ABSTRACT

Title of Dissertation: ON THE IMPLICATIONS OF NEW POLICIES, MARQUEE SELLERS, AND GREEN NUDGES IN ONLINE SECONDARY MARKETS FOR DURABLE IT PRODUCTS: EVIDENCE FROM EMPIRICAL STUDIES

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The rapid pace of product development in the IT sector has led to a volume surge of product returns, giving rise to critical environmental threats that can potentially have significantly adverse ecological effects. One possible avenue to mitigate these negative effects pertains to the establishment of robust secondary markets for these products, so that their useful life can be enhanced. My dissertation seeks to study multiple aspects aimed at enhancing the efficiency of online secondary markets for durable IT products, using economic and behavioral theories. The first essay examines the extent to which firm policies in the primary market mitigate inefficiencies caused by adverse selection in the secondary market for IT products. I find that policies implemented by firms in the primary market with respect to their products can have beneficial effects in addressing adverse selection in the secondary markets. The second essay studies how adding a *marquee* seller to a B2B secondary

market platform for IT products affects other sellers, in terms of the prices they obtain for comparable products. I show that the entry of a marquee seller has a positive effect on the prices obtained by other sellers on the platform. I further show that this positive effect on final prices is moderated by bidders multi-homing activity, and their level of involvement in the marquee seller's site. Finally, through behavioral experiments performed on Amazon MTurk, my third essay examines the extent to which the use of behavioral interventions, in the form of green nudges, can enhance the propensity of used IT products being purchased in the secondary market, thereby increasing the lifetime of these products. I find that the efficacy of using green nudges to impact consumer behavior depends on the kind of motivation (i.e., internal versus external motivation) the nudge is delivering. I further find that the effectiveness of green nudges can vary based upon product price and perceived quality, and consumer demographics and latent personalities. Collectively, the findings from these studies in my dissertation provide valuable theoretical as well as practical insights about the effectiveness of different mechanisms for enhancing the efficiency of online secondary markets for durable IT products.

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by

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Dedication

I dedicate my dissertation to my family. A special feeling of gratitude to my loving parents and wife, whose words of encouragement and push for tenacity continuously ring in my ears.

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This dissertation was five years' worth of work, dedication, and sacrifice, but it was not done alone. The luckiest among us are blessed with people in our path who help us become our best selves and reach our greatest potential. The civil rights activist and lawyer Derrick Bell summed it up best: "However self-sufficient we may fancy ourselves, we exist only in relation — to our friend, family, and life partners; to those we teach and mentor; to our coworkers, neighbors, strangers; and even to forces we cannot fully conceive of, let alone define. In many ways, we are our relationships."

This quote perfectly sums up the experience of bringing this dissertation to fruition. It is a byproduct of the tremendous support and love from an enviable network of loved ones, mentors, and advisers, who propped me up when I needed it, pushed me to challenge myself and make the most of this opportunity, and made it possible for me to cross the finish line when it often felt out of reach.

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She is a true partner who is unwavering in her support, even after she started her own challenging Ph.D. program shortly after I began mine. Through it all, we have had two beautiful children together and worked as a true partnership to support each other and help ensure we each realize our dreams. This has not been an easy endeavor, but we promised to reach the end of the tunnel together, and she got me to the end of mine. I am thrilled to see her nearing the end of hers, and know this journey has only made us stronger. I am grateful to have such a strong, compassionate and generous partner to go through all of this with.

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Table of Contents

List of Tables

Table for Chapter 2

Table for Chapter 3

Table for Chapter 4

List of Figures

Figure for Chapter 2

Figure for Chapter 3

Figure for Chapter 4

Chapter 1: Introduction and Overview

Economic, technological, and social trends have led to rapid growth in the market for used and remanufactured goods. In particular, online platforms have facilitated the rapid growth of the secondary market by reducing the cost of connecting sellers directly to buyers who are interested in used products (Hristova 2019). Secondary markets have attracted interest from both theoretical and empirical scholars. The prominent benefit of secondary markets lies in allowing durable goods to be efficiently reallocated to the people who value them most (Lee and Whang 2002). However, a number of existing factors can affect the performance and efficiency of secondary markets – mostly associated with types of information asymmetries and pathologies (Sweeting 2019). Reducing the efficiency of secondary markets leads to negative ramifications on consumer surplus and social welfare, and critical threats to the environment that can result in major adverse ecological effects.

Within the domain of secondary markets, those for used IT products have a particularly noteworthy role to play for several reasons. Due to the rapid pace of product development in the IT sector (Mendelson and Pillai 1999), enhancing the efficiency of secondary markets for durable IT products is desirable since they retain value, but also has ecological and market value. From an economic perspective, improving the efficiency of secondary markets can help support new product prices in the primary market (Bester 1998, Zhao and Jagpal 2006). Furthermore, from an ecological perspective, e-waste is a global ecological issue. E-waste that ends up in landfills causes significant environmental damage, which can be avoided by extending the life of these products (Elmaghraby et al. 2018). It raises concern about air pollution, water pollution, soil pollution, information security, and even human exploitation (Weiss et al. 2016). Hence, beyond the general importance of secondary markets for durable goods, ensuring the long-run efficiency of secondary markets for durable IT products is imperative and remains a central concern for policy makers and managers alike.

Secondary markets for durable IT products exist in both physical and virtual formats, and allow for different types of transactions, i.e., business-to-business or business-to-consumer. There are multiple characteristics of these market exchanges. They can be public or private, auction or direct, and one-to-many or many-to-many, which includes numerous sellers and numerous buyers (Lee and Whang 2002). Sellers in secondary markets are heterogeneous, e.g., large recyclers, liquidation players, mom-and-pop stores, individual resellers, and flea markets. The pricing model in these markets also exists in multiple forms, e.g., auctions, bulk purchases, and posted prices. Products in secondary markets vary in terms of quality and condition. The variation in product quality and extant information asymmetry in these markets lead to issues of adverse selection and moral hazard (Lewis 2011, Klein et al. 2016). These issues have become more salient in the last decade due to the large increase in volume, reduction in product life cycles, and concurrent presence of multiple generations of IT products (Camarda et al. 2019).

The volume surge of IT product returns urges retailers to liquidate their excess inventory through existing online liquidation platforms in the secondary market. The online liquidation market promises to grow in the coming years, with the amount of returns expected to exceed $1 trillion within the next few years (PYMNTS 2019). In my dissertation, I focus on this subsector of the secondary market – liquidation markets for used IT products. The liquidation market includes B2B auctions, posted price B2B sales, and B2C sales on sites like Amazon and eBay. These liquidation markets are mostly online, so they suffer from similar factors that affect online platforms and sellers and need to be managed effectively. Their efficiency is of importance, since they constitute a large component of the durable IT secondary markets context and also create a significant amount of e-waste. Addressing the efficiency of these markets, in their diverse forms, requires the use of multiple theoretical and empirical perspectives in order to generate insights for both managers and policy makers. Therefore, my dissertation consists of three essays that use different theoretical lenses to study aspects of secondary markets for IT products as a way to enhance their functioning and efficiency. My work reported here aims at enhancing the efficiency of online secondary markets from (1) an information asymmetry perspective, (2) platforms perspective, and (3) a behavioral economics perspective. In the following paragraphs, I briefly describe these essays, each of which forms a chapter in my dissertation.

The first essay in my dissertation examines the extent to which firm policies in the primary market mitigate inefficiencies caused by adverse selection in the secondary market for IT products. Online B2B auctions are afflicted by the same challenges facing other electronic markets for used products; specifically, they are significantly affected by adverse selection, since uncertainty about product quality from their first life remains in place. I study how these adverse selection costs may be identified and reduced in online B2B auctions for mobile phones using a proprietary data set for pallets of iPhone devices. In particular, I identify a clear method by which these adverse selection costs may be reduced – through policies implemented in the *primary market*. I argue that policies implemented by firms in the primary market with respect to their products can have beneficial effects in addressing adverse selection in the secondary markets. While extant literature has studied how secondary markets affect demand in the primary market (Arunkundram and Sundararajan 1998; Chen et al. 2013), I consider the reverse by focusing on how decisions in the primary market can affect market efficiency in the secondary market. This essay has significant implications for enhancing the efficiency of secondary markets for IT products, by virtue of highlighting the connections between primary and secondary markets. It also adds to the literature on platforms by showing how adverse selection continues to affect platforms for the resale of IT products.

The second essay studies how adding a *marquee* seller to a B2B secondary market platform for IT products affects other sellers, in terms of the prices they obtain for comparable products. Prior research has focused on factors that impact prices on two-sided platforms, including network effects and switching costs, demand interdependency and cross-side trust within a platform (Eisenmann et al. 2011, Farrell and Klemperer 2007, Rochet and Tirole 2003, Wilbur 2008, Evans 2009). Scholars have furthermore shed light on the effects of new entrants on prices for either side of the platform, and showed that market prices reduce as a result of the increase in competition (Wright 2004, Chandra and Collard-Wexler 2009, Zhu et al. 2019). Despite the increase in competition resulted from adding new sellers, the entry of a "marquee" seller could possibly result in positive network effects across both sides of the platform as well as serve as a price anchor. Using proprietary data of secondary market auctions for IT products hosted by a leading online B2B platform, I examine how the entry of a marquee seller influences prices of other sellers for comparable products on the platform. Drawing on theory in *reference prices*, I show that the entry of a marquee seller has a positive impact on the prices obtained by other sellers on the platform, while controlling for increased supply and demand. I further show that this positive effect on final prices is moderated by the extent to which bidders are active on multiple seller sites on the same platform, and the extent to which bidders participate in the marquee seller's site. I explain these effects using theory in multi-homing and involvement, in terms of how reference prices are set. Thus, beyond the presence of network effects on the platform per se, this essay extends the literature by showing that adding new sellers to the platform can have more nuanced effects on prices obtained on the platform.

While the first two essays explore different mechanisms that make secondary markets more effective, the third essay seeks to enhance the efficiency of secondary markets by studying how consumers may be induced into purchasing durable used IT products, rather than new products. Cannibalization of used IT products is increasingly being viewed as an economic problem. However, from an environmental and social perspective, there are many different social as well as ecological benefits that can be gained from enhancing the cannibalistic impact of used products in the secondary market. Within the realm of durable IT products, I study whether sellers could possibly enhance the likelihood of used IT products being purchased through the use of behavioral interventions, in the form of *green nudges*. The need to better understand what motivates people to adopt pro-environmental behaviors has taken a new urgency with the increasing emphasis on sustainability. E-waste has received limited attention in spite of being the fastest growing segment of household waste (Dao et al. 2011, Saphoresa et al. 2012). The global E-waste annual report shows that the world dumped a record of 53.6 million tons of e-waste in 2019, of which only 17.4% was recycled (Reuters 2020).

In order to test how highlighting the negative externalities of e-waste could possibly enhance the chances of used electronic products being purchased in the B2C secondary market, I conduct experimental studies using subjects recruited from Amazon MTurk. I examine the extent to which the use of green nudges can alter consumer preferences towards purchasing used IT products, relative to the counterpart new products. My results show the efficacy of using a green nudge depends upon the type of motivation the nudge delivers to the average consumer. Drawing on theories in conspicuous conservation and emotional empathy, I show that providing an external motivation via the green nudge can be very effective in impacting the likelihood of used IT products being purchased. I further argue and show that the efficacy of the green nudge can vary based upon the used product price and perceived quality. Moreover, consumer demographics and latent personality traits can play a significant role in moderating the efficacy of green nudges, depending upon the type of motivation they deliver to consumers. This essay provides guidance and proposes different methods for sellers in secondary markets to apply in their marketplaces as they create offers of used IT products in the B2C marketplace.

Collectively, the findings from these studies in my dissertation will provide valuable theoretical as well as practical insights about the effectiveness of different mechanisms for enhancing the efficiency of online secondary markets for IT products.

Chapter 2: Adverse Selection in B2B Secondary Market Online Auctions for IT Equipment: An Empirical Analysis

2.1. Introduction

Consumer spending on new IT products in the United States in 2019 was estimated to be $1.69 Trillion, according to IDC, representing an increase of 5.3% over the previous year.[1] A large part of this spending goes into mobile phones, computers, and communication equipment that are largely durable and can provide value for many years. However, as these are replaced by newer models, these used technologies enter business-to-business (B2B) and business-to-consumer (B2C) *secondary* or *liquidation markets*. These markets process the resale of products that have passed through the primary market in some form (Elmaghraby et al. 2018; Lee and Whang 2002), either as customer returns, unsold inventory, or from buyback programs (Tibben-Lembke 2004). The efficient functioning of these secondary markets is desirable, since these 'older' products are functional and continue to provide value (Pilehvar et al. 2017). Moreover, their second life prevents them from ending up in landfills where they can cause environmental damage (Tibben-Lembke 2004).

A recurring issue faced by secondary markets for IT products, such as computers and mobile devices (Pilehvar et al. 2017) pertains to uncertainty about product quality (Ghose 2009). Specifically, secondary markets are prone to adverse selection, due to uncertainty about the quality of products sold therein, as shown by a significant body of evidence in the context of used durable goods (Akerlof 1970, Garicano and Kaplan 2001; Overby and Mitra 2014). Uncertainty about quality manifests as *adverse selection costs:* reduced prices relative to conditions where full information is provided to buyers (Dewan and Hsu 2004). Adverse

[1] https://www.cnet.com/news/consumers-will-spend-1-7-trillion-on-tech-this-year-idc-predicts/

selection can also lead to market failure, which in the case of IT equipment leads to greater e-waste and environmental degradation (Tibben-Lembke 2004) as well as lost opportunities for the sale of equipment in other settings where demand exists (Neto et al 2016).

Potential solutions to adverse selection in secondary markets have largely focused on providing information at *the point of sale* – these include quality attestations, warranties, third-party certifications, signals, and relational measures that build trust (Overby and Mitra 2014; Ozpolat et al. 2013; Klein et al. 2016; Pavlou et al. 2007). However, this focus on the point of sale misses the influence of factors from the *primary market* that can help reduce uncertainty in the secondary market. Arguably, information from the primary market can have a positive effect on prices in the secondary market as well. Prior literature on the interconnectedness between the primary and secondary markets (Arunkundram and Sundararajan 1998; Chen et al. 2013) have discussed how the secondary market negatively affects demand in the primary market. However, the reverse is also possible – decisions in the primary market taken by critical players, such as the makers of original equipment or firms that are important value-added resellers, as a way to enhance their value in the primary market, can positively affect market efficiency and prices in secondary markets. My empirical research question therefore is: *to what extent do product design and feature decisions by key players in the primary market (such as original equipment makers and telecom service providers) reduce adverse selection in the secondary market for the same set of IT products?* In this essay, I provide empirical validation of this effect within B2B secondary markets for iPhones.

In the typical B2B secondary markets for IT products, pallets of equipment are sold to a set of pre-registered business buyers through an online auction platform. The auction platform acts as an intermediary, connecting big-box retailers that are interested in moving older or used products from their shelves / warehouses, to buyers who bid for these pallets. The platform does not handle any of the pallets, since they are shipped directly from the retailer to the eventual buyer. Bidders are themselves resellers, and include flea market operators, eBay power sellers, and independent stores that vary in bidding activity and purchase volumes (Pilehvar et al. 2017). Since this equipment is sold “as-is” by retailers, they rarely come with clearly specified quality assurance in terms of functionality and appearance (Elmaghraby et al. 2018), leaving residual uncertainty about the devices in the pallets.

In my empirical analysis, I focus on how policies implemented in the primary market impact the residual uncertainty about one specific aspect of the products being sold, thereby reducing adverse selection costs. I focus on Apple iPhone devices; in the U.S. alone, secondary market auctions for mobile phones were roughly $25 billion in 2017. In the secondary markets, the quality of mobile phones remains uncertain on many dimensions – software, physical condition, presence of warranties, and feature sets. In this essay, I focus on one source of uncertainty – whether the device runs the risk of being *jailbroken*. *Jailbreaking* is an (unauthorized) process by which the user is able to gain root access to the phone. Users jailbreak iPhones for two main reasons (Cheng 2010) – to gain greater control over the device and bypass the “walled garden” model used by Apple (Wolk 2009), and to untether the device from a specific carrier (“unlocking” the device). Unlocked phones can thus operate on any carrier that offers similar technology (such as GSM). Unlocked phones are more valuable as they are not “locked-in” to a single carrier, and command higher prices in the primary market.

In the US market, both locked and unlocked iPhones are sold in the B2B secondary markets in pallets. However, unlocked iPhones can manifest in these markets in multiple ways. First, they may have been sold as “factory-unlocked” in the primary market. Alternatively, they may have been unlocked by the specific carrier (such as Verizon or AT&T). Finally, they may have been unlocked as a result of jailbreaking. Jailbreaking is not uncommon - 5% of all iPhones in 2010 were found to be jailbroken (22.8M devices), rising to 11.2% in 2013 in the US alone (NY Times 2010; CoderProof 2013). While factory-unlocking and carrier-facilitated unlocking do not affect the intrinsic quality of the phone in any way, *jailbreaking-to-unlock* results in the loss of manufacturer warranties and maintenance support from the device maker and renders the jailbroken devices more susceptible to malicious software, resulting in potential future software issues (Miller 2011).[2] Thus, while all iPhones may be jailbroken for reasons of control, the risk of obtaining a jailbroken phone is amplified for unlocked devices that cannot be verified as factory-unlocked or carrier-facilitated unlocked. When a potential buyer in the secondary market encounters a pallet of unlocked iPhones, she cannot verify if the pallet is free of jailbroken ones. This uncertainty introduces adverse selection costs, i.e. buyers will reduce their bids for such pallets (Dewan and Hsu 2004). Detailed information about the phones and their provenance may help but are rarely provided in these markets (Pilehvar et al. 2017). As a result, the usual mechanisms by which adverse selection may be resolved, such as warranties, signals, and certifications, do not apply here.

Interestingly, some of the adverse selection costs associated with unlocked phones would reduce if it were established that *all* such devices were safely unlocked, without the need for jailbreaking. As part of a deal with the Federal Communications Commission (FCC), Verizon announced in 2012 that all 4G LTE devices (starting with iPhone 5 models) would be "factory-unlocked", i.e., they would be operable on other networks as well. Other carriers did not adopt this policy. This policy implemented in the primary market inadvertently resulted in eliminating

[2] Apple discourages jailbreaking, directly stating that '*Unauthorized modification of iOS can cause security vulnerabilities, instability, shortened battery life, and other issues*.' (https://support.apple.com/en-us/HT201954)

the need to jailbreak these phones for the purpose of unlocking them, thereby alleviating some residual uncertainty in the secondary market. I empirically examine how this exogenous policy change affects prices for Verizon phones, relative to those offered by other carriers, and the magnitude of adverse selection costs. The empirical analysis addresses two questions: first, is there evidence of adverse selection costs associated with jailbreaking-to-unlock, reflected in the prices of unlocked iPhones? Second, does the policy change reduce these adverse selection costs for unlocked Verizon phones, as would be expected from a reduction in uncertainty?

My analysis finds that, unlike the traditional literature in adverse selection which emphasizes signals, certification, return policies and seller reputation to tackle adverse selection (Ozpolat et al. 2013; Ghose 2009; Overby and Mitra 2014; Klein et al. 2016), appropriate policies from the primary market can have a salubrious effect in the secondary market. I conduct the analyses using a proprietary dataset on B2B auctions obtained from a leading online intermediary B2B secondary market platform. My sample contains auction data of iPhone pallets spanning the period from January 2014 to July 2017. I restrict the sample to auctions of two different iPhone generations that span the policy change – the *iPhone 4* and *iPhone 5* models, leading to a sample of 8,179 unique auctions.

A model-free comparison of prices shows the presence of adverse selection costs – unlocked phones are priced lower than locked phones ($46. 90 versus $63.70 for *iPhone 4* models; $88.30 versus $94.50 for *iPhone 5* models) when the phones cannot be guaranteed to be factory- or carrier-facilitated unlocked. This price ordering stands in stark contrast to the ordering found in the primary market, where unlocked phones command a price premium to locked phones. However, this is not the case with Verizon iPhone 5 models, which are guaranteed carrier-unlocked; these devices command a significant premium, with an average price of $137.40. Based on this preliminary evidence, I investigate auction-level prices across all of the iPhone auctions hosted by sellers on the B2B auction platform. I first test for the presence of jailbreaking-to-unlock adverse selection costs, by comparing pallets where the locked/unlocked status of the phones is not disclosed to those where this information is provided. Subsequently, I consider prices for Verizon iPhone 5 pallets, where phones need not be jailbroken for the purpose of unlocking, to see if prices are higher, relative to similar models offered by other carriers where the uncertainty from jailbreaking-to-unlock remains.

The regression results, reported later, provide clear support for the presence of adverse selection costs (Dewan and Hsu 2004) – locked phones generate higher prices when the risk of jailbreaking-to-unlock remains in unlocked phones. These risks remain in place when the pallet is marked as unlocked and when no information is provided about the status of the phones in the pallet. However, when the uncertainty pertaining to jailbreaking-to-unlock is removed through Verizon's policy change, prices for unlocked phones are significantly higher, matching the price structures observed for unlocked phones in the primary market (Felin and Zenger 2014).

This essay makes two primary contributions to the literature. First, I extend prior work studying adverse selection in secondary markets, especially for IT products, by showing that the ill effects of information asymmetry may be partially handled by policies from the primary market. In my case, the policy may not have been specifically implemented for the benefit of secondary markets, but capitalizes on the extent to which primary and secondary markets are interlinked (Lee and Whang 2002; Ghose 2009). Second, I contribute to the literature on secondary markets of durable goods that create environmental problems. Well-run secondary markets as well as programs to refurbish and remanufacture products remain critical to reduce e-waste (Tibben-Lembke 2004; Neto et al. 2016). Policies from the primary market, based on the complete lifecycle of IT products, can help ensure robust secondary markets, while also limiting e-waste (Kumar and Putnam 2008).

From the perspective of implementing policy that can help create sustainable reverse logistics programs, I show the value of forward-looking policies that can benefit both primary and secondary markets. For carriers like Verizon and AT&T, the essay primes them to consider the downstream implications of their strategic decisions, and the benefits thereof. For online secondary market auctioneers like my research partner, the essay shows how they benefit from providing complete information, thereby ensuring better market outcomes (Pilehvar et al. 2017). In the next section, I provide details about two important aspects of this essay – the B2B secondary market context and jailbreaking, before delving into the empirical analysis.

2.2. Related Research and Theoretical Background

My work here draws from prior research in B2B secondary markets for IT products as well as from theory on adverse selection in the context of durable goods. I start with reviewing prior work in secondary markets in IT products below.

2.2.1. Secondary Markets for IT Products

The rapid rate of new product development of IT products and their quick adoption has led to contexts where multiple generations of the same technologies are available to users concurrently in the market (Carrillo 2005; Mendelson and Pillai 1999). For instance, it is easy to observe sales of new iPhone devices as well as a robust marketplace for multiple generations of used but functional previous-generation iPhones. Even in the context of corporate IT infrastructure, it is possible for used equipment like servers and desktops to be resold in the aftermarket since they are functional and valuable.[3] In other cases, IT equipment can be returned to the retailer or remain unsold in the primary market (Guide et al. 2003). The process of managing these products in their after-market, whether returned, unsold, or in their second life, remains the focus of secondary markets and reverse logistics (Guide and Wassenhove 2001; Ghose 2009).

The efficient functioning of secondary markets, especially in the context of IT products, is particularly desirable. The rapid rate of new technology introduction ensures that products that no longer represent the latest technologies are still useful, and can satisfy demand for computing services in alternative markets (Neto et al. 2015). Furthermore, “throwing” away IT equipment such as mobile phones and computers creates harmful e-waste (Robinson 2009; Oteng-Ababio 2010). Over 40 million tons of e-waste is generated every year, leading to over 70% of the toxic waste created in the world.[4] The use of secondary or liquidation markets helps address both these concerns – they process the resale of products that have a useful lifespan beyond their first lives, while also preventing them from being dumped in landfills. IT products that reach the secondary markets can come from customer returns, unsold inventory, buy-back programs run by retailers, as well as firms migrating to newer technology (Guide et al. 2003; Thibodeau 2013).

The linkages between primary and secondary markets have been a topic of considerable research. Interdependencies between these markets exist for both IT products (Lee and Whang 2002; Arunkundram and Sundararajan 1998) as well as for non-IT products like books (Ghose et al. 2005), cars (Purohit 1992), and tickets for sporting and cultural events (Sweeting 2012; Bennett et al. 2015). The first-order interdependency is, of course, cannibalization of demand (Waldman 2003), wherein sales in the primary markets are affected by the presence of a secondary market (Debo et al. 2005; Ferguson and Toktay 2006). For example, a firm’s pricing

[3] https://searchitchannel.techtarget.com/feature/Secondary-market-resellers-thrive-in-the-tech-industry
[4] https://www.theworldcounts.com/challenges/planet-earth/waste/electronic-waste-facts

decisions in the primary market can be influenced by sales and quality of products in the secondary market (Ghose et al. 2005; Moorthy and Png 1992), which in turn can affect sales in the primary market. Furthermore, the current move to "return-to-manufacturer" regulations being considered in many settings are designed to promote an appropriate closed loop mindset when selecting product design, distribution and end-of-life decisions across both the primary and secondary markets (Souza 2008; Miao et al. 2018; Alev et al. 2019). Thus, for firms offering products in the primary market, the influence of the secondary market is not trivial and can inform their decisions in the primary market.

The sale of second-hand or used electronic and computing equipment has garnered the attention of researchers, particularly during the early days of research into eBay and Amazon (Bapna et al. 2004; Arunkundram and Sundararajan 1998), but has primarily focused on the B2C sector. More recently, researchers have studied the larger and more impactful B2B secondary market for IT equipment, where large volumes of equipment are sold in the form of pallets to business buyers (Pilehvar et al. 2017). The B2B channel is of particular importance since this is the first stage where products enter the secondary market, before being sold as individual products in the subsequent (secondary) B2C markets (Thibodeau 2013). B2B secondary markets for IT products can exist in several forms, but a particularly visible form is the *B2B online auction* (Pilehvar et al. 2017), wherein pallets of equipment are auctioned to a set of pre-registered buyers. Since many pallets in secondary markets are idiosyncratic and non-standard, auctions are a preferred market mechanism to facilitate price discovery (Pinker et al. 2003).

A recurring source of inefficiency within the secondary markets for durable goods, particularly with IT products, pertains to uncertainty about the quality of the products on sale (Neto et al. 2016). Since these products are in their second life, they rarely come with clearly specified quality information with regard to functionality and appearance. They are typically sold in an "as-is" condition by the sellers (Pilehvar et al. 2017), whereby quality uncertainty affects their valuations, and hence bidders' willingness to pay (valuation). This is analogous to quality uncertainty studied in the B2C market for IT products as well (Ghose 2009). Some of this uncertainty could be resolved by disclosing more product information (Lu et al. 2017). Extant literature has demonstrated that it would be beneficial for the seller to provide more information (Milgrom and Weber 1982) and reduce uncertainty for buyers (Goeree and Offerman 2002). However, retailers looking to dispose their products quickly tend to not invest time in generating this detailed information (Pilehvar et al. 2017). Thus, pallets are assembled with roughly similar products, with neither the retailer nor the auction platform bearing responsibility for the contents, leading to residual concerns about quality given the paucity of information. Hence, sellers are often unable to provide the level of detail about the condition and prior use of the products on sale in B2B secondary market.

As a result, these auction markets are characterized by significant information asymmetry, which affects their functioning as a result of adverse selection (Akerlof 1970). While some models of adverse selection may include the strategic withholding of information about sellers or products so as to benefit from the resulting information asymmetry (Klein et al. 2016), this is typically not the case here. Rather, information asymmetry emerges from the context, where information on the first life of the products is incomplete by definition. I next review the literature on adverse selection, while also outlining the specific form I study here.

2.2.2. Adverse Selection in the B2B Secondary Market for IT Products

Adverse selection occurs when buyers of products cannot identify the true quality of the product or service that is offered prior to purchase (Akerlof 1970). In such situations, buyers are unwilling to pay for the true but unknown quality of the product and instead, are only willing to pay the lowest prices in the market. This forces out sellers of high-quality products, thereby only leaving an “adverse selection” of products and sellers in the market. To the extent that “true” quality is observable to sellers, there may be strategic behavior on their part to pass their products off as high quality. However, in other settings, true quality may be unknown even to the sellers and may be structural to the context. In extreme cases, markets characterized by adverse selection can lead to market failure, where no market exchanges are possible (Akerlof 1970).

As mentioned earlier, several mechanisms can be used to reduce the effects of adverse selection. Third-party quality attestation or certification is one mechanism by which the seller’s or product’s quality can be verified prior to purchase (Ozpolat et al. 2013). Alternatively, quality signals can be issued by the seller to the market, thereby reducing the perceived risk for buyers (Ghose 2009; Overby and Mitra 2014). Signals can provide information about sellers (Klein et al. 2016), products (Dewan and Hsu 2004), and the processes within the firm (Gao et al. 2010). Sellers can also offer warranties, trial periods, generous return policies, and post-sales service contracts as ways to reduce information asymmetry (Overby and Mitra 2014; Peterson and Schneider 2014). Finally, intangible assets like brand, reputation, and trust can reduce the effects of adverse selection in markets (Dimoka et al. 2012; Pavlou et al. 2007; Kirmani and Rao 2000).

Early work on adverse selection was based on empirical data from the used car leasing and sales markets (Bond 1982; Genesove 1993; Garicano and Kaplan 2001; Johnson and Waldman 2003). The quality of the product is hard to gauge in such markets, and a similar dynamic exists with IT equipment in the secondary market (Ghose 2009; Elmaghraby et al. 2018; Neto et al. 2016). The advent of the Internet, and the reduction of search costs, has not resolved these information asymmetries in full, as shown in multiple papers (Ghose 2009; Resnick et al. 2006; Klein et al. 2016).

The impact of adverse selection in secondary markets can show up on multiple market outcomes. First, it can lead to the exit of high-quality sellers and products, thereby reducing the average quality of products in the market (Akerlof 1970). Adverse selection can also lead to higher quality products taking longer to sell, even in the presence of signals (Ghose et al. 2009). Finally, average prices for products are likely to be lower since buyers cannot distinguish the quality of the product; therefore, they tend to systematically pay lower prices (Ghose 2009; Dewan and Hsu 2004). When the resulting information asymmetry is lifted, even partially, average prices increase in the market – scholars have termed this difference *adverse selection costs* (Dewan and Hsu 2004; Garicano and Kaplan 2001).

The mechanisms for reducing information asymmetry in the market, as discussed above, can help reduce these adverse selection costs; their benefits are likely even more relevant in B2B secondary market contexts since sellers are unlikely to provide detailed information (Pilehvar et al. 2017). Paradoxically, the typical mechanisms to reduce information asymmetry are less likely to be used in B2B auctions that I study due to the minimal oversight and investment made in the flow of goods from the primary to secondary market. In the case of IT equipment, where replenishment cycles are fast and generations of technologies overlap in good measure, I argue that adverse selection costs in the secondary markets may be significantly reduced by policies instituted in the primary markets by original equipment manufacturers. Specifically, policies from the primary market that serve as free and informative signals of quality to all players in the market can help mitigate adverse selection in the secondary market, discussed in the next section.

2.2.3. Jail-breaking and Adverse Selection Costs in Mobile Phones

The market for used iPhones is large and active, with multiple generations of phones being available in the market at the same time (Elmaghraby et al. 2018). As mentioned above, pallets of similar devices are bundled together and sold in auction lots in an "as-is" state. Since the phones that go into these pallets can come from several sources (buy-backs, returned products, unsold inventory), there is significant variability in their quality. Retailers provide some baseline information about the state and generation of the phones in the pallets; retailers are asked to 'self-report' the quality of the phone along generic quality classifications (e.g., A, A/B, B, B/C, C, D or salvage; details are in Figure 2.1.). These quality classifications are meant to capture the level of functionality and cosmetic issues with the devices and are broad in scope so as to minimize the burden on sellers as they create similar pallets, without providing details about specific devices. Thus, there are several sources of uncertainty that buyers face with respect to product quality (Dimoka et al. 2012) – technical quality of the phone, cosmetic appearance, reliability of the software and applications, issues in functionality, and the presence of warranty include some of the features that remain unspecified (Pilehvar et al. 2017).

Among these factors, one such important source of uncertainty pertains to whether the pallet contains phones that are *jail-broken-to-unlock*. Mobile devices in the US are typically characterized by their ability to operate on multiple network carriers or be restricted to a single carrier. Devices that are *locked* to a single carrier can only be used with that carrier, such as Verizon or AT&T, and represent a closed platform ecosystem at the carrier level (Boudreau 2010). Alternatively, devices can be *unlocked*, and usable on multiple carriers, depending on the user's preference. From a platforms perspective, unlocked phones are more attractive since they allow users to switch carriers with ease (Zhu and Zhou 2012); they are also more expensive in the primary market.[5] In contrast, locked phones tend to lock the customer into one carrier, thereby increasing switching costs and reducing consumer surplus (Cho et al. 2014). In an ideal secondary market, the price premium on unlocked phones should remain in place, since these allow the buyer greater choice in terms of carriers, all else being equal.

However, from a quality perspective, all unlocked phones are not the same. As mentioned earlier, phones can be safely factory-unlocked or carrier-facilitated unlocked. Original equipment manufacturers (such as Apple) typically coordinate with carriers (such as Verizon or AT&T) to facilitate the carrier-unlocking procedure. Phones that are unlocked in this manner retain all relevant warranties and generally provide a baseline level of system performance that is associated with an untampered smartphone. However, this is not the case when a phone is unlocked through jailbreaking. Jailbreaking is a process by which restrictions placed on the phone by the device maker, in terms of "root" access, installation of non-compliant apps, security and privacy restrictions, and carrier access, are removed. Jailbroken phones can thus be freed from carrier restrictions imposed by the manufacturer (Apple, for instance) and the carrier (Verizon, for instance) (Miller 2011). Whether the device is jailbroken for the purposes of greater control or to unlock it, it results in the loss of manufacturer warranties and maintenance support from the device maker, thereby lowering its value. Jailbroken devices are also more susceptible to malicious software resulting in potential future software issues

When a buyer encounters an unlocked iPhone pallet, it is not clear *how* the devices were unlocked. To be clear, not all unlocked iPhones are jailbroken, and not all jailbroken phones are unlocked, since many users jailbreak their phones in order to exert greater control over the device per se (Cheng 2010). However, unlocked phones carry a heightened risk of having been

[5] When iPhone 5 was introduced, a closed phone of this generation was priced at $199 for the 16GB model, whereas an open 16GB model was at $649. (http://www.forbes.com/sites/kellyclay/2012/09/12/the-real-cost-of-an-iphone-5)

tampered with due to the possibility of *jailbreaking-to-unlock*. The potential presence of jail-broken unlocked phones within a pallet of unlocked phones thus creates an additional adverse selection problem. This problem manifests in two ways in this domain. First, if the status of the phones (whether or not they contain locked or unlocked phones) in a pallet is not disclosed, the buyer is uncertain with regards to the composition and hence the degree of jailbreaking risk, leading to reduced valuations and bids for the pallet (Akerlof 1970; Klein et al. 2016; Ghose 2009), and lower final prices (Pilehvar et al. 2017). This is akin to the lemons problem where no information is provided to the market (Akerlof 1970).

Second, if the pallet is clearly labeled as including unlocked phones, here again, the buyer cannot be sure whether the phones are jail-broken, factory-unlocked or carrier-facilitated-unlocked. In the first case, there is the possibility of additional damage to the device, which is less likely with the other two contingencies. Therefore, final prices are likely to be lower for unlocked pallets. While the risk of jailbroken devices exists even in locked pallets, there is no such residual uncertainty about jail-breaking-to-unlock per se. Thus, the adverse selection costs that result are likely to be higher in auctions where no information on locked or unlocked status is provided, and for unlocked phones. Interestingly, this is contrary to the primary market where unlocked phones generate the highest prices, while locked phones are cheaper.

The traditional mechanisms for reducing adverse selection are not available here – seller reputation is largely constant while detailed information on the pallets is not available. Online reviews and third-party warranties are largely infeasible in this context. Therefore, at the point of sale, adverse selection continues to be a source of inefficiency (Neto et al. 2016; Ghose et al. 2009). However, the incremental uncertainty associated with unlocked devices would be selectively removed if all unlocked devices were determined to be factory-unlocked by default.

This would reduce the jailbreaking-to-unlock component of residual uncertainty faced by unlocked phone pallets, thereby reducing adverse selection costs.

Such an exogenous change occurred in 2012 when Verizon announced that all of their 4G LTE devices, starting with the iPhone 5 models, would be factory unlocked. Other carriers, in contrast, continued to offer a mix of locked and unlocked phones. Thus, this exogenous policy change allows me to gauge firstly, the presence of adverse selection costs arising from a reduction in the need to jailbreak-to-unlock, and second, the extent to which this adverse selection cost may be reducing the efficiency of the information-starved secondary market. I explore these adverse selection costs empirically by studying iPhone pallets offered by Verizon, as well as other carriers who did not change policies. In lieu of formal hypotheses, I allow the empirical analysis to provide us with guidance. Since the B2B secondary market auction setting is rather unique, I describe the context and the research site in some detail next, before moving on to describe the dataset and empirical analyses.

2.3. Research Context

The research site is a leading online intermediary platform that specializes in running online auctions. The platform serves as a shopfront for big-box retailers who create their own virtual "shopfronts" on the platform where auctions are hosted. In order to maintain a consistent look and feel for the platform's bidders, all the retailer's "shopfronts" are generated by the platform using a consistent user interface. In contrast to prior research where auction sites took possession of merchandise (Elmaghraby et al. 2018; Pilehvar et al. 2017), the auction platform here only hosts and manages the auction process.

Neither the platform nor the bidder determines what goes into a pallet, and the platform does not bear responsibility for the condition of the contents (Pilehvar et al 2017). Each pallet contains a bundle of products that are typically of the same category (e.g. mobile phones, laptops), but not necessarily identical. More importantly, neither the platform nor the seller is required to or expected to invest any effort in restoring any of the technology items on sale to factory conditions. While such practices may exist in the B2C context, the current lens through which retailers view the B2B secondary market is that such efforts are generally not worthwhile for their bottom line. Bidders are not able to physically inspect the pallets in advance and have to rely on whatever information is disclosed on the auction site as well as relevant information gleaned from the primary market.

In the specific case of mobile phones, pallets are typically formed of devices that are of the same operating system, brand, and generation (for instance, *Android, Samsung, Galaxy*) with occasional exceptions. Since I focus on iPhones, pallets in this case are typically formed of a number of iPhones of the same generation (iPhone 4 or iPhone 5), but with varying feature sets. However, all phones in a pallet typically are either unlocked or locked to a particular carrier, in order to facilitate easy processing of the merchandise for the retailer as well as the bidder.[6] This sorting is carried out at the retailer's site, and is part of the pallet preparation process agreed upon between the platform and retailer firms.

While the general template of auction information is similar across different retailer sites, and information pertaining to the contents of the pallet[7] is often included in the auction information, the specific information attributes shown can vary from one auction to another based upon what the retailer provides. Table 2.1 illustrates several examples of auctions and their

[6] Occasionally, pallets can include mixed-generation devices, as opposed to pallets with only one generation of products. For example, a pallet may contain a combination of iPhone 4 and iPhone 6 models. In most cases, retailers would keep pallets limited to a specific generation of iPhones (for instance, only unlocked iPhone 7 models). Within these pallets, the individual physical conditions of the devices may vary, as would their storage capacities.

[7] Pallet information listed on the auction page may include product type, model, memory size, carrier, locked/unlocked status, color, units, condition, retail price, and shipment location.

associated information content. In the data set, I observe product type, units and condition of the devices present in all auctions; the carrier of the devices is available in 70% of auctions, and the locked/unlocked status of the devices is available in 16% of the auctions. Figure 2.2.A illustrates an auction listings sample where none of the auctions disclose the locked/unlocked status of the auctions, whereas Figure 2.2.B displays an example auction page where the locked status of the phone is provided.

All auctions use the second-price auction format, where winners pay the second-highest bid plus a bid increment (Pilehvar et al. 2017). To prevent sniping, the platform automatically extends the auction's end time if they receive a last-minute bid, i.e., popcorn bidding rule. Bidders register separately for each retailer site, with no restrictions on cross-participation. The specific details of the dataset used for the analyses are described next.

2.4. Data and Methodology

I use a proprietary dataset obtained from the research site described above. I focus on pallets of pre-used iPhones that include devices of a single generation so as to minimize extraneous variation in the pallets and concentrate on the specific effects of interest around locked and unlocked pallets. These devices can vary in terms of their physical conditions, which are captured in broad terms and a relatively coarse scale. All iPhones in such pallets are either locked to a specific carrier or unlocked, with no mixed pallets. However, there is variation across pallets in terms of the physical condition of the phones and other attributes such as memory size and carrier. I only use pallets containing iPhone 4 and iPhone 5 models (separately) in the analyses for reasons pertaining to policy changes in the primary market described below.

I have data on a sample of 8,179 unique auctions for iPhones across the time period January 2014 to July 2017. These auctions are hosted by 9 major retailers and include 2,929 unique bidders. For each auction, I collect information pertaining to the retailer, the number of units in each pallet, the starting and final prices of the auction, the number of bidders, and the date and time of the auction. Additional information on the products in the pallet is available on the auction listing, such as the physical condition of the devices, their models and storage capacities, and the network carrier. The sample includes phones from four carriers: Verizon, AT&T, T-Mobile, and Sprint. The largest number of pallets is from Verizon (39.61%) with the other three carriers making up the remainder. All four carriers are also associated with locked and unlocked device pallets in the sample. Since my interest is in evaluating the implications of Verizon's new policy on unlocked versus locked devices, I describe the sample through this variable in some detail.

The sample consists of auctions where the locked or unlocked status of the devices in the pallet is disclosed by the retailer, as well as auctions where this information is simply not disclosed. When the status is disclosed, all phones in a pallet are either unlocked or locked with respect to a particular carrier, as mentioned earlier. However, in the majority of the cases, no information on this status is provided: 6,907 auctions do not provide any information on whether the devices are locked or unlocked, while the remaining 1,272 auctions provide this information. The distribution of the pallets across these three conditions (no information, locked, unlocked) in the sample is depicted in Figure 2.3 for clarity. The omission of status information in the auction listing could either be a result of retailers simply not having that information easily available, or a conscious choice to withhold the information. However, this propensity to not disclose is observable across all carriers as well as both generations of iPhones in the sample. All four carriers are also associated with locked and unlocked device pallets in the sample. While I cannot clearly state why this information is not provided in this context, this does not affect the results since the identification is provided by the external policy change enacted by Verizon, as discussed later in this section.

The unit of analysis here is the auction, while the dependent variable of interest is the auction final price, normalized by the number of devices in the pallet, i.e. final price per unit, consistent with prior research (Pilehvar et al. 2017; Elmaghraby et al. 2018). The main independent variable is the status of the pallet, which can take the value of locked, unlocked, or undisclosed. The average final price per device in the sample is $116.01, with standard deviation of $68.80. The distribution of auction final prices in the sample is positively skewed. Therefore, I take the natural logarithm of final price to symmetrize the residuals. A description of the all the variables in the dataset is shown in Table 2.2, while summary statistics and correlation tables are provided in the Appendix (Tables A2.1–A2.3).

Since my goal is to understand the extent to which adverse selection costs are present in this context with respect to the locked/unlocked status of the devices, a simple comparison of final prices across the three types of pallets (locked, unlocked, no information) could be carried out. However, the results I obtain from a simple comparison are likely biased since I cannot fully account for unobservable factors that may drive the presence of locked or unlocked (or undisclosed) pallets in the market. Therefore, from an identification perspective, I require an exogenous shock that removes the influence of any strategic decisions by the retailers with respect to the locked/unlocked status of pallets on auction. Such an exogenous shock is provided by the policy change implemented by Verizon discussed earlier. Thus, in addition to representing the core of my theoretical argument for the beneficial effects of primary market policies on secondary market efficiency, this policy change also provides me with a clean identification strategy (Cook et al. 2002). Regardless of whether status information on a pallet of phones is provided or not, the policy change significantly reduces the uncertainty faced by buyers for all Verizon iPhone 5 models, compared to devices sold by other carriers, ceteris paribus. Since the policy change occurs with iPhone 5 phones, I restrict the dataset to two specific iPhone generations (iPhone 4 and iPhone 5) that span the exogenous policy change. In the case of iPhone 4, all four carriers carried and sold both locked and unlocked phones. I capitalize on this policy change to construct the analyses in stages, as described below.

2.5. Empirical Results and Discussion

Recall that I aim to answer two empirical questions – whether adverse selection costs with respect to jail-breaking-to-unlock exist, and the impact of the policy change in reducing these costs. I present models to test the two empirical questions in order below.

2.5.1. The Presence of Adverse Selection Costs

Before I establish the positive effects of Verizon's policy change, I first test for the presence of adverse selection costs in the sample. I do this in two ways – first, I compare pallets where information is disclosed to those where no information is provided. Second, I compare across (*disclosed*) locked and unlocked pallets. My intuition is as follows: when no information on the status of the pallet is provided, the bidder faces greater uncertainty surrounding the phones and their status (locked or unlocked), since some proportion of the phones could easily be jailbroken. If the pallet is unlocked, here again, this source of uncertainty concerning jailbreaking-to-unlock the phone remains. It is only in locked pallets that no residual concerns about jailbreaking-to-open exist, all else being equal. Thus, I would expect pallets where no information is provided to generate lower prices, all else being equal, compared to those pallets where some information is disclosed (Goeree and Offerman 2002). Similarly, when I compare locked to unlocked pallets where jailbreaking-to-open can exist, I expect lower prices for unlocked pallets. I thus proceed with the analysis along these two lines of reasoning.

To estimate the effect of lack of information about the pallets, I propose the following model, to be estimated on the full sample of 8,179 auctions:

$$ln\ (FP_{ij}) = \lambda_o + \lambda_1 Undisclosed_{ij} + \lambda_2 Model_{5ij} + \lambda_3 Verizon_{ij} + \vartheta X_{ij} + \tau_i + \pi_j + \eta_{ij} \quad (1)$$

In equation (1), *ln* (FP_{ij}) is the natural log of the final price per unit of auction *i* of seller *j*. The main independent variable is $Undisclosed_{ij}$, indicating whether the status of the devices is provided. I do not differentiate here between locked and unlocked pallets; I differentiate between those that have information from those that are unspecified, in the interest of interpretation.[8] The variable $Model_{5ij}$ is 1 if the pallet contains iPhone 5 models, 0 otherwise, in order to capture premiums attached to iPhone 5 models, relative to iPhone 4 models. I also include a dummy variable $Verizon_{ij}$ to designate pallets offered by Verizon. I include X_{ij} as a vector of control variables. To account for the unobserved heterogeneity among sellers, I include seller fixed effects (π_j). I also control for seasonality by including time fixed effects in the model (τ_i). Finally, ϵ_{ij} are independent and identically distributed random errors.

I use OLS to estimate this model shown in equation (1). To account for the possible issue of heteroscedasticity, I run a Breusch-Pagan test and find it to reject the hypothesis that errors are homoscedastic across auctions (p-value < 0.001). I accordingly use heteroscedastic-robust standard errors clustered at the auction level (Angrist and Pischke 2008), which allows for heteroscedastic errors across auctions. I also test for multicollinearity in my models by calculating the variance inflation factor (VIF). None of the variables has a VIF greater than 10 (Petter et al. 2007), indicating no serious multicollinearity (Mason and Perrault, 1991; O'Brien,

[8] In unreported regressions, I have separated the auctions into all three cases (open, close, undisclosed) with fully consistent results, which are available upon request.

2007). The results, shown in Column 1 of Table 2.3, show a negative and significant coefficient of the undisclosed variable (–0.70, p<0.05). Final prices are thus lower when no information is disclosed in the auction, consistent with the presence of adverse selection costs, since providing no information enhances the perception of risk and reduces prices.[9]

I now consider the effect of locked versus unlocked pallets. I use a similar regression model, estimated only on 1,272 auctions where locked/unlocked status is provided:

$$\ln\,(FP_{ij}) = \delta_o + \delta_1 Locked + \delta_2 Verizon_{ij} + \delta_3 Model_{5ij} + \gamma X_{ij} + \alpha_i + \lambda_j + \epsilon_{ij} \qquad (2)$$

In equation (2), $Locked_{ij}$ indicates whether the devices are locked to a certain network. Similar to equation (1), I add a variable $Verizon_{ij}$ to denote Verizon pallets.[10] I include X_{ij} as a vector of control variables and use time and seller fixed effects ($\alpha_i$and λ_j). The econometric specification is identical to that shown in equation (1). The OLS results are shown in Columns 1 and 2 of Table 2.4 for iPhone 4 and iPhone 5 models respectively. Since I only want to demonstrate the presence of adverse selection costs here, I focus on iPhone 4 models only (In the next section, I expand my analysis to include iPhone 5 models and Verizon's policy change). As shown in Column 1, the results show that unlocked devices are priced lower (1.33, p<0.05), since they incorporate the risk of jailbreaking-to-open. Interestingly, final prices here are markedly different from those in the primary market where unlocked phones are more expensive. I see no premium attached to Verizon iPhone 4 models, relative to the other carriers. Consistent with prior work, I see significant effects of the number of units in the pallet and the number of bidders in the auction (Elmaghraby et al. 2018). The model fit is high, with a R-squared value of 0.77.

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[9] I also conducted a Heckman two-stage analysis to account for the endogeneity of the *Undisclosed* variable. The first stage was instrumented for by the total number of auctions initiated by the retailer in that week. The variable measures how busy the retailer was in terms of disposing merchandise into the secondary market, capturing the extent to which they may be willing to provide detailed information about pallets. The results are fully consistent with those reported here and are available upon request from the authors.
[10] In unreported regressions, I separated the four carriers with their own fixed effects, with fully consistent results.

In summary, I provide evidence for adverse selection costs, which affect auctions for pallets of unlocked phones where no information is provided. I now consider the impact of the Verizon policy change.

2.5.2. The Impact of Verizon's Policy Change on Adverse Selection Costs

In studying the effects of the policy change, I return to equation (1), where undisclosed pallets are compared to those where information is provided. As per the new policy, all Verizon iPhone 5 devices are factory-unlocked, thereby eliminating an important reason to jailbreak them. Therefore, post-policy change, for B2B buyers considering Verizon iPhone 5 pallets, lack of disclosure should have no effect on bidders' willingness-to-pay, thereby reducing the discounting of prices associated with unlocked phones. As a result, the final prices for Verizon iPhone 5 pallets should be higher than final prices for unlocked iPhone 5 pallets offered by *other* carriers, which should continue to see some price discounting since jailbreaking-to-unlock continues to be a risk. The policy change allows the identification of information disclosure on final prices by exogenously reducing information asymmetry in the market for Verizon iPhone 5 devices.

To test this, I introduce an interaction term between $Model_{ij}$, $Verizon_{ij}$, and $Undisclosed_i$ to the specification in equation (1). This provides a way to establish how prices for Verizon iPhone 5 pallets may deviate from the norm, consistent with differences-in-differences models (Bertrand et al. 2004). Since the regression includes a three-way interaction, I include all two-way interactions in the model, with the results shown in Columns 2 and 3 of Table 2.3. In Column 2, the two-way interactions show a consistent effect associated with lack of disclosure; the net effect of lack of disclosure on final prices is negative. Since my main interest is in the three-way interaction in Column 3, I caution against interpreting the results of the model in Column 2.

To understand the effect of the new policy on Verizon iPhone 5 pallets, I look at the three-way interaction in Column 3. This three-way interaction is part of the “cube view” of eight possible cells that exist when interpreting three-way interactions of categorical or dummy variables (Aral et al. 2012); here, I am interested in the coordinates (1,1,1), which maps to the set $\{$*Verizon, iPhone5, undisclosed*$\}$. Paradoxically, this three-way interaction is negative (–0.458, $p<0.05$), showing that prices are lower when no information is provided. To calculate the true marginal effect of the *Undisclosed* variable here, I contrast predicted prices across different sets of relevant iPhones pallets here. Using the coefficients from Column 3, I see the predicted price for a Verizon iPhone 5 device, where information is disclosed, is \$163, while a comparable Verizon iPhone 5 device where no information is provided is \$134. This \$29 difference in final prices is counter-intuitive, since disclosing the status of the phones has no diagnostic value. These results are also shown in diagrammatic form in Figure 2.4.

A possible explanation for this counter-intuitive finding could be that bidders are not fully aware that Verizon iPhone 5 devices are factory-unlocked. If so, this effect may fade over time through information diffusion or observed behavior on the auction platform. I therefore examine final prices over time to examine this possibility. I split the sample into a Verizon (2,818 auctions), and non-Verizon subsample (5,361 auctions). Further, to see if bidding behavior changes over time, I divide these subsamples into two periods of two years each. Within each subsample, I interact the *Undisclosed* variable with *Model 5* to examine price trends for iPhone 5 models when no information is provided. The results are shown in Table 2.5, with the first two columns for Verizon and the remaining for non-Verizon carriers.

The results in Column 1 for Verizon in 2014-2015 show the counter-intuitive negative interaction term (-0.272, $p<0.10$). The effect of disclosure of status of the unlocked iPhone 5 device from Verizon causes the predicted price to significantly increase from \$152 to \$181 (a difference of \$29, statistically significant). However, in the second time-span of 2016-2017, this negative coefficient loses significance entirely, showing that bidders bid similarly for iPhone 5 models whether or not their status is disclosed. The effect size in this time-period is roughly \$8 (\$127 to \$135) and not significant. In contrast, the results for the non-Verizon carriers retain the negative interactions, in significance and magnitude (Columns 3 and 4). The difference in predicted prices per unit in 2014-2015 is \$23 and remains roughly equivalent in 2016-2017 (\$20). These results show that bidders learn about the Verizon iPhone 5 policy change, and its implications, over time and respond as expected.

I now consider the policy's effect in the sample where the status of the devices is provided, using equation (2). Recall that Column 1 in Table 2.4 showed the effect of the locked status for iPhone 4 models – I augment this analysis with results for iPhone 5 models across all carriers. All Verizon iPhone 5 devices are factory-unlocked while other carriers produce a mix of locked and unlocked devices. Given the high proportion of Verizon pallets in the sample, I would expect the marginal effect of the *Locked* variable to change. As expected, the results in Column 2 of Table 2.4 now show higher final prices for unlocked devices (1.28, $p<0.05$). I also observe a small but significant premium for Verizon iPhone 5 pallets (0.12, $p<0.05$). To further establish this difference, I estimate the same regression model with only non-Verizon iPhone 5 pallets, in Column 3. As expected, the original positive marginal effect for locked phones re-emerges (1.167, $p<0.05$), supporting the thesis that lower valuations for unlocked pallets reflect the uncertainty associated with jailbreaking-to-unlock.

Since the policy change generates unlocked devices without compromising the integrity of the device, I consider only unlocked pallets across carriers to estimate the extent to which adverse selection costs are mitigated specifically for Verizon iPhone 5 pallets. I therefore consider a subsample of only *unlocked* devices across both iPhone 4 and iPhone 5 generations (N=910), and add an interaction term between $Verizon_{ij}$ and $Model_{5ij}$. These results are shown in Table 2.4 in Columns 4 and 5. As shown in Column 5, the interaction between *Verizon* and *Model 5* is positive and significant (1.55, $p<0.05$). In terms of predicted prices, the difference between Verizon and non-Verizon iPhone 4 models is small at $5 ($48 versus $43, respectively). This difference, however, is significantly higher with iPhone 5 models, at $66 ($164 versus $98). While a portion of this premium can be associated with the Verizon brand, the remainder of the price difference can be attributed to the reduction in uncertainty for Verizon iPhone 5 models. This finding further reinforces my argument that new policies from the primary market could reduce adverse selection costs for unlocked phones in the secondary market.

The positive implications of the policy change can be shown graphically as well by plotting the predicted final prices using the coefficients reported in Table 2.4. Figure 2.5 shows Verizon unlocked iPhone 4 devices to have approximately similar values to those of the other carriers, prior to the new policy. However, after the policy change, the value of Verizon iPhone 5 phones increases considerably, relative to similar unlocked iPhones from the other carriers. This positive effect of Verizon's iPhone 5 on final prices can thus be attributed to reducing the adverse selection costs pertained to unlocked phones. The predicted price of an unlocked iPhone 5 sold by non-Verizon carriers is $75.2, while the price of a locked iPhone 5 devices from the same carriers is higher at $107.8. At the same time, the predicted price for an unlocked Verizon iPhone 5 is $141.2, representing a $66 price difference. This price differential is approximately how much bidders withhold in value to avoid the risk of buying damaged or jailbroken phones.

The value of the policy change in the primary market can be gleaned by this difference in prices for unlocked Verizon iPhone 5 models versus similar non-Verizon models.

2.5.3. Placebo Tests For Falsification

The analysis reported above relies on the exogeneity of Verizon's policy change, and changes in the associated risks of jail-breaking-to-unlock. Therefore, I consider Verizon Model 5 phones to be "treated", with the "control" sample composed either of Verizon Model 4 phones or all phones offered by the three other firms. The observed effects of the *Undisclosed* variable in Table 2.3 and the *Locked* and *Model 5* variables in Table 2.4 therefore form the core of my analysis. However, it is possible that I capture spurious correlations here that are not linked to the Verizon policy change per se but represent other unobservable factors (Bertrand et al. 2004). To test for these spurious correlations, I conduct a set of placebo tests to examine how robust the estimated treatment effects are with respect to the results in Tables 2.3 and 2.4, specifically with respect to the *Undisclosed*, *Locked* and *Model 5* variables.

I follow prior work (Burtch et al. 2018) in conducting the placebo tests through random implementation of the treatment variable. I start with the estimates shown in Table 2.3, Column 1, where the estimates of *Undisclosed* on final prices are shown for the full sample. I then generate a set of new *pseudo-treatments* by randomly assigning the *Undisclosed* status to auctions within the sample of 8179 auctions, but retaining the ratio of treated to untreated (control) observations. By definition, these new random treatments should be unrelated to final prices. The results from this analysis are shown in Table 2.6, Column 1. As expected, the coefficient of the placebo variable *Undisclosed_Rand* is insignificant. I repeat this random assignment process 1000 times and store the estimated beta coefficients for the *Undisclosed* placebo variable. I then plot these coefficients, shown in Figure 2.6. As shown, the mean of the coefficients estimated is close to zero, with standard deviation of 0.016, relative to the coefficient estimated originally (–0.707, $p<0.01$). Subsequently, all interaction terms with this randomly generated treatment variable are also insignificant and close to zero. This placebo test allows me to establish some robustness for the estimated effect of lack of disclosure on final prices.

I now focus on the results in Columns 1 and 2 of Table 2.4, which show the variation in the effect of the *Locked* variable across locked and unlocked phones within Models 4 and 5 respectively. The differences in the coefficients was attributed to the fact that Model 5 Verizon phones were less risky since they were all factory-unlocked. I apply the same placebo analysis by randomizing the *Locked* variable, with the results shown in Columns 2 and 3 of Table 2.6. As expected, both coefficients are close to zero. The plots of the estimated coefficients, in Figures 2.7 and 2.8, also show no systematic effect. I thus conclude that the coefficients estimated in the original analyses were not based on spurious correlations or other unobservable factors.

I finally consider the results in Columns 4 and 5 of Table 2.4, where I showed that unlocked Verizon iPhone 5 models enjoy a premium due to the change in Verizon's policy. Thus, the focal result here is the interaction term between *Verizon* and *Model 5* variables (0.155, $p<0.01$). As a placebo test, I randomly generate values of the *Model 5* variable, and include this variable as well as interaction with *Verizon* in the regression. The results are shown in Columns 4 and 5 of Table 2.6 - both the direct effect of *Model 5* and the interaction term are insignificant and close to zero. The plots of the coefficients of the interaction term across 1000 random draws, shown in Figure 2.9, also show no significant effect. In summary, the placebo tests across the important specifications in my analysis provide clear support for the fact that the Verizon policy changes are indeed associated with the results I report earlier.

2.5.4. Robustness Checks: Bidder-Level Analysis

The results reported thus far are centered at the auction-level, but do not provide visibility into bidder-level behavior. As robustness, I consider bidder-level analysis; I study bidders who bid for both disclosed and undisclosed iPhone pallets within the same time-period and contrast their bidding behavior across these pallets. Bidder-level analysis helps dispel concerns about bidder self-selection and unobservable biases (bidders choosing to participate in only disclosed or only undisclosed auctions) while accounting for bidder idiosyncratic behavior that is not fully observable in auction-level analysis. I first identify bidders who issued a bid on comparable auctions within the same calendar month, i.e. bidders who participate in auctions where the pallet status (locked or unlocked) is disclosed as well as those where this information is omitted. Intuitively, this resembles a quasi-experimental setup where the same bidder's behavior is observed across pallet types. To simplify the analysis, I consider three periods where the sample of bidders identified in this manner is large enough for statistical analysis: January, May, and November 2016. Across these months, I have 8,912 observed bids by bidders across auctions. If a bidder submitted multiple bids in a single auction, I only include the last submitted bid reflecting maximum willingness-to-pay. I include control variables that are similar to those used in equations (1) and (2) as well as bidder fixed effects and a variable that indicates the order of each submitted bid within an auction, to capture potential order effects (Pilehvar et al. 2017). Finally, to capture time trends, I separately estimate models for each of the three months, to examine the effects of information diffusion. The dependent variable is the natural log of the value of each submitted bid; I estimate an OLS regression.

I separate the analyses for Verizon (Table 2.7) and non-Verizon carriers (Table 2.8), to capture the effects of the policy change. The first column combines the three months, while the remaining three columns provide month-wise results. A three-way interaction for Verizon (*non-Verizon*) iPhone 5 models is included, as before. Across both tables, I see the negative effect of non-disclosure of status information, as expected. Interestingly, the three-way interaction showing the specific impact of the Verizon policy change is significant and negative, but smaller in magnitude for the Verizon analysis (-0.533, $p<0.05$) than the non-Verizon analysis (-0.993, $p<0.05$). As before, the Verizon results are counter-intuitive, since providing this information is non-diagnostic given the new policy. However, when I consider the three months separately, this effect for Verizon auctions fades away; in November 2016, the interaction term is largely negligible indicating that information about the policy change has diffused completely. However, the effect remains in place for non-Verizon auctions, suggesting that the adverse effects of lack of information remains in place. Effectively, individual bids across Verizon and non-Verizon iPhone 5 pallets clearly diverge over time as information about the policy change diffuses within the community, as shown in Figure 2.10. These results provide additional support for the beneficial effects of primary market policies in reducing adverse selection costs, but at the bidder level.

2.6. Conclusion and Implications

Secondary markets are a significant station in the lifespan of electronic equipment – they are instrumental in putting durable products into their second life as well as reducing e-waste (Thibodeau 2013). However, these markets suffer from adverse selection, i.e. residual uncertainty about the quality and functionality of the products that are sold there. Resolving these uncertainties has often needed mechanisms at the point of sale, such as guarantees, warranties, and certifications. However, there is an alternate way in which adverse selection can be reduced – by adopting appropriate policies in the primary market for durable goods. By definition, primary and secondary markets for durable goods are linked (Guide et al. 2003). These links can be used to incentivize manufacturers and retailers of technology products into consider adopting policies in the primary markets that can continue to benefit the secondary markets. In this essay, I provide an example of such a salubrious effect by showing how a policy change in the primary market for iPhone devices by Verizon reduces adverse selection in secondary market, by reducing the uncertainty associated with jailbreaking-to-open. Adverse selection costs reduce significantly for iPhone devices in their aftermarket as a result of Verizon's policy change, consistent with prior theory in information asymmetry in durable products (Dewan and Hsu 2004, Ghose 2009).

The analysis allows me to estimate the extent to which adverse selection may be mitigated, based on the specific iPhones market I study. In 2014, the unit price for a used Verizon *unlocked* 16 GB iPhone 5 was approximately $200 in the *B2C* secondary market.[11] In my models, the predicted price for a similar device in the *B2B* secondary market to be $141. These devices are factory-unlocked, and hence devoid of risk due to jailbreaking-to-unlock. It is reasonable for B2B prices to be lower than those in the B2C market, so as to allow B2B buyers to generate margins. The comparable iPhone 5 predictive price from non-Verizon carriers in my model, where factory-unlocking is not guaranteed, is $75. The price differential of roughly $66 ($141 versus $75) represents an indirect measure of adverse selection costs borne by sellers.

Beyond these costs, it is also evident from my analysis that B2B buyers continue to leave value on the table. In 2013, 11.2% of the phones in the US were jailbroken; since this figure includes all phones, it serves as a conservative estimate of the proportion of a pallet of unlocked phones that may have been jailbroken. The average cost to repair an iPhone is approximately $89, including, for example, battery replacement and fixing screen responsiveness that are

[11] https://www.latimes.com/business/technology/la-fi-tn-sell-apple-iphone-5s-5c-5-20140902-story.html

common device performance issues that could result from jailbreaking.[12] Therefore, when faced with a pallet of unlocked devices and rounding up this proportion of jailbreaking to 15%, a reasonable reduction in willingness-to-pay for a pallet of such devices should reflect this partial discounting (price reduction proportional to 15% of pallet size x $89 in repairs). However, bidders systematically underbid by $66 per unit, thereby over-estimating the risk of jailbreaking and creating inefficiencies in the market.

Do bidders who actual win pallets realize that they may be underbidding for pallets by overestimating the risks of jailbreaking? Possibly, bidders who win unlocked iPhone 4 or non-Verizon iPhone 5 pallets can examine the actual pallet and re-evaluate their bidding strategy. I run some model-free analysis to consider this possibility. I consider bidders who bid in both locked and unlocked auctions and have *won* pallets in unlocked auctions, leading to a relatively small sample. I correlate their average bidder willingness-to-pay against the number of times they *won* in locked or unlocked auctions, excluding Verizon iPhone 5 auctions where there is no risk of tampering. I find that the average price (bid) for locked phones is relatively steady over time. In contrast, bidders who win multiple unlocked phones tend to submit *higher bids over time*. This upward trajectory of bids may potentially be explained by bidders initially overestimating the potential losses associated with jailbroken phones but learning over time by winning. In my rough analyses, I find that bidders tend to bid higher for unlocked phones after their fourth win. These analyses are available upon request. I leave a more rigorous examination of these dynamics from winning auctions on adverse selection to future research.

While it is plausible that Verizon's policy change was done without much consideration of its (shown) salubrious effects on secondary market valuations, the primary message of this essay – namely, the interconnectedness of primary and secondary markets and the ability of

[12] https://www.pcmag.com/feature/363248/how-and-where-to-get-your-iphone-repaired

changes in the primary market to positively impact secondary market prices in the presence of adverse selection concerns – *is* strategically acted upon in a wide range of industry settings. For example, the diamond industry has adopted blockchain certification in the primary market in the hopes of providing valuable information to customers regarding the product's origin, thereby positively influencing resale values further downstream (Sumkin et al. 2020). The blockchain certification acts as a "*single, tamper-proof digital record for diamonds*" (Krawitz 2019) to ameliorate concerns surrounding 'blood diamonds' and other unconscionable supply chain practices. Within the IT industry more specifically, hardware producers are often concerned with the risks of malicious circuitry (hardware Trojans) in chip design. To counter these risks, and enhance the current as well as future performance of the hardware (and as a result, their future resale value), chip designers have explored a range of methods to identify 'backdoor' entry points and fortify them from attack.[13] These initiatives in the primary market help enhance resale in the secondary markets by ruling out the possibility for tampering.

While the above examples describe situations where steps have already been taken to tamper-proof products in the primary market, thereby helping in the secondary market, I believe there are many opportunities where more can be done. As the need to reduce the environmental effects of e-waste becomes more pressing, it will be necessary to consider strategies that help keep older technologies around for longer than otherwise expected. Interestingly, even governments are participating in these efforts; the French Government, for instance, is requiring technology makers like Apple and Microsoft to provide a "repairability score" for products that can then be used to extend the life of these products (Beres 2021). Similarly, Google is implementing the notion of "circularity" in their servers and devices, ensuring that these used technologies can re-enter the secondary market with adequate quality and performance

[13] https://www.techdesignforums.com/practice/guides/design-security/

assurances.[14] These initiatives are designed to ensure that secondary markets for these products have more complete information so as to enhance their efficiency. These links between primary and secondary markets can thus be used to enhance value in both markets – my work here provides evidence for such an effect but within the context of jailbreaking of iPhones.

This essay is subject to certain limitations. First, while I theorize about jailbreaking-to-unlock, I do not directly observe phones that are jailbroken. Nevertheless, the changes in prices I observe from the exogenous policy change across multiple analyses are fully consistent with expectations of jailbreaking. Second, strategic decisions by sellers could play a role in the prices I observe. However, I do not have the visibility into seller data to identify why they choose to auction locked versus unlocked phone pallets. Third, I study iPhones, arguably the most well-specified mobile device in the IT industry. Although other brands (e.g. Samsung) may be perceived differently by bidders, I believe that my work provides some directions to how firm policies in the primary market could lead address adverse selection in the B2B secondary market.

There are several managerial implications that emerge from this essay. For policy-makers considering sustainable reverse logistics programs in the IT industry, I show the value of forward-looking policies that can benefit both primary and secondary markets. For carriers like T-Mobile and AT&T that sell locked and unlocked devices, it is useful to consider the downstream implications of factory unlocking as they design strategies in the primary market (Lee and Whang 2002; Guide and Li 2010). For secondary market auctioneers, I show that withholding information, whether intentionally or by omission, has a negative effect on prices. I quantify such adverse selection costs that are borne by sellers in the market. Knowing these costs is useful since it places an upper bound on how much sellers may be willing to invest in remedying this quality uncertainty, in terms of investing in "factory-unlocking" devices before

[14] https://www.responsibilityreports.com/HostedData/ResponsibilityReports/PDF/NASDAQ_GOOG_2020.pdf

placing them on the auction site. As mobile devices become increasingly more durable, they remain longer in circulation (Pilehvar et al. 2017), making the efficient functioning of secondary markets a desirable objective. From a market efficiency perspective, this essay thus calls for a holistic approach to policies from the primary market but can have far-reaching ramifications.

Chapter 3: Impressionable or Immune? On Examining The Influence of Marquee Sellers in B2B Secondary Market Platforms for IT Products

3.1. Introduction

"The participation of "marquee users" can be especially important for attracting participants to the other side of the network."

(Eisenmann et al. 2006, p6)

"The basic strategy for credibility building is to attract a marquee platform contributor."

(Edelman 2015, p7)

Double-sided digital platforms are increasingly ubiquitous in the economy today, giving rise to a body of literature enhancing our understanding of how they operate, and the drivers of performance (Eisenmann et al. 2011, Farrell and Klemperer 2007, Rochet and Tirole 2003, Wilbur 2008, Evans 2009). The influence of network effects, and their implications for switching costs and pricing continue to be highly relevant within much of this work (Zhu et al. 2019). However, there are specific aspects on competitive behavior on platforms discussed in the theoretical or managerial literature that remain relatively untested empirically. Amongst these, one recurring theme pertains to building same-side and cross-side networks through the acquisition of *marquee* players (Eisenmann et al. 2006, Edelman 2015). Stated plainly, platform owners can benefit by attracting high-visibility, high-quality sellers or buyers, since they increase same-side participation on the platform while also attracting greater cross-side participation through network effects. However, the economic impact of adding marquee sellers or buyers to the platform has not been clearly established – I address this particular gap in this essay. Specifically, I study how the addition of a marquee seller on a two-sided platform affects prices obtained by *other* existing sellers for similar products.

The impact of adding sellers to a platform has been shown to reduce prices on average on platforms (Wright 2004, Chandra and Collard-Wexler 2009, Zhu et al. 2019) through the increase in competition and the associated increase in supply. New entry of sellers can also kickstart negative same-side network effects, leading to lower prices, to the point where sellers potentially leave the market entirely (Rochet and Tirole 2003, Caillaud and Jullien 2003, Chen and Tse 2008). However, the addition of a *marquee* seller may spur different dynamics on the platform. First, marquee sellers may better attract users (or consumers) on the cross-side of the platform, thereby offsetting the increase in supply, and reducing the extent to which prices fall on the platform (Eisenmann et al. 2006). Second, absent any price externality effects, they may attract additional high-quality sellers to the platform who, by offering higher-quality products that command a higher price, increase the average price of a product sold on the platform. Finally, in the presence of price externality effects, they may induce higher valuations for products sold on the platform by virtue of *reference price effects*, since they provide a new set of price and quality anchors for users on the platform (Monroe 1973, Rao and Monroa 1989). That is, all else equal, marquee sellers may raise prices for *other* sellers on the platform, thus increasing value for platform owners.

In this essay, I argue and show that prices faced by other sellers *increase* for similar products after the entry of a highly visible marquee seller who commands high prices for its products. While supply does increase upon entry, I do not observe a concurrent increase in the number of buyers associated with the observed higher prices. Similarly, I do not observe new sellers entering the platform either. Thus, through a series of tests, I show that the effect of the marquee seller on prices faced by other sellers is largely explained by the *reference price* effect, suggesting that beyond network effects, it is important to consider how price anchors and reference prices are also influential in platform settings.

I locate this study of marquee sellers in the context of business-to-business (B2B) secondary market auctions for IT products, specifically mobile devices. The B2B secondary market is one form of secondary markets in which pallets of equipment are sold to pre-registered business buyers through an online auction portal. These markets process the resale of products that have passed through the primary market in some form, either as customer returns, unsold inventory, or from buyback programs where old devices are turned in for discounts on newer devices (Lee and Whang 2002, Tibben-Lembke 2004, Elmaghraby et al. 2018). For this essay, I use data from a leading online intermediary platform that specializes in running online auctions for big-box retailers, thereby allowing them to liquidate their excess inventory through independent and specifically created retailer storefronts. In this context, the research site is the platform provider, connecting big-box retailers on the one side, to B2B buyers/bidders on the other side. These B2B bidders are themselves resellers, including flea market operators and independent stores that vary in bidding activity and purchase volumes. Consistent with the literature, the platform provider has worked towards adding more retailers to the platform, since this encourages growth on the buyer side (Eisenmann et al. 2006, Bakos and Katsamakas 2008). The addition of one such marquee retailer forms the basis of this study.

Specifically, I exploit the exogenous entry of AT&T, a marquee seller in the mobile industry, to the platform as a seller of iPhone devices, to study prices obtained by other sellers of comparable products. I focus on auctioned pallets of iPhone mobile devices in the analysis. The sample contains auction data of iPhone pallets spanning the period from January 2014 to July 2017, which includes the time-period when AT&T entered the platform as a seller. The sample contains data of 21,284 bids in 3,605 unique auctions and includes 1,241 unique B2B bidders. As a starting point, I first establish that the prices obtained by AT&T's pallets, all else equal, are higher than those obtained by others, thereby indicating that there is a premium attached to the retailer. Subsequently, I consider prices for other sellers of mobile phone pallets, using a differences-in-differences approach, and see clear evidence of reference price effects, i.e. the higher prices associated with comparable AT&T auctions act as price anchors and lead to increased prices for other sellers post-entry.

Beyond this direct effect, I also consider heterogeneity in terms of where and how these reference price effects manifest. Specifically, I consider two moderating influences. First, I consider the role of *multi-homing* bidders, i.e. those bidders who bid for pallets in multiple retailer storefronts versus those who participate in only one particular retailer's site. Prior research shows that multi-homing consumers manifest different behavior relative to single-homers (Gabszewicz and Wauthy 2004, Landsman and Stremersch 2011). Relative to single-homers, multi-homers are exposed to a wider range of prices on the platform, and therefore the addition of a single new price anchor, even from a marquee seller, may have a smaller or no effect. Second, I consider the impact of *involvement* on multi-homers (Petty and Cacioppo 1979), i.e. when multi-homing bidders bid on AT&T auctions. Prior work argues that involvement with a task can reduce the extent to which the new anchor is assimilated. Therefore, bidders who actively bid across multiple retailer storefronts, including AT&T auctions, may not be as readily influenced by AT&T's prices. I see clear evidence for the moderating role of *involved multi-homing* in the analysis.

This essay contributes to the literature in multiple ways. First and foremost, I address the gap in the digital platforms literature pertaining to the ostensible effect of marquee sellers – I focus here on the cross-side price effects of such sellers. Using a reference prices framework, I show how marquee sellers can affect prices, while controlling for increased supply and demand. Second, I highlight the role of multi-homing and involvement, in terms of their moderating effects. The results go beyond the implications of adding users per se in two-sided platforms. I show that adding new sellers to the platform can have more nuanced effects on prices obtained on the platform.

This essay also contributes, albeit not directly, to research on secondary markets for durable IT products (Elmaghraby et al. 2018). Secondary markets for IT products are important from a societal perspective since they help reduce e-waste (Tibben-Lembke 2004), direct supply of durable computing equipment to lesser-served parts of the economy, and help extract greater value from functional and usable IT equipment.

3.2. Literature Review and Research Hypotheses

This essay is positioned at the intersection of three streams of research. The first stream studies online two-sided platform markets while the second pertains to research studying the effects of reference prices on consumers' willingness to pay. The third stream focuses on how involvement affects bidder behavior. I review these streams of work next.

3.2.1. Two-Sided Platforms and Marquee Participants

Two-sided platforms involve two distinct types of users, each of whom obtains value from interacting with users of the opposite type (Rochet and Tirole 2003, Parker and Van Alstyne 2005). In recent years, a significant body of literature has sought to understand the strategies required for digital platforms to scale and compete, including studying optimal pricing strategies (Parker and Van Alstyne 2005), business models (Parker et al. 2017, Tian et al. 2018), interactions among competing platforms (Koh and Fichman 2014, Niculescu et al. 2018, Song et al. 2018), matching efficiency between buyers and sellers (Hong and Pavlou 2017), multi-homing across competing platforms (Rochet and Tirole 2003, Eisenmann et al. 2006, Li and Zhu 2019), platforms' investment decisions (Anderson et al. 2014), and competition with new entrants to a platform (Wright 2004, Chandra and Collard-Wexler 2009, Zhu et al. 2019).

One factor that has often been suggested to allow a platform to gain traction has pertained to the presence of so-called marquee participants. The effect of marquee participants is based on the observation that "all users of two-sided networks are not created equal. The participation of "marquee users" can be especially important for attracting participants to the other side of the network", (Eisenmann et al. 2006, p6). More recently, Edelman (2015) argues that the presence of a marquee seller signals credibility to buyers, thereby enhancing cross-side effects. To the extent that a marquee seller could be convinced to exclusively operate on the platform, the platform would benefit but would need to compensate the seller for any losses of revenues from joining other platforms. Thus, the platform's value from a marquee seller is more nuanced, since the benefits in terms of cross-side effects may not outweigh the costs of compensating the seller.

How does the presence of a marquee seller influence prices and buyer behavior on the cross-side? This remains relatively under-explored in the research literature. Prior work has argued that the addition of any sellers on the platform can induce, through same-side effects, greater supply on the seller side (Zhang et al. 2020), which tends to reduce average prices (Chandra and Collard-Wexler 2009). Through cross-side effects, adding sellers to the platform can attract more buyers, but the presence of lower transaction costs and low switching costs within the platform environment can reduce prices. Thus, the entry of new sellers and the downward pressure on prices can even result in sellers choosing to leave the market (Rochet and

Tirole 2003, Caillaud and Jullien 2003, Chen and Tse 2008). When a marquee seller joins, the positive network effects kick in across the platform, since this signals credibility and makes the platform more appealing to buyers (Edelman 2015).

However, beyond new buyers entering the platform and changing demand, I argue that the *higher prices* that marquee players are likely to generate can have yet another effect on other sellers in the short term. An immediate effect of a marquee player's entry pertains to the consequence of the marquee's new (higher) price on the market at large. On platforms where there is considerable uncertainty about the underlying product, bidders or buyers are likely to condition their valuations on information gleaned from other concurrently sold products (Pilehvar et al. 2017). Thus, price information on other comparable products provide external information cues and operate as anchors, offering benchmark prices for the focal products (McGee and Sawyer 2003, Mazumdar et al. 2005). The marquee seller entering the platform, therefore, not only kickstarts positive cross-side network effects in the medium to long-term but immediately provides higher price anchors that can influence prices faced by other sellers already on the platform through the pathway of reference prices. I briefly describe reference prices next.

3.2.2. Reference Prices and Bidders Heterogeneity

Reference prices are benchmarks against which the price of a product is judged (Mazumdar et al. 2005). They may be internal to the individual or externally observed in the broader environment. For products of a similar category, externally observed prices provide an alternative standard for the price of the product that is rooted in the specific context. Buyers make decisions by comparing prices to a set of reference prices that provide external anchors for valuation (Yadav and Seiders 1998, Kamins et al. 2004, Elmaghraby et al. 2018). External reference prices become more influential when uncertainty is more salient (Simonson and Drolet 2004).

In the platforms context, auction prices for comparable products that are concurrently on sale can provide reasonable external reference prices for the focal product (Pilehvar et al. 2017). As marquee sellers often enjoy a price premium on their products, it is reasonable to expect that the set of reference prices available to buyers on the platform is likely to be higher. Whether the buyer conditions on the average of the comparable prices or the range of prices, I would expect the external reference prices to increase, thereby leading to higher prices for other sellers on the platform as well (Kamins et al. 2004).

In the B2B secondary market context where I focus this study, buyers face significant uncertainty about the actual contents of the pallets for which they bid (Elmaghraby et al. 2018). In the presence of such uncertainty, bidders are more likely to depend on external information sources, such as the prices observed across the platform for similar products (McGee and Sawyer 2003, Pilehvar et al. 2017). In an auction setting, individual bids made by bidders in the presence of a marquee seller are therefore expected to be higher than they would be, prior to the entry of the marquee seller, since they provide viable price anchors. In the platform I study, I exploit the entry of AT&T – a company with a strong brand name in the mobile phone industry. Upon joining the platform, AT&T's auction prices are higher, as expected of marquee sellers with significant brands (Rao and Monroa 1989, Teas and Agarwal 2000). As these prices are also incorporated into the external reference prices for bidders, other sellers of comparable products gain. Therefore, I propose:

H1. The reference price effect from the entry of AT&T positively impacts prices in other marketplaces for comparable products.

While H1 argues for an overall effect of AT&T's entry at the level of an individual product (pallet in this case), I now consider how the marquee seller influences individual bids by bidders, in addition to final prices. Bidders on platforms are heterogeneous with respect to their multi-homing activity (Koh and Fichman 2004); they vary in terms of the number of individual retailer marketplaces in which they are registered. I can thus segment bidders into single-homers, i.e., those who operate in one retailer's marketplace only, and multi-homers, i.e. those who participate in multiple retailer marketplaces on the platform. I note that this definition of multi-homing varies slightly from the one commonly observed in the literature. I refer to *multi-homers* as those who choose to bid in auctions offered on different retailer storefronts, while the definition adopted in the literature pertains to users operating on different platforms (Armstrong 2006, Eisenmann et al. 2006, Landsman and Stremersch 2011). Since each retailer operates independently and bidders are expected to register separately for each retailer, I adopt the notion of multi-homing, while acknowledging the nuanced differences (Zhu et al. 2019).

In this setting, therefore, I define *single-homers* as B2B bidders who register and participate (i.e. bid) in the marketplace operated by a single retailer, i.e. all their bids are issued on auctions posted by a single seller (retailer) on the B2B platform. By virtue of registering on a seller's marketplace on the platform, bidders are able to issue bids and receive instant updates (via email) about the focal and concurrent auctions (e.g. current prices, number of placed bids) offered by that retailer only. As a result, they only observe the price dynamics of various auctions in their *home* marketplace. These single-homers may also *passively* observe prices in other marketplaces in which they are not registered (see Figure 3.1) but do not receive email updates or detailed information about bid dynamics. They thus need to exert incremental effort to access this information for other marketplaces manually through the typical search processes offered by most platforms.[15]

Multi-homers, on the other hand, register at and participate (i.e. bid) in more than one seller's marketplace, thereby receiving updates and bid information from each of these individual marketplaces. An advantage of multi-homing is that bidders observe a wider range of prices on the platform for concurrent and similar products with little incremental effort, and so are more aware of prices from multiple sellers' marketplaces relative to single-homers. Reference price effects on individuals exposed to price anchors from multiple marketplaces tend to be aggregate effects, which have greater inertia (Rajendran and Tellis 1994). Hence, the marginal impact of AT&T's entry and the higher reference prices observable, would be lower for multi-homers than single-homers. Hence, I hypothesize:

> *H2. The reference price effect on bidders' willingness-to-pay is greater for single-homers than passive multi-homers.*

3.2.3. Bidders Involvement

To what extent does bidding on AT&T auctions influence the reference price effects I hypothesized about above? I consider this source of heterogeneity here. I classify bidders by virtue of their participation in auctions offered by AT&T, and study how they are affected in terms of their bids in their *home* markets. I classify bidders in two categories: The first set of bidders never participate (i.e. bid on a pallet) in a single AT&T auction, i.e. they *passively* observe prices from the marquee seller without any further involvement. This category of bidders can include both single-homers and multi-homers. The second set of bidders includes multi-homers who *actively* participate in AT&T auctions and, thus, are more aware of the prices and

[15] Individual marketplaces provide general information regarding product offerings and prices to unregistered buyers, while detailed auction information is withheld and shared only with registered bidders.

the product types sold by the marquee seller. I refer to the first set of bidders as *passive* bidders, while the second set of bidders are referred to as *active* bidders. Figure 3.2 illustrates these different bidder types in the dataset (Sellers A and B and AT&T).

To understand how participation in AT&T auctions may influence how bidders incorporate the potential reference prices set by AT&T auctions in the bids submitted in their *home* markets, I invoke prior work in *involvement theory* (Lee et al. 1999, Chandrashekaran and Grewal 2003, Lo et al. 2013). Recall that reference prices represent price anchors for bidders as they consider suitable bids for the focal pallet – while these external reference prices are easily available, they may not be fully representative of the appropriate value that bidders should ascribe to the focal product. In other words, external reference prices may not necessarily represent the "true" value for focal product (Nunes and Boatwright 2004). Products sold by marquee sellers may include a significant premium for the brand, all else being equal, which need not apply to products sold by non-marquee sellers. Involvement in auctions posted by the marquee seller can, interestingly, lessen the extent to which these price anchors are influential on bidders.

Research shows that involvement can positively influence decision makers' susceptibility to a variety of common judgment and decision biases (Lee et al. 1999, Chandrashekaran and Grewal 2003, Lo et al. 2013). Involvement here is defined as the degree of personal relevance arising from the underlying task, such as a purchase decision. Thus, the act of making a deliberate purchase decision can induce involvement, which can lead to greater reasoned and deliberative decision making and less bias (Petty et al. 1983, Zaichkowsky 1985). Applying this logic, I argue that participating (i.e. bidding) in AT&T auctions influences bidders by inducing them to process information from the marquee seller more diligently and fully (Cacioppo and

Petty 1979, Richins et al. 1992, Meyers-Levy and Peracchio 1996). Those who do not participate in these auctions are more likely to use simple heuristics in applying these price anchors in their *home* markets, leading to a more pronounced reference price effect (Chandrasekaran and Grewal 2003).

High-involvement (also referred to as *involved)* individuals, on the other hand, scrutinize the information and process central aspects of the price anchors more diligently, specifically evaluating how and why reference prices may vary from their own willingness to pay and bids. In contrast, uninvolved individuals tend to process the same information less rigorously, depending upon superficial aspects, e.g. the mere presence of a reference price and other contextual and semantic cues (Chandrashekaran and Grewal 2003). These active bidders are more likely to evoke central processing and to scrutinize the reference prices from AT&T auctions, making them less susceptible to the reference price effects. Furthermore, I expect that this scrutiny applied to references prices will grow in discernment over time, as these bidders continue to remain active. I thus hypothesize:

> *H3A. The reference price effect on bidders' willingness-to-pay is greater for passive bidders, relative to active bidders.*
>
> *H3B. The reference price effect on willingness-to-pay is mitigated sooner for active bidders, relative to passive bidders.*

3.3. Research Context

This essay is set in the B2B liquidation market auctions for pallets of mobile devices, specifically iPhone models. The research site is a leading online intermediary platform effectively acts as a market-maker, hosting a platform on which big-box retailers create their own independent auction markets to liquidate their excess inventory. In contrast to prior research in secondary markets where auction sites took possession of merchandise (Pilehvar et al. 2017), my research site only hosts and manages the auction process. Retailers who operate on the auction platform create their own virtual "shopfronts" where the auctions are hosted. Each pallet contains a bundle of products that are typically of the same category (e.g. mobile phones, laptops, etc.), but not necessarily identical. Depending on the retailer, the pallet composition can vary with respect to the category and number of items included. Neither the research site nor the bidder determines what goes into a pallet. Retailers typically form the pallets and list them online for an auction as rapidly as possible, so as liquidate their excess inventory as soon as possible (Pilehvar et al 2017).

In the specific case of mobile phones, pallets are typically formed of devices that are of the same operating system, brand, and generation (for instance, *Android, Samsung, Galaxy*) with occasional exceptions. Since I focus on iPhones, pallets are typically formed of a number of iPhones of the same generation (e.g. iPhone 6 or iPhone 7), but with varying feature sets.

In order to maintain a consistent look and feel for the platform's bidders, the auction site, i.e., the shopfront, for different retailers are generated using a consistent user interface. While the information is provided similarly across different retailers' sites, information attributes may vary from one auction to another based on the information available to the retailer. All auctions use the second-price auction format, where winners pay the second-highest bid plus a bid increment (Pilehvar et al. 2017). To prevent sniping, the platform automatically extends the end time of the auction if they receive a last-minute bid, i.e. popcorn bidding rule. All bidders are business buyers who must pass through a separate registration process for each auction site in which they wish to bid, while staying on the same underlying platform. They can register across multiple retailer sites; no restrictions are placed on their bidding activities therein. Furthermore, the platform does not enforce reserve prices for which a seller would be willing to provide a certain quantity; hence, there should be no effect on final prices or the decision to bid with respect to reserve prices. This also indicates that supply on the platform is completely exogenous.

In order to ensure some homogeneity as well as retain parsimony in the analysis, I study the two largest independent sellers on the platform in which all multi-homers in the sample have participated; Seller A and Seller B (I do not disclose names on request from the research site). Focusing on two of the largest retailers, outside of the marquee seller (AT&T), allows me to measure multi-homing behavior more accurately. While there are more sellers on the platform, they rarely offer pallets of iPhones, compared to Sellers A and B. In the time-period of the study, over 85% of the iPhone pallets offered on the platform came from these two retailers, while other retailers made up the remaining collectively. Therefore, I focus my attention on Sellers A and B, in addition to AT&T as the marquee seller. In robustness tests reported later, I expand the analysis to all retailers, with no substantive change in the results. The specific details of the dataset used for the analyses are described next.

3.4. Data and Methodology

I use a proprietary dataset obtained through a formal research collaboration with the platform provider. I focus only on pure pallets of iPhones so as to minimize extraneous variation in the pallets and concentrate on the specific effects of interest around the entry of AT&T. The pallets typically carry one specific generation of iPhone devices, although individual models can vary. However, there is variation *across* pallets in terms of the physical condition of the phones, generation, and other attributes of the devices (such as memory size and carrier). This information is provided, albeit in a condensed and non-specific manner, in the auction page for each pallet (see Figure 3.1). As discussed above, since all pallets are sold as-is, it is largely up to the bidder to evaluate the value of the pallet and bid accordingly. It is here that external price anchors are influential.

My dataset includes 21,284 bids issued in 3,605 unique auctions for iPhones pallets across the time period January 2014 to July 2017. As mentioned earlier, these auctions are hosted by two retailers, Sellers A and B, with each retailer hosting its own shopfront on the platform, and include 1,241 unique bidders.[16] For each auction, I collect information pertaining to the retailer offering the pallet, the number of units in each pallet, the final price of the auction, the number of bidders who participated in the auction, and the date and time of the auction. Additional information on the products in the pallet included physical condition of the devices, device models and memory sizes, and the network carrier associated with the device. A description of the variables in the dataset as well as summary statistics and correlation tables are provided in the Appendix in Tables A3.1–A3.4.

My identification strategy is offered by the exogenous entry of AT&T as the marquee seller to the platform. The platform introduced AT&T as a new seller in January 2017 and started hosting auctions for AT&T iPhone pallets. Auction final prices for AT&T pallets were clearly higher than observed on the platform for the two other retailers, as would be expected by virtue of AT&T's marquee status. Since my focus is not on AT&T auctions, but prices obtained for auctions offered by Sellers A and B, for these retailers, the entry of AT&T can clearly be viewed as exogenous (entry of retailers on the platform site is the result of private negotiations between the interested parties and is typically not revealed to other sellers). Therefore, in the analysis, I

[16] The original sample contains eight different sellers, excluding AT&T. I elect to include two sellers only for the following reasons. First, Sellers A and B account for the majority of auctions for iPhone devices on the platform, i.e., 85% of the auctions. Second, in order to test my hypotheses, the sellers must contain bidders that are both single and multi-homers, with a subset of multi-homers being involved in AT&T auctions. Sellers A and B provide me with this requirement, whereas the other sellers have inconsistency with respect to single and multi-homers, i.e., one seller has either single or multi-homers on their platform.

restrict the sample only to Sellers A and B auctions, while excluding AT&T auctions. I conduct the analysis in stages, as described below.

As a first step, I aim to address the baseline research question – does the entry of AT&T lead to higher prices for comparable Sellers A and B auctions, all else being equal? Recall that in this analysis, I control for *same-side* network effects, since there are no other new retailers joining the platform as a seller during my observation window. I use the auction as the unit of analysis here, while the dependent variable of interest is the auction final price, normalized by the number of devices in the pallet, i.e., final price per unit, consistent with prior work (Pilehvar et al. 2017, Elmaghraby et al. 2018). The main independent variable is the entry of AT&T, captured as a binary variable. The average final price per unit in the sample is \$175 (sd = \$125). The average pallet has 73 devices (sd = 125) suggesting significant variation in the number of devices across pallets.

After I establish the baseline results, I then move to testing my hypotheses pertaining to how individual bidders may response to the marquee seller. These analyses are performed at the *bid-level* for individual bidders. The bid-level analysis quantifies the difference in the magnitude of the effects among different populations of bidders based on their multi-homing and participation activities, thereby addressing H2 and H3. The dependent variable is the value of each bidder's final submitted bid in an auction. The main independent variables are whether a bidder is single-homer or multi-homer, and whether s/he is an active or passive bidder. Recall that I define active bidders as multi-homers that participate in AT&T auctions. The total number of single-homers in the sample is 530, while multi-homers number 711.[17] Of these multi-homers, 115 have participated in AT&T auctions and are classified as active bidders (Figure 3.3). To

[17] In order to maintain a clear distinction between single- and multi-homers, I remove six bidders from the sample who changed their status from single-homers to multi-homers after the entry of AT&T. As a robustness check, I run an additional analysis including these bidders, and the results are fully consistent.

further establish that these bidders continue to bid on AT&T's site, i.e., to ensure their active status, I track their bid activity on AT&T auctions for the seven months post-entry in my observation period. The proportion of bidders who remain active by bidding in auctions on a monthly basis on AT&T's site remains high (approximately 80%), as shown in Figure A3.1 in the Appendix. All active bidders continue to bid on AT&T auctions for multiple months after their first observed bid, thereby ensuring their involvement with the AT&T marketplace.[18] Although excluded from the sample, AT&T initiated 946 unique auctions in the period from January to July of 2017, i.e., an average of 135 auctions per month.

I first start with some model-free evidence to examine how final prices behave for iPhone pallets, before and after AT&T's entry. Figure 3.4 shows average final prices per unit in Sellers A and B marketplaces, and as is evident, there is a clear uptick in average prices that result from AT&T's entry. Figure 3.5 further shows differences in average prices between single- and multi-homers. I see that the difference in average prices between single- and multi-homers is small in the period before AT&T's entry. Post-entry, however, there exists a clear difference in average prices with single-homers showing relatively higher average prices. Recall that in auctions, the final prices are a function of bidder willingness to pay, so these prices reflect underlying valuations of individual bidders. Both graphs provide evidence indicating that the differences in final prices are not random but likely associated with the exogenous entry of the marquee seller. In the next section, I delve into more formal econometric models to examine these effects.

[18] There may be cases where bidders register with AT&T on the platform but never issue a bid. I, however, do not have visibility into such data and therefore classify these bidders as passive. In robustness tests described later, I reclassify some of these bidders as active based on their observed bids in AT&T auctions, with fully consistent results.

3.5. Results and Discussion

3.5.1. Baseline Results

I start with proposing an econometric model to capture the effect of AT&T's entry on prices obtained by Sellers A and B on the platform, at the auction level. I model the final prices per unit, with the auction as the unit of analysis, as shown below:

$$FP_{ij} = \delta_o + \delta_1 Att\_entry_{ij} + \gamma X_{ij} + \alpha_i + \lambda_j + \epsilon_{ij} \quad (1)$$

In equation (1), FP_{ij} is the final price per unit of auction i in marketplace j, j={A,B}. The main independent variable is *Att_entry*, and is a dummy variable representing the period after the entry of AT&T. I also include X_{ij} as a vector of control variables such as the number of bidders in the auction, number of iPhones (units) in the pallet, the physical condition, generation, carrier and memory capacity of the phones. To account for the possible unobserved heterogeneity among sellers, I include marketplace fixed effects (λ_j). I also control for seasonality by including time fixed effects in the model (α_i). Finally, ϵ_{ij} are independent and identically distributed random errors. I would expect that the coefficient of *Att_entry* is positive and significant, showing that there is a systematic increase in average prices post-entry. These results are shown in Table 3.1.

Column 1 of Table 3.1 shows that there is indeed a positive effect on final prices obtained after the entry of AT&T to the platform (33.63, $p<0.01$). Post-entry, final prices in both Sellers A and B auctions increased, on average, by \$33.6 per unit, ceteris paribus. To establish this as being a result of the reference price effect, I need to rule out the possible confounding effects of changing supply of pallets in the two marketplaces, i.e., are there fewer or more pallets listed on the platform by Seller A or B as a result of AT&T's entry? In addition, the entry of a new seller like AT&T could result in positive network effects by attracting new participants/bidders to the network, resulting in a possible demand increase on the platform. The increase in the number of bidders on the platform could further lead to a rise in within-auction competition among bidders, resulting in higher auction prices. I test for these confounding effects below.

First, I consider the effects of changing supply offered by Sellers A and B on the platform. I compare the monthly supply of pallets for 7 months prior to the entry of AT&T to supply in the 7 months post-entry. On average, the monthly supply pre-entry was 140 pallets while post-entry was roughly 190, across both retailers. I run an ANOVA, where the dependent variable is the monthly supply for each firm while the independent variable is the AT&T entry dummy variable. The analysis shows that the differences in the pre- and post-entry period are marginally significant (p=0.07), with post-entry supply being higher than pre-entry. Thus, the marginally higher supply of pallets, when combined with the increased supply from AT&T, should *reduce* prices (Bapna et al. 2009, Pilehvar et al. 2017) rather than increase prices.

I now consider the possibility of new bidders joining the platform. The total number of unique bidders who bid on auctions hosted by Sellers A and B on the platform before and after AT&T's entry does not change significantly, i.e., there are 486 unique bidders in the 7-month pre-entry period, and 435 unique bidders in the 7-month post period, of which 89.7% participated in the 7-month pre entry period. Furthermore, I consider the ratio of supply to demand on the platform for Sellers A and B iPhone pallets before and after entry. Supply here is the number of pallets while demand is the total number of unique participating bidders on these auctions. While there are many buyers registered on the platform, I am most interested in those buyers who actively pursue iPhone pallets. In the 7 months prior to entry, the supply to demand ratio is 66.7 while the post-entry period ratio is 75.4. This increase is due to the increased number of auctions posted post-entry as noted above, rather than an increase in buyers. Again, given the increased supply relative to demand, I would expect final prices to *reduce* and not increase, as observed in simultaneous auctions (Pilehvar et al. 2017, Bapna et al. 2009).

I further run two separate regressions to assess whether there is increased competition *within* an auction post-entry that may drive prices up. Within-auction competitive dynamics have been observed to increase willingness to pay in experimental settings (Haubl and Popkowski Leszczyc 2019). I first examine if there is a difference in the number of bidders per auction before and after entry. In column 1 of Table 3.2, the dependent variable is the number of bidders issuing bids in an auction, where the auction is the unit of analysis. The results show that, on average, the number of bidders in an auction marginally *decreased* post AT&T's entry (–0.842, $p<0.1$). The decrease in the number of bidders is consistent with increased supply of pallets, which leads to fewer bids per auction (Bapna et al. 2009, Pilehvar et al. 2017) and is typically associated with lower final prices (Pilehvar et al. 2017) rather than higher final prices I observe here. In column (2), I test for whether the number of submitted bids, rather than bidders, has changed in the period post-entry, reflecting an increase in the within-auction competition among bidders which may induce bidders to bid multiple times in an auction. Thus, the dependent variable is the number of submitted bids in an auction. As evident, the number of submitted bids does not change after AT&T's entry (1.586, ns), indicating no systematic differences in competitive intensity within an auction that affect final prices.

Furthermore, I look at how bidders may change their bidding behavior post-entry by plotting *when* they submit a bid. The timing of bids in an auction can influence willingness to pay by arousing competitive instincts in bidders, especially when bids are compressed in time (Adam et al. 2015, Haubl and Popkowski Leszczyc 2019). Alternatively called "auction fever", these effects typically occur in contexts where social competition is high and competitors tend to respond quickly. I plot bid timing on Sellers A and B auctions before and after AT&T's entry to see if there are any systematic changes in this competitive intensity. Figure 3.6 shows the proportion of issued bids, on average, through the three-day period of the typical auction. I see bidders tend to bid heavily in the first day, and then again on the third day. More to the point, these trends are similar before and after AT&T's entry. I also consider bidding behavior on the third day to look for changes in sniping behavior, as shown in Figure 3.7 and see no differences in the rate at which bids are issued. In summary, these analyses show no systematic and significant differences in supply, demand, or within-auction competition, supporting my thesis that the increased willingness to pay is associated with reference price effects from AT&T.

I finally consider the impact of AT&T's entry on individual bidders, rather than at the auction level. If the reference price argument holds true, then these effects should be manifest in individual bids, which in turn leads to the increase in auction final prices. I thus examine how AT&T's entry impacts individual bidders' willingness-to-pay. To accommodate bidder-level variation, I include two additional control variables here. First, I include a variable to capture the order of the submitted bid, i.e., whether the bid was the first, second, and so on, in the auction. Arguably, later bids in the auction are likely to be higher in value (Pilehvar et al. 2017). Second, I include a dummy variable capturing whether the bidder is a single-homer or a multi-homer, as described in the previous section. I also include bidder-specific fixed effects to capture individual heterogeneity across bidders. These results are shown in Columns 2 and 3 of Table 3.1, which show a positive effect on bidders' willingness-to-pay after the entry of AT&T, adding robustness to the findings. In summary, across these analyses, I conclude that Hypothesis 1 is supported.

3.5.2. Bidder Heterogeneity – Multihoming and Active Bidders

I now turn to testing the effects of multi-homing and involvement, pertaining to H2 and H3. Recall that single-homers and multi-homers are based on whether bidders are observed to participate only in their home markets versus multiple markets. Therefore, I divide bidders based on their observed behavior prior to the entry of AT&T. Similarly, active bidders are those multi-homers who bid in AT&T auctions post-entry, while passive bidders do not bid in AT&T auctions. To understand the effect of reference prices from AT&T on these bidders, I conduct subsample analyses for single- and multi-homers as well as active and passive bidders so as to ease interpretation of the results. I adopt a difference in difference specification (Bertrand et al. 2004), as shown below:

$$Bid_{ijk} = \lambda_1\, Att\_entry_{ijk} + \lambda_2\, Single\_h_{ijk} + \lambda_3\, (Att\_entry_{ijk} \times Single\_h_{ijk}) + \vartheta X_{ijk} + \alpha_i + \tau_j + \pi_k + \eta_{ijk} \tag{2A}$$

$$Bid_{ijk} = \delta_1\, Att\_entry_{ijk} + \delta_2\, Active_{ijk} + \delta_3\, (Att\_entry_{ijk} \times Active_{ijk}) + \theta X_{ijk} + \alpha_i + \tau_j + \pi_k + \eta_{ijk} \tag{2B}$$

For this analysis, I use the full sample of 21,284 individual bids. In Equation (2), the dependent variable $Bids_{ijk}$ is the highest bid submitted by bidder i in auction j at marketplace k (i.e., home market). The independent variable Att_entry_{ijk} indicates the period after AT&T's entry. My main interest is in the interaction between AT&T's entry and bidder status as single-homers or active bidders, respectively. To simplify the interpretation of the findings, however, I run separate regressions for each population of bidders. I include X_{ijk} as a vector of control variables. I also use individual-bidder and marketplace fixed effects to account for the possible unobserved heterogeneity (α_i and π_k), and time fixed effects to account for seasonality (τ_j). The rest of the econometric specification is identical to that shown in Equation (1).

As shown in Columns 1 and 2 of Table 3.3, the coefficient of *Att_entry* is positive and significant for both single- and multi-homers (33.74 and 22.60, $p<0.01$), indicating that AT&T's entry has impacted the bidding behavior of both populations of bidders. However, the magnitude of the effects varies, with the reference price effect on single-homers being greater than that on multi-homers. As argued earlier, this difference in willingness-to-pay may be attributed to the fact that multi-homers observe a wider range of price anchors on the platform, since they operate on multiple retailer sites. Thus, I receive support for H2.

To create a clearer distinction between both populations, I further examine the differences between active and passive bidders, shown in Columns 3 and 4 of Table 3.3. The marginal effect of AT&T's entry on willingness-to-pay is higher for passive than active bidders (25.61 and 14.17, $p<0.01$). This difference in magnitude indicates that involvement in AT&T auctions moderates the reference price effect obtained after AT&T's entry to the platform, thereby showing support for H3A. Since passive bidders may be single-homers or multi-homers, the results in Column 3 show a slight difference in willingness-to-pay between single-homers and passive multi-homers (2.713, $p<0.05$), with single-homers bidding higher. This difference is consistent with the broader result showing that multi-homers are less influenced by reference prices from the marquee seller, all else being equal (Rajendran and Tellis 1994).

While I see that active bidders are less influenced, on average, by prices observed on AT&T auctions, I test for whether there is a decay in the reference price across active and passive bidders. For this analysis, I only consider the period after AT&T's entry (7 months). To examine the monthly change in bids, I include a linear spline, with the knot of the spline set at the point when AT&T entered the platform (Greenwood et al. 2017). The spline (*Time*), captures the variation in bidders' willingness to pay post-entry. As shown in Column 1 of Table 3.4, the linear spline shows a small and marginally significant decay over time for passive bidders (-1.886, $p<0.10$). The interaction term for single-homers is not significant, showing no discernible difference between single-homers and multi-homers within the passive set of bidders. In other words, I see no evidence of a significant downward trend in bids by passive bidders post-entry of AT&T.

In contrast, Column 3 of Table 3.4 shows the effect of the spline for active bidders, i.e., those bidders who compete for pallets offered by the marquee seller. Arguably, these bidders should see a significant decay in their bids since their continuing involvement over time reduces the reference price effect. As evident, the coefficient of the spline is significant and larger in magnitude (–6.658, $p<0.01$). By virtue of participating in AT&T auctions, active bidders are more likely to evoke central processing and to scrutinize the prices from AT&T auctions more deliberatively, making them less susceptible to the reference price effect over time. In other words, the reference price effect on willingness-to-pay depletes through bidders' involvement.

It is worth asking if prices on *AT&T auctions* also experience the same level of decay as seen in the case of active bidders – if so, it could be argued that active bidders are still influenced by these decaying AT&T prices and that the reference price effect remains intact. I therefore conduct a similar analysis but only for AT&T auctions. These results, shown in Column 4 of Table 3.4, show a very small decay in bids for AT&T auctions (–0.835, $p<0.1$), indicating that the price premium for the marquee seller remains largely in place. In Column 5 of Table 3.4, I consider only the bids on AT&T auctions issued by active bidders, i.e., those who actively bid on AT&T as well as Seller A/Seller B auctions – these bids do not experience a significant decay over time (–1.103, $p<0.1$). Thus, while competing in AT&T auctions require higher bids to remain competitive, active bidders tend to adjust their bids in their *home* markets back to their pre-entry levels, thereby mitigating the reference price effects in their *home* markets. In summary, I see support for Hypotheses 3A and 3B.

3.5.3 Robustness checks

In this section, I report the results of additional robustness tests that were conducted to establish the validity of the results reported above. First, I examine whether there exist differences between active bidders who bid in AT&T auctions and those that actually win AT&T auctions. Prior work suggests that win experience matters in auctions (Wilcox 2000). Therefore, I check if the lower willingness-to-pay in active bidders manifested in the previous results is associated with winning and not just participating. In Table 3.5, I use two groups of active bidders. The first group contains bidders who won at least one AT&T auction in the first two months after AT&T's entry. The second group contains bidders who never won an AT&T auction up until the last month in the data set. I then study the period in between, i.e., from March to June of 2017 (T= 4 months), to examine any differences in their bidding behavior.

The results in Column 1 show a small but significant difference in willingness-to-pay (at home) between active bidders who win AT&T auctions and those who bid but did not win (–3.633, $p<0.05$). Consistent with prior literature, bidders tend to change their behavior after winning an auction (Elmaghraby et al. 2018). However, the interaction with the linear spline, shown in Column 2, indicates no significant difference in the decay of willingness-to-pay between the two groups over time. The results show that the decay in willingness to pay, representing the effects of reference prices, is not conditioned on active bidders winning AT&T auctions per se.

I note that in the prior analyses, I defined a bidder as *active* if they submit a bid in an AT&T auction at any point in the 7-month window after AT&T's entry. It is possible that some of the bidders labeled as *active* officially registered and joined AT&T's marketplace later during my observation window (in the third month post-entry, for instance). In such cases, these bidders would start off as *passive* and then transition to *active* during the observation window. In this robustness test, I modify the definition of active bidders as follows – I change the status of a bidder to active only *after* their first bid is observed on AT&T auctions, post-entry. Fortunately, this set of bidders who change status is small: 21 bidders change their status during and after the second month post-entry. These bidders issued a total of 67 bids in their *home* markets in the period *after* AT&T entered the platform, but *before* they bid on their first AT&T auction. I aggregate the bids across the passive and active bids from Table 3.4 (4278 + 868 individual bids) and estimate a model where active bidders are defined based on this new definition.

As shown in Table 3.6, the results corroborate those observed earlier. Active bidders issue lower bids in their *home* markets relative to passive bidders (–13.79, $p<0.01$). Active bidders also reduce their bids faster than passive bidders, as shown by the interaction with the linear spline (–6.773, $p<0.01$). This finding further supports the proposed underlying mechanism that involved bidders tend to scrutinize the reference prices from AT&T auctions, rendering them less susceptible to the reference price effects.

3.6. Discussion and Conclusion

Two-sided platforms are prominent in today's economy, and have generated consistent interest in the IS literature for several reasons. Platforms play a significant role throughout the economy, as they minimize transactions costs between market sides. They also appear to be one of the most powerful business models in the digital economy due to their adaptability to business needs, rapid scale-up, and value capture. Airbnb, eBay, Uber, and Google are remarkable success examples. Such businesses have demonstrated remarkable growth and achieved high financial valuations. Scholars have shown significant interests by studying multiple factors that impact prices on two-sided platforms, including competition with network effects and switching costs (Rochet and Tirole 2003, Eisenmann et al. 2011), optimal business models (Parker et al. 2017, Tian et al. 2018), interactions among competing platforms (Koh and Fichman 2014, Niculescu et al. 2018, Song et al. 2018), and competition with new entrants to a platform (Wright 2004, Chandra and Collard-Wexler 2009, Zhu et al. 2019).

In this essay, I investigate how the entry of a new seller with a marquee brand name could impact prices of other sellers for comparable products on the platform. I study this question in the context of B2B secondary market auction platforms for IT products, specifically mobile devices. I am able to observe the exogenous addition of a high-visibility and high-quality marquee seller to the platform and evaluate its effects on other sellers in the platform. In particular, I exploit the exogenous entry of AT&T, a marquee seller, on the platform as a seller of iPhone devices, and study how this entry affects prices obtained by other sellers. The use of proprietary data, combined with an identification strategy made possible by the entry of AT&T, allows me to provide clear evidence for how reference prices and the level of bidder-involvement could influence bidders' willingness to pay in two-sided platforms.

This essay is subject to certain limitations. First, I conjecture that the underlying difference in the magnitude of the effects between single- and multi-homers is due to the amount of price information bidders observe on the platform. However, due to the available data in the market, I cannot directly measure how much information bidders are observing on the platform. Second, I do not have the visibility into seller data in the subsequent resale market to understand how demand in the B2C market could impact their willingness-to-pay in the B2B auctions. Third, there may be a case where bidders register in AT&T but never issue a bid. Hence, they are active bidders by definition since they receive all auction information and price dynamics vis-à-vis AT&T auctions. However, I do not have visibility into such data and, therefore, cannot move these bidders from the passive to active group, if they exist. I hope to address these limitations in future work, potentially through field experiments.

This essay contributes to the literature in multiple ways. First, I extend the literature studying the two-sided platform models (Armstrong 2002, Rochet & Tirole 2003, Parker and Van Alstyne 2005). By relying on reference prices theory, I show that the entry of marquee sellers can positively impact prices of other sellers for comparable products on the platform. I argue and provide evidence that bidders on the platform view AT&T prices as new external anchors that positively impact their willingness-to-pay, resulting in higher auction prices on the platform. I also show that the price effects resulting from the entry of AT&T vary based upon bidders multi-homing activity on the platform. Relying on involvement theory, I further show that by virtue of participating in AT&T's auctions, i.e., the source of the effect, bidders are relatively less prone to the reference price effects. The literature on platforms has argued for the effects of network effects in terms of bringing consumers and sellers to the platform, but there is little work considering the role of price dynamics on the platform as a result of reference prices.

Beyond network effects resulting for the addition of new users to one side of the platform, this essay extends this literature by showing that the value of new users depends on their brand quality, which can have a significantly positive impact on prices of other users on the platform. The findings can be extended to other industries as well. For instance, in the lodging industry sharing economy, Airbnb has officially opened up its platform for hotel distribution by allowing hotels to list on its site.[19] When a hotel with a marquee brand name lists on the site, local or lower quality hosts could view the hotel's prices as new external anchors on the

[19] https://hospitality-on.com/en/sharing-economy/airbnb-officially-opens-platform-hotel-distribution

platform. These hosts would potentially increase their prices closer to the new hotel's prices, resulting in an overall price increase on the platform. These dynamics have significant implications for both the platform owner as well as other local hotels that may now see interesting externalities in their prices from the marquee seller.

Second, this essay contributes to the context of secondary markets for durable IT products (Tibben-Lembke 2004, Elmaghraby et al. 2018). Enhancing the effectiveness of secondary markets for these products is desirable since they retain value, but also understanding the price dynamics of the B2B market is critical in ensuring the long-run efficiency of secondary markets for durable IT products. Furthermore, efficient and viable secondary markets for IT products have ecological and market value. From an ecological perspective, E-waste that ends up in landfills causes significant environmental damage, which can be avoided by extending the life of these products (Elmaghraby et al. 2018). The IT industry is renowned for its ability to produce, market and sell IT equipment, which have justifiably led to significant economic value. However, the ecological implications of these developments have only started to receive attention in recent years (Tibben-Lembke 2004). If the benefits offered by digital platforms can help mitigate some of the high transaction costs that exist in secondary markets for IT products, the payoff for the environment would be significant. My work contributes by highlighting how the recruitment of marquee sellers into the secondary market platform can be used to enhance the efficiency of these platforms, thereby helping the environment as well. A deeper dive into the link between secondary markets and the environment is out of the scope of this essay, but interested readers are referred to the 2019 Sustainability Report issued by the Consumer Technology Association. [20]

[20] https://www.cta.tech/sustainability-report/CTA-2019-Sustainability-Report.pdf?v2

There are several managerial implications that emerge from this essay as well. For secondary market platform providers, I show that the entry of a seller with a "marquee" brand name has a positive impact on prices of other sellers on the platform. It is imperative for the platform's provider to understand such price effects to create guidance when targeting new sellers to join the platform. In other words, it is essential to understand how the entry of a major seller could impact average prices on the entire platform. This essay suggests that platform owners should consider and target sellers with marquee brand names as they can result in a "sugar rush" for prices of other sellers on the platform. As the overall prices increase on the platform, platform owners can benefit by generating higher revenue gains. On the opposite side, adding a relatively cheaper seller could negatively pull prices down on the platform. However, these effects can also be mitigated over time through the twin forces of involvement and multi-homing. Therefore, the advice to recruit marquee sellers has to be viewed keeping these opposing dynamics in mind. Beyond the network effects per se, intra-platform pricing dynamics continue to be challenging for platform owners, since the decentralized model of double-sided platforms tend to take many of these decisions away from platform owners. Being aware of these dynamics, manifesting through reference prices and their dissipation over time, is critical in ensuring that sellers and buyers are appropriately recruited and managed on the platform. I hope that this essay sparks off more work on studying pricing dynamics on platforms, in addition to the common elements of network effects and winner-take-all dynamics.

Chapter 4: Doubling Down on Cannibalization: The Use of Green Nudges in Used Mobile Phone Markets

4.1. Introduction

The tension between the primary and secondary markets has been of great interest to both researchers and managers in the last two decades. Many scholars have explored the cannibalistic impacts of secondary markets on products in the primary markets (Ghose 2006, Chen et al. 2013). The general consensus is that used product sales cannibalize new product sales and, consequently, are harmful to suppliers (Ghose 2005, Atasu et al. 2010). In particular, sellers of new products firmly believe that a used or remanufactured version of a product is potentially harmful since it cannibalizes market share from new products (Atasu et al. 2010). In the context of IT equipment, the literature shows firms or OEMs attempting to limit the impact of the secondary market by adopting various mechanisms such as charging high licensing fees or buying back their own equipment (Oraiopoulos et al 2012, Li et al. 2019). For example, to prevent cannibalization between new and remanufactured/ used products, Apple has implemented a disassembly and recycling strategy for used products collected through its reuse/ recycling program (Li et al. 2019).

The average consumer's desire for new devices with faster and newer state-of-the art technology has lead to a continuous expansion of the electronic market for new products and to shortened innovation cycles for electronic goods (Mendelson and Pillai 1999). In the context of smartphones, the number of used mobile phones is expected to rise in the next couple of years. Experts are anticipating that there will be a boost to the secondary market in the next couple of years by virtue of the move to the 5G technology as it becomes available in more markets.[21]

[21] https://www.rcrwireless.com/20190122/opinion/readerforum/mobile-phone-second-hand-market-reader-forum

Consumers then could sell back today's flagship devices for tomorrow's 5G enabled devices. What then is to become of these older devices?

Secondary markets exist for products with a lifespan that extends beyond their possession by their first user (Lee and Whang 2002, Elmaghraby et al. 2018). The efficient functioning of these markets is desirable for several reasons. First, these markets handle products that are functional, robust, and can continue to provide value in many contexts (Pilehvar et al. 2017). Second, their second life prevents them from ending up in landfills where they can cause environmental damage (Tibben-Lembke 2004).

While secondary markets for IT products exist, they often struggle since they are competing with new products in the primary market, as discussed in the literature studying the spillovers that exist from secondary markets to primary markets, and vice versa (Ghose et al. 2005, Oraiopoulos et al. 2012). Despite the negative cannibalization effects presented in prior work, other research has argued that the sale of used products, from consumer perspective, increases consumer surplus and social welfare (Ghose et al. 2006, Guide et al. 2010). In addition, some level of secondary market cannibalization, from ecological perspective, is beneficial in preventing IT products from ending up in landfills. E-waste is a health and environmental hazard because it contains toxic additives or hazardous substances that, if dumped in landfills, could result in negative environmental externalities. Research has shown that extending the lifespan of smartphones, for example, by just one year can save as much carbon emissions as taking two million cars off the road each year (Middleton 2019). Therefore, every device that can have another life means less damage caused to our planet, and a device put in the hands of someone who otherwise would simply not be able to afford it (Nair 2020). Hence, are there ways by which we can retain or enhance the sale and cannibalization effect of used IT products, in the presence of corresponding new products, so as to promote social welfare and reduce environmental degradation? This is the broad research question I address in this essay.

In order to first understand how used products may be rendered more attractive to the average consumer, I start by considering factors that influence their sale. The literature shows that there are different attributes that could impact the sale of secondhand products, such as consumer preferences (Kim et al. 2005, Agrawal et al. 2015), quality uncertainty and search costs (Tibben-Lembke 2004, Kuruzovich et al. 2008), and prices (Ghose 2009, Elmaghraby et al. 2018). In the specific context of smartphones, the main attributes that shape consumer purchase decision are product features and functions, brand name and loyalty, and social influence (Guleria 2015, Rahim et al. 2016, Kim et al. 2020). Other influential factors are related to durability, external appearance and intrinsic consumer characteristics. In this essay, I introduce a new dimension that may possibly influence consumer decisions and enhance the appeal of used smartphones – behavioral interventions that highlight environmental factors associated with used smartphones.

To the extent that durable electronic products in the market still have life and can provide perfectly good service, there is potentially value in being able to sell them in a convincing manner while highlighting the beneficial values of recycling and the negative effects of e-waste. Therefore, the primary research question I study here is – how can IT products in the secondary market be made more attractive relative to new products by making e-waste and its effects more salient? In other words, within the realm of used smartphones, can sellers enhance the odds that a consumer will choose to purchase the used smartphone rather than a new phone by virtue of behavioral interventions, otherwise known in the literature as *nudges*?

A nudge is generally interpreted as a change in any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives (Thaler and Sunstein 2008). The concept of nudging has also been used in the context of environmental policy, viz., *green nudges*. A green nudge is a nudge that helps reduce environmental negative externalities, without significantly changing economic incentives (Carlsson et al. 2019). While the literature has shown how nudges can alter consumer behavior in different markets, there is no work that demonstrates whether using behavioral interventions (i.e. nudges) can help alter consumer preferences towards lightly used electronics in the secondary market, relative to new products. This question has yet to be answered in the literature, and its importance lies in the implications and environmental externalities of e-waste (Carlsson et al 2019).

Most green nudges discussed in the literature target the quantity and quality of people's energy consumption, with the goal of energy conservation. In some instances, these nudges have proved highly effective relative to alternative mechanisms such as incentives, education campaigns, or moral suasion (Schubert 2017). In my context, I examine the efficacy of green nudges on products for which consumers may already have specific preferences. Framing the choice in this manner, in the presence of a green nudge, may significantly enhance the odds of the consumer being willing to purchasing a used phone in lieu of a new phone. In terms of devising potential green nudges, I consider sources of intrinsic and extrinsic motivation. In terms of extrinsic motivation, I consider the impact of conspicuous conservation (Sexton and Sexton 2014), while for intrinsic motivation, I consider the role of empathy in devising the nudges.

C*onspicuous conservation* theory (Sexton and Sexton 2014), related to conspicuous consumption, argues that individuals seek status through displays of austerity amid growing concern about environmental protection (*external motivation*). The theory's main premise is that society awards superior status to those who undertake pro-environmental actions, provided those actions are conspicuously visible. Through the demonstration of austerity that minimizes the environmental impact of consumption, individuals would gain a social status with respect to environmental protection. Hence, I argue that using a nudge that highlights conspicuous conservation may lead to an increase in the willingness to purchase a used phone, relative to a new phone.

The second intrinsic mechanism relates to the role of *empathy*, defined as the presence of a prosocial emotion that includes awareness of another's suffering and affective participation in the other's feelings (Huber and MacDonald 2012). The literature has demonstrated that empathy is associated with more sustainable behavior, and individuals with a high level of empathy towards a natural object are found to display stronger environmental attitudes and behavior (Ericson et al. 2014, Berenguer 2007). Hence, empathy plays an important role in moving individuals toward pro-environmental and conservation behavior. It is, therefore, plausible that the use of an empathy-evoking nudge in this context could effectively increase consumers' pro-environmental behavior, resulting in consumers electing to purchase used technology products over new ones for the advocated cause, viz., reducing e-waste. Hence, the use of an empathy-evoking green nudge would increase the likelihood of a used technology product being purchased in the secondary market.

In order to test for the effectiveness of the two forms of green nudges in terms of enhancing the willingness to buy used products, I conduct a set of behavioral experiments where consumers are presented with two alternatives – a used phone and a similar new phone, and asked to choose which phone they would be willing to purchase. By exogenously varying the presence of the nudge, as well as price points for the used phone, I am able to identify the specific impact of the nudge as well as moderating influences of prices and other individual characteristics on the willingness to purchase the used phone versus the new phone. The use of experimental techniques allows me to provide causal evidence linking the presence of the nudges to the perceptions of individual subjects.

My analyses provide three main results that are of particular interest to practitioners and researchers in secondary markets for IT products. First, I observe that the nudge based on conspicuous conservation provides a clear treatment effect on the willingness to buy used phones, all else equal. While the baseline willingness to purchase a used phone displays a U-shaped relationship with price, with low and high prices of the used phone showing higher willingness to purchase used phones, the presence of the nudge leads to a clear and significant increase in the propensity to purchase used devices across prices.

Second, the direct effect of empathy is notably absent in terms of enhancing the appeal of used phones. This intriguing result is contrary to prior work. However, I note that empathy is influential in increasing the willingness to buy in specific subsamples – women and older subjects are more likely to respond positively to empathy-based nudges. In interaction analyses, I observe that interactions of the treatment with gender and age are significant and positive. The interactions with price do not provide any significant results.

Finally, I conduct a series of post-hoc analyses where I consider the role of the Big Five personality traits (Goldberg 1992), in order to examine if these traits may moderate the effects of the nudges. Interestingly, I find that specific personality traits do significantly moderate the impact of the nudges, suggesting that the efficacy of these nudges are likely to be clearly heterogeneous in the population. While factors like age and gender may be conditioned on by resellers in terms of selecting which nudges to use, the use of latent personality traits are more difficult to use by managers in assessing the efficacy of nudges. However, the presence of specific heterogeneities associated with traits like Extroversion and Neuroticism suggest the need for more work in this area.

My essay contributes to the literature in multiple ways. First, I contribute to the literature studying how used IT products, especially common devices like smartphones, may be retained in the marketplace for longer durations by strategically enhancing the potential for cannibalization of new products (Ghose et al. 2005, Oraiopoulos et al. 2012). From an ecological perspective, keeping used smartphones in circulation keeps them from landfills for a longer time-period, while also increasing the general supply of phones that can be used in parts of the world where new devices can either not be purchased or supported. To the extent that these devices can be kept out of landfills for longer periods of time, the ecological damage done by them is reduced while also allowing for newer methods to be developed by which their impact may be minimized. In effect, the use of green nudges calls for more obvious cannibalization of new products, rather than less, as has been suggested in the literature on secondary markets. The implications of my experiments are towards finding strategies to increase social welfare by keeping used devices around for longer, while also potentially reducing environmental externalities by delaying their eventual disposal into landfills.

Second, I contribute to the literature studying the use of behavioral interventions, i.e. nudges, and its implications on consumer behavior (Thaler and Sunstein 2008). I extend the literature by focusing on the implications of green nudges and how they could possibly alter consumer preferences in favor of used IT products. More importantly, I provide boundary conditions for which nudges may work in this particular context and how they may be deployed effectively, based on specific attributes of the target audience. Little extant work has studied the use of green nudges in the specific context of re-using smartphones, a significant source of e-waste. This essay addresses this gap in the literature. Furthermore, my results provide direct measures by which managers may be able to devise behavioral interventions at scale to make used products more attractive, especially when combined with pricing strategies. In the next section, I discuss the theoretical arguments underlying green nudges in more detail.

4.2. Theoretical Background and Hypotheses

This essay draws from several streams of research. First, I explore the literature studying cannibalism in the marketplace. Second, I draw on literature on secondary markets and the implications of e-waste. Third, I focus on the literature studying behavioral interventions in the form of nudges and their impacts on individual's behavior. Last, I draw on research studying the role of conspicuous conservation (external motivation) and emotion (internal motivation) in enhancing individual's pro-environmental behavior.

4.2.1 Cannibalization Effect

Cannibalization is an economic phenomenon that has been of interest for many scholars in the past decades. It is defined as a reduction in sales volume, sales revenue, or market share of a product after introducing a newer product by the same company (Moorthy and Png 1992). Cannibalization effects materialize when a consumer's interest for a product shifts after an alternative product is introduced (Copulsky 1976). They occur from close identification of a new product with the launching company's older products. Scholars have examined the notion of cannibalization for a wide variety of products, companies, and industries – e.g., cigarettes (Mason and Milne 1994), computers (Ruebeck 2005), and new versus used books (Ghose et al.

2006). Cannibalization is usually analyzed in relation to a company's product (Chandy and Tellis 1998) or technology innovations (Cravens et al. 2002) – rendering existing products or technologies uncompetitive and obsolete (Atasu et al. 2010).

The notion of cannibalization has occurred within and across both the primary and secondary markets. Within the primary market, for instance, scholars have examined cannibalization among products within a product line and develop different mechanisms to mitigate it (Fruchter et al. 2006). The literature also illustrations that cannibalization occurs when a company produces a product with two different qualities and applies price discrimination to high and low type consumers (Desai 2001). Recent research further shows how different forms of the same product would result in cannibalization. In specific, Lee et al. (2020) provide a comprehensive understanding of the economic impacts of eBooks on the existing print book channel by studying how the introduction of an eBook cannibalizes the sales of its printed version.

The cannibalization literature also demonstrates the cannibalization effects between new and used products. Scholars have argued that the secondary market creates a substitution effect from the fact that new goods face competition from used goods, which results in some new good consumers shifting to the used good market (Waldman 1997, Ghose et al. 2005). For example, Ghose et al. (2006) study the degree to which used books cannibalize sales of new books. Other scholars study different mechanisms and strategies that firms adopt in order to eliminate or limit the cannibalistic effects of used products in secondary markets (Oraiopoulos et al. 2012, Li et al. 2019). The literature also shows that there exists a subtle relationship between consumer preferences and the cannibalistic effects of used products (Chen et al. 2013). In specific, when consumer preferences for used products are persistent, closing the secondary market will not eliminate the cannibalization effects. In my context, there are different reasons for why a consumer would prefer to purchase a new smartphone from the primary market over used one from the secondary market.

Secondary markets of electronic goods are characterized by uncertainty about product quality (Ghose 2009). Such quality uncertainty can be a hindrance in moving used products to the hand of new users. For example, it is reasonable for a person with high willingness to pay to elect purchasing a brand new phone while having the option to purchase a similar secondhand mobile phone due to their inherent quality uncertainty. Aside from quality uncertainty, consumers may choose to buy a new smartphone over a used one from an older generation simply for the new features and functions smartphone companies like to bring to market.[22] However, to the extent that smartphones in the market are durable, still have life and can provide perfectly good service, there is potentially economic as well as ecological value in being able to resell them in the secondary market, while highlighting the beneficial values of recycling and the negative externalities of e-waste.

4.2.2. Secondary Markets and E-waste

The need to better understand what motivates people to adopt pro-environmental behaviors has taken a new urgency with the increasing emphasis on sustainability. Electronic waste (e-waste) – defined as all broken, obsolete, or out of fashion products containing a circuit board that reach the waste stream – has received limited attention in spite of being the fastest growing segment of household waste (Dao et al. 2011, Saphoresa et al. 2012). In 2019, less than 18% of the 53.6 million metric tons of generated e-waste was recycled, threatening the environment and the well being of individuals since it contains toxic additives and hazardous substances (Reuters 2020).

[22] https://www.forbes.com/sites/chrisversace/2013/08/21/what-do-consumers-want-in-a-new-smartphone/#678fbf622ee8

The exponential growth of e-waste may further be compounded by a reduction of the useful life of existing devices driven by the rapid pace of development and release of electronic products with new features (Mendelson and Pillai 1999, Saphoresa et al. 2012). From an ecological perspective, increasing the lifetime of electronic goods could potentially reduce the amount of e-waste dumped in landfills today. One economically promising solution is to send these electronic secondhand products to the secondary market.

In industries composed of products with short life cycles, used or end-of-lease products are collected by resellers and distributed in secondary markets either in an as-new condition or an as-is condition (Robotis et al. 2005). The literature shows that there are different factors that could impact the sale of secondhand products, such as consumer preferences (Cestre and Darmon 1998, Kim et al. 2005, Agrawal et al. 2015), quality uncertainty and search costs (Tibben-Lembke 2004, Kuruzovich et al. 2008), and price (Chou et al. 2013, Ghose 2009, Elmaghraby et al. 2018). For example, consumers could elect to buy a new model over an older generation of used mobile phones merely for the new features they provide (Kim et al. 2005). Furthermore, the inherent quality uncertainty of used products could impact the decision of consumers towards purchasing new products (Hendel and Lizzeri 1999, Ghose 2009). Nevertheless, prior work has also explored the cannibalistic impacts of secondary markets on products in the primary market. The literature shows that, from consumer perspective, used products increase consumer surplus and social welfare (Ghose et al. 2006, Guide et al. 2010). From retailer perspective, the general consensus is that used product sales cannibalize new product sales and, consequently, are harmful to suppliers (Ghose et al. 2005). In my context, I argue that some level of secondary market cannibalization, from an ecological perspective, is beneficial in increasing the lifetime of IT products and, as a result, reducing the amount of these devices ending up in landfills. A potential mechanism to induce the sale of used electronics is through the use of behavioral interventions, i.e. nudges.

4.2.3. Nudges and Green Nudges

Recent years have seen a keen interest in the use of behavioral interventions “nudges” – defined as methods that steer people in particular directions, but that also allow them to go their own way (Thaler and Sunstein 2008, Thaler 2016, Cadario and Chandon 2020). In daily life, an “app” that tells people how many calories they consumed during the previous day is an example of a nudge; so is a text message, informing customers that a bill is due or that an appointment is scheduled for the next day. In government, nudges span an exceptionally wide range. They include graphic warnings for cigarettes (Klein et al. 2017), labels containing information about energy efficiency or fuel economy (Brandon et al. 2018), “nutrition facts” panels on food (Cadario and Chandon 2020), texts and email messages (Yeung and Nguyen-Hoang 2020), and even the design of government websites, which list certain items before others and in large fonts (Krug 2014).

The IS literature has explored the use of digital interventions, particularly mobile messaging, to influence user behavior (Luo et al. 2014, Ghose et al. 2015, Sun et al. 2019). A number of studies have examined the moderating effect of user geographic location (Ghose et al. 2013, Fang et al. 2015), shopping path (Ghose et al. 2015), timing (Luo et al. 2014), and weather (Li et al. 2017) on the response of customers to digital messages. This strand of research has established the effectiveness of digital messages in influencing user behavior, such as clicking on ads (Andrews et al. 2016), purchasing tickets (Luo et al. 2014), and encouraging prosocial activities (Sun et al. 2019). In these cases, and many others, nudges work by altering the “choice architecture,” understood as the background against which choices are made (Balz et al. 2013).

The concept of nudging has also been found in the realm of environmental policy, i.e., green nudges. A green nudge is a change in any aspect of the choice architecture that is intended to alter people's behavior in a predictable way and result in a reduction of a negative external effect without forbidding any options or significantly changing the economic incentives (Carlsson et al. 2019). It aims at promoting environmentally responsible behavior to reduce negative externalities. Most green nudges discussed in the literature target the quantity and quality of people's energy consumption, hence aiming at energy conservation. In some instances, nudges of this kind have proved highly effective relative to potential alternatives, such as incentives, education campaigns, or moral suasion (Schubert 2017). Examples of green nudges are found in the eco-labeling of products (Schubert 2017), small posters advertising the importance of buying an environmentally responsible product (Becchetti et al 2018), restaurants' menu order and presentation (Kurz 2018), plate size in restaurants (Kallbekken and Saelen 2013), financial rewards and goal attainments (Pellerano et al. 2017, Loock et al. 2013). The literature has shown that green nudges tend to increase pro-environmental behavior of individuals. In particular, green nudges can make pro-environmental attitudes more salient and increase the probability of willingness to pay something for the sake of environmental protection (Carlsson et al. 2019). It further reminds people of what they are losing, i.e. the environment and quality of life. Hence, in my context, it is reasonable to assume that the use of green nudges could possibly alter consumer behaviors and preferences towards purchasing used over new electronics by highlighting the implications and environmental externalities associated with harmful E-waste.

4.2.4. Conspicuous Conservation and Empathy

For several decades, social and psychology scientists have investigated the motivations of individuals to gaining a detailed understanding of why individuals undertake pro-environmental behavior (Clark et al. 2003, Graves et al. 2013). Many studies have established that individual decisions are based on a specific definition of rational self-interest (Stern et al. 1993, Ryan and Deci 2002, Clark et al. 2003). Much of the psychology research on pro-environmental behavior tends to focus on the relationship between internal and external motivations or factors with behavioral intentions (Fransson and Garling1999, provide a full review). Internal motivations involve performing an activity because it is inherently interesting or derives spontaneous satisfaction from the activity itself (Gagne and Deci 2005). External motivations, in contrast, require a means between the activity and some independent consequences such as tangible or verbal rewards; hence, satisfaction comes not from the activity itself but rather from the extrinsic consequences to which the activity leads (Clark et al. 2003, Gagne and Deci 2005). They involve pursuing an activity because of external contingencies (e.g., pay, approval, or threat of punishment).

One important external driver of human behavior is the desire for prestige, success relative to others, and esteem. There is extensive empirical evidence that people care about their status and relative consumption (Frank 1985, Johansson-Stenman et al. 2002). Sexton and Sexton (2014) use the term “conspicuous conservation” to describe consumption that signals pro-environmental action and generates green status. This theory stems from the notion of conspicuous consumption, which explains, “in order to gain and hold the esteem of man it is not sufficient merely to possess wealth or power. The wealth or power must be put in evidence, for esteem is awarded only on evidence” (Veblen 1899, p. 36). A strand of literature has then explored the concept of conspicuous consumption and its implications in various settings, with particular focus on purchases that signal prestige, luxury and exclusivity (Braun and Wicklund 1989, Ireland 1998, Wiedmann et al. 2009).

Following this concept, conspicuous conservation is a phenomenon related to conspicuous consumption in which individuals seek status through displays of austerity amid growing concern about environmental protection. For instance, ownership of luxurious estates, automobiles, and fashion surely still affords a certain social status today. However, amid growing concern about environmental damage and global climate change, an evolution of social norms suggests that status is increasingly conferred upon demonstration of austerity rather than ostentation – particularly austerity that minimizes the environmental impact of consumption. Consumers may, therefore, undertake costly actions in order to exhibit prosocial behavior with respect to environmental protection, i.e., paying a higher price for, while making visible, an energy efficient home heating and cooling technologies or a hybrid and electric-powered vehicles (Sexton and Sexton 2014, Sachdeva et al. 2015, Schubert 2017). Adopting this theory in my context, I presume that consumers may seek social status by electing to buy a used technology product over a new one for the intrinsic cause of the purchase, i.e., reducing e-waste. Through the demonstration of austerity that minimizes the environmental impact of consumption, individuals would gain social status with respect to environmental protection. Hence, I hypothesize:

H1: Conspicuous conservation nudging increases the likelihood of consumers purchasing secondhand electronic products in the B2C secondary market.

The role of emotion in prosocial action, i.e. an internal motivation, has been a topic of philosophical interest for centuries. One significant driver of human prosocial behavior is empathy. Indeed, the idea that empathy is a major determinant of prosocial and altruistic responding has been widely accepted among psychologists (Eisenberg and Miller 1987). There are numerous descriptions and definitions of empathy in the literature. One common definition depicts empathy as a prosocial emotion that includes awareness of another's suffering and affective participation in the other's feelings (Huber and MacDonald 2012). The literature demonstrates that empathy is associated with more sustainable behavior (Ericson et al. 2014). Furthermore, several empirical studies show a link between empathy with the environment and self-reported environmental concern and attitude. For instance, Schultz et al. (2004) finds that the extent to which an individual believes that s/he is part of nature is positively associated with a biosphere-related concern. Similarly, individuals who demonstrate a high (as compared to low) empathy level towards a natural object are found to display stronger environmental attitudes and behavior (Berenguer 2007). Demonstrated in an experimental setting, individuals with higher environmental concerns are also found to more likely take environmental actions (Czap and Czap 2010). This evidence suggests that appealing to empathy is likely to positively affect conservation decisions. Hence, empathy plays a vital role in moving individuals toward pro-environmental and conservation behavior. I, therefore, postulate:

H2: Empathy nudging increases the likelihood of consumers purchasing secondhand electronic products in the B2C secondary market.

4.2.5. Price and Perceived Quality

The sale of used IT products and consumer purchase decisions in the secondary market are impacted by multiple different factors. Prior research has show that there are different attributes that could impact the sale of secondhand products, such as consumer preferences (Kim et al. 2005, Agrawal et al. 2015), quality uncertainty and search costs (Tibben-Lembke 2004, Kuruzovich et al. 2008), and price (Ghose 2009, Elmaghraby et al. 2018). In specific, the price of a used relative to a new product could be an important factor when making a decision to purchase. Indeed, prices are shown in the literature to impact consumer decision and willingness-to-pay in both the primary and secondary markets (PK Kannan 2001, Gupta et al. 2004, Seiler 2013, Chou et al. 2013, Elmaghraby et al. 2018). Moreover, the price of a product can determine the period of which the product would stay on shelves. For example, used goods with higher prices are found to take longer time to sell in the market (Ghose 2009). Hence, higher prices can negatively impact the willingness to buy used IT products in the secondary market.

On the other hand, in the case of used products, the marketing literature shows that there is a positive relationship between price and perceived quality of a product whenever there is potential risk or uncertainty involved in its use (Peterson 1970, Gerstner 1985, Erdem et al. 2008). In the situation where consumers have imperfect information with regards to used products, price can serve as a signal for a specific level of quality – a higher price signals higher quality of a product (Wolinsky 1983, Chang and Wildt 1994). The literature in marketing science further shows that a signal of higher quality can increase the purchase intention of consumers in markets where information asymmetry exists (Chang and Wildt 1994). Hence, prices can be a key factor in driving the decision to buy used IT products in the market, which could also possibly offset or moderate the effects, if any, of using green nudges. However, it is not clear how or in what direction a certain price would impact the efficacy of using green nudges in altering consumer preferences in favor of the used products.

4.2.6. Consumer Characteristics

The purchase behavior and product preferences for consumers can vary based upon different consumer characteristics, being observable or latent. For instance, consumer purchase behavior can differ based on gender, age and social class (Gupta et al. 2004, Bigne et al. 2005). Furthermore, using green nudges could display heterogeneous effects, if any, on different consumer characteristics. In particular, prior research has shown that men and women are motivated differently, and that gender plays an important role in shaping determinants of pro-environmental behavior (Wymer and Samu 2002, Davis et al. 2014, Vicente-Molina et al. 2018, Briscoe et al. 2019). The literature also presents that there are generational differences when it comes to motivations and values, particularly with respect to taking pro-environmental actions such as recycling (Saphores et al. 2012, Acar 2014, Reese and Jacob 2015). Hence, observable consumer characteristics, such as age and gender, could moderate the efficacy of the green nudge in enhancing consumers' willingness to buy used IT products.

Moving from the observables to the latent space of characteristics and traits, i.e., consumer personality, research in personality and individual differences has shown that personality affects various aspects of individual behavior, including job performance, academic motivation, and attitudes toward computer and information systems (Komarraju and Karau 2005, Devaraj et al. 2008). Focusing on consumer preferences, prior work has demonstrated that personality characteristics can predict whether people would be more likely to accept a suggested product or service (Hu and Pu 2011). Likewise, prior literature indicates that personality also affects the human decision-making process, such as consumers' brand preferences and effectiveness of recommendation agents (Lin 2002, Adamopoulos and Todri 2015). Therefore, in my context, consumer latent characteristics could moderate the efficacy of using green nudges in altering consumer preferences towards used IT products.

It is widely accepted today that there are five robust factors of personality that can serve as a meaningful taxonomy for classifying personality attributes (Goldberg 1981). The most influential taxonomy of personality attributes is admittedly the "Big Five" taxonomy, and it serves as a useful integrative framework for thinking about individual differences at a fairly high level of abstraction (Baumgartner 2002). The five-factor taxonomy proposes a comprehensive theoretical framework of five factors necessary and sufficient to represent human personality in terms of traits. It is a framework for distinguishing, ordering, and naming the behavioral, emotional, and experiential characteristics of individuals (John and Srivastava 1999).

The literature generally defines the latent personality dimensions as follows. The first dimension, i.e., *Agreeableness*, captures a person's tendency to be compassionate and cooperative toward others. This factor is associated with altruism, cooperation, trustfulness, empathy, and compliance. The second dimension is *Conscientiousness*, which describes a person's tendency to act in an organized or thoughtful way. Individuals characterized by high levels of Conscientiousness tend to be driven, deliberate, organized, persistent, and self-assured. The third dimension of the Big Five–factor model is the *Extraversion* dimension that refers to a person's tendency to seek stimulation in the company of others. Extraversion consists of outgoingness, sociability, assertiveness, and excitement-seeking behaviors. The fourth dimension is emotional range (i.e., *Neuroticism*), which describes the extent to which a person's emotions are sensitive to the individual's environment. The tendency of an individual to be worried, depressed, self-conscious, and hedonistic is captured by the aforementioned dimension. Finally, the fifth dimension is that of *Openness*, which refers to the extent to which a person is open to experiencing a variety of activities. Adventurousness, intellect, creativity, and liberalism define the Openness to experience of individuals (see, John and Srivastava 1999, for more details). All these personality dimensions suggest different individual behavior that could manifest in consumers' willingness to buy used IT products after receiving green nudges.

4.3. Experiment

I begin by discussing the design and procedure of my experiments. I then move to the results of the first stimulus, being a conspicuous conservation nudge (Study I). Finally, I discuss the results of the second stimulus, i.e., an empathy evoking-nudge (Study II).

4.3.1. Designs and Procedure

I conduct behavioral experiments using the Mechanical Turk online panel offered by Amazon (MTurk). MTurk has been successfully used in experimental research in several different fields (e.g. Capraro et al. 2019, Agrawal et al. 2015, Erat and Bhaskaran 2012, Chiou and Tucker 2012). It matches the U.S. population more closely than college student subject pools or other Internet panels, i.e., a reasonable source of subjects for my study, and there is recent evidence that results obtained from it do not significantly differ from those found in laboratory settings (Paolacci et al. 2010). The experiment is restricted to participants based in the United States and each participant is paid $1. This payment is competitive with other studies on MTurk and is equivalent to $8/hr based on the average completion time of 7 minutes (Agrawal et al. 2015). Responses are obtained from 360 unique participants, with an average age between 35-44 years and 42% are female. In order to ensure reliability and high quality of responses, I use a screening condition where I restrict the pool of participants to those how have HIT approval rate of 90% and higher (Stewart et al. 2015). The HIT approval rate represents the proportion of completed tasks that are approved by requesters – a tool I leverage to direct my studies to experienced participants on MTurk. [23]

In terms of design parameters, my main interest is in used technology products in the B2C secondary markets. Considering that small technology products are found to account for the

[23] https://blog.mturk.com/qualifications-and-worker-task-quality-best-practices-886f1f4e03fc

largest share of the overall e-waste management market in 2019, especially those with continuously updating models and higher replacement rates (Meticulous Market Research 2020), I therefore focus on used smartphones, iPhones in specific. For the pricing model, I use posted prices due to the greater flexibility they provide me in studying consumers' decisions between new and used smartphones (Einav et al. 2016).

In order to effectively test for my hypotheses, I consider and control for possible heterogeneity that could have significant impacts on consumer behavior. For instance, the price of a used relative to a new product could be an important factor when making a decision to purchase. Indeed, prices are shown in the literature to impact consumer decision and willingness-to-pay in both the primary and secondary markets (PK Kannan 2001, Gupta et al. 2004, Seiler 2013, Chou et al. 2013, Elmaghraby et al. 2018). Hence, prices can be a key factor in driving the decision to buy for any of the offered products in the market, which could possibly offset the effect, if any, of using green nudges. I therefore consider three price points reflecting real market prices (Table 4.1).[24]

Experiment Procedure. For each study in my experiment, I use a 3x3 between-subjects design, where each participant is randomly assigned to one of nine possible cells. First, each participant is assigned to one of three possible conditions: control, treatment 1, and treatment 2. Second, the participant receives one price point from three different options: low price, medium price, and high price. The diagram in Figure 4.1 depicts the flow of participants' assignment in each cell. Finally, participants receive a set of choices between a new and used iPhone of the same generation. The subject is asked then to choose between the two phones in terms of willingness to buy. Each participant takes part in two such tasks, where the iPhone models on offer come from different generations. Thus, all participants receive two separate tasks of offers,

[24] All price points are obtained from www.camelcamelcamel.com

one for a newer generation smartphone (iPhone 11) and the second for an older generation smartphone (iPhone XR), with the order of these offers being randomized across subjects. The reason for using two different iPhone generations is to account for potential generation effects, i.e. demand for older generations of smartphones may structurally vary from demand for the newer generation. Participants in the treated groups are provided with a green nudge embedded in the offer of the used iPhone. The type of green nudge remains the same for both tasks that participants receive, i.e. a subject receiving treatment 1 in the first task also receives treatment 1 in the second task. There are no stimuli (green nudges) provided in the control group (Figure A4.2). All used phones offered to the participants have the same specifications and quality condition, i.e., Refurbished.[25]

Before starting the experiments, all participants are provided instructions for the experiments followed by a short summary about the context of the lifecycle of smartphones (shown in Figure 4.2). Subsequently, participants are asked a set of 5-point scale statements as manipulation checks to ensure that my treatments hold (Table A4.1). After each task, participants who elect to buy the new iPhone are asked for the reasoning behind not considering the used iPhone (Table A4.3). At the end of the experiment, participants are asked to provide their demographics, such as age, gender, ethnicity, education, and marital status.

To measure the big five personality traits of the participants, I use the lexical big five inventories, i.e., Goldberg's (1992) Big Five Factor Markers. During the experiment, participants are given 50 short statements or phrases that are randomly distributed throughout the experiment, consistent with the "Big-Five" taxonomy (Goldberg 1992). They were asked to agree or disagree, on a scale of 1 to 5, to each phrase. Based on their answers, the results show where

[25] Refurbished products are returned items that are fully tested and inspected by highly trained technicians and restored to original factory specifications (Agrawal et al. 2015).

each participant falls on a spectrum for each trait (Goldberg 1992, Judge and Bono 2000). In order to have a reasonable measure for each personality trait, I run a confirmatory factor analysis to find the minimum set of independent linear combinations of responses that can explain as much variance as the original items for each personality trait. The factor analysis procedure provides factor loadings of these individual items on the underlying latent factors. Factor loadings are the correlation coefficients for the variable and latent factor. An item that is heavily associated with a certain latent factor will mostly have high loading on that factor (Ford et al. 1986). Hence, following prior work in the literature, I use the score of 0.6 as the baseline for my factor loadings (Hair et al. 2011, Baistaman et al. 2020). I then use these factors in my main models.

4.3.2. Preliminary Analysis of Nudges on Willingness to Buy

Before I start my analysis, I ensure that randomizations with respect to participants' demographics and the manipulation checks with respect to both treatments, i.e., whether the message of the treatment is delivered, hold. Using ANOVA to test for the difference in means between different demographics of participants in the treated and control groups, I find no significant difference in means between both groups with respect to age, gender, ethnicity and education ($p>0.1$). Furthermore, the Bartlett's test for equal variances shows that there is no difference with respect to homogeneity of variances across both groups. I also examine the difference in means of participants' responses to the manipulation check statements between both groups, and found that there is a significant difference in means between the treated and control groups ($p<0.01$); hence, the manipulation holds.

To examine my hypotheses with respect to the impact of the internal and external motivations the green nudges deliver on consumers' willingness to buy a used smartphone, I conduct logistic regressions with consumer decision to purchase a used iPhone as the dependent variable. The main independent variable in my model is the type of green nudge used, i.e. treatment 1 is the conspicuous conservation nudge and treatment 2 is the empathy nudge. I control for potential generation effects by including the generation of the offered iPhone. I also account for potential order effects by including a control variable accounting for which offer was presented first between iPhone 11 and iPhone XR (Hogarth and Einhorn 1992). I further include participants' demographics as controls (see Table 4.2 for details of variable operationalization).

First, I start a preliminary analysis by using the full 3x3 model that includes both treatments in my logistic regression, while holding the control group as a base. The results are in Table 4.3. In column 1, the results show that the conspicuous conservation nudge has a positive and significant impact on the propensity of consumers purchasing the used iPhone (0.256, $p<0.05$). However, I find that the direct effect of the empathy nudge is absent (0.107, ns). Furthermore, in columns 2 and 3, the interactions between the newer model, i.e. iPhone11, with both treatments yield significant and positive impacts on participants willingness to buy used iPhones, indicating that the efficacy of the nudge is higher on newer iPhone generations. Using the low price point as a base, I find that the price level shows different impacts on participants' willingness to buy. In specific, the middle price point shows a negative and significant impact relative to the low price, whereas the high price point shows a similar positive impact on the willingness to buy used iPhones, albeit insignificant.

The preliminary analysis shows underlying treatment-level heterogeneities that need further attention. Therefore, in the following sections, I dive into the separate treatments in more detail by selecting the appropriate cells for each analysis. I first consider the conspicuous conservation nudge, and select only the cells that relate to this treatment and the control group.

Subsequently, I focus on examining the second treatment in detail by selecting the cells pertaining to the Empathy nudge and the control group.

4.3.3. Study I (Conspicuous Conservation Nudging)

This section examines how the use of conspicuous conservation green nudges could impact the propensity of participants to purchase used electronic products, i.e., a pro-environmental action. Hence, participants in the treated group are presented with a green nudge that includes a pro-environmental message with a default option of disclosing their purchase with friends on a social media platform to evoke conspicuous conservation (Figures 4.3). Using logistic regressions, the results in column 1 of Table 4.4 show that after adding the treatment, i.e., a conspicuous conservation green nudge, to the used iPhone offer, the propensity of participants to purchase used iPhones has significantly increased (0.271, $p<0.05$). The results show that allowing consumers to share their pro-environmental actions within their friends' community (i.e., an external motivation) has positively impacted their preferences towards purchasing the used product by 31%, all else equal. Hence, H1 is supported. In column 2, the interaction between the treatment and iPhone 11 further shows that the impact of the green nudge is greater for the newer generation of iPhones (0.316, $p<0.05$). In specific, the green nudge shows a higher impact on participants' willingness to buy the used iPhone 11 (the newer model) than the used iPhone XR (the older model) by 15%, ceteris paribus. This effect could be due to the fact that older generations have been in use for a longer period of time relative to newer generations of iPhones and, hence, they have relatively higher uncertainty with respect to their quality.[26] In both columns 1 and 2, I see that price has a diverse impact on the willingness to buy a used iPhone

[26] In unreported regressions, I have separated the iPhone generations into two different samples with fully consistent results, which are available upon request.

with, paradoxically, medium prices showing a higher negative impact relative to the other two price points (–0.463, $p<0.01$).

I, therefore, explore how participants respond to the treatment given different prices for the used iPhone. By so doing, I examine the impact of the different price points on the efficacy of the green nudge. For better interpretations of the results, I stratify the sample into three different sub-populations based on each price point. In columns 3-5, I see that the treatment shows a different impact based on the price provided to the participants. I plot the predicted probabilities of purchasing a used iPhone for each price point (Figure 4.4).

The results in Figure 4.4 produce a U-shaped effect of price on the likelihood to purchase a used phone, and this pattern exists for both the control and treated groups. The results suggest that participants are interpreting the price level as a signal of quality for the used iPhone. Indeed, the marketing literature shows that there is a positive relationship between price and perceived quality of a product whenever there is potential risk or uncertainty involved in its use (Peterson 1970, Gerstner 1985, Erdem et al. 2008). Hence, the utility function of the participants is influenced by price and perceived quality. At a low price point, the price seems to dominate the decision and so becomes the most important factor, which results in increasing the participant's utility. At the high price point, the price can signal a high quality for the used phones, thereby increasing the participant's utility (Gerstner 1985). On the contrary, at the middle price point, disadvantage of the low price and high quality yields lowest utility to participants. This notion further explains the difference in magnitude for the effect of the green nudge at different price points, where a participant's response to the treatment is relatively higher at the low and high price points compared to the middle one.

To further verify my logic with respect to the impact of price, I ask the participants – particularly those who elected to purchase a new phone – at the end of each task for their reasoning behind not considering the used iPhone. The question consists of four choices: 1) the price of the used iPhone is too high, 2) I am concerned about the quality of the used iPhone, 3) I don't buy used phones, and 4) Other. The responses indicate that participants are concerned the least about price at the low price point (37%) and quality at the high price point (32%), whereas the results are mixed at the middle point. I further explore participants' open ended reasoning for not considering the used iPhone. The responses reflect my conjecture about price and quality. For instance, a participant who received a low price offer and decided to purchase the new phone, said: "*I'd rather pay more for the new phone, more reliable*." Similar responses repeat at the low price level where the main concern of participants is quality. On the other hand, participants at the high price level express concerns with respect to price rather than quality. For example, one participant explained: "*if I'm throwing down 500 dollars for a used phone, I might as well pay an extra 18% for a brand new one,*" where another participant added: "*High price point where the gap between refurbished and new isn't large enough for me to consider the saving potential*." The responses show a similar pattern to my hypothesis with respect to the effect of price and quality. Hence, the data provide me with further support to my logic for the difference in the efficacy of the treatment at different price levels.

4.3.3.1. Conspicuous Conservation Nudging on Different Populations

To better understand the impact of the conspicuous conservation nudge on different populations, I explore how participants respond to the treatment based on their gender and age. The literature shows that men and women are motivated differently, and that gender plays an important role in shaping determinants of pro-environmental behavior (Wymer and Samu 2002, Davis et al. 2014, Vicente-Molina et al. 2018, Briscoe et al. 2019). The literature further shows that there are generational differences when it comes to motivations and values, particularly with respect to taking pro-environmental actions such as recycling (Saphores et al. 2012, Acar 2014, Reese and Jacob 2015). Therefore, I further examine how conspicuous conservation green nudging can impact different genders and generations with respect to purchasing used smartphones.

Conspicuous conservation theory argues that individuals seek status through display of personal pro-environmental actions (Sexton and Sexton 2014). Research in social psychology and gender differences argues that men's behaviors reflect a desire for social status relative to women (Baumeister and Sommer 1997, Anderson et al. 2001, Kwang et al. 2013). In particular, psychologists and social theorists have argued that status is relatively less important to women than to men (Anderson et al. 2001), and that "men are predicted to be higher in status striving than women" (Buss 1999, p. 43). Therefore, it is reasonable to expect that men would have a relatively higher response to the conspicuous conservation nudge that women do. Therefore, I postulate that:

H3A. *Conspicuous conservation nudging has a higher impact on men's behavior towards purchasing a used iPhone relative to women.*

Furthermore, research in generational differences show that younger people tend to be more social and have greater social networks relative to older people, and older people spend less time with others than younger people do (Lang and Baltes 1997, Marcum 2013). Other research in social and behavioral sciences shows that younger generation consumers respond better to social media marketing relative to older generations (Balakrishnan et al. 2014). For marketing campaigns, marketers tend to use different approaches to target older generation consumers relative to the younger generation (Kuligowski 2020). Therefore, I posit that:

H3B. *Conspicuous conservation nudging has a higher impact on younger generations' behavior towards purchasing a used iPhone relative to older generations.*

In Table 4.5, the baseline model in column 1, shows that, in general, there is no difference in purchasing a used iPhone between men and women (-0.0521, ns), and participants who are 45 years and older compared to the younger population (-0.139, ns); 45 is the median for the range of participants' age in my sample. The results also reconfirm the positive effect of the treatment in increasing the willingness to buy used iPhones (0.244, $p<0.05$). I now examine the impact of the green nudge with respect to different gender and age. In column 2, I look at the interaction between men and my treatment. The results suggest that there are no gender differences when participants are externally motivated, via a green nudge, to purchase the used iPhone, i.e., gaining a social status by taking a pro-environmental action (-0.319, ns). In column 3, the results show that there is a marginal significant generational effect when receiving the treatment (-0.220, $p<0.1$). In particular, participants who are 45 years and older are relatively less likely to purchase the used iPhone when provided the opportunity to share their purchase decision on a social media platform. Figure 4.5 plots the predicted probabilities of purchasing used iPhones for both generation participants. The figure shows a clear difference in the magnitude of the green nudge effect between both generations. In specific, I find that the willingness to buy a used iPhone for the older participants increases by approximately 5% after receiving the green nudge, whereas the propensity of buying a used iPhone increases by 28% for the younger participants after given the green nudge.

As previously discussed, I find that the literature supports this behavior from the younger generation (Balakrishnan et al. 2014). Research conducted by a social media analytics platform shows that 40% of individuals in the United States who are above the age of 49 have never posted anything on social media, whereas 12% of younger individuals have never posted on social media, indicating that younger individuals are more active on social media.[27] In my context, I find that there exists a marginal difference between younger and older participants when receiving the conspicuous conservation green nudge. The younger participants tend to respond marginally higher to the treatment, which indicates that sharing the purchase with friends on social media is an appealing aspect of the purchase. On the other hand, this option is less appealing for the older participants to change their willingness to buy. In the next section, I expand my examination by studying to what extent a conspicuous conservation nudge could impact different participants based on their personality traits.

4.3.3.2. Conspicuous Conservation Nudging and Personality Traits

To gain deeper insights into the user's characteristics that accentuate or attenuate the effectiveness of green nudges and extend the characteristics from the observable (e.g., gender and age) to the latent space of characteristics and traits (e.g., personality), I draw from established theories in psychology and social sciences to examine whether the personality traits of the participants attenuate or accentuate the effectiveness of green nudges.

Conspicuous conservation theory argues that socially responsible products, i.e., green products, provide a value to their consumers in social interactions (Iyer and Soberman 2016). This theory further argues that consumers have extrinsic social comparison preferences that are based on their meetings with others in social interactions. The frequency of these meetings is endogenous to the consumption choices of consumers. A consumer enjoys a social comparison benefit if her consumption decision is more socially responsible than the consumer that she meets in a social interaction, and a social comparison cost if it is less socially responsible (Iyer and Soberman 2016). Using the Big-Five taxonomy of personality traits in my context, I would

[27] https://www.synthesio.com/blog/social-media-usage-statistics-by-age/

expect that people who seek stimulation in the company of others (i.e., extraverted participants) would more likely choose to purchase the used iPhone after highlighting the environmental benefits of buying a used phone and sharing the purchase within their social milieu. I therefore postulate that participants with higher levels of Extraversion are more likely to purchase a used iPhone when given the conspicuous conservation nudge.

Furthermore, research in psychology shows that individuals associated with higher levels of Neuroticism are young adults (Donnellan and Lucas 2008). As discussed earlier, younger adults tend to be more social and have greater social networks relative to older people (Lang and Baltes 1997, Marcum 2013). Therefore, it is reasonable to assume that individual who scores higher on neuroticism are more likely to respond to the conspicuous conservation nudge. I then argue that participants with higher levels of Neuroticism are more likely to purchase a used iPhone when given the conspicuous conservation nudge.

Measures and Results. To measure the big five personality traits of the participants, I use the lexical big five inventories, i.e., Goldberg's (1992) Big Five Factor Markers, combined with a confirmatory factor analysis in order to have a reasonable measure for each personality trait. I then use the resulting factors in my logistic regressions. The results are in Table 4.6.

The variable *Extraversion* in column 1 shows that participants who obtained higher scores on the Extraversion dimension are, on average, less likely to purchase a used smartphone (-1.689, $p<0.01$). However, the interaction in column 2 shows that using a conspicuous conservation nudge can significantly enhance the propensity of extraverted individuals to purchase a used iPhone (2.571, $p<0.05$). The results suggest that the social aspect of the nudge has motivated extraverted participants to make a pro-environmental action.

In column 3, I find that individuals who score higher on the *Neuroticism* factor are marginally more likely to purchase a used iPhone (0.977, $p<0.1$). However, their propensity to purchase a used iPhone significantly increases after given the treatment, column 4 (2.113, $p<0.1$). Beside the argument that Neuroticism is associated with younger individuals, people with higher scores on Neuroticism tend to be emotionally affected by their environment. The results suggest that sharing a positive message with friends delivers positive feelings to individuals with higher scores on Neuroticism and, hence, yields a higher propensity to purchase a used phone when given the conspicuous conservation nudge.

The remaining three personality traits have no theoretical underpinning to show significant association with the conspicuous conservation nudge. For instance, individuals who obtain higher scores on Openness tend to be adventurous, intelligent, and creative (John and Srivastava 1999). Research shows that intelligent and creative people are more likely to be loners, and are not strongly motivated by social acceptance and conformity because of their interests and views on bigger ideas about which they care (Piketty 1998, Berman 2018). Hence, I theoretically assume that the conspicuous conservation nudge would not have a significant impact on this group of individuals.[28]

4.3.4. Study II (Empathy Nudging)

In this section, I focus on studying the impact of an internal and emotional motivation by examining to what extent the use of an empathy-evoking green nudge could impact the propensity of participants to purchase used smartphones. Participants in the treated group are presented with a green nudge that includes an empathy-evoking message that focuses on activating empathy feelings for the participants (Figures 4.6). The results for the main effect of

[28] I also examine the effect of the treatment with respect to the remaining three personality traits, and find no significant change in behavior, as anticipated. The results are available upon request.

the treatment are shown in Table 4.7. In column 1, I find that adding an empathy-evoking green nudge has no significant impact on the willingness to buy a used iPhone (0.113, ns). The results suggest that, opposite to conspicuous conservation, using an internal motivating nudge does not significantly change consumer behaviors towards used electronics.

I further examine whether the empathy treatment shows different effects based on different iPhone models, i.e. older versus newer generations. In column 2, the interaction between the treatment and the new generation of iPhones (i.e., iPhone 11) shows a marginally positive impact on participants' behavior towards purchasing the used iPhone 11 (0.179, $p<0.1$). It is reasonable to assume that newer generations of used smartphones tend to have relatively less quality uncertainty compared to older generations due to the time for which they have been in use. The experimental data further support this premise. For example, 57% of participants who elected to purchase the new iPhone of the older generation (iPhone XR) show concerns about quality, relative to 44% for the newer generation (iPhone 11). Similarly, the open ended reasoning for not purchasing the used iPhone of the older generation indicates a higher level of quality concerns compared to the used iPhone of the newer generation. Participants share comments expressing the level of concerns about quality and generation, such as "*older model to be bought used, risky*," and "*I'd like to be more green, but might end up bearing the cost of older versions*." Therefore, the results imply that lower uncertainty with respect to the used phone could, to some extent, enhance the efficacy of the empathy-evoking nudge.

I further explore how participants respond to the treatment given different prices for the used iPhone. Similar to study 1, I stratify the sample into three different sub-populations based on each price point. In columns 3-5, I see that the treatment shows a different impact based on the price provided to the participants. The results show that the empathy nudge is marginally significant and has a positive effect at the low price point (0.190, $p<0.1$). I plot the predicted probabilities of purchasing a used iPhone for each price point (Figure 4.7).

Interestingly, the results in Figure 4.7 produce a U-shaped effect of price on the willingness to buy a used phone, similar to the effect in study 1 (Figure 4.4), suggesting that participants are interpreting the price level as a signal of quality for the used iPhone. I see that the empathy nudge is, relatively, more effective at the low price level, which indicates that a combination of a low price offer and an empathy nudge could, marginally, impact consumer behavior towards purchasing the used iPhone.

Overall, the empathy green nudge seems to have less effectiveness in altering consumer behavior towards used smartphones. The literature in nudging and decision-making shows that individuals who felt confident in their ability to make good decisions about, for instance, healthy eating or spending money wisely were less comfortable about being nudged than those who knew they needed help (Felsen et al. 2013). The authors of this research work further argue that it is not the case where such individuals think that spending money wisely is a bad idea, but rather they are less amenable to giving up autonomy if they felt they could do it themselves. Following this logic, it is probable that a number of participants in the experiment are less comfortable about being nudged to contribute to the environment and well being of those living around e-waste, even when they agree with the action and cause. Nevertheless, it is plausible that the internal motivation of the empathy nudge could impact populations differently. In the next section, I examine the efficacy of the empathy treatment with respect to different age and gender of the participants.

4.3.4.1. Empathy Nudging on Different Populations

As discussed in section 4.3.3.1, the literature focusing on gender differences indicates that individuals can be motivated differently based on their gender, and that gender plays an important role in shaping determinants of pro-environmental behavior (Davis et al. 2014, Briscoe et al. 2019). In addition, prior research shows that men tend to show lower levels of empathy than women do, and that women's brains show more empathy when watching others suffering (Schieman and Van Gundy 2000, Toussaint and Webb 2005, Christov-Moore and Iacoboni 2019). Hence, when provided with an empathy-evoking green nudge, I would assume women to have a higher response to the nudge relative to men. I then posit that:

> *H4A. Empathy nudging has a higher impact on women's behavior towards purchasing a used iPhone relative to men.*

The literature further shows that there are generational differences when it comes to motivations and values, particularly with respect to taking pro-environmental actions (Saphores et al. 2012, Acar 2014, Reese and Jacob 2015). Moreover, research in social psychology shows that the level of self-reported empathy varies between individuals based on their age, with higher levels of reported empathy among older adults (Schieman and Van Gundy 2000). Therefore, I posit that older generation adults tend to respond higher to the empathy nudge relative to the younger adults.

> *H5B. Empathy nudging has a higher impact on older generations' behavior towards purchasing a used iPhone relative to younger generations.*

In Table 4.8, I find that the main effect of the empathy green nudge remains insignificant in all three models. However, in column 2, the interaction between the treatment and Female is positive and significant (0.189, $p<0.05$). The results show that, on average, women relative to men are willing to change their purchase behaviors in favor of the used iPhones when provided with the empathy nudge. Consistent with prior literature, women respond positively to the treatment by showing more empathy towards the cause of the purchase. Likewise, in column 3, I find the interaction between the treatment and participants who are above the age of 45 is positive and significant, indicating that older generation individuals respond positively to the empathy nudge and have higher propensity to purchase the used iPhone (0.565, $p<0.05$). I plot the predicted probabilities of purchasing used iPhones for both gender and age for better visualizations of the results (Figures 4.8 and 4.9).

Figure 4.8 shows the difference in probabilities between men and women. The propensity of women to purchase the used iPhone increases by 23.5% after receiving the empathy green nudge, whereas men do not significantly respond in the same direction. Similarly, in Figure 4.9, I find that older participants tend to positively respond to the empathy treatment through enhancing their propensity of purchasing the used iPhone by 20.4%. The younger generation, on the other hand, shows different behavior after receiving the empathy nudge. These two patterns by men and younger individuals are consistent with the premise that there are individuals who are less amenable or comfortable for being nudged to contribute to the environment and well being of those living around e-waste, even if they agree with the action and cause. In the next section, I further expand my investigation by studying how the empathy nudge impacts different participants based on their personality traits.

4.3.4.2. Empathy Nudging and Personality Traits

Using the big five taxonomy for personality traits (Goldberg 1981), I examine how an empathy-evoking nudge would impact the decision of the participants based on their personality. One latent personality dimension in the big five taxonomy is *Extraversion*, which refers to individuals who are social and seek stimulation in the company of others. Prior literature in social sciences and networking shows that high levels of extraversion is correlated with high subjective well-being, and further argues that empathy can be an intermediating variable between extraversion and subjective well-being (Kalpdor 2017, Chan 2014).[29] Hence, I would assume that participants with higher levels of Extraversion are more likely to purchase a used iPhone when given the empathy nudge.

Furthermore, another personality dimension is *Agreeableness*, which captures a person's tendency to be compassionate and cooperative toward others. This factor is associated with altruism, cooperation, and empathy. Research in age differences and personality traits shows that agreeableness is positively associated with age, i.e., people in the post 50s show higher levels of Agreeableness (Donnellan and Lucas 2008). I also find earlier that age is positively associated with the empathy nudge. Hence, I posit that participants with higher levels of Agreeableness are more likely to purchase a used iPhone when given the empathy nudge.

Furthermore, prior research in human psychology shows that empathy enhances emotional intelligence and boosts creativity, which, in turn, facilitates innovation and invention, rendering empathy positively associated with creativity (Carlozzi et al. 1995, Bergland 2021). *Openness*, as a personality dimension, refers to the extent to which a person is open to experiencing a variety of activities. Adventurousness, intellect, creativity, and liberalism define the Openness to experience of individuals. Henceforth, I conjecture that participants with higher levels of Openness are more likely to purchase a used iPhone when given the empathy nudge.

Measures and Results. The results are shown in Table 4.9. Consistent with previous findings, the variable *Extraversion* in column 1 shows that participants who obtain higher scores on the Extraversion dimension are less likely to purchase a used smartphone (-1.487, $p<0.01$).

[29] https://www.grin.com/document/448549

However, the interaction in column 2 shows that using an empathy nudge can significantly enhance the propensity of extraverted individuals to purchase a used iPhone (2.571, $p<0.05$). The results indicate that an empathy-evoking nudge increases the willingness to buy of extraverted individuals to take a pro-environmental behavior with respect to used smartphones.

In column 3, I find that individuals who score higher on the *Agreeableness* factor have a higher propensity to purchase a used iPhone (2.773, $p<0.01$). However, their tendency to purchase a used iPhone marginally increases after given the treatment, column 4 (1.019, $p<0.1$). This result can further support my pervious argument that some individuals who agree with the action or the cause, even if their personality is associated with empathy, may be less amenable or comfortable about being nudged for it. Finally, with respect to the relationship between creativity and empathy, the results in column 6 show that individuals who have higher scores on Openness are marginally responding to the treatment and, therefore, their decision to purchase a used product does not significantly change when given the empathy treatment (2.372, $p<0.1$).[30]

4.4. Conclusion and Implications

In this essay, I use behavioral experiments to investigate the effect of behavioral interventions in the form of green nudges in enhancing consumers' willingness to buy used smartphones. I use two orthogonal motivations as nudges and examine their efficacy in altering consumer purchase behavior: 1) external motivation embedded in conspicuous conservation, and 2) internal motivation targeting consumers' emotional empathy.

I find that using a conspicuous conservation green nudge has a positive impact in altering consumer behavior towards used smartphones. Individuals who receive this treatment show a higher propensity to purchase the used iPhone. The results from my first experimental study

[30] I also examine the effect of the treatment with respect to the remaining personality traits, and find no significant change in behavior. The results are available upon request.

suggest that the effect of the external motivation green nudge is consistent based on different individual characteristics, such as age and gender. However, the efficacy of the nudge varies based on different personality traits. I further find that the impact of the conspicuous conservation nudge varies based on the price and model of the used iPhone. I argue that this difference could be due to the perceived quality from low prices and older models of the used iPhone.

In my second experimental study, I find that the use of an internal motivation green nudge targeting emotional empathy can be effective conditional on certain individual demographics. In specific, women and older participants are willing to change their purchase behaviors in favor of the used iPhone when provided with an empathy-evoking green nudge. Furthermore, participants tend to respond differently to the treatment based on certain personality traits. I also find that the treatment is marginally more effective for the newer iPhone model, which I conjecture that this effect is due to the inherent higher quality uncertainty for the older model relative to the newer one. It is nevertheless important to note that, on average, the *main effect* of the empathy treatment is absent in my experiment. A potential explanation is that, when provided with an internal motivating green nudge such as emotional empathy, a number of individuals feel less amenable to giving up autonomy if they felt they could do it themselves (Felsen et al. 2013). In other words, they are less comfortable about being nudged to contribute to the environment and human well being, even when they agree with the action and cause. In sum, my study shows that the utility consumers derive from taking a pro-environmental action is relatively higher when the reward or motivation is external relative to internal.

There are several imperative implications of this essay. First, my results have important implications for the literature studying how used IT products cannibalize newer products, and how to manage the cannibalization impacts of secondary markets (Ghose et al. 2005, Oraiopoulos et al. 2012). I extend the literature by arguing that enhancing the used product's cannibalization effect, from an ecological perspective, is beneficial. Enhancing the sale and increasing the lifetime of used IT products would eventually reduce the amount of e-waste dumped in landfills today and, therefore, the adverse effects of e-waste around the world.

Furthermore, from an economic perspective, maintaining the viability and enhancing the efficiency of the secondary market could positively impact prices of new products in the primary market. In particular, the effect of the secondary market on product-line pricing manifests in that secondhand customers pay a relatively lower price for the second-generation product, whereas upgraders pay a higher price when secondhand markets exist (Zhao and Jagpal 2006). The relatively lower prices of the used products impact primary market consumers to pay higher prices for newer products with less quality uncertainty (Bester 1998). Also, prices of secondhand products are a percentage of the new product price, where the percent difference depends on quality (Stephenson 2005). Hence, prices between primary and secondary markets are linked, with prices moving in the same direction. I show in this essay how the use of green nudges can significantly enhance sale of used IT products (i.e., smartphones) at a high price level. Enhancing the sale of higher used product prices, via the use of green nudges, can be used to support higher primary market prices. Retailers can, therefore, charge higher prices in the primary market for the brand new products.

Second, this essay focuses on the implications of green nudges and how they could possibly alter consumer preferences in favor of used IT products. I demonstrate how mechanisms can be used as "nudges" to enhance the willingness to buy used electronics for the sake of environmental protection. Furthermore, I explore the role of individuals' internal and external motivations to perform pro-environmental behavior (Czap 2015). My contribution lies in showing the effectiveness of different types of green nudges and motivations in impacting consumers' willingness to buy in the context of used and durable IT products.

From managerial perspective, this essay provides guidance and proposes different methods for resellers to apply when creating their offers of used IT products in the B2C secondary market. It provides insights leading to actionable strategies for managers who would like to effectively utilize and design green nudges. In particular, I show how different types of nudges work on different individual demographics, such as age and gender. A conspicuous conservation green nudge shows a positive impact on almost all different populations of consumers, with a higher marginal impact on younger individuals. An internal motivation green nudge, i.e., an emotional empathy nudge, only works on certain groups of consumers such as female and older individuals.

I conclude by discussing other future directions for research. I carried out experiments for two types of smartphone products (iPhone 11 and iPhone XR) and three different price points. As I see a possible impact of quality uncertainty with respect to older models and lower prices, more research is required to examine the green nudge effects I identify across different product categories and for a wider range of prices. Moreover, in unreported analysis, I find that the efficacy of the nudge with respect to the type of targeted motivation can vary across populations of different race. For instance, I find that Black or African American participants show a higher response to the conspicuous conservation nudge relative to individuals from other race, whereas Hispanic participants are more likely to purchase a used iPhone when they receive the empathy treatment. Hence, a promising direction for future research would be to explore different incentives for used IT products and secondary markets and whether there is a race component that interests that directly.

Chapter 5: Conclusion

The rapid pace of technological innovation and product development today has resulted in shorter product life cycles for electronic goods. This phenomenon has led to a plethora of IT product returns that are durable and can provide value for many years. According to IDC, the market for used smartphones, for instance, is anticipated to have a compound annual growth rate of 13.6% from 2018 to 2023, and a market value of $67 billion in 2023.[31] This volume surge in IT product returns calls for scholars and practitioners to ensure higher levels of secondary market efficiency and enhance the sale of durable IT secondhand products for various beneficial reasons. First, from a consumer perspective, enhancing the sale of used products increases consumer surplus and social welfare. Every IT product that can have another life means less damage caused to our planet, and a product put in the hands of someone who otherwise would simply not be able to afford it. Second, from an economic perspective, there exists a significant relationship between primary and secondary market prices, with prices moving in the same direction. Hence, maintaining the viability and enhancing the efficiency of the secondary market can be used to support primary market prices. Last, from an ecological perspective, reducing the efficiency of the secondary market leads to critical threats to the environment that can have significant major adverse ecological effects. E-waste that ends up in landfills causes significant environmental damage, which can be avoided by extending the life of these products. Improving the sale of used IT products means less products being dumped in landfills and, therefore, less damage to the environment. Hence, my dissertation seeks to propose different mechanisms aimed at enhancing the efficiency of online secondary markets for durable IT products and the propensity of these products being purchased by other consumers.

[31] https://www.idc.com/getdoc.jsp?containerId=prUS45865720

In the first two essays, I focus on different mechanisms to enhance the efficiency of the online secondary market for durable IT products. In my first essay, I study the extent to which product decisions by key players in the primary market reduce adverse selection in the secondary market for the same set of IT products. I find that policies implemented in the primary market can significantly impact residual uncertainty about products being sold, thereby reducing adverse selection. Even if such policies have not been specifically implemented for the benefit of secondary markets, they can provide benefits by capitalizing on the extent to which primary and secondary markets are interlinked. In my second essay, I show how the addition of a marquee, i.e., high-visibility and high-quality, seller on a two-sided platform in the secondary market can impact prices obtained by *other* existing sellers for similar products. I thus address a gap in the digital platforms literature pertaining to the ostensible effect of marquee sellers. My findings go beyond the implications of adding users in two-sided platforms. I show that adding new sellers to the platform can have more nuanced effects on prices obtained on the platform. In my third essay, I take a different approach by proposing a different mechanism aimed at increasing the propensity of used IT products being purchased in the market. In specific, I show how the use of behavioral interventions in the form of green nudges can impact consumer preferences towards purchasing used and durable IT products. I contribute to the literature studying the use of behavioral interventions and its implications on consumer behavior by demonstrating how mechanisms can be used as “nudges” to enhance the chance of used electronics being purchased, in attempt to reduce environmental externalities.

Taken collectively, the findings of this dissertation provide valuable theoretical as well as practical insights about the effectiveness of different mechanisms for enhancing the efficiency of online secondary markets for IT products. First, by examining my questions using secondary datasets, I am able to examine real time market decisions and quantify their economic effects in the secondary market for durable IT products. Second, by introducing randomness into the specifications of all three essays, I am able to mitigate many of the endogeneity problems in relative previous research, which allows me to make causal claims about the effects I observe. Third, this dissertation provides several managerial insights. For policy-makers considering sustainable reverse logistics programs in the IT industry, I show the value of forward-looking policies that can benefit both primary and secondary markets. For secondary market platform providers, I show that the entry of a seller with a "marquee" brand name has a positive impact on prices of other sellers on the platform. It is imperative for the platform's provider to understand such price effects to create guidance when targeting new sellers to join the platform. Finally, for sellers in the secondary markets, I provide guidance and propose different methods to apply when creating their offers of used electronic products. Furthermore, I offer insights leading to actionable strategies for managers who would like to effectively utilize and design green nudges.

Tables

Table 2.1. Sample of Auction Descriptions

Auction Description	Locked/Unlocked Status
Apple iPhone 4, 16GB, AT&T, Unlocked, 35 Units, Grade B, Original Retail $5,000, Plainfield, IN	Unlocked
Apple iPhone 4, Black, 32GB, AT&T, Locked, 25 Units, A/B Condition, Carrollton, TX	Locked
Apple iPhone 4, 16GB, Verizon, Locked, 15 Units, Grade B, Loveland, CO	Locked
Apple iPhone 5, 32GB, T-Mobile, Unlocked - 100 Units - Grade B - Louisville, KY	Unlocked
Apple iPhone 5, 16GB, Verizon, Unlocked - 120 Units - Grade C - Louisville, KY	Unlocked
Apple iPhone 5, 16GB, AT&T, Unlocked, 10 Units, A/B Condition, Est. Original Retail $6,500, Palos Hills, IL	Unlocked
Apple iPhone 5, 16GB, AT&T - 50 Units - Grade B - Louisville, KY	Undisclosed
Apple iPhone 5, 32GB, Sprint - 80 Units - A/B Condition - Dallas, TX	Undisclosed
Apple iPhone 5, 16GB, Verizon - 80 Units - D Condition - Dallas, TX	Undisclosed
Apple iPhone 5, Black, 64GB, T-Mobile, 96 Units, A/B Condition - Dallas, TX	Undisclosed

Table 2.2. Variable Operationalization

Variables	Description
Dependent Variable	
FP_{ij}	The final price of (auction *i*, seller *j*)
Independent Variables	
$Locked_{ij}$	1 if the status of the smartphones is locked in (auction *i*, seller *j*), 0 if unlocked
$Undisclosed_{ij}$	1 if the seller *j* did not provide the status of the smartphones in auction *i*, 0 otherwise
$Model\ 5_{ij}$	1 if the pallet in (auction *i*, seller *j*) is for Model 5 iPhones, 0 otherwise
$Verizon_{ij}$	1 if carrier is Verizon in (auction *i*, seller *j*), 0 otherwise
Control Variables	
$Bidders_{ij}$	The total number of bidders participated in (auction *i*, seller *j*)
$Units_{ij}$	The total number of units in (auction *i*, seller *j*)
$StartingPrice_{ij}$	The starting price in (auction *i*, seller *j*)
$Condition_{ij}$	The average condition of the devices in (auction *i*, seller *j*).
$MemorySize_{ij}$	The memory size of the smartphones in (auction *i*, seller *j*) (e.g. 32 GB, 64 GB)
$Seller_{ij}$	The seller (retailer) *j*
Day_{ij}	Vector of dummies indicating the day of the week for start of (auction *i*, seller *j*)
$Month_{ij}$	Vector of dummies indicating the month of (auction *i*, seller *j*)
$Year_{ij}$	Vector of dummies indicating the year of (auction *i*, seller *j*)

Table 2.3. The Effect of Status Disclosure on Final Prices

VARIABLES	(1) OLS	(2) OLS	(3) OLS
Undisclosed	-0.707***	0.834***	0.751***
	(0.0461)	(0.0783)	(0.0822)
Verizon	0.435***	0.321***	0.168***
	(0.135)	(0.0816)	(0.0435)
Model 5	0.848***	0.839***	0.679***
	(0.0178)	(0.0816)	(0.101)
Bidders	0.0390***	0.0379***	0.0421***
	(0.00296)	(0.00296)	(0.00272)
Units	0.0092***	0.0091***	0.0091***
	(0.00059)	(0.00059)	(0.00058)
(Verizon x Undisclosed)		-0.262***	-0.381***
		(0.0803)	(0.137)
(Verizon x Model 5)		0.352***	0.510***
		(0.0316)	(0.163)
(Undisclosed x Model 5)		-0.656***	-0.634***
		(0.0671)	(0.0734)
(Verizon x Model 5 x Undisclosed)			-0.458***
			(0.163)
Constant	4.188***	4.160***	4.207***
	(0.0815)	(0.0916)	(0.0889)
Time FE	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes
Observations	8,179	8,179	8,179
R-squared	0.743	0.747	0.749
Adjusted-R^2	0.741	0.744	0.746

Note. Additional control variables included, such as the physical condition of phones, memory size, and auction starting price. Standard errors (in parentheses) are heteroscedasticity robust and clustered by auctions. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 2.4. The Effect of Disclosed Status (Locked versus Unlocked) on Final Prices

VARIABLES	(1) iPhone 4	(2) iPhone 5	(3) Non-Verizon	(4) Unlocked	(5) Unlocked
Locked	1.333***	-1.284***	1.167***		
	(0.154)	(0.0903)	(0.0962)		
Verizon	-0.128	0.122**		0.150***	0.163**
	(0.0877)	(0.0508)		(0.0541)	(0.0790)
Bidders	0.0373**	0.0236***	0.0216***	0.0196***	0.0197***
	(0.0154)	(0.00287)	(0.00298)	(0.00289)	(0.00290)
Units	0.00137***	0.00635***	0.00877***	0.00574***	0.00573***
	(0.000150)	(0.000278)	(0.000273)	(0.000321)	(0.000323)
Model 5				0.684***	0.685***
				(0.0328)	(0.0334)
(Verizon x Model 5)					0.155***
					(0.00901)
Constant	3.731***	5.391***	4.149***	4.103***	4.097***
	(0.331)	(0.135)	(0.116)	(0.101)	(0.107)
Time FE	Yes	Yes	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes	Yes	Yes
Observations	452	820	645	910	910
R-squared	0.771	0.882	0.866	0. 886	0. 888
Adjusted R^2	0.764	0.872	0.854	0. 877	0. 879

Note. Additional control variables are included in the models such as the physical condition of phones, memory size, and auction starting price. Standard errors (in parentheses) are heteroscedasticity robust and clustered by auctions. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 2.5. The Effect of Disclosed Status for Verizon and non-Verizon Final Prices

VARIABLES	(1) Verizon Years 2014-2015	(2) Verizon Years 2016-2017	(3) Other Carriers Years 2014-2015	(4) Other Carriers Years 2016-2017
Undisclosed	0.224***	0.221	0.540***	0.486***
	(0.0756)	(0.270)	(0.0539)	(0.0812)
(Undisclosed x Model 5)	-0.272*	-0.306	-0.687***	-0.597***
	(0.164)	(0.272)	(0.176)	(0.169)
Model 5	1.223***	1.256***	1.012***	0.986***
	(0.165)	(0.271)	(0.141)	(0.0871)
Constant	4.027***	3.741***	3.952***	3.373***
	(0.378)	(0.310)	(0.165)	(0.103)
Time FE	Yes	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes	Yes
Observations	1,420	1,398	2,743	2,618
R-squared	0.835	0.886	0.686	0.683
Adjusted R-squared	0.829	0.882	0.677	0.674

Note. This sample only contains Verizon auctions of both generations of iPhones. Additional control variables are included such as the physical condition of phones, memory size, and auction starting price. Standard errors (in parentheses) are heteroscedasticity robust and clustered by auctions. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 2.6. Placebo Analysis for Falsification (Based on Analyses Reported Earlier)

VARIABLES	(1) *Table 3, Column 1*	(2) *Table 4, Column 1*	(3) *Table 4, Column 2*	(4) *Table 4, Column 4*	(5) *Table 4, Column 5*
Undisclosed_Rand	0.000786				
	(0.0171)				
Locked_Rand		-0.0744	0.0293		
		(0.0982)	(0.0387)		
Verizon	0.454***	-0.232*	0.158***	0.212***	0.197***
	(0.129)	(0.139)	(0.0597)	(0.0582)	(0.0717)
Model5	0.857***				
	(0.0181)				
Model5_Rand				-0.00138	-0.00497
				(0.0214)	(0.0223)
(Verizon x Model5_Rand)					0.0538
					(0.0894)
Bidders	0.0429***	0.0457**	0.0322***	0.0276***	0.0278***
	(0.00295)	(0.0185)	(0.00357)	(0.00316)	(0.00317)
Units	0.00934***	0.00194***	0.00536***	0.00929***	0.00929***
	(0.000597)	(0.000162)	(0.000258)	(0.000416)	(0.000417)
Constant	4.831***	3.603***	4.153***	4.164***	4.167***
	(0.0934)	(0.437)	(0.141)	(0.125)	(0.126)
Time FE	Yes	Yes	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes	Yes	Yes
Observations	8,179	452	820	910	910
R-squared	0.731	0.667	0.823	0.837	0.838
Adjusted R-squared	0.728	0.542	0.809	0.825	0.826

Note. Additional control variables are included in the models such as the physical condition of phones, memory size, and auction starting price. Standard errors (in parentheses) are heteroscedasticity robust and clustered by auctions. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 2.7. The Effect of Status Disclosure on Bidders (Bids) Over Time (Verizon)

VARIABLES	(1) Three Months	(2) Jan 2016	(3) May 2016	(4) Nov 2016
Undisclosed	0.531**	0.914***	-0.665***	0.488***
	(0.247)	(0.258)	(0.0487)	(0.0393)
Verizon	0.204***	0.269***	0.229***	0.189
	(0.00556)	(0.0481)	(0.0421)	(0.167)
Model 5	1.730***	1.739***	0.919***	0.873***
	(0.139)	(0.215)	(0.0267)	(0.0413)
Units	0.00184***	0.00168***	0.00122***	0.00165***
	(0.000119)	(0.000170)	(0.000153)	(0.000158)
(Verizon x Undisclosed)	-0.915***	-0.932***	-0.319***	-0.207***
	(0.0599)	(0.300)	(0.0609)	(0.0245)
(Verizon x Model 5)	0.407***	0.498***	0.401***	0.187***
	(0.0861)	(0.135)	(0.0439)	(0.0628)
(Undisclosed x Model 5)	-1.020***	-1.632***	-0.102**	-0.719***
	(0.144)	(0.264)	(0.0417)	(0.0497)
(Verizon x Model 5 x Undisclosed)	-0.533***	-1.265***	-0.260**	-0.0125
	(0.106)	(0.350)	(0.106)	(0.297)
Constant	4.538***	5.410***	4.724***	4.283***
	(0.172)	(0.240)	(0.0712)	(0.0698)
Time FE	Yes	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes	Yes
Observations	8,912	3,055	2,008	3,849
R-Overall	0.652	0.635	0.757	0.732
R-Within	0.645	0.624	0.720	0.712

Table 2.8. The Effect of Status Disclosure on Bidders (Bids) Over Time (Non-Verizon)

VARIABLES	(1) Three Months	(2) Jan 2016	(3) May 2016	(4) Nov 2016
Undisclosed	0.494***	-0.873***	-0.616***	1.126***
	(0.155)	(0.175)	(0.115)	(0.151)
Non-Verizon	-0.204***	-0.162***	-0.295***	-0.292***
	(0.00556)	(0.0571)	(0.0160)	(0.0192)
Model 5	1.734***	1.549***	0.874***	0.651***
	(0.140)	(0.135)	(0.0375)	(0.0584)
Units	0.00185***	0.00167***	0.00124***	0.00162***
	(0.000121)	(0.000166)	(0.000151)	(0.000163)
(Non-Verizon x Undisclosed)	-0.100**	-0.263***	-0.527***	-0.506***
	(0.0407)	(0.0253)	(0.115)	(0.100)
(Non-Verizon x Model 5)	0.226***	0.292***	0.231***	0.215***
	(0.0556)	(0.0182)	(0.0252)	(0.0412)
(Undisclosed x Model 5)	-1.025***	-1.148***	-0.296***	-0.761***
	(0.146)	(0. 240)	(0.116)	(0.152)
(Non-Verizon x Model 5 x Undisclosed)	-0.993***	-1.168***	-0.404***	-0.845***
	(0.0971)	(0.268)	(0.121)	(0.105)
Constant	4.144***	5.981***	5.323***	4.625***
	(0.173)	(0.0679)	(0.0896)	(0.164)
Time FE	Yes	Yes	Yes	Yes
Seller FE	Yes	Yes	Yes	Yes
Observations	8,912	3,055	2,008	3,849
R-Overall	0.658	0.767	0.744	0.749
R-Within	0.651	0.731	0.723	0.704

Note. Additional control variables included (physical condition of phones, memory size, bid order). Standard errors (in parentheses) are heteroscedasticity robust and clustered by bidders. ***p-value <0.01, **p-value <0.05, *p-value <0.1.

Table 3.1. Analysis of the Impact of AT&T entry on Final Prices

VARIABLES	(1) OLS Auction-Level	(2) OLS Bidder-Level	(3) FE Bidder-Level
Att_entry	33.63***	23.89***	23.75***
	(5.293)	(3.447)	(2.865)
Units	-0.0928***	-0.148***	-0.164***
	(0.0142)	(0.00744)	(0.0102)
Bidders	0.609**		
	(0.279)		
Single_h		3.868***	2.255**
		(1.333)	(1.141)
Bid_order		2.382***	2.444***
		(0.0422)	(0.0998)
Constant	157.6***	211.6***	224.2***
	(7.768)	(11.22)	(11.10)
Observations	3,605	21,284	21,284
Marketplace FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Bidder FE	No	No	Yes
R-squared	0.906	0.758	0.742
Adjusted R^2	0.905	0.757	
R-Overall			0.756

Note. Additional control variables are included in the models such as the physical condition of the device, model, carrier, memory size, unlocked status, auction starting price and pallet location. Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 3.2. The Impact of AT&T's entry on Demand and Within-auction Competition

VARIABLES	(1) DV: Bidders	(2) DV: Number of Bids
Att_Entry	-0.842*	1.586
	(0.448)	(2.389)
Bidders		3.034***
		(0.0700)
Units	0.00221***	0.0339***
	(0.000743)	(0.00336)
Constant	1.402***	7.036***
	(0.396)	(1.595)
Observations	3,605	3,605
Marketplace FE	Yes	Yes
Time FE	Yes	Yes
R-squared	0.396	0.468
Adjusted R-squared	0.388	0.462

Note. Additional control variables are included in the models such as the physical condition of the device, model, carrier, memory size, unlocked status, auction starting price and pallet location. Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 3.3. Analysis of the Impact of AT&T entry on Bidders Behavior

VARIABLES	(1) FE Single_H	(2) FE Multi_H	(3) FE Passive	(4) FE Active
Att_entry	33.74***	22.60***	25.61***	14.17***
	(6.442)	(3.538)	(2.944)	(4.84)
Units	-0.218***	-0.151***	-0.168***	-0.112***
	(0.0243)	(0.00972)	(0.0107)	(0.0227)
Bid_order	2.822***	2.349***	2.474***	2.331***
	(0.164)	(0.0844)	(0.0996)	(0.204)
Single_h			2.713**	
			(1.190)	
Constant	206.1***	224.3***	223.6***	161.5***
	(13.59)	(11.55)	(11.45)	(29.62)
Observations	3,442	17,842	20,096	1,188
Marketplace FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Bidder FE	Yes	Yes	Yes	Yes
R-squared	0.701	0.755	0.741	0.765
R-Overall	0.718	0.772	0.755	0.778

Note. Additional control variables are included in the models such as the physical condition of the device, model, carrier, memory size, unlocked status, and pallet location. Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4. Analysis of the Impact of AT&T entry on Individual Bids

VARIABLES	(1) FE Passive	(2) FE Passive	(3) FE Active	(4) FE AT&T Auctions	(5) FE Active (AT&T Auctions)
Single_h	2.94**	2.63**		-4.97***	
	(1.453)	(1.244)		(1.56)	
Time	-1.886*	-1.584*	-6.658***	-0.835*	-1.103*
	(1.052)	(0.915)	(1.249)	(0.476)	(0.594)
(Single_h x Time)		-0.862			
		(0.993)			
Bid_order	2.769***	2.767***	2.331***	2.412***	2.556***
	(0.133)	(0.133)	(0.204)	(0.199)	(0.194)
Units	-0.392***	-0.392***	-0.122***	-0.115***	-0.113***
	(0.0364)	(0.0363)	(0.0227)	(0.0029)	(0.0022)
Constant	176.5***	175.5***	145.8***	149.34***	153.69***
	(3.253)	(3.365)	(12.83)	(5.498)	(6.101)
Observations	4,278	4,278	868	3,596	1,644
Marketplace FE	Yes	Yes	Yes	No	No
Bidder FE	Yes	Yes	Yes	Yes	Yes
R-Overall	0.829	0.830	0.778	0.882	0.864
R-Within	0.820	0.821	0.765	0.877	0.858

Note. Additional control variables are included in the models such as the physical condition of the device, model, carrier, memory size, unlocked status, and pallet location. Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5. Analysis of the Impact of AT&T entry on active bidders behavior

VARIABLES	(1) FE Active	(2) FE Active
$Won_{AT\&T}$	-3.633**	-3.364*
	(1.554)	(1.918)
Time	-5.278***	-5.162***
	(1.244)	(1.122)
($Won_{AT\&T}$ x Time)		-4.988
		(3.823)
Bid_order	3.368***	3.307***
	(0.304)	(0.303)
Units	-0.672***	-0.667***
	(0.145)	(0.144)
Constant	158.5***	168.4***
	(16.57)	(23.81)
Observations	496	496
Marketplace FE	Yes	Yes
Bidder FE	Yes	Yes
R-Overall	0.776	0.776
R-Within	0.759	0.761

Note. Additional control variables are included in the models such as the physical condition of the device, model, carrier, memory size, unlocked status, and pallet location. Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 3.6. The Impact of AT&T' entry on bidders' behavior – Changes in Status

VARIABLES	(1) FE Post-Entry	(2) FE Post-Entry
Active	-13.79***	-12.55***
	(3.131)	(4.28)
Time	-4.283***	-4.254***
	(1.137)	(1.339)
(Active x Time)		-6.773***
		(2.337)
Units	-0.152***	-0.151***
	(0.0125)	(0.0124)
Bid_order	2.872***	2.869***
	(0.129)	(0.128)
Constant	166.7***	165.8***
	(10.75)	(10.92)
Observations	5,146	5,146
Marketplace FE	Yes	Yes
Bidder FE	Yes	Yes
R-squared	0.748	0.750
R-Overall	0.762	0.764

Note. Additional control variables are included in the models such as the physical condition of the device, model, carrier, memory size, unlocked status, and pallet location. Robust standard errors are in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 4.1. Market Prices for Used iPhones of Two Different Generations

Price Point	Product Type	$ Dollar	Product Type	$ Dollar
Low Price	iPhone 11	$427	iPhone XR	$320
Medium Price	iPhone 11	$460	iPhone XR	$339
High Price	iPhone 11	$429	iPhone XR	$359

Table 4.2. Variable Operationalization

Variables	Description
Dependent Variable	
$Used_i$	1 if participant *i* elects to purchase a used iPhone
Independent Variables	
$C_{Conservation\_i}$	1 if participant *i* receives an offer for iPhone *j* containing a green nudge evoking conspicuous conservationism
$Empathy_i$	1 if participant *i* receives an offer for iPhone *j* containing a green nudge evoking emotional empathy
Control Variables	
$iPhone11_i$	1 if participant *i* receives an offer for iPhone 11, 0 if iPhone XR
$Price\_Low_i$	1 if participant *i* receives an offer of a low price iPhone
$Price\_Med_i$	1 if participant *i* receives an offer of a Medium price iPhone
$Price\_High_i$	1 if participant *i* receives an offer of a High price iPhone
$Order\_11_i$	1 if participant *i* receives an offer for an iPhone 11 first, 0 if iPhone XR is first
$Male_i$	1 if participant *i* is male, 0 if female
$Age45_i$	1 if participant *i* is 45 year or older, 0 if younger
$Education_i$	Vector of dummies indicating the level of education for participant *i*
Age_i	Vector of dummies indicating the age range for participant *i*
$Ethnicity_i$	Vector of dummies indicating the ethnicity of participant *i*

Table 4.3. The Impact of Green Nudges on the Decision to Buy Used iPhones

Used_iPhones	(1) Logit	(2) Logit	(3) Logit
$C_{Conservation}$	0.256**	0.113**	0.256**
	(0.115)	(0.054)	(0.115)
Empathy	0.107	0.107	0.0713
	(0.208)	(0.208)	(0.216)
iPhone11	0.0856*	0.0790*	0.0818*
	(0.046)	(0.044)	(0.045)
$C_{Conservation}$ x iPhone11		0.291**	
		(0.124)	
Empathy x iPhone11			0.191*
			(0.098)
Price_Med	-0.483**	-0.483**	-0.483**
	(0.204)	(0.204)	(0.204)
Price_High	0.0322	0.0332	0.0321
	(0.199)	(0.199)	(0.199)
Order_11	-0.210**	-0.211**	-0.210**
	(0.089)	(0.089)	(0.089)
Constant	0.296**	0.334**	0.299**
	(0.128)	(0.138)	(0.129)
Observations	700	700	700
Pseudo-R	0.0926	0.0930	0.0928
Log-Likelihood	-435.3	-435.1	-435.3
Chi-squared	75.60	76.10	75.62
Prob Wald	4.33e-08	7.01e-08	8.38e-08

Note. Additional control variables for the participants are included in the models such as age, gender, level of education, and ethnicity. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4.4. The Effect of Conspicuous Conservation Green Nudging on Decision to Buy

Used_iPhone	(1) Logit	(2) Logit	(3) Logit Low Price	(4) Logit Medium Price	(5) Logit High Price
$C_{Conservation}$	0.271**	0.091*	0.348**	0.143*	0.329**
	(0.120)	(0.048)	(0.187)	(0.079)	(0.152)
iPhone11	0.0792*	0.0770*	0.0974*	0.0651	0.0833
	(0.044)	(0.042)	(0.054)	(0.124)	(0.131)
$C_{Conservation}$ x iPhone11		0.316**			
		(0.126)			
Price_Med	-0.463***	-0.461***			
	(0.147)	(0.147)			
Price_High	-0.188	-0.187			
	(0.247)	(0.247)			
Order_11	-0.441**	-0.443**	-0.578***	-0.296*	-0.367**
	(0.209)	(0.210)	(0.218)	(0.165)	(0.174)
Constant	0.582**	0.662**	0.679**	0.467*	0.564*
	(0.256)	(0.265)	(0.268)	(0.239)	(0.280)
Observations	464	464	152	158	154
Pseudo-R	0.122	0.123	0.114	0.142	0.156
Log-Likelihood	-279.5	-279.2	-174.2	-173.5	-165.2
Chi-squared	70.97	71.54	54.96	51.03	62.34
Prob Wald	6.34e-08	1.02e-07	1.69e-06	4.11e-06	2.10e-07

Note. Additional control variables for the participants are included in the models such as age, gender, level of education, and ethnicity. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4.5. The Effect of Green Nudging with Respect to Consumer Demographics

Used_iPhone	(1) Logit	(2) Logit	(3) Logit
$C_{Conservation}$	0.244**	0.312**	0.345**
	(0.102)	(0.138)	(0.140)
iPhone11	0.0806*	0.0819*	0.0808*
	(0.045)	(0.046)	(0. 045)
Price_Med	-0.422***	-0.425***	-0.405***
	(0.152)	(0.152)	(0.153)
Price_High	-0.145	-0.145	-0.130
	(0.244)	(0.245)	(0.246)
Male	-0.0521	0.145	-0.0573
	(0.121)	(0.196)	(0.120)
$C_{Conservation}$ x Male		-0.319	
		(0.326)	
Age45	-0.139	-0.186	-0.131
	(0.256)	(0.257)	(0.250)
$C_{Conservation}$ x Age45			-0.220*
			(0.118)
Order_11	-0.475**	-0.481**	-0.476**
	(0.204)	(0.205)	(0.204)
Constant	0.317**	0.240**	0.237**
	(0.132)	(0.106)	(0.097)
Observations	464	464	464
Pseudo-R	0.109	0.110	0.112
Log-Likelihood	-284.9	-284.6	-284.1
Chi-squared	64.39	66.26	67.27
Prob Wald	4.37e-08	4.47e-08	2.98e-08

Note. Additional control variables for the participants are included in the models such as level of education, and ethnicity. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4.6. The Effect of Conspicuous Conservation Nudging Based on Consumer Personality

VARIABLES	(1) Logit	(2) Logit	(3) Logit	(4) Logit
$C_{Conservation}$	0.276**	0.143**	0.264**	0.161**
	(0.112)	(0.064)	(0.110)	(0.070)
iPhone11	0.0840*	0.0847*	0.0823*	0.0829*
	(0.045)	(0.046)	(0.044)	(0.044)
Price_Med	-0.635***	-0.634***	-0.646***	-0.652***
	(0.218)	(0.218)	(0.220)	(0.221)
Price_High	-0.160	-0.165	-0.145	-0.154
	(0.247)	(0.248)	(0.250)	(0.251)
Order_11	-0.491**	-0.482**	-0.510**	-0.476**
	(0.216)	(0.219)	(0.215)	(0.217)
Extraversion	-1.689***	-1.982***		
	(0.565)	(0.619)		
$C_{Conservation}$ x Extraversion		2.571**		
		(1.136)		
Neuroticism			0.977*	0.00668
			(0.523)	(0.683)
$C_{Conservation}$ x Neuroticism				2.113**
				(1.066)
Constant	1.676***	2.289***	1.181**	0.672**
	(0.571)	(0.669)	(0.516)	(0.293)
Observations	464	464	464	464
Pseudo-R	0.136	0.141	0.128	0.134
Log-Likelihood	-275.1	-273.5	-277.7	-275.6
Chi-squared	78.65	82.78	72.65	71.76
Prob Wald	6.65e-09	2.75e-09	6.68e-08	1.83e-07

Note. Additional control variables for the participants are included in the models such as age, gender, level of education, and ethnicity. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4.7. The Effect of Empathy Nudging on Decision to Buy

Used_iPhone	(1) Logit	(2) Logit	(3) Logit Low Price	(4) Logit Medium Price	(5) Logit High Price
Empathy	0.113	0.0757	0.190*	0.0916	0.0582
	(0.209)	(0.228)	(0.102)	(0.232)	(0.211)
iPhone11	0.0879*	0.0880*	0.0973*	0.0847*	0.0723
	(0.049)	(0.049)	(0.051)	(0.047)	(0.057)
Empathy x iPhone11		0.179*			
		(0.097)			
Price_Med	-0.360**	-0.357**			
	(0.156)	(0.155)			
Price_High	0.106	0.106			
	(0.247)	(0.247)			
Order_11	-0.187***	-0.188***	-0.237**	-0.160**	-0.194**
	(0.054)	(0.054)	(0.104)	(0.068)	(0.083)
Constant	0.390*	0.244*	0.439*	0.392**	0.181*
	(0.219)	(0.133)	(0.235)	(0.174)	(0.091)
Observations	470	470	160	154	156
Pseudo-R	0.100	0.100	0.165	0.109	0.136
Log-Likelihood	-288.2	-288.1	-165.4	-194.7	-185.3
Chi-squared	56.40	56.51	65.10	43.62	53.49
Prob Wald	2.53e-05	4.24e-05	3.28e-08	0.000389	1.19e-05

Note. Additional control variables for the participants are included in the models such as age, gender, level of education, and ethnicity. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4.8. The Effect of Empathy Nudging Based on Consumer Demographics

Used_iPhone	(1) Logit	(2) Logit	(3) Logit
Empathy	0.132	0.121	0.125
	(0.204)	(0.230)	(0.231)
iPhone11	0.0868*	0.0868*	0.0869*
	(0.048)	(0.048)	(0.048)
Price_Med	-0.377**	-0.381**	-0.399**
	(0.161)	(0.162)	(0.163)
Price_High	0.110	0.109	0.0887
	(0.242)	(0.242)	(0.241)
Female	-0.185*	-0.294	-0.186*
	(0.105)	(0.170)	(0.105)
Empathy x Female		0.189**	
		(0.087)	
Age45	0.630**	0.631**	0.343
	(0.248)	(0.248)	(0.244)
Empathy x Age45			0.565**
			(0.237)
Order_11	-0.160***	-0.162***	-0.151***
	(0.049)	(0.049)	(0.048)
Constant	0.261*	0.299*	0.286*
	(0.137)	(0.143)	(0.140)
Observations	470	470	470
Pseudo-R	0.0948	0.0950	0.0980
Log-Likelihood	-283.1	-282.8	-282.4
Chi-squared	53.55	55.41	56.42
Prob Wald	2.30e-05	2.41e-05	2.69e-05

Note. Additional control variables for the participants are included in the models such as level of education, and ethnicity. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 4.9. The Effect of Empathy Nudging Based on Consumer Personality

VARIABLES	(1) Logit	(2) Logit	(3) Logit	(4) Logit	(5) Logit	(6) Logit
Empathy	0.311	1.142*	0.260	0.443*	0.208	1.883*
	(0.223)	(0.639)	(0.221)	(0.253)	(0.216)	(1.049)
Price_Med	-0.375**	-0.396**	-0.274**	-0.281**	-0.339**	-0.362**
	(0.157)	(0.159)	(0.128)	(0.128)	(0.156)	(0.157)
Price_High	0.120	0.128	0.135	0.137	0.164	0.165
	(0.247)	(0.248)	(0.252)	(0.253)	(0.247)	(0.248)
Order_11	-0.160**	-0.144**	-0.153**	-0.155**	-0.158**	-0.140**
	(0.072)	(0.068)	(0.071)	(0.071)	(0.072)	(0.067)
Extraversion	-1.487***	-2.317***				
	(0.537)	(0.743)				
Empathy x Extraversion		1.782**				
		(0.921)				
Agreeableness			2.773***	2.218**		
			(0.612)	(0.899)		
Empathy x Agreeableness				1.019*		
				(0.517)		
Openness					-0.276	-1.602*
					(0.677)	(0.929)
Empathy x Openness						2.372*
						(1.305)
Constant	1.135*	1.679**	1.663**	1.274**	1.367**	1.411**
	(0.619)	(0.712)	(0.650)	(0.588)	(0.641)	(0.647)
Observations	470	470	470	470	470	470
Pseudo-R	0.112	0.116	0.135	0.136	0.100	0.106
Log-Likelihood	-284.5	-283.1	-277.1	-276.7	-288.1	-286.4
Chi-squared	64.96	68.83	71.93	73.76	56.23	60.41
Prob Wald	2.21e-06	1.01e-06	1.72e-07	1.67e-07	4.67e-05	1.94e-05

Note. Additional control variables for the participants are included in the models such as iPhone model, participant's age, gender, level of education, and ethnicity. Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Figures

Figure 2.1. Quality Classifications

CONDITIONS

A Grade: Like New	Minor Wear Cosmetics and Fully Functional. System has passed all our quality control tests and may show slight signs of use. Perhaps a few minor scratches less than 2” in length or nicks on the plastics but no scratches on the screen. Wear does not affect the use of the item and no major defects.
B Grade: Very Good	Noticeable Wear Cosmetics and Fully Functional. System has passed all quality control tests and will show signs of use. Perhaps one or two small scratches less than 2” in length or minor dent on the plastics small to medium in size but no scratches on the screen. Wear does not affect the use of the item and no major defects.
C Grade: Used	Major Wear Cosmetics and Fully Functional. System has passed all quality control tests and will show signs of use. Perhaps a major scratch, scuff or dent on the plastics or bad pixels on the screen.
D Grade: Broken	Major Wear Cosmetics. Full Functionality not guaranteed. Units may contain major scratches, scuffs or dents on the plastics or bad pixels on the screen.

Figure 2.2.A. Example of Mobile Phones Auction Listings

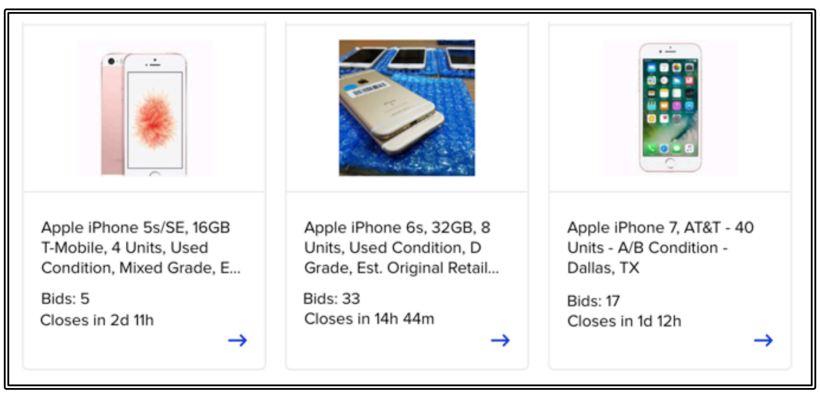


Figure 2.2.B. Auction Page for Unlocked Mobile Phone Pallet

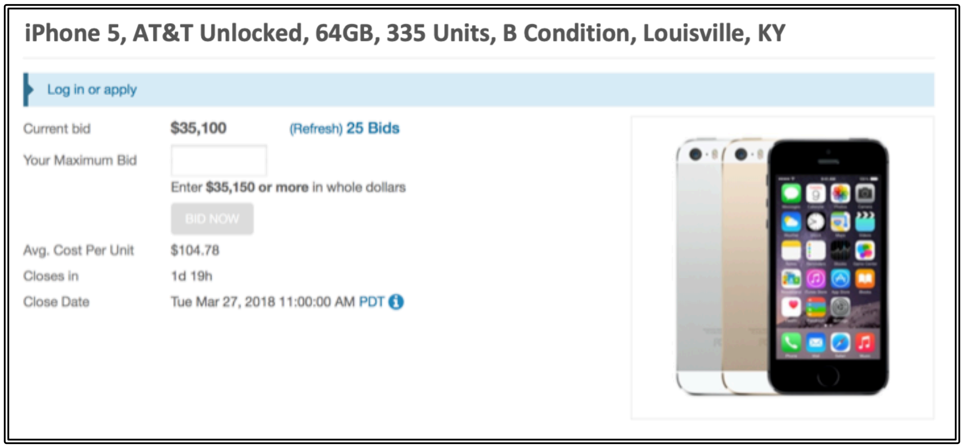


Figure 2.3. Data samples used in analyses

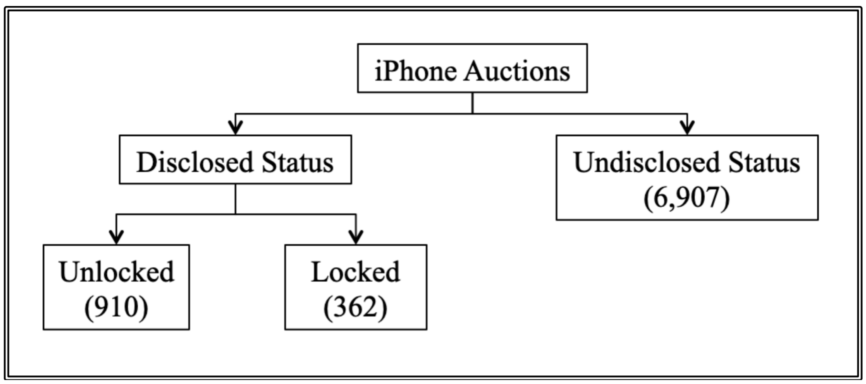


Figure 2.4. Predicted Prices of iPhones Associated with Disclosure of Status

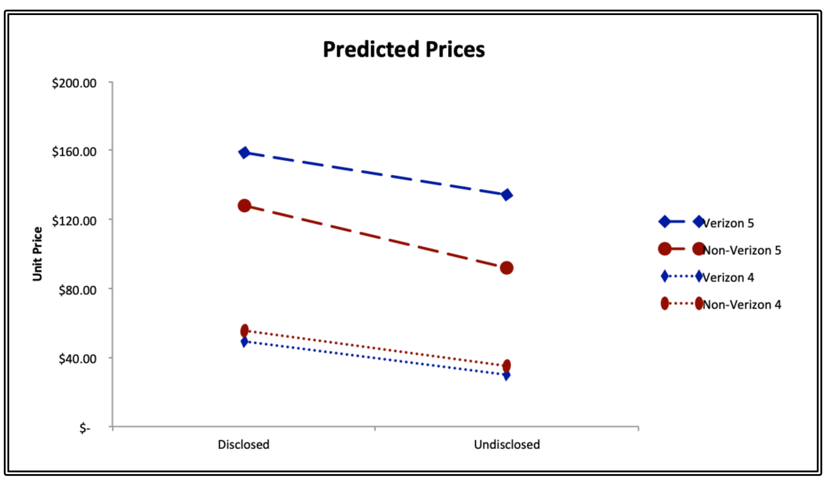


Figure 2.5. Predicted Final Prices of Unlocked Phones

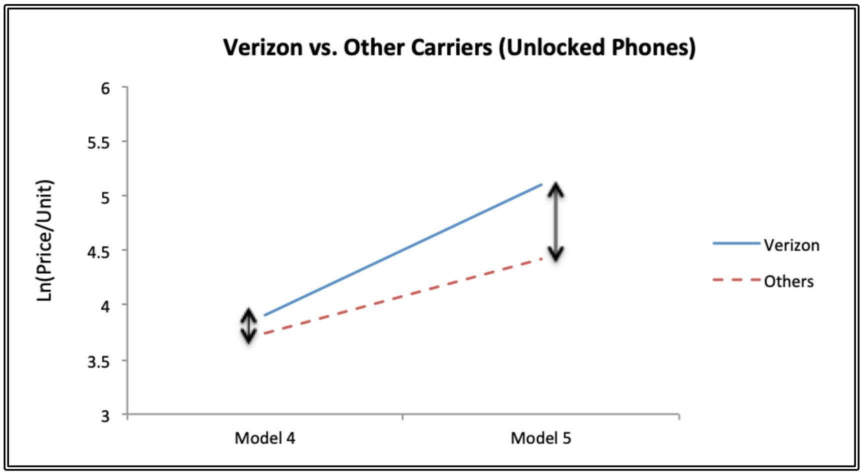


Figure 2.6. Beta Coefficients from Placebo Analysis (Table 6, Column 1) Results from 1000 Random Draws for *Undisclosed*

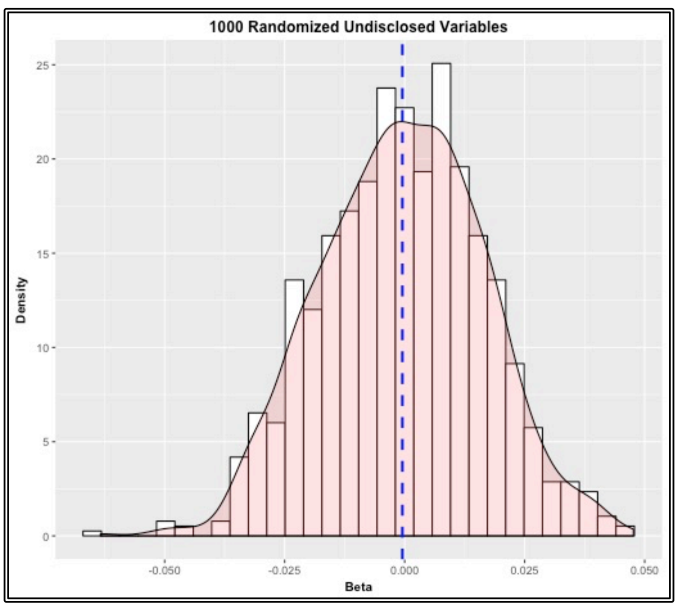


Figure 2.7. Beta Coefficients from Placebo Analysis (Table 6, Column 2) Results from 1000 Random Draws of *Locked* for iPhone 4 Models

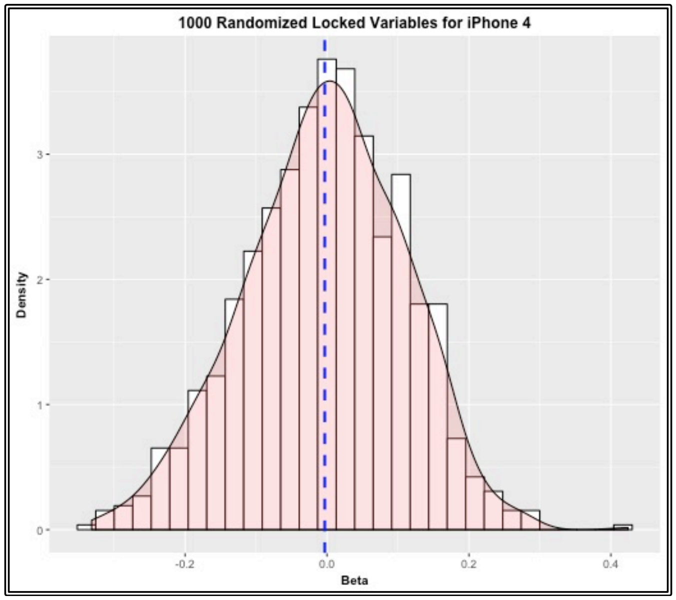


Figure 2.8. Beta Coefficients from Placebo Analysis (Table 6, Column 3) Results from 1000 Random Draws of *Locked* for iPhone 5 Models

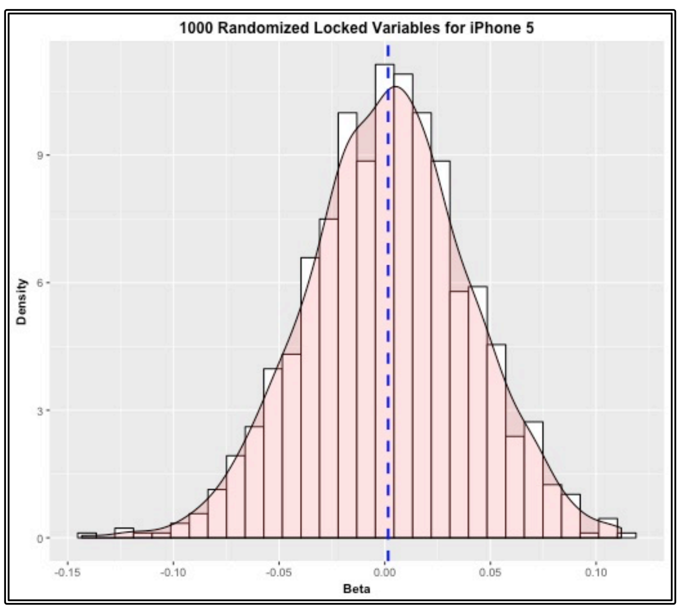


Figure 2.9. Beta Coefficients from Placebo Analysis (Table 6, Column 5)
Results from 1000 Random Draws for (*Verizon X Model 5)* Interaction Term (Unlocked Sample)

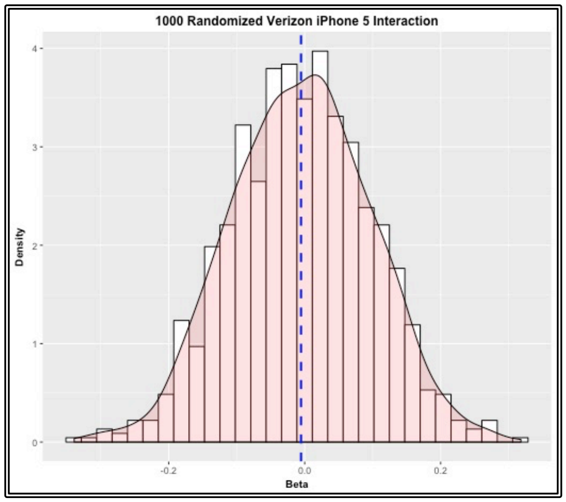


Figure 2.10. Predicted Bids (Bidder-level Analysis) for Undisclosed iPhone 5 Pallets: Verizon versus Non-Verizon

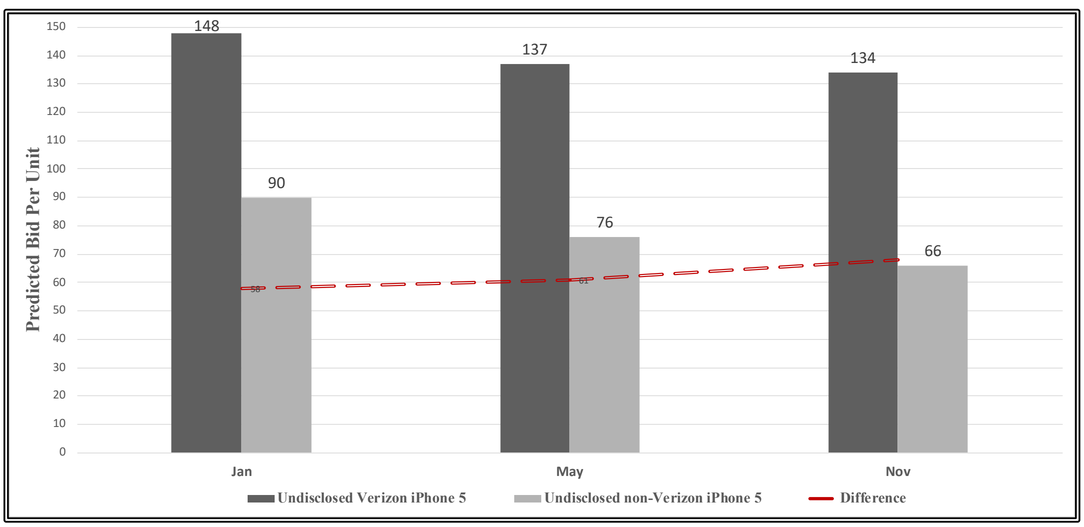


Figure 3.1. Auction Information Presented on Seller's Site

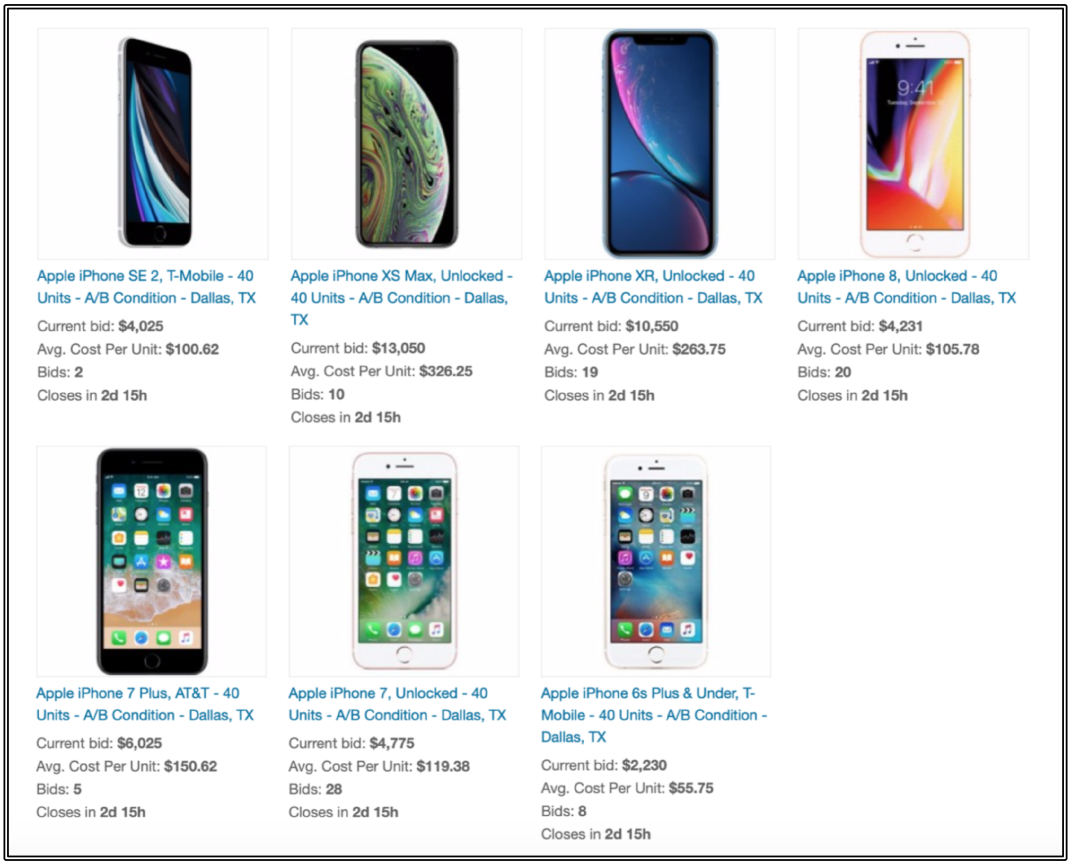


Figure 3.2. Different Bidder Populations in the Study

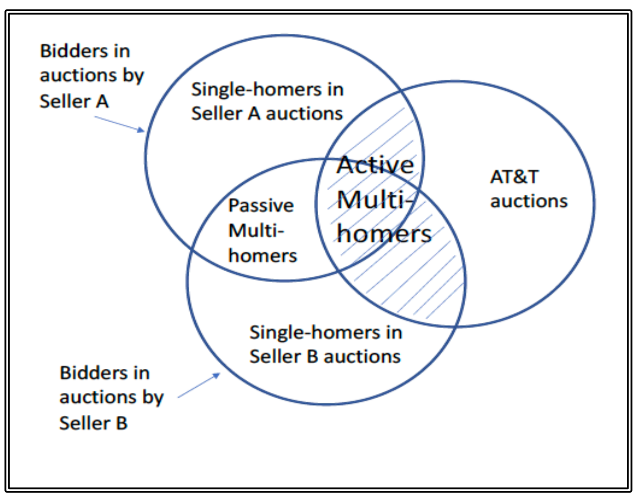


Figure 3.3. Populations of Single-Homers, Passive Multi-Homers, and Active Multi-Homers

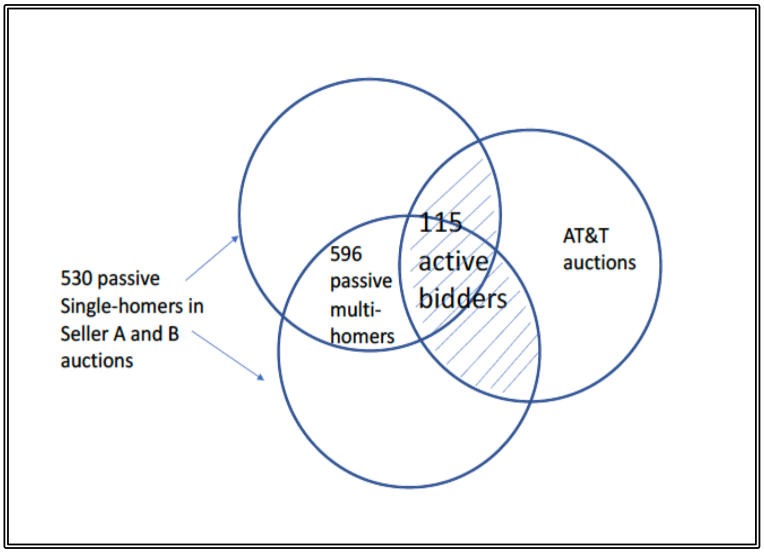


Figure 3.4. Market Average Prices

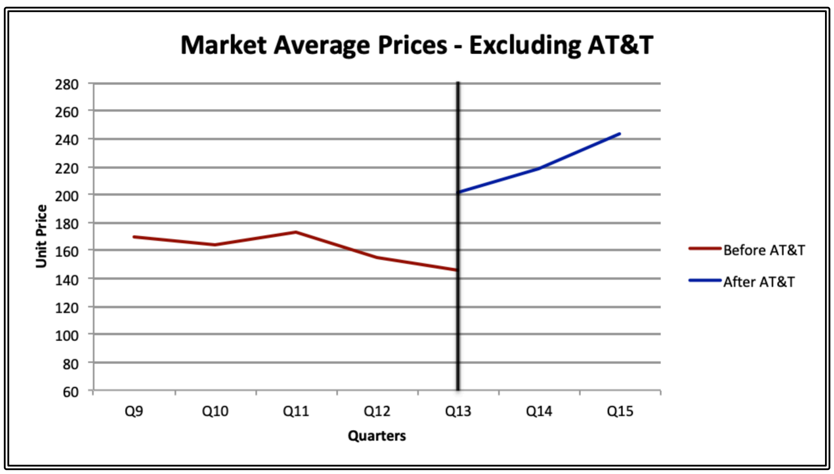


Figure 3.5. Average Prices for Single-homers Versus Multi-homers

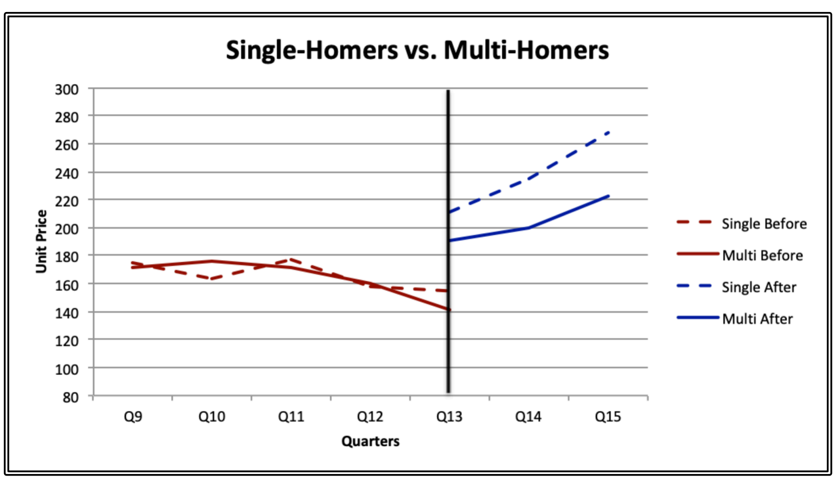


Figure 3.6. Submitted Bids over the Three-Day Duration of an Auction

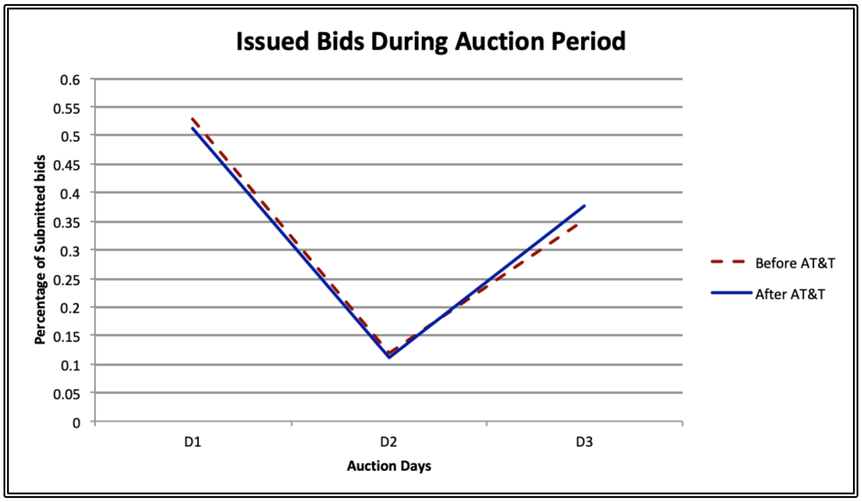


Figure 3.7. Submitted Bids in the Last Day Before the Ending Time of an Auction

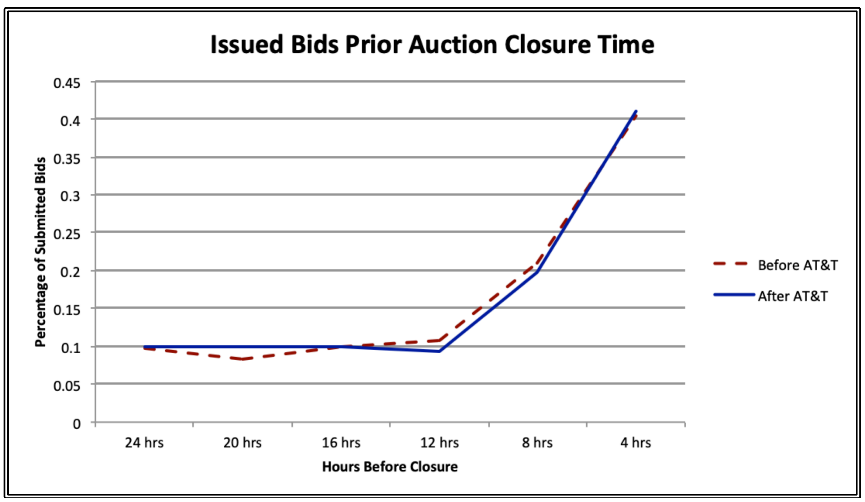


Figure 4.1. Participants Random Assignment in the 'Impact of Green Nudging' Experiments

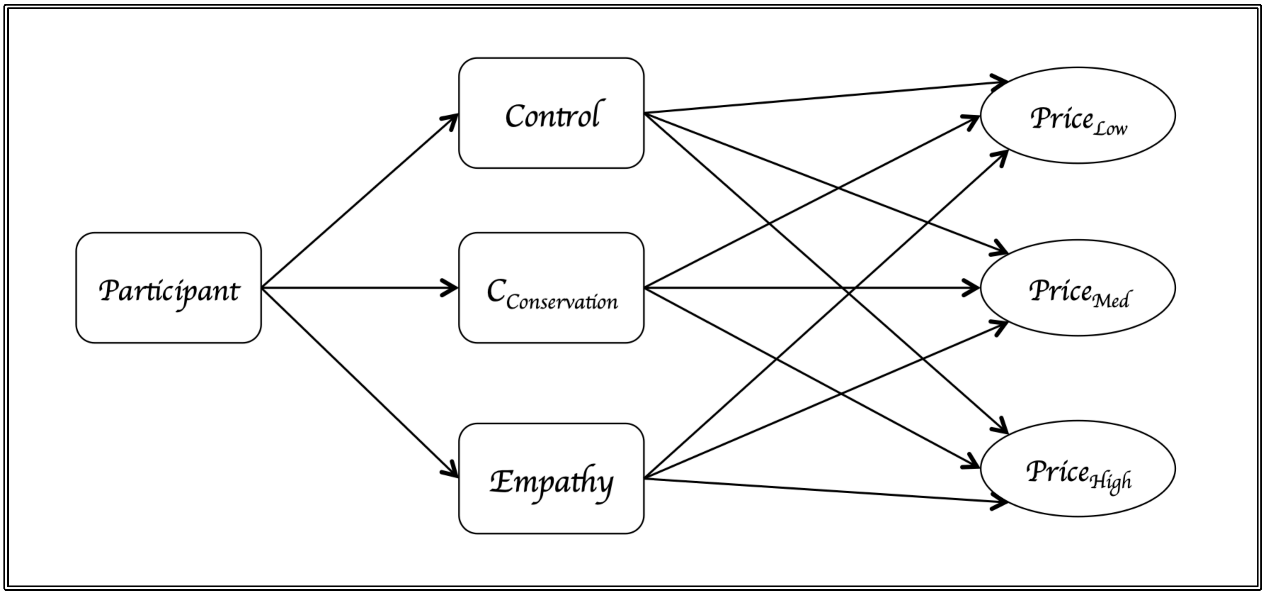
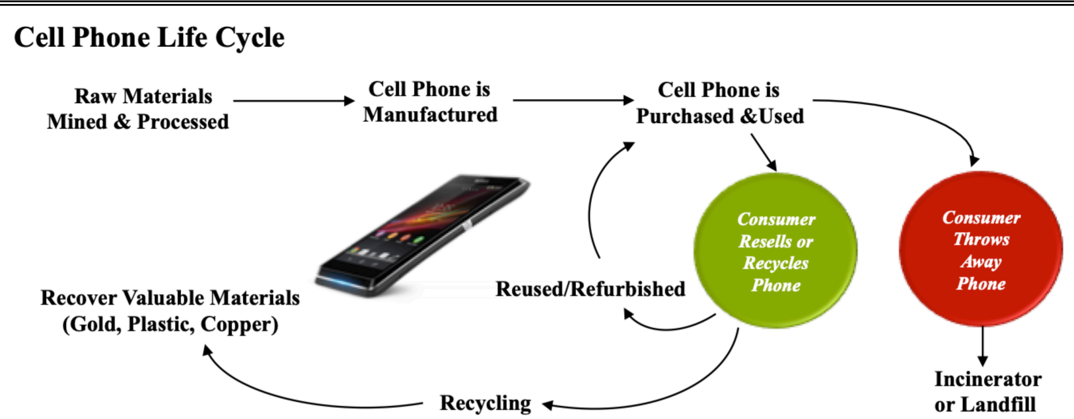


Figure 4.2. Cell Phones Life Cycles



The average American household uses about 28 electronic products such as personal computers, mobile phones, televisions and electronic readers (e-readers). For cell phones, consumers nowadays have the choice of purchasing new or old phones with the future option of reselling, recycling or disposing them. If older phones do not get resold or properly recycled, they will end up in landfills. Unfortunately, 20 to 50 million metric tons of environmentally harmful e-waste are disposed worldwide every year. Small technology products, such as older cell phones, account for the largest share of the overall e-waste.

Figure 4.3. Set of Offers for iPhone 11 including a Conspicuous Conservation Nudge

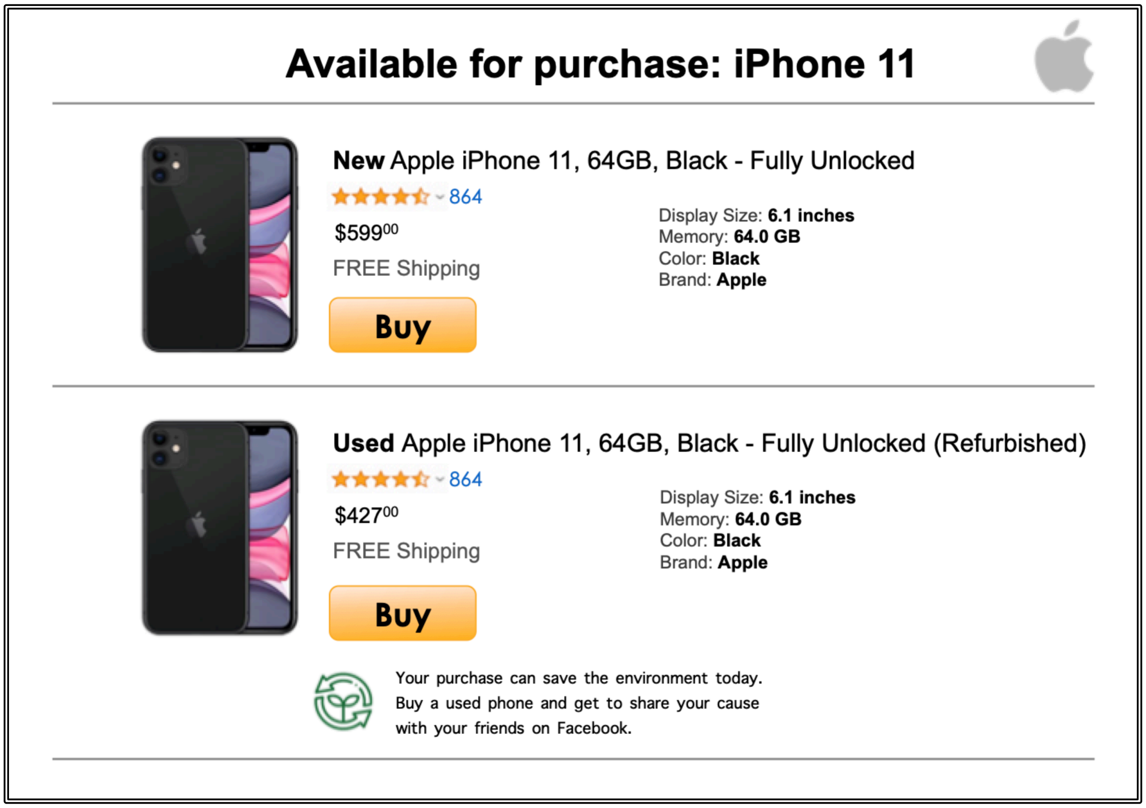


Figure 4.4. The Efficacy of the Conspicuous Conservation Nudge Based on Price

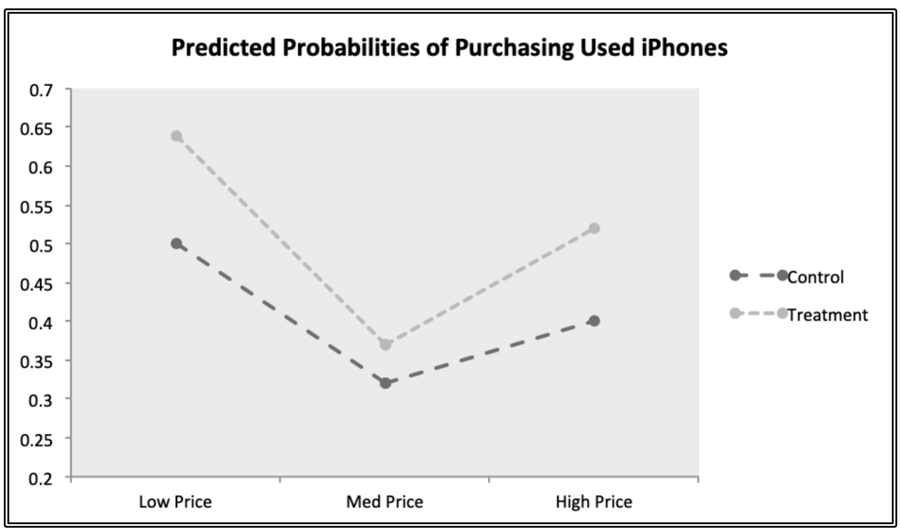


Figure 4.5. Age Differences with Respect to Conspicuous Conservation Nudging

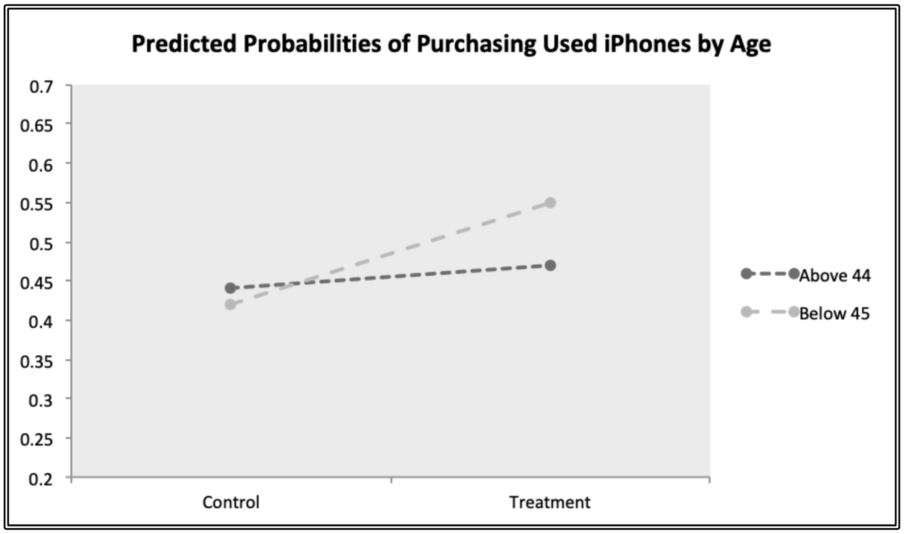


Figure 4.6. Set of Offers for iPhone 11 including an Empathy Nudge

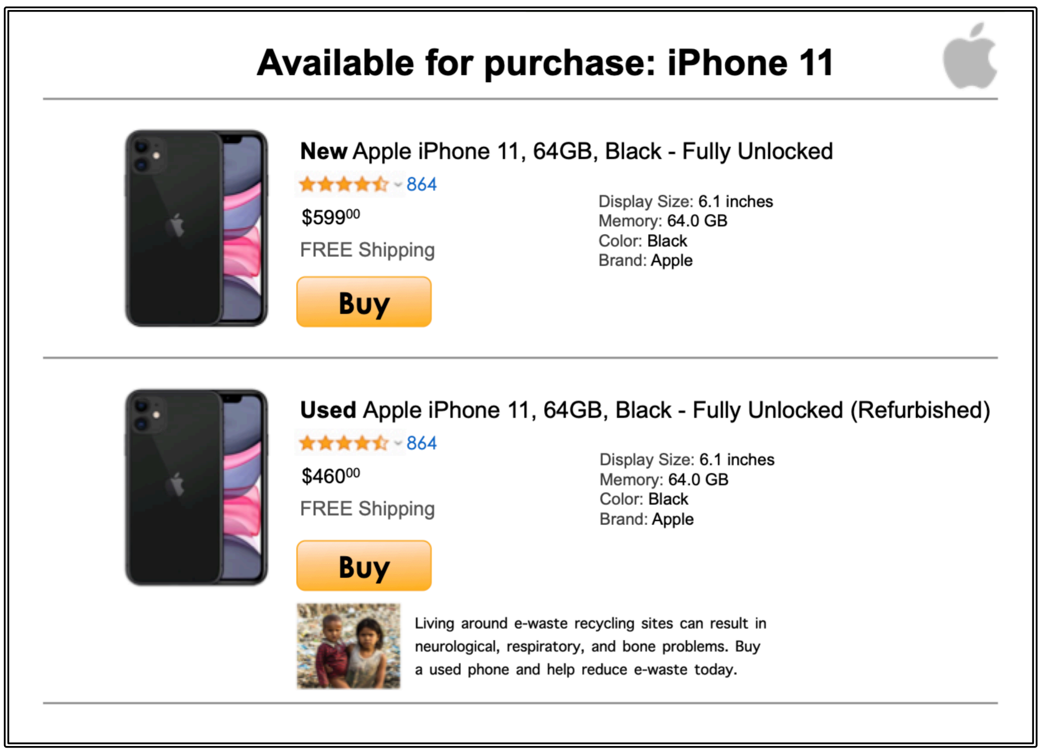


Figure 4.7. The Efficacy of the Empathy Nudge Based on Price

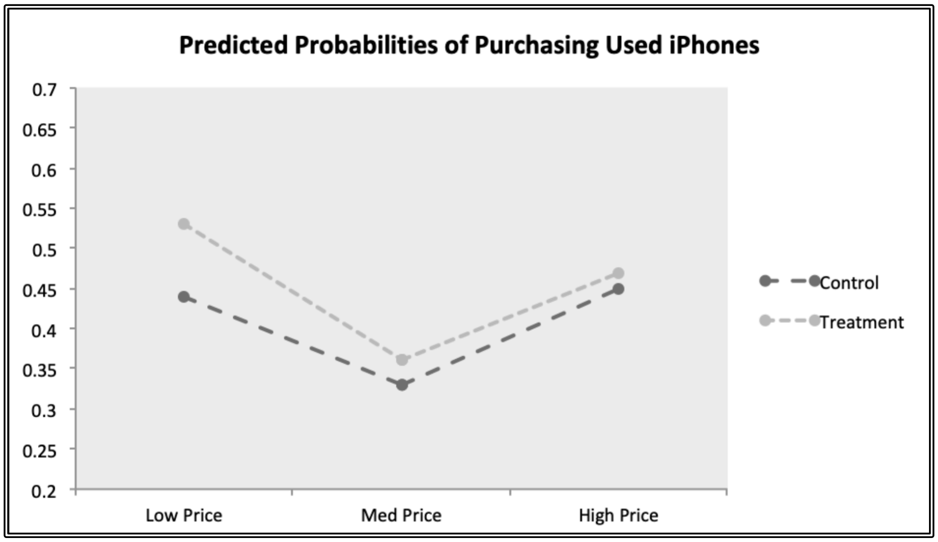


Figure 4.8. Gender Differences with Respect to Empathy Nudging

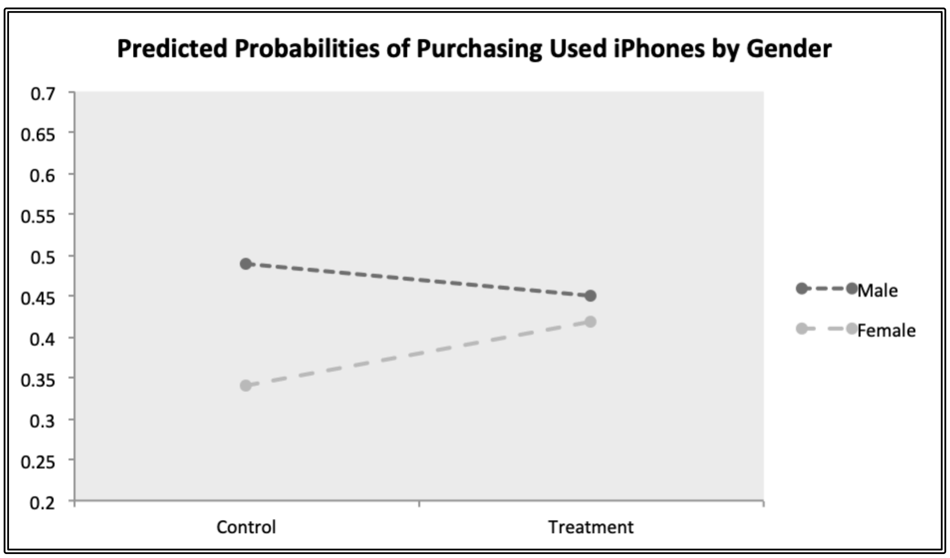
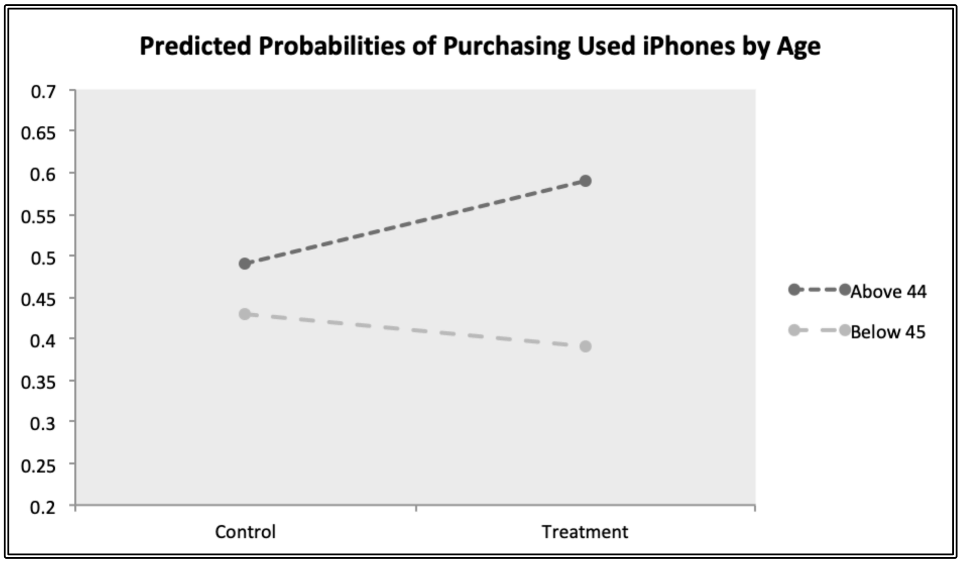


Figure 4.9. Age Differences with Respect to Empathy Nudging


Predicted Probabilities of Purchasing Used iPhones by Age
0.7
0.65
0.6
0.55
0.5
0.45
0.4
0.35
0.3
0.25
0.2
Control
Treatment
Above 44
Below 45

Appendices

Table A2.1. Summary Statistics

Variables	**# of Obs.**	**Mean**	**Std. Dev.**
FP_{ij}	8,179	116.0096	68.79865
$Undisclosed_{ij}$	8,179	0.8444798	0.3623999
$Locked_{ij}$	1,272	0.2845912	0.4512195
Model 5 $_{ij}$	8,179	0.6686637	0.4706937
$Verizon_{ij}$	8,179	0.3961364	0.4890934
$Bidders_{ij}$	8,179	6.301626	3.156915
$Units_{ij}$	8,179	74.84844	126.9718
$Starting\_Price_{ij}$	8,179	4022.29	7690.07

Table A2.2. Correlation Matrix (Status Disclosure Analysis)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FP	1.000						
(2) Undisclosed	-0.123*	1.000					
(3) Verizon	-0.013	0.132*	1.000				
(4) Model_5	0.017	-0.071*	-0.093*	1.000			
(5) Bidders	-0.009	-0.039*	0.019*	0.103*	1.000		
(6) Starting_Price	0.912*	-0.110*	-0.019*	0.027*	-0.172*	1.000	
(7) Units	0.844*	0.105*	-0.033*	-0.064*	-0.066*	0.846*	1.000

* significant at the .05 level

Table A2.3. Correlation Matrix (Locked and Unlocked Analysis)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FP	1.000						
(2) Locked	0.191*	1.000					
(3) Verizon	-0.013	-0.168*	1.000				
(4) Model_5	0.017	0.529*	-0.093*	1.000			
(5) Bidders	-0.009	0.205*	0.019*	0.103*	1.000		
(6) Starting_Price	0.912*	0.045	-0.019*	0.027*	-0.172*	1.000	
(7) Units	0.844*	0.089*	-0.033*	-0.064*	-0.066*	0.846*	1.000

* significant at the .05 level

Table A3.1. Variable Operationalization

Variable	Description
Dependent Variable	
FP_{ij}	The final price of auction *i* in marketplace *j*.
Bid_{ijk}	The highest submitted bid by bidder *i* in auction *j* at marketplace *k*.
Independent Variables	
Att_entry_{ij}	A binary variable representing the period in which AT&T entered the platform for auction *i* in marketplace *j*.
$Single\_h_{ijk}$	If the bidder *i* is a single-homer bidding in auction *j* at marketplace *k*.
$Passive_{ijk}$	If the bidder *i* is a passive single- or multi-homer bidding in auction *j* at marketplace *k*.
$Active_{ijk}$	If the bidder *i* is an active multi-homer bidding in auction *j* at marketplace *k*.
Control Variables	
$Bidders_{ij}$	The total number of bidders participated in auction *i* and marketplace *j*.
$Units_{ij}$	The total number of units in auction *i* and marketplace *j*.
$Start\_price_{ij}$	The starting price in auction *i* and marketplace *j*.
$Condition_{ij}$	The average condition of the devices in auction *i* and marketplace *j* (e.g. like new, very good, used).
$Memory_{ij}$	The memory size of the smartphones in auction *i* and marketplace *j* (e.g. 32 GB, 64 GB).
$Model_{ij}$	The model of the auctioned phones in auction *i* and marketplace *j* (e.g. iPhones of model 6).
$Carrier_{ij}$	If the main carrier in auction *i* and marketplace *j* is Verizon, AT&T, T-Mobile, or Sprint.
$Marketplace_j$	The seller *j* who is auctioning the devices.
Bid_order_{ijk}	The order of a submitted bid by bidder *i* in auction *j* at marketplace *k*
$Month_{ij}$	Vector of dummies indicating the month in which auction *i* started in marketplace *j*.
$Year_{ij}$	Vector of dummies indicating the year in which auction *i* started in marketplace *j*.

Table A3.2. Summary Statistics

Variables	Obs.	Mean	Std. Dev
FP_{ij}	21,284	174.9149	124.667
$Single\_H_{ijk}$	21,284	0.1620749	0.3685282
$Multi\_H_{ijk}$	21,284	0.8379251	0.3685282
Att_entry_{ijk}	21,284	0.2409841	0.4276907
$Passive_{ijk}$	21,284	0.9444315	0.229092
$Active_{ijk}$	21,284	0.0555685	0.229092
$Units_{ijk}$	21,284	72.98082	76.93273
$Bidders_{ij}$	3,605	8.138594	3.139924

Table A3.3. Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) FP	1.000								
(2) Att_entry	0.297	1.000							
(3) Single_h	0.186	0.015	1.000						
(4) Active	-0.221	0.285	-0.007	1.000					
(5) Marketplace	-0.017	0.225	0.137	0.038	1.000				
(6) Bidders	0.089	0.014	-0.033	0.008	0.049	1.000			
(7) Bid_order	0.321	-0.002	-0.008	0.013	0.023	0.293	1.000		
(8) Start_price	0.195	0.090	0.072	-0.036	0.255	-0.187	0.073	1.000	
(9) Units	-0.057	0.042	0.064	0.033	0.277	-0.139	0.083	0.744	1.000

Table A3.4(A). Individual Summary Statistics for single-homers

Variables	Obs.	Mean	Std. Dev	Min	Max
Final Price	3,442	182.2764	134.9377	28.7	727.5
Starting Price	3,442	67.53978	93.71203	3.9	558.5
Units	3,442	109.3351	204.2633	2	2831
Bids	3,442	3.892175	2.073953	1	29
Winning	3,442	0.4190723	0.2269939	0	1

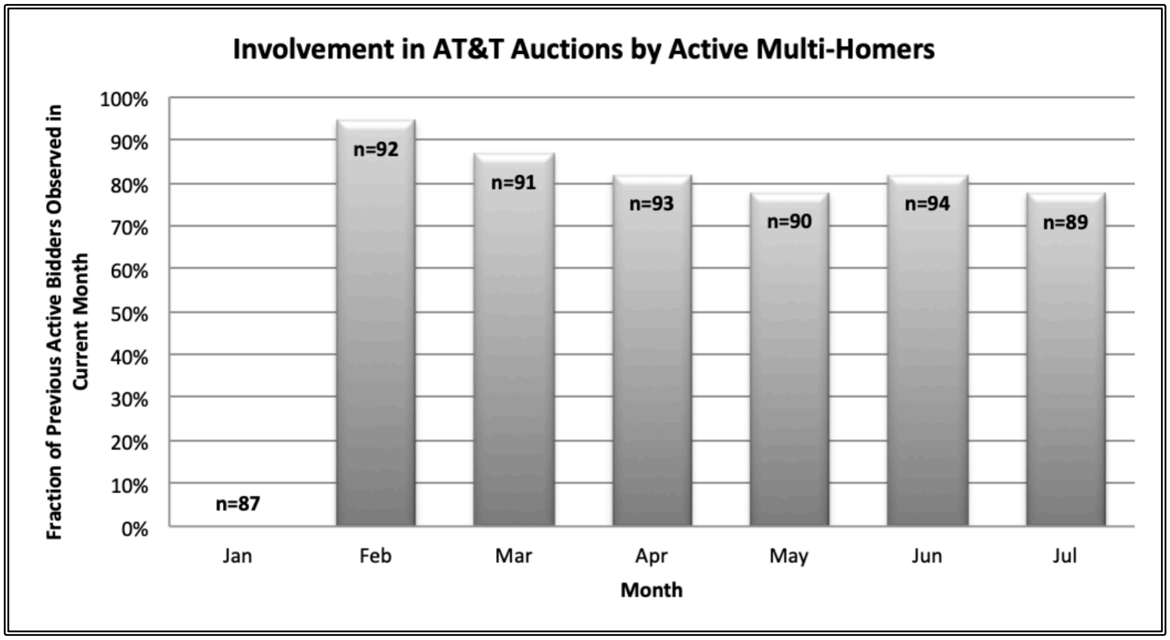
Table A3.4(B). Individual Summary Statistics for passive multi-homers

Variables	Obs.	Mean	Std. Dev	Min	Max
Final Price	16,654	174.9235	126.7206	18.4	715.3
Starting Price	16,654	65.36438	77.19309	1.5	554.5106
Units	16,654	83.9092	129.164	2	2831
Bids	16,654	3.322285	1.820361	1	27
Winning	16,654	0.3721664	0.1660474	0	1

Table A3.4(C). Individual Summary Statistics for active multi-homers

Variables	Obs.	Mean	Std. Dev	Min	Max
Final Price	1,188	176.8204	135.4606	30.2	720
Starting Price	1,188	71.03612	76.76112	2.8	533.3
Units	1,188	116.1131	215.1759	3	2400
Bids	1,188	3.43687	1.935667	1	17
Winning	1,188	0.3823003	0.1777349	0	1

Figure A3.1. Active Bidders Involvement in AT&T Auctions Over Time



Note. 76% of the total 115 multi-homers who became active, i.e. participated in AT&T for the first time, started bidding on AT&T auctions during the first month post-entry. By the second month, 87% of these bidders had bid at least once in AT&T auctions. Most bidders who participated in AT&T auctions continued to stay active in this market over the duration of my study, as shown by the proportion of bidders who remain active towards the end of the observation window (approximately 80%). All bidders remained active across multiple months during the observation window, even if they did not bid on all months.

Table A4.1. Manipulation Checks to Ensure the Delivery of the Treatment's Message

Treatment	Statement
Conspicuous Conservation	Sharing with my friends was an appealing aspect of purchasing the used phone.
Conspicuous Conservation	Purchasing a used iPhone can help reduce e-waste around the globe.
Empathy	The negative effects on people living near e-waste impacts my purchase decisions.
Empathy	Purchasing a used iPhone can help reduce the adverse effects of e-waste around the world.

Figure A4.2. Set of Offers for iPhone 11 (Control Group)

Table A4.3. Set of Offers for iPhone 11 (Control Group)

Question	Why did you choose to not purchase the used iPhone?
1	The price of the used iPhone is too high
2	I am concerned about the quality of the used iPhone
3	I don't buy used phones
4	Other

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