normalize the variable to reduce skew. In line with Fremstad (2017), we control for business activity by including the number of *Business Establishments* in the county; this variable was obtained from Sage Stats and was subsequently log transformed. Next, we control for median *Age* and *Education,* using the percent of population with a college degree. The data on age and education was obtained from the U.S. Census Bureau. Next, we also used *Housing Price Index* as an additional control since real estate prices can impact the size of homes and therefore waste generated. This information was obtained from the Federal Housing Finance Agency for available metropolitan areas, which were matched to the corresponding county.

Furthermore, we control for the recycling infrastructure in the region using two key variables. First, in line with recent studies (Dhanorkar 2019; 2017), we control for the presence of Craigslist, which has been shown to mitigate MSW. To determine when Craigslist entered a specific county in CA and FL, we collected data directly from Craigslist on the timing of new website launches.[7] *Craigslist* is coded '1' in the subsequent years following Craigslist's entry into a county; '0' otherwise. A similar approach has been used in recent studies (Chan and Ghose 2014; Dhanorkar 2019; Greenwood and Agarwal 2015), which examine the impact of Craigslist on various social and environmental outcomes. Second, we account for the state-level recycling

[7] http://www.craigslist.org/about/expansion Retrieved May 5, 2015

infrastructure. The state of California has been at the forefront of environmental initiatives such as fees for plastic bags, fees for disposal of paint, bans on disposable plastics, bottle bills, and mandatory single-stream curbside recycling, to mention a few. Several recycling-related laws enacted in California could directly impact MSW. Examples of such laws would be: Senate Bill SB1729 – Plastic Containers Recycling and Senate Bill SB1346 – Tire Recycling. To account for the impact of such legislation, we collected information on all the state-level recycling-related laws that have been passed since 1995 from CalRecycle (2018). We use this information to define $\textit{Recycling Laws}_{st}$ as the logarithmic count of recycling-related laws, other than e-waste legislation, that were enacted in state 's' (i.e., California) in time 't'. This variable allows us to capture the impact of the other waste-related legislation that can potentially affect MSW. Since it is possible that other environmental laws (e.g., related to biodiversity) may also impact MSW, we redid our analysis using an alternative control – *All Environmental Laws*. This does not affect our findings. Tables 1 and 2 show the summary statistics and the correlations, respectively, for the variables used in our analysis.

Additionally, we use county dummies to control for factors within counties that could influence MSW trends. We use indicator variables that identify the calendar year relevant to our data. Finally, to account for any natural differences in MSW levels across Florida and California, we include state-specific trends to account for factors that are specific to a region but may change over time (Bertrand and Mullainathan 2003). Together, these variables control for potential spatial and temporal factors that could affect our analyses.

Table 1. Summary Statistics

	CALIFORNIA					FLORIDA				
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
Ln(MSW per Capita)	798	0.616	0.219	0.000	1.443	938	0.838	0.270	0.186	2.652
EWL(Policy)	798	0.642	0.479	0.000	1.000	938	0.000	0.000	0.000	0.000
EWL(Implementation)	798	0.497	0.760	0.000	3.689	938	0.000	0.000	0.000	0.000
Online Connectivity	798	2.129	0.703	0.035	4.043	938	2.078	0.690	0.041	4.297
Offline Proximity	798	4.582	1.916	0.917	9.780	938	4.903	1.338	2.237	8.130
Income	798	11.411	0.310	10.734	12.393	938	11.160	0.289	10.452	12.042
Housing Price Index	798	6.200	0.625	4.632	7.383	938	5.490	0.517	4.216	7.179
Age	798	37.486	5.527	28.930	52.540	938	40.913	5.726	28.650	64.600
Education	798	31.974	6.437	12.500	58.100	938	36.362	6.266	13.100	64.100
Business Establishments	798	9.217	1.799	4.533	13.734	938	8.666	1.674	5.352	12.863
Craigslist	798	0.186	0.389	0.000	1.000	938	0.189	0.391	0.000	1.000
Recycling Laws	798	4.182	0.222	3.584	4.419	938	0.000	0.000	0.000	0.000

Table 2. Correlations

S. No	Variables	1	2	3	4	5	6	7	8	9	10	11
1	MSW per Capita	1										
2	EWL(Policy)	-0.2970*	1									
3	EWL(Implementation)	-0.1812*	0.6165*	1								
4	Online Connectivity	0.0940*	0.2853*	0.4307*	1							
5	Offline Proximity	0.3468*	-0.0594*	0.2207*	0.4726*	1						
6	Income	0.1356*	0.4533*	0.4183*	0.5914*	0.5304*	1					
7	Housing Price Index	-0.0186	0.4962*	0.4234*	0.3393*	0.4629*	0.6420*	1				
8	Median Age	0.0597*	-0.1365*	-0.2040*	-0.0212	-0.1370*	-0.1017*	-0.2640*	1			
9	Education	0.0955*	-0.3998*	-0.2974*	-0.3339*	-0.1405*	-0.4310*	-0.3596*	0.2434*	1		
10	Business Establishments	0.2973*	0.1387*	0.3679*	0.5035*	0.8646*	0.6492*	0.6193*	-0.1743*	-0.1999*	1	
11	Craigslist	0.0636*	0.1253*	0.2694*	0.4200*	0.3163*	0.2548*	0.2349*	-0.1150*	-0.1993*	0.3442*	1
12	Recycling Laws	-0.2107*	0.4621*	0.1481*	-0.2178*	-0.0718*	0.1493*	0.3956*	-0.2380*	-0.1231*	0.0886*	-0.0745*

Pairwise Correlations reported; * *p<0.10*

6. Empirical Approach

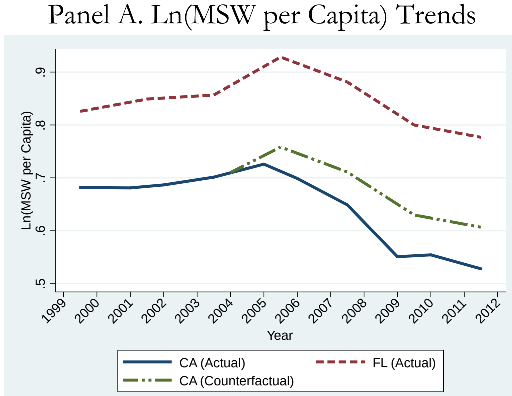
6.1 Identification

Our identification approach encompasses two sets of inter-related analyses. First, we use a *difference-in-differences* analysis to test our hypotheses for all the counties in CA and FL. Recent studies in operations management have successfully used this methodology to examine the effect of policy interventions (Dhanorkar 2019; Dutt and King 2014; Staats et al. 2017). Second, we use propensity score matching (Rosenbaum and Rubin 1983) to augment comparability, which allows us to match similar counties in CA and FL. Then, we evaluate our hypotheses for the matched counties. All the analyses were done in Stata 14.1.

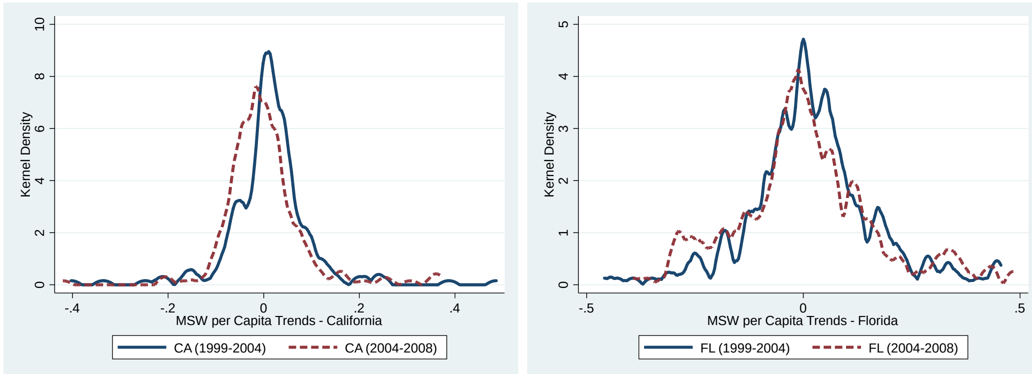
Since our approach uses a difference-in-differences analysis, we must verify whether the MSW data from counties in CA and FL satisfy the parallel trends assumption. In other words, we need to validate that CA and FL have similar MSW trends before the treatment (i.e., the introduction of e-waste legislation). Consequently, we use the method proposed by Angrist & Pischke (2008) and plot the pre- and post-treatment Ln(MSW per Capita) trends for CA and FL counties, in Figure 1 (Panel A). We observe that the trends are similar before treatment, but they diverge after the enactment of the e-waste legislation in CA. Furthermore, Figure 1 (Panel B) presents the pre- and post-event kernel density graph for MSW per Capita trends for CA and FL counties. We observe that the post-event curve for California has shifted to the left in comparison to the pre-event curve. Finally, we conduct additional formal analysis of the parallel trends assumption (Angrist and Pischke 2008) using the leads-lags approach used in recent econometric studies (Atkin, Faber, and Gonzalez-Navarro 2018; Greenwood and Agarwal 2015). Specifically, the test involves including pre-treatment as well as post-treatment dummy variables to show the (i) lack of significant pre-treatment (i.e., pre-EWRA) differences in MSW trends between the treatment (CA counties) and control (FL counties) units and (ii) presence of significant post-treatment (i.e., after passage of EWRA) differences in MSW trends between treatment and control units. The formal analysis is shown in the Appendix A1. These results validate the parallel trends assumption underlying the difference-in-differences methodology.

Figure 1. Comparison between CA and FL Counties

Panel A. Ln(MSW per Capita) Trends



Panel B. Kernel Density Plots



6.2 Model Specification

We evaluate H1 that examines the effect of e-waste legislation in California with the following specification:

$$Ln(MSW\ per\ Capita)_{ist} = \propto_0 + \boldsymbol{\propto}_i + \boldsymbol{\propto}_t + \boldsymbol{\propto}_{st} + \beta_1 EWL_{ist} + \gamma \boldsymbol{X}_{ist} + \varepsilon_{ist} \qquad \ldots (1)$$

where $\propto_0$ is the intercept, $\boldsymbol{\propto}_i$ is a vector of county fixed effects, $\boldsymbol{\propto}_t$ is a vector of year fixed effects, and $\boldsymbol{\propto}_{st}$ is a vector for state-time trends. Additionally, the vector $\boldsymbol{X}_{ist}$ includes the time-varying control variables (population, income) to account for factors that vary within each region over time. The other variables *Ln(MSW per Capita)$_{ist}$* and *EWL$_{ist}$* are as defined in §5.

To examine how internet access augments the effect of e-waste regulation (i.e., H2), we modify specification (1) by introducing Online Connectivity$_{ist}$ – as defined in §5 to obtain the following specification:

$$Ln(MSW\ per\ Capita)_{ist} = \propto_0 + \boldsymbol{\propto}_i + \boldsymbol{\propto}_t + \boldsymbol{\propto}_{st} + \gamma \boldsymbol{X}_{ist} + \beta_1 EWL_{ist} + \beta_2 Online\ Connectivity_{ist} + \beta_{12} EWL_{ist} \times Online\ Connectivity_{ist} + \varepsilon_{ist} \qquad \ldots (2)$$

To examine whether the physical proximity of consumers augments the effect of e-waste regulation (i.e., H3), we modify specification (1) by introducing Offline Proximity$_{ist}$ – as defined in §5 to obtain the following:

$$Ln(MSW\ per\ Capita)_{ist} = \propto_0 + \boldsymbol{\propto}_i + \boldsymbol{\propto}_t + \boldsymbol{\propto}_{st} + \gamma \boldsymbol{X}_{ist} + \beta_1 EWL_{ist} + \beta_3 Offline\ Proximity_{ist} + \beta_{13} EWL_{ist} \times Offline\ Proximity_{ist} + \varepsilon_{ist} \qquad \ldots (3)$$

We estimate specifications (1), (2), and (3) using panel data regression with county fixed effects, time fixed effects and other time-varying controls.

6.3 Propensity Score Matching

In addition to the difference-in-differences technique, we use the propensity score matching (PSM) approach to minimize the differences across counties treated (i.e., CA counties) with e-waste legislation and counties that remain untreated (i.e., FL counties). Using the PSM approach allows us to generate a matched sample of untreated (i.e., control) counties that are similar to the treated counties, with respect to the observed characteristics (Heckman, Ichimura, and Todd 1997). We matched the observations on wealth index, population density, broadband connectivity, median age and year, using a caliper size of 0.2. These variables are obtained from Sage Business Stats, except broadband connectivity, which was obtained from FCC.

We explored three different PSM approaches – (i) nearest five neighbors (NN5) (ii) nearest three neighbors (NN3) (iii) one-to-one matching without replacement – that substantially reduced the imbalance for the matched covariates. Specifically, the matching process significantly reduced the bias in means (across treated and control units) for matched covariates but maintained high similarities in the pre-treatment MSW per capita trends. In line with previous literature (Dhanorkar 2019; Haviland, Nagin, and Rosenbaum 2007; Xu et al. 2016), we show the improvements in balance between treated and control units following PSM in Table 3. For subsequent analysis, we use the matching results from the NN5 algorithm because it provided the most improvement in balance.

Table 3. Balance for Matched Covariates (Before vs. After PSM)

Matching Variables	Difference in Means (Before)	Difference in Means (After)	Percent Bias Reduction	Difference in Means (After)	Percent Bias Reduction	Difference in Means (After)	Percent Bias Reduction
	Before Matching	*Nearest Five Neighbors with Replacement*		*Nearest Three Neighbors with Replacement*		*One-to-One Matching without Replacement*	
Broadband Connectivity	0.0508	0.0098	41.3%	0.0378	25.7%	0.0460	9.5%
Population Density	0.3210	0.0903	71.9%	0.1123	65.0%	0.2032	36.7%
Age	3.4270	2.0080	41.4%	2.1320	37.8%	2.1120	38.4%
Wealth Index	0.1386	0.0944	32.0%	0.1061	23.5%	0.1360	3.4%
MSW per Capita Trend	0.0091	0.0098	8.3%	0.0160	-76.0%	0.0080	11.6%

7. Results, Robustness Checks and Plausibility Analysis

Next, we discuss our results, describe the various robustness checks and present the plausibility analysis.

7.1 Results

The results for the estimation of specifications (1), (2), and (3) with 'EWL Policy' and 'EWL Implementation' are shown in Table 4. Columns (1-6) provide the results for the full sample and columns (7-12) provide the results for the PSM matched sample.

To evaluate H1 that seeks to assess the impact of e-waste legislation on MSW, we examine Table 4. For the results related to 'EWL Policy', we refer to columns (1 and 7) and for the results related to 'EWL Implementation', we refer to columns (4 and 10). Since the dependent variable is log transformed, we can interpret the coefficients of the independent variables as percentages (Chan and Ghose 2014; Greenwood and Wattal 2017). From columns (1 and 7), we observe that the coefficients of EWL are negative (-0.0601, -0.0493) and significant ($p<0.01$, $p<0.01$). Also, from columns (4 and 10), we observe that the coefficients of EWL are negative (-0.0470, -0.0424) and significant ($p<0.01$, $p<0.01$). These results indicate that the introduction of e-waste legislation resulted in significant reductions in MSW per capita by at least 4.93%; also, the implementation of e-waste legislation resulted in significant reductions in MSW per capita by at least 4.24% for every logarithmic unit increase in the number of collection centers. Thus, our results support H1.

Next, we assess H2 that seeks to examine the moderating effect of online connectivity. To evaluate the moderating effect between online connectivity and 'EWL Policy', we refer to columns (2 and 8); to evaluate the moderating effect between online connectivity and 'EWL Implementation', we refer to columns (5 and 11). We observe that the coefficients of 'EWL Policy x Online Connectivity' are both negative (-0.0297, -0.0344) and significant ($p<0.05$, $p<0.10$). Also, the coefficients of 'EWL Implementation x Online Connectivity' are both negative (-0.0196, -0.0222) and significant ($p<0.01$, $p<0.01$). These results indicate that increased online connectivity enhances the effect of e-waste legislation – i.e., MSW per capita reduces by at least 2.97% for every logarithmic unit increase in Online Connectivity. In other words, at least 2.97% additional reduction in MSW per capita can be realized when the number of broadband providers in a county increase from the average value of 4.5 to 12. Additionally, in Figure 2 (Panel A) we plot the interaction effects for the combined impact of online connectivity and e-waste legislation, for varying levels of online connectivity. We observe consistent a decline in MSW with increased broadband connectivity. Thus, our results support H2.

Now, we evaluate H3 that seeks to examine the moderating effect of offline proximity. To evaluate the moderating effect between offline proximity and 'EWL Policy', we refer to columns (3 and 9); to evaluate the moderating effect between offline proximity and 'EWL Implementation', we refer to columns (6 and 12). We observe that the coefficients of 'EWL Policy x Offline Proximity' are both negative (-0.0210, -0.0259) and significant ($p<0.01$, $p<0.01$). Also, the coefficients of 'EWL Implementation x Offline Proximity' are both negative (-0.0162, -0.0181) and significant ($p<0.01$, $p<0.01$). We plot the interaction effects in Figure 2 (Panel B) for the combined effect of offline proximity and e-waste legislation, for varying levels of offline proximity (i.e., population density). These results indicate that offline proximity enhances the effect of e-waste legislation – MSW per capita reduces by at least 2.10% for every logarithmic unit increase in Offline Proximity. Thus, our results support H3.

To clarify the moderating effects, we present the marginal effects of online connectivity and offline proximity on MSW in Table 5. We observe that the marginal effects are significant above the 20^{th} percentile for online connectivity and offline proximity. Thus, these results illustrate that the beneficial effects of EWL seem to kick in even at moderate levels of Online Connectivity and Offline Proximity. For policy makers, this finding underscores the importance of these two attributes in amplifying the benefits of e-waste legislation.

Table 4. Main Regression Results

	Full Sample						Matched Sample					
	EWL = Policy			EWL = Implementation			EWL = Policy			EWL = Implementation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EWL	-0.0601***	0.0138	0.0471*	-0.0470***	0.0129	0.0605**	-0.0493***	0.0368	0.0852***	-0.0424***	0.0255	0.0770***
	(0.0131)	(0.0369)	(0.0262)	(0.0056)	(0.0209)	(0.0265)	(0.0174)	(0.0516)	(0.0316)	(0.0072)	(0.0242)	(0.0285)
EWL x Online Connectivity		-0.0297**			-0.0196***			-0.0344*			-0.0222***	
		(0.0131)			(0.0064)			(0.0183)			(0.0074)	
EWL x Offline Proximity			-0.0210***			-0.0162***			-0.0259***			-0.0181***
			(0.0038)			(0.0036)			(0.0045)			(0.0039)
Online Connectivity	-0.0190*	-0.0085	-0.0119	-0.0131	-0.0098	-0.0113	-0.0030	0.0175	0.0130	0.0069	0.0131	0.0107
	(0.0101)	(0.0121)	(0.0103)	(0.0102)	(0.0104)	(0.0102)	(0.0137)	(0.0190)	(0.0145)	(0.0140)	(0.0144)	(0.0140)
Offline Proximity	-0.0927	-0.0954	-0.1262	-0.0868	-0.0843	-0.1000	-0.0521	-0.0787	-0.1557	-0.0917	-0.0967	-0.1293
	(0.0956)	(0.0952)	(0.0947)	(0.0935)	(0.0933)	(0.0939)	(0.1423)	(0.1418)	(0.1393)	(0.1394)	(0.1394)	(0.1404)
Income	0.0753	0.0782	0.0707	0.0493	0.0478	0.0601	-0.0155	-0.0028	-0.0087	-0.0236	-0.0145	-0.0033
	(0.0587)	(0.0586)	(0.0587)	(0.0574)	(0.0574)	(0.0577)	(0.0806)	(0.0790)	(0.0796)	(0.0804)	(0.0798)	(0.0809)
Housing Price Index	-0.0285	-0.0317	-0.0282	-0.0297	-0.0295	-0.0291	0.0176	0.0075	0.0106	0.0156	0.0161	0.0151
	(0.0294)	(0.0293)	(0.0291)	(0.0294)	(0.0294)	(0.0294)	(0.0398)	(0.0398)	(0.0389)	(0.0395)	(0.0395)	(0.0396)
Age	0.0214***	0.0208***	0.0178***	0.0196***	0.0195***	0.0190***	0.0140*	0.0119	0.0059	0.0112	0.0109	0.0100
	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0042)	(0.0080)	(0.0081)	(0.0083)	(0.0081)	(0.0081)	(0.0081)
Education	0.0002	0.0003	0.0006	0.0009	0.0010	0.0009	0.0014	0.0014	0.0017	0.0019	0.0020	0.0020
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0012)	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0013)
Business Establishments	-0.0126	-0.0131	0.0231	0.0155	0.0199	0.0282	-0.1320*	-0.1351*	-0.0626	-0.0948	-0.0879	-0.0691
	(0.0522)	(0.0520)	(0.0511)	(0.0520)	(0.0521)	(0.0526)	(0.0715)	(0.0717)	(0.0698)	(0.0689)	(0.0694)	(0.0705)
Craigslist	0.0128	0.0137	0.0161	0.0199*	0.0197*	0.0202*	0.0213	0.0211	0.0221	0.0246	0.0254	0.0248
	(0.0106)	(0.0105)	(0.0105)	(0.0104)	(0.0104)	(0.0104)	(0.0188)	(0.0187)	(0.0187)	(0.0184)	(0.0183)	(0.0183)
Recycling Laws	-0.0001	-0.0032	-0.0003	-0.0036	-0.0045	-0.0031	-0.0027	-0.0058	-0.0030	-0.0057	-0.0067	-0.0051
	(0.0029)	(0.0032)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0041)	(0.0044)	(0.0040)	(0.0042)	(0.0042)	(0.0041)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1736	1736	1736	1736	1736	1736	1324	1324	1324	1324	1324	1324
R-squared	0.839	0.840	0.841	0.840	0.841	0.841	0.877	0.878	0.880	0.879	0.879	0.880

** p<0.10; ** p<0.05; *** p<0.01; DV = Ln(MSW per Capita); OLS models with robust standard errors.*
For Columns 7-12, results shown for propensity score matched samples with nearest neighbor matching using five neighbors; caliper = 0.2.

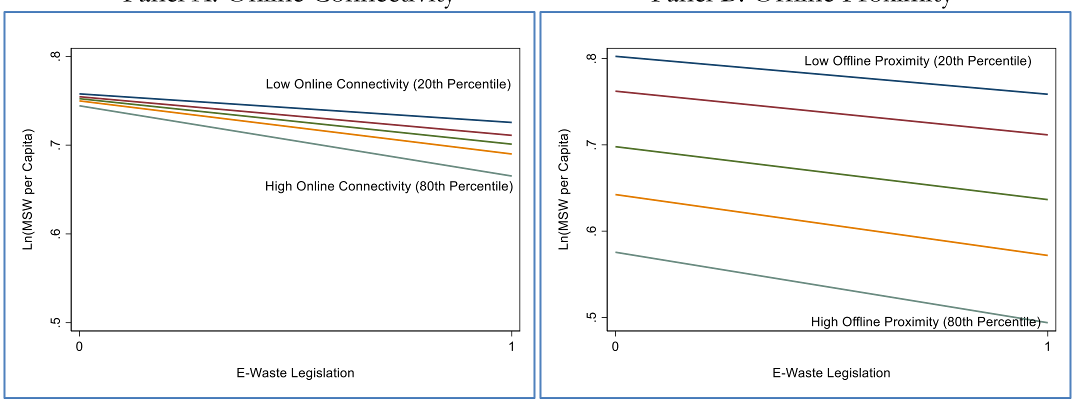
Table 5. Marginal Effects of *Online Connectivity* and *Offline Proximity* on MSW

Online Connectivity	Marginal Effect	Std. Error	t-statistic	p-value	95% Confidence Interval	
20th Percentile	-3.221%	1.926%	-1.670	0.095	-6.999%	0.558%
35th Percentile	-4.349%	1.592%	-2.730	0.006	-7.472%	-1.226%
50th Percentile	-5.121%	1.420%	-3.610	0.000	-7.906%	-2.336%
65th Percentile	-5.983%	1.308%	-4.570	0.000	-8.548%	-3.417%
80th Percentile	-7.913%	1.440%	-5.500	0.000	-10.737%	-5.089%

Offline Proximity	Marginal Effect	Std. Error	t-statistic	p-value	95% Confidence Interval	
20th Percentile	-4.394%	1.409%	-3.120	0.002	-7.158%	-1.630%
35th Percentile	-5.065%	1.355%	-3.740	0.000	-7.724%	-2.407%
50th Percentile	-6.135%	1.288%	-4.760	0.000	-8.661%	-3.610%
65th Percentile	-7.059%	1.250%	-5.650	0.000	-9.510%	-4.607%
80th Percentile	-8.170%	1.233%	-6.630	0.000	-10.589%	-5.752%

Figure 2. Interaction Plots

Panel A. Online Connectivity   Panel B. Offline Proximity



7.2 Robustness Checks

We conduct several robustness checks using alternative matching methods, placebo treatment and data from additional states to validate our results. These robustness checks enhance the confidence in our main findings.

7.2.1 Alternate Matching Approaches

In our main analysis, we use PSM with the NN5 algorithm. For robustness, we conduct two additional analyses that impose tighter restrictions for matching observations. First, we use one-to-one matching to further restrict our treated and control units. Second, in line with recent research (Xu et al. 2016), we use PSM with matching on pre-treatment values (i.e., year 2002) of the dependent variable – i.e., Ln(MSW per Capita). Although these alternative matching approaches further reduce our sample, they would ensure closer comparability between the treated (CA) and control (FL) counties. The results with these alternate matching approaches are shown in Table 6 and they are aligned with our main results and conclusions.

7.2.2 Placebo Analysis

As a falsification test, we conduct a placebo analysis to show that randomly assigned treatment for e-waste legislation does not provide significant effects. For this analysis, we follow the approach adopted by earlier causal studies (Dhanorkar 2019; Greenwood and Wattal 2017) to eliminate the possibility that our results are driven by spurious confounding variables or trends. In brief, we create a dummy variable *EWL Policy (Placebo)* that randomly assigns a treatment year i.e., year of e-waste legislation (between 2000 and 2008) to all counties. *EWL Policy* is then coded '1' for remaining years. Next, we create a dummy variable *EWL Legislation (Placebo)* that randomly assigns the presence of collection centers to CA and FL counties. These two approaches mimic random (i.e., unsystematic) passing of e-waste policy and implementation, which should not provide any interpretable results. Using these variables, we redid our regression models to test whether the results observed in the main analysis are idiosyncratic. These results are shown in the Table 7. We find that, as expected, none of the hypotheses are supported using these random 'placebo' treatment variables for E-waste legislation (policy and implementation). This provides additional evidence that our original results are not idiosyncratic, but rather support the theoretical predictions made above.

7.2.3 Additional Data

Next, we collected data on additional states that have passed e-waste legislation. Specifically, we extend the dataset by including data from North Carolina and Minnesota; both states implemented e-waste legislation in 2007. Although more states in the U.S. have passed e-waste laws, the limited availability of reliable annual county-level MSW data constrains our choice of states used for the analysis (e.g., see Dhanorkar 2019; Fremstad 2017). Our discussions with multiple environmental officials revealed that county-level MSW generation data is not collected by all states, unless mandated by the state environmental agency. Currently, no central repository (such as the US Census Bureau) collects and maintains MSW generation data. An exhaustive search of disparate databases at the county-level revealed two states – Minnesota and North Carolina – that published quality data on MSW Generation for the years 1999-2012. As a result, data availability guides our choice of using Minnesota and North Carolina for the robustness analysis. For Minnesota, we obtained data on its 87 counties from the Minnesota Pollution Control Agency (MPCA). For North Carolina, we extracted county-level data for its 100 counties from its annual MSW reports provided by the NC Department of Environmental Quality (NCDEQ).

We conducted a parallel trend test to examine the comparability of these states with our original sample (CA and FL counties); the results (available upon request) validated the parallel trends assumption underlying our econometric models. The robustness analyses with the two additional states are shown in Table 8. Although the laws in these states differ to some extent in terms of product coverage, funding mechanisms (Esenduran and Kemahlıoğlu-Ziya 2015) and public data on collection centers in these states was quite limited, it is encouraging to see that these findings are aligned with our main results in Table 4.

Furthermore, in Appendix 2, we examine whether the ability of collection centers to handle other forms of waste in addition to e-waste (columns 1–3 and 7–9) and the accessibility of collection centers (columns 4–6 and 10–12) affects our results. Even after we control for these aspects, our results are comparable. In Appendix A3, we verify whether our results are driven by counties with unusually low- or high-MSW. To this end, we restricted our data by excluding information from such counties and redid our analysis. Our results remain similar to the main findings.

Table 6. Results with Alternate Matching Approaches

	One-to-One Matching						Matching on Pre-Treatment MSW					
	EWL = Policy			EWL = Implementation			EWL = Policy			EWL = Implementation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EWL	-0.0649***	0.0132	0.0409	-0.0477***	0.0093	0.0570**	-0.0430**	0.1175***	0.0906***	-0.0478***	0.0526**	0.0558**
	(0.0139)	(0.0394)	(0.0267)	(0.0059)	(0.0210)	(0.0267)	(0.0201)	(0.0427)	(0.0291)	(0.0073)	(0.0229)	(0.0283)
EWL x Online Connectivity		-0.0316**			-0.0186***			-0.0684***			-0.0329***	
		(0.0141)			(0.0064)			(0.0155)			(0.0071)	
EWL x Offline Proximity			-0.0209***			-0.0158***			-0.0268***			-0.0157***
			(0.0039)			(0.0036)			(0.0039)			(0.0038)
Online Connectivity	-0.0203*	-0.0079	-0.0120	-0.0138	-0.0103	-0.0118	-0.0089	0.0372**	0.0092	0.0026	0.0132	0.0057
	(0.0108)	(0.0134)	(0.0111)	(0.0109)	(0.0112)	(0.0109)	(0.0129)	(0.0164)	(0.0128)	(0.0128)	(0.0131)	(0.0127)
Offline Proximity	-0.1058	-0.1223	-0.1572	-0.1015	-0.0991	-0.1154	0.3134**	0.3055**	0.2161	0.2740**	0.2924**	0.2480*
	(0.1056)	(0.1058)	(0.1041)	(0.1043)	(0.1042)	(0.1047)	(0.1364)	(0.1337)	(0.1318)	(0.1288)	(0.1280)	(0.1308)
Income	0.0433	0.0432	0.0341	0.0156	0.0147	0.0273	0.0993	0.1322*	0.0905	0.0720	0.0860	0.0919
	(0.0608)	(0.0606)	(0.0606)	(0.0599)	(0.0600)	(0.0603)	(0.0745)	(0.0747)	(0.0736)	(0.0739)	(0.0735)	(0.0738)
Housing Price Index	-0.0409	-0.0444	-0.0402	-0.0430	-0.0429	-0.0425	0.0178	-0.0009	0.0182	0.0209	0.0222	0.0219
	(0.0298)	(0.0297)	(0.0295)	(0.0297)	(0.0297)	(0.0297)	(0.0317)	(0.0307)	(0.0312)	(0.0316)	(0.0316)	(0.0319)
Age	0.0193***	0.0171***	0.0130**	0.0169***	0.0166***	0.0161***	0.0290***	0.0281***	0.0201***	0.0263***	0.0272***	0.0252***
	(0.0054)	(0.0055)	(0.0055)	(0.0054)	(0.0054)	(0.0054)	(0.0068)	(0.0067)	(0.0070)	(0.0066)	(0.0066)	(0.0066)
Education	-0.0001	-0.0000	0.0003	0.0008	0.0008	0.0007	0.0037***	0.0035***	0.0038***	0.0041***	0.0042***	0.0041***
	(0.0007)	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0011)	(0.0010)	(0.0011)	(0.0010)	(0.0010)	(0.0010)
Business Establishments	-0.0523	-0.0558	-0.0162	-0.0188	-0.0140	-0.0047	-0.1121	-0.0847	-0.0172	-0.0597	-0.0387	-0.0358
	(0.0578)	(0.0577)	(0.0568)	(0.0574)	(0.0576)	(0.0582)	(0.0744)	(0.0742)	(0.0705)	(0.0721)	(0.0725)	(0.0737)
Craigslist	0.0113	0.0115	0.0138	0.0187*	0.0184	0.0189*	0.0467***	0.0423**	0.0458***	0.0481***	0.0485***	0.0483***
	(0.0114)	(0.0113)	(0.0112)	(0.0113)	(0.0113)	(0.0112)	(0.0173)	(0.0170)	(0.0171)	(0.0159)	(0.0156)	(0.0158)
Recycling Laws	0.0003	-0.0030	-0.0000	-0.0035	-0.0043	-0.0031	0.0084**	0.0034	0.0081**	0.0059*	0.0045	0.0063*
	(0.0031)	(0.0033)	(0.0031)	(0.0031)	(0.0031)	(0.0031)	(0.0033)	(0.0035)	(0.0033)	(0.0033)	(0.0033)	(0.0033)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1610	1610	1610	1610	1610	1610	1145	1145	1145	1145	1145	1145
R-squared	0.844	0.844	0.846	0.845	0.845	0.846	0.890	0.892	0.894	0.893	0.895	0.895

** p<0.10; ** p<0.05; *** p<0.01; DV = Ln(MSW per Capita); OLS models with robust standard errors.*

For Columns 1-6, results shown for sample based on 1-to-1 matching; For Columns 7-12, results shown for sample based on matching with additional covariate (pre-treatment MSW values from 2002);

Table 7. Placebo Analysis

	Full Sample						Matched Sample					
	EWL = Policy			EWL = Implementation			EWL = Policy			EWL = Implementation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EWL	0.0046	0.0072	-0.0052	-0.0003	-0.0007	-0.0010	0.0100	-0.0113	-0.0138	-0.0001	-0.0002	-0.0004
	(0.0058)	(0.0198)	(0.0169)	(0.0002)	(0.0006)	(0.0006)	(0.0086)	(0.0245)	(0.0198)	(0.0003)	(0.0008)	(0.0007)
EWL x Online Connectivity		-0.0012			0.0002			0.0098			0.0001	
		(0.0084)			(0.0003)			(0.0112)			(0.0004)	
EWL x Offline Proximity			0.0021			0.0001			0.0048			0.0001
			(0.0030)			(0.0001)			(0.0038)			(0.0001)
Online Connectivity	-0.0200**	-0.0194*	-0.0201**	-0.0197*	-0.0242*	-0.0195*	-0.0041	-0.0085	-0.0043	-0.0035	-0.0055	-0.0033
	(0.0102)	(0.0115)	(0.0102)	(0.0102)	(0.0128)	(0.0102)	(0.0137)	(0.0153)	(0.0138)	(0.0138)	(0.0161)	(0.0138)
Offline Proximity	-0.0108	-0.0105	-0.0111	-0.0102	-0.0111	-0.0109	-0.0046	-0.0052	-0.0080	-0.0098	-0.0083	-0.0065
	(0.0939)	(0.0939)	(0.0938)	(0.0940)	(0.0939)	(0.0941)	(0.1399)	(0.1387)	(0.1393)	(0.1392)	(0.1391)	(0.1392)
Income	0.0486	0.0488	0.0478	0.0486	0.0487	0.0492	0.0114	0.0103	0.0094	0.0060	0.0062	0.0068
	(0.0577)	(0.0578)	(0.0577)	(0.0577)	(0.0577)	(0.0576)	(0.0822)	(0.0820)	(0.0821)	(0.0809)	(0.0810)	(0.0810)
Housing Price Index	-0.0370	-0.0371	-0.0370	-0.0361	-0.0367	-0.0361	0.0120	0.0119	0.0113	0.0123	0.0122	0.0128
	(0.0297)	(0.0298)	(0.0297)	(0.0297)	(0.0297)	(0.0297)	(0.0400)	(0.0400)	(0.0400)	(0.0399)	(0.0399)	(0.0400)
Age	0.0216***	0.0216***	0.0215***	0.0218***	0.0218***	0.0220***	0.0155**	0.0153**	0.0153*	0.0148*	0.0149*	0.0150*
	(0.0041)	(0.0041)	(0.0041)	(0.0042)	(0.0042)	(0.0042)	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)
Education	0.0007	0.0007	0.0007	0.0007	0.0007	0.0007	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Business Establishments	0.0026	0.0025	0.0027	0.0013	0.0021	-0.0007	-0.1007	-0.1024	-0.1011	-0.1045	-0.1043	-0.1070
	(0.0530)	(0.0530)	(0.0529)	(0.0530)	(0.0532)	(0.0532)	(0.0715)	(0.0709)	(0.0711)	(0.0708)	(0.0709)	(0.0708)
Craigslist	0.0199*	0.0199*	0.0200*	0.0194*	0.0197*	0.0204*	0.0301*	0.0301*	0.0298	0.0305*	0.0307*	0.0311*
	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0106)	(0.0183)	(0.0182)	(0.0183)	(0.0179)	(0.0181)	(0.0180)
Recycling Laws	-0.0020	-0.0020	-0.0020	-0.0019	-0.0019	-0.0020	-0.0044	-0.0043	-0.0046	-0.0041	-0.0041	-0.0042
	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0042)	(0.0042)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1736	1736	1736	1736	1736	1736	1324	1324	1324	1324	1324	1324
R-squared	0.837	0.837	0.837	0.838	0.838	0.838	0.877	0.877	0.877	0.876	0.876	0.876

** p<0.10; ** p<0.05; *** p<0.01; DV = Ln(MSW per Capita); OLS models with robust standard errors.*
For Columns 7-12, results shown for propensity score matched samples with nearest neighbor matching using five neighbors; caliper = 0.2.

Table 8. Using Data from Additional States

	Full Sample						Matched Sample					
	EWL = Policy			EWL = Implementation			EWL = Policy			EWL = Implementation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
EWL	-0.0578**	0.0426**	0.0944***	-0.0265***	0.0391***	0.0677***	-0.0932*	0.0242	0.0899***	-0.0197***	0.0269*	0.0440**
	(0.0262)	(0.0206)	(0.0145)	(0.0050)	(0.0127)	(0.0128)	(0.0552)	(0.0382)	(0.0314)	(0.0070)	(0.0158)	(0.0214)
EWL x Online Connectivity		-0.0201**			-0.0175***			-0.0031			-0.0112**	
		(0.0080)			(0.0043)			(0.0131)			(0.0050)	
EWL x Offline Proximity			-0.0203***			-0.0134***			-0.0145***			-0.0083***
			(0.0023)			(0.0019)			(0.0041)			(0.0031)
Online Connectivity	-0.0087	0.0013	-0.0037	-0.0058	-0.0043	-0.0081	0.0154*	0.0100	0.0098	0.0167**	0.0155*	0.0073
	(0.0062)	(0.0090)	(0.0057)	(0.0062)	(0.0061)	(0.0055)	(0.0080)	(0.0142)	(0.0067)	(0.0081)	(0.0088)	(0.0067)
Offline Proximity	-0.1635***	-0.1445**	-0.1145*	-0.1595***	-0.1580***	-0.1499**	-0.2561**	-0.2984**	-0.2354**	-0.2582**	-0.3068**	-0.2926**
	(0.0585)	(0.0597)	(0.0595)	(0.0584)	(0.0597)	(0.0597)	(0.1097)	(0.1231)	(0.1193)	(0.1096)	(0.1223)	(0.1228)
Income	0.1802***	0.2392***	0.1924***	0.1529***	0.2315***	0.2061***	0.1288**	0.1894***	0.1703***	0.1030*	0.1840***	0.1737***
	(0.0411)	(0.0403)	(0.0401)	(0.0400)	(0.0406)	(0.0423)	(0.0594)	(0.0598)	(0.0584)	(0.0569)	(0.0601)	(0.0613)
Housing Price Index	0.0124	0.0216*	0.0208	0.0108	0.0209	0.0206	0.0540**	0.0564***	0.0558***	0.0529**	0.0579***	0.0558***
	(0.0137)	(0.0129)	(0.0129)	(0.0137)	(0.0131)	(0.0131)	(0.0217)	(0.0195)	(0.0195)	(0.0213)	(0.0202)	(0.0201)
Age	0.0123***	0.0108***	0.0085***	0.0116***	0.0104***	0.0098***	0.0079	0.0074	0.0052	0.0065	0.0068	0.0063
	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0029)	(0.0029)	(0.0050)	(0.0054)	(0.0052)	(0.0048)	(0.0053)	(0.0053)
Education	0.0001	0.0000	0.0002	0.0003	0.0001	0.0001	0.0014**	0.0005	0.0006	0.0015***	0.0004	0.0005
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Business Establishments	-0.0319	-0.0281	-0.0004	-0.0210	-0.0213	-0.0075	-0.0636	-0.1283*	-0.0993	-0.0394	-0.1272*	-0.1097
	(0.0302)	(0.0297)	(0.0291)	(0.0301)	(0.0297)	(0.0299)	(0.0683)	(0.0679)	(0.0683)	(0.0697)	(0.0662)	(0.0675)
Craigslist	-0.0034	-0.0034	0.0059	0.0025	-0.0018	0.0018	-0.0087	-0.0065	-0.0008	-0.0040	-0.0095	-0.0095
	(0.0079)	(0.0076)	(0.0076)	(0.0079)	(0.0076)	(0.0076)	(0.0108)	(0.0131)	(0.0130)	(0.0107)	(0.0126)	(0.0126)
Recycling Laws	-0.0857***	0.0029	0.0035	-0.0674**	0.0034*	0.0033*	-0.0551	0.0072	0.0059	-0.0522	0.0084***	0.0081***
	(0.0277)	(0.0025)	(0.0023)	(0.0277)	(0.0021)	(0.0020)	(0.0585)	(0.0052)	(0.0051)	(0.0590)	(0.0030)	(0.0031)
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4340	4340	4340	4340	4340	4340	2133	2133	2133	2133	2133	2133
R-squared	0.837	0.831	0.832	0.838	0.831	0.832	0.912	0.903	0.903	0.912	0.903	0.903

** p<0.10; ** p<0.05; *** p<0.01; DV = Ln(MSW per Capita); OLS models with robust standard errors.*

For Columns 7-12, results shown for propensity score matched samples with nearest neighbor matching using five neighbors; caliper = 0.2.

Matching substantially reduced the sample size since FL was the only “control” state without EWL policy/implementation. Limited data on EWL implementation was available for MN and NC.

7.3 Plausibility of Behavioral Spillovers

Our analysis provides evidence that the enactment and implementation of e-waste legislation contributes to significant MSW reductions. Next, we conduct additional sensitivity analysis to validate the plausibility of our causal arguments (Emrah Aydinonat 2018). Such analysis is commonly used to examine whether or not the obtained estimates conform to expectations (Dhanorkar 2019; Epstein et al. 2014). To this end, we determine the range of feasible MSW reduction values that should result from e-waste reduction. Then, we compare these values with the actual MSW reduction estimates obtained from our analysis. The differences in the MSW reductions should, therefore, inform us of the potential range of the behavioral spillover effects that can be attributed to e-waste legislation.

We start by examining information from the waste characterization studies by CalRecycle presented in Table 9. Although other agencies such as the United Nations and Forbes provide waste characterization estimates, the assessment is done at the country level (e.g., USA, Canada, France) which precludes their use in our analysis. As a result, our estimates of the behavioral spillover are calculated based on waste characterization studies from CalRecycle that provides information specific to California. Pre-2003 data on e-waste as a percentage of total MSW is unavailable since e-waste as not recognized as a distinct category of waste in California before 2003. From Table 9, we observe that e-waste constituted approximately 1.2% of total MSW in 2003 (i.e., before the enactment of e-waste legislation) and 0.5% of total MSW in 2008 (i.e., after the enactment of e-waste legislation). This reduction in e-waste is "…expected due to passing of the EWRA" (CalRecycle Environmental Scientist 2018). As the average per capita generation of MSW in California was 1.05 tons (2100 lbs.) in 2003, on average the e-waste per capita was 25.2 lbs. (0.012 X 2100 lbs.). Similarly, in 2008, the average per capita generation of MSW in California was 0.95 tons (1900 lbs.), which means the average e-waste per capita fell to 9.5 lbs. (0.005 X 1900 lbs.). As a result, the reduction in e-waste from 2003 to 2008 based on the two waste characterization studies can be calculated as an average of 15.7 lbs. (25.2 – 9.5) per capita, which represents the average estimate of e-waste diverted from landfills. Based on the above discussion, we can characterize 15.7 lbs. per capita as the ceiling i.e., upper limit for the expected e-waste reductions.

Next, we compare the above numbers with our regression estimates to calculate the extent of behavioral spillover effects. Our estimates from regression models (Note that—for the plausibility analysis—we chose the conservative estimate of e-waste reduction from Table 8) suggest approximately 5.78% reductions in per capita MSW after the passage of EWRA in California. Assuming an average per capita MSW generation of 1 ton per capita (i.e., 1.05 ton in 2003 and 0.95 ton in 2008), our regression coefficient estimates indicate total MSW reductions of approximately 115.60 lbs. per capita. Therefore, even in the conservative case (i.e., ignoring the multiplier effect of online connectivity and offline proximity), we observe approximately 99.90 lbs. (115.60 lbs. – 15.7 lbs.) greater per capita MSW reductions than can be attributed purely to a decline in e-waste levels.

Factoring in the moderating effects, we notice that the estimates of MSW reductions are far larger (i.e., up to 187.98 lbs. per capita accounting for online connectivity and offline proximity).

Table 9. Waste Characterization for California

Type of Waste	2003	2008
Organic	30.20%	32.40%
Construction and Demolition	21.70%	29.10%
Paper	21.00%	17.30%
Plastic	9.50%	9.60%
Metal	7.70%	4.60%
Glass	2.30%	1.40%
Special Waste	5.10%	3.90%
Household Hazardous Waste	0.20%	0.30%
Mixed Residue	1.10%	0.80%
Electronics	**1.20%**	**0.50%**
Total	100%	100%

Source: CalRecycle's Waste Characterization Studies

Table 10. Plausibility Analysis

Description	Units	California	Minnesota	North Carolina
E-waste as % of MSW (Pre-legislation)	Percent	1.20%	1.80%	1.40%
E-waste as % of MSW (Post-legislation)	Percent	0.50%	1.20%	0.60%
E-waste Per Capita (Pre-legislation)	lbs.	25.20	39.24	28.00
E-waste Per Capita (Post-legislation)	lbs.	9.50	26.16	12.00
Actual Reduction in E-waste after legislation	lbs.	15.70	13.08	16.00
Estimated Reductions in MSW from Table 8	Percent	5.78%	5.78%	5.78%
Estimated Per Capita Reductions in MSW	lbs.	115.60	124.85	113.29
Estimated Per Capita Spillover Effect on MSW	lbs.	99.90	111.77	97.29

To augment the plausibility analysis for California, we obtained additional information[8] on the waste characterization studies conducted by Minnesota and North Carolina. Using this information, we repeated the above steps to estimate the spillover for MN and NC (we again chose the conservative estimate (i.e., 5.78%) from Table 8). In Table 10, we summarize the plausibility analysis for all three states (i.e., CA, MN and NC).

To further validate our proposed mechanism, we also obtained data on the per capita e-waste collection rates from the Electronics Recycling Coordination Clearinghouse (ERCC). The ERCC started collecting such data in 2009 and in Table 11 we provide the state-reported information from 2009 to 2012. We observe that on average 5.31 lbs., 6.25 lbs. and 2.17 lbs. of e-waste has been collected through formal channels (e.g., registered recycling facilities) in CA, MN and NC, respectively. However, from the waste characterization studies, we observe that the overall reduction in e-waste (as shown in Table 10) was 15.70 lbs., 13.08 lbs. and 16.00 lbs. for CA, MN and NC, respectively. Therefore, the remaining e-waste reductions (10.40 lbs., 6.83 lbs. and 13.83 lbs., respectively) are likely to have occurred through behavioral shifts in consumers actions (e.g., higher reuse and repair)—in addition to proper disposal of e-waste through the registered recycling facilities. Thus, the above analysis confirms behavioral adjustments even within the e-waste category of MSW subsequent to the enactment of e-waste legislation, which provides evidence to support the notion of behavioral spillovers.

[8] U.S. State and Local Waste and Materials Characterization Reports.https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/advancing-sustainable-materials-management-0. Retrieved January 30, 2020

In sum, the above discussion indicates that the EWRA could not have only changed e-waste disposal behaviors but quite likely also had a more widespread and far-reaching impact on consumer's attitudes and on reuse and recycling behaviors. We also discussed these findings with several government officials at CalRecycle, Minnesota Pollution Control Agency (MPCA), Electronics Recycling Coordination Clearinghouse (ERCC) and National Electronics Recycling Council (NERC). Our interviews confirmed that the observed MSW reductions could not be attributed to e-waste alone, since the "…reductions are far greater than the overall volume of e-waste as a part of MSW to begin with" (NERC Official 2018). This provides additional evidence that behavioral spillovers are the most likely explanation for the magnitude of MSW reductions observed in our data.

Table 11. Additional Evidence of Behavioral Spillovers

State	Per Capita E-waste Collection Rates Through Formal Collection Channels [A] 2009 (lbs.)	2010 (lbs.)	2011 (lbs.)	2012 (lbs.)	Average (lbs.)	Overall E-waste [B] Reductions (lbs.)	Behavioral Spillover in E-waste category (lbs.)
California	5.03	5.29	5.25	5.65	5.31	15.70	10.40
Minnesota	5.75	6.54	6.17	6.53	6.25	13.08	6.83
North Carolina	0.83	0.96	2.51	4.39	2.17	16.00	13.83

[A] *ERCC, Per Capita E-waste Collection Numbers (lbs.), data was collected starting from 2009*
[B] *Solid Waste Characterization Studies independently conducted by California, Minnesota and North Carolina*

8. Discussion

8.1 Main Findings & Implications

Many countries are grappling with the challenges of managing the rapidly increasing quantities of e-waste (Greenpeace 2017). Due to the presence of several toxic chemicals, the challenges involved in handling e-waste get compounded because improper disposal of e-waste can result in adverse environmental and health consequences for the soil, atmosphere, waterways, and groundwater (Lerner 2011). The European Union has already passed several laws governing the generation and handling on e-waste. However, in the United States the implementation of such laws has occurred at the state level in a staggered manner. Several individual states (e.g., California, Minnesota) have introduced legislation to divert e-waste away from landfills and to properly dispose hazardous materials (Atasu and Subramanian 2012). However, a senior environmental scientist in CalRecyle mentions, "the actual [direct and indirect] benefits of e-waste legislation have been difficult to quantify." Specifically, we examine whether such laws can have an impact that extends beyond just reducing e-waste. Our study uses a difference-in-differences analysis based on data from California (with Florida as control state) to analyze the benefits of such legislative efforts. California serves as an ideal testbed because (i) it was one of the first states to implement an overarching e-waste legislation and (ii) its legislation is focused on curbing e-waste through a "fee-upon-sale" regulation (Plambeck and Wang 2009), which is expected to directly alter consumer behaviors. We find that California's EWRA led to a substantial reduction of at least 4.93% in the generation of MSW per Capita. We attribute this effect to "behavioral spillovers." The associated fee-upon-purchase as well as the collection & recycling systems established as a part of the legislative effort could have created "behavioral spillovers" that not only impacted the disposal of e-waste (Lerner 2011) but also other consumer generated waste i.e., MSW. In other words, we argue that the e-waste legislation could also have altered individuals' behaviors, by raising awareness about electronics repair or reuse, thus extending the life of existing products. While we do find that the passing of the law (i.e., EWL policy) has a significant effect on MSW reduction, the importance of EWL Implementation is also worth noting. From the policy makers' perspective providing increased access to e-waste recycling constitutes a crucial step. For example, such policy efforts may involve engaging local recycling companies to develop more collection centers, which can enhance access to e-waste recycling opportunities.

From an academic perspective, prior studies (Esenduran and Kemahlıoğlu-Ziya 2015; Gui et al. 2015; Plambeck and Wang 2009) have also discussed the relevance of various e-waste legislation schemes. While we use California's EWRA for our main analysis due to its heavier consumer focus (i.e., upfront recycling fee), we also later investigated the effects of other e-waste laws (e.g., Minnesota and North Carolina) that take a more traditional approach by specifying collection and recycling requirements for manufacturers. Thus, we empirically illustrate that e-waste legislation can provide additional benefits through behavioral spillovers, which has been overlooked in prior analytical models and can also inform future analytical work. Our results also provide evidence that the fundamental approach of legislating e-waste seems to be having the desired effect.

From the perspective of net reduction in MSW, our study suggests that California's EWRA could provide substantial environmental benefits. For instance, Lou and Nair (2009) find that a conventional landfill releases up to approximately 1.287 ton CO_2 equivalent per ton of MSW. Correspondingly, our results suggest that reduction in MSW due to the passing and implementation of the e-waste legislation could plausibly lower CO_2 equivalents by up to 5 million lbs. Furthermore, a reduction of e-waste from the landfills can have significant benefits for surface water since landfill leachate often amplifies the toxicity of surface water (Kjeldsen et al. 2002). Further, legislative efforts such as California's EWRA often rely on individuals, who can play a crucial role in the success of e-waste legislation.

Increased access to the internet (i.e., online connectivity) can provide useful information regarding available opportunities for effective reuse, recycling and disposal of e-waste. Also, access to online used goods markets (e.g., Craigslist) can enable individuals to connect with other individuals to buy or sell used electronics, which can in turn divert electronics from the waste stream. As a result, enhanced access to reuse or recycling options can further boost legislative efforts aimed at restricting the generation of e-waste. In line with this idea, we find that broadband connectivity can amplify the benefits from e-waste laws. Our results convey that regions with greater broadband connectivity may accrue at least 2.97% higher reductions in MSW per Capita following the passing of e-waste legislation. These findings have two implications for policy makers. First, information availability can play a significant role in augmenting the effectiveness of legislative efforts, especially when the legislation aims to induce behavioral changes in individuals. Thus, policy makers could also focus on enhancing broad band connectivity for regions with limited access to the internet (e.g., rural counties, counties with aging population) to enhance the effectiveness of the legislative efforts. Second, development of online markets and information channels can also play a crucial role in the success of legislative efforts. The usage of online used goods markets (e.g., Craigslist, FreeCycle, eBay Classifieds) has increased substantially over the last two decades (Dhanorkar 2019). Such online channels can facilitate consumer participation in extending the life of products and thereby amplify the effectiveness of government-led waste prevention efforts. We also find that offline proximity can also boost the behavioral spillover effect of legislations by at least an additional 2.10%. This may be true due to two reasons. First, "neighborhood effect" is a likely explanation, which mainly arises because of social interaction and local imitation among residents of a community. Furthermore, offline proximity could also enhance the power of online connections and reveal additional opportunities for reuse/recycling that were earlier unavailable.

8.2 Generalization to the Management of Waste and Other Industries

Our paper examines the effectiveness of e-waste legislation by investigating longitudinal data from the waste industry. Two key features of our analysis indicate that our results are generalizable for the management of waste. First, our analysis indicates that the enactment of e-waste legislation provides behavioral spillovers that lead to overall reduction in MSW. Thus, our results illustrate that behavioral spillovers can provide positive implications for social welfare. As such, these findings suggest that policy makers can consider targeted legislations for specific forms of waste (e.g., plastics) to leverage behavioral spillovers and drive down MSW. Relatedly, policy makers could also exploit behavioral spillovers in other similar settings such as reuse, recycling and conservation to enhance social welfare. For example, it might be worth examining the spillover effects of recycling (e.g., bottle bills) policies on generic consumer behaviors such as reducing use of plastics. In the context of decentralized environmental policy, it might also be interesting to examine the spillover effects of voluntary environmental certification schemes (e.g., ISO 14001, LEED) on other aspects of firm behaviors such as governance, human rights and philanthropy. Second, our analysis shows that the increased access to markets through online connectivity and offline proximity increases the effectiveness of e-waste laws. The critical role played by access to markets is also likely to apply for other forms of waste management legislations.

We note that though the problem of waste management is relevant for many other sectors and industries (e.g., oil exploration, industrial machining, solar industry), our results cannot be generalized as-is to other settings because of specific differences from electronic products. For instance, electronic products can have some residual value which makes access to markets useful to extract value from used products. More importantly, legislations focused on electronics tend to impact individual consumers, which led us to propose and test the hypothesized effects. By contrast, industrial cuttings (in industrial machining) or drill cuttings (in oil exploration) may not have residual value that can be economically extracted. Moreover, industry-specific supply chain issues may not allow generalization to other industrial settings (Davies and Joglekar 2013; Joglekar et al. 2016). Overall, while our results can be sufficiently generalized to other consumer-oriented contexts, this may not be true of industrial and commercial contexts.

8.3 Limitations

Our study has some limitations. We use California as the research setting due to its early foray into e-waste legislations and the consumer focus of its legislation. Yet, several other states have also recently passed similar laws that prohibit certain types of electronics from entering the waste stream. Future research could empirically examine the effectiveness of various types of e-waste laws in reducing waste. Yearly data on e-waste levels does not exist for California prior to the passage of the EWRA. As a result, it is not feasible to replicate our MSW data analysis with e-waste data. Furthermore, several states neither collect nor publish yearly e-waste data, which makes direct comparisons of e-waste levels challenging. Given the lack of data, our estimates of the effects of spillover may be not be precise. To address this issue, we indicate the ranges for the MSW reductions that are realized subsequent to the enactment of e-waste legislation. Next, our choice of Florida as a control state is based on the availability of MSW data as well as its comparability with California, as described previously. Yet, other states (e.g., Texas) could also serve as appropriate control groups. It is also plausible that state and municipal governments experienced spillover effects of EWL that prompted them to increase their collection and recycling efforts for other forms of MSW. This could be an interesting idea for exploration in future research (we could not explore the behavioral spillover effects for government agencies due to data limitations). Although we include MN and NC in our robustness checks, much more thorough analysis would evidently be needed to confirm the causal impact of e-waste laws for those states. Our study indicates that policy makers can amplify the impact of e-waste laws by enhancing connectivity in two ways: increasing broadband access and focusing on populated locations. However, other potential options such as focusing on central constituents in a network (Garg et al. 2017; Steinfield 2004) and leveraging homophily in social networks (e.g., McPherson, Smith-Lovin, and Cook 2001) could provide policy makers alternative mechanisms to enhance connectivity. Moreover, depending on the context of study, the scope of offline i.e., geographic proximity itself might change to subsume narrower (e.g., metros, cities) or larger (e.g., countries, continents) geographic regions. We believe such alternative options can serve as fruitful avenues for future research. Notwithstanding these limitations, our study provides empirical validation for the "behavioral spillovers" emanating from e-waste legislation as well as the complementary role of market access (i.e., online connectivity and offline proximity) in enhancing the effectiveness of such legislation.

Acknowledgements

We thank April Gomez and Andrew Hurst of CalRecycle for the valuable insights about California's EWRA policy and its implementation. We thank Lynn Rubinstein from Northeast Recycling Council (NERC) and Amanda Cotton from Minnesota Pollution Control Agency (MPCA) for their constructive suggestions. The data collection effort was supported by the Smeal College of Business Small Research Grant. We thank Prof. Nitin Joglekar, the Senior Editor and the three reviewers for their constructive suggestions, which significantly enhanced the paper.

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