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When Product Markets Become Collective Traps: The Case of Social Media†

By Leonardo Bursztyn, Benjamin Handel, Rafael Jiménez-Durán, and Christopher Roth*

Individuals might experience negative utility from not consuming a popular product. With such externalities to nonusers, standard consumer surplus measures, which take aggregate consumption as given, fail to appropriately capture consumer welfare. We propose an approach to account for these externalities and apply it to estimate consumer welfare from two social media platforms: TikTok and Instagram. Incentivized experiments with college students indicate positive welfare based on the standard measure but negative welfare when accounting for these nonuser externalities. Our findings highlight the existence of product market traps, where active users of a platform prefer it not to exist. (*JEL* D62, D83, D91, L82, Z13)

Much of consumption is highly social in nature. In many contexts, the utility that an individual derives from consuming a product or service increases as more people consume it. Going to a concert or dinner with friends is more enjoyable than going alone. Yet consumption can also negatively affect others (Frank 2005). Indeed, the literature on conspicuous consumption and positional externalities (Frank 1985; Bursztyn et al. 2018; Imas and Madarász 2024; Pesendorfer 1995) has highlighted that one's utility can be negatively impacted by others' incomes or consumption, for instance, as a result of social comparisons (Bottan and Perez-Truglia 2022; Clark and Oswald 1996; Cullen and Perez-Truglia 2022; Luttmer 2005; Perez-Truglia 2020).

These social forces play a vital role in the context of social media. For a given platform, a larger number of users may increase the benefits of joining, by expanding the network of individuals available for interaction. Beyond that, the size of the network may also affect the utility of potential nonusers. Such externalities to

* Bursztyn: University of Chicago and NBER (email: bursztyn@uchicago.edu); Handel: University of California, Berkeley and NBER (email: handel@berkeley.edu); Jiménez-Durán: Bocconi University, IGIER, Stigler Center, and CESifo (email: rafael.jimenez@unibocconi.it); Roth: University of Cologne, Max Planck Institute for Research on Collective Goods, CESifo, NHH, and CEPR (email: roth@wiso.uni-koeln.de). Pietro Ortoleva was the coeditor for this article. We thank three anonymous referees for insightful comments that improved the paper. We are also grateful to Daron Acemoglu, Eliana La Ferrara, Matthew Gentzkow, Alex Imas, Ro'ee Levy, Matthew Lowe, Ricardo Perez-Truglia, Aakaash Rao, Gautam Rao, Jean Tirole, as well as many seminar participants for useful comments. Caroline Boone, Pietro Ducco, Maximilian Fell, Paul Grass, Anastasiya Nebolsina, Ewan Rawcliffe, Christoph Ziegler, and especially Beyza Gulmezoglu provided excellent research assistance. Roth acknowledges funding from the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy EXC 2126/1-390838866. The research described in this article was approved by the University of Chicago Social and Behavioral Sciences Institutional Review Board (IRB23-0797) and pre-registered in AsPredicted (nos. 137878, 142247, and 144630). This study was also registered as AEARCTR-0016196 (Bursztyn et al. 2025a).

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nonusers can be driven by mechanisms such as social exclusion or a fear of missing out (FOMO) (Gupta and Sharma 2021). As the total number of platform users increases, marginal users may participate because they want to avoid the negative externalities imposed on nonusers but may still have negative overall utility from the platform's existence.

In the presence of such externalities to nonusers, standard measures of consumer surplus that take aggregate consumption of a product as given do not appropriately capture the welfare of its *users*. In particular, when nonuser utility is negative, these measures overstate the total welfare associated with the product because they use an incorrect outside option, namely, not consuming the product while holding fixed others' consumption. Instead, the relevant outside option for calculating welfare in the presence of negative nonuser utility is the nonexistence of the product market. Negative nonuser utility can also give rise to *product market traps*: a situation similar to a Prisoner's Dilemma where some users would prefer the product not to exist, yet they find it optimal to consume it. In such traps, some users' utility is negative but would have been even more negative had they not used the product, which is why they continue using it. Such traps can arise from social forces even with fully rational expectations and without behavioral frictions, such as a lack of self-control and naïveté.

In this paper, we propose an approach to measure consumer welfare in the presence of such externalities to nonusers and network effects and apply it to the welfare analysis of social media platforms. We implement our methodology in pre-registered online experiments with more than 1,000 students from various colleges in the United States. We focus on two prominent social media platforms: TikTok and Instagram. These platforms have been the subject of concern, among other reasons, due to their potential adverse effects on mental health (Faelens et al. 2021).[1]

In the experiment, we employ standard tools to measure consumer welfare, leveraging an incentivized Becker-DeGroot-Marschak (BDM) mechanism (Becker, DeGroot, and Marschak 1964), which we implement using an iterative multiple price list (MPL). The experiment proceeds in three main steps. In Step 1, we measure individual-level willingness to accept (WTA) to deactivate one's social media for four weeks while keeping constant others' social media consumption. This step provides us with the standard measure of individual consumer surplus (*Valuation Keeping Network*). In Steps 2 and 3, we plausibly reduce the size of our respondents' networks by presenting the possibility of a large-scale deactivation where all participating students at their university deactivate their accounts. Participants are told that this large-scale deactivation will be conducted if we recruit two-thirds of students at their university. To measure network effects, in Step 2 we measure individual WTA to deactivate conditional on all other participating students having been asked to deactivate their account in exchange for monetary compensation (*Valuation Removing Network*). Finally, in Step 3, we measure welfare differently, taking as the outside option the nonexistence of the market. To do so, we elicit individuals'

[1] The TikTok survey was conducted in July 2023, followed by the Instagram survey in August and September 2023. Both surveys are virtually identical except that in the second survey we added more questions and clarified some of the instructions. We describe the differences in Section IIB and present the full set of instructions in Supplemental Appendix G.

preferences over the deactivation of the social media accounts of all participating students, including themselves. In particular, we measure whether individuals are willing to forgo payment or instead require a payment to deactivate all participating students' accounts (*Product Market Valuation*).

We start by presenting results on the traditional welfare measure that does not account for nonuser externalities: individual consumer surplus. This measure suggests substantial average positive welfare, with active users in our sample requiring a payment of \$55 and \$47 to *individually* deactivate their TikTok and Instagram account, respectively. Ninety-two percent of TikTok users and 86 percent of Instagram users in our sample require a positive payment. These findings are in the ballpark of estimates in the literature for Facebook (Mosquera et al. 2020; Allcott et al. 2020).

We next turn to product market surplus, our preferred measure of welfare that accounts for externalities to nonusers. Our main finding is that 60 percent and 46 percent of active TikTok and Instagram users in our sample, respectively, have positive willingness to pay (WTP) to have others, including themselves, deactivate TikTok and Instagram, respectively. Average product market surplus is significantly lower compared to individual consumer surplus for both TikTok ($p < 0.01$) and Instagram ($p < 0.01$). Users have an average WTP, rather than a willingness to accept, of \$24 and \$6 to have others, including themselves, deactivate TikTok and Instagram, respectively. Overall, our evidence shows the existence of a *social media trap* for a large share of consumers in our sample, who find it individually optimal to use the product even if they derive negative welfare from it.

Finally, we present our estimates of network effects by comparing the valuation removing the network against the valuation keeping the network. The fraction of users requiring positive payments to deactivate their account drops to approximately 72 percent and 69 percent of users in our samples for TikTok and Instagram, respectively. Compared to the valuation keeping network, the average willingness to accept significantly drops by approximately 29 percent and 21 percent, to \$39 and \$37 for TikTok and Instagram, respectively. This drop provides evidence that network effects are positive and quantitatively significant, consistent with canonical theoretical frameworks (Rohlfs 1974; Katz and Shapiro 1985). Moreover, the fact that the valuation removing the network is larger than the product market valuation is consistent with recent evidence of preferences for exclusion (Imas and Madarász 2024).

To ensure high levels of understanding, we restrict our main analysis to respondents who pass several attention checks and do not regret their choices, though our results are robust to considering different selection criteria (including regretters and inattentive respondents) and correcting for measurement error generated by anchoring caused by the initial offer given to participants, as in Luttmer and Samwick (2018). Moreover, we confirm our findings with a hypothetical qualitative question that asks respondents whether they would prefer to live in a world without the social media platform. Indeed, a large share of users in our samples report preferring to live in a world without TikTok and Instagram, respectively.

One possible concern with our empirical design is that respondents may think that it is unlikely that we will actually conduct the large-scale deactivation study. However, the perceived likelihood that the large-scale Instagram deactivation study will be implemented is not low, at approximately 45 percent. Moreover, for respondents deeming the large-scale deactivation study more likely, the estimated product market surplus is even more negative, suggesting that our elicitation provides a conservative estimate of how negative the product market surplus is. More broadly, given that even in the case of the large-scale deactivation study not all users would deactivate their account, our study plausibly identifies lower bounds for the size of the negative product market surplus.

One limitation for the external validity of our findings on the incentivized valuations—just like the findings of any deactivation study—arises from the self-selected nature of the sample. Specifically, only 57 percent and 46 percent of respondents who initially began our TikTok and Instagram surveys chose to participate in the deactivation study, leaving some uncertainty about product market surplus across the broader user population. Another notable feature of our sample is that a larger fraction are female compared to the average TikTok and Instagram user. Beyond these observable characteristics, people willing to participate in a deactivation study may also differ in unobservable ways from those unwilling to participate.

One possible explanation for the differences in valuations between Step 1 and Step 3 could be factors such as a "repugnance" (Roth 2007) toward digital products, animus against big tech companies, or a distaste for others spending time on their phones. To examine this mechanism, we conduct an experiment with an identical design but with a product that creates plausibly less pronounced negative externalities for nonusers: navigation and maps smartphone apps (hereafter referred to simply as "Maps"). For these apps, our estimates of product market surplus significantly decrease, yet remain positive, large, and highly significant ($p < 0.01$). Besides elucidating the underlying mechanisms, the positive product market surplus for Maps also suggests that the negative product market surplus we document for TikTok and Instagram is not driven by mechanical factors.

The wedge between individual consumer surplus and product market surplus highlights an important role of externalities to nonusers. To shed light on the motives behind active users' preferences for living in a world without their social media platform, we ask them an open-ended question on why they still use the platform. These data indicate that the fear of missing out is the most prevalent motive for both TikTok and Instagram. Paired with our main estimates, the evidence of these underlying mechanisms supports the notion that accounting for externalities to nonusers is crucial to assessing the welfare effects of social media platforms. These externalities to nonusers may arise from anticipated social exclusion that would actually occur in case of deactivation or could arise from misperceptions or other psychological biases.

One implication of our framework is that producers have incentives to use technologies or marketing campaigns that decrease nonuser utility—increasing the cost of not consuming the product. Indeed, large tech companies commonly use tools that might decrease nonconsumer surplus, such as increasing the salience of being a nonconsumer or tying messaging apps and social media platforms.[2] More generally,

[2] An example of such technology is the "green bubble" messages on iPhones. While messages exchanged between iPhones appear as blue-colored bubbles, messages from Android users appear as green bubbles on iPhones, making it salient when they interact with non-iPhone users. The green bubbles feature might increase demand for

our findings challenge the standard revealed-preference argument that the mere existence of a product implies positive welfare for its consumers, even if they are fully rational. Indeed, our experiments provide evidence of a product that creates negative welfare for many of its consumers. This finding suggests a heightened need for regulators to assess whether different products create traps for consumers and, potentially, diminish competition between platforms. More broadly, these patterns could apply to other markets. We provide suggestive hypothetical survey evidence of a large fraction of consumers preferring to live in a world without luxury goods and to slow down the release frequency of products with different vintages.

Our paper also speaks to work assessing the welfare generated by social media (Brynjolfsson, Collis, and Eggers 2019; Mosquera et al. 2020; Allcott et al. 2020; Allcott, Gentzkow, and Song 2022; Brynjolfsson, Kim, and Oh 2024; Brynjolfsson et al. 2023); see also Aridor et al. (2024) for a review. The papers in this space measure consumer surplus by either taking the aggregate level of consumption as given or assuming that externalities to nonusers are zero. Existing work finds large user valuations for social media, consistent with the large amount of time spent on these platforms (2.5 hours per day on average (Kemp 2022)), while at the same time documenting that the expansion and use of these platforms can harm individual well-being and mental health (Allcott et al. 2020; Braghieri, Levy, and Makarin 2022). Our results regarding the switch in the sign of consumer welfare after accounting for nonuser utility help reconcile these seemingly contradictory findings and paint an integrated and more pessimistic picture of the welfare effects of social media. Additionally, we provide the first incentivized evidence of network effects in the context of social media, which has proven difficult aside from hypothetical estimates (Benzell and Collis 2023).

We also contribute to a long-standing literature in industrial organization that models consumer choice in the presence of network effects (Rohlfs 1974; Katz and Shapiro 1985; Farrell and Klemperer 2007; Rochet and Tirole 2003). Our work differs from this literature in a few key ways. First, a standard procedure in this literature is to normalize the utility from not using a product to zero, effectively ruling out externalities to nonusers.[3] We develop an experimental framework to elicit the magnitude of network effects and externalities to nonusers. We simultaneously identify and quantify both positive network effects for users and negative externalities to nonusers. Second, the literature has pointed to coordination failures that arise in the presence of network effects in cases where one firm becomes dominant despite not being the most efficient supplier (Farrell and Saloner 1985; Farrell and Klemperer 2007). While this coordination failure occurs in the presence of multiple competing platforms and externalities among product users, our work highlights the possibility

the iPhone, not because it improves its "intrinsic" value but because it avoids the social stigma of not using an iPhone. This social stigma has received widespread attention in the mass media; see https://www.wsj.com/articles/why-apples-imessage-is-winning-teens-dread-the-green-text-bubble-11641618009 (accessed November 8, 2024).

[3] One exception is Bhattacharya, Dupas, and Kanaya (2024), who also relax this assumption and show that welfare effects are not point identified in models with externalities. They apply their model to the evaluation of the welfare effects of bed nets in a discrete-choice econometric framework with a focus on health externalities arising from contagious diseases.

of a Prisoner's Dilemma that can arise even with a single platform due to the presence of externalities to nonusers that lock consumers into using the product.[4]

This paper proceeds as follows: Section I provides a simple conceptual framework for measuring welfare in the presence of externalities to nonusers. Section II provides the empirical design. In Section III, we present results for individual and product market surplus and network effects. Finally, Section IV discusses the policy implications of our findings.

I. Conceptual Framework: Product Market Traps

Setup.—There is a set of individuals and an indivisible product. Individual i derives utility from their own consumption of the product, $x_i \in \{0,1\}$, and from the fraction of other individuals who consume it, X. For ease of exposition, we assume that utility is quasilinear in income, given by $u_i(x_i, X) - p$, where p is the price of the product.

We leverage the presence of X in the utility to model two distinct phenomena: consumption externalities and network effects. First, we allow for consumption externalities, the extent to which utility changes in response to others' consumption. Concretely, i exhibits positive (negative) consumption externalities from the product if their utility increases (decreases) when the fraction of others consuming it increases. Without loss of generality, we normalize to zero the utility that i receives when no one else consumes the product, $u_i(0,0) = 0$. Besides this normalization, most prior work on network effects, and prior empirical work on social media, assumes a constant *nonuser utility*; that is, $u_i(0,X) = u_i(0,X')$ for all X, X', which implies that $u_i(0,X) = 0$ for all X. We relax this assumption and allow for consumption externalities for nonusers so that, generically,

$$u_i(0,X) \neq u_i(0,X'),\ X \neq X'.$$

For instance, if the utility of nonusers decreases when more people use the product, we say that the product exhibits negative consumption externalities for nonusers. Allowing for this possibility is empirically relevant; for example, feelings of being left out likely increase as the number of people who are "in" increases.

Second, given this relaxation, we need to distinguish between consumption externalities and network effects. We use a definition of direct network effects based on strategic complementarities in consumption. Concretely, i's utility exhibits positive network effects when their marginal utility of consumption increases with others' consumption:

$$u_i(1,X') - u_i(0,X') > u_i(1,X) - u_i(0,X),$$

[4] While we focus on the latter coordination failure, in the presence of multiple platforms, both kinds of coordination failures could be present simultaneously. However, the empirical patterns of social media use, paired with our finding of negative welfare among single- and multihomers (those who use one platform or multiple platforms, respectively), suggest product market traps above and beyond the coordination failure in Farrell and Saloner (1985). This relates to recent literature documenting forms of the Prisoner's Dilemma in the industry generated by different mechanisms (Cheyre and Acquisti 2024; Sullivan 2024).

for $X' > X$. In the absence of consumption externalities for nonusers, this definition is equivalent to the standard definition of network effects in the literature of users having positive consumption externalities, $u_i(1,X') > u_i(1,X)$. However, in our setting, it is possible that positive network effects (as defined above) coexist with negative consumption externalities; that is, $u_i(1,X) < u_i(1,0)$, for $X > 0$. This flexibility allows, for example, the presence of both preferences for exclusivity (which manifest as negative consumption externalities) and positive network effects.

Welfare Measures.—There are two ways of measuring the welfare that individuals get from a product.

The first measure compares the utility that i gets from consuming the product relative to their utility when they do not consume it, holding fixed the fraction of others consuming it. This is the standard measure of welfare, which we refer to as the *individual* consumer surplus, *ICS*, in the sense that it only accounts for i's individual choice:

$$ICS_i(p,X) := \begin{cases} u_i(1,X) - p - u_i(0,X) & \text{if } i \text{ consumes}, u_i(1,X) - p \geq u_i(0,X) \\ u_i(0,X) - u_i(0,X) = 0 & \text{if } i \text{ does not consume}, u_i(1,X) - p < u_i(0,X). \end{cases}$$

In practice, researchers estimate this measure by eliciting individuals' willingness to accept to give up a product in exchange for a monetary payment, or their willingness to pay to get it, holding constant the others' consumption.

The second measure compares the utility of consuming the product with the utility subject i would receive if the product did not exist. We call this measure the *product market surplus*, *PMS*, given by i's utility from consuming relative to their utility when no one consumes:

$$PMS_i(p,X) := \begin{cases} u_i(1,X) - p - u_i(0,0) = u_i(1,X) - p & \text{if } i \text{ consumes} \\ u_i(0,X) - u_i(0,0) = u_i(0,X) & \text{if } i \text{ does not consume.} \end{cases}$$

The key difference between these measures is the outside option each uses. Product market surplus is the correct measure when the goal is to compute the total welfare generated by the existence of a product. Without consumption externalities, both measures are identical. More generally, however, the individual consumer surplus will be biased upward or downward depending on whether $u_i(0,X)$—the nonuser utility—is negative or positive, respectively:

$$ICS_i(p,X) = PMS_i(p,X) - u_i(0,X).$$

For example, when i has a fear of missing out, their individual surplus will be biased upward, as it reflects not only their valuation of the product but also their distaste for being left out when they do not consume it.

Product Market Traps.—Our framework allows for the possibility of a Product Market Trap for individuals, where, for a given price and aggregate consumption of the product,

(i) i chooses to consume the product: $ICS_i(p,X) > 0$.

(ii) i would be better-off if no one consumed it (i's welfare is negative): $PMS_i(p,X) < 0$.

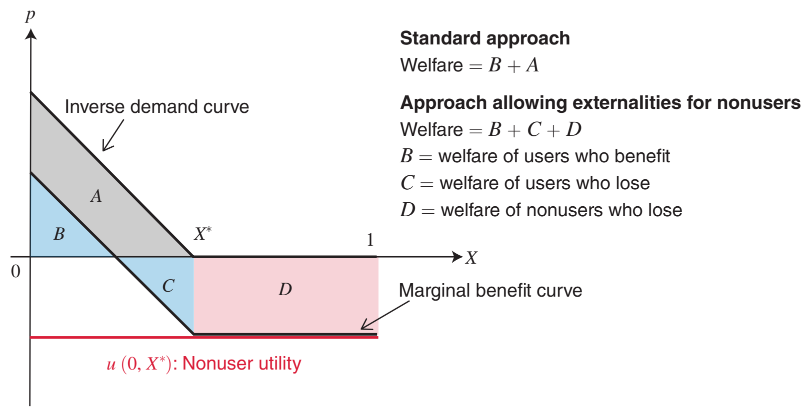

Figure 1. Comparison between Welfare Measures Given Market Share X^*

Notes: This figure illustrates how welfare calculations differ between our setting and the standard setting that ignores consumption externalities for nonusers, conditional on an observed market share equal to X^* and a price equal to zero. For ease of exposition, this figure assumes a mass unit of individuals with homogeneous nonuser utility, $u(0,X^*)$, and uniformly distributed user utility $u_i(1,X^*)$. The inverse demand curve describes $ICS_i(0,X^*)$ at every level of demand. The marginal benefit curve describes $PMS_i(0,X^*)$ at every level of demand.

Note that this situation is possible only when consumer i experiences negative nonconsumer surplus ($u_i(0,X) < 0$); negative externalities to nonusers are necessary to generate product market traps. Individuals in a product market trap would like to coordinate with others to not consume, but they cannot commit. They are "trapped" into consuming because others do so. Hence, the revealed-preference argument that the existence of a product implies that users benefit from it fails to apply.

The experiments we describe below seek to estimate individual consumer surplus and product market surplus in the context of social media. Figure 1 illustrates how our welfare calculations differ from the standard setting that ignores externalities for nonusers, given the observed market share, X^*, and a price fixed at 0. For simplicity, we assume a mass unit of individuals with homogeneous nonuser utility $u(0,X^*) < 0$ and uniformly distributed user utility $u_i(1,X^*)$. The standard welfare analysis calculates the average individual consumer surplus, equal to areas A + B. This approach concludes that those who use the product benefit from it and that everyone who does not use it gets zero welfare. In our framework, the welfare impact is positive and equal to B for users who benefit from the product (whose user utility is positive, $u_i(1,X^*) > 0$); negative and equal to C for users who lose out from the product (whose user utility is negative but still choose to consume, $0 > u_i(1,X^*) > u(0,X^*)$); and negative and equal to D for nonusers who lose out from the product's existence (since $u(0,X^*) < 0$), giving a total welfare B+C+D.

II. Measuring Individual and Product Market Surplus

A. *Sample*

College Student Sample.—We recruited college students to participate in our experiments through a partnership with College Pulse, a company specialized in recruiting college students for online experiments. We focus on college students for various reasons. First, they are of high policy relevance, as they are among the most active on social media (Pew Research Center 2021b). Second, social media usage has been linked to the increasing prevalence of depression among college students (Braghieri, Levy, and Makarin 2022). Third, even if other fellow college students might not represent the entire network of friends of our participants (corresponding to X in our theoretical framework), they constitute a significant subset of students' social networks. Consistent with this conjecture, our respondents estimate that an average 60 percent of their mutual friends on Instagram are fellow college students.

Pre-registration.—The pre-registrations include the experimental design, hypotheses, analysis, sample sizes, and exclusion criteria. The pre-registrations of the two data collections can be found on AsPredicted #137878 and #142247.[5] While we pre-registered pooling 28 pilot responses with the pre-registered data in the Instagram and Maps experiment, we deviate from this plan and instead only report the pre-registered data. Supplemental Appendix F shows that our main results remain unchanged including this pre-registered data.

TikTok.—In July 2023, we recruited 1,713 respondents who began our experiment, out of which 66 percent had used TikTok in the past month, our measure of activity on the platform.[6] All active users are then asked whether they are willing to participate in the deactivation study. Fifty-seven percent of TikTok users in our sample were willing to provide their handle to participate in the study. One potential concern is that those unwilling to participate in the study derive more positive welfare from social media. While this likely means that our elicitations underestimate the welfare created by social media, some of the selection does not simply arise from an unwillingness to deactivate their accounts, with 40 percent of participants mentioning privacy concerns and 32 percent mentioning the fear of missing out as motives for not being willing to participate in the study (see Supplemental Appendix Figure A2). Nonetheless, this selection into our study severely limits our ability to measure average welfare among the population of college students.

We restrict our sample to respondents aged between 18 and 30, and we exclude respondents who failed any attention checks or regretted their valuations for a second time.[7] Our final sample consists of 707 college students, with 371 TikTok users and 336 nonusers.

Instagram and Maps.—To provide evidence for a second social media platform and for another smartphone application that is not a social media platform, we recruited college students who had not taken our TikTok experiment to participate

[5] We also pre-registered running an in-person experiment at the University of Chicago at the end of May 2023 (https://aspredicted.org/WDF_DFH). However, we only managed to collect 12 pre-registered responses from active users who passed the sample inclusion criteria. The very small sample thus makes it difficult to draw meaningful conclusions.

[6] We assess our sample's representativeness in terms of social media usage by comparing it to the 2021 American Trends Panel (ATP) data (Pew Research Center 2021a). To approximate a college-student sample, we filter by age (18–29) and education level (some college, no degree). In this filtered group, 54 percent reported using TikTok.

[7] To further ensure high data quality, we also exclude six respondents who leave the compulsory open-ended questions in our survey blank.

in a second wave in August and September 2023.[8] Respondents were randomly assigned to complete a version of the experiment about (i) Instagram or (ii) Maps (the following navigation and maps smartphone apps: Google Maps, Apple Maps, and Waze). All active users are asked for their willingness to participate in the deactivation study, while nonusers proceed directly to the practice questions and the *Product Market Valuation*.

We randomize a total of 935 and 854 respondents into the Instagram and Maps experiments, respectively. Out of those, 94 percent reported actively using Instagram and 99.8 percent reported using Maps.[9] All active users are then asked whether they are willing to participate in the deactivation study. Forty-six percent of Instagram users in our sample were willing to provide their handle to participate in the study, while 58 percent of Maps users were willing to participate. As with TikTok, much of this selection is not simply a result of their unwillingness to deactivate their accounts, with 32 percent and 27 percent of participants mentioning privacy concerns for Instagram and Maps, respectively, and 41 percent and 17 percent mentioning "not wanting to be without their account while their friends are still on the platform" as motives for not participating in the study, for Instagram and Maps, respectively.[10] This selection likely leads us to underestimate welfare and makes it difficult to make statements about average welfare among the population of students. However, the hypothetical survey questions that we elicited also among those unwilling to participate allow us to examine the nature of selection. Even among respondents unwilling to participate in our Instagram deactivation study, a large share (39 percent) prefer living in a world without Instagram, compared to 56 percent among those users willing to participate. While these data provide evidence that those unwilling to participate likely derive higher welfare from the product, the fraction likely deriving negative utility is still quite high.

Our main sample consists of 235 Instagram users, 25 respondents not active on Instagram, and 272 Maps users. As with TikTok, we restrict our sample to respondents aged between 18 and 30 and exclude—as prespecified—respondents failing any attention checks or regretting any of their final valuations.[11]

Sample Characteristics.—Respondents in our samples are all undergraduate students from 365 universities attending four-year colleges. On average, 7 percent of the undergraduate student body is part of College Pulse in the colleges in our sample. This is above the entire College Pulse average of approximately 4 percent. Sixty-four percent of our sample are from public universities, while 36 percent are from private universities. Moreover, our sample is well spread out across the United States, making it geographically fairly representative. The majority of our students

[8] Our experiments took place during the university summer break, when in-person interactions were less accessible. This timing may increase respondents' valuation of social media, as it serves as a substitute for face-to-face social interactions.

[9] In the ATP college-student sample (see footnote 6), 75 percent of respondents reported using Instagram.

[10] Participation in the deactivation study required respondents to provide their TikTok/Instagram handles and submitting screenshots of their phone's usage statistics. Given these hassle costs, the elicitation captures the combined effect of not using the service and the associated hassle.

[11] As opposed to the case of Instagram and Maps, our TikTok pre-registration did not specify dropping inattentive users or those who regret their choices, but we add these filters to increase comparability across samples. However, results are similar without these filters (see Supplemental Appendix Figure A8).

(59 percent) attend universities in the top 150 in the *U.S. News* ranking of universities. Only a relatively small fraction of students (9 percent) from our sample attend top 20 universities. Our sample is mostly female: Among respondents, 68 percent are female, while among active users, 72 percent are female. Their average age is 21 years.[12]

B. *Design*

The purpose of the experiment is to measure welfare while accounting for externalities to nonusers. Below, we describe the core experimental instructions. The full set of instructions can be found in Supplemental Appendix G.

TikTok and Instagram.—Our main evidence focuses on consumers' valuation of two popular social media platforms, TikTok and Instagram, that have been the subject of concern regarding their impact on individual well-being. While both TikTok and Instagram are social media platforms that focus on visual content, they differ in several key ways. TikTok specializes in short-form video content, often featuring music, dance, and challenges, and utilizes a unique algorithm that prioritizes content discovery, allowing even unknown creators to go viral. Instagram, on the other hand, started as a photo-sharing platform, and its discovery mechanisms are more reliant on existing social networks and hashtags, making it generally harder for new creators to gain visibility.

Overview.—We now turn to the structure of our experiments, which is also summarized in Figure 2 for the case of the Instagram and Maps experiment.[13] For active social media users, the experiment proceeds in four steps. In Step 0, we measure individual-level WTA to deactivate an example product: a ride-sharing app. This elicitation considers the individual-level decision conditional on aggregate consumption and is meant to accustom respondents to the instructions. In Step 1 (*Valuation Keeping Network*), we measure individual-level WTA to deactivate one's social media account for a period of four weeks, taking others' social media consumption as given. In Steps 2 and 3, we present respondents with the possibility of a large-scale deactivation study where all participating students at their university deactivate their accounts. In Step 2 (*Valuation Removing Network*), we measure individual WTA conditional on all participating students being asked to deactivate their account in exchange for monetary compensation. In Step 3 (*Product Market Valuation*), we measure individuals' preferences over the deactivation of social media accounts of all participating students, including themselves. In particular, we elicit students' WTP or their WTA to deactivate everyone's account.

Respondents who are not active social media users take a modified version of the experiment. After completing the practice, they proceed to a customized *Product*

[12] In the ATP data (see footnote 6), 64 percent of TikTok users and 51 percent of Instagram users who are college students identify as female (Pew Research Center 2021a) compared to 75 percent and 68 percent in our final analysis sample of users. Among respondents from the Instagram and TikTok surveys, the percent of females who started our survey is virtually identical to the percent of females completing it ($p = 0.48$).

[13] The TikTok experiment has a similar structure but with only one platform.

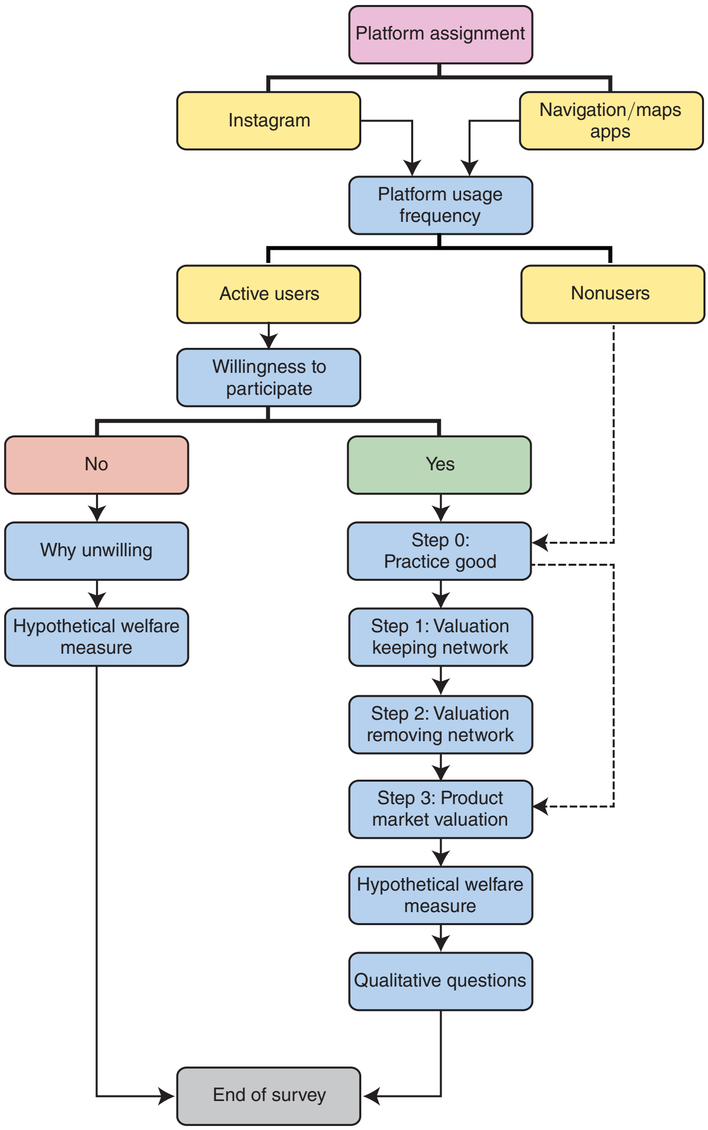

Figure 2. Structure of Experiment: Instagram and Maps

Notes: Figure 2 presents the structure of the experiment. At the beginning of the experiment, the platform is cross-randomized between Instagram and Maps. Active users and nonactive users are directed to a distinct path. Active users are asked whether they are willing to participate in a deactivation study. The experiment ends for those unwilling to participate after two subsequent questions. The active users willing to participate are directed to Steps 0 to 3, followed by the hypothetical welfare measure and a series of qualitative questions. Nonusers proceed to Steps 0 and 3, as indicated by the dashed arrows. The yellow boxes indicate embedded data, the blue boxes indicate question blocks, and the pink box indicates randomization. The flow of the TikTok experiment from July 2023 is identical except that there was no initial random platform assignment and that we did not elicit hypothetical welfare measures among respondents unwilling to participate in the study. This structure applies to both social media (TikTok and Instagram) and Maps users, but for simplicity, we refer to all these platforms as "social media." We reintroduce the distinction when we talk separately about Maps in Section IIID. Interested readers can access an identical example of our Instagram/Maps survey at the following link: https://ssd.az1.qualtrics.com/jfe/form/SV_br1qh5JMfdw0Bfg.

Market Valuation, where we measure their preferences over the deactivation of social media accounts of all participating students who are active social media users.

Introduction.—We inform all respondents that we will conduct a deactivation study in which we will ask students at their university to deactivate their social media accounts for four weeks in exchange for monetary compensation. To enhance the credibility of our deactivation study, we inform them that "deactivation studies like this have been conducted in the past (e.g., by Allcott et al. 2020 and Mosquera et al. 2020)." We explain that they can go back to using their account whenever they want, with their content and network unchanged, but they would then forgo any monetary payment. We also tell respondents that, to verify that they deactivate their accounts, we will visit their profiles and require them to upload screenshots of their app usage, preventing them from substituting between different accounts on the same platform. To ensure high levels of attention, we inform respondents they will receive an additional bonus payment if they correctly respond to all comprehension questions included in the experiment.

Willingness to Accept Elicitation.—The core object of interest in our experiment concerns people's willingness to accept the deactivation of their social media accounts for four weeks. We combine an incentivized BDM elicitation (Becker, DeGroot, and Marschak 1964) with an iterative MPL.

Our MPL places participants' valuation in one of 12 ranges, with lower and upper limits at \$0 and \$200 and internal increments of \$20: $(-\infty, \$0]$, $[\$0, \$20]$, ..., $[\$180, \$200]$, $[\$200, \infty)$. In Step 3, we expand the limits to $-\$200$ and \$200, to account for the possibility of having a WTP as well as a WTA, resulting in 22 ranges. The algorithm proceeds sequentially, starting from an initial monetary offer and upper and lower bounds for the valuation. In each step, we present respondents with two options: either deactivating their social media account and receiving the monetary offer or keeping their social media account active. If the respondent accepts the offer (i.e., chooses to deactivate), her upper bound is set to that amount. Similarly, if she rejects the offer (i.e., keeps her account active), her lower bound is set to that amount. The algorithm then selects the next offer as the midpoint between her new bounds, resulting in progressively narrower valuation ranges with each response. The elicitation ends once we can narrow down the respondent's WTA to a \$20 range or once we surpass one of the upper or lower limits, which can take between 1 and 6 choices depending on the initial random offer and the respondent's answers.

To ensure that choices are incentive compatible, we inform respondents that a computer will generate an amount of money to offer them to participate in the deactivation study. We further tell them that we will ask them a series of questions offering them different payment scenarios in case they are selected for the deactivation study. If they accept any price scenario lower than the computer's offer, we will invite them to the deactivation study and give them the computer's offer. If, on the other hand, they do not accept any price scenario lower than the computer's offer, we will not invite them to the deactivation study even if they are the selected participant. To examine comprehension, we ask respondents whether demanding a higher amount affects their likelihood of receiving any payment. Reassuringly, 87 percent of respondents pass this comprehension check.

Step 0: Practice Good.—To enhance comprehension, we start with a hypothetical example good (Dizon-Ross and Jayachandran 2022). We measure individual-level willingness to accept the deactivation of respondents' ride-sharing (Uber) accounts, taking aggregate consumption as given.

Step 1: Valuation Keeping Network.—In Step 1, we measure individuals' WTA to deactivate their social media accounts, taking aggregate consumption as given. We tell respondents that, to establish appropriate payment amounts for the deactivation study, we will ask them to decide whether to deactivate their social media account in exchange for different monetary amounts. We also reiterate that one student from their university will be randomly selected to participate in the study. We start the MPL with a randomly drawn offer between \$0 and \$200 in \$20 increments.[14] Respondents then proceed to the MPL procedure, where they decide between either (i) deactivating their social media account (with none of the students at their university deactivating) and sequentially varying amounts of money or (ii) not deactivating their account.[15]

Step 2: Valuation Removing Network.—To assess the role of network effects in shaping individual consumer surplus, we measure individuals' valuation of their social media accounts when all participating students at their university are asked to deactivate their social media accounts. We start by presenting our participants with the possibility of a large-scale deactivation study at their university, where all participating students are asked to deactivate their accounts. In particular, we tell our respondents:

> College Pulse has a panel exceeding 650,000 university students. We are targeting universities with a high penetration of College Pulse.
>
> We will now ask you to consider two additional options for a large-scale deactivation of TikTok [Instagram] at your university. One of them will be randomly implemented if we manage to recruit more than two-thirds of the students at your university.
>
> We expect 90 percent of students to comply with deactivation based on previous studies (e.g., by Mosquera et al. 2020 and Allcott et al. 2020).

Thereafter, we inform respondents that we will randomly choose one of two options (described in Step 2 and Step 3, respectively) for conducting this larger-scale deactivation study. We then proceed with describing the first option: We tell respondents that we will ask all participating students at their university sequentially whether they would like to deactivate their accounts. We then measure respondents' WTA to deactivate their social media accounts, conditional on us having asked all participating students at their university to deactivate their accounts in exchange

[14] For Instagram, we draw the random offer between \$20 and \$200.

[15] To make the choices more intuitive, we framed the decisions of all three steps in terms of "taking a break from social media" in the August and September 2023 collection. This collection also emphasizes on the decision screen that the respondent would not receive any monetary payment when the offer equals \$0.

for monetary payment. Respondents choose between (i) deactivating their account (when all other participating students have also been asked to deactivate) and receiving varying amounts of money sequentially and (ii) keeping their account active. To economize time, we randomize the initial offer between the lower and upper bounds of the respondent's valuation from Step 1 (unless respondents are at the lower or upper ends of the WTA interval, in which case we offer them again this bound).

Step 3: Product Market Valuation.—In Step 3, we measure the product market valuation by eliciting individuals' preferences over the deactivation of the social media accounts of all participating students, including themselves.

Respondents are told that we know how much we need to pay every participating student at their university to deactivate their accounts for four weeks.[16] We inform respondents that we will randomly select one of the students to anonymously choose between the following two options: (i) keep things as they are, or (ii) deactivate the accounts of all participating students.[17] We clarify that if they decide for all participating students to deactivate their accounts, the researchers will pay the other students the amount they require. Moreover, they are told that we will establish their payment, if any, below.

To clarify the incentive compatibility of the mechanism, respondents learn that the deactivation study will be stopped for everyone only if the chosen respondent goes back to using the platform before the end of the four weeks. In particular, the chosen respondent will not receive payment, and the other students will be paid based on the actual time they spend in the study. For example, if the study was stopped after two weeks because the chosen respondent did not comply with the deactivation, then another participating student who required a payment of $40 for the deactivation in Step 2, who complied with the deactivation for the two weeks, would receive a payment of $20. Finally, if a participating student who was not chosen to decide on the large-scale deactivation goes back to using the platform before the end of the study, they will not receive any payment.[18] Supplemental Appendix Table A1 illustrates the incentive compatibility of our elicitation in more detail.

Subsequently, we remind people that the choice they make is incentivized and that their final payoffs, in case Step 3 is implemented, will depend on their valuation as well as the randomly drawn offer. Respondents then proceed to the first main decision screen, where they decide between (i) all participating students at their university deactivating their accounts (Option A) and (ii) all participating students

[16] Note that the information we collect through Step 2 provides us with the necessary information to compensate respondents for participation in the large-scale deactivation in case someone else decides to deactivate for everyone in step 3. Since respondents in Step 2 did not anticipate Step 3, both elicitations are incentive compatible under the assumption that respondents believe that others have an accurate assessment of their valuation of social media when the large-scale deactivation study takes place.

[17] Being pivotal is a low-probability event, meaning that there is relatively little expected incentivization. Reassuringly, prior literature finds that stake size often does not significantly alter behavior (Enke et al. 2023). We leave it to future work to examine whether perceived stake size matters in shaping people's valuations in our setting.

[18] This design choice allows our elicitation to account for the option value that individuals might have of reactivating their account even when they initially reported that they wished to deactivate for everyone. By interrupting the study (returning to the status quo) in case the respondent exercises this option, the elicitation compares the utility of the status quo with the utility of joint deactivation. Moreover, the respondent can always choose to not comply with deactivation. Our elicitations account for these option values in each of the three steps, as detailed in Supplemental Appendix Table A1.

at their university keeping their accounts active (Option B) when the deciding participant does not receive payment. This incentivized choice effectively splits the participants' valuation into the positive or negative range, which will be key for the subsequent results. Consider the scenario where a respondent prefers Option A, of all participating students deactivating their accounts. In the following screen, they make a decision between all participating students deactivating their accounts versus all participating students keeping their accounts active plus a random dollar amount, \$X, drawn between \$20 and \$200 in increments of \$20. If the respondent chooses Option A once again, then she is willing to forgo a payment worth \$X. As in the previous steps, the subsequent offers are made iteratively to narrow down the respondent's WTP. Symmetrically, if she chooses Option B in the first screen, we then employ the iterative MPL algorithm to elicit her WTA to have all participating students deactivate their accounts.

Computing Welfare Based on the MPL.—Responses to the MPL questions establish the lower and upper bounds of each respondent's WTA/WTP, effectively assigning them to one of the MPL ranges. For simplicity, we assign the mean of the endpoints for each range in order to have a unique WTA/WTP value; for instance, a range of [\$60, \$80] is assigned a value of \$70. In Section IIIC, we consider an alternative way of assigning valuations.

C. *Discussion of the Design*

Elicitation Scales.—The scale of our elicitation in Step 3 differs from those used in the other steps. In Step 3, we elicit respondents' positive WTA or their negative WTA (WTP) to deactivate their accounts depending on their response to the first question. In Steps 1 and 2, on the other hand, we only elicit respondents' WTA to deactivate their social media accounts. This difference reflects that it is likely unnatural and inconceivable for individuals to pay to deactivate their accounts individually, when they could deactivate their own accounts for free. Indeed, in contrast to measuring WTA, eliciting WTP in Steps 1 and 2 would not be incentive compatible, as there is no way of penalizing respondents with positive WTP if they deactivate their account. In Step 3, on the other hand, WTP is incentive compatible, as we can punish the respondent chosen to decide by stopping the large-scale deactivation in case they deviate from their deactivation. The differences in scale between Step 3 (where we ask respondents questions that allow them to state WTAs between −\$200 and \$200) and Steps 1 and 2 (where we ask respondents questions that allow them to state WTAs between \$0 and \$200) could lead to results that overstate our effects because of noise or anchoring. However, Section IIIC shows that differences in scales are very unlikely to explain differences in valuations across the different steps.

Concerns about Borderline Deception.—A key challenge for our design concerns the large-scale deactivation study. The instructions in our experiment rely on language suggesting to participants that the implementation of the large-scale deactivation study is likely. Given that we did not manage to recruit two-thirds of students at any participant's university, no large-scale deactivation study was implemented.

While we do not lie to participants, our approach may come close to the boundary of deception.[19] We decided to adopt this approach because it appeared to us as the only practically feasible way to elicit valuations for the occurrence of the large-scale deactivation study while maintaining incentive compatibility.

III. The Social Media Trap

A. *Main Results*

We next proceed with presenting our main results for both TikTok and Instagram. First, we present the traditional welfare measure, which does not account for externalities to nonusers. We then report the results of our preferred measure of welfare accounting for these externalities. Finally, we present estimates of network effects.

Individual Consumer Surplus.—Panels A and B of Figure 3 display the distribution of valuations of the individual consumer surplus for TikTok and Instagram, respectively. These panels illustrate that there is substantial variation in valuations for the individual consumer surplus. As Panels A and B of Figure 4 show, roughly 90 percent of users in our samples require a positive payment to deactivate their accounts, while the remaining users in our samples indicate requiring no payment for deactivating their account.

We next turn to average welfare effects. The dark blue bars in panels C and D of Figure 4 show that users in our sample require a payment of approximately \$50 on average (with a median of \$30) for TikTok and Instagram.[20]

Product Market Surplus.—We next turn to product market surplus, our preferred measure of welfare that accounts for externalities to nonusers. Panels A and B of Figure 3 illustrate that there is strong heterogeneity, with a significant portion of consumers deriving positive and negative welfare from the platforms, respectively.

We then present results on the fraction of active users in our sample deriving negative welfare from the platforms, which is based on a single binary question. Compared to our estimates of average welfare, this statistic is less susceptible to the framing of response options and to the scales used in this elicitation. Figure 4 shows that 60 percent and 46 percent of active TikTok and Instagram users, respectively, are willing to pay to have their own and others' accounts deactivated. Among nonusers, 83 percent and 56 percent are willing to pay to have others deactivate their TikTok and Instagram account, respectively.

Panels C and D of Figure 4 report the average PMS in our sample. Average PMS is significantly lower compared to individual consumer surplus for both TikTok $(p < 0.01)$ and Instagram $(p < 0.01)$. Hence, the standard individual consumer surplus measure overstates welfare in this context, which is confirmed by Supplemental

[19] We received ethical approval from the University of Chicago Social and Behavioral Sciences Institutional Review Board.

[20] These estimates are lower than those in Allcott et al. (2020), who find a \$100 median valuation for Facebook. Aside from measuring welfare for different platforms, a possible explanation for their higher valuations is that their sample consists of more active participants given their recruitment with Facebook ads.

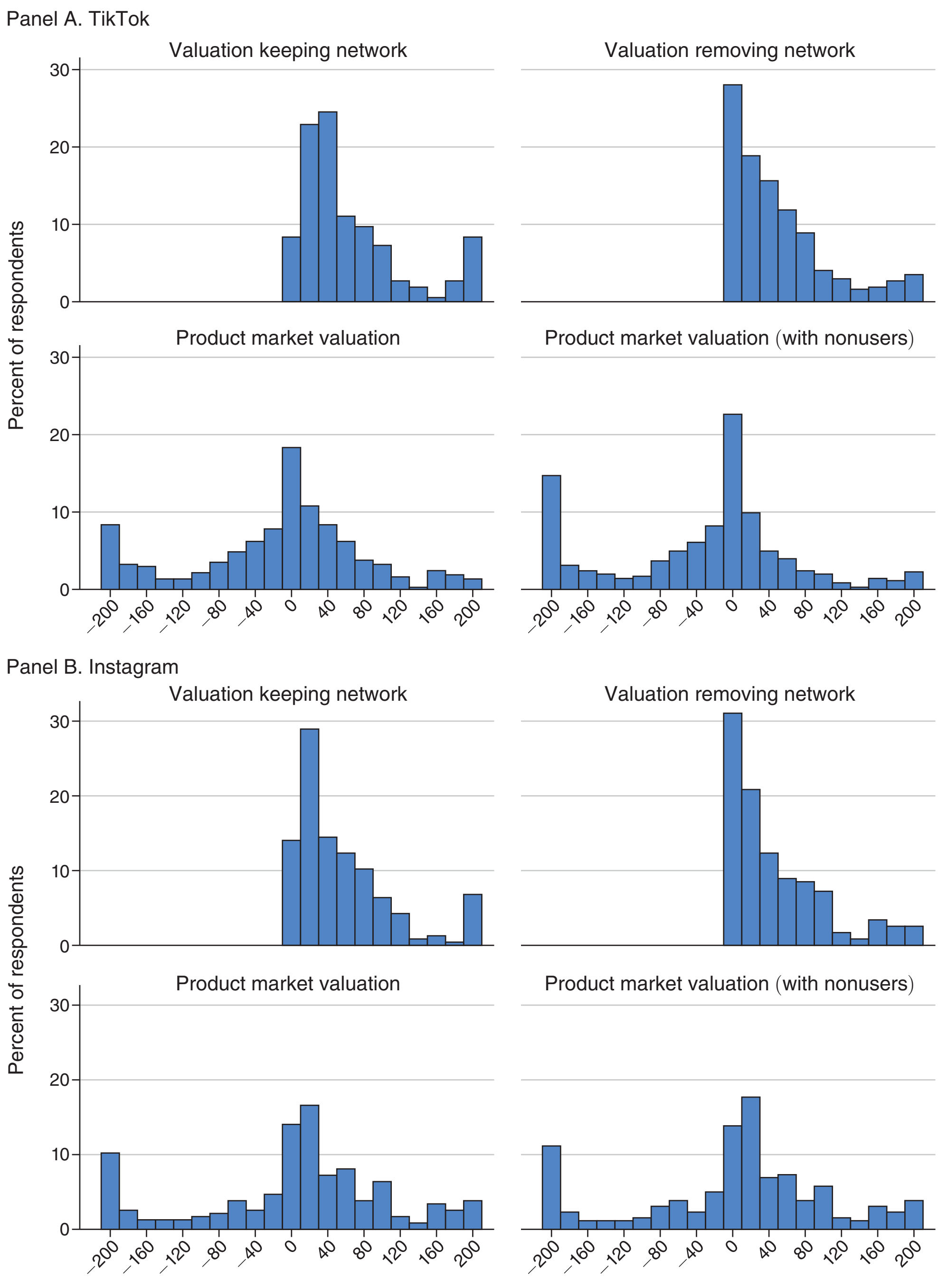

Figure 3. Distribution of Consumer Surplus across Welfare Measures

Notes: Figure 3 presents the probability density function of valuations for the different welfare measures. Panel A presents the results for TikTok, and panel B presents the results for Instagram. Respondents who agree with their elicited valuations and those who pass all of the attention checks are included.

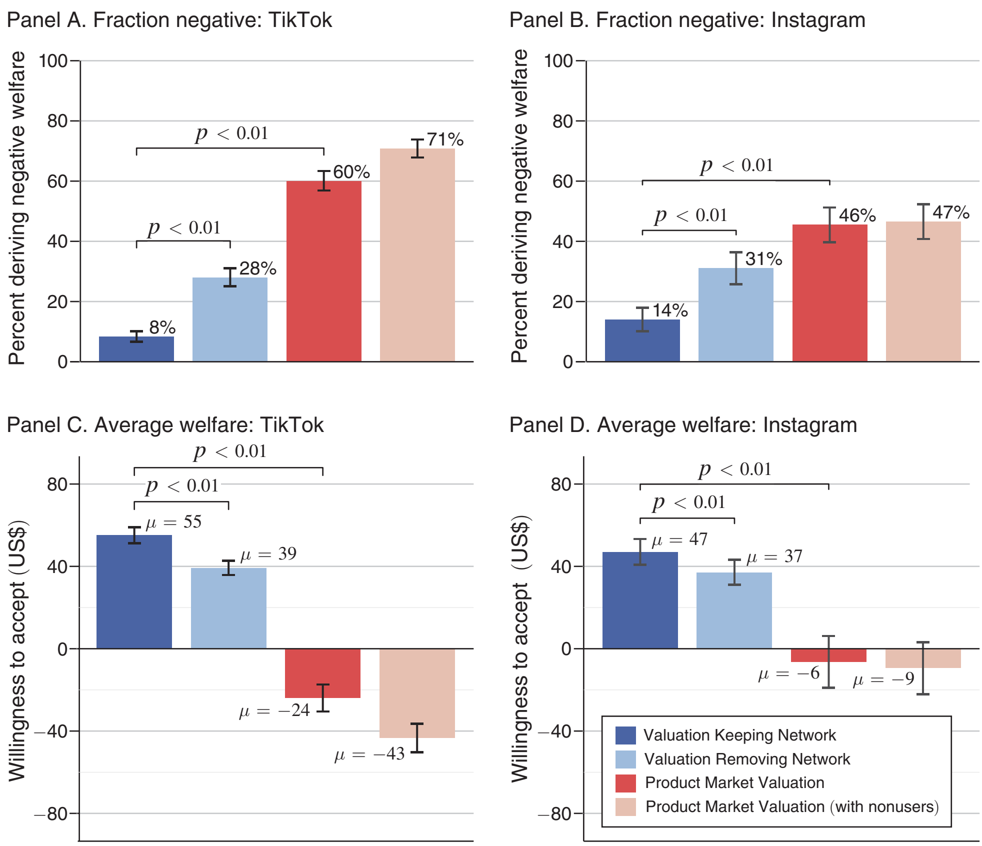

FIGURE 4. CONSUMER SURPLUS ACROSS WELFARE MEASURES

Notes: Panels A and B present the percentage of respondents with negative product valuations across our different welfare measures. Panels C and D present averages. Panels A and C present the results for TikTok, and panels B and D present the results for Instagram. The first three bars in each panel represent valuations exclusively for active users. The dark blue bar denotes *Valuation Keeping Network*, the light blue bar denotes *Valuation Removing Network*, and the red bar denotes *Product Market Valuation* for users. The pink bar represents the average *Product Market Valuation* of active users and nonusers. Respondents who agree with their elicited valuations and those who pass all of the attention checks are included. Error bars represent 95 percent confidence intervals.

Appendix Figure A3, where the inverse demand curve lies almost uniformly above the product market surplus curve. On average, users are *willing to pay* \$24 and \$6 to have others, including themselves, deactivate TikTok and Instagram, respectively. The median valuation is −\$10 and \$10 for TikTok and Instagram, respectively. Nonusers have an average WTP of \$65 and \$39 to have others deactivate TikTok and Instagram, respectively. These estimates are statistically significantly below zero for both TikTok ($p < 0.01$) and Instagram ($p < 0.05$).

Our results highlight an important role of externalities to nonusers. Many users require substantial payments to individually deactivate their social media accounts. This is not because they derive positive welfare from the platform but because they would experience negative utility if they were the only ones to be excluded from it. In that sense, a large fraction of active users in our sample are in a *social media trap*.

Our findings also suggest that college students are sophisticated about how others' social media consumption affects their own valuation.

Network Effects.—Finally, we present our estimates of network effects, as defined in Section I. We first present results on the fraction of respondents whose valuation removing network (Step 2) is lower than their valuation keeping network (Step 1). Fifty-eight percent of TikTok users have lower valuations in Step 2, 36 percent have the same valuation, and 6 percent have a higher valuation. Similarly, 42 percent of Instagram users have lower valuations in Step 2, 52 percent have the same valuation, and 6 percent have a higher valuation. Moreover, and strikingly, only approximately 70 percent of users on both platforms require a positive payment to deactivate their account in Step 2, compared to approximately 90 percent in Step 1. Turning to average effects, Figure 4 uncovers a significant drop in average valuations between Step 1 and Step 2 of 29 percent ($p < 0.01$) and 21 percent ($p < 0.01$) for TikTok and Instagram users, respectively. Taken together, these results indicate that network effects are positive and quantitatively important, consistent with canonical theoretical frameworks (Rohlfs 1974; Katz and Shapiro 1985).

Our estimates also reveal that participants' average utility from using these platforms is positive when they are among the few ones in their college using it but negative in the status quo case where the rest of their school uses it as well. This pattern suggests that there are negative consumption externalities conditional on use ($u(1,X)$ is decreasing in X) but that nonuser consumption externalities are even larger ($u(0,X)$ is decreasing in X faster than $u(1,X)$).

These results could be partly driven by, e.g., our participants having a preference for the status of being one of the few ones in their school with access to the social media world, consistent with important work on preferences for exclusion (Imas and Madarász 2024). In this setting, aggregate use is not really zero (since the rest of the world keeps using the platform), and people might enjoy being the "gatekeepers" with access to the new trends when part of their network is excluded from the platform. These results could also be driven by a preference to use social media for broader informative purposes paired with a relative distaste for direct social interactions on the platform (with even stronger FOMO or negative externalities when not using social media). These results suggest that the product market trap could be difficult to resolve by only introducing a coordination device that moves to a lower use equilibrium. Instead, it could result from a dominant strategy in a Prisoner's Dilemma where people are initially interested in using social media but become worse off (both as users and nonusers) as overall use increases. It is important to note that a full characterization of a dynamic network formation equilibrium is beyond the scope of this paper and would depend on (i) heterogeneity in how user and nonuser utility functions depend on X and (ii) the precise notion of equilibrium.

B. *Correlates of Consumer Surplus*

Supplemental Appendix Table A2 examines heterogeneity in our different surplus measures along several demographics and displays regression coefficients from multivariate regressions. There are no significant correlations between gender and any of the surplus measures for both TikTok and Instagram. Individual valuations of TikTok, with and without network, slightly increase with age, although the correlation is only marginally significant. For Instagram, there are no significant correlations with any of the surplus measures. As one would expect, the frequency in platform usage is positively and significantly correlated with individual welfare measures for TikTok. Indeed, using the platform daily, as opposed to less frequently, is associated with a \$23 and \$14 increase in respondent's valuation for TikTok and Instagram, respectively. Coefficients of daily platform usage are lower and more noisily measured for the product market valuation, compared to the individual measures.

C. *Robustness*

Measurement Differences across Steps.—Our *Valuation Keeping Network* does not allow for negative welfare, as it would require people being willing to pay for the deactivation of their account individually. As a result, there is an asymmetry in measurement between *Valuation Keeping Network*, where those requiring no payment for deactivation are coded as having a valuation of −\$10, and the *Product Market Valuation*, where negative values of up to −\$210 are possible.[21]

To provide a conservative examination of whether this asymmetry in measurement explains the sharp differences in valuation across *Valuation Keeping Network* and *Product Market Valuation*, we conduct a bounding exercise. In this exercise, we assume that participants that require no payment for the deactivation of their account in *Valuation Keeping Network* have a valuation of −\$210. Reassuringly, even under this very conservative exercise, *Valuation Keeping Network* remains positive and large at \$38 for TikTok ($p < 0.01$) and \$19 for Instagram ($p < 0.01$), respectively.

Measurement Error.—We designed our survey to reduce the importance of measurement error. First, we measure respondents' agreement with their valuations and provide an opportunity to revise them. Second, we ask a series of binary questions, commonly perceived to be easier to understand than questions directly eliciting respondents' reservation price on a continuous scale.

Despite these design choices, one concern with our elicitation is that measurement error could affect valuations in Step 1 and Step 3 differentially. Among many potential sources of measurement error, one particularly concerning one regards anchoring caused by the initial offer given to participants, given that valuations in Step 1 and Step 3 are measured on different scales. Valuations in Step 1 (and Step 2) are elicited on a scale from −\$10 to \$210, while valuations in Step 3 are measured on a scale from −\$210 to \$210. Noise might therefore upwardly bias estimates for Step 1 if the true distribution is close to zero, but no such upward bias will occur in Step 3.

[21] Reassuringly, only a small fraction of respondents (8 percent and 14 percent for TikTok and Instagram, respectively) require no payment for the deactivation of their account in *Valuation Keeping Network*.

To gauge the importance of noise, we examine to what extent the final valuations in Steps 1 and 2 are affected by the initial offers respondents receive.[22] Following the approach in Luttmer and Samwick (2018), which we explain in more detail in Supplemental Appendix C.1, we regress final valuations from Step 1 on individuals' initial offers, which were randomized. As Supplemental Appendix Table A5 shows, the initial offers are not significantly related to the final valuations for both TikTok ($p = 0.33$) and Instagram ($p = 0.55$), respectively. Moreover, initial offers only explain 0.3 percent and 0.1 percent of the variation in final valuations for TikTok and Instagram, respectively. In Step 2, we did not fully randomize the set of offers, but we can leverage that we randomized whether respondents receive the upper or lower bound of the Step 1 valuation as the initial offer, for some individuals. Our analysis suggests that the initial offer significantly increases valuations by \$9 for TikTok ($p = 0.02$) and by an insignificant \$3 for Instagram ($p = 0.48$). In other words, we find evidence for measurement error in the case of TikTok.

We then adjust our estimates for measurement error generated by anchoring caused by the initial offer given to participants, following the approach in Luttmer and Samwick (2018). This approach assumes that the measured valuation is a weighted average of the respondent's true underlying valuation and the initial offer they receive. Supplemental Appendix Table A6 reports these adjustments. In the case of Step 1, both the average WTA and the proportion of individuals with a negative valuation remain stable after the correction, across both platforms. For Step 2, the WTA in the case of Instagram also remains virtually unchanged after the correction, but the WTA for TikTok is revised downward. This evidence makes it unlikely that this form of measurement error drives the differences in valuations that we observe between Step 1 and Step 3. If anything, the presence of measurement error might have resulted in an underestimation of network effects in the case of TikTok since valuation removing network might be overestimated.

Regret.—To ensure data quality, we ask respondents whether they agree with a statement about what their choices mean in terms of their valuation. For example, in the case of the practice good, a respondent with an implied valuation of between \$X1 and \$X2 is asked whether they agree with the statement that "According to your answers to the previous questions, you would require a payment worth between \$X1 and \$X2 to deactivate your Uber account for four weeks." If respondents do not agree, they are asked to complete the multiple price list questions one more (and final) time. Our main sample is restricted to respondents who do not regret their final answers in any of the steps, but we discuss below that results still hold when we also include those who regret their final choice.

Overall, 33 percent of respondents regret their choices once, and a smaller fraction of 5 percent regret their choices twice. Supplemental Appendix Figure A4 illustrates that this pattern holds for each step: After being redirected to the MPL questions, fewer participants disagree with their elicited WTA. The extent of regret fluctuates across steps. The percent of respondents regretting their choices is relatively high in the practice section, with 22 percent disagreeing with their elicited WTA initially

[22]We do not conduct these exercises for Step 3, since all participants started with an initial offer of zero. Additionally, we did not record data on the subsequent randomized offer.

and 5 percent after completing the MPL questions a second time. In the subsequent steps, the fraction of respondents regretting their final answers fluctuates around 3 percent. These patterns suggest that comprehension and data quality are high and that the practice questions helped improve comprehension.

Perceived Stakes and Credibility.—The key design challenge for our paper concerns the large-scale deactivation study. One concern with our empirical design is that respondents may not have found it likely that we would manage to recruit two-thirds of university students at their university, the condition for the large-scale deactivation study. To examine whether people perceived as credible that the large-scale deactivation study would take place, we asked respondents in our Instagram and Maps experiments about the percent chance that the researchers will recruit more than two-thirds of the students at their university. On average, participants perceive this likelihood to be 45 percent and 46 percent for Instagram and Maps, respectively.[23] Moreover, we examine how this perceived probability is correlated with our estimated valuations. Panel E of Supplemental Appendix Figure A5 illustrates that individuals who deem the large-scale deactivation study as more probable do not have a less negative product market valuation. This heterogeneity suggests that our design is conservative and likely underestimates the extent of negative welfare. More broadly, given that even in the case of the large-scale deactivation study not all users would deactivate their account, our study plausibly identifies lower bounds for the size of negative product market surplus and for the size of network effects.

Hypothetical Welfare Measures

Live in a World Without: After the price elicitation, we present respondents with a series of hypothetical qualitative questions. To assess the boundary conditions of our results (i.e., extrapolating to a hypothetical case where every user in the world stops using their social media), we ask respondents whether they would prefer to live in a world with or without the social media platform. As Figure 5 shows, 57 percent and 58 percent of respondents (including users and nonusers) prefer to live in a world without TikTok and Instagram, respectively. Even among users, 33 percent and 57 percent prefer to live in a world without TikTok and Instagram, respectively. Panels A and B of Supplemental Appendix Figure A5 validate these hypothetical survey questions with the incentivized measure of product market surplus. The figures illustrate that the hypothetical question is strongly correlated with the incentivized measure for both TikTok ($p < 0.01$) and Instagram ($p < 0.01$).

Preference Rankings: To understand the preferences of university students of social media usage among their peers, we ask them to rank three hypothetical scenarios: (i) They deactivate the platform, and every other student at their university keeps using it; (ii) every student at their university, including themselves, deactivates the platform; and (iii) no one deactivates the platform.

[23] Experimenter demand effects may somewhat distort respondents' responses to this question.

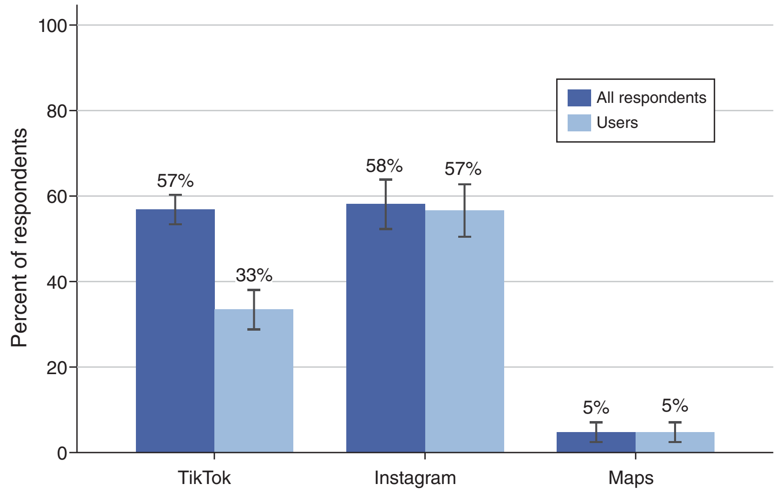

Figure 5. Percentage of Respondents That Prefer to Live in a World without the Platform

Notes: Figure 5 displays the percent of the respondents who stated they would prefer to live in a world without the platform for TikTok, Instagram, and Maps separately. The dark blue bar represents the fraction among all respondents, and the light blue bar represents the fraction among active users of the respective platform. Respondents who agree with their elicited valuations and those who pass all of the attention checks are included. Error bars represent 95 percent confidence intervals.

The results based on these rankings support our main findings. The most preferred scenario is that every student deactivates their social media account (Supplemental Appendix Figure A6). Among TikTok users, 40 percent prefer this option, while 49 percent of Instagram users prefer it. In contrast, the least preferred scenario is where no one deactivates their account, with 50 percent and 52 percent of respondents citing this option as their least preferred one for TikTok and Instagram, respectively.[24]

Panels C and D of Supplemental Appendix Figure A5 validate these hypothetical measures with the incentivized measure of product market surplus. This figure illustrates that the hypothetical question is strongly correlated with the incentivized measure. Indeed, while respondents who preferred deactivation for everyone have highly negative product market valuation for both Instagram and TikTok, respondents for whom deactivation for everyone was the least preferred option have positive product market valuation. The differences in product market surplus across these survey measures are highly significant for both Instagram ($p < 0.01$) and TikTok ($p < 0.01$).

Substitution across Social Media Platforms.—One concern is that product market valuation is so low given users' opportunity to substitute their consumption to another platform, based on an argument similar to the one in Farrell and Saloner (1985). Specifically, even in the absence of nonconsumer surplus, with

[24] "Only I deactivate" is the most preferred option for 33 percent and 29 percent of TikTok and Instagram users, respectively. This is somewhat higher than the fraction of users who would accept to deactivate their accounts without compensation. This difference could arise from differences in the elicitations, such as the lack of incentives and the time horizon of the deactivation.

two technologies, where an "alternative" technology is superior to the predominant one, individuals' welfare could be improved if they all stopped using the inferior technology. However, several pieces of evidence can help rule out this story and shed light on how substitution affects our estimates.

First, structural estimates of diversion ratios suggest that the outside option (offline or other online activities) is the most important substitution channel for social media, including Instagram and TikTok (Aridor 2025). This pattern suggests that individuals do not all substitute toward a "better" platform. Second, the vast majority of users in our data are multihomers, with very few users having only a TikTok ($n = 6$ in the first survey) or an Instagram account ($n = 17$ in the second survey). This adoption pattern makes it unlikely that users are trapped in Instagram or TikTok because they cannot switch to a better alternative. Third, our estimates show that both respondents who multihome and those who single-home have a negative product market valuation, which alleviates concerns that the negative product market surplus is driven by cross-platform substitution.[25]

Other Robustness Checks

Distributional Assumptions: As a robustness check against potential censoring in valuations, we assume a triangular distribution for those values that lie in these ranges. This gives more weight to the upper and lower bounds in the elicitation and thus allows gauging the sensitivity to extreme valuations at the tails. Given the higher mass at the lower end of the distribution (Figure 3), the estimates based on the triangular distribution are more negative than our main estimates (Supplemental Appendix Figure A15). Supplemental Appendix C.3 provides additional details.

Robustness to Sample Restrictions: In our main analysis, we reported results for respondents who passed all attention checks and did not regret any of their final choices. Supplemental Appendix Figure A8 confirms our results for the full sample without those exclusions; Supplemental Appendix Figure A9 confirms our findings with a sample that includes inattentive respondents and excludes respondents regretting their final choice. Supplemental Appendix Figure A10 demonstrates the robustness of our findings to including respondents regretting their final choice and only excluding inattentive respondents. Finally, Supplemental Appendix Figures A11 to A14 show that our findings are robust to considering the initial responses of those participants who regret their choices instead of their final responses.

D. *Mechanisms*

Repugnance toward Digital Products.—One explanation for the drop in welfare from the individual to the product market surplus could be repugnance toward digital products. To test this possibility, we run a similar elicitation with a digital good that plausibly does not cause strong externalities to nonusers: Maps applications. These

[25] Among individuals who only have a TikTok account ($n = 6$) and only an Instagram account ($n = 17$), the product market surplus is even more negative at $-\$43$ and $-\$44$, respectively. Among users who multihome, the estimates are $-\$24$ for TikTok and $-\$3$ for Instagram.

applications likely have more muted externalities on nonusers, as they do not create social costs of exclusion and are less likely to impact relative social standing. The instructions are virtually identical to our main experiment, except for the product name and the way the deactivation is monitored (deactivation of Maps is only monitored through screenshots).

Supplemental Appendix Figure A7 shows that both the individual consumer surplus and the product market surplus are positive and significantly different from zero in the case of Maps.[26] The product market surplus is significantly lower than the individual consumer surplus ($p < 0.01$), which might result from various motives. First, respondents may dislike "Big Tech" companies and their associated market power and therefore prefer a ban of products that underlie the market power of big tech companies. Second, respondents may feel repugnance toward digital products, such as mobile phones and modern technologies. Third, respondents may have a distaste for others using their phone.

To test whether the drop in welfare between individual consumer surplus and product market surplus is larger for Instagram compared to Maps, we conduct a difference-in-differences exercise, computing the change between valuation keeping network and product market valuation between Instagram and Maps. Supplemental Appendix Table A4 shows that the coefficient on the interaction term (of an indicator of Instagram and the product market valuation) is large and significant ($p < 0.01$). This corroborates that negative externalities to nonusers are larger on Instagram than they are for Maps.

The evidence on the positive product market valuation of Maps and the significant difference-in-differences estimate also alleviate concerns that the wording of the elicitation mechanically induces negative welfare estimates, that is, respondents providing positive willingness to pay to ban others using the product. Naturally, given the many differences between Maps apps and social media platforms, this evidence remains limited in disentangling mechanisms underlying our main findings.

Motives behind Consumption

Social Media Platforms: To provide additional evidence on mechanisms, we asked active users who said that they prefer to live in a world without the platform an open-ended question to better understand the motives behind their usage: "You mentioned you would prefer to live in a world without [platform]. Why do you still use it?" To quantitatively analyze the data, we used a simple hand-coding scheme with five (not mutually exclusive) categories. "FOMO" responses usually mention feeling left out ("I feel like if I stop using it, I will be completely out of the loop").[27] "Entertainment" responses talk about the high entertainment value of the platform ("It's a very good source of entertainment and it's always something to do

[26] These findings are also qualitatively in line with the hypothetical ranking question, where we find that the most preferred scenario is for no one to quit Maps (46 percent), while only 25 percent of respondents have a preference for everyone to quit maps (see Supplemental Appendix Figure A7(d)).

[27] Social media platforms like TikTok and Instagram may cultivate FOMO among users through specific platform features and content dynamics. TikTok's video format and evolving trends may create social pressure to remain continually informed. Conversely, Instagram's feature of shared content that is only available for a limited time on the platform may foster a fear of being left out.

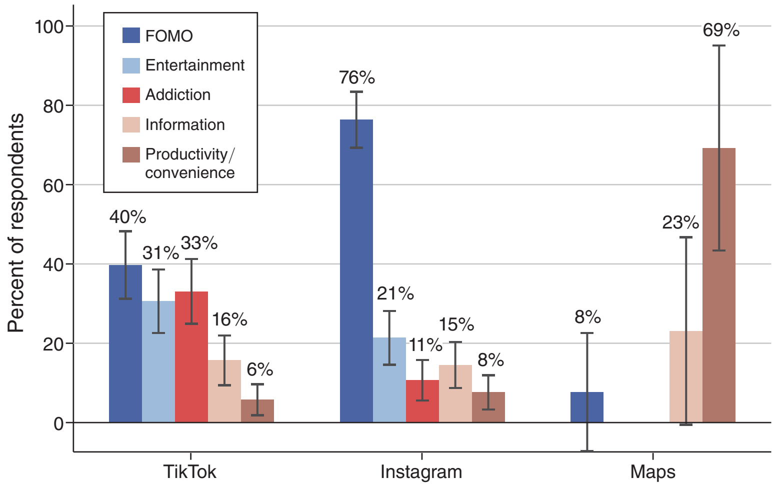

FIGURE 6. MOTIVES FOR SOCIAL MEDIA CONSUMPTION DESPITE A PREFERENCE TO LIVE IN A WORLD WITHOUT IT

Notes: Figure 6 presents the fraction of respondents mentioning different motives in their open-ended responses. Active users who said that they prefer to live in a world without the platform were asked the following open-ended question: "You mentioned you would prefer to live in a world without [platform]. Why do you still use it?" "FOMO" denotes responses mentioning the fear of missing out or related social concerns. "Entertainment" denotes responses mentioning the entertainment value of the platform. "Addiction" denotes responses indicating the addictive nature of the platform and self-control problems. "Information" denotes responses mentioning informational purposes such as following the news or keeping abreast of college events. "Productivity" denotes responses mentioning productivity benefits, such as using the platform for business purposes. The categorization of the open-ended answers is not mutually exclusive. Respondents who agree with their elicited valuations and those who pass all of the attention checks are included. Nonsensical responses were dropped from the analysis. The underlying sample sizes are 121 for TikTok, 131 for Instagram, and 13 for Maps. Error bars represent 95 percent confidence intervals.

when bored"). "Addiction" responses mention self-control problems and addiction ("It's very addicting and I cannot stop"). "Information" responses indicate receiving useful information ("I follow pages that keep me up to date with the largest news"). Finally, "Productivity/Convenience" responses mention using the platform for productive use or convenience ("I still use Instagram for business purposes"). Supplemental Appendix Table A7 provides an overview of the hand-coding scheme and provides further example responses.

Figure 6 illustrates the quantitative distribution of the hand-coded data for TikTok, Instagram, and Maps. It reveals that the fear of missing out is the most reported motive of why some participants continue using Instagram (76 percent) or TikTok (40 percent) despite preferring them not to exist. Moreover, entertainment motives also are frequently reported as driving people's social media consumption (31 percent of TikTok and 21 percent of Instagram users), consistent with evidence on people's news preferences (Bursztyn, Rao et al. 2023). Consistent with prior evidence (Allcott, Gentzkow, and Song 2022), addiction is an important reason for TikTok (33 percent), though somewhat less important for Instagram (11 percent). Only a small fraction of users (6 percent and 8 percent on TikTok and Instagram, respectively) cite productivity/convenience as a reason for using the platform. While this evidence suggests that FOMO is an important mechanism, it does not conclusively show that it is the main mechanism behind our findings.

Maps: We also conducted a similar coding procedure for the Maps experiment. Figure 6 reveals that 69 percent of respondents mention productivity reasons, 23 percent mention information, and only 8 percent mention the fear of missing out ("[…] still use navigation maps because it is what everyone uses"). The strikingly different patterns for navigation apps are suggestive evidence against experimenter demand effects driving the uncovered patterns.

Direct Evidence on Mechanisms behind Externalities to Nonusers

Social Media Platforms: To provide direct evidence on the mechanisms behind externalities to nonusers, we asked all respondents an open-ended question about the nature and motives behind their nonuser utility. In particular, we asked them, "How would you feel if you were the only one who deactivated [platform] and everyone else kept using it?"

Based on the open-ended responses, we devised a coding scheme to capture the most common topics. "FOMO" responses talk about the fear of missing out ("I would definitely feel a bit left out"). "Negative" responses express negative emotions without explicitly mentioning the fear of missing out ("[…] it would be a little unfair"). "Indifferent" responses indicate that they do not expect the deactivation to have strong effects on them ("That wouldn't be a big deal"). "Beneficial" responses mention the benefits of not using the respective platforms ("I would be able to focus on more important things").

Figure 7 illustrates the results. Panel A shows results for respondents who prefer to live in a world without the platforms, and panel B shows results for those who prefer to live in a world with the platforms. Among TikTok users who would prefer to live in a world without it, 35 percent express FOMO, 33 percent are indifferent, 7 percent have generic negative feelings, and 17 percent see it as beneficial. Among Instagram users who would prefer to live in a world without it, 38 percent express FOMO, 35 percent are indifferent, 8 percent have generic negative feelings, and 18 percent see it as beneficial. Among Instagram users who would prefer to live in a world with Instagram, 41 percent express FOMO, 25 percent are indifferent, 13 percent have generic negative feelings, and 15 percent see it as beneficial.

Maps: We hypothesized that the nature of externalities for navigation and maps smartphone applications would be different from social media platforms. Figure 7 confirms this conjecture.

Other-Regarding Preferences.—Our design in Step 3 tries to hold constant other-regarding preferences by telling participants that other respondents would receive *just enough* money to deactivate their accounts. As such, we aimed to clarify that there would be no surplus left for other respondents, as we would compensate them at their indifference point. This point should be quite salient since we asked those who regretted their initial valuation to retake the questions.

Of course, other-regarding preferences could still be a mechanism underlying the empirical patterns we document. For example, people with paternalistic preferences could believe that others have self-control problems and could therefore choose the

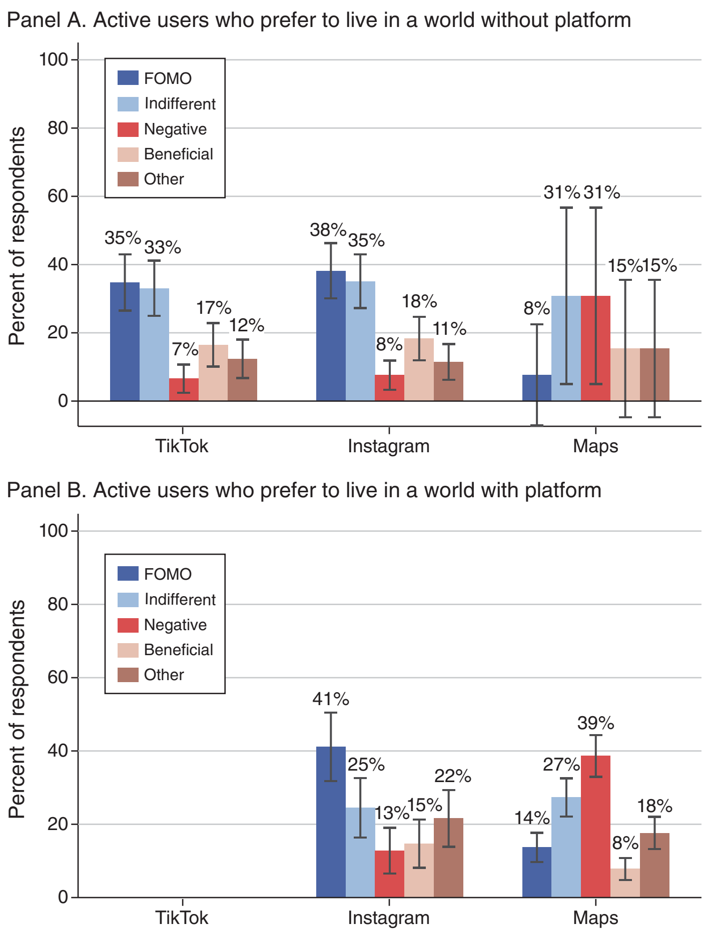

Figure 7. Evidence on Mechanisms behind Externalities to Nonusers

Notes: Figure 7 presents the fraction of respondents expressing different emotions in their open-ended responses. Panel A shows results for respondents who prefer to live in a world without the respective platform, while panel B shows results for those who prefer to live in a world with the respective platform. Active users were asked the following open-ended question: "How would you feel if you were the only one who deactivated [platform] and everyone else kept using it?" Data for TikTok are missing for panel B, as this question was only directed to TikTok users who stated they would rather live in a world without TikTok. "FOMO" denotes responses mentioning the fear of missing out or related social concerns. "Indifferent" denotes responses expressing they would not be particularly affected. "Negative" denotes responses expressing negative emotions, whereas "Beneficial" denotes responses where respondents mention a potential benefit of deactivation. "Other" denotes a diverse set of responses that mention different motives. The categorization of the open-ended answers is not mutually exclusive. Respondents who agree with their elicited valuations and those who pass all of the attention checks are included. Nonsensical responses were dropped from the analysis. Responses indicating indifference conditional on payment/contribution to research were placed in the "Other" category. The underlying sample sizes are 121 for TikTok, 233 for Instagram, and 269 for Maps. Error bars represent 95 percent confidence intervals.

large-scale deactivation thinking it would be beneficial to the others' well-being. The evidence presented in Section IIID suggests that paternalistic concerns are at least not top of mind when respondents are asked how they would feel if they were the only ones deactivating. Hand-coding the open-ended responses reveals that less than 1 percent of the answers expressed paternalistic sentiments ("Self-deactivation can benefit other people") for TikTok and Instagram.

E. *Other Applications: Luxury Goods and Product Vintages*

To probe the external validity of our findings beyond social media, we provide suggestive evidence from contexts in which positional concerns are plausible drivers of externalities to nonusers: luxury goods and products with different vintages. We use pre-registered surveys with a sample of 500 US respondents recruited on Prolific. Supplemental Appendix E provides additional details on the sample and design.

Among respondents who owned any luxury brand, 44 percent preferred to live in a world without it. Among respondents not owning any of these brands, the fraction preferring to live in a world without them is higher, at 69 percent. We next examine preferences regarding the frequency of product variations. Among iPhone owners, a striking 91 percent of them would prefer Apple to release the iPhone every other year rather than every year. Among respondents not owning the iPhone, 94 percent prefer Apple to release the iPhone every other year rather than every year.

IV. Conclusion

In the traditional assessment of consumer welfare, the emphasis is predominantly on individual-level evaluations, holding aggregate consumption fixed. Such measures do not accurately reflect welfare in settings with externalities to nonusers. We introduce a new method to gauge welfare in these contexts, which we apply to widely used social media platforms through incentivized experiments involving college students. While traditional measures of individual consumer surplus suggest positive welfare, the *Product Market Valuation* that accounts for externalities to nonusers tells a different story: It reveals average negative welfare in our sample, with a notable portion of users experiencing a disutility from the platform. This evidence is consistent with *product market traps*, where consumers continue to use a product even though they prefer it not to exist. Intriguingly, such product market traps can arise even with fully rational expectations and without any behavioral frictions.

Our empirical evidence of a *social media trap* could help reconcile the seemingly contradictory findings in the literature of a large consumer surplus coexisting with negative effects on well-being. More generally, these findings challenge the standard revealed-preference argument that the mere existence of a product implies that its consumers derive positive welfare. The presence of product market traps underscores the need for more research on whether companies introduce features that exacerbate nonuser utility and diminish consumer welfare rather than enhance it, increasing people's need for a product without increasing the utility it delivers to them. Our framework also highlights a few important levers for policymakers: First, regulation can counteract producers' incentives to use technologies that decrease nonuser utility. Second, given that larger networks decrease nonuser utility, optimal antitrust policy may involve reducing the size of networks.

While our evidence shows that a large fraction of active users in our sample derive negative utility from the platform's existence, one limitation for the external validity arises from the self-selected nature of the sample, which has a higher fraction of females compared to the population of users. Moreover, it is an open question whether people would be willing to jointly deactivate their social media accounts above and beyond the temporary four-week deactivation. Future work should also examine whether coordination devices could enable users to actually deactivate their social media accounts persistently or whether they would go back to using social media platforms after an initial period of deactivation.

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