Non-User Utility and Market Power: The Case of Smartphones*

Leonardo Bursztyn† **Rafael Jiménez-Durán**‡

Aaron Leonard§ **Filip Milojević**¶ **Christopher Roth**‖

September 29, 2025

Abstract

Firms can increase the demand for their products and consolidate their market power by increasing their users' utility but also by strategically decreasing the utility of competing products' users. We study this mechanism in the smartphone market, analyzing Apple's strategy of differentiating messages sent to Androids with "green bubbles." In surveys with U.S. college students, we show that green bubbles are widely stigmatized and that a majority of both iPhone and Android users would prefer green bubbles to no longer exist. An incentivized deactivation experiment reveals that iPhone users have a significant willingness to pay to prevent their messages from appearing as green bubbles on other iPhones. Finally, we examine the market implications and document that removing green bubbles substantially increases respondents' likelihood of choosing an Android over an iPhone.

Keywords: Non-user utility; Stigma; Market Power; Consumer Welfare; Antitrust.

JEL Classification: D83, D91, P16, J15

*We thank Ruben Durante, Aakaash Rao, Julian Wright, and various seminar participants for useful and constructive comments. Jiawei Chen and Utkarsh Dandanayak provided excellent research assistance. Roth acknowledges funding from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy EXC 2126/1-390838866. This work was partially supported by the RCN through its CoE Scheme, FAIR project No 262675. The research described in this article was approved by the University of Chicago Social and Behavioral Sciences Institutional Review Board.

†University of Chicago and NBER, bursztyn@uchicago.edu

‡Bocconi University, IGIER, CESifo, and Stigler Center, rafael.jimenez@unibocconi.it

§University of Chicago, aaronleonard@uchicago.edu

¶University of Chicago, milojevic@uchicago.edu

‖University of Cologne, NHH, Max Planck Institute for Research on Collective Goods, IZA, and CEPR, roth@wiso.uni-koeln.de

1 Introduction

The demand for a product may increase when the utility from consuming it rises but also when the disutility from *not consuming it* increases. This possibility gives companies strategic incentives to design product features that reduce non-user utility. As a result, users end up paying more for the same product, while non-users must settle for inferior alternatives without adequate price compensation. These tactics raise welfare concerns, particularly when dominant firms use them to entrench their market power.

One example of such strategies can be found in the U.S. smartphone market, where Apple is the dominant player, particularly among young people. Recent discussions have questioned whether certain iPhone features are intentionally designed not only to enhance the user experience but also to degrade the experience for Android users. This debate has received considerable attention in various news outlets and is, in fact, central to the most recent Department of Justice (DOJ) case against Apple, above and beyond recently resolved compatibility issues that marked iPhone-to-Android communication.[1] In particular, the lawsuit highlights how messages sent from iPhones to Android devices appear as green bubbles on iPhones, in contrast to the blue bubbles that mark iPhone-to-iPhone communication—prominently distinguishing iPhone users from non-users. Historically, this color distinction was associated with different communication standards that led to compatibility issues. Although Apple resolved most of these compatibility issues in the latest iOS update (iOS 18), the color distinction remains.

In this paper, we examine how a dominant company can increase its market power by decreasing the utility of non-users, using the smartphone market as a case study. To do so, we conduct incentivized experiments with U.S. college students to measure the impact of green bubbles on the demand for iPhones and study how they impact the welfare of users and non-users. We also shed light on social stigma as an important mechanism through which green bubbles reduce non-user utility. Finally, we present a series of case studies on product features that plausibly aim to decrease non-user utility to increase market power across various markets.

Measuring welfare in this setting is challenging. As we argue with our model, the

[1] For popular press coverage on the DOJ case and the "green bubble culture," see "Green bubble shaming at play in DOJ suit against Apple" and "Why Apple's iMessage Is Winning: Teens Dread the Green Text Bubble."

difficulty arises because both increases in user utility and decreases in non-user utility can generate the same market outcomes. Thus, the welfare effects from features such as green bubbles cannot be identified from product choice data alone.

To provide direct evidence on negative non-user utility, we leverage a tailored survey of U.S. college students recruited on Prolific. The data shows that a large majority of Android (79%) and iPhone (67%) users reported wanting access to a hypothetical software change that would remove the green bubble differentiation, making all messages appear as blue bubbles on iPhones. The non-user utility plausibly arises from social stigma associated with green bubbles: approximately 90% of our respondents believe that green bubbles stigmatize Android users, commonly associating them with lower social status and attractiveness. Indeed, in an open-ended question asking users to compare Android and iPhone users, roughly 39% of iPhone users explicitly mentioned stigma and social status. Additionally, most respondents believe that removing green bubbles *enhances* the perceived quality of Androids, while leaving perceptions of iPhone quality largely unchanged. Taken together, this descriptive evidence is inconsistent with green bubbles generating user utility for most users. Instead, it suggests that this iPhone feature harms consumers by generating non-user disutility through the reduction of Android users' perceived social status.

Having established that green bubbles primarily impact consumers through non-user utility, we next provide quantitative estimates on their willingness to pay to avoid green bubbles through an incentivized deactivation experiment. In this experiment, we hold the user experience of iPhone owners constant and vary whether their messages appear as green (as opposed to blue) bubbles to themselves and other iPhone users. If respondents are willing to forgo money, it must be because they experience lower utility when their messages appear as green rather than blue bubbles to themselves and to others. We inform participants that the study involves temporarily deactivating certain phone features and that one of two deactivation options will be implemented. In Option 1, we ask how much money they would require to adjust their phone settings so that their messages appear as green bubbles instead of blue bubbles on other iPhones for a period of four weeks. We further clarify that this change in their phone settings would not affect any other aspect of their phone user experience.[2] Option 2 involves either deactivating iMessage or deactivating the

[2]This deactivation option is not feasible in practice, so we implement Option 2 for all respondents. As we discuss in more detail in Section 3.3, we adopt this design to isolate the effect of deactivating blue bubbles, rather than the feasible iMessage deactivation involving a bundle of features. However, this design requires respondents to believe the option is feasible. Reassuringly, respondents estimate

camera of their phone for a duration of four weeks.

This deactivation experiment reveals that U.S. college iPhone users, on average, require a payment of \$49 to have their messages appear as green instead of blue bubbles on other iPhones for four weeks. In a control condition, designed to measure the privacy and hassle cost of participation, Option 1 simply involves uploading screenshots and receiving a weekly text message as part of the study. In this control condition, participants only require a payment of \$17, significantly below the payment required in the blue bubble deactivation experiment ($p < 0.001$). The median valuation in the blue bubbles group of \$25 is also significantly above the median valuation in the control condition of \$7.5 ($p < 0.01$). This exercise provides strong evidence of an economically sizable utility loss arising from green rather than blue bubbles, significantly above the hassle and privacy cost of participating in the study.

We benchmark this magnitude by comparing it to the median payment required to deactivate other features.[3] The median valuation of blue bubbles is \$25, compared to a valuation of \$45 for iMessage and \$95 for their phone camera. Thus, the median valuation of blue bubbles corresponds to 56% and 26% of the median valuation of iMessage and the phone camera, respectively. Our estimates show that respondents put a high value on avoiding green bubbles relative to these benchmark features, underscoring the economic significance of the welfare cost.

Next, we examine the market implications of non-user disutility through an incentivized experiment with U.S. college students that quantifies how green bubbles influence the relative demand for iPhones over Androids. We measure respondents' preferences for iPhones versus Androids under two contingent scenarios, which differ only in whether iPhones retain the green bubbles feature or not. To fix beliefs, we inform all participants that the DOJ lawsuit against Apple's anti-competitive practices could result in the removal of green bubbles in the coming months. We then ask respondents to choose between receiving an iPhone or an Android of similar quality in a lottery that will be held if a certain future scenario occurs.[4] Respondents are then randomly assigned to either a "green bubble treatment" or a "blue bubble treatment." Respondents in the green bubble treatment make their choice for a scenario where

the likelihood of the blue bubble deactivation being implemented at approximately 50%, similar to their beliefs regarding the other deactivation option.

[3]We focus on the median rather than the mean for benchmarking as the former is not affected by differential top-coding across product features which would mechanically bias the benchmarking of means.

[4]The Android choice also includes a monetary payment to equalize the market value of the two options.

Apple loses the DOJ lawsuit but green bubbles remain. In contrast, respondents in the blue bubble treatment make their choice for a future scenario where Apple also loses the DOJ lawsuit but where green bubbles are banned—and thus the color of all messages becomes blue.

Consistent with our main hypothesis, the experiment shows that, in the contingency when green bubbles are removed, respondents are 7.3 percentage points (p.p.) more likely to choose the Android option over the iPhone option ($p < 0.05$). This is a sizable effect size that corresponds to a 46% increase in the share of respondents choosing the Android option, from a base of 15.8% when green bubbles remain. This evidence suggests that green bubbles significantly increase the demand for iPhones and contribute to its dominant market position in the US among our demographic of interest. In an additional experiment, we demonstrate the robustness of our finding when measuring the effects of green bubbles on participants' continuous willingness to pay for an iPhone over an Android using a different treatment manipulation.

alternate between p.p and %—inconsistent but is it intentional?

alternates between US and U.S.

We conclude by presenting a series of case studies on product features that diminish non-user utility. We argue that this phenomenon is widespread across various industries and illustrate how companies can strategically strengthen their market power. For example, streetwear brands such as *Supreme* and *Nike* use time-limited product "drops" and frequent model updates (e.g., the Air Jordan series) to generate feelings of obsolescence and exclusion among non-owners. Collectible toy makers like *Pop Mart* fuel repeated purchases through blind-box packaging, where characters such as *Labubu* are hidden until unboxed, creating scarcity-driven subcultures in which ownership signals belonging. Luxury fashion houses such as *Hermès* magnify exclusion through waiting lists for the Birkin bag. In technology markets, *Apple*'s "Get a Mac" campaign directly targeted non-users, portraying PC users as outdated and inferior. Across these cases, firms do not merely respond to pre-existing positional preferences; they actively manufacture non-user disutility to entrench dominance. Recognizing the endogenous creation of such disutility highlights how competition in markets for positional goods diverges from standard models, with implications for welfare and regulation. One noteworthy feature of social non-user disutility is that companies enable social equilibria that are difficult to regulate.

Our work also raises an important methodological challenge: When there is no outside option without the product (e.g. as in the smartphone market where virtually everyone owns a smartphone), it is not possible to distinguish—based on choice and price data alone—cases when user utility increases from cases in which in non-user

second 'in' is redundant

utility falls. This lack of identification arises because both cases, which carry opposite welfare implications, can result in the same market equilibria, thereby complicating any welfare analysis. Our paper highlights how rich survey and experimental data can overcome this identification problem.

Our analysis relates to a large literature on positional externalities (Frank, 2005, 2000; Luttmer, 2005; Perez-Truglia, 2020; Clark and Oswald, 1996) and the consumption of status goods (Pesendorfer, 1995; Frank, 1985a,b; Heffetz and Frank, 2011; Bagwell and Bernheim, 1996; Veblen, 1899; Bailey et al., 2022). Previous empirical work has documented a large demand for status goods (Bursztyn et al., 2018), and a higher willingness to pay for more exclusive products (Imas and Madarász, 2022). We contribute to this literature by studying how a dominant firm in the smartphone market leverages social concerns to increase profits and sustain market power. Moreover, our mechanism evidence shows that the social stigma associated with being an Android user is an important motive behind consumers' willingness to pay for iPhones. Our case study evidence further reveals that companies strategically exploit social concerns by introducing product features that decrease non-user utility and enable inefficient social equilibria.

We also contribute to a classic literature on industrial organization that shows that companies have strategic incentives to raise rivals' costs (Salop and Scheffman, 1983), reduce their own quality (Deneckere and Preston McAfee, 1996), reduce compatibility (Katz and Shapiro, 1985; Farrell and Saloner, 1985), and exploit behavioral biases (Heidhues and Kőszegi, 2018).[5] We contribute by documenting how a feature that initially arose as a technological incompatibility eventually solidified into social stigma, increasing demand among a segment of the market. While much of the literature has focused on anti-competitive firm strategies that operate on the supply-side (like raising rivals' costs), we focus on a demand-side mechanism. Unlike practices such as tying, which can be more easily regulated, stigma embeds itself in social norms and popular culture, making it potentially harder to counteract with traditional policy instruments: the stigma can persist even if the compatibility differences between products are removed (like in the case of iPhones). These effects might be further magnified if non-user disutility makes consumers become inattentive to quality improvements (Allcott et al., 2024), further increasing switching costs.

[5]We also relate to a literature on advance sales (Courty and Hao, 2000; Nocke et al., 2011). Advance sales operate by reducing the utility of consumers who delay purchase, either through higher future prices or reduced availability. By contrast, our setting reduces the utility of non-users through social stigma, even when intertemporal scarcity is absent.

Relatedly, recent theoretical and empirical work on product market traps examines how naturally arising network effects can lock in users because of externalities to non-users (Bursztyn et al., 2025a; Hagiu and Wright, 2025). Unlike the non-strategic network effects emphasized in this literature, our setting focuses on the strategic creation of non-user utility. As such, our work sheds light on the supply-side of non-user utility and connects to work on negative advertising (Bostanci et al., 2023) and negative or fear-inducing political campaigning (Lau et al., 2007; Campante et al., 2024).

Our paper proceeds as follows. Section 2 provides a model for interpreting how the strategic creation of non-user utility affects competition and consumer welfare. Section 3 provides evidence on the welfare effects of green bubbles. Section 4 studies the implications of non-user utility on product demand. Section 5 provides a series of case studies highlighting company strategies that create non-user disutility. Finally, Section 6 concludes.

2 Model

Two firms, A and B, sell an indivisible product—such as a smartphone—at prices p_A and p_B, respectively. They both have an equal and constant marginal cost $c > 0$. A continuum of heterogeneous users, with a total mass of one, decide which firm to purchase from.[6] Users have utility that is quasilinear in income. Their utility from consuming product A is u^i_A and that of consuming B is u^i_B. These utilities are distributed according to a smooth distribution with full support.

We assume that one firm can adjust its product design to create *non-user disutility*. For example, Apple chooses to distinguish text messages that are sent from iPhones to Android phones (which appear as green bubbles) from those sent to other iPhones (which appear as blue bubbles). This distinction, as we show empirically, generates a disutility on Android users in the form of social stigma. Concretely, we assume that firm A's product design generates a disutility g on consumers of B.[7] For simplicity, we assume that only one firm can create non-user disutility and take it as exogenous, but we microfound both of these features on Appendix A. In our microfoundation,

[6] To match our empirical application, we assume that consumers must choose one of two products, with no outside option. Note that over 99% of US undergraduates own a smartphone (see Denoyelles et al. 2021). In this market, Apple and Android have a market share above 99%.

[7] In practice, what matters is users' expectations about g, rather than the actual costs, since users select firm A specifically to avoid incurring the cost and therefore never actually experience it.

both user and non-user utility arise due to social image concerns associated with buying the product. Intuitively, when consumers care about the type of users buying the product, one of the firms has a "better" composition of users and benefits from inducing stigma. The firm with a "worse" composition of users will not deepen the stigma, since it would decrease its own demand.

After firm A's product design choice g, both firms compete in prices. Consumers solve the following problem given prices and non-user disutility:

$$\max \left\{ u_A^i - p_A, u_B^i - g - p_B \right\}.$$

Let $Q(p_A - p_B - g)$ denote the aggregate demand for product A and note that $1 - Q$ is the demand for B. We now impose a standard assumption on these demands which ensures a unique Bertrand-Nash equilibrium in the subgame that follows firm A's product design decision.

Assumption 1. *The density f of the difference in utilities, $u_A^i - u_B^i$, is log-concave.*

Lemma 1. *Under Assumption 1, there exists a unique Bertrand-Nash equilibrium.*

Consider now firm A's product design decision. Suppose that it can marginally and costlessly decrease non-user utility, by increasing g. For example, Apple can rewrite a few lines of code to change the color of messages sent to Androids from blue to green. The next proposition summarizes how this decision changes the market equilibrium.

Proposition 1. *When firm A marginally and costlessly decreases non-user utility, its markup, market share, and profits increase. The markup, market share, and profits of firm B decrease.*

The reduction in non-user utility gives firm A a strategic advantage by increasing the demand for its product and decreasing its competitor's demand. These changes create upward pressure in the price of A and downward pressure in the price of B, but these price changes are not enough to offset the initial demand changes.

One thing to note is that the equilibrium prices and quantities would have been identical if we had assumed that firm A could increase *user utility* instead of decreasing *non-user utility*. That is, when consumers solve: $\max \{u_A^i + g - p_A, u_B^i - p_B\}$, demands remain unchanged. In this model, the source of the increase in g does not alter the market equilibrium. However, it will matter for welfare, as the next proposition shows.

Proposition 2. *In equilibrium, consumer welfare decreases when firm A creates non-user disutility and increases when it creates user utility.*

The cases in which firm A creates user utility or non-user disutility are observationally equivalent in terms of their impact on prices and quantities (and thus on profits, market power, and concentration), but carry opposite welfare implications. In the former case, welfare increases because the firm only extracts part of the consumer surplus it creates among its consumers, without harming non-users—in fact it even benefits non-users by generating downward price pressure on its competitor. In this case, the firm becomes more dominant because it adds more value to its users. In the latter case, the firm increases its market power at the expense of both users and non-users: users pay more for the same product and non-users experience a worse product without enough price compensation.

The empirical implication of Propositions 1 and 2 is that standard choice data of prices and quantities is not sufficient to understand the welfare implications of product characteristics such as green bubbles that may generate user utility or non-user disutility. This identification challenge arises in settings where no outside option exists without the product. Intuitively, when an outside option is available, the welfare effects of product characteristics (such as green bubbles) are only identified by observing how demand for that outside option responds. Specifically, demand for the outside option increases if the feature creates non-user disutility, and decreases if it provides user utility. In what follows, our experiments will help show that green bubbles can indeed increase the demand for Apple while simultaneously worsening non-user utility without large impacts to user utility.

3 The Welfare Effects of Green Bubbles

3.1 Setting

In this section, we discuss the U.S. smartphone market and the compatibility issues between iPhones and Androids, including the green bubbles that appear on iPhones when messaging an Android device. Appendix B provides additional details on the smartphone market.

The U.S. smartphone market The U.S. smartphone market is valued at $61 billion, as of 2024 (Market Research Future, 2024). Apple's U.S. smartphone market share is high: the company holds an overall market share of 56% (StatCounter, 2024b), 68% among 18 to 29 year olds (Statista, 2024) and a striking 87% among teenagers (Axios, 2021). Android sales are mostly comprised of the established leader Samsung (StatCounter, 2024b) and increasingly popular Google devices (Schoon, 2024).

Compatibility issues In 2011, Apple introduced iMessage, a proprietary messaging platform that facilitated communication between Apple devices. Messages sent between these devices appear as blue bubbles. iPhones with cellular plans also have access to text messages via short message service (SMS) and multimedia messaging service (MMS), which appear as green bubbles on iPhones, as displayed in Figure 1. Notably, while SMS/MMS messages between iPhones also appear as green bubbles, iMessage is the default system for iPhone to iPhone communication.[8] Thus, green bubbles commonly indicate, and indeed strongly signal, communication with an Android user. There are several other prominent compatibility differences when comparing iMessage to SMS/MMS on iPhones. For example, typing indicators and read receipts are not available when using SMS/MMS on iPhones. These compatibility issues might plausibly contribute to the perception that green bubbles are associated with low quality devices and hence, could signal a low socioeconomic status of the user.

I believe it should be capitalized when first introduced: Short Messaging Service/ Multimedia Messaging Service

Apple's newest operating system for iPhones, iOS 18, was released on September 16, 2024. As part of the update, Apple introduced support for rich communication services (RCS), a new text messaging protocol to replace SMS/MMS. RCS fixed many existing compatibility issues between iPhones and Androids, including enabling typing indicators, read receipts, and the ability to send high-quality photos and videos (Apple Inc., 2024).[9] However, the green text message bubble color, a pronounced visual contrast to iMessage, remains with this update.

'green' and 'color' seems redundant

Antitrust cases against Apple Apple has faced increasing regulatory scrutiny over its anti-competitive practices. In March 2024, the DOJ, along with 16 state attorneys general, filed an antitrust lawsuit against Apple that accuses the company of violating Section 2 of the Sherman Act (U.S. Department of Justice, 2024). The lawsuit addresses various aspects of the iPhone ecosystem and explicitly argues that

[8] Prior to iMessage in 2011, all messages between smartphones were sent via SMS/MMS and appeared as green.

[9] It is possible that Apple adopted RCS as an anticipated response to the rising pressures from the DOJ lawsuit and European Digital Markets Act (U.S. News & World Report, 2024).

Figure 1: Blue versus Green Bubbles on iPhones

(a) Blue Bubbles on iMessage

(b) Green Bubbles on SMS/MMS

Notes: Figure 1 Panel (a) displays an interaction between two iPhones via iMessage, where messages always show up as blue bubbles. In contrast, Panel (b) shows an interaction via SMS, where messages are displayed as green bubbles on iPhones. While SMS messaging can take place between iPhones, it is not the default. Therefore, it is primarily associated with texting between an iPhone and an Android device. The pictures are from Apple Support (2024).

Apple deliberately degrades cross-device messaging features to increase profits and market share. In particular, the lawsuit highlights the role of green bubbles in creating a social stigma against Android users by introducing a visually salient indicator of smartphone ownership.

The lawsuit also presents direct evidence that Apple is aware that iMessage and its blue bubbles make it more difficult for users to switch smartphones, thereby reinforcing its market power. For example, in 2013, Apple's Senior Vice President of Software Engineering explained that enabling cross-platform messaging on iMessage "would simply serve to remove [an] obstacle to iPhone families giving their kids Android phones" (U.S. Department of Justice, 2024). In March 2016, Apple's Senior Vice President of Worldwide Marketing forwarded an email to CEO Tim Cook making a similar point: "moving iMessage to Android will hurt us more than help us" (U.S. Department of Justice, 2024). A more detailed discussion of the DOJ lawsuit and other regulatory action against Apple is in Appendix C.

Green bubbles as a strategic choice When Apple introduced blue bubbles in 2011, their primary purpose was likely technological, signaling to users that their messages were sent via iMessage rather than SMS. Over time, however, green bubbles may have endogenously evolved into a signal associated with lower socioeconomic status. Apple's continued distinction between green and blue bubbles now appears to be a deliberate strategy aimed at reinforcing its market dominance while reducing the appeal and utility of non-iPhone devices. Direct evidence supports this interpretation: In a 2022 interview, Apple CEO Tim Cook dismissed concerns regarding the green bubble issue. When asked about improving cross-platform messaging, he responded, "Buy your mom an iPhone." Furthermore, even with the release of iOS 18, Apple has notably refrained from promoting enhancements to cross-platform messaging, despite persistent user dissatisfaction. In contrast, Android manufacturers and carriers actively promote the new RCS support on iPhones, emphasizing the improvements while exposing Apple's deliberate strategy of sustaining incompatibility.

3.2 Survey Evidence

To provide evidence on the welfare effects of green bubbles among both Android and iPhone, we collect rich survey data.[10]

android devices and iPhone? —currently one's an operating system and the other is a device

3.2.1 Sample

Student sample We recruited 476 students from the US aged between 18 and 22 through Prolific in early September 2024, prior to the release of iOS 18. We allowed for a natural distribution of phone types, resulting in 16% Android users and 84% iPhone users, closely reflecting the observed market shares for this demographic. We focus on college students for several key reasons. First, this younger segment of the market is particularly important given the potential lock-in effects, as early brand preferences can influence long-term consumer loyalty. This demographic is also plausibly more sensitive to social image concerns and dating market considerations, where green bubbles may play a significant role. As a result and as seen in popular culture, the green bubble stigma is primarily associated with teenagers and young adults, making them the most relevant demographic for welfare considerations from a policy perspective.

[10] For reference, Appendix D provides details of all data collection activities discussed in this paper.

Pre-registration The pre-registration for the data collection can be found on AsPredicted #188972 and includes the experimental design, hypotheses, primary and secondary outcomes, sample size, and exclusion criteria.[11]

Sample characteristics Our final sample size consists of 476 participants.[12] Our final sample is 53% female, with an average age of 20.4 years. Summary statistics for our sample can be found in Appendix Table A3.

3.2.2 Design

In this survey, we measure consumers' stereotypes about Android users, preferences for green versus blue bubbles, and collect rich data about their general perceptions. After asking our respondents a series of open-ended questions, we inform participants about the recent DOJ lawsuit against Apple related to its alleged anti-competitive practices in order to increase respondent motivation to engage with the survey questions. We inform them that Apple could be forced to eliminate green bubbles and that the survey aims to gather information about the representative opinion of everyday users with no vested interest in the outcome of the case. We tell respondents that we are creating a report that will feature the average statistics from the responses to this survey and that we plan to widely circulate the findings on social media and in academic conferences. More than half of the respondents self-report to have put in more effort as a result of the public report covering their responses, while virtually no respondents indicate exerting lower effort. We provide additional discussion in Appendix E.2. In addition, Section J.1 of our Online Appendix contains the instructions and questions for this survey.

3.2.3 Results

In this section, we present our main pre-registered results.

Smartphone stereotypes and the green bubble stigma We start by providing evidence on the stereotypes associated with Android users. To do so, we ask participants an unprompted open-ended question at the very start of the survey. In particular, we ask: "When you think of someone who owns an Android instead of an iPhone, what comes to mind?" To analyze the unstructured text data, we devise

[11] For details, see `https://aspredicted.org/r27m-69c8.pdf`.

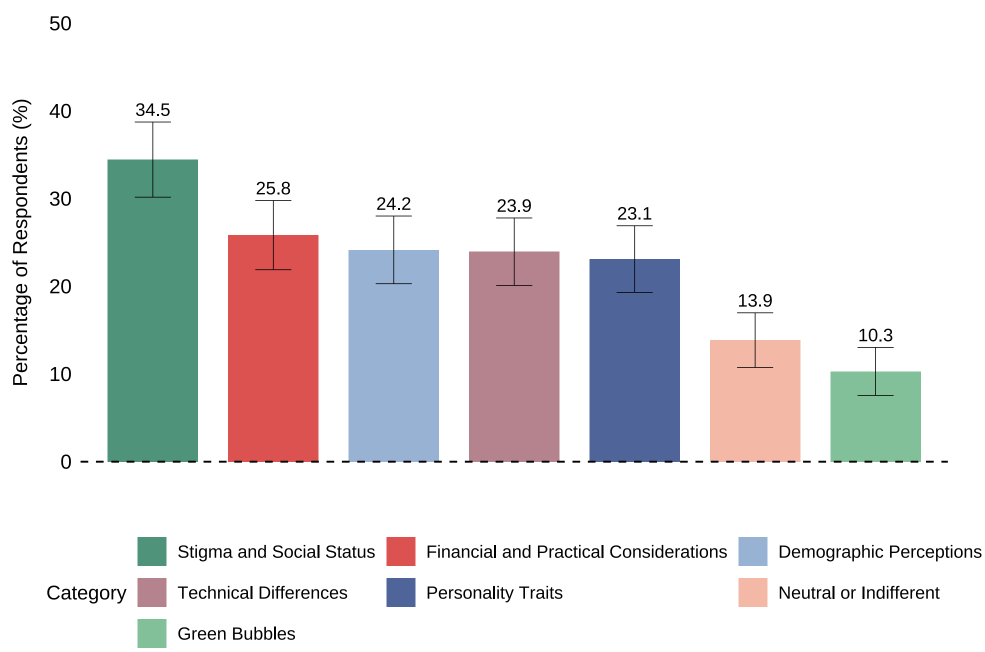
[12] As per the pre-registration, we exclude participants based on one incentivized attention check.

a simple coding scheme with seven non-mutually exclusive categories. *Stigma and Social Status* responses mention social judgment, peer pressure, or negative status perceptions (e.g. "I think they are someone more average. They are not as wealthy. They also have fewer friends" or "When i think of someone who owns an Android instead of an iPhone think there is a clear difference in social class."). *Personality* responses mention specific personality characteristics (e.g. "I think they're someone who is outside the norm in a way. They also may be more technically savvy" or "I think they are someone who doesn't care about the opinions of other people".). *Green bubble* responses explicitly mention green bubbles (e.g. "I think of the green text bubbles and limited communication as I cannot send pdf to an android user. The two makes are not that compatible"). *Demographic* responses mention specific demographic characteristics that are associated with iPhone or Android users, such as age (e.g. "I would think a person with an android would be a middle aged or older."). *Financial and Practical* responses mention cost, affordability, or practical reasons for using Android (e.g. "I think it's more cost efficient and the newer models have a lot of cool features that iPhones don't have"). *Technical* responses mention technical differences in quality or features between Androids and iPhones (e.g. "I think they probably have a lower camera quality"). *Neutral or Indifferent* responses show indifference to the distinction between Android and iPhone users ("Nothing really, I don't think anything different of them" or "They prefer the Android brand"). We categorize responses by hand-coding the responses from two independent research assistants who reconcile any differentially coded responses. We also validate the coding scheme with the OpenAI API and find similar conclusions.

Figure 2 displays the distribution of the responses across the seven categories from our hand-coding procedure. The largest fraction of responses (34.5%) mention stigma and perceptions of social status, primarily related to the perceived lower social status of Android users and the negative connotations of not owning an iPhone. Similarly, 24.2% of responses relate to demographic differences, often implicitly alluding to social concerns. For example, many demographic responses emphasize the older age of Android users, which may be seen as an undesirable trait to signal among our young adult sample. A substantial fraction of responses (25.8%) cite financial or practical reasons, associating Android devices with being cheaper or suggesting that people who prefer customization choose Androids. Technical reasons such as differences in camera quality or compatibility issues, which worsen the user experience when interacting with Android devices are cited by 23.9% of respondents.

Personality-related perceptions are mentioned by 23.1% of respondents, suggesting that some view Android users as having specific personality traits, such as being tech-savvy. A smaller but notable fraction (13.9%) of responses are classified as neutral. Finally, 10.3% of respondents explicitly mention green bubbles in this open-ended question.[13] Notably, among respondents who mentioned green bubbles, 28.6% also raised concerns about stigma and social status, underscoring their significant role in shaping associations about Android users. Furthermore, as shown in Figure A12 of our Online Appendix, stigmatizing references to Android users come predominantly from iPhone users, whereas Android users focus on personality traits. Overall, we interpret these responses as compelling evidence that the salience of owning an Android promotes the formation of associations, often leading to unfavorable stereotypes about Android users held by iPhone users.

Figure 2: Android User Stereotypes



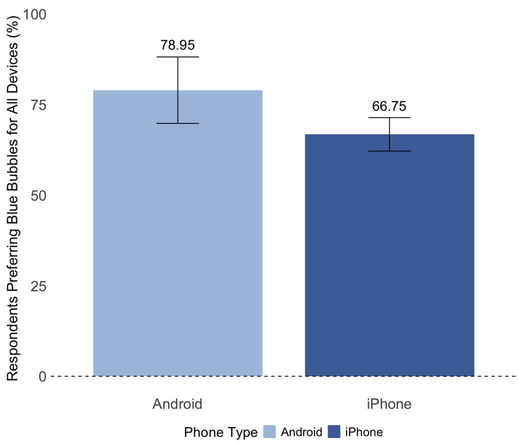
Notes: Figure 2 presents the results from our open-ended classification scheme for the question "When you think of someone who owns an Android instead of an iPhone, what comes to mind?". Two research assistants reviewed and hand-coded responses into one of seven (non-mutually exclusive) categories independently, with a high degree of correlation, and then reconciled any differences. We reach similar conclusions when we classify responses using the OpenAI API.

[13]Moreover, over 97% of respondents were aware of the green bubble messaging feature prior to starting our survey, highlighting the widespread recognition among our demographic.

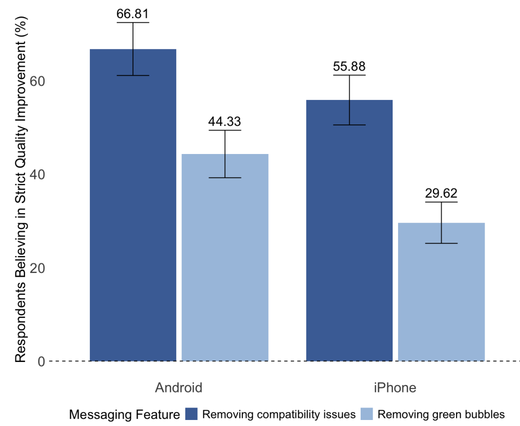
While this open-ended evidence highlights the significance of social concerns, the unstructured nature of the data complicates quantitative interpretation (Haaland et al., 2025). Therefore, we complement these measures with evidence from structured questions, as seen in Appendix E.3. We find that an overwhelming majority (90%) of respondents believe there is a social stigma against Android users, whose text messages appear as green bubbles on iPhones, and that Android users are perceived to earn 10.5% less income than iPhone users in the US. We also find that 91% of iPhone users, as well as the majority of Android users (57%), perceive iPhone users as more attractive than Android users. Collectively, this data points to a series of social mechanisms that drive non-user utility.

Preferences over green bubbles As a next step, we examine whether respondents would prefer a software change that replaces green bubbles with blue bubbles for all users, even after iOS 18 has resolved many of the previously longstanding compatibility issues. Remarkably, as shown in Figure 3, Panel (a), we find that a large majority of Android users (79%) would prefer such a software change. This holds true even among iPhone users, where a majority (67%) would prefer such a software change. We explicitly state that this software change would only affect the color of the bubbles and inform respondents about the compatibility improvements already implemented by iOS 18 before they make their decision. We elicit respondents' explanations for their preferences and display our open-ended classification in Figure A13 of our Online Appendix. We find that social stigma is the overwhelming reason Android users prefer blue bubbles. For iPhone users, while a substantial portion also have concerns about the social stigma, many also perceive the removal of green bubbles to itself increase the quality of the iPhone through improving the user interface and experience. Further, as shown in Section 4, they may now prefer switching to an Android device, or value having the option to switch in the future. Taken together, this is direct evidence on substantial non-user disutility created by green bubbles. The next section provides some more direct evidence on the question of whether some users and non-users value green bubbles.

Figure 3: Mechanism Evidence on Non-User Utility from Green Bubbles



(a) Fraction of Respondents that Prefer a Software Giving Blue Bubbles For Everyone



(b) The Effect of Compatibility Issues or Green Bubbles on Perceived Quality

Notes: Figure 3 Panel (a) presents the results by phone ownership for the fraction of people that prefer a software update making all messages appear as blue bubbles to everyone. Panel (b) presents the results for how removing compatibility issues or green bubbles affects the perceived quality of Androids and iPhones. We plot the percentage of people that think there is a strict quality improvement (4 or 5 on a 1-5 Likert scale). We only include respondents that pass all attention checks and bot detection protocols as per our pre-registration. We report 95% confidence intervals in both panels.

Perceived quality From the perspective of our model, the strong preference for the blue bubble update could arise from either an increase in user utility or a reduction in non-user utility. To disentangle these effects, we measure the perceived impact of removing compatibility issues or green bubbles on the quality of both Androids and iPhones, using perceived quality as a proxy for user utility. As shown in Figure 3, Panel (b), adding read receipts and typing indicators to text messaging on iPhones would strictly improve the perceived quality of Androids for approximately two-thirds of respondents and the perceived quality of iPhones for about half of respondents. Additionally, removing green bubbles would significantly enhance the perceived quality of Androids for a sizable portion of participants. However, as detailed in Appendix E.3, we find that the perceived quality of iPhones remains unchanged for over 60% of respondents when green bubbles are removed. Furthermore, Figure 3, Panel (b), shows that iPhone user utility is lower for 30% of respondents in the presence of green bubbles. At the same time, 10% of respondents rated the perceived quality of iPhones as higher with green bubbles.

For these 10% of respondents, two potential mechanisms could explain this preference: first, some individuals may value knowing whether they are communicating with an Android or an iPhone. Second, the status benefits associated with blue bubbles may enhance perceived quality. Our evidence from Figure 3, Panel (a), which shows that a majority of both users and non-users prefer the removal of green bubbles, suggests that decreases in user utility are not the dominant effect compared to increases in non-user utility resulting from the software change. Furthermore, our open-ended responses do not indicate that either of these two mechanisms is a primary driving force. As shown in Panel (b) of Figure A11 in our Online Appendix, only 10% of respondents mention signal detection and few mention status benefits as reasons for preferring not to have the software update.

We interpret these findings as evidence that green bubbles do not primarily drive demand for iPhones by increasing user utility but rather by reducing non-user utility. Moreover, this supports the idea that Apple's product feature decisions can directly influence the absolute perceived quality of the outside option—Androids. We present quantified estimates of the welfare effects in Section 3.3, which reinforce the important role of green bubbles in changing non-user utility.[14]

To gauge the extent to which our sample perceives green bubbles as a marker of Androids having lower phone quality, we ask our respondents why they think messages sent from Androids appear as green bubbles on iPhones.[15] Consistent with the evidence from the structured question, we find that some participants view the green bubbles as an indicator of the lower quality of Android devices. At the same time, we find that a large fraction (39%) of respondents think that Apple strategically created green bubbles to create social pressure by alienating Android users and increase exclusivity and brand loyalty to maximize its profits.

3.3 Deactivation study

While the previous evidence suggests that there are substantial consumer welfare costs from green bubbles, it does not involve monetary stakes and does not capture preference intensities. In this section, we provide incentivized evidence on the quan-

[14]Our findings on typing indicators and read receipts, which were addressed in iOS 18, suggest that these technical compatibility issues may also contribute to a decrease in non-user utility. Specifically, they indicate that Apple faced a trade-off between reducing user utility for iPhone users and decreasing non-user utility for Android users. Adding read receipts and typing indicators for Android-iPhone messaging on iPhones strictly improves the perceived quality of both devices for the majority of respondents (67% and 56% respectively).

[15]We ask this question before presenting information on the DOJ lawsuit.

titative difference in utility experienced by iPhone users due to having green bubbles instead of blue ones.

3.3.1 Sample

Student Sample We recruited a sample of college students aged 18 to 25 through College Pulse, a company specializing in recruiting U.S. college students for online surveys.[16] Since our design only applies to users with iMessage on their phones, we exclusively targeted iPhone users. Our data collection was conducted in October 2024, following the release of iOS 18 in mid-September.

Pre-registration Our data collection was pre-registered on AsPredicted (#195544) and includes the experimental design, hypotheses, primary and secondary outcomes, sample size, and exclusion criteria.[17]

began ***agreed***

Sample characteristics Among respondents who begin the survey, 83% agree to participate in our four-week deactivation study, which requires providing their phone number and screenshots of their phone settings if selected to participate in the deactivation stage. As a result, we are unable to collect incentivized data from those who do not consent to participate, and we acknowledge that our sample consists of a selected group of respondents.[18] Selection likely results in underestimating welfare losses, as those experiencing the highest social costs of deactivation may be less inclined to participate in the experiment. However, we may also underestimate the privacy and hassle cost of participation for the same reason.[19] Given this, we can only speak to the average welfare loss among those who consent, which still represents the vast majority of our sample. Our initial sample size is 402 participants. After adjusting our sample to align with our pre-registration and accounting for respondents potentially affected by a coding error, our final sample comprises 357 participants.[20] Our sample

redundant

were

did

[16] In this experiment, we recruited respondents through College Pulse as our design requires the ability to access personally identifiable information (phone numbers) from all respondents.

[17] For details, see `https://aspredicted.org/xxyp-s8qx.pdf`.

[18] We interpret 83% selecting into participation as a relatively high number, given that the deactivation runs for a significant period of time and requires PII. In addition, it is comparable to other participation rates in related literature, such as 57% in Bursztyn et al. (2025a) and 43% in Allcott et al. (2020).

[19] Even if we assume that the 17% of respondents who opted out are indifferent between blue and green bubbles, our findings still suggest a substantial disutility associated with green bubbles.

[20] Some respondents who regretted their initial valuation experienced a minor coding error that caused the MPL to skip certain increments during their second attempt (e.g., an ascending MPL

i believe section 3.2.1 (which is also about sampling) is in past tense but section 3.3.1 isn't—these tenses should be consistent across all sections

is 57% female, with an average age of 20.4 years. Demographic summary statistics on our sample can be found in Appendix Table A4.

3.3.2 Design

The experimental design is summarized below. A full description is provided in Appendix Figure A5.

Background on deactivation study Before consenting to the experiment, participants are informed that we will ask about the amount of money they would require to participate in two different deactivation options. We elicit this amount of money using a BDM procedure with a multiple price list with ascending offers.[21] We provide identical information to participants across the treatment arms before they consent, in order to prevent differential selection across arms. Respondents are truthfully told that only one of the two options will be implemented for 1 out of 10 responses.[22] Respondents are randomly assigned to one of two different treatment groups: the "blue bubble deactivation" group and "privacy and hassle cost" control group.

Blue bubble deactivation group In Option 1, respondents indicate the amount of money they would require to agree to modify their phone's settings and deactivate blue message bubbles. Consequently, all the iMessages they send would appear as green bubbles (instead of blue) on their own and recipients' iPhones for four weeks. We emphasized that everything else about their phone remains constant.[23]

omitting the \$60 increment between \$0 and \$150). To be conservative, we exclude all respondents ($N = 42$) who regretted their initial valuation for Choice 1 or 2 from our primary analysis. Additionally, we remove 3 observations flagged as duplicates according to pre-registered criteria, identified only after examining the data post-collection. In Appendix Figure A8, we demonstrate that our results remain virtually unchanged when analyzing the full set of 402 participants.

[21]The offers range from zero to 150 in increments of 5 until 20, and then increments of 10 until 150.

[22]In practice, only Option 2 is technically feasible for all respondents, so we always implement Option 2 for respondents chosen to participate in the deactivation study. We also debrief them about this at the end of the study.

[23]It is possible that, even if we specified that everything else remains constant, some users could still believe that they would also lose the option of distinguishing others' phones. However, our survey data (discussed in Section 3.2) suggest being able to distinguish others' phones is not a primary concern for our respondents. Specifically, we find that the majority of iPhone users actually prefer removing green bubbles. Additionally, open-ended responses reveal that only 10% of all respondents cite signal detection as a reason for opposing the software update. Moreover, even with the change, participants can still differentiate between iPhone and Android users on their own devices because messages to other iPhone users continue through iMessage, a service unavailable to

In Option 2, respondents are assigned to one of two cross-randomized benchmark goods. Respondents specify the amount of money they would need to disable either iMessage or their phone camera for four weeks. To verify iMessage deactivation, we require a screenshot of respondents' phone settings and send them text messages at a random time each week, while for camera deactivation, we request both a screenshot of their settings and, randomly once a week, their weekly screen time. The difference between the blue bubble deactivation and the iMessage deactivation is that, under the blue bubble deactivation, participants retain iMessage functionality, but any messages they send appear as green bubbles. Even after iOS 18, iMessage and RCS differ in more ways than just bubble color (e.g., end-to-end encryption), thus, the blue bubble deactivation is needed to isolate the welfare effects of green bubbles.

Privacy and hassle cost control To identify an individual's utility cost of having green rather than blue bubbles separately from their privacy and hassle costs of participation, we include a control group. For this group, in Option 1, we instead ask participants for their WTA to participate in a study which involves uploading a screenshot of their phone settings and receiving a weekly text message at a random time. Participants are informed that no changes will be made to their phone during the study period.

Borderline deception Our design requires measuring a person's WTA to deactivate their blue bubbles. However, this option is technically infeasible. While we do not outright deceive participants as we truthfully say we will only implement 1 out of the 2 deactivation options, our design relies on people believing that the blue bubbles deactivation is possible. We adopted this approach because we believed that it was the only feasible way to elicit incentivized WTA to deactivate blue bubbles. In our treatment group, we debrief participants about how Option 1 is infeasible at the end of the survey.[24]

3.3.3 Results

As shown in Figure 4, iPhone users require an average of $49 to have their messages appear as green rather than blue bubbles for four weeks. In the control, participants

Android users. Furthermore, exclusive features like FaceTime and location sharing remain limited to iPhone users, maintaining this distinction.

[24]The 95% deactivation compliance rate provides suggestive evidence that people took our experimental instructions seriously.

only require an average payment of \$17, which is approximately \$32 below the average payment required in the treatment group ($p < 0.001$). The median valuation in the green bubbles group of \$25 is also significantly above the median valuation in the control condition of \$7.5 ($p < 0.01$). Because participants' experience remains unchanged except for their messages appearing as green bubbles, this compensating differential—above hassle costs—suggests that they are willing to pay to avoid incurring the green bubble stigma. Thus, these results provide strong evidence on sizable disutility of green rather than blue bubbles, above the privacy and hassle cost of participating in the study. Taken together with our survey evidence, where we found a substantial social stigma of green bubbles with limited evidence on status benefits, we argue that green bubbles impose welfare costs from increasing non-user disutility as opposed to decreasing user utility.

sizable

Our estimates on the valuation of avoiding green bubbles are sizeable compared to the average WTA for deactivating iMessage or the camera for four weeks. Respondents, on average, require \$67 for deactivating iMessage and \$84 for deactivating the camera. Yet, comparing these effect sizes across product features is complicated by differential top-coding at our maximum value of \$150. For our hassle and privacy cost measure, 0% of responses were top-coded. In contrast, the top-coding rates for *missing comma* blue bubbles, iMessage and phone camera were 12.4%, 24.1%, and 36.6%, respectively. This differential top-coding downward biases the estimated difference between blue bubbles and the control condition, but upward biases the estimated differences between blue bubbles and the benchmark goods.

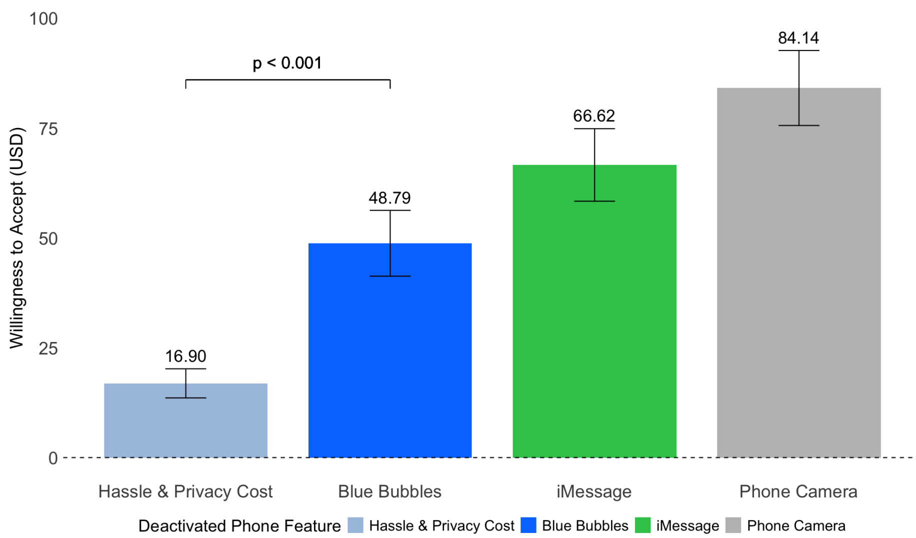
To circumvent this top-coding issue, we benchmark the valuation of blue bubbles against these other product features, focusing on the median payment required, which is unaffected by the top-coding. The median valuation of blue bubbles is \$25, compared to a valuation of \$45 for iMessage and \$95 for the phone camera.[25] This suggests that the median valuation of blue bubbles corresponds to 56% and 26% of the median valuation of iMessage and the phone camera, respectively. Our estimates show that respondents put a relatively high value on avoiding green bubbles relative to these benchmark features, underscoring the economic significance of the welfare cost.[26] While we focus on a four-week deactivation period, the cost of avoiding green

[25]Figure A7 displays the median WTA for deactivating each of the features. Our camera valuation is comparable to the estimates in Brynjolfsson et al. (2025), who find a median valuation of €68, with a wide confidence interval between €34 and €137.

[26]The finding suggests that over half of the welfare cost of deactivating iMessage is solely from avoiding having green bubbles, rather than from additional iMessage features such as location shar-

bubbles may be non-linear over time, as there could be large initial costs to being perceived as an Android user. Our estimates are not sensitive to including control variables, as shown in Appendix Table A5. Finally, we find minimal differences in average treatment effects by gender or relationship status (see Appendix Table A6).

Figure 4: Average WTA to Deactivate Phone Features by Treatment



Notes: Figure 4 displays the average WTA to deactivate various features of participants' iPhones for four weeks. We report 95% confidence intervals.

3.3.4 Robustness

Perceived credibility As discussed, our design relies on respondents believing that the blue bubbles deactivation is technically feasible. To evaluate respondents' perceptions, we ask them to rate the likelihood of each option being implemented. Given that each respondent is informed about two options, the benchmark probability is 50%, assuming they perceive the decision as a random coin toss. As shown in Appendix Figure A6, we find that all options have similar perceived likelihoods, ranging from 37% to 47%. The blue bubbles deactivation has the highest perceived likelihood, suggesting that participants did not view this option as infeasible. In Appendix Table A7, we also examine how treatment effects vary with perceived credibility and find little heterogeneity.

ing, end-to-end encryption, or other compatibility issues discussed earlier.

Additional robustness Appendix F.3 provides additional evidence on the robustness of our findings. Specifically, we demonstrate that our results remain robust to variations in top-coding thresholds and to the treatment of respondents who expressed regret over their valuations. Finally, Appendix F.4 provides details on the implementation and compliance of the deactivation study, noting that 95% of our selected participants successfully completed the entire deactivation.

4 Non-User Utility and Product Demand

Having established large negative welfare effects of green bubbles, we next turn to their market implications. Our experiment is designed to allow us to study incentivized demand under different relevant policy counterfactuals, offering insights that may be directly relevant to the ongoing lawsuit. Specifically, the experiment quantifies how green bubbles influence the demand for iPhones compared to Androids.

4.1 Sample

Student sample Similar to our previous data collections, we recruited a sample of US students aged 18 to 25 through Prolific. Data collection was carried out in November and December 2024.

Pre-registration This experiment was pre-registered on AsPredicted (#201569) and includes the experimental design, hypotheses, primary and secondary outcomes, sample size, and exclusion criteria.[27]

Sample inclusion criteria As pre-specified, we screen for individuals who are iPhone users and are actively considering purchasing a new phone, as this represents the target demographic for our experiment. We focus on iPhone users rather than Android users since they are more likely to be affected by the non-user utility of green bubbles, and, by currently owning an iPhone, they directly contribute to Apple's dominant market position. We exclude anyone who fails our attention checks and regrets their phone choice twice. We also pre-specified exclusion criteria based on Qualtrics' scores of suspected fraudulent activity, reCAPTCHA scores, and duplicate

[27]For details, see `https://aspredicted.org/54y4-s5jj.pdf`.

IDs.[28] We discuss these criteria in more detail in Appendix G.3.

Sample characteristics Our initial sample consists of 575 participants. After excluding some respondents who did not align with our pre-registered sample inclusion criteria, we are left with a final sample of 468 respondents.[29] Our final sample is 60.5% female, with an average age of 21.5 years.[30] Summary statistics for our sample can be found in more detail in Appendix Table A8.

4.2 Design

In this section, we describe an overview of the experimental design. A full description of the structure is provided in Appendix Figure A9.

4.2.1 Background and conditional choice explanation

Background information Respondents are informed that, following this survey, a lottery will be held where they could win a new smartphone. They are then given the option to choose between an iPhone 16 (current price of $800) or a Google Pixel 9 (current price of $650) along with $150, a comparison designed to equalize the value of the options based on market prices at the time of the experiment.[31] Participants are also informed that both phones are comparable in overall quality, including features like the camera, battery, and display.[32]

Conditional choice procedure We then outline the lottery procedure to participants, explaining that they will select their preferred phone option under a potential

[28]We also implemented a series of pre-registered bot prevention measures in Qualtrics, including randomized screening questions. In particular, we randomize validated text-input questions at the beginning of our survey.

[29]We accidentally collected responses from Canadians, non-students, respondents aged 26-27 and from respondents who own a version of the iPhone 16. Our results are virtually identical when including all 575 participants, as seen in Table A14.

[30]Due to Prolific's sample availability for our pre-specified screening criteria, we prioritized maximizing sample size over balancing gender. We demonstrate the robustness of our results by showing that results for males are stronger in Table A10.

[31]Both phones are top-sellers for their brands, of similar quality, and released in fall 2024, making them a natural choice for participants considering a new smartphone. These prices were sourced directly from the phone providers' websites at the time of the experiment and reflected the Black Friday and Cyber Monday discount for the Google Pixel 9.

[32]This is reflected in expert smartphone reviews and rankings from DXOMARK, a global leader in smartphone evaluations for over 15 years.

future scenario. Next, participants are told that if the future scenario occurs, a lottery will be conducted, and winners will receive their preferred phone option. The lottery selects one winner per 500 participants. Participants are then told that it is in their best interest to truthfully indicate their preferred choice. We explain that—in order to preserve anonymity—the phone will be sent to an Amazon locker or PO Box near the participant's zip-code. Participants' understanding of the conditional choice procedure is verified with a simple comprehension question, and only those who pass are allowed to proceed with the rest of the experiment.

Common information on the DOJ lawsuit All respondents are first reminded of compatibility issues between Androids and iPhones. In particular, respondents are told that the messages sent between Androids and iPhones appear as green bubbles on iPhones, while texts between iPhones appear as blue bubbles. All participants are then introduced to the recent DOJ lawsuit against Apple, which accuses the company of engaging in anti-competitive practices related to its iMessage service. We inform them that the lawsuit specifically highlights green bubbles and that, as a result of the lawsuit, Apple might be compelled to eliminate green bubbles and standardize blue bubbles across all devices. Additionally, participants are informed that experts anticipate the trial to commence in the coming months and that a decision will follow shortly after.

4.2.2 Conditional choice of preferred phone

On the decision screen, all respondents choose between an iPhone 16 and a Google Pixel 9 plus $150. Respondents make this binary choice under one of two randomly assigned scenarios: one where green bubbles persist after the lawsuit (green bubbles treatment) and another where they are banned (blue bubbles treatment). These scenarios are described in more detail below.

Green bubbles treatment Respondents are asked to choose their preferred phone in a scenario where Apple loses the DOJ lawsuit, faces significant fines, but green bubbles are not banned. Next, they are explicitly informed that messages exchanged between Androids and iPhones would continue to appear as green bubbles, accompanied by a screenshot illustrating how green bubbles would remain in such conversations.

Blue bubbles treatment Respondents are asked to choose their preferred phone in a scenario where Apple loses the DOJ lawsuit, faces significant fines, and that green bubbles are banned. Next, they are explicitly informed that messages exchanged between Androids and iPhones would now appear as blue bubbles, accompanied by a screenshot illustrating this change.

Design discussion We offer respondents a simple binary choice revealing their phone preference under market prices at the time of the experiment. We use a binary outcome to maintain a straightforward elicitation method while capturing the market share of both operating systems, our key metric for assessing market power. We focus exclusively on iPhone and Android phones as choice options, as they account for over 99% of the overall market share. These design choices are intended to enhance the external validity of our measure in reflecting actual purchasing decisions.

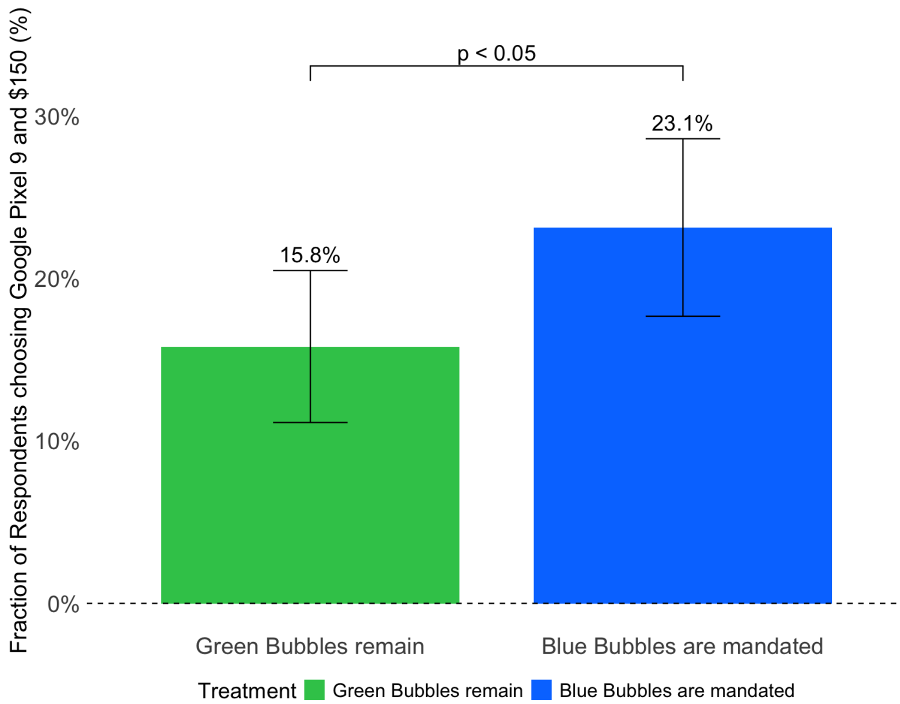
We use an active control group design in which both treatment scenarios involve Apple losing the lawsuit. This ensures that the only difference between the treatment and control groups is whether losing the lawsuit leads to a ban on green bubbles, minimizing differences in beliefs about other potential impacts of the lawsuit between treatment arms.[33] The active control design also helps mitigate concerns about differential experimenter demand effects across treatment groups (Haaland et al., 2023). Possible experimenter demand effects and social desirability biases are further mitigated by the incentivized nature of our outcome data (Bursztyn et al., 2025b) and appear unlikely given the heterogeneous treatment effects, which we discuss later.

4.3 Results

Figure 5 displays our main pre-registered results. Respondents in the blue bubble treatment choose the Google Pixel option 7.3 p.p. more compared to respondents in the green bubble treatment ($p < 0.05$) on a base of 15.8%. These effects are substantial, representing a 46% increase in the choice share of the Android phone option. The results provide strong evidence that a product feature, by reducing non-user utility, can significantly increase demand for the product. In this case, our evidence demonstrates that green bubbles contribute to the iPhone's dominant market position in the US.

[33] We cannot fully rule out the possibility that respondents interpret the removal of green bubbles as a signal that other features might also be removed, and that this interpretation differs from that of the control group.

Figure 5: Percentage of Respondents Choosing the Google Pixel 9 Option over the iPhone 16 Option



Notes: Figure 5 displays the percentage of respondents choosing the Google Pixel 9 and $150 over the iPhone 16 by treatment status. The blue bar represents the blue bubbles treatment condition, whereas the green bar is the green bubbles treatment condition. Error bars are 95% confidence intervals.

4.4 Mechanisms

This section examines the potential mechanisms driving the changes in phone preferences identified in our experiment.

Social concerns Building on the social mechanisms in Section 3.2, we analyze heterogeneous treatment effects based on relationship status. Notably, we observe the strongest treatment effects for those who are single, where the social costs of being a non-user are likely higher due to dating market concerns. This constitutes suggestive evidence that demand effects are less likely to be an important driver of treatment effects. The full results can be found in Appendix Table A10.

Other equilibrium changes One equilibrium mechanism through which the expectation of eliminating green bubbles might influence consumers' willingness to pay for iPhones over Android phones is the anticipated shift in user composition within social networks. To evaluate this, we first asked respondents about the current proportion of their friends who use iPhones versus Android devices.[34] Respondents then estimated how these proportions would change one year into the future, conditional on their assigned scenario (i.e., the DOJ either banning or not banning green bubbles). This allowed us to quantify expected equilibrium shifts within each respondent's social network.

Our findings indicate that a majority (69%) expect no changes in network size. However, respondents in the blue bubbles scenario anticipate the proportion of friends using iPhones to decline by an additional 3.8 percentage points ($p < 0.001$) compared to those in the green bubbles scenario. This represents only a 4.5% change in network size as at baseline, approximately 85% of participants' friends are iPhone users. Additionally, there is only a weak correlation (-0.08) between expected network composition changes and choosing an Android device. Hence, network effects may play some role, our data suggest they are not the primary mechanism behind our treatment effects.

Another potential equilibrium change involves differences in perceived resale values of phones. Using the same question structure, we observe a relatively small correlation (-0.20) between expected resale value and selecting the Google Pixel 9 option. Furthermore, only 33% of these respondents anticipate reselling their phones if they win the lottery, and treatment effects are stronger among respondents who do not intend to resell, as detailed in Appendix Table A11. Participants in the blue bubbles scenario anticipate the resale value of an iPhone to be $44 lower than those in the green bubbles scenario, although this difference lacks statistical significance at conventional levels ($p = 0.06$). This suggests that resale prices may play some role, but are also not the primary mechanism behind our treatment effects.

4.5 Robustness

Perceived credibility Our design relies on respondents believing that the possible future scenarios could occur. To assess the perceived stakes, we ask them to rate how likely it is that their scenario will be implemented. As an example, in the green bubbles treatment we ask: "How likely do you believe it is that the DOJ lawsuit against Apple will succeed in making them pay significant fines but that

[34]Due to a coding error, this data was only collected from approximately 40% of respondents.

green bubbles will remain in the coming months?" We find that people perceive the likelihood, on average, as 49% in the green bubbles treatment and 45% in the blue bubbles treatment, which suggests participants found the scenarios (similarly) credible. We also find stronger treatment effects among those who perceive their scenario as more likely, as shown in Appendix Table A12. This suggests that our estimates may underestimate the true change in market share that could result from a successful DOJ lawsuit removing green bubbles.

Additional robustness In Appendix G.3, we present additional robustness exercises. Specifically, we show that our results are robust to how we treat respondents who regret any of their choices and to different sample inclusion criteria.

4.6 Additional Demand Experiment

We conducted an additional pre-registered experiment that provides further evidence on how green bubbles increase demand for iPhones, using a different experimental design. In this experiment, we measure incentivized willingness to pay for an iPhone 16 Pro Max over a Samsung Galaxy S24 Ultra using a continuous BDM elicitation. Respondents are randomly assigned to either the green bubble or blue bubble treatment group. The green bubble group is informed that green bubbles will remain, while the blue bubble group learns that Android messages will appear as blue bubbles in the future—with the help of a recent technological advance that makes this change in color possible. Section H of our Online Appendix provides additional details on the design and data collection.

Consistent with our main findings, respondents in the blue bubbles group have approximately a 4% lower WTP for the iPhone 16 Pro Max over the Samsung Galaxy S24 Ultra compared to our control group ($p < 0.05$). We observe an increase in the fraction of respondents preferring the Android over the iPhone, from 4.9% to 6.8%. While this represents a substantial 39% rise in Android's share, our study is not sufficiently powered to detect statistically significant effects on the extensive margin.

The intensive and extensive effect size reported in the robustness experiment should be interpreted with caution for at least four reasons: first, the Android phone used in the elicitation is not the usual outside option that iPhone users would consider as it is even more expensive than the iPhone. Second, we do not measure the first stage of expectations about text messages between Androids and iPhones appearing as blue on iMessage in the future. This likely means that we underestimate the effects of green bubbles on the demand for iPhones over Androids. Further, people may be uncertain over the relative quality of the phones as we do not provide information to benchmark quality. Indeed, we show in Section H.5 of our Online Appendix that there are widespread misperceptions over the quality of the Samsung Galaxy S24 Ultra compared to the iPhone 16 Pro Max. Finally, we do not screen for respondents who are looking to buy a new smartphone and thus, this sample is less informative about how green bubbles affects new purchasing decisions.

Despite these concerns, we view these results as evidence of robustness of our main treatment effect across demand elicitation methods (i.e., WTP versus binary choice) and brand of Android phone (i.e., the result is not specific to Google Pixels).

5 The Strategic Creation of Non-User Disutility

Since humans are inherently social animals, consumption decisions reflect not only product attributes but also how products position individuals relative to one another. Firms with market power can exploit these social dynamics by introducing design choices that increase non-user disutility and create social equilibria that are difficult to regulate. In this section, we document how firms systematically use product features to exploit stigma and social status concerns to increase non-user disutility as a deliberate method for creating and sustaining market power.

Time-Limited Drops The purchase of various products is often linked to a specific one-time opportunity, such as product "drops" or attending live entertainment. As a result, non-users can feel socially excluded, particularly for events that occupy a large amount of the market or an individual's social network.

A clear example of this is how apparel brands rely on time-sensitive "drops" to manufacture cultural momentum. For example, Fear of God has built status through scarcity, but the mechanism becomes more powerful in the hands of corporations with global reach. Nike's SNKRs app illustrates the point: by releasing limited sneakers at scale, Nike can both ignite resale markets and amplify the cultural resonance of its products, entrenching its dominance and large market share in the $74 billion global sneaker market. Relatedly, the frequent release of updated versions of the same product erodes the perceived quality of past versions to create feelings of exclusion and stigma among those with older iterations. For example, even if limited innovation has occurred, new versions of smartphones and shoes (e.g., Air Jordan series) are released at least once a year.

Artificial Scarcity Through Blind-Boxing Outside of visible markers in the apparel industry, numerous industries use blind-box packaging to increase non-user disutility. Notably, Pop Mart, a Chinese collectibles company valued in the billions, has transformed “Labubu” figurines into cultural status symbols through blind-box packaging and rare editions. Labubus are projected to bring in over a billion dollars in revenue, and their annual sales are outpacing even Barbie and Hot Wheels toys. Blind boxes induce over-consumption by obscuring the identity of each figure, prompting repeated purchases and fueling lucrative resale markets where scarcity commands large markups. At the same time, Labubu toys function as social markers. As media outlets emphasize, ownership signals membership in a community of “young, trendy collectors,” and even the act of opening a blind box is a shared cultural experience.[35]

Visible Markers of Exclusivity Luxury brands position their products as markers of prestige and affluence (Frank, 2000). While owners derive utility from signaling, others incur disutility from exclusion and comparison. Hermès, for example, manufactures exclusion and scarcity—through waiting lists, controlled supply, and limited collaborations—that not only sustains high demand among users but also deepens the disutility of non-users, even within the top income percentile. A similar mechanism underlies design features that magnify visibility. Handbags with oversized monogram prints (e.g., Louis Vuitton), as an example, ensure that ownership is legible and absence is stigmatizing.

Negative Advertising Traditional negative advertising focuses on tarnishing the reputation or perceived quality of competitors. A variation of these campaigns instead emphasize the perceived shortcomings of non-users, instead of the competitor product, relative to users to drive social stigma. A clear example of this strategy is Apple’s “Get a Mac” campaign (2006–2009), which contrasted a cool, young Mac user with a nerdy, outdated PC user to imply that non-users were less capable and out of touch with modern technology. This ad campaign served as a strategic effort to rejuvenate the Mac brand, which held only a 3% market share in the mid-2000s (Statista, 2018).

[35]See South China Morning Post (2023), “Pop Mart’s blind box craze explained,” and The Guardian (2022), “The cult of Labubu: why Chinese Gen Z can’t stop buying blind boxes.”

Discussion The cases reviewed here illustrate how the strategic mechanism underlying green bubbles on iPhones extends to other product features: firms actively engineer non-user disutility through visible design markers, artificial scarcity, time-sensitive releases, and negative advertising about non-users. Rather than taking positional concerns as exogenous, companies deliberately amplify them to sustain market power. This perspective suggests that theories of competition and welfare in markets for positional goods must explicitly incorporate the endogenous creation of non-user disutility as a strategic choice by firms.

6 Conclusion

In this paper, we provide evidence that companies can influence demand for their products not only through increasing user utility but also through creating non-user disutility. As motivated with our model, the mechanism through which demand is affected has significant implications for consumer welfare: firms that increase demand by increasing non-user disutility harm consumer welfare. Using the case of iPhone "green bubbles," we provide survey and experimental evidence that a simple design choice stigmatizes Android owners, lowers their perceived social status, and thereby shifts demand toward iPhones. iPhone users reveal a sizable willingness to pay to avoid green bubbles, and removing them substantially increases the relative attractiveness of Android devices among U.S. college students.

Our findings inform the ongoing DOJ lawsuit against Apple concerning alleged anticompetitive practices, particularly those involving iMessage. Despite Apple's adoption of RCS in iOS 18 to address certain compatibility issues, our evidence indicates that removing green bubbles would increase non-user utility and consumer welfare among U.S. college students. This case exemplifies how dominant firms may leverage social concerns to entrench their market power, reducing the attractiveness of rival products without necessarily improving the core functionality of their own.

A promising direction for future research is to explore—both theoretically and empirically—the interplay between pre-existing market power and the strategic generation of non-user disutility. A key open question is whether, and to what extent, firms with greater market power are more effective in creating non-user disutility. This issue has significant welfare implications, as the creation of non-user disutility is particularly detrimental if it reinforces the dominance of the most powerful firms in the market. The increase in market power can lead to less innovation and fewer incentives to develop user-centric improvements, resembling exploitative innovation (Heidhues et al., 2016).[36] However, if companies with low market power and small market shares create non-user disutility, the overall welfare effects could be ambiguous, as the welfare benefits from increased competition might outweigh any direct negative effects from the rise in non-user disutility.

While the focus of this paper is on the smartphone market, we also present case studies which illustrate how companies across a variety of markets strategically create non-user disutility using social mechanisms. Future research could investigate the broader effects of non-user utility across industries and over time. Such insights could provide valuable guidance for policymakers aiming to regulate and mitigate anti-competitive behaviors by firms.

[36] As opposed to exploitative innovation, the creation of non-user disutility we study affects users but also has incidence over non-users. Additionally, hidden fees can be targeted through policies of consumer protection and disclosure rules, but reducing stigma embedded in design and social norms likely requires very different instruments.

References

Allcott, Hunt, Juan Camilo Castillo, Matthew Gentzkow, Leon Musolff, and Tobias Salz, "Sources of Market Power in Web Search: Evidence from a Field Experiment," *Working Paper*, July 2024.

_ , Luca Braghieri, Sarah Eichmeyer, and Matthew Gentzkow, "The welfare effects of social media," *American Economic Review*, 2020, *110* (3), 629–676.

Apple Inc., "iOS 18 is available today, making iPhone more personal and capable than ever," 2024.

Apple Support, "Apple Addresses DOJ Lawsuit Allegations," 2024.

Axios, "Teen iPhone Use and Spending Habits," 2021.

Bagwell, Laurie Simon and B Douglas Bernheim, "Veblen effects in a theory of conspicuous consumption," *The American economic review*, 1996, pp. 349–373.

Bailey, Michael, Drew Johnston, Theresa Kuchler, Johannes Stroebel, and Arlene Wong, "Peer effects in product adoption," *American Economic Journal: Applied Economics*, 2022, *14* (3), 488–526.

Bénabou, Roland and Jean Tirole, "Incentives and prosocial behavior," *American Economic Review*, 2006, *96* (5), 1652–1678.

Bostanci, Gorkem, Pinar Yildirim, and Kinshuk Jerath, "Negative advertising and competitive positioning," *Management Science*, 2023, *69* (4), 2361–2382.

Brynjolfsson, Erik, Avinash Collis, W. Erwin Diewert, Felix Eggers, and Kevin J. Fox, "GDP-B: Accounting for the Value of New and Free Goods," *American Economic Journal: Macroeconomics*, 2025.

Bursztyn, Leonardo and Robert Jensen, "Social image and economic behavior in the field: Identifying, understanding, and shaping social pressure," *Annual Review of Economics*, 2017, *9* (1), 131–153.

_ , Benjamin Handel, Rafael Jimenez-Duran, and Christopher Roth, "When Product Markets Become Collective Traps: The Case of Social Media," *American Economic Review*, 2025.

_ , Bruno Ferman, Stefano Fiorin, Martin Kanz, and Gautam Rao, "Status goods: experimental evidence from platinum credit cards," *The Quarterly Journal of Economics*, 2018, *133* (3), 1561–1595.

_ , Ingar K Haaland, Nicolas Röver, and Christopher Roth, "The Social Desirability Atlas," Technical Report, National Bureau of Economic Research 2025.

Campante, Filipe, Emilio Depetris-Chauvin, and Ruben Durante, "The Virus of Fear: The Political Impact of Ebola in the United States," *American Economic Journal: Applied Economics*, 2024, *16* (1), 480–509.

Clark, Andrew E and Andrew J Oswald, "Satisfaction and comparison income," *Journal of public economics*, 1996, *61* (3), 359–381.

Courty, Pascal and Li Hao, "Sequential screening," *The Review of Economic Studies*, 2000, *67* (4), 697–717.

Deneckere, Raymond J and R Preston McAfee, "Damaged goods," *Journal of Economics & Management Strategy*, 1996, *5* (2), 149–174.

Denoyelles, Aimee, Tim Brown, Ryan Seilhamer, and Baiyun Chen, "The Evolving Landscape of Students' Mobile Learning Practices in Higher Education," `https://er.educause.edu/articles/2023/1/the-evolving-landscape-of-students-mobile-learning-practices-in-higher-education` 2021. Accessed: 2024-11-28.

Designveloper, "Android vs iPhone Users: What's the Difference?," 2024.

Farrell, Joseph and Garth Saloner, "Standardization, compatibility, and innovation," *the RAND Journal of Economics*, 1985, pp. 70–83.

Frank, Robert H, *Choosing the right pond: Human behavior and the quest for status.*, Oxford University Press, 1985.

_ , "The demand for unobservable and other nonpositional goods," *The American Economic Review*, 1985, *75* (1), 101–116.

_ , *Luxury fever: Money and happiness in an era of excess*, Princeton University Press, 2000.

_ , "Positional externalities cause large and preventable welfare losses," *American economic review*, 2005, *95* (2), 137–141.

Haaland, Ingar, Christopher Roth, and Johannes Wohlfart, "Designing information provision experiments," *Journal of economic literature*, 2023, *61* (1), 3–40.

Haaland, Ingar K, Christopher Roth, Stefanie Stantcheva, and Johannes Wohlfart, "Understanding Economic Behavior Using Open-ended Survey Data," *Journal of Economic Literature*, 2025.

Hagiu, Andrei and Julian Wright, "Platform Traps," Technical Report, Working paper 2025.

Heffetz, Ori and Robert H Frank, "Preferences for status: Evidence and economic implications," in "Handbook of social economics," Vol. 1, Elsevier, 2011, pp. 69–91.

Heidhues, Paul and Botond Kőszegi, "Behavioral industrial organization," *Handbook of Behavioral Economics: Applications and Foundations 1*, 2018, *1*, 517–612.

_ , _ , and Takeshi Murooka, "Exploitative innovation," *American Economic Journal: Microeconomics*, 2016, *8* (1), 1–23.

Imas, Alex and Kristóf Madarász, "Superiority-Seeking and the Preference for Exclusion," *Review of Economic Studies*, 2022.

International Data Corporation, "Worldwide Smartphone Market Forecast to Grow 6.2

Katz, Michael L and Carl Shapiro, "Network externalities, competition, and compatibility," *The American economic review*, 1985, *75* (3), 424–440.

Lau, Richard R, Lee Sigelman, and Ivy Brown Rovner, "The effects of negative political campaigns: A meta-analytic reassessment," *The Journal of Politics*, 2007, *69* (4), 1176–1209.

Luttmer, Erzo FP, "Neighbors as negatives: Relative earnings and well-being," *The Quarterly journal of economics*, 2005, *120* (3), 963–1002.

Market Research Future, "US Smartphone Market Size, Share and Growth Report 2032," 2024.

Nocke, Volker, Martin Peitz, and Frank Rosar, "Advance-purchase discounts as a price discrimination device," *Journal of economic theory*, 2011, *146* (1), 141–162.

Perez-Truglia, Ricardo, "The effects of income transparency on well-being: Evidence from a natural experiment," *American Economic Review*, 2020, *110* (4), 1019–1054.

Pesendorfer, Wolfgang, "Design innovation and fashion cycles," *The american economic review*, 1995, pp. 771–792.

Precedence Research, "Smartphones Market Size, Share, Growth Analysis Report, 2024," 2024.

Salop, Steven C and David T Scheffman, "Raising rivals' costs," *The American economic review*, 1983, *73* (2), 267–271.

Schoon, Ben, "Google Pixel 9 Launch Leads to 'Highest-Ever' Quarterly Sales," 2024.

StatCounter, "Mobile Operating System Market Share in the United States of America," 2024.

_ , "Mobile Vendor Market Share United States Of America," 2024.

Statista, "Global Apple Mac Sales in the Fiscal Years from 2002 to 2018," 2018.

_ , "WhatsApp Usage Share Among Messaging App Users by Country in 2023," 2023. Accessed: 2024-12-14.

_ , "Market share of mobile operating systems worldwide from 2009 to 2024, by quarter," 2024.

U.S. Department of Justice, "Justice Department Sues Apple for Monopolizing Smartphone Markets," 2024.

U.S. News & World Report, "How Europe's Regulatory Battle With Apple Could Signal What's to Come," 2024.

Veblen, Thorstein, *The Theory of the Leisure Class: An Economic Study of Institutions*, New York: Macmillan, 1899.

Visual Capitalist, "The Top Companies by Global Smartphone Market Share," 2024.

World Population Review, "iPhone Market Share by Country 2024," 2024. Accessed: 2024-12-14.

Zhukova, Anya, "Why WhatsApp Never Took Off in the U.S.," 2022. Accessed: 2024-12-12.

Supplemental Appendix: Not for publication

Our supplementary material is structured as follows. Section A provides additional details related to the model. Section B provides background information on the smartphone market and Section C provides additional details on the antitrust cases against Apple. Section D provides the overview of our data collection activities. Section E includes additional tables and figures for the mechanism survey. Section F includes additional tables and figures for the iMessage deactivation experiment. Section G includes additional tables and figures for the market demand experiment.

A Mathematical Appendix

A.1 Main Proofs

In what follows, let $\mu_j := p_j - c$ denote the markup of firm j and $\pi_j(p_j, p_{-j})$ denote its profit function.

Proof of Lemma 1. As it is well known, the log-concavity Assumption 1 ensures that the second-order conditions of each firm hold. To see why, note that the log-concavity of f implies the log-concavity of $Q = 1 - F(p_A - p_B - g)$ and $1 - Q = F(p_A - p_B - g)$. In turn, the log-concavity of Q implies that $Q'^2 - Q''Q > 0$ and the log-concavity of $1 - Q$ implies that $Q'^2 + Q''(1 - Q) > 0$.

Focusing on firm A, we take the second derivative of the profit function to verify that the second-order conditions hold. Note that $\partial^2\pi_A/\partial p_A^2 = Q''\mu_A + 2Q'$. After substituting the value of μ_A from the first-order condition (FOC), we get $-Q''Q/Q' + 2Q'$. Multiplying times $-Q'$ gives $Q''Q - 2Q'^2 < Q''Q - Q'^2$, which is negative by log-concavity. A similar procedure shows that firm B's second-order conditions hold.

Let $P_j(p_{-j})$ denote the best response function of j. Note that $P_j' \in (0, 1)$. To see why, focus on firm A and use the implicit function theorem (applied to the firm's FOC) to get: $P_A' = \frac{Q'^2 - Q''Q}{2Q'^2 - Q''Q}$. A similar procedure applies to B's best response. Finally, note that $P_j(p_{-j}) > c > 0$. This condition and the bounds on the derivative of P_j ensure that the best responses of both firms cross at prices above marginal cost and that they do so only once. ■

Proof of Proposition 1. Consider a marginal increase in g, dg. Applying the implicit function theorem over the FOCs of A and B, we get:

$$\frac{dp_A}{dg} = \frac{Q'^2 - QQ''}{Q''(1-2Q) + 3Q'^2}$$
$$\frac{dp_B}{dg} = -\frac{Q'^2 + Q''(1-Q)}{Q''(1-2Q) + 3Q'^2}$$

Note that the denominator of both equations is positive, since it equals the addition of three terms: $Q''(1-Q)+Q'^2$, plus $Q'^2 - Q''Q$ (both positive due to Assumption 1), and Q'^2. The numerators in both expressions are positive again due to log-concavity, implying that $dp_A/dg > 0$ and $dp_B/dg < 0$. Hence, firm A's equilibrium markup increases and firm B's equilibrium markup decreases in response to dg. Moreover, note that the numerator in both cases is lower than the denominator, implying that $dp_A/dg < 1$ and $-dp_B/dg < 1$. Additionally, $(dp_A - dp_B)/dg < 1$, which implies that demand for A, $Q(p_A - p_B - g)$, increases, and demand for B decreases. ■

Proof of Proposition 2. Let $\mathbf{u} = (u_A, u_B)$. Consumer welfare is given by:

$$W(g_u, g_n) := \underbrace{\int_{\mathbf{u}:\, u_A - p_A \geq u_B - p_B - g} (u_A + g_u - p_A) f(\mathbf{u}) d\mathbf{u}}_{\text{Welfare of } A\text{'s consumers}} + \underbrace{\int_{\mathbf{u}:\, u_A - p_A < u_B - p_B - g} (u_B - g_n - p_B) f(\mathbf{u}) d\mathbf{u}}_{\text{Welfare of } B\text{'s consumers}}.$$

Differentiate W:

$$dW = Q(dg_u - dp_A) - (1-Q)(dg_n + dp_B).$$

Consider first the case when A only creates non-user disutility; that is, when $dg = dg_n$ and $dg_u = 0$. In this case, consumers of A are unambiguously worse off since they experience an increase in p_A and no offsetting increase in user utility. Moreover, consumers of B are also worse off since the decrease in price p_B is not enough to offset the increase in g, so $-dg - dp_B < 0$. Thus, $dW < 0$.

Consider now the case when A only creates user utility; that is, when $dg = dg_u$ and $dg_n = 0$. In this case, consumers of A are unambiguously better off since they experience an increase in g which is large enough to offset the increase in p_A, so

$dg - dp_A > 0$. Moreover, consumers of B are also better off since they experience a decrease in p_B, without a decrease in their non-user utility. Hence, $dW > 0$. ■

A.2 Microfoundation

This subsection presents a duopoly model where firms compete in prices and where they can influence the stigma associated with consuming their products, effectively creating non-user disutility for some consumers and user utility for others. The purpose of the section is to microfound the model presented in Section 2, endogenizing two features that were exogenous in that model: the non-user utility term g and the fact that only one company could generate non-user disutility. We will show that only the company that is relatively more associated with "high types" will choose to generate non-user disutility.

Setup. The setup is similar to the model in Section 2, but with a continuum of consumers of two types: "high," H, (of mass γ) and "low," L, (of mass $1-\gamma$). Consumers must choose which of the two products they buy. The total utility that they get from a product comes from two channels: 1) a direct utility from consuming it and 2) a social image concern.

Concretely, the value that i gets from buying product $j \in \{A, B\}$ is:

$$\underbrace{u_j^i}_{\text{Direct utility}} + \underbrace{S(q_j^H, q_j^L)(\lambda_A + \lambda_B)}_{\text{Social image}} - p_j,$$

where q_j^θ is the demand of type $\theta \in \{H, L\}$ for product j and $\mathbf{q} = (q_A^H, q_A^L)$ is the vector of demands for product A.[37] We index consumers by the difference in their direct utility from product A vs. B, $u^i := u_A^i - u_B^i$. We assume that u^i is distributed according to a strictly increasing smooth distribution F^θ with bounded density f^θ with full support for each type.

The social image term $S(q_j^H, q_j^L)(\lambda_A + \lambda_B)$ follows the framework in Bursztyn and Jensen (2017) extended from Bénabou and Tirole (2006). The function S represents how other individuals perceive i given i's purchase decision. This function is positive or negative whenever there are positive or negative image concerns, respectively. To

[37]Note that $q_A^H + q_B^H = \gamma$ and $q_A^L + q_B^L = 1 - \gamma$, so it is enough to keep track of the demand for product A, without loss of generality.

fix ideas, we assume the following functional form, although the main results hold with more general functional forms:

$$S(q_j^H, q_j^L) := (1-\gamma)q_j^H - \gamma q_j^L$$

This function takes a value of zero—the social image concern disappears—when the fraction of H purchasing the product equals the fraction of H in the population (γ). That is, when the posterior likelihood of being a high type given purchase of j is equal to the prior—when phone choice is uninformative of individual type. Additionally, note that S is increasing in q_j^H and decreasing in q_j^L, to capture that i's image improves as more H individuals purchase the same product and worsens as more L individuals do.

The non-negative parameters λ_A, λ_B correspond to the importance or salience of the social image concern and are determined by platforms' product choices. For example, firm A can marginally increase the saliency of social image relative to an initial baseline of zero—say, by allowing its customers to distinguish which phone other customers have. In this case, A customers face social image concerns vis-à-vis other A customers equal to $S(q_A^H, q_A^L)\lambda_A$, and B customers face $S(q_B^H, q_B^L)\lambda_A$ vis-à-vis A customers. We have assumed, for simplicity, that firms impose the same salience of the social image concerns on both users and non-users, thereby creating user and non-user utility simultaneously. This assumption can be relaxed by allowing these parameters and the function S to differ between users and non-users, but the main implications of the model remain unchanged. Note also that our assumptions imply that only one phone—the one relatively more associated with H customers—will have positive image concerns. Therefore, by increasing saliency of social image, the company that sells that phone will increase user utility and decrease non-user utility, while the other company will do the reverse.

Timing. The timing of the model is as follows. First, firms choose simultaneously their product design: whether to costlessly and marginally increase the salience parameter λ_j. After this decision, both firms compete in prices.

Equilibrium. Let $Q_j^{c,\theta}\left(p_j^D - S^D(q_j^H, q_j^L)(\lambda_A + \lambda_B)\right)$ denote the aggregate demand of type θ for product j, conditional on (expected) quantities, where $p_j^D := p_j - p_{-j}$ is the price difference and $S^D(q_j^H, q_j^L) := S(q_j^H, q_j^L) - S(\gamma - q_j^H, (1-\gamma) - q_j^L)$ is the difference in social image concerns between products. We impose, for tractability, an assumption that ensures that network effects are not too strong.

Assumption 2. *The salience of the social image concerns is not too high:* $\lambda_j \in \{0, d\lambda_j\}$*, where* $d\lambda_j \to 0$*.*

In words, we restrict attention to the case where social image concerns are arbitrarily small, so that firms' product design choices can be interpreted as an infinitesimal perturbation around the benchmark without image concerns. This allows us to abstract from higher-order effects that complicate the analysis but do not qualitatively change the mechanisms we highlight.

Given Assumption 2, the next lemma shows that downward-sloping demand functions exist given firm product design choices λ. Without loss of generality, we focus on the demand for A since $Q_B^H = \gamma - Q_A^H$ and $Q_B^L = 1 - \gamma - Q_A^L$.

Lemma 2. *Fix* $\lambda := \lambda_A + \lambda_B$ *and the price difference* p_A^D*. Under Assumption 2, there exist downward-sloping demand curves* $Q_A^\theta(p_A^D, \lambda)$ *which solve the following fixed-point problem:*

$$q_A^\theta = Q_A^{c,\theta}\left(p_A^D - S^D(q_A^H, q_A^L)(\lambda_A + \lambda_B)\right) \tag{1}$$

Proof. Define the mapping $\Phi(q_A^H,\, q_A^L) = (Q_A^{c,H}, Q_A^{c,L})$. We will show that Φ is a contraction on a compact, convex set ($[0,\gamma]\times[0,1-\gamma]$) and apply the Banach Fixed-Point Theorem.

Consider two points, $(q_A^H,\, q_A^L)$ and $(q_A'^H,\, q_A'^L)$. By the mean-value theorem,

$$\left|\Phi^\theta(q_A^H,\, q_A^L) - \Phi^\theta(q_A'^H,\, q_A'^L)\right| \;\leq\; \max_x\, f^\theta(x)\cdot\left|S^D(q_A^H, q_A^L) - S^D(q_A'^H, q_A'^L)\right|\cdot(\lambda_A+\lambda_B).$$

Since S is continuously differentiable,[38]

$$\left|S^D(q_A^H, q_A^L) - S^D(q_A'^H, q_A'^L)\right| \;\leq\; \|\nabla S^D\|_\infty\left(\left|q_A^H - q_A'^H\right| + \left|q_A^L - q_A'^L\right|\right).$$

Hence,

$$\left|\Phi^\theta(q_A^H,\, q_A^L) - \Phi^\theta(q_A'^H,\, q_A'^L)\right| \;\leq\; \|f^\theta\|_\infty\cdot\|\nabla S^D\|_\infty\cdot(\lambda_A+\lambda_B)\cdot\left(\left|q_A^H - q_A'^H\right| + \left|q_A^L - q_A'^L\right|\right).$$

[38]Here, $\|\cdot\|_\infty$ denotes the supreme norm.

By Assumption 2, and since $\|\nabla S^D\|_\infty \leq 2$,[39] and f^θ is bounded, $\|f^\theta\|_\infty \cdot \|\nabla S^D\|_\infty \cdot (\lambda_A + \lambda_B) < 1$, so Φ is a contraction. To see why the resulting demands $Q_A^\theta(p_A^D, \lambda)$ are downward-sloping, apply the Implicit Function Theorem on Equation (1) to get:

$$\frac{\partial Q_A^\theta}{\partial p_A^D} = \frac{Q_A^{c,\theta\prime}}{1 + 2(\lambda_A + \lambda_B)\left[(1-\gamma)Q_A^{c,H\prime} - \gamma Q_A^{c,L\prime}\right]}. \tag{2}$$

The numerator of this expression is negative and the denominator is positive (and close to one) by Assumption 2. ■

We now impose a set of assumptions that will ensure that demands are log-concave.

Assumption 3. *The densities f^θ are strictly log concave.*

Assumption 4. *Demands have bounded curvatures:*

$$f^{H\prime\prime}(1 - F^L) + f^{L\prime\prime}(1 - F^H) \geq \max\left\{f^{H\prime\prime} + f^{L\prime\prime}, 0\right\} + 2f^H f^L$$

Lemma 3. *Under Assumptions 2 to 4, the demand curve $Q_A(p_A - p_B, \lambda) := Q_A^H(p_A - p_B, \lambda) + Q_A^L(p_A - p_B, \lambda)$ is log-concave in p_A and the demand curve $Q_B := 1 - Q_A$ is log-concave in p_B.*

Proof. We begin by showing that Q_A is log concave; that is, that $Q_A'' Q_A \leq {Q_A'}^2$, where $Q_A' := \frac{\partial Q_A}{\partial p_A}$ and Q_A'' is defined accordingly. Let $D_A := (1-\gamma)Q_A^{c,H\prime} - \gamma Q_A^{c,L\prime}$ and note that ${Q_A^\theta}' = Q_A^{c,\theta\prime}/(1 + 2\lambda D_A)$ from Equation (2) (where $1 + 2\lambda D_A$ is the denominator, which is positive as argued above). Similarly, let $E_A := (1-\gamma)Q_A^{c,H\prime\prime} - \gamma Q_A^{c,L\prime\prime}$. Differentiating ${Q_A^\theta}'$ we get: ${Q_A^\theta}'' = \frac{Q_A^{c,\theta\prime\prime}}{(1+2\lambda D_A)^2} - 2\lambda \frac{Q_A^{c,\theta\prime} E_A}{(1+2\lambda D_A)^3}$. Then, the inequality $Q_A'' Q_A \leq {Q_A'}^2$ can be written as:

$$\left[\frac{Q_A^{c,H\prime\prime} + Q_A^{c,L\prime\prime}}{(1+2\lambda D_A)^2} - 2\lambda E_A \frac{Q_A^{c,H\prime} + Q_A^{c,L\prime}}{(1+2\lambda D_A)^3}\right]\left(Q_A^{c,H} + Q_A^{c,L}\right) \leq \frac{{Q_A^{c,H\prime}}^2 + {Q_A^{c,L\prime}}^2 + 2Q_A^{c,H\prime}Q_A^{c,L\prime}}{(1+2\lambda D_A)^2}$$

We can rewrite this expression as:

$$\begin{aligned}&\left[\left(Q_A^{c,H\prime\prime}Q_A^{c,H} - {Q_A^{c,H\prime}}^2\right) + \left(Q_A^{c,L\prime\prime}Q_A^{c,L} - {Q_A^{c,L\prime}}^2\right)\right] \\ &+ \left[Q_A^{c,H\prime\prime}Q_A^{c,L} + Q_A^{c,L\prime\prime}Q_A^{c,H} - 2Q_A^{c,H\prime}Q_A^{c,L\prime}\right] \leq 2\lambda E_A \frac{Q_A^{c,H\prime} + Q_A^{c,L\prime}}{(1+2\lambda D_A)} Q_A.\end{aligned} \tag{3}$$

[39] This is by the definition of S, which guarantees that $|S| \leq 1$.

The first row in Equation (3) is negative because of the log-concavity of $Q_A^{c,\theta}$ inherited from f^θ (Assumption 3). The left-hand side of the second row of Equation (3) can be rewritten as: $-f^{H'}(1-F^L) - f^{L'}(1-F^H) - 2f^H f^L$. This expression is negative by Assumption 4. Lastly, the right-hand side of Equation (3) approaches 0 by Assumption 2. Thus, we confirm that the inequality holds.

Next, we repeat a similar procedure to show that $Q_B'' Q_B \leq {Q_B'}^2$, where $Q_B' := \frac{\partial Q_B}{\partial p_B}$ and Q_B'' is defined accordingly. We can rewrite the relevant inequality as:

$$\begin{aligned} &\left[\left(Q_B^{c,H''} Q_B^{c,H} - Q_B^{c,H'^2}\right) + \left(Q_B^{c,L''} Q_B^{c,L} - Q_B^{c,L'^2}\right)\right] \\ &+ \left[Q_B^{c,H''} Q_B^{c,L} + Q_B^{c,L''} Q_B^{c,H} - 2Q_B^{c,H'} Q_B^{c,L'}\right] \leq 2\lambda E_B \frac{Q_B^{c,H'} + Q_B^{c,L'}}{(1+2\lambda D_B)} Q_B. \end{aligned} \tag{4}$$

As above, the first row in Equation (4) is negative because of the log-concavity of $Q_A^{c,\theta}$ inherited from f^θ and the right-hand side of the inequality approaches 0 by Assumption 2. Given that $Q_B = 1 - Q_A$, we can rewrite the left-hand side of the second row of Equation (4) as:

$$Q_A^{c,H''} Q_A^{c,L} + Q_A^{c,L''} Q_A^{c,H} - 2Q_A^{c,H'} Q_A^{c,L'} - Q_A^{c,H''} - Q_A^{c,L''}.$$

This expression is negative by Assumption 4.

■

Now, consider the subgame that follows firms' product design choices λ_j.

Lemma 4. *Under Assumptions 2 to 4, there exists a unique Nash equilibrium in the subgame that follows firms' product design choices λ_j. Let $p_j(\lambda)$ denote the equilibrium prices in that subgame.*

Proof. The proof follows from applying Lemma 3 to show that demands are log-concave, and following a similar procedure as in Lemma 1. ■

In the following proposition, we characterize the equilibria of this game. We will show that, in the more interesting case when firms are slightly differentiated, only one firm will choose to make social image concerns salient in equilibrium. In this case, the company that chooses to make social image concerns salient in equilibrium is the one that is relatively more associated with the high types in the absence of social image concerns.

Before presenting the proposition, we introduce some useful notation. Let $p_A^D(0)$

denote the equilibrium price difference between product A and B in the subgame when $\lambda_j = 0$ (which exists and is unique by Lemma 4). Let $Q_A^{\theta,0} := Q_A^{\theta}(p_A^D(0), 0)$ denote the equilibrium demand for A by type θ in that subgame, and $S^0 := S^D(Q_A^{H,0}, Q_A^{L,0})$ denote the equilibrium difference in social image terms between A and B. Note that $S^0 > 0$ ($S^0 < 0$) if A (B) is relatively more associated with high types in that subgame, while $S^0 = 0$ if both firms have the same ratio of high types and low types.

Proposition 3. *Under Assumptions 2 to 4, if $S^0 \neq 0$, there exists a unique subgame perfect equilibrium in this game where only one firm—the one relatively more associated with high types—chooses to make the social image concerns salient; firm A if $S^0 > 0$ and B otherwise. If $S^0 = 0$, both companies are indifferent between making the social image concerns salient or not, so there are multiple equilibria.*

Proof. The key to this proof is to notice that, when $\lambda \approx 0$, we can write:

$$q_A = Q(p_A - p_B - g), \tag{5}$$

where $g := \lambda S^0$. Suppose without loss of generality that $S^0 > 0$. Consider the profit function of firm A conditional on product choices λ (and, hence, g):

$$\pi_A(\lambda) := [p_A(\lambda) - c]\, Q(p_A - p_B - g(\lambda)).$$

Differentiate with respect to λ:

$$\pi_A' := p_A' \left[Q + (p_A - c)Q'\right] + (p_A - c)\left[-Q'g' - Q'p_B'\right] = (p_A - c)\left|Q'\right|(g' + p_B'),$$

where we have used that the term $Q + (p_A - c)\frac{\partial Q}{\partial p_A}$ is zero by A's FOC in the final subgame. This FOC also implies that $p_A - c > 0$. Thus, the sign of π_A' depends on the sign of $g' + p_B'$. Note that $g' = S^0$ by the definition of g. Since $p_B' = \frac{dp_B}{dg}\frac{dg}{d\lambda} = \frac{dp_B}{dg}S^0$, we have that $g' + p_B' = S^0(1 + \frac{dp_B}{dg})$. We can then use the same procedure from the proof of Proposition 1 to show that $1 + \frac{dp_B}{dg} > 0$, which implies that $\pi_A' > 0$.

Following a similar argument, $\pi_B' = (p_B - c)\left|Q'\right| S^0(\frac{dp_A}{dg} - 1)$. From the proof of Proposition 1, $\frac{dp_A}{dg} - 1 < 0$. Therefore, when $S^0 > 0$, $\pi_A' > 0$ and $\pi_B' < 0$. ■

Thus, we have microfounded that 1) the non-user disutility term of Section 2 can arise from a model where companies choose to make social image concerns salient, and 2) in such a model, only one company chooses to make these image concerns salient in equilibrium: the company that is relatively more associated with high types.

B Background information on Apple and the Smartphone Market

In this section, we present further information about the smartphone market both globally and within the United States. We then expand on compatibility issues between iPhones and Android devices.

The Global Market for Smartphones The global smartphone market is substantial and growing, valued at $566.12 billion (Precedence Research, 2024) with 1.24 billion smartphone shipments expected to occur in 2024 (International Data Corporation, 2024). The market is characterized by a duopoly of smartphone operating systems: Android and iOS. Globally, Android and iOS devices represent 71.65% and 27.62% of the market share of users, respectively (Statista, 2024).[40] Android market share is comprised of many differentiated brands, led primarily by Samsung (Visual Capitalist, 2024).

Apple's Dominance in the U.S. Smartphone Market The U.S. smartphone market is valued at $61 billion (Market Research Future, 2024). High smartphone penetration rates and the prevalence of iOS devices, which are typically much pricier than Androids, are the primary drivers of this trend (Designveloper, 2024). Moreover, in the US, the share of iOS devices is around twice the global average at 56% market share (StatCounter, 2024a). Android sales are mostly driven by established leader Samsung (StatCounter, 2024b) and increasingly popular Google devices (Schoon, 2024).

Cross-country Variation in Messaging Platforms There are drastic differences in smartphone operating system ownership across countries, even after controlling for income levels. The most striking example of this pattern is the difference between the US and Canada compared to Europe. Table A1 below illustrates this by showing iPhone market share and WhatsApp penetration levels in European and North American countries, highlighting their negative correlation. The statistics are consistent with iPhone users disproportionally using iMessage and SMS/MMS texting

[40] Less than 1% of smartphones use a different operating system, comprised of many smaller systems.

to communicate with other smartphones, as opposed to other third-party messaging platforms. Further, it also suggests that the US and Canada's smartphone messaging norms are substantially different than the rest of Europe. It is likely that WhatsApp became much more prevalent than text messaging in Europe because the cost of text messaging was historically very high in European countries, in contrast to the unlimited texting plans that were common in the US (Zhukova, 2022). Further, there is a greater need for cross-border communication in Europe, which may have pushed people to find alternative options to expensive international messaging fees.

Appendix Table A1: WhatsApp and iPhone Market Shares by Country as of 2022

Country	iPhone Market Share (%)	WhatsApp Market Share (%)
Spain	21.40	92.20
Russia	26.16	83.70
Italy	29.31	97.00
Germany	37.67	95.50
Austria	39.49	94.40
Netherlands	40.31	92.90
United Kingdom	51.63	71.30
Switzerland	55.92	95.90
United States	56.74	41.20
Canada	57.84	42.40

Notes: Table A1 presents iPhone and WhatsApp market shares in 2022 for selected European countries, as well as Canada and the US. iPhone market data are sourced from World Population Review (2024), and WhatsApp market data are sourced from Statista (2023).

C Antitrust Cases Against Apple

C.1 Department of Justice Lawsuit

In March 2024, the Department of Justice (DOJ), along with 16 other state and district attorneys general, filed a case against Apple for violating antitrust laws. The lawsuit argues that Apple has created a monopoly in the smartphone market, in violation of Section 2 of the Sherman Act, through various practices which stifle competition and innovation, while enabling the company to extract higher prices from its customer base.

Key allegations include blocking innovative super apps, which combine smaller apps and services into a singular application and could hence reduce reliance on the iOS App Store, and restricting cloud streaming services like Xbox Cloud Gaming and Google Stadia, which allow high-quality gaming on remote servers rather than powerful hardware. Other examples cited are limiting third-party apps' functionality to position Apple's services like iMessage and its digital wallet as superior, which increases the switching cost for consumers.

Another claim is that Apple has worsened the quality of cross-messaging features. Messages from non-iPhone users are displayed as green bubbles instead of blue, are not encrypted, and do not have typing or editing indicators. This could lead to perceived lower quality of non-iPhones and social stigma towards non-iPhone users, especially among teenagers.

C.2 European Union's Digital Markets Act

The Digital Markets Act (DMA) is a piece of legislation by the European Union intended to regulate the market power of digital platforms that the act classifies as "gatekeepers". The main objectives of the DMA are to promote fair competition, allow smaller companies a level playing field to innovate, and provide consumers with greater choice of digital services.

Apple is classified as a gatekeeper under the DMA as it meets all three criteria. Firstly, it has "significant impact on the internal market", with an annual turnover above EUR 7.5 billion and an average market capitalization exceeding EUR 75 billion. Secondly, it provides a gateway between businesses and end users, through the iOS App Store which allows developers to access a large customer base and exceeds the DMA's thresholds for monthly active end users and yearly active business users. Lastly, Apple's core platform services, including the App Store and iOS, have sustained a strong economic position over time, which qualifies the company as having an "entrenched and durable position".

D Summary of Data Collections

Appendix Table A2: Overview of Data Collections

Data Collection	Sample	Treatment Arms	Main Outcomes	Pre-registration
Panel A: Welfare Evidence				
Mechanism Survey (Aug 2024)	Prolific ($n = 476$)	None	Android Stereotypes, Preferences Over Green Bubbles, Perceived Quality	`https://aspredicted.org/r27m-69c8.pdf`
Deactivation Exp. (Oct 2024)	College Pulse ($n = 357$)	Blue Bubbles deactivation, Privacy and hassle cost control	WTA for deactivation	`https://aspredicted.org/xxyp-s8qx.pdf`
Panel B: Demand Experiments				
Main Demand Exp. (Nov 2024)	Prolific ($n = 468$)	Blue Bubbles, Green Bubbles treatment	Choice: iPhone 16 or Google Pixel 9 + $150	`https://aspredicted.org/54y4-s5jj.pdf`
Robustness Exp. (Aug-Sep 2024)	College Pulse, Prolific ($n = 1,385$)	Blue Bubbles, Green Bubbles treatment	WTP: iPhone 16 Pro Max vs. Samsung Galaxy S24 Ultra	College Pulse: `https://aspredicted.org/4tp9-tvzr.pdf`, Prolific: `https://aspredicted.org/4ytf-zgwq.pdf`

Notes: Table A2 provides an overview of data collections, grouped by section. The mechanism survey and robustness demand experiment had a hard cutoff on Sept 16, 2024, due to iOS 18's introduction. The main demand experiment had a hard cutoff on Dec 2, 2024, due to Cyber Monday sales ending.

E Mechanism Survey: Additional Tables and Figures

E.1 Demographic Summary Statistics

Appendix Table A3: Demographics Summary Statistics for Mechanism Survey Sample

Variable	Mean
Panel A: Demographics	
Gender (Ind. for Female)	0.53
Age	20.39
Relationship Status (Ind. for Single)	0.63
Panel B: Operating System	
iOS (Ind. for Yes)	0.84
MacBook (Ind. for Yes)	0.51
Observations	476

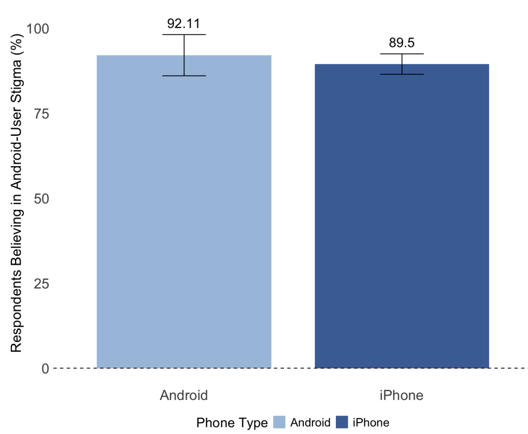
Notes: Table A3 summarizes key demographic statistics for the mechanism survey sample. Variables are presented with their respective means. The total number of observations is 476. 19.0% of individuals fail our attention check.

E.2 Incentives

At the end of the survey, we ask respondents how having their answers count towards the average statistic that is featured in our widely circulated report affected both their effort levels and extremism of opinions. We find that 52.1% of the respondents self-report putting in more effort as a result of our incentivization strategy. 47.7% of people report no changes to their effort level and only one person reported putting in less effort. We then asked people how this affected how extreme they reported their opinions. Reassuringly, the vast majority of respondents (90.6%) reported that there was no effect to how extremely they reported their opinions. 7.8% reported expressing more extreme opinions, and 1.7% less extreme opinions. Overall, the self-reports suggest that the our incentivization strategy was effective at improving the engagement of respondents. We also find that respondents have a 57.3% mean perceived likelihood that the believe the results of this study will be published in a major news outlet, suggestive that our incentives were credibly perceived. Respondents also report an average of a 41.3% chance that the DOJ lawsuit is successful in forcing Apple to remove green bubbles.

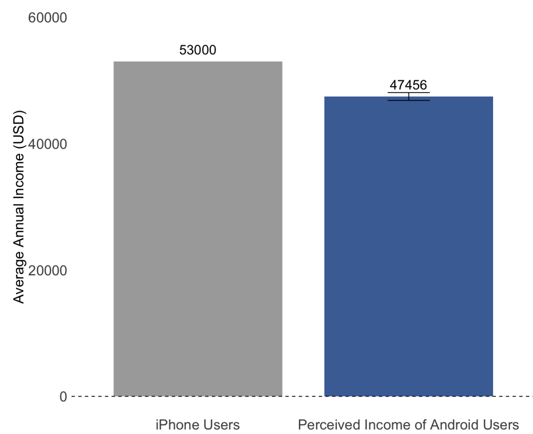
E.3 Additional figures

Appendix Figure A1: Fraction of Respondents that Believe there is a Green Bubble Stigma



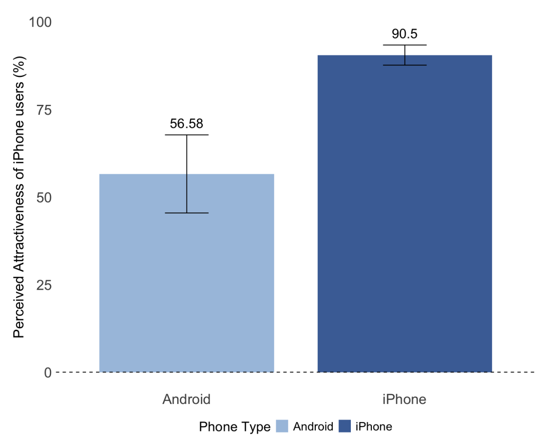
Notes: Figure A1 displays the percentage of respondents that agree there is a social stigma with green bubbles by operating system type. In particular, we ask "Do you think that there is a social stigma against Android users whose text messages appear as green bubbles on iPhones?". We only include respondents that pass all attention checks and bot detection protocols as per our pre-registration. We report 95% confidence intervals.

Appendix Figure A2: iPhone Users Believe that Android Users have Substantially Lower Income



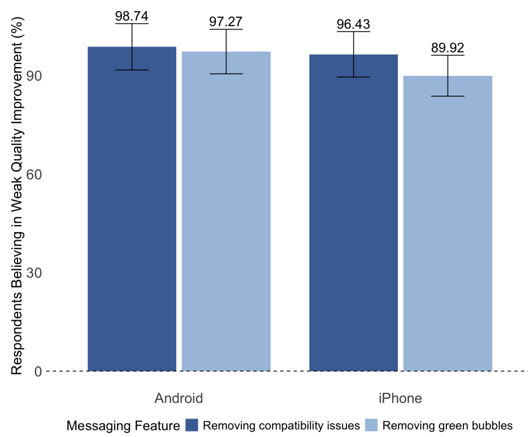
Notes: Figure A2 displays the average guess amount respondents provide regarding the average income of Android users in the US, relative to iPhone users at $53,000. On average, people think the average income of Android users is $47,456. We compute the average by taking the mid-point of the various income brackets in the choice options, as per our pre-registration. We only include respondents that pass all attention checks and bot detection protocols as per our pre-registration. We report 95% confidence intervals.

Appendix Figure A3: Fraction of Respondents Believing iPhone Users are More Attractive



Notes: Figure A3 displays the percentage of respondents that think the average iPhone user is more attractive than the average Android user. In particular, we ask "Do you think that the average iPhone user is more or less attractive than the average Android user?". We only include respondents that pass all attention checks and bot detection protocols as per our pre-registration. We report 95% confidence intervals.

Appendix Figure A4: The Effect of Green Bubbles on Perceived Quality



Notes: Figure A4 presents the results for how removing compatibility issues or green bubbles affect the perceived quality of Androids and iPhones. We plot the percentage of people that think there is a weak quality improvement (3, 4 or 5 on a 1-5 Likert scale). We only include respondents that pass all attention checks and bot detection protocols as per our pre-registration. We report 95% confidence intervals.

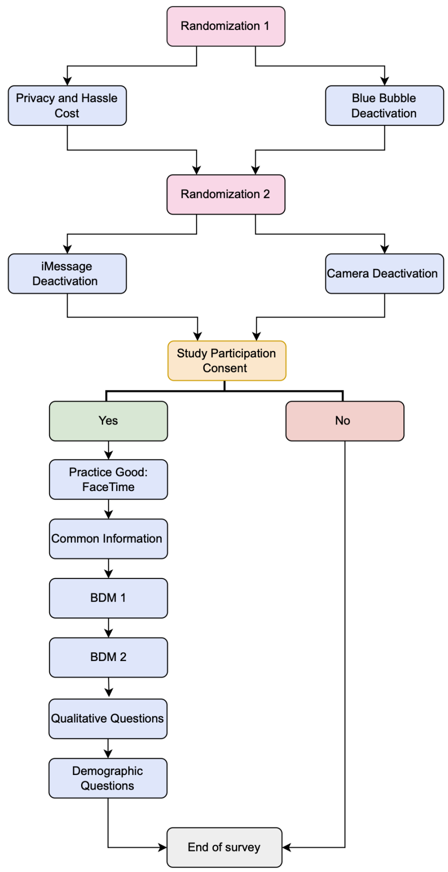
F Deactivation Study

Appendix Table A4: Demographics Summary Statistics for Deactivation Study Sample

Variable	Mean
Panel A: Demographics	
Gender (Ind. for Female)	0.57
Age	20.43
Relationship Status (Ind. for Single)	0.56
Observations	357

Notes: Table A4 summarizes key demographic statistics for the deactivation study sample. Variables are presented with their respective means. The total number of observations is 357. 75.7% of individuals fail our attention checks.

Appendix Figure A5: Structure of Experiment: Deactivation Study



Notes: Figure A5 displays the structure of the experiment. Participants are randomized into either the privacy and hassle cost control or the blue bubble deactivation, and then randomized into either the iMessage deactivation or camera deactivation option. Participants then consent to participating in the experiment before their deactivation options are revealed to them. Participants who consent proceed with the practice good for the BDM elicitation, receive common information on green bubbles, and then do the BDM elicitation for their two deactivation options, as determined by treatment status. The experiment concludes by collecting responses to qualitative questions and demographic characteristics. The yellow boxes indicate embedded data, the blue boxes indicate question blocks, and the pink box indicates randomization. We include several attention checks in our survey to ensure attentive respondents and proper comprehension of our deactivation study.

F.1 Results

Appendix Table A5: Regression Results: Blue Bubbles Deactivation vs. Control

	(1)	(2)
Blue Bubbles	31.89***	30.78***
	(3.93)	(3.30)
Practice Good WTA		0.38***
		(0.03)
Male (Indicator=1)		3.22
		(3.32)
Constant	16.90***	-1.46
	(2.64)	(2.94)
Observations	357	355
R-squared	0.156	0.408
Controls	No	Yes

Notes: Table A5 displays the regression results for our main specification without (Column 1) and with (Column 2) control variables. Both of these regressions were pre-specified. Column 2 contains two less observations due to two respondents not identifying as male or female. The coefficients on Blue Bubbles represent the difference in deactivation WTA between the Blue Bubbles group versus the privacy and hassle cost control. Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F.2 Heterogeneity

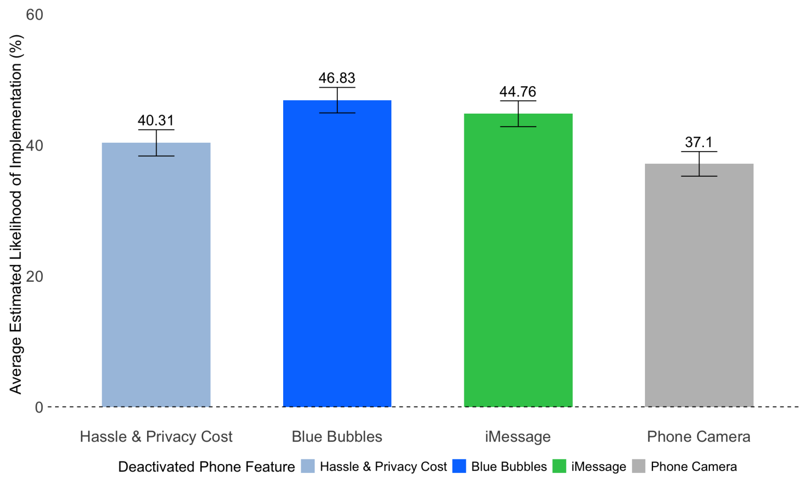
Appendix Table A6: Heterogeneity for Regression Results: Blue Bubbles Deactivation vs. Control

	In a Relationship	Single	Males	Females
Blue Bubbles	34.49***	29.81***	34.12***	29.22***
	(5.90)	(5.30)	(6.24)	(5.07)
Constant	16.21***	17.43***	17.69**	16.35***
	(4.00)	(3.54)	(4.29)	(3.34)
Observations	157	200	152	203
R-squared	0.180	0.138	0.166	0.142

Notes: Table A6 displays the regression results for our main specification for different demographic subgroups of our sample, which were not pre-specified. Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F.3 Robustness

Appendix Figure A6: Perceived Credibility of Deactivation Options



Notes: Figure A6 displays the average perceived credibility that each of the deactivation options would be implemented. In particular, we ask "For those respondents who are chosen to get their choices implemented, how likely do you think it is that the study just described in Option 1 will be the one selected for implementation?". We only include respondents that pass all attention checks and bot detection protocols as per our pre-registration. We report 95% confidence intervals.

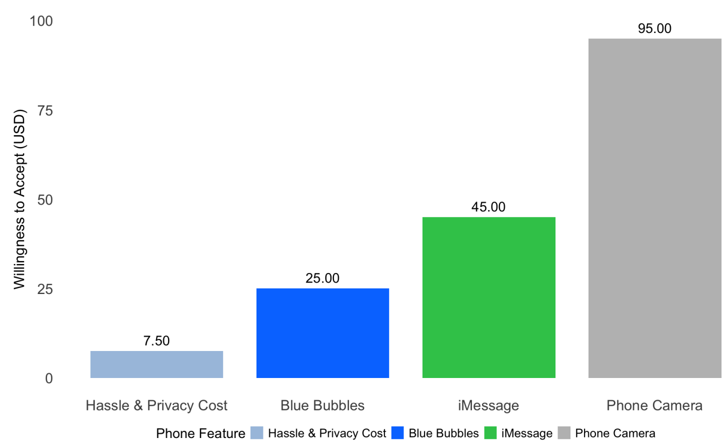
Appendix Table A7: Regression Results: Blue Bubbles Deactivation by Perceived Likelihood

	Above Median Likelihood	Equal or Below Median Likelihood
Blue Bubbles	27.45***	37.44***
	(5.58)	(5.66)
Constant	17.74***	16.27***
	(4.05)	(3.48)
Observations	177	180
R-squared	0.121	0.197

Notes: Table A7 presents regression results from our main specification, separately for respondents whose perceived likelihood of Option 1's implementation falls below or above the median. Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Top-coding We find differential top-coding at our maximum value of $150 between the treatment and control condition, which suggests our estimate of the welfare cost of green bubbles is conservative. However, at the same time, we find significant differences in top-coding between the blue bubbles, iMessage, and camera deactivation, which make our benchmark valuations likely understated. To address this issue, we focus on the median willingness-to-accept (WTA) compensation required to deactivate the phone features, as shown in Figure A7. The median WTA for blue bubbles is \$25, which is substantially higher than the median hassle and privacy cost of \$7.5 and represents around 56% and 26% of the median iMessage and phone camera valuation, respectively. This still suggests a large economic significance to the consumer welfare costs of green bubbles compared to our benchmarks.

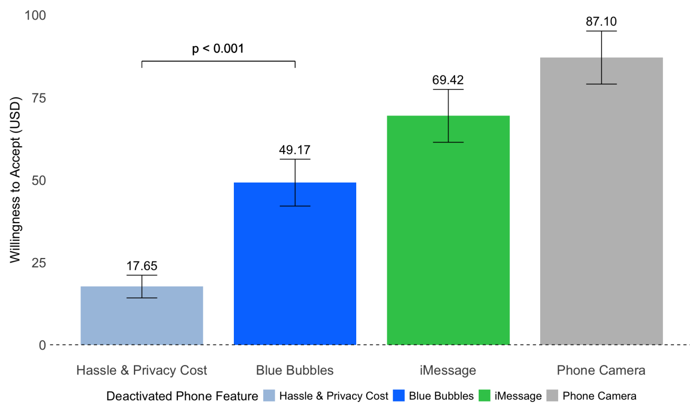
Appendix Figure A7: Median WTA to Deactivate Phone Features by Treatment



Notes: Figure A7 displays the median WTA to deactivate various features of participants' iPhones for four weeks.

Regret We allow our respondents to regret their valuations to ensure accurate data quality. After completing the MPL, we ask them if they would agree to participate in the deactivation for their implied valuation. Specifically, we ask whether they agree with the valuation implied by their answers to the MPL "According to your answers to the previous questions, you would need at most $\$X$ to participate and deactivate iMessage rather than not participate in the study". If they disagree, they are redirected to the start of the MPL and allowed to complete their decisions a second time. We asked them if they regret their choice a second time, but everyone proceeds with the next step regardless of their answer. In Option 1, we find that 5.0% of people regret their choice once and 0.99% of people regret their choice twice. In Option 2, we find that 5.8% of people regret their choice once and 0.25% of people regret their choice twice. In accordance with our pre-registration, we exclude anyone that regrets their choice twice, which is no respondent in our sample. Further, some respondents who regretted their initial valuation experienced a coding error causing the MPL to skip certain values on their second iteration (an ascending MPL omitting certain increments between \$0 and \$150). To err on the side of caution, we exclude anyone who regretted their initial valuation for Choice 1 or 2 (10.5%) from our main analysis. In Appendix Figure A8, we demonstrate that our results remain robust to their inclusion.

Appendix Figure A8: Average WTA to Deactivate Phone Features by Treatment (Including Single Regretters)



Notes: Figure A7 displays the average WTA to deactivate various features of participants' iPhones for four weeks, including respondents who regretted their stated valuation for at least one feature once.

F.4 Implementation and Compliance

As pre-specified, we selected 1 out of 10 respondents to be in the deactivation study, for a total of 40 participants. We exclude anyone with valuations outside our bounds, as well as anyone with a negative WTA as these are not incentive compatible. We then conduct the random computer draw, where we end up with 30 participants (14 iMessage and 16 camera) that we invite to participate in the deactivation study. We received a response indicating interest in participation from 22 (73%) people.[41] The deactivation period started on Monday, November 4th and ended on Sunday, December 1st. We find that 95%, or 21 out of 22, of our participants successfully completed the deactivation, for an average payout of \$93. These results are comparable to previous large-scale deactivation experiments (Allcott et al., 2020) and provide further support that our design was perceived as credible.

[41] An additional person expressed interested in participating but encountered technical difficulties with their phone not receiving text messages so opted to not begin the deactivation.

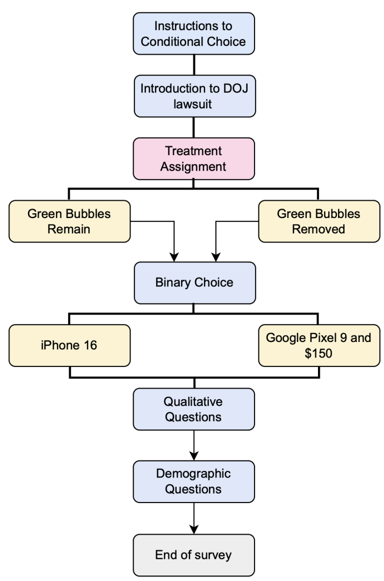
G Main Demand Experiment: Additional Tables and Figures

Appendix Table A8: Demographics Summary Statistics for Demand Experiment Sample

Variable	Mean
Panel A: Demographics	
Gender (Ind. for Female)	0.60
Age	21.45
Relationship Status (Ind. for Single)	0.54
Observations	468

Notes: Table A8 summarizes key demographic statistics for the demand experiment sample. Variables are presented with their respective means. The total number of observations is 468. 10.9% of individuals fail our attention checks.

Appendix Figure A9: Structure of Experiment: Product Demand



Notes: Figure A9 displays the structure of the experiment. Participants are first told about the incentivized phone choice between the iPhone 16 and the Google Pixel 9 and $150 and are then informed about the ongoing DOJ lawsuit. Next, treatment assignment takes place and each respondents is brought their respective decision screen for the binary choice. The experiment concludes by collecting responses to qualitative questions and demographic characteristics.

G.1 Main Result

Appendix Table A9: Regression Results: iPhone vs Android Choice

	(1)
Android Share	0.073**
	(0.037)
Constant	0.158***
	(0.024)
Observations	468
R-squared	0.008

Notes: Table A9 displays our main pre-registered regression. The coefficient represents the effect of our treatment on the choice of the Google Pixel 9 and $150 over the iPhone 16. Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G.2 Heterogeneity

Appendix Table A10: Heterogeneity for Regression Results: iPhone vs Android Choice

	Males	Females	Single	In a Relationship
Android Share	0.087	0.067	0.114**	0.024
	(0.062)	(0.045)	(0.049)	(0.054)
Constant	0.181***	0.143***	0.138***	0.180***
	(0.040)	(0.030)	(0.031)	(0.037)
Observations	180	283	254	214
R-squared	0.011	0.008	0.020	0.001

Notes: Table A10 displays the regression results for our main specification for different demographic subgroups of our sample, which were not pre-specified. For the first two columns, we exclude five individuals who identify as "other gender." Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A11: Regression Results: iPhone vs Android Choice by Resale Lottery Phone Response

	Plan to sell preferred phone	Do not plan to sell preferred phone
Android Share	-0.083	0.130***
	(0.082)	(0.040)
Constant	0.244***	0.112***
	(0.048)	(0.026)
Observations	113	355
R-squared	0.008	0.027

Notes: Table A11 displays our main pre-registered regression based on whether or not participants planned to resell the phone if they win the lottery. We place respondents in the same group who say they do not plan to sell or their plans to sell depend on which phone wins, as we assume these people would not plan to re-sell their preferred phone. The coefficient represents the effect of our treatment on the choice of the Google Pixel 9 and $150 over the iPhone 16. Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A12: Regression Results: iPhone vs Android Choice by Likelihood

	Above Median Likelihood	Below Median Likelihood
Android Share	0.148***	0.001
	(0.053)	(0.051)
Constant	0.136***	0.183***
	(0.031)	(0.037)
Observations	234	234
R-squared	0.0336	0.0000

Notes: Table A12 displays our main pre-registered regression based on whether or not participants are above or below the median perceived likelihood of their future scenario occurring. The coefficient represents the effect of our treatment on the choice of the Google Pixel 9 and $150 over the iPhone 16. Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

G.3 Robustness

Regret We allow our respondents to regret their valuations to ensure accurate data quality. If they disagree with their initial choice, they are redirected to the decision screen and allowed to complete their decision a second time. We asked them if they regret their choice a second time, but everyone proceeds with the next step regardless of their answer. We find that 2% of people regret their choice once and 0% of people regret their choice twice. Our low values of regret are likely helped by including several attention and comprehension checks before participants proceed to the decision.

Appendix Table A13: Regression Results: iPhone vs Android Choice (Excluding All Regretters)

	(1)
Android Share	0.078**
	(0.037)
Constant	0.153***
	(0.024)
Observations	459
R-squared	0.010
Root MSE	0.393

Notes: Table A13 displays our main pre-registered regression when we exclude respondents who regretted their valuations at least once. The coefficient represents the effect of our treatment on the choice of the Google Pixel 9 and $150 over the iPhone 16. Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Robustness to Sample Restrictions

We show in Table A14 that including Canadians, respondents aged 18-27, and iPhone 16 users does not change our results.

Appendix Table A14: Regression Results: iPhone vs Android Choice (Including all respondents)

	(1)
Android Share	0.086**
	(0.034)
Constant	0.163***
	(0.024)
Observations	575
R-squared	0.011
Root MSE	0.402

Notes: Table A14 displays our main regression including all collected responses. The coefficient represents the effect of our treatment on the choice of the Google Pixel 9 and $150 over the iPhone 16. Robust standard errors are in parentheses. Stars indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.