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Abstract

We leverage Becker's time allocation theory to examine consumer demand and market competition for time-intensive goods. The Beckerian model predicts higher diversion ratios for goods with substantial time shares and those with high time costs relative to monetary prices. Applying this model to data from two field experiments, we analyze demand for Facebook and Instagram, focusing on substitution patterns across online activities and offline time use. Our findings indicate that users exhibit low elasticity to ad load, the primary user cost, and that time shares and time costs significantly influence diversion ratios. We explore the implications for user costs and benefits on these platforms and assess the potential impact of a Federal Trade Commission-proposed de-merger of Facebook and Instagram.

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1 Introduction

In his seminal 1965 work, "A Theory of the Allocation of Time", Gary Becker established a foundational framework for analyzing household production, consumer demand, and time allocation. Becker posited that consumers combine purchased market goods with time through a household production function to create utility-generating commodities. Rather than deriving utility directly from goods or time, consumers value these commodities. Consequently, consumer demand and substitution patterns are shaped by both market prices and time costs, where the latter reflect the time required to consume a commodity multiplied by its opportunity cost.

Our paper applies Becker's theory of time allocation to empirically investigate consumer demand and market competition for time-intensive goods, focusing on online leisure activities such as social media, gaming, and streaming. The emergence of online platforms has transformed how people engage in recreation, connection, and communication.[1] Unlike traditional business models, these platforms typically generate revenue through advertising while charging users little to no monetary cost.

In recent years, researchers and policymakers have become more deeply engaged in understanding consumer demand and market competition for online leisure activities. One perspective holds that these activities form distinct, highly concentrated submarkets, each providing differentiated goods with unique functions and features (see e.g. Wu, 2019; CMA, 2020; Morton and Dinielli, 2022). In contrast, another view posits that online leisure platforms compete broadly for users' limited time and attention, making their goods close substitutes despite differing functionalities (Evans, 2013; Renner, 2020). Existing research has struggled to reconcile these competing views. Resolving this debate is critical for understanding how economic conditions and government policies shape demand and competition in online leisure markets.

These competing perspectives are central to the high-profile antitrust lawsuit filed by the Federal Trade Commission (FTC) against Meta, the parent company of Facebook and Instagram. The FTC asserts that Facebook wields market power in the personal social networking (PSN) market, defined as online services for maintaining personal relationships and sharing experiences, encompassing Facebook, Instagram, and Snapchat. Conversely, Meta contends that Facebook competes broadly for users' time and attention, facing robust competition from diverse online leisure platforms and offline activities (Facebook, Inc., 2021).

To lend insights into each perspective, we develop a Beckerian demand model where consumers combine time and market goods to produce utility-generating commodities. We adapt this model to online leisure activities, such as social media and streaming, and analyze the factors driving substitution. Our findings demonstrate that, ceteris paribus, diversion ratios are higher for commodities with greater time shares and those that are more time-intensive, meaning their time costs significantly outweigh their monetary costs.

[1] According to the 16th annual Digital Future Report by the USC Annenberg School's Center for the Digital Future, the weekly time spent online by the average internet user in the US (age 12 and over) went from 9.4 hours in 2001 to 22.5 hours in 2018.

The importance of time shares in determining diversion ratios parallels the established finding that diversion to a good increases with its consumption share (e.g. Conlon and Mortimer, 2021). In our Beckerian framework, however, consumption is measured by the time spent on a good, not just its monetary expenditure. Time intensity affects diversion ratios because reducing demand for a time-intensive commodity lowers the opportunity cost of time. This reduction encourages consumers to shift toward other time-intensive commodities rather than less time-intensive ones.

A key implication of these findings is that time-intensive commodities can be close substitutes, even when their market goods differ in features and functions. For instance, while consumers may not perceive Facebook and YouTube as functionally similar, their high diversion ratio may stem from both being time-intensive or YouTube's substantial time share. This logic extends to other time-consuming commodities, such as offline activities like preparing dinner or providing childcare. The time required for these activities can render them substitutes for online leisure, despite differing purposes or perceived comparability.

While Becker's model provides deep insights on key individual trade-offs, quantitative evidence is necessary to understand actual demand and diversion in a market, as consumer responses to changes in prices or other factors must be measured ceteris paribus. Inspired by the Beckerian model, we use two field experiments to empirically examine demand for Facebook and Instagram, focusing on substitution patterns across online activities and offline time use. The first field experiment was a large-scale pricing study designed by us to estimate the responsiveness of users to financial incentives. More specifically, we randomly offered pecuniary rewards to a representative sample of users to decrease their time on Facebook or Instagram. We track usage of these platforms and diversion to other online activities and offline time via a phone-based activity monitoring app.

Experimental results reveal significant own-price effects, with the pricing experiment substantially reducing time spent on both platforms. Cross-price estimates indicate that this reduction led to increased time allocation to non-personal social networking (PSN) commodities, including other apps and offline activities, with nearly all app categories acting as substitutes for Facebook and Instagram. By integrating own- and cross-price effects, we calculate diversion ratios, which indicate the proportion of reduced time on Facebook or Instagram reallocated to other commodities. A diversion ratio of one (zero) implies all (none) of the reduced time shifts to a given commodity.

Our findings on diversion ratios show that offline activities account for a significant share of diverted time (39% for Facebook, 29% for Instagram), with the remainder redistributed to other apps. Our analysis of app-specific diversion ratios reveals that only 6% of reduced Facebook time shifts to other personal social networking (PSN) platforms (Instagram and Snapchat), while 16% of reduced Instagram time diverts to other PSNs (Facebook and Snapchat). These ratios are notably lower than those for certain non-PSN apps with markedly different features and functions. For instance, gaming apps, which serve distinct purposes from Facebook, exhibit the highest diversion ratio for Facebook. Similarly, YouTube, despite being excluded from the FTC's PSN market definition due to its differing functionality, has the highest diversion ratio for Instagram.

The Beckerian model provides a compelling explanation for these field experimental results: substantial diversion to offline activities or non-PSNs can occur, even if they differ in purpose or perceived similarity from PSNs, when commodities have high time shares or time intensity. By comparing diversion ratios (influenced by time shares) to cross-price elasticities (independent of time shares), we find that high time shares drive significant diversion from Facebook and Instagram to offline activities and certain online activities, like gaming. Conversely, high time intensity accounts for the notable diversion to TikTok and YouTube, which show strong cross-price elasticities despite their distinct features.

While the pricing experiment effectively reveals diversion ratios, it does not estimate the elasticity of user time on Facebook and Instagram with respect to ad load, the primary user cost. To estimate this key parameter, we analyze a second field experiment, initiated by Meta in 2013 to examine the long term effect of ad load. This ongoing study includes a holdout group of randomly selected users who see no ads on either platform. By comparing this group to a control group exposed to ads, we assess the impact of ad load on platform usage (see also Brynjolfsson et al., 2024). Our findings show that typical ad impression levels reduce daily usage by 2.0 minutes on Facebook and 0.62 minutes on Instagram compared to the ad-free group. At these levels, we estimate an average elasticity of user time to ad load of 0.09 for Facebook and 0.04 for Instagram.

With these estimates and results from our first field experiment in hand, we can evaluate the costs and benefits of Facebook and Instagram for users. We adopt a linear demand system, consistent with our findings, and assume additive separability between commodity consumption and the disutility of ads in the utility function, enabling integration of pricing and ad load variation data. Consumer surplus, measured as the area under the inverse demand curve, represents the net consumption value in this case. On average, we estimate a daily consumer surplus per user of around \$3.4 for Facebook and \$2.1 for Instagram.[2]

These estimates of the daily consumer surplus on Facebook and Instagram can be complemented by estimates of the cost paid by the user. Given a monetary price of zero, the cost to users corresponds to the dis-utility stemming from watching ads. The cost of ads to users can be recovered by comparing the reduction in user time on the platform due to the change in prices compared to ads. We estimate that the cost to the user of the ads is equivalent to a daily tax per user of \$0.70 on Facebook \$0.20 on Instagram. This suggests that Facebook captures only 17 percent of the consumption value of the platform, while Instagram captures about 8 percent.

The key reason for the large consumer surplus is that both platforms choose an ad load in the inelastic range of the demand curve. The core empirical question becomes: why is this case? In a traditional model with one-sided markets, no profit-maximizing firm will choose to operate in the inelastic range of its demand curve. To delve deeper into the economics of this question, we develop and estimate a model of two-sided media platforms that rationalizes the

[2]This implies a yearly consumer surplus of \$1,241, which is fairly comparable to the estimates reported in previous studies. For example, Allcott et al. (2020) reports a yearly consumer surplus for the median Facebook user of approximately \$1,300. Other studies reporting similar estimates include Mosquera et al. (2020); Brynjolfsson et al. (2019a,b); Corrigan et al. (2018); Benzell and Collis (2020).

choice of ad load, where the platforms (imperfectly) compete with each other for both users and advertisers.

Our model is based on standard models of media platforms such as Anderson and Peitz (2020), but allows for non-zero diversion ratios between platforms on the advertising side, consistent with user multi-homing as in Anderson et al. (2017). It contains three distinct mechanisms that could rationalize why both Facebook and Instagram choose the ad load in the inelastic range of the demand curve. The first mechanism is network externalities, which may lead aggregate demand to be more elastic than suggested by the estimates from the ad holdout experiment.[3] Therefore, the profit-maximizing level of the ad load may be lower. The second mechanism is the two-sided nature of the market. Facebook and Instagram are best characterized as two-sided platforms where users and advertisers interact. The technological and demand conditions in the advertising market can reduce the profit-maximizing level of the ad load. The third mechanism is substitution in the advertising market. Internalizing the possible diversion of advertisers between Facebook and Instagram, both owned by Meta, may lower the profit-maximizing level of ad load.

We employ our model to examine demand and competition in online leisure services, analyzing the effects of a proposed FTC de-merger of Facebook and Instagram. Our analysis centers on changes in ad load—the primary user price—and consumer surplus. A de-merger produces two counteracting effects on ad load. First, non-zero user diversion between the platforms incentivizes higher ad loads under a merger, as user and revenue losses from increased ad load on one platform are partially offset by gains on the other. Second, non-zero advertiser diversion encourages lower ad loads when merged, since reducing ad load on one platform boosts advertiser demand and ad prices on the other. Consequently, the net impact of a de-merger on ad load is theoretically indeterminate, hinging on the magnitude of user and advertiser diversion ratios and the demand elasticities of both groups.

To empirically evaluate the de-merger, we integrate our field experimental data with additional sources to estimate the model's structural parameters. We leverage internal Facebook and Instagram data to derive measures of: (i) the social multiplier, capturing network effects on user demand; (ii) ad blindness, reflecting how ad load affects user interaction with ads; (iii) marginal costs; and (iv) current equilibrium ad loads, user time, and ad prices. These measures are combined with results from the pricing and holdout experiments to identify parameters governing user demand. Next, we explain how the own-price effects on advertiser demand can then be recovered if one knew or assumed the magnitude of the cross-price effects in the ad market. The argument is that the observed equilibrium choices of the ad load of Facebook and Instagram contain information about the demand they must face in the advertising market. The only unknown parameters are then the cross-price effects in the ad market. Our data do not allow us to quantify these parameters. We therefore present results for different values of the cross-price effects corresponding to a wide range of diversion ratios in the ad market, from no diversion to full diversion from Instagram to Facebook. We

[3] Bursztyn et al. (2024) find evidence of positive consumption externalities between Facebook users. See also Bursztyn et al. (2025), who show that valuations of alternative social apps increase more in response to a collective TikTok ban than to an individual TikTok deactivation.

show that this approach produces economically informative lower and upper bounds on the quantities of interest.

The bounds deliver two key conclusions. The first is that we can rule out that the de-merger would materially benefit the users of Facebook and Instagram. The largest possible gains to users from the de-merger are very close to zero, obtained if one believes that there is no diversion of advertisers between Facebook and Instagram. The second conclusion is that the de-merger would be harmful to users of Facebook and Instagram if one believes that advertisers view these platforms as substitutes. The harm is significant if there is a sizable diversion of advertisers between Facebook and Instagram. For example, if one assumes that the advertiser diversion ratio of a platform is equal its market share, then the de-merger would increase the ad load on Facebook and Instagram by 3.7 and 9.8 %, while the consumer surplus of Facebook and Instagram users would fall by about 1.0 %.

We compare these findings with results obtained using the FTC's market definition, which limits the relevant user market to Facebook, Instagram, and Snapchat. This definition assumes that time-intensive commodities are not substitutes unless they share similar functionality, restricting substitutability to these three platforms. Adopting the FTC's approach erroneously suggests that a de-merger would consistently increase consumer surplus. This discrepancy underscores the critical need to account for time's role in shaping demand, diversion, and competition within online leisure markets.

We view our study as contributing to several literatures. First, we extend Becker's time allocation theory to digital platforms, showing that time, not just monetary price, drives demand and substitution in time-intensive markets. In doing so, the study introduces time shares and time intensity as key determinants of diversion ratios, offering a new lens for studying consumer behavior in digital economies. In this manner, it is related to the literature that uses a Beckerian model to study the allocation of time across different activities.[4] The existing literature often examines how time allocation to non-market activities affects labor supply. For instance, Aguiar et al. (2021) estimate a demand system for various activities, suggesting that technological advancements increasing the marginal utility of online leisure contribute significantly to the declining labor supply among young men. In contrast, our paper pursues a distinct objective: it develops a theoretical framework to guide future research on digital markets, leisure activities, and other time-intensive goods, enhancing economic models of household production and consumption.

Our paper also contributes to a growing body of experimental research examining the use and impact of social media. These studies typically offer financial incentives to reduce or deactivate usage of apps like Facebook or Instagram, then assess the effects on outcomes such as well-being (Mosquera et al., 2020; Allcott et al., 2020; Collis and Eggers, 2022), political attitudes (Mosquera et al., 2020; Allcott et al., 2020; Guess et al., 2023; Allcott et al., 2024), and time allocation to other (online or offline) activities (Allcott et al., 2024; Aridor, 2025). In terms of experimental design, the closest study to ours is arguably Allcott et al. (2024). Similar to our work, they randomize financial incentives to reduce time on

[4] See Heckman (2015); Chiappori and Lewbel (2015); Aguiar and Hurst (2016) for reviews of Becker's model of time allocation and its many applications in economics.

Facebook or Instagram and have large sample sizes. However, the goal of their study is much different, and, they do not analyze consumer demand and market competition for online leisure activities. By comparison, Aridor (2025) considers a sample of 366 students, analyzing the impact of randomly deactivating YouTube or Instagram for a week. Due to the small sample size, the estimated impacts on time allocation to other activities are relatively noisy. However, the point estimates indicate considerable diversion of time from Instagram and YouTube to both offline activities and to Facebook, consistent with our findings.

Finally, we view our study as contributing to the area of law and economics. By advancing the application of the Beckerian model to analyze demand and competition in online leisure services, focusing on the proposed FTC de-merger of Facebook and Instagram, our study provides actionable evidence to navigate complex antitrust issues in digital markets. This is achieved by emphasizing the need to incorporate time-based competition and consumer surplus into regulatory decisions via a theoretically-inspired field experiment (to our knowledge, our work is the first field experiment conducted for a major federal anti-trust trial). By showing that non-PSN platforms (e.g., YouTube, gaming) and offline activities are substitutes for Facebook and Instagram due to time constraints, the paper challenges traditional market definitions based on functional similarity. This finding critiques the FTC's approach and encourages academics to rethink market boundaries with time-intensive goods.

Our de-merger analysis is focused entirely on potential anti-competitive effects on users from both Facebook and Instagram being owned by Meta, and we assume that a de-merger would not increase costs or reduce efficiency. We make this assumption because existing merger guidelines have a highly skeptical stance towards efficiency arguments (Kaplow, 2025), and because our data do not allow us to credibly quantify impacts on costs or efficiency. By comparison, Katz and Allcott (2025) perform a de-merger analysis in which Meta can achieve efficiency gains by using knowledge of which ads were seen by a given user on both platforms to improve ad targeting.[5] Their analysis also suggests that a de-merger does not increase user surplus.

The remainder of our study proceeds as follows. The next section presents a Beckerian model of demand, tailored to online leisure activities, to characterize substitution patterns driven by time shares and time intensity. Section 3 introduces our two field experiments, detailing their designs to assess demand and diversion for Facebook and Instagram. Section 4 evaluates the costs and benefits for users, estimating consumer surplus and ad-related costs. We then discuss our two-sided model in Section 5. Section 6 analyzes the proposed FTC de-merger of Facebook and Instagram, using our model to estimate effects on ad load and consumer surplus. Finally, Section 7 concludes by summarizing our findings, compares them with the FTC's market definition, and discusses implications for digital market competition.

[5]In practice, both legal and technical constraints may limit Meta's ability to exploit cross-platform ad exposure data in this manner, motivating our focus on potential anti-competitive effects while abstracting from efficiency gains.

2 Time use and the demand for social networking services

2.1 A model of the allocation of time

Preferences. Consider a consumer with utility function $\mathcal{U}(z, n, C)$. The utility function has three distinct arguments. The first is $z = (z_0, ..., z_N)'$, which represent a set of commodities $\mathcal{Z}$. Following Becker (1965), consumers need to combine time and market goods to produce these commodities. As a normalization, we assume that time spent on each commodity is equal to z_i. This allows us to measure the quantity of each commodity in terms of minutes spent on it. The second argument of the utility function is the composite market good C. It differs from $\mathcal{Z}$ in that it requires no time to produce. The last argument of the utility function is $n = (n_0, ..., n_N)'$, which captures that the consumer may have to provide some service n_i as she produces each unit of commodity i. The quantity of services provided enters directly (and negatively) into the utility function. In our setting, n_i captures that users may have to see ads while consuming i.

Production of commodities. We assume that each unit of z_i requires one unit of time, p_i units of market goods (measured in dollars), and α_i units of n_i, implying that $n_i = \alpha_i z_i$. For example, α_i could denote the ad load for a good such as Facebook. These assumption can be micro-founded by z_i being produced with a Leontief production function:

$$f_i(H_i, x_i, n_i) = \min\left\{H_i, \frac{x_i}{p_i}, \frac{n_i}{\alpha_i}\right\}$$

where H_i and x_i are, respectively, time and market goods spent on commodity i.

Budget constraint and income function. The financial budget constraint is given by

$$C + \sum_{i=0}^{N} p_i z_i = Y. \tag{1}$$

where the price of the composite (time-free) consumption C is normalized to 1. As in Becker (1965), the consumer can allocate her time to market work and leisure $H \equiv \sum_{i=0}^{N} H_i$. Market work produces income (after tax) Y according to the following earnings function:

$$Y = \overline{Y} - wH^{\eta} \tag{2}$$

where $\overline{Y}$ is the maximum income the consumer can earn if she has no leisure, and the parameters (w, η) map total leisure time to income.

We assume that $\eta \geq 1$, implying that income is a concave function of total leisure time. If $\eta = 1$, the consumer can trade-off leisure with market consumption at a fixed wage rate w. As noted in the review article by Chiappori and Lewbel (2015), Becker thought this case was 'special and unlikely'. Instead, Becker argued the marginal wage rate is likely to be lower than the average wage rate (i.e. $\eta > 1$). This could, for example, reflect decreasing marginal productivity or a progressive tax system.

2.2 Personal social networking services and other commodities

We now specialize the Beckerian framework presented above to analyze the demand for and substitution between different types of commodities. In particular, we are interested in the distinction between Personal Social Networking (PSN) and non-PSN commodities.

We borrow the term PSN from the FTC's definition of the market that Facebook and Instagram operate in. They characterize PSN services as "online services that enable and are used by people to maintain personal relationships and share experiences with friends, family and other personal connections in a shared social space" (FTC, 2021, §165). The FTC considers the set of PSNs to include Facebook, Instagram, and Snapchat, but one could argue that also other goods should be classified as PSNs.

For the purpose of our analysis, we think of PSNs as including commodities that have a similar *functionality* to Facebook. For this reason, the elasticity of substitution in consumers' preferences may be larger across PSNs commodities than between a PSN and a non-PSN commodity. To allow for this in a parsimonious way, we index commodities in the set of PSN activities $\mathcal{P} \subset \mathcal{Z}$ by $0 \leq i \leq P$, and then assume the following structure on the preferences

$$\mathcal{U}(z, n, C) = u(z) - v(n) + C \tag{3}$$

where the (dis)utility of provided services n is given by

$$v(n) = \sum_{i=0}^{N} \kappa_i n_i$$

and the utility over commodities z has the nested-CES structure

$$u(z) = \left(\omega_{\mathcal{P}} \underbrace{\left(\sum_{i=0}^{P} \delta_i z_i^{\theta} \right)^{\frac{\rho}{\theta}}}_{\equiv z_{\mathcal{P}}^{\rho}} + \sum_{i=P+1}^{N} \omega_i z_i^{\rho} \right)^{\frac{\gamma}{\rho}}$$

The parameter $\frac{1}{1-\theta}$ is the elasticity of substitution between PSN commodities in the consumers' preferences, and $\frac{1}{1-\rho}$ is the elasticity of substitution between the non-PSN commodities and the composite PSN commodity $z_{\mathcal{P}}$. The similarity in functionality between PSNs is captured by the assumption that $\frac{1}{1-\rho}$ is weakly lower than $\frac{1}{1-\theta}$. We normalize $\delta_0, ..., \delta_P$ so that $\left[\sum_{i=0}^{P} \delta_i^{\frac{1}{1-\theta}}\right]^{\frac{\theta-1}{\theta}} = 1.$[6]

[6] Under this normalization, whenever the full price of each PSN commodity is equal, i.e. whenever $P_j = P_k$ $\forall j, k \in \mathcal{P}$, the composite PSN commodity $z_{\mathcal{P}}$ is measured in number of minutes spent on all PSN commodities.

2.3 The consumer problem and solution

The consumer maximizes utility function (3) under the constraints defined by (1) and (2). Assuming an interior solution in C, the first-order conditions $\forall k \in \mathcal{P}$ are given by:

$$\gamma\left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho}+\sum_{i=P+1}^{N} \omega_i z_i^{\rho}\right)^{\frac{\gamma}{\rho}-1} \omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho-1}\left(\sum_{i=0}^{P} \delta_i z_i^{\theta}\right)^{\frac{1}{\theta}-1} \delta_k z_k^{\theta-1}=\underbrace{\nu+\kappa_k \alpha_k+p_k}_{\equiv P_k}, \tag{4}$$

and the first-order conditions $\forall g \in \mathcal{Z} \setminus \mathcal{P}$ are given by:

$$\gamma\left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho}+\sum_{i=P+1}^{N} \omega_i z_i^{\rho}\right)^{\frac{\gamma}{\rho}-1} \omega_g z_g^{\rho-1}=\underbrace{\nu+\kappa_g \alpha_g+p_g}_{\equiv P_g} \tag{5}$$

where $\nu \equiv \eta w H^{\eta-1}$ is the opportunity cost of leisure time at the margin.

Equations (4) and (5) define the *full prices* P_k and P_g of a unit of k and g, respectively. Each full price generally has three components: the opportunity cost of time ν, the monetary cost p_i, and the dis-utility cost associated with providing α_i units of n_i for each minute spent on i. The relative importance of each of the three components will generally differ between commodities. The *time-intensity* of commodity $i \in \mathcal{Z}$ is defined as the opportunity cost of leisure time relative to the full price:

$$\tau_i \equiv \frac{\nu}{\nu+\kappa_i \alpha_i+p_i}.$$

For notational simplicity, we assume that time-intensity is uniform across PSN activities, such that $\tau_k=\tau_{\mathcal{P}}$ for all $k \in \mathcal{P}$.

The solution to the consumer problem determines the allocation of time, and the resulting optimal choice of z and C. The solution also determines the share of total leisure time spent on each commodity as a function of prices and utility parameters, which will be important to understand consumer demand and substitution. To provide an expression for these *time shares*, it is useful to define a price index for the composite PSN commodity $\overline{P}_{\mathcal{P}} \equiv \left[\sum_{i \in \mathcal{P}} \delta_i^{\frac{1}{1-\theta}} P_i^{\frac{\theta}{\theta-1}}\right]^{\frac{\theta-1}{\theta}}$. In Appendix A.2.1, we derive the share of time spent on non-PSN commodity g,

$$\psi_g^H \equiv \frac{z_g}{H}=\frac{\omega_g^{\frac{1}{1-\rho}} P_g^{\frac{1}{\rho-1}}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}+\sum_{i \in \mathcal{Z} \setminus \mathcal{P}} \omega_i^{\frac{1}{1-\rho}} P_i^{\frac{1}{\rho-1}}},\ \forall g \in \mathcal{Z} \setminus \mathcal{P} \tag{6}$$

and the share of time spent on PSN commodity k,

$$\psi_k^H \equiv \frac{z_k}{H}=\frac{\delta_k^{\frac{1}{1-\theta}} P_k^{\frac{1}{\theta-1}}}{\sum_{i \in \mathcal{P}} \delta_i^{\frac{1}{1-\theta}} P_i^{\frac{1}{\theta-1}}} \times \frac{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}+\sum_{i \in \mathcal{Z} \setminus \mathcal{P}} \omega_i^{\frac{1}{1-\rho}} P_i^{\frac{1}{\rho-1}}},\ \forall k \in \mathcal{P} \tag{7}$$

where $\rho \leq \theta \leq 1$,

Equations (6) and (7) show that the time share of a commodity increases in its marginal utility (that is, in δ_k and $\omega_{\mathcal{P}}$ for PSNs, and in ω_g for non-PSNs) and decreases in its own full price (that is, in P_k for PSNs and P_g for non-PSNs). The degree to which the time share of a commodity decreases in its own full price depends on its elasticity of substitution with other goods (that is, the magnitudes of $\frac{1}{1-\theta}$ and $\frac{1}{1-\rho}$).

2.4 Consumer responses to changes in price vs ad load

We are interested in understanding the demand and substitution for different types of commodities. To this end, it is useful to differentiate the first-order conditions (4) and (5) to characterize the substitution of time across commodities j and i in response to a change in p_j or α_j. The following proposition shows that the model forges a tight link between (both own and cross commodity) responses to a change in p_j versus α_j:

Proposition 1. *For any two commodities j and i:*

$$\frac{\partial z_j}{\partial \alpha_j} = \kappa_j \frac{\partial z_j}{\partial p_j} \text{ and } \frac{\partial z_i}{\partial \alpha_j} = \kappa_j \frac{\partial z_i}{\partial p_j} \tag{8}$$

Proof. See appendix A.1. □

As discussed in greater detail in the empirical analysis, this proposition has two key implications. The first is that the diversion ratio D_{ij}, defined as the share of the reduction in time on the origin commodity j that is diverted to destination commodity i, is invariant as to whether the price or the ad load is changed:

$$D_{ij} \equiv -\frac{\frac{\partial z_i}{\partial p_j}}{\frac{\partial z_j}{\partial p_j}} = -\frac{\frac{\partial z_i}{\partial \alpha_j}}{\frac{\partial z_j}{\partial \alpha_j}} \tag{9}$$

This invariance property becomes useful for combining estimates from the pricing experiment with evidence based on exogenous variation in ad load. The second implication is that we can recover the (non-monetary) cost κ_j of providing services n_j, by comparing the reduction in time spent on z_j due to a change in p_j versus a change in α_j.

2.5 Determinants of substitution between commodities

To understand the substitution of time across commodities, we next express the diversion ratio in terms of the model parameters, then perform comparative statics with respect to key parameters. We refer to Appendix A.3 for the analytical expressions of the diversion ratios, and summarize the key insights from the comparative statics in Proposition 2 and a few corollaries presented below.

Proposition 2. *Assume $\eta > 1$. The diversion ratio between a PSN origin commodity $j \in \mathcal{P}$ and some destination commodity $i \in \mathcal{Z}$ is strictly:*

- *increasing in the time share of destination commodity (i.e. ψ_i^H),*
- *increasing in the relative time-intensity of the destination commodity (i.e. $\tau_i - \sum_{l=0}^{N} \psi_l^H \tau_l$),*

- *increasing in the relative time-intensity of the origin commodity (i.e.* $\tau_{\mathcal{P}} - \sum_{l=0}^{N} \psi_l^H \tau_l$*),*
- *increasing in* $\frac{1}{1-\theta}$ *when* i *is a PSN commodity, and decreasing in* $\frac{1}{1-\theta}$ *when* i *is non-PSN commodity.*

Proof. The comparative statics follow directly from the analytical expressions for diversion ratios presented in Propositions 4 and 5 in Appendix A.3. □

Proposition 2 shows that, everything else equal, the diversion ratios are higher to destination commodities with a high time share, between commodities that have a higher elasticity of substitution in the consumer's preferences, and between commodities that are relatively more time-intensive. A key implication is that commodities that have a large time share (ψ_i^H) or a high time-intensity (τ_i) may be close substitutes even if they differ in functionality so that the elasticity of substitution in preferences ($\frac{1}{1-\rho}$ or $\frac{1}{1-\theta}$) is low. For example, it is possible that the consumer has preferences such that the elasticity of substitution between Facebook and YouTube is low, yet that the diversion ratio from Facebook to YouTube is high due to the time-intensive nature of both commodities or due to YouTube having a high time share. The same logic could, of course, apply to a range of commodities that require time to consume, including offline activities such as eating dinner (which requires preparing a meal) or child care (which requires time with the child). The fact that production of such commodities requires time could make them close substitutes to PSNs even if they are not used for the same purpose or seen as comparable by consumers.

The importance of time shares in determining diversion ratios is analogous to a well-established result that diversion to a product tends to increase in the consumption share (e.g. Conlon and Mortimer, 2021). The only difference in our Beckerian framework is that the measure of consumption share should include the time spent on the commodity.

The reason why time-intensity plays a role in determining diversion ratios is due to the endogenous response of the opportunity cost of time and the associated substitution effect. The intuition is the following: An increase in p_j (or α_j) reduces time allocation to z_j, which lowers the opportunity cost of time. The lower opportunity cost leads the consumer to allocate more time to destination commodities that are relatively time-intensive as compared to those that are less time-intensive. The size of this substitution effect is increasing in the relative time-intensity of z_j, since a given price increase causes a larger reduction in the opportunity cost of time if the production of the origin commodity is time-intensive.

It is useful to observe how this substitution effect depends on the role of the concavity of the income function. If $\eta = 1$, the consumer can trade-off leisure and market consumption at a fixed wage rate. As a result, the opportunity cost of time is constant under $\eta = 1$, and relative time-intensity becomes irrelevant for the substitution between commodities, as stated in Corollary 1 below.[7] However, even when $\eta = 1$, the diversion ratios will be increasing in the time share of the destination commodity, everything else equal.

[7]It is straightforward to prove that the diversion ratio is the same under $\eta = 1$ as it would be if we change the production function so that commodities can be produced without time as an input.

Corollary 1. *The diversion ratio between PSN origin commodity $j \in \mathcal{P}$ and some destination commodity $i \in \mathcal{Z}$ is independent from the relative time-intensity of j (i.e. $\tau_{\mathcal{P}} - \sum_{l=0}^{N} \psi_l^H \tau_l$) and from the relative time-intensive of i (i.e. $\tau_i - \sum_{l=0}^{N} \psi_l^H \tau_l$) whenever $\eta = 1$.*

Proof. See appendix A.3. □

It is straightforward to also prove that, everything else equal, a higher η leads to a smaller decrease in leisure time in response to a change in p_j (or α_j), and, thus, more diversion to other commodities in $\mathcal{Z}$ relative to the composite good C. As η tends to infinity, individuals do not adjust their labor supply to a change in in p_j (or α_j), and all the diversion is to commodities in $\mathcal{Z}$. To see this, let $\psi_j^S \equiv \frac{(\nu+\alpha_j\kappa_j+p_j)z_j}{\sum_{l=0}^{N}(\nu+\alpha_l\kappa_l+p_l)z_l}$ be the share of j in full spending, and $\psi_{\mathcal{P}}^S$ be the total share of PSN commodities in full spending. In Appendix A.2.2, we show that for any $j \in \mathcal{P}$, the response of leisure time to a change in p_j is $\frac{\partial \ln H}{\partial \ln p_j} = -\left(\psi_j^S/\psi_{\mathcal{P}}^S\right) \times \frac{p_j}{\nu+\alpha_j\kappa_j+p_j} \times \Sigma_{\mathcal{P}}$ where

$$\Sigma_{\mathcal{P}} \equiv \frac{\frac{\gamma-\rho}{1-\rho}\psi_{\mathcal{P}}^S + \frac{1-\gamma}{1-\rho}\psi_{\mathcal{P}}^H}{1-\gamma+(\eta-1)\sum_{l=0}^{N}\left(\frac{\gamma-\rho}{1-\rho}\psi_l^S + \frac{1-\gamma}{1-\rho}\psi_l^H\right)\tau_l}$$

It follows directly that the response of total leisure time to a change in p_j is decreasing in η.

Relative importance of time shares, time-intensity, and functionality. It is interesting to empirically distinguish the importance of time shares (ψ_i^H), time-intensity (τ_i), and functionality (ρ or θ) in shaping diversion ratios. In Corollary 2, we show that comparing the relative cross-price elasticities across commodities with the relative diversion ratios isolates the role of time shares. The reason is that the relative cross-price elasticities do not depend on the relative time shares of the commodities. As a result, if some commodity k has a relatively high diversion ratio but low cross-price elasticity as compared to some other commodity g, it implies that the time share on k is large.

Corollary 2. *Consider an increase in the price of PSN commodity $j \in \mathcal{P}$. The ratio of cross-price elasticities for PSN commodity $k \in \mathcal{P}$ and non-PSN commodity $g \in \mathcal{Z} \setminus \mathcal{P}$ is given by:*

$$\frac{d\ln z_k/d\ln p_j}{d\ln z_g/d\ln p_j} = \frac{\frac{1}{1-\theta} - \frac{1}{1-\rho}\left(\left(1-\psi_{\mathcal{P}}^H\right) - \left(\tau_k - \sum_{i=0}^{N}\psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right) - \Sigma_{\mathcal{P}}}{\frac{1}{1-\rho}\left(\psi_{\mathcal{P}}^H + \left(\tau_g - \sum_{i=0}^{N}\psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right) - \Sigma_{\mathcal{P}}}$$

The ratio of diversion ratios (or, equivalently, of cross-price responses) for PSN commodity $k \in \mathcal{P}$ and non-PSN commodity $g \in \mathcal{Z} \setminus \mathcal{P}$ is given by:

$$\frac{D_{kj}}{D_{gj}} = \frac{\psi_k^H}{\psi_g^H} \times \frac{\frac{1}{1-\theta} - \frac{1}{1-\rho}\left(\left(1-\psi_{\mathcal{P}}^H\right) - \left(\tau_k - \sum_{i=0}^{N}\psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right) - \Sigma_{\mathcal{P}}}{\frac{1}{1-\rho}\left(\psi_{\mathcal{P}}^H + \left(\tau_g - \sum_{i=0}^{N}\psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right) - \Sigma_{\mathcal{P}}}$$

Proof. See Appendix A.4.2 □

In addition, the importance of time-intensity can be assessed by comparing cross-price elasticities between goods with the same functionality versus those with different functionalities. As we show in Appendix A.5, finding a large cross-price elasticity between two commodities that are functionally different (e.g. a PSN and a non-PSN commodity) would imply that they are relatively time-intensive.

3 Demand for PSNs: Experimental Evidence

Our study draws on evidence from two field experiments. The first field experiment sought to exogenously reduce users' time on Facebook or Instagram and measure how they reallocated that time to other activities. In this pricing experiment, we randomly offered financial incentives to Facebook users to decrease their time on Facebook and to Instagram users to decrease their time on Instagram. We tracked participants' phone activity using an app installed on their devices.

The second field experiment, initiated by Meta in 2013 and previously analyzed by Brynjolfsson et al. (2024), is an ongoing study that exogenously varies users' ad exposure on Facebook and Instagram to assess its impact on time spent on these platforms. A randomly assigned holdout group, which sees no ads, is compared to a control group identical in all respects except ad exposure. In the parlance of Harrison and List (2004), our first field experiment is classified as a framed field experiment; the second is a natural field experiment. We now discuss the design and findings of these experiments in sequence.

3.1 Design of the pricing experiment

Recruitment and timeline of the experiment. We conducted the pricing experiment from May 1 to July 1, 2023. Participants were recruited via ads on Facebook and Instagram, third-party publishers, and online panels maintained by firms for internet-based market research, a method used in similar studies (Allcott et al., 2022; Haaland et al., 2023). Recruitment materials, detailed in Appendix C.1, avoided mentioning Facebook, Instagram, or usage reduction.

Interested individuals were directed to a screening survey to confirm eligibility. Criteria included being 18 or older, residing in the U.S., primarily using Facebook or Instagram on an Android device (with sole access to that device), and having an average daily usage of at least 15 minutes on Facebook or 10 minutes on Instagram over the prior 28 days, based on Meta's internal data. These thresholds ensured sufficient baseline usage for observing time diversion, covering 97.8% of Facebook and 94.2% of Instagram engagement time.

Eligible participants were instructed to download a RealityMine app from the Google Play Store, developed for passive device monitoring, and received $5 upon installation. They were guided to enable activity tracking, which recorded time spent on all apps on their Android device. Participants who successfully installed the app, enabled tracking, and could be matched to Meta's data via email and Facebook or Instagram IDs were compensated an additional $10, provided their actual usage met the daily criteria.

Recruitment occurred on a rolling basis from May 1 to May 23. Participants meeting all requirements received $5 weekly during the pre-experiment period for providing at least one day of device monitoring data, incentivizing retention while recruitment continued. Randomization was conducted on June 1 to ensure at least one week of baseline data for all participants. The treatment period ran from June 4 to July 1, concluding the experiment (see Appendix Figure D.1 for the timeline).

Experimental design. We conducted two concurrent experiments: one for Facebook and one for Instagram. As detailed in Appendix D.2, participants were first assigned to either the Facebook or Instagram experiment. Within each experiment, we then randomly allocated participants to either the treatment or control group. On June 3, the day before the treatment period began, participants were notified via the RealityMine app whether they were assigned to the control group ("study group") or the treatment group ("bonus group"). Those in the treatment group were informed they would receive payments for reducing their average daily use of either Facebook or Instagram below their baseline levels.

To establish each participant's baseline, we identified the week with the highest average daily use from the four weeks before the treatment period. For instance, a participant with average daily use of 25 minutes in weeks 1, 2, and 3, and 35 minutes in week 4 would have a baseline of 35 minutes per day. This baseline was rounded up to the nearest quarter hour. For example, a participant with a high-week average of 35 minutes would have a compensation baseline of 45 minutes, and payments would be based on reducing usage below this 45-minute daily average.[8]

Participants in the treatment groups of both the Facebook and Instagram experiments received $4 per hour (prorated for partial hours) for reducing engagement below their compensation baseline. The $4-per-hour incentive was designed to be easily divisible, and participants were informed they would earn $1 for each quarter-hour reduction in average daily engagement per week (equivalent to $7 for each 15-minute reduction in average daily use of Facebook or Instagram over a week), with a maximum of $125 per week in incentive payments. Compensation for treatment group participants was calculated weekly and reset each week during the study period. At the end of the four-week study, total incentive and participation payments were tallied for each participant and disbursed via the RealityMine app.

Participants in the control groups received compensation for continued data provision via their device monitor but faced no financial incentives to reduce engagement. Their weekly compensation was set at one of three levels based on baseline engagement: $15 for low-engagement users, $20 for medium-engagement users, and $25 for high-engagement users.[9] This weekly compensation aimed to reduce attrition by offering financial incentives comparable to those in the treatment groups.

During the treatment period, participants accessed a daily-updated "dashboard" via the

[8]The use of a compensation baseline set above the average daily use over the last 28 days does not affect participants' marginal incentives to reduce engagement because the incentive to reduce time spent is a constant price per hour regardless of whether compensation is calculated relative to high-week average daily use or an average based on the last 28 days. This method also minimizes the risk participants have had counterfactual engagement above the compensation threshold such that they would have had to reduce engagement to the threshold level before receiving compensation.

[9]For Facebook participants, engagement levels were less than 40 minutes, 40–89 minutes, and 90 or more minutes. For Instagram participants, the engagement levels were less than 30 minutes, 30–59 minutes, and 60 or more minutes.

RealityMine app, available through a link on the app's home screen (see Appendix C.3). For treatment group participants in the Facebook (Instagram) experiment, the dashboard displayed: the experiment's timeline, including the current week (of four total) and the day for which data were current; the participant's compensation baseline; their week-to-date average daily use of Facebook (Instagram) based on Meta's internal data; the projected incentive compensation for the week if the week-to-date engagement level persisted; the maximum possible incentive compensation (capped at $125 per week or based on zero engagement); and the total compensation accrued to date. For control group participants, the dashboard showed: the experiment's timeline, including the current week and day; their week-to-date average daily use of Facebook (Instagram); the fixed weekly compensation; and the total compensation accrued to date.

As noted, we collected data on daily minutes spent on phone applications using the RealityMine Android app. RealityMine records foreground usage, excluding inactive periods exceeding 30 seconds, except for video-watching time. Data collection paused if the device monitor was deactivated or during connectivity disruptions. To enhance data reliability, we sent reminders to participants if their device monitor failed to transmit data for 24 hours.

The RealityMine data recorded participants using over 35,000 distinct apps during the experiment. For manageability, we grouped these into fifteen categories, including the focal apps (Facebook for the Facebook experiment and Instagram for the Instagram experiment), other major apps like Snapchat, TikTok, and YouTube, and app categories defined by RealityMine based on Google Play Store classifications. Additional details on the aggregation categories are provided in Appendix D.1.[10]

The Facebook experiment included 3,500 participants, and the Instagram experiment included 2,768 participants. As previously noted, we set minimum baseline usage thresholds of 15 minutes for Facebook in the Facebook experiment and 10 minutes for Instagram in the Instagram experiment. Based on their baseline usage, participants could be eligible for the Facebook experiment only, the Instagram experiment only, or both. Of the 3,500 Facebook experiment participants, 83% were eligible for Facebook only, and 17% were eligible for both experiments, aligned with Meta's population data. Of the 2,768 Instagram experiment participants, 41% were eligible for Instagram only, and 59% were eligible for both experiments, compared to a target of 56% Instagram-only and 44% for both, also to reflect Meta's population data. The lower-than-targeted proportion of Instagram-only participants resulted from recruitment challenges (see Appendix D.2 for a detailed discussion of how we arrived at these sample sizes).

Randomization and Baseline Characteristics. Participants were assigned to either the Facebook or Instagram experiment. Within each experiment, we randomly allocated half to the treatment group and half to the control group, stratifying randomization by baseline usage

[10]The analysis excludes apps that primarily capture time from background activities rather than active user engagement. These include screensaver apps displaying images or text, launcher apps organizing apps or widgets on the home screen, and utilities such as background services, file management tools, and operating system settings.

of Facebook, Instagram, and Snapchat. We followed the re-randomization approach described in List (2025) to ensure balance across demographics, baseline usage of other apps and app categories, baseline Facebook friend count, and baseline Instagram follower and following counts (see Appendix D.3 for more detail).

Tables 1 and 2 present the app categories considered in the Facebook and Instagram experiments, respectively, along with their baseline usage by treatment group. As shown, approximately 80% of the daily "Total Phone Minutes" for participants in our sample is spent on the categories included in either experiment.[11] Additional baseline characteristics are balanced, as reported in Appendix Table D.2. Column (4) of the balance tables confirms no statistically significant differences between treatment and control groups at baseline.

Table 1 presents the average daily usage of Facebook and Instagram in the Facebook experiment, based on RealityMine data, alongside comparable data from Meta. RealityMine estimates are lower than Meta's due to off-phone usage and differences in handling periods of inactivity. Table 2 provides similar data for the Instagram experiment, showing consistent patterns with the Facebook experiment. To prevent substitution to other platforms, we used Meta's usage metrics for feedback and payments.

In the Facebook experiment, participants averaged 70.2 minutes daily on Facebook and 8.1 minutes on Instagram. In the Instagram experiment, participants averaged 42 minutes daily on Facebook and 43 minutes on Instagram. These differences stem primarily from recruitment criteria, which required minimum pre-period usage of Facebook for the Facebook experiment and Instagram for the Instagram experiment. Participants in both experiments also spent considerable time on Games, YouTube, TikTok, and Snapchat, despite no selection based on usage of these apps.

Appendix Table D.3 compares the demographics and app usage of the Meta-based population with the experimental samples. Males are under-represented in both the Facebook and Instagram experimental samples. In the Facebook sample, younger users are over-represented, while in the Instagram sample, they are under-represented. The middle age group is over-represented in both samples, and older users are under-represented compared to their respective target populations. "Single-homers" (users exclusively using Facebook or Instagram) are under-represented in both samples relative to "multi-homers." Additionally, the Facebook sample under-represents high-usage Instagram users, and both samples include fewer high-usage users of their respective focal apps (Facebook for the Facebook sample, Instagram for the Instagram sample) compared to the target populations.

To address non-representativeness, we reweighted the experimental samples to align with the target population's characteristics, as detailed in Appendix D.4. We constructed sample weights for the analysis in Section 3.3 to account for differences between the recruited samples and target populations. Specifically, we developed app usage weights to match the combined

[11] Browser apps are those used to access websites, such as Chrome or Safari. Communication apps are those used for texting, such as SMS and Gmail. Entertainment apps pertain to leisure or having fun, such as Netflix and Spotify. Game apps are video games. Lifestyle apps are those that define an individual's lifestyle, for example, Twitter, Reddit, or Pinterest. Productivity apps are meant to improve an individual's efficiency such as CashApp or DoorDash. Shopping apps are those that allow customers to browse or buy products from a retailer, for example, Amazon, eBay, or Instacart.

Table 1: Balance Usage in the Facebook Experiment

		Treatment Arm		
	All (1)	Control (2)	Treatment (3)	p-value test (4)
Facebook Minutes	70.164	70.055	70.273	0.914
	(1.001)	(1.395)	(1.437)	
Facebook Minutes (Meta)	75.078	74.945	75.210	0.896
	(1.015)	(1.405)	(1.465)	
Instagram Minutes	8.113	8.280	7.946	0.631
	(0.348)	(0.497)	(0.487)	
Instagram Minutes (Meta)	8.528	8.617	8.439	0.810
	(0.370)	(0.507)	(0.540)	
Snapchat Minutes	3.536	3.508	3.565	0.887
	(0.201)	(0.304)	(0.263)	
YouTube Minutes	21.069	21.103	21.036	0.967
	(0.801)	(1.108)	(1.158)	
TikTok Minutes	15.139	15.259	15.018	0.856
	(0.662)	(0.894)	(0.978)	
Browser Minutes	62.041	61.882	62.200	0.866
	(0.940)	(1.354)	(1.304)	
Games Minutes	74.645	74.687	74.603	0.979
	(1.633)	(2.311)	(2.308)	
Communication Minutes	46.422	46.502	46.342	0.905
	(0.668)	(0.932)	(0.957)	
Entertainment Minutes	30.427	29.834	31.019	0.481
	(0.840)	(1.156)	(1.220)	
Lifestyle Minutes	16.622	16.792	16.451	0.712
	(0.461)	(0.658)	(0.646)	
Messenger Minutes	21.561	21.455	21.666	0.846
	(0.543)	(0.774)	(0.760)	
Productivity Minutes	18.968	18.975	18.962	0.987
	(0.403)	(0.567)	(0.573)	
Shopping Minutes	16.781	16.317	17.245	0.254
	(0.407)	(0.546)	(0.603)	
Other App Minutes	18.803	19.366	18.240	0.258
	(0.498)	(0.721)	(0.688)	
Total Phone Minutes	424.291	424.016	424.567	0.927
	(3.009)	(4.271)	(4.241)	
Observations	3,500	1,750	1,750	

Notes: Table presents means and then standard errors in parentheses for the Facebook experiment sample. Column (1) uses the full sample. Column (2) uses those who did not receive incentives to reduce Facebook Usage. Column (3) uses those who do receive incentives to reduce Facebook usage. Column (4) reports the p-value of a test of equal means across the two treatment groups. Data collected from RealityMine unless otherwise stated.

Table 2: Balance Usage in the Instagram Experiment

		Treatment Arm		
	All	Control	Treatment	p-value test
	(1)	(2)	(3)	(4)
Facebook Minutes	42.453	41.873	43.034	0.578
	(1.043)	(1.453)	(1.497)	
Facebook Minutes (Meta)	44.682	44.703	44.662	0.984
	(1.048)	(1.499)	(1.465)	
Instagram Minutes	42.862	43.370	42.353	0.543
	(0.835)	(1.236)	(1.124)	
Instagram Minutes (Meta)	47.046	47.520	46.572	0.603
	(0.912)	(1.376)	(1.197)	
Snapchat Minutes	4.967	5.004	4.931	0.917
	(0.350)	(0.513)	(0.476)	
YouTube Minutes	32.071	31.616	32.526	0.704
	(1.195)	(1.627)	(1.751)	
TikTok Minutes	20.672	20.528	20.816	0.879
	(0.944)	(1.376)	(1.292)	
Browser Minutes	59.306	59.576	59.035	0.789
	(1.012)	(1.406)	(1.456)	
Games Minutes	56.437	57.200	55.674	0.626
	(1.565)	(2.190)	(2.235)	
Communication Minutes	45.367	45.621	45.113	0.743
	(0.774)	(1.038)	(1.148)	
Entertainment Minutes	31.926	32.753	31.099	0.382
	(0.946)	(1.361)	(1.315)	
Lifestyle Minutes	21.842	21.275	22.408	0.393
	(0.663)	(0.914)	(0.960)	
Messenger Minutes	11.276	11.636	10.915	0.423
	(0.450)	(0.606)	(0.666)	
Productivity Minutes	17.392	17.529	17.256	0.760
	(0.447)	(0.546)	(0.709)	
Shopping Minutes	15.273	15.336	15.211	0.895
	(0.477)	(0.696)	(0.653)	
Other App Minutes	22.548	22.084	23.011	0.518
	(0.717)	(0.946)	(1.078)	
Total Phone Minutes	424.393	425.402	423.383	0.768
	(3.420)	(4.852)	(4.822)	
Observations	2,768	1,384	1,384	

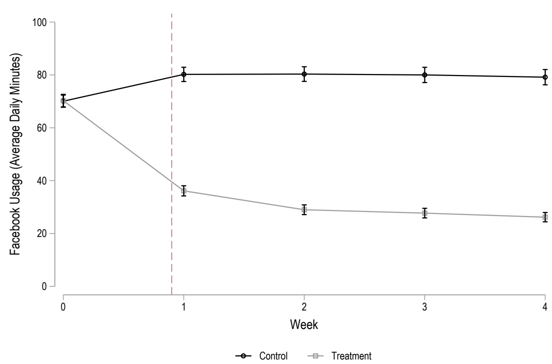
Notes: Table presents means and then standard errors in parentheses for the Instagram experiment sample. Column (1) uses the full sample. Column (2) uses those who did not receive incentives to reduce Instagram Usage. Column (3) uses those who do receive incentives to reduce Instagram usage. Column (4) reports the p-value of a test of equal means across the two treatment groups. Data collected from RealityMine unless otherwise stated.

Facebook and Instagram usage in each experiment's target population. As shown in Appendix Table D.3, the reweighted samples more closely align with the target population's baseline usage and demographic characteristics.[12]

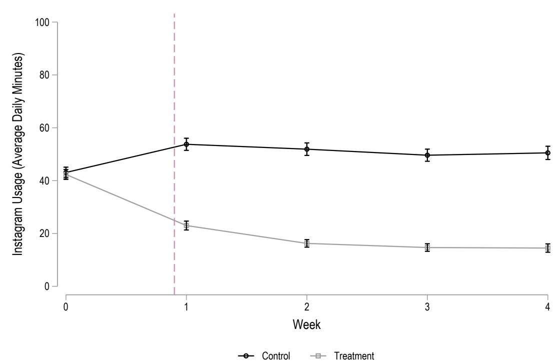
3.2 Treatment effects on time (re)allocation.

We first analyze the impact of incentives on focal app usage. Figure 1 presents a weekly time series of average daily usage for the control and treatment groups. Panel (a) shows results for the Facebook experiment, and Panel (b) shows results for the Instagram experiment. Without incentives, control group usage may increase due to time effects, corrected beliefs about usage, or heightened awareness from dashboard information. In the Facebook experiment, control group usage rises by approximately 10 minutes (14%) to 80 minutes daily after the experiment begins. In the Instagram experiment, control group usage increases by 8 minutes (19%) to 51 minutes. Conversely, treatment groups, facing a pecuniary cost for using the focal app, reduced usage. In the Facebook experiment, treatment group usage drops by about 30 minutes (58%), resulting in a 50.2-minute weekly difference between treatment and control groups. In the Instagram experiment, treatment group usage falls by 25 minutes (60%) to 17.1 minutes, yielding a 34.3-minute difference between groups. These differences are both substantial and statistically significant.[13]

Figure 1: Changes in Focal App Usage Across Weeks



(a) Facebook



(b) Instagram

Notes: Figure presents average daily usage for the focal app by week of the experiment and 95% confidence intervals. Panel (a) displays Facebook usage for 3,500 users 16,719 user-week observations. Panel (b) displays the Instagram usage for 2,768 users and 13,272 user-week observations

We next examine the effects on app categories. As noted earlier, the PSN category follows the definition proposed by the FTC and the Competition and Markets Authority (CMA, 2020; FTC, 2021). For studying diversion, the PSN category in Panel(b) includes diversion to the non-focal app (e.g., Instagram in the Facebook experiment) and Snapchat. The Non-PSN category encompasses all other phone apps not covered by the FTC and CMA definitions. Off-phone time is a residual category capturing offline time and usage on other devices.

[12] Reweighted versions of the baseline tables appear in Appendix Table D.4 - D.6.

[13] Appendix Figure B.1 displays the treatment effects on the distribution of focal app usage.

Figure 2 illustrates modest increases in the usage of other PSNs compared to the control group. By the final week, other PSN usage rises by approximately 4 minutes in the Facebook experiment and 9 minutes in the Instagram experiment. In contrast, non-PSN app usage increases by about 31 minutes in the Facebook experiment and 14 minutes in the Instagram experiment. Additionally, non-phone time grows by roughly 17 minutes in the Facebook experiment and 13 minutes in the Instagram experiment.

3.3 Estimates of diversion ratios and cross-price elasticities

We utilize the pricing field experiment to estimate diversion ratios, as defined in equation (9) of Section 2, and cross-price elasticities, which describe substitution patterns across commodities. The diversion ratio from commodity j to i represents the proportion of reduced time on j, due to an increase in p_j, that is reallocated to i. Suppressing individual and time subscripts, we denote treatment status by $T_p \in \{0,1\}$ and the average daily minutes per week on i by z_i. To estimate the diversion ratios, where j is either Facebook or Instagram and $i \neq j$, we employ the following Wald estimand:

$$\frac{\mathbb{E}\left[z_i \mid T_p = 1\right] - \mathbb{E}\left[z_i \mid T_p = 0\right]}{\mathbb{E}\left[z_j \mid T_p = 1\right] - \mathbb{E}\left[z_j \mid T_p = 0\right]} \tag{10}$$

where the denominator represents the first-stage effect, capturing the own-price impact of treatment on average daily user time. The numerator reflects the reduced-form effect, indicating the cross-price impact. To calculate the cross-price elasticity, we divide the reduced-form effect by baseline usage.

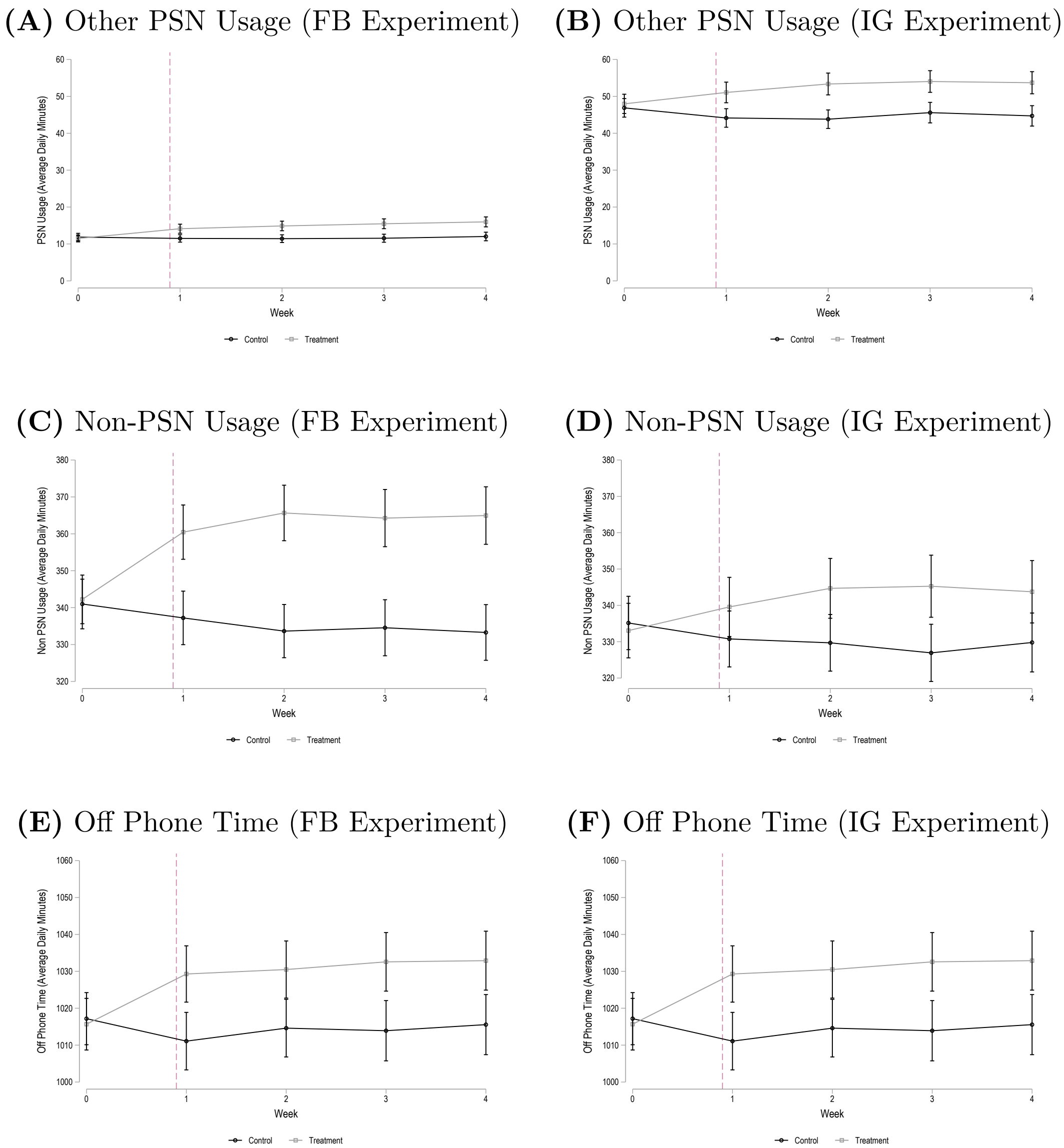
We employ 2SLS to estimate Equation (10), incorporating week fixed effects and a vector of pre-treatment characteristics, including demographics and baseline app usage, to enhance precision.[14] Standard errors are clustered at the individual level. Our primary analysis focuses on weeks 2-4, after treatment group usage stabilizes. We compute separate diversion ratios and cross-price elasticities for each app category. As these categories are mutually exclusive and exhaustive, a one-minute reduction in time spent on the origin commodity is offset by a one-minute increase across other categories, ensuring the diversion ratios sum to 1.

Own- and cross-price effects. Table 3 presents estimates of own-price effects, cross-price effects, cross-price elasticities, and diversion ratios.[15] The own-price effects demonstrate that the pricing experiment significantly reduced time spent on Facebook and Instagram. The cross-price effects indicate that this price-induced reduction led to substantial increases in time spent on non-PSN commodities, including other apps and offline activities. Point estimates suggest that nearly all individual app categories are substitutes for Facebook and Instagram.

[14] Controls include gender, age group, region (northeast, midwest, south, west), recruitment source, Facebook average friend count, Instagram average followers and followings counts, and baseline engagement on each of the individual apps and app categories reported in Tables 1 and 2.

[15] Appendix D.5 shows that our results are robust to attrition.

Figure 2: Changes in Substitute App Usage Across Weeks



Notes: Figure presents the average daily usage for the different commodity characteristics by week of the experiment along with 95% confidence intervals. Panel (A) presents average usage of combined Instagram and Snapchat in the Facebook Experiment. Panel (B) presents average usage of combined Facebook and Snapchat in the Instagram experiment. Panel (C) presents average usage of all apps other than Facebook, Instagram, and Snapchat in the Facebook Experiment. Panel (C) presents average usage of all apps other than Facebook, Instagram, and Snapchat in the Instagram Experiment. Panels (E) and (F) present average amount of time spent off the phone for the Facebook and Instagram experiments, respectively. Facebook experiment panels present time allocation data for 16,719 user-week observations for 3,500 unique users. Instagram experiment panels present time allocation data for for 13,272 user-week observations for 2,768 unique users.

Diversion ratios. The diversion ratio estimates reveal the proportion of reduced time on the origin commodity j reallocated to destination commodity i. A diversion ratio of one (zero) indicates that all (none) of the reduced time on Facebook or Instagram shifts to that commodity. Panel (a) of Table 3 shows that 55 percent of the reduced time is diverted to non-PSN commodities, with substantial shares redirected to offline activities (39 percent for Facebook and 29 percent for Instagram). Diversion to other PSNs is limited, at 6 percent for Facebook and 16 percent for Instagram.

These findings suggest that commodities requiring time can be close substitutes, even if their functionalities differ. Panel (b) of Table 3 supports this view. For instance, while Facebook and gaming apps serve distinct purposes, gaming exhibits the highest diversion ratio for Facebook. Similarly, YouTube has the highest diversion ratio for Instagram, despite not being included in the FTC's market definition for these platforms due to differing functionality. As shown in Proposition 2 of Section 2, the time-intensive nature of these commodities can make them close substitutes to PSNs, even if consumers do not perceive them as directly comparable or use them for the same purpose.

Relative importance of time shares, time-intensity, and functionality. As outlined in Corollary 2, we can assess the role of time shares in diversion ratios by comparing diversion ratio estimates (which depend on time shares) to cross-price elasticities (which do not). Table 3 indicates that high time shares significantly drive the substantial diversion from Facebook and Instagram to offline activities and certain online activities, such as gaming and browsing. Conversely, the limited diversion to Snapchat results from its low time share, not a small cross-price elasticity.

Table 3 further reveals that some commodities with high diversion ratios, such as YouTube and notably TikTok, also exhibit large cross-price elasticities, despite their distinct features and functionality. This suggests that high time intensity is a primary factor explaining the significant diversion from Facebook and Instagram to these non-PSN commodities.

Specification checks. We assess the robustness of our diversion ratio estimates to alternative specifications. Appendix Table D.10 presents specification checks for the Facebook experiment, and Appendix Table D.11 does the same for the Instagram experiment. Column (1) in each table restates the results from our main specification. Columns (2)–(6) report results for alternative specifications. Specifically, Column (2) adjusts the significance level for multiple hypothesis testing, following List et al. (2019), with most estimates remaining significant at conventional levels. Columns(3) and (4) demonstrate robustness to different control variable specifications. Column (5) shows that including the first post-treatment week does not substantially alter the diversion ratio estimates. Column (6) indicates that missing usage data for a small number of observations has minimal impact on our estimates. Further details on each specification check are provided in Appendix D.6.

Table 3: Main Results

	Facebook Experiment			Instagram Experiment		
	(1) Own/Cross Price Effects	(2) Diversion Ratios	(3) Cross-Price Elasticity	(4) Own/Cross Price Effects	(5) Diversion Ratios	(6) Cross-Price Elasticity
Panel (a): Aggregated						
PSN Time	3.204***	-0.057***	0.350***	5.512***	-0.156***	0.156***
	(0.644)	(0.012)	(0.070)	(1.314)	(0.037)	(0.037)
Non-PSN Time	30.795***	-0.550***	0.094***	19.521***	-0.552***	0.057***
	(5.261)	(0.093)	(0.016)	(5.100)	(0.145)	(0.015)
Offline Time	22.014***	-0.393***	0.021***	10.344*	-0.292*	0.010*
	(5.448)	(0.094)	(0.005)	(5.457)	(0.150)	(0.005)
Panel (b): Individual Apps						
Facebook	-56.013***			4.726***	-0.134***	0.158***
	(2.414)			(1.129)	(0.032)	(0.038)
Instagram	2.814***	-0.050***	0.397***	-35.377***		
	(0.603)	(0.011)	(0.085)	(2.101)		
Snapchat	0.390*	-0.007*	0.189*	0.785	-0.022	0.144
	(0.207)	(0.004)	(0.100)	(0.662)	(0.019)	(0.121)
Messenger	0.537	-0.010	0.027	-0.766**	0.022**	-0.100**
	(1.112)	(0.020)	(0.056)	(0.385)	(0.011)	(0.050)
TikTok	2.619**	-0.047**	0.271**	3.711***	-0.105***	0.182***
	(1.079)	(0.019)	(0.112)	(1.405)	(0.040)	(0.069)
YouTube	4.724***	-0.084***	0.207***	6.674***	-0.189***	0.163***
	(1.783)	(0.032)	(0.078)	(2.118)	(0.061)	(0.052)
Browser	5.332***	-0.095***	0.085***	6.469***	-0.183***	0.104***
	(1.899)	(0.034)	(0.030)	(1.766)	(0.051)	(0.028)
Communication	3.195**	-0.057**	0.074**	-0.250	0.007	-0.006
	(1.325)	(0.024)	(0.031)	(1.374)	(0.039)	(0.032)
Entertainment	1.890	-0.034	0.069	0.201	-0.006	0.006
	(1.596)	(0.028)	(0.058)	(1.739)	(0.049)	(0.055)
Games	8.108**	-0.145**	0.110**	1.022	-0.029	0.020
	(3.429)	(0.061)	(0.046)	(2.849)	(0.080)	(0.055)
Lifestyle	0.586	-0.010	0.036	1.306	-0.037	0.051
	(1.418)	(0.025)	(0.086)	(1.562)	(0.044)	(0.061)
Productivity	1.966**	-0.035**	0.109**	-1.276	0.036	-0.074
	(0.889)	(0.016)	(0.049)	(0.857)	(0.024)	(0.049)
Shopping	0.210	-0.004	0.014	0.443	-0.013	0.032
	(0.866)	(0.015)	(0.057)	(0.602)	(0.017)	(0.043)
Other	1.627	-0.029	0.087	1.989	-0.056	0.077
	(1.043)	(0.018)	(0.056)	(1.477)	(0.042)	(0.057)
F Stat. on instrument		39.22			33.97	
Subjects	3,361	3,361	3,361	2,677	2,677	2,677
Observations	9,844	9,844	9,844	7,832	7,832	7,832

Notes: Significant at *10%, **5%, ***1%. Standard errors in parentheses are clustered at the individual level. This table reports OLS and 2SLS estimates of regressions discussed in Section 3.3. Columns (1), (2), and (3) report the results from the Facebook Experiment, and Columns (4), (5), and (6) report the results from the Instagram experiment. Panel (b) reports the estimates from separate regressions for each commodity where the dependent variable is weekly usage in the commodity. Panel (a) reports analogous results but for aggregated commodity categories. The PSN category contains the non-focal Meta app and Snapchat. The Non-PSN category contains all other apps and excludes off-phone time.

Unweighted versus weighted results. Column (7) of Appendix Tables D.10 and D.11 highlight the value of Meta's representative internal data on user characteristics. As described in Section 3.1, these data enable us to reweight the experimental sample to match the observable characteristics of the target population of all users. The unweighted samples underrepresent men, older Facebook users, younger Instagram users, and single-platform users (those using only Facebook or only Instagram). Using Meta's data, we reweight the sample by age, gender, and baseline Facebook and Instagram usage, leveraging the observed distributions in both the experimental sample and the representative internal data.

Column (7) of Table D.10 shows that unweighted results are generally similar to weighted results, with a notable exception: without reweighting, the substitution between Instagram and Facebook is overstated. The diversion ratio from Instagram to Facebook is 0.21 in the unweighted data, compared to 0.13 after reweighting. This discrepancy arises because the unweighted sample overrepresents dual users, who more readily substitute between the two platforms.

External validity. A potential external validity concern is that iOS technical limitations prevented us from measuring non-Meta app usage on iPhones, whereas our ideal study population would include both Android and iOS users of Facebook and Instagram. This raises the possibility that our Android-only sample may respond differently to exogenous price changes compared to iOS users. While we cannot estimate cross-price effects for iOS users, we assessed own-price effects for both Android and iOS users in a pilot experiment.

Detailed in Appendix E, the pilot experiment examined the impact of exogenous price changes on Facebook and Instagram usage among 756 Android users and 641 iPhone users over four weeks. As shown in Table E.2, the own-price effects for Android and iPhone users were similar and statistically indistinguishable. These comparable treatment effects in the pilot suggest no significant differences in diversion patterns between iOS and Android users.

Intertemporal substitution. As treated users know the experiment is temporary, they might reallocate time not only across apps within a week but also across weeks for a given app. Such intertemporal substitution could influence diversion ratio estimates if substitution opportunities vary across apps. To explore this, Appendix Figure B.2 plots the average daily usage of Facebook and Instagram for treatment and control groups before, during, and after the experiment. No evidence suggests that the treatment group increases usage post-experiment compared to the control group, indicating that treated users do not defer focal app usage to the period after incentives end.

3.4 Holdout Experiment: Design and Results

We now turn to the second field experiment, initiated by Meta in 2013 and previously studied by Brynjolfsson et al. (2024). This natural field experiment exogenously varies users' ad load on Facebook or Instagram and measures the resulting impact on their time spent on these platforms.

Description of the holdout experiment. Both Facebook and Instagram include a holdout group. Users are randomly assigned to this group upon creating a new account, and Meta tracks their engagement compared to a control group exposed to standard "production" ad levels. Launched in April 2013 and still ongoing, this holdout experiment enables Meta to assess the impact of ads on user engagement. Randomization ensures that holdout users are identical to the control group, differing only in ad exposure. As of January 2023, approximately 0.5% of Facebook users were in the holdout group. The control group is about 7 times larger than the holdout group. As of January 2023, there were 2,194,433 individuals in the Facebook holdout group. The control group includes 15,348,759 users. On Instagram, the sample includes a holdout group of 3,786,138 users and a control group of 7,562,901 users.

We obtain Meta data on ad exposure and engagement for both the control and holdout groups in the Facebook and Instagram experiments. Ad load is defined as the percentage of ad impressions relative to total impressions.[16] Ad load values are normalized to reflect relative magnitudes compared to Facebook's ad load in June 2022. We observe average daily minutes spent by users in the treatment and control groups during January 2023. Our primary focus is the own-commodity response to ad load, as defined in (8), which captures users' demand for a commodity with respect to its price, the ad load. We suppress individual and time subscripts and let $T_\alpha \in \{0, 1\}$ indicate treatment status, and α_i denote the ad load on commodity i. Letting j be either Facebook or Instagram, we use the following Wald estimand to measure the own-commodity response on j:

$$\frac{\mathbb{E}\left[z_j \mid T_\alpha = 1\right] - \mathbb{E}\left[z_j \mid T_\alpha = 0\right]}{\mathbb{E}\left[\alpha_j \mid T_\alpha = 1\right] - \mathbb{E}\left[\alpha_j \mid T_\alpha = 0\right]} \tag{11}$$

where the denominator represents the first-stage effect, capturing the impact of treatment on ad exposure, while the numerator reflects the reduced-form effect, indicating the impact on average daily user time. Due to the large sample sizes, standard errors are effectively zero and thus omitted from Table 4.

Estimates of own-commodity responses. Table 4 presents estimates of equation (11) for Facebook and Instagram, along with the corresponding first-stage and reduced-form results. The ad load change in Column (1) is normalized relative to Facebook's ad load in June 2022. By design, the control group experiences greater ad exposure than the treatment group.

Reduced-form estimates in Column (2) show that users reduce time spent on the platform in response to increased ad load. Despite the control group facing a 100 percent higher ad load than the treatment group, the percentage decrease in usage is relatively small for both Facebook and Instagram. Our Facebook estimates align closely with those of Brynjolfsson et al. (2024), who analyzed the same experiment over an earlier period.

Column (3) reports the own-commodity responses from equation (11). On average, users exposed to typical production-level ad impressions reduce daily Facebook usage by 2.0 minutes and Instagram usage by 0.62 minutes. These estimates yield an elasticity of user time to ad load of approximately 0.04 for Instagram and 0.09 for Facebook.

[16] Impressions are measured as ViewPort View ("VPV") impressions, counted when content is visible for at least 250 milliseconds, either fully visible or covering at least 50% of the screen height.

Table 4: Ad Holdout Experiments

	First-Stage		**Reduced-Form**		**Wald Estimate**	
Outcome variable:	Ad load		User Time			
	(1)		(2)		(3)	
		%	Min.	%	*Own-Resp.*	*Implied Elast.*
Panel (a): Facebook						
Estimates	-1.0	-100	2.0	9.0	-2.0	0.09
Panel (b): Instagram						
Estimates	-0.74	-100	0.46	4.1	-0.62	0.04

Notes: Columns (1)-(2) report treatment effects calculated by taking the difference in means between treatment and control group. The treatment group is composed of a randomly selected set of users who are not exposed to ads on Facebook. The own-commodity response in Column (3) is a Wald estimate obtained by taking the ratio of the treatment effect on user time to the treatment effect on ad load. The implied elasticity in the last column multiplies the Wald estimate by the ratio of average user time to average ad load in the control group. Ad load in (1) is defined as ad impressions as a percent of total impressions in June 2022. The reported values for ad load are normalized to reflect relative magnitudes compared to Facebook's ad load in June 2022. For Facebook, the measure of user time in (2) is based on U.S. data as of January 2023 and restricted to users with an identified gender and age group and a primary OS of Android or iOS. Time use excludes FB messenger and includes inactive users. For Instagram, the measure of user time in (3) and (2) includes U.S. and other countries as of June 2022. It also includes inactive users.

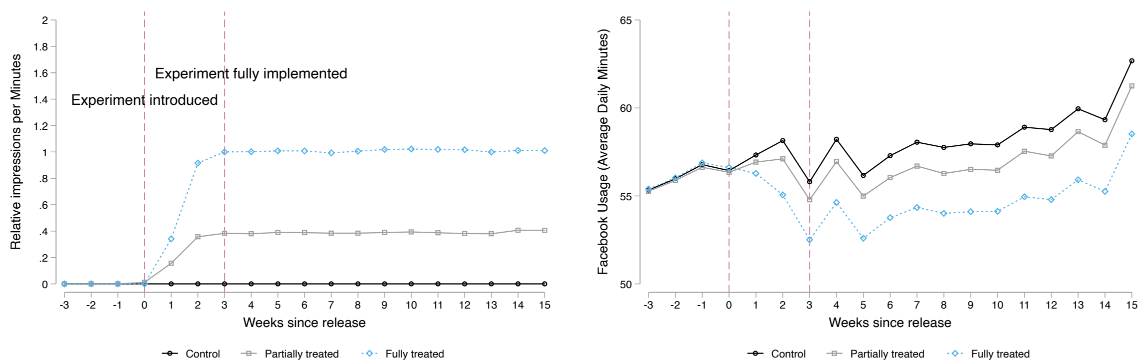
Choice of estimation sample. The holdout field experiment includes both Android and iOS users, whereas the pricing field experiment is limited to Android users, raising potential concerns about the comparability of the estimation samples. For the Facebook holdout experiment, we observe users' primary operating system, enabling us to replicate the analysis in Table 4 separately for Android and iOS users. Results, presented in Appendix Table B.1, show that the elasticity of user time to ad load on Facebook is approximately 0.09 for both Android and iOS users.

Non-linearity of demand. Table 4 provides estimates of the average elasticity of demand with respect to ad load. Unless demand is log-linear in ad load, this elasticity varies with ad load levels. In Sections 4 and 6, we adopt a linear demand system, which allows elasticity to vary with ad load but assumes a constant slope, imposing a restrictive form. To test for demand linearity in ad load, we analyze a third experiment. In June 2023, Facebook reduced its ad holdout group size. Approximately half of the users removed from the holdout group were exposed to the same ad load as non-holdout users (fully treated), while the remaining users formed a "partially treated" group, seeing 39% of the fully treated group's ad load. We compare ad exposure and time use of both treated groups to users remaining in the holdout group, now labeled the "control group" in this holdout deprecation experiment.

Panel (a) of Figure 3 illustrates the increase in ad impressions per minute for the two treated groups, normalized relative to ad impressions in week 3 for the fully treated group. After full implementation, the partially treated group is exposed to 39% of the ad load of the fully treated group. Panel (b) shows the average daily time spent on Facebook (among active users) for the treated and control groups. Randomization ensures nearly identical time use before the experiment. Post-experiment, both treated groups reduce their Facebook usage compared to the control group, with the fully treated group showing a larger decrease than the partially treated group. Due to the gradual rollout, the full response emerges over a few weeks.

Table 5 uses data from Figure 3 to estimate the own-commodity response to ad load for the fully treated and partially treated groups separately, relative to the control group. We apply the Wald estimand defined in equation (11) to each treated group, yielding estimates of the average own-commodity response across different segments of the demand curve. The results show an own-commodity response of approximately 3.5 for both groups, supporting a linear demand model. A demand slope of 3.5 implies varying elasticities: 0.023 at the ad load level of the partially treated group and 0.063 at the level of the fully treated group.

Figure 3: Responses to Release from Ad Holdout Group.



(a) Average ad impressions per minute.

(b) Average daily time use among active users.

Notes: Average time spent and relative ad impressions per minutes on Facebook across three randomly selected groups of users. Reported ad impressions are normalized to reflect relative magnitudes compared to ad impressions in week 3 for the fully treated group. The control group is the holdout group: a random sample of users who see no ads on Facebook. The fully treated group is a random sample of users, originally placed in the holdout group, who started facing standard production levels of ad load. The partially treated group is a random sample of users, originally placed in the holdout group, that started seeing a bit less than 40 percent as many ads as the fully treated group. The official release was on June 15 2023, but we see a (very) slight increase in ad load already on June 8 for the partially treated group, and on June 13 for the fully treated group. Therefore, week 0 corresponds to the week of June 5 - 11. Average daily time use is measured as total time spent in the group divided by the number of active users that day. A user is active if they log into Facebook that day.

4 Implications for consumer benefits and costs of PSNs

We now consider implications of the empirical results in Section 3 for the costs and benefits of PSNs to users. In both the pricing and holdout experiments, a small share of users is treated. Therefore, we would expect both the behavior of users outside of the experiment and

Table 5: Release from Ad Holdout Experiment (Facebook)

	First-Stage		**Reduced-Form**		**Wald Estimate**	
Outcome variable:	Ad Impressions per Minute		User Time			
	(1)		(2)		(3)	
		%	Min.	%	*Own-Resp.*	*Implied Elast.*
Panel (a): Partially treated group (relative to control)						
Estimates	0.39	100	-1.34	-2.3	-3.49	0.02
Panel (b): Fully treated group (relative to control)						
Estimates	1.0	100	-3.79	-6.9	-3.79	0.07

Notes: Columns (1)-(2) report treatment effects calculated by taking the difference in means between treatment and control groups. Reported ad impressions per minutes are normalized to reflect relative magnitudes compared to ad impressions in the post-experiment period for the fully treated group. The control group is a randomly selected set of users who remain in the holdout group. The fully treated group is a random sample of users, originally placed in the holdout group, who started facing standard production levels of ad load. The partially treated group is a random sample of users, originally placed in the holdout group, that started seeing a bit less than 40 percent as many ads as the fully treated group. The own-commodity response in Column (3) is a Wald estimate obtained by taking the ratio of the treatment effect on user time to the treatment effect on ads per minute. The implied elasticity in the last Column multiplies the Wald estimate by the ratio of average user time to average ad impressions in the treated group. The official release was on June 15 2023, but we see a (very) slight increase in ad load already on June 8 for the partial release group, and on June 13 for the full release group. Therefore, week 0 corresponds to the week of June 5 - 11. The pre-release period includes three weeks of data (between May 15 and June 4). The post-release period includes 13 weeks covering June 25 to September 17. Average daily minutes are per active user. An active user is a user that logged into Facebook that day.

the (pricing) behavior of competing platforms to remain approximately unaffected. Thus, the two experiments are informative about the demand and individual willingness-to-pay (WTP) for Facebook and Instagram holding the behavior of other users and price of other platforms fixed.[17]

Market demand. Suppose that individual demand for commodities $z_i(p, \alpha)$ aggregate into a linear demand system. Formally, let $Z_i(p, \alpha)$ denote total time spent by all users on commodity i as a function of vectors of prices p and ad loads α:

$$Z_i(p, \alpha) \equiv \tilde{a}_i - d_{ii} \times (p_i + \kappa_i \alpha_i) + \sum_{j \neq i} d_{ij} \times (p_j + \kappa_j \alpha_j) \;\; \forall i \in \mathcal{Z} \tag{12}$$

Given observed prices p^c and ad loads α^c, we can define demand at current equilibrium $Z_i^c \equiv Z_i(p^c, \alpha^c)$.

The demand system in (12) imposes two key restrictions. First, responses to ad load on i are proportional to the corresponding price responses by κ_i. This formulation is consistent

[17] See Bursztyn et al. (2024) for an analysis of how consumer surplus estimates may be affected by consumption externalities between Facebook users.

with the additive separability between z_i and n_i in Section 2, which gives us the invariance of diversion ratios to either a change in price or ad load (see Proposition 1).

The second key restriction is that the demand system is linear in prices. A linear specification is frequently used in merger analysis, both in economic research (e.g. Froeb and Werden (1992); Shapiro (1996); O'Brien and Wickelgren (2003); Hausman et al. (2011)) and by practitioners such as the FTC (e.g. Nelson (2015)) or the European Commission.[18] Reassuringly, the empirical evidence from the holdout experiment presented in Section 3.4 suggests linearity is broadly consistent with observed responses to changes in ad load of varying magnitude.

Identification. Under the assumption that the demand system is linear in prices, the own- and cross-price effects reported in Table 3 divided by $p_j = 0.067$ directly identify the own- and cross-price effects d_{ii} and d_{ij}. Similarly, the own-commodity responses from the holdout experiments reported in table 4 identify $d_{ii}\kappa_i$. Thus the disutility of each ad κ_i is identified from the ratio of responses to ad holdout and pricing experiment. Consistent with both experiments, we treat ad load and price on other commodities constant. As a result, we can combine these estimates of $d_{ii}\kappa_i$ with the observed current consumption Z_i^c and observed levels of ad load α_0^c and α_1^c to identify the intercept $\tilde{a}_i + \sum_{j\geq 2} d_{ij} \times (p_j + \kappa_j \alpha_j)$.

Consumer surplus and costs. The gross consumption value of platform i can be decomposed into the consumer surplus and the cost paid by the user. Given a monetary price of zero, the cost to users corresponds to the dis-utility stemming from watching ads. The consumer surplus measures the net value derived by the average user. It can be measured as the area under the inverse demand curve, between zero and the current quantity consumed. Using (12) and the fact that the current monetary price $p_i^c = 0$, gross benefits can be expressed as:

$$\text{Gross benefit of } i = \underbrace{\frac{1}{2}\frac{(Z_i^c)^2}{d_{ii}}}_{\text{CS of } i} + \underbrace{\kappa_i \alpha_i^c \times Z_i^c}_{\text{Cost of ads on } i} \tag{13}$$

Results. Letting 0 index Facebook and 1 index Instagram, the estimates in Table 3, suggest $d_{00} = 836$ and $d_{11} = 528$. Using (13), we find an average daily consumer surplus of \$3.37 per user for Facebook. The latter corresponds to an average consumer surplus of \$94 over a four week period. Using a similar reasoning, we obtain an estimated average daily consumer surplus of \$2.10 per user for Instagram. The latter corresponds to an average consumer surplus of about \$59 over a four week period.

Using (13) and the ratio of responses to ad holdout and pricing experiment, we find that ad load is equivalent to a daily tax per user of $\alpha_0\kappa_0 \times Z_0^c = \$0.68$ on Facebook and $\alpha_1\kappa_1 \times Z_1^c = \$0.19$ on Instagram. The latter numbers correspond to a cost of \$19.0 over a four week period for Facebook and \$5.5 for Instagram. Thus, comparing the cost of ads to the gross benefit, we find that Facebook captures only about 17% of its consumption value, while Instagram captures about 8%. Since both platforms choose an ad load in the inelastic range of the demand curve, the consumer surplus becomes large.

[18] Valletti and Zenger (2021) p. 188 "In merger control practice, the European Commission has often assumed linear demand for the calibration of price effects."

Discussion. The large consumer surplus raises the question of why the platforms choose an ad load in the inelastic range of the demand curve. In the standard model (with one-sided markets), no profit maximizing firm would ever fix the output for its product at any level where demand for its product is inelastic.[19] In the remainder of the paper, we will develop and apply a model with three distinct mechanisms that each could rationalize why platforms choose an ad load in the inelastic range of the demand curve. The first is network externalities, which may lead aggregate demand to be more elastic than suggested by the estimates from the ad holdout experiment. Therefore, the profit maximizing level of ad load may be lower. The second is a two-sided market. Facebook and Instagram are best characterized as two-sided platforms where users and advertisers interact. Technology and demand conditions on the advertising market may lower the profit maximizing level of ad load. The third is substitution in the advertisement market. Internalizing the possible diversion of advertisers between Facebook and Instagram may lower the profit maximizing level of ad load.

5 A Model of Two-Sided Media Platforms

5.1 Model

We model Facebook and Instagram as two-sided media platforms where users and advertisers interact. Our model follows closely standard models of media platforms such as Anderson and Peitz (2020), but allows for non-zero diversion ratios between platforms on the advertising side, consistent with user multi-homing as in Anderson et al. (2017).

Consistent with data (and similar to Anderson and Peitz (2020)), we assume that the platforms earn revenue exclusively from advertising and charge no monetary fee to users. Facebook and Instagram set ad load so as to maximize profit. Formally each platform's profit is given by:

$$\pi_i(\alpha) \equiv [R_i(\alpha) - c_i] \times \alpha_i \overline{Z}_i(\alpha) \tag{14}$$

where $R_i(\alpha)$ is the average revenue per ad impression on platform i, $c_i \geq 0$ is the marginal cost per ad, and $\overline{Z}_i(\alpha)$ is total aggregate user time. Total number of ad impressions is $Q_i^A(\alpha) \equiv \alpha_i \overline{Z}_i(\alpha)$. We will now specify the user demand $\overline{Z}_i(\alpha)$ and advertising revenue $R_i(\alpha)$, before turning to the firm's problem and the optimal ad load.

5.1.1 User Demand

We assume that demand is downward-sloping $\frac{\partial \overline{Z}_i}{\partial \alpha_i} \leq 0$ and allow for platforms to be substitutes from the point of view of users $\frac{\partial \overline{Z}_i}{\partial \alpha_j} \geq 0$. While the empirical analysis will assume linear demand, our theoretical results do not depend on this assumption. In this section, we therefore allow the demand function to be potentially non-linear in ad load.

[19] In Appendix F, we compute what the optimal ad load of Facebook and Instagram would have been if one assumes a one-sided market, no social multiplier, and a constant marginal cost. These ad loads are 7-10 times larger than those we observe in the data.

We also allow for the possibility that, due to network effects, aggregate demand faced by the platform $\overline{Z}_i(\alpha)$ is more elastic than the sum of individual demands holding other users' behavior constant $Z_i(\alpha)$. The social multiplier, $\mu_i \geq 1$, captures the importance of network effects:

$$\overline{Z}_i(\alpha) \equiv h_i + \mu_i Z_i(\alpha) \tag{15}$$

where $h_i \equiv (1-\mu_i) Z_i^c$ is a constant that ensures $\overline{Z}_i(\alpha_i^c) = Z_i^c$. Meta documents recognize the possibility that their internal estimates of individual responses to ad load understate the elasticity of aggregate user time because of the possibility that $\mu_i > 1$.[20]

5.1.2 Advertising Revenue

The platforms raise revenue from each ad impression. We assume that average revenue per ad is given by:

$$R_i(\alpha) \equiv \lambda_i(\alpha_i) \times P_i\left(Q^A\right)$$

where $Q^A = \left(Q_0^A, ..., Q_N^A\right)' \equiv \alpha \overline{Z}(\alpha)$, $\frac{\partial \lambda_i}{\partial \alpha_i} \leq 0$, $\frac{\partial P_i}{\partial Q_i^A} \leq 0$, and $\frac{\partial P_i}{\partial Q_j^A} \leq 0 \ \forall j \neq i$. This specification of the revenue function assumes that average revenue per ad of platform i is weakly decreasing in i's quantity of ad impressions Q_i^A, in i's ad load, α_i (holding Q_i^A fixed), and in the quantity of ad impressions on platforms other than i.

There are two reasons we allow for a downward sloping demand for ads on a given platform by letting R_i be decreasing in Q_i^A. The first is to capture that as the platform increases the number of ads, the new ads they show are lower ranked ads and less relevant. This "composition effect" leads to a negative relationship between the number of ad impressions and average revenue per ad. Such a composition effect is recognized in Meta's own analyses of advertising prices and revenues.[21] The second reason is that advertisers may have heterogeneous willingness to pay for ads on a given platform, even in the absence of composition effects. As a consequence, the platform may face a downward sloping demand for ads, resulting in a negative relationship between the number of ad impressions and average revenue per ad.

The motivation for assuming that R_i is weakly decreasing in α_i is to capture that users may respond to increased ad load by reducing their propensity to click on or interact with ads, a phenomenon known as 'ad blindness' (CMA, 2020). Meta recognizes that user engagement with ads (e.g., as measured by the click-through rate) decreases when a user has higher ad load.[22]

The reason for assuming that R_i is weakly decreasing in the quantity of ad impressions on platforms other than i is to let the platforms be substitutes from the point of view of advertisers. If platforms are substitutes, then an increase in the number of ads sold by one

[20] "It is possible that randomized experiments underestimate the cost of ad load because they do not account for network effects." (Meta, Internal Doc., 0143, at 945)

[21] "As we increase ad load, new ads we show are lower ranked ads and less relevant. They have lower conversion rate and thus CPM." (Meta, Internal Doc., 0123a); "Increasing ad load increases revenue but each extra ad is always the next best ad." (Meta, Internal Doc., 0123b)

[22] "We know that when you increase ad load you get a less-than-proportionate increase in conversions even if the quality of ads is the same." (Meta, Internal Doc., 0119, at 680)

platform may divert some advertiser to another platform and, therefore, increase its revenue. Such diversion between platforms in the advertising market is ruled out by the assumption that users single-home in Anderson and Peitz (2020). Our model allows users to be be single- or multi-homers.

5.2 Optimal ad load in the absence of the merger

Each platform i is assumed to choose ad load to maximize the profit function (14), taken as given the ad loads of the other platforms. To succinctly express the resulting first order conditions, it is useful to introduce some notation: Let $\overline{\varepsilon}_i^Z \equiv -\frac{\partial \ln \overline{Z}_i}{\partial \ln \alpha_i} \geq 0$ denote the elasticity of user time to own ad load, $\overline{\varepsilon}_{ji}^Z \equiv \frac{\partial \ln \overline{Z}_j}{\partial \ln \alpha_i} \geq 0$ denote the cross-price elasticity of user time, $\varepsilon_i^A \equiv -1/(\frac{\partial \ln P_i}{\partial \ln Q_i^A}) \geq 0$ denote the elasticity of residual advertiser demand, $\varepsilon_{ji}^{A,Inv} \equiv -\frac{\partial \ln P_j}{\partial \ln Q_i^A} \geq 0$ denote the inverse cross-price elasticity of advertiser demand, and $\xi_i \equiv -\frac{\partial \ln \lambda_i}{\partial \ln \alpha_i}$ denote the degree of ad-blindness.

As before, let us index Facebook by 0 and Instagram by 1. Given this notation, the first order conditions can be expressed as:

$$f\left(\alpha^d\right) \equiv \begin{bmatrix} f_0\left(\alpha^d\right) \\ f_1\left(\alpha^d\right) \end{bmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix} \tag{16}$$

where

$$f_i\left(\alpha\right) \equiv \left(1 - \frac{c_i}{\lambda_i P_i} - \frac{1}{\varepsilon_i^A}\right) \times \left(1 - \overline{\varepsilon}_i^Z\right) - \xi_i - \sum_{k \neq i} \overline{\varepsilon}_{ki}^Z \times \varepsilon_{ik}^{A,Inv} \qquad \text{for } i = 0, 1. \tag{17}$$

Note that $P_i\left(Q_i^A\right)$, and the elasticities ε_i^A, $\overline{\varepsilon}_i^Z$, $\varepsilon_{ik}^{A,Inv}$, and $\overline{\varepsilon}_{ki}^Z$ may generally vary with ad load so that $f\left(.\right)$ is a non-trivial function of α. The term $\sum_{k \neq i} \overline{\varepsilon}_{ki}^Z \times \varepsilon_{ik}^{A,Inv}$ in (17) reflects that i takes into account that the number of ads sold on other platforms will depend on its own choice of ad load because it affects the allocation of user time across platforms.

To understand the determinants of the optimal ad load, it is useful to define the semi-elasticity of user time to own ad load as $\overline{\sigma}_i^Z \equiv -\frac{\partial \ln \overline{Z}_i}{\partial \alpha_i} \geq 0$, and the semi-elasticity of user time holding networks constant as $\sigma_i^Z \equiv -\frac{\partial \ln Z_i}{\partial \alpha_i} \geq 0$. Evaluated at the observed equilibrium Z_i^c, it follows from (15) that we can write the semi-elasticity as $\overline{\sigma}_i^Z = \mu_i \times \sigma_i^Z$. This allows us to re-express (16) as:

$$\alpha_i^d = \left(1 - \frac{\xi_i + \sum_{k \neq i} \overline{\varepsilon}_{ki}^Z \times \varepsilon_{ik}^{A,Inv}}{1 - \frac{c_i}{\lambda_i P_i} - \frac{1}{\varepsilon_i^A}}\right) \times \frac{1}{\mu_i \sigma_i^Z} \qquad \text{for } i = 0, 1 \tag{18}$$

Equation (18) suggests the optimal ad load is decreasing in the social multiplier (μ_i), the degree of ad-blindness (ξ_i), the inverse elasticity of residual demand in the advertising market ($1/\varepsilon_i^A$), the marginal cost per ad (c_i), and the semi-elasticity of individual user time to ad load holding networks constant (σ_i^Z).

5.3 How a merger affects incentives to set ad load

In reality, Facebook and Instagram are jointly owned. We assume that Facebook and Instagram then set ad load to maximize their joint profit:

$$\max_{\alpha_0,\alpha_1} \left[\lambda_0 P_0 - c_0\right] \alpha_0 \overline{Z}_0 + \left[\lambda_1 P_1 - c_1\right] \alpha_1 \overline{Z}_1$$

Let $\alpha^m \equiv (\alpha_0^m, \alpha_1^m)$ denote the optimal ad load under a merger. The first order conditions can then be expressed as:

$$h\left(\alpha^m\right) \equiv \begin{bmatrix} h_0\left(\alpha^m\right) \\ h_1\left(\alpha^m\right) \end{bmatrix} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}. \tag{19}$$

where for $i = 0, 1$

$$\begin{aligned} h_i\left(\alpha\right) \equiv & \underbrace{\left(1 - \frac{c_i}{\lambda_i P_i} - \frac{1}{\varepsilon_i^A}\right)\left(1 - \overline{\varepsilon}_i^Z\right) - \xi_i - \sum_{k \neq i} \overline{\varepsilon}_{ki}^Z \times \varepsilon_{ik}^{A,Inv}}_{\equiv f_i(\alpha)} \\ & + \underbrace{\frac{\lambda_j P_j \alpha_j \overline{Z}_j}{\lambda_i P_i \alpha_i \overline{Z}_i}\left(\overline{\varepsilon}_{ji}^Z\left(1 - \frac{c_j}{\lambda_j P_j} - \frac{1}{\varepsilon_j^A}\right) - \varepsilon_{ji}^{A,Inv}\left(1 - \overline{\varepsilon}_i^Z\right)\right)}_{\equiv g_i(\alpha)} \end{aligned} \tag{20}$$

Equation (20) consists of two distinct components: the first-order conditions when the platforms are not merged, $f_i(\alpha)$, and the change in first-order conditions due to the merger, $g_i(\alpha)$. Letting $g(\alpha) \equiv \left[g_0\left(\alpha\right), g_1\left(\alpha\right)\right]'$, Proposition 3 provides a first-order approximation to the change in ad load induced by a merger between Facebook and Instagram. The effect of a de-merger is symmetric.

Proposition 3. *If $h = f + g$ is invertible, then a first-order approximation of the change in ad load induced by a merger is given by:*

$$\Delta\alpha = -\left(\frac{\partial f}{\partial \alpha}\left(\alpha^d\right) + \frac{\partial g}{\partial \alpha}\left(\alpha^d\right)\right)^{-1} \cdot g\left(\alpha^d\right)$$

Proof. The proof follows Jaffe and Weyl (2013). Since $f\left(\alpha^d\right) = 0$, $h\left(\alpha^d\right) = g\left(\alpha^d\right) \equiv r$. We want to find α^m (the equilibrium ad load under a merger) such that $h\left(\alpha^m\right) = 0$. If h is invertible, then

$$\begin{aligned} \alpha^m - \alpha^d = h^{-1}\left(0\right) - h^{-1}\left(r\right) &= \left(\frac{\partial h^{-1}}{\partial h}\left(r\right)\right)\left(0 - r\right) + \mathcal{O}\left(\|r\|^2\right) \\ &\approx -\left(\frac{\partial f}{\partial \alpha}\left(\alpha^d\right) + \frac{\partial g}{\partial \alpha}\left(\alpha^d\right)\right)^{-1} \cdot g\left(\alpha^d\right) \end{aligned}$$

□

As shown in Proposition 3, the effect of a merger on each α_i depends crucially on $g\left(\alpha^d\right)$. It contains two opposing effects on the change in ad load induced by a merger between platform i and j.[23] The first effect arises because non-zero user diversion between i and j creates an incentive to increase ad load. This is because some of the reduction in users and ad revenue following an increase in ad load by i will be re-captured by j. The second effect arises because non-zero user advertiser diversion between i and j gives an incentive to lower ad load. The reason is that the reduction in ads and ad revenue following a decrease in ad load by i will increase the demand of advertisers and the ad price on j.

The overall effect of a merger on the ad load is theoretically ambiguous. It depends not only on the size of the diversion ratios of users and advertisers, but also on the elasticity of demand of both users and advertisers. The incentive from the user-side to raise ad load on platform i is proportional to $\left(1 - c_j/\lambda_j P_j - 1/\varepsilon_j^A\right)$. Importantly, it is increasing in the elasticity of advertiser demand to ad price on platform j. With (im)perfectly elastic advertiser demand, an additional user minute to platform j would generate as much (less) ad revenue as the average user minute at j, and, therefore, create strong (weak) incentives for i to increase ad load in response to the merger. The incentive from the advertiser-side to decrease ad load on platform i is proportional to $\left(1 - \overline{\varepsilon}_i^Z\right)$. Importantly, it is declining in the elasticity of user demand to ad load on platform i. With inelastic user demand, a decrease in the ad load of platform i will cause a large decline in the number of ads it sells, and, therefore divert many advertisers from i to j. (In)elastic user demand therefore creates weak (strong) incentives for i to decrease ad load in response to a merger.

5.4 Taking the model to the data

We now describe how to take our model to the data, providing identification arguments in the text while summarizing the moments used to quantify the parameters of interest in Table 6.

The identification argument consists of three steps. We begin by showing how internal data from Facebook and Instagram allows us to construct measures of the social multipliers (μ_i), the ad blindness (ξ_i), and the marginal cost (c_i), as well as the ad loads, user time, and ad prices in the current equilibrium (α_i^c, $\overline{Z}_i^c$, and R_i^c). Next, we show how to combine these measures with the pricing and holdout experiments to identify the parameters determining user demand (a_i, b_{ii}, and b_{ij}). Lastly, we explain how the own-price effects on advertiser demand (β_{00} and β_{11}) then can be recovered if one knew or assumed the magnitude of the cross-price effects in the ad market (β_{01} and β_{10}). The argument is that the observed equilibrium choices of ad load by Facebook and Instagram contain information about the demand they must face in the advertising market.

The only unknown parameters are then the cross-price effects in the ad market.[24] Our

[23] The result that "factors that depress price on one side of the market tend to raise price on the other side" (Jullien et al., 2021) is well known in theoretical work on mergers between two-sided platforms. It is often referred to as the "seesaw principle" (Rochet and Tirole, 2006). In our context, the price is the ad load.

[24] Strictly speaking, the analysis also depends on the term $\sum_{k \neq i} \overline{\varepsilon}_{ki}^Z \times \varepsilon_{ik}^{A,Inv}$. In practice, however, this term plays little if any role in the results of the merger analysis. The reason is that it enters in the same way in the first order conditions both with and without the merger. Therefore, it only matters for the effects of the merger through non-linearities. In the baseline analysis, we assume ad-side diversion D_{ik}^A is zero if user-side

data do not allow us to quantify these parameters. We therefore present results for different values of the cross-price effects (β_{01}, β_{10}) corresponding to a wide range of diversion ratios in the ad market, from no diversion to full diversion from Instagram to Facebook. As a result, we obtain lower and upper bounds on the quantities of interest.

Table 6: Mapping from Data Moments to Model Parameters

Model Parameter	Mapping	Data Moments
	Panel A: User Demand	
Social multiplier: $\mu_i = 1.5$	$\mu_i = \hat{\mu}_i$	**Meta internal estimate:** $\hat{\mu}_i = 1.5$
Own-commodity: $b_{00} = 0.40$ $b_{11} = 0.12$	$b_{00} = (\hat{\rho}_{00} \times Z_0^c)\frac{1}{\alpha_0^c}$ $b_{11} = (\hat{\rho}_{11} \times Z_1^c)\frac{1}{\alpha_1^c}$	**Elasticity of user time to ad load (see Table 4):** $\hat{\rho}_{00} = 0.09$ $\hat{\rho}_{11} = 0.04$ **Current engagement (billion hours):** $Z_0^c = 4.47$ $Z_1^c = 2.25$ **Current ad load:** $\alpha_0^c = 1.00$ $\alpha_1^c = 0.74$
Cross-commodity: $b_{01} = 0.02$ $b_{10} = 0.02$	$b_{01} = \hat{D}_{01}^U \times b_{11}$ $b_{10} = \hat{D}_{10}^U \times b_{00}$	**Diversion ratios (see Table 3):** $\hat{D}_{01}^U = 0.13$ $\hat{D}_{10}^U = 0.05$
Intercepts: $a_0 = 3.37$ $a_1 = 1.57$	$a_0 = \frac{Z_0^c}{\mu_0} + b_{00} \times \alpha_0^c - b_{01} \times \alpha_1^c$ $a_1 = \frac{Z_1^c}{\mu_1} + b_{11} \times \alpha_1^c - b_{10} \times \alpha_0^c$	
	Panel B: Other Parameters	
Ad-blindness: $\xi_i = 0.2$	$\xi_i = \hat{\xi}_i$	**Meta internal estimate:** $\hat{\xi}_i = 0.2$
Ad prices: $P_0^c = 0.673$ $P_1^c = 0.651$	$P_0^c = \frac{\mathcal{R}_0^c/Z_0^c}{\alpha_0^{c\,1-\xi_0}}$ $P_1^c = \frac{\mathcal{R}_1^c/Z_1^c}{\alpha_1^{c\,1-\xi_1}}$	**Gross adv. revenue:** $\mathcal{R}_0^c = \$3,009$ (million) $\mathcal{R}_1^c = \$1,158$ (million)
Marginal cost: $c_0 = 0.15$ $c_1 = 0.15$	$c_0 = s_i \times (\alpha_0^c)^{-\xi_0} P_0^c$ $c_1 = s_i \times (\alpha_1^c)^{-\xi_1} P_1^c$	**Meta's cost share of revenue:** $s_i = 0.22$

Social Multipliers. Meta estimates that the multiplier on Facebook μ_0 is 1.5, meaning that the aggregate effect of ad load on time spent is 50% larger than the average impact observed at an individual level.[25] We are not aware of any similar estimates for Instagram and thus assume $\mu_0 = \mu_1$. We evaluate the sensitivity of the results to a wide range of other values of

diversion D_{ki}^U is nonzero for platforms other than Facebook and Instagram. Empirically, the results barely change if we relax this simplifying assumption.

[25] See Meta, Internal Doc. (0051) at 594.

μ_i. Note that $\mu_i = 1$ corresponds to no network effects.

Ad blindness. Meta estimates that a 1% increase in ad impressions decreases the average click-through rate ("CTR") by about 0.2%.[26] Assuming a constant elasticity, this estimate suggests $\lambda_i(\alpha) = \alpha^{-\xi_i}$ with ξ_i of 0.2. We evaluate the sensitivity of the results to other values of ξ_i.

Current ad load and user engagement. Estimates of current ad load are from Table 4. In June 2022, total user time was $Z_0^c = 4.47$ billion hours on Facebook and $Z_1^c = 2.25$ billion hours on Instagram.[27]

Current price per ad. In June 2022, Meta reports a gross advertising revenue $\mathcal{R}_0^c = \$3,009$ million on Facebook and $\mathcal{R}_1^c = \$1,158$ million on Instagram. This gives a price of $P_0^c = 0.673$ and $P_1^c = 0.651$ since $P_i^c = \frac{\mathcal{R}_i^c / Z_i^c}{\alpha_i^{c\,1-\xi_i}}$.

Marginal cost per ad. According to public financial filings, Meta's variable cost share of revenue in 2022 was 22%.[28] We therefore assume a marginal cost of 22% implying $c_0 = 0.15$ and $c_1 = 0.15$. We evaluate the sensitivity of the results to other values of marginal cost.

User Demand. Inserting the linear demand function from (12) in (15), we obtain the following user demand in terms of total user minutes per month:

$$\overline{Z}_0 = \mu_0 \times (a_0 - b_{00}\alpha_0 + b_{01}\alpha_1)$$
$$\overline{Z}_1 = \mu_1 \times (a_1 - b_{11}\alpha_1 + b_{10}\alpha_0)$$

where, letting N_i be the number of users on platform i, $a_i \equiv \frac{h_i}{\mu_i} + \tilde{a}_i N_i$, $b_{ii} \equiv d_{ii}\kappa_i N_i$, and $b_{ij} \equiv d_{ij}\kappa_j N_i$. We refer to Section 4 for how $\tilde{a}_i$, b_{ii}, b_{ij}, κ_i, and κ_j are identified. The number of users N_i is known from internal Meta data on observed total user engagement in June 2022.

Advertisers' Demand. We assume that advertiser demand is linear in the price of advertising.

$$\alpha_0\overline{Z}_0 \equiv Q_0^A = x_0 - \beta_{00}P_0 + \beta_{01}P_1$$
$$\alpha_1\overline{Z}_1 \equiv Q_1^A = x_1 - \beta_{11}P_1 + \beta_{10}P_0$$

If one knew or assumed the values of the cross-price effects in the advertising market, $\{\beta_{01}, \beta_{10}\}$, one could identify the parameters of advertisers' demand, $\{\beta_{00}, \beta_{11}\}$ from the constraint that the model rationalizes the current equilibrium. The intuition is that the observed equilibrium level of ad load contains information about the demand that platforms must be facing on the advertising market. The identification argument is the following: consider the vector of first-order conditions $h(.)$ from (19) as a function of

[26] "CTR decreases by about 0.2% for each 1% increase in Impressions[.] There maybe [sic] several reasons for this from increased ad blindness to placing the same 'good' ad at lower positions due to more slots." (Meta, Internal Doc., 0122)

[27] Source: Meta, Internal Doc. (0170a,b)

[28] Meta's 10-K (p. 69) reports that the global cost of revenue in 2022 was \$25.2 billion compared to revenue of \$116.6 billion. That equates to a cost margin of 22%. The global cost of revenue includes all cost incurred in producing, marketing, and distributing a product.

both the level of ad load α and model parameters $h \equiv h(\alpha, \beta_{00}, \beta_{11}; \Gamma)$, where $\Gamma \equiv (\xi_0, \xi_1, \mu_0, \mu_1, b_{00}, b_{11}, b_{01}, b_{10}, a_0, a_1, c_0, c_1, \beta_{01}, \beta_{10})'$ is a vector of known parameters. Next we find the values of $\{\beta_{00}, \beta_{11}\}$ s.t.

$$h(\alpha^c, \beta_{00}, \beta_{11}; \Gamma) = 0 \tag{21}$$

We confirm empirically that, given the values of Γ that we consider, there exists a unique set of values (β_{00}, β_{11}) that satisfies (21).

The only remaining parameters that we need to know are (β_{01}, β_{10}). Unfortunately, our data does not allow us to recover the cross-price effects in the ad market. We therefore present results for different values of (β_{01}, β_{10}), corresponding to a wide range of diversion ratios in the advertising market from no diversion to full diversion from Instagram to Facebook. As a result, we obtain lower and upper bounds on the quantities of interest. In our baseline specification we compute these bounds under the assumption that the cross-price responses are symmetric $\beta_{01} = \beta_{10}$. This assumption could for example be motivated by the advertiser demand system being derived from a representative agent with quasilinear utility. In our robustness analysis, we show sensitivity to deviations from symmetry.

6 Model based insights

We now use the model in Section 5 to analyze a de-merger between Facebook and Instagram. Our de-merger analysis is focused entirely on the effects on ad load, and we assume that a de-merger would not increase costs or reduce efficiency.[29] We also do not examine the de-merger effects on producer surplus (of platforms and advertisers), since it would require additional data or very strong assumptions about the technology or demand conditions in the advertising market.

6.1 De-merger analysis

Figure 4 presents the results from a de-merger of Facebook and Instagram for values of β_{ij} (and, by symmetry, β_{ji}). The values range from 0 (implying $D_{01}^A = D_{10}^A = 0$) to 67 (implying $D_{01}^A = 1.0$ and $D_{10}^A = 0.8$). Each value of β_{ij} results in different estimates of the residual demand curve of advertisers (reported in Panel A) as well as the de-merger induced change in ad load (reported in Panel B) and consumer surplus (reported in panel C).

The results in Figure 4 give upper and lower bounds on the quantities of interest for any possible value of diversion and point estimates for a given value of diversion. A natural point estimate is given by the vertical grey line where the diversion ratio from Instagram to Facebook is equal to Facebook's market share in the online advertisement market (excluding

[29] We make this assumption because existing merger guidelines have a highly skeptical stance towards efficiency arguments (Kaplow, 2025), and because our data do not allow us to credibly quantify impacts on costs or efficiency. Similarly, while a de-merger could also affect other margins — such as the platform quality on the user-side — our analysis does not model such responses.

Instagram).[30] This would be the case if there is no substitution between offline and online markets and all online advertisement platforms are perfect substitutes. Using 2024 data from Insider Intelligence, we estimate Facebook's market share of the online advertisement market to be 17.4 percent while Instagram's market share is 6.8 percent.[31]

The results in Figure 4 may be summarized with two broad conclusions. The first is that we can rule out that the de-merger would materially benefit the users of Facebook and Instagram. The largest possible gains to users from the de-merger are very close to zero, obtained if one believes $\beta_{ij} = 0$ so there is no diversion of advertisers between Facebook and Instagram. Ad load would then decrease by 0.13% on Facebook and 0.25% on Instagram, while consumer surplus for the users of Facebook and Instagram would increase by 0.03%.

To understand why the de-merger would not materially benefit the users, recall the comparative statics in Proposition 3: if there is no diversion of advertisers between Facebook and Instagram, users will necessarily gain from the de-merger. However, in order for the gains to be large, there needs to be both high user diversion ratios between Facebook and Instagram and highly elastic advertiser demand to ad price. Our data suggest neither is the case. We experimentally estimate user diversion ratios of 0.13 for Facebook and 0.05 for Instagram. Furthermore, the advertiser demand cannot be too elastic to rationalize the observed equilibrium level of ad load, especially when there is no diversion of advertisers between Facebook and Instagram.

The second conclusion is that the de-merger would be harmful to users of Facebook and Instagram if one believes that advertisers view these platforms as substitutes. Larger advertising diversion ratios between Facebook and Instagram have a direct effect and an offsetting indirect effect. On the one hand, larger diversion ratios directly increase the incentives to lower ad load under joint ownership. On the other hand, larger diversion ratios mean advertiser demand needs to be more elastic to rationalize the observed equilibrium level of ad load. This indirect effect amplifies the incentive to increase ad load due to non-zero user diversion ratio between Facebook and Instagram.

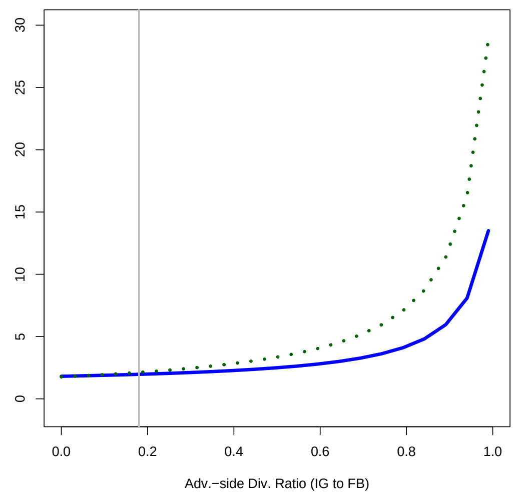
Our estimates suggest the direct effect tends to dominate. The estimated fall in consumer surplus due to the de-merger is largest at $\beta_{ij} = 67$, implying advertising diversion ratios of $D^A_{01} = 1.0$ and $D^A_{10} = 0.8$. Ad load would then increase by 6.4% on Facebook and 104.1% on Instagram, while consumer surplus for the users of Facebook and Instagram would decline by 4.4%. By comparison, the point estimates where the advertiser diversion ratio of a platform is equal to its market share suggest that the de-merger would increase the ad load on Facebook and Instagram by 3.7 and 9.8%, while the consumer surplus of Facebook and Instagram users would fall by 1.0%.

[30] Due to the assumption of symmetry of β_{ji}, the diversion rate from Facebook to Instagram also becomes approximately equal to Instagram's market share in the online advertisement market (excluding Facebook).

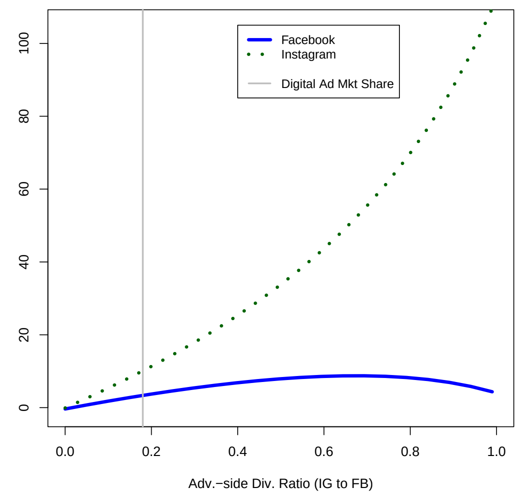
[31] We define the online advertisement market to include Facebook, Instagram, Google, Microsoft, TikTok, YouTube, Amazon, Apple, eBay, Etsy, Hulu, IAC, iHeartMedia, Instacart, LinkedIn, Pinterest, Reddit, Roku, Snapchat, Spotify, Twitter, Walmart, and Yelp.

Figure 4: Results of De-Merger Analysis (Main Specification)

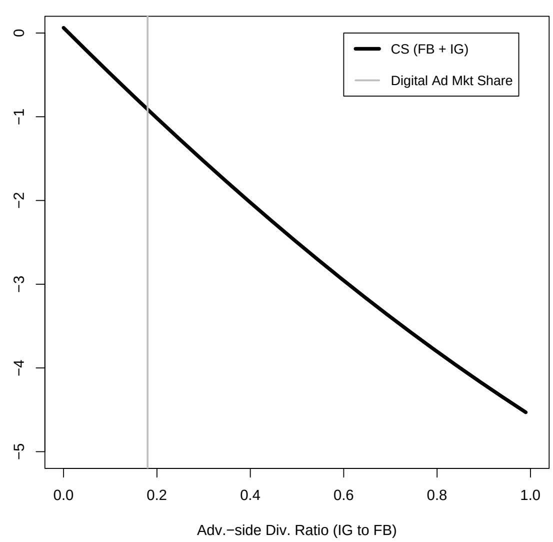
(A) Implied Elasticity of Adv. Residual Demand



(B) Percentage Change in Ad Load (De-Merger)



(C) Percentage Change in Joint Consumer Surplus (De-Merger)



Notes: Figure (A) shows the implied own-price elasticity of advertiser demand evaluated at the current equilibrium: $-1/\frac{\partial \ln P_i}{\partial \ln Q_i^A}$. Figure (B) shows the estimated percentage change in ad load caused by a de-merger between Facebook and Instagram: $\left(\alpha_i^d - \alpha_i^c\right)/\alpha_i^c$. Figure (C) shows the estimated percentage change in joint consumer surplus from Facebook and Instagram. The joint consumer surplus after the de-merger is given by $\frac{1}{2}\kappa_0\left(\overline{Z}_0^d\right)^2/b_{00} + \frac{1}{2}\kappa_1\left(\overline{Z}_1^d\right)^2/b_{11}$ where $\overline{Z}_i^d$ is estimated total user minutes after the de-merger. The joint consumer surplus before the de-merger is given by $\frac{1}{2}\kappa_0\left(\overline{Z}_0^c\right)^2/b_{00} + \frac{1}{2}\kappa_1\left(\overline{Z}_1^c\right)^2/b_{11}$. The specification assumes $\mu_0 = \mu_1 = 1.5$, $\xi_0 = \xi_1 = 0.2$, $c_0 = 0.15$, and $c_1 = 0.15$. Both marginal costs estimates c_i correspond to 22% of current average revenue per unit. The specification also assumes that the diversion ratios between Facebook and Instagram correspond to our experimental estimates from Section 3: $D_{01}^U = 0.13$ and $D_{10}^U = 0.05$.

6.2 Robustness of results

We now run a battery of sensitivity checks, showing that our two main conclusions are robust to changes in the parameter values of (μ_i, ξ_i, c_i), to deviations from symmetry in cross-price effects β_{ij} on the advertisement market, and to allowing the platforms' ad load decisions to be strategic complements. We can still rule out that the de-merger would materially benefit users, and the de-merger remains harmful to users if one believes that advertisers view Facebook and Instagram as substitutes.

Sensitivity with respect to (μ_i, ξ_i, c_i). In Table 7, we report the results from our sensitivity analysis with respect to (μ_i, ξ_i, c_i). In panel B-D, we vary one parameter at a time, while Panel E varies all three parameters at once. In each case, we re-estimate the model to make sure we rationalize the current equilibrium.

The first column of Table 7 shows the upper-bound on potential gains to users of the de-merger between Facebook and Instagram. The second column presents the point estimates when the diversion ratio from Instagram to Facebook is equal to Facebook's market share in the online advertisement market (excluding Instagram). The third column shows the upper-bound on harms to users. Across all rows, we can rule out that a de-merger materially benefits users. The upper bound on the increase in consumer surplus is usually close to zero and never exceeds 1%. However, the harm to users can be substantial, around 3-5% for most specifications and up to 11% when the social multiplier is large.

Deviations from Symmetry. Throughout the analysis, we have maintained the assumption that cross-price effects on the advertising market are symmetric $\beta_{01} = \beta_{10}$. In appendix Figure G.1, we explore the effect of relaxing this assumption on the estimated effects of a de-merger. Specifically, we quantify the sensitivity of the results to assuming $\beta_{10} = k * \beta_{01}$ for $k \in \{0.9, 1.1\}$. It is reassuring to find that these deviations from symmetry barely move the estimated effects on consumer surplus.

Strategic interactions. Our model assumes that each platform chooses ad load to maximize the profit, taking as given the ad loads of the other platforms. Although the interactions between platforms will not be strategic, the actions of one platform, such as an ad load change, affect demand for other platforms because users and advertisers may switch across platforms. Incorporating strategic interactions in our model is empirically challenging since it would require knowledge of user and advertiser demand for platforms other than Facebook and Instagram. However, it is common to assume that prices, such as ad load, are strategic complements. Incorporating strategic interactions would reinforce the two key conclusions above.

The reason is that competing platforms would then have an incentive to lower ad load in response to Facebook or Instagram lowering their ad load. An important way such strategic interactions would affect our estimates is through the user demand becoming more inelastic to changes in ad load than what we find in the holdout experiment (which changes the ad load for a small set of users, so competitors do not respond). Less elastic user demand would contribute to larger decreases in the ad loads in response to the merger.

Table 7: Robustness - Estimated Impact on Ad Load and Consumer Surplus of a De-Merger between Facebook and Instagram

Mode Parameters			**Largest gain to users**			**Diversion equal to market share**			**Largest harm to users**		
			Δ ad load			**Δ ad load**			**Δ ad load**		
μ_i	ξ_i	c_i	**FB**	**IG**	**Δ CS**	**FB**	**IG**	**Δ CS**	**FB**	**IG**	**Δ CS**
			Panel A: Baseline Model								
1.5	**0.2**	**0.22**	**0.00**	**0.00**	**0.00**	**0.04**	**0.10**	**-0.01**	**0.10**	**1.04**	**-0.04**
			Panel B: Sensitivity on μ_i								
1.0	0.2	0.22	0.00	0.00	0.00	0.04	0.10	-0.01	0.09	1.07	-0.03
1.5	**0.2**	**0.22**	**0.00**	**0.00**	**0.00**	**0.04**	**0.10**	**-0.01**	**0.10**	**1.04**	**-0.04**
2.0	0.2	0.22	0.00	0.00	0.00	0.04	0.10	-0.01	0.10	1.00	-0.06
3.0	0.2	0.22	0.00	-0.01	0.00	0.04	0.09	-0.02	0.11	0.89	-0.09
4.0	0.2	0.22	-0.01	-0.01	0.00	0.03	0.08	-0.02	0.10	0.75	-0.11
5.0	0.2	0.22	-0.01	-0.02	0.01	0.02	0.07	-0.02	0.08	0.59	-0.11
			Panel C: Sensitivity on ξ_i								
1.5	0.1	0.22	0.00	0.00	0.00	0.04	0.10	-0.01	0.08	1.24	-0.04
1.5	**0.2**	**0.22**	**0.00**	**0.00**	**0.00**	**0.04**	**0.10**	**-0.01**	**0.10**	**1.04**	**-0.04**
1.5	0.3	0.22	0.00	0.00	0.00	0.04	0.09	-0.01	0.12	0.84	-0.05
1.5	0.4	0.22	0.00	-0.01	0.00	0.03	0.08	-0.01	0.14	0.64	-0.04
1.5	0.5	0.22	-0.01	-0.01	0.00	0.03	0.06	-0.01	0.13	0.42	-0.04
			Panel D: Sensitivity on c_i								
1.5	0.2	0.00	0.00	0.00	0.00	0.04	0.11	-0.01	0.10	1.24	-0.05
1.5	0.2	0.11	0.00	0.00	0.00	0.04	0.10	-0.01	0.10	1.15	-0.05
1.5	**0.2**	**0.22**	**0.00**	**0.00**	**0.00**	**0.04**	**0.10**	**-0.01**	**0.10**	**1.04**	**-0.04**
1.5	0.2	0.33	0.00	0.00	0.00	0.03	0.09	-0.01	0.10	0.91	-0.04
1.5	0.2	0.44	0.00	0.00	0.00	0.03	0.08	-0.01	0.10	0.75	-0.04
1.5	0.2	0.55	0.00	0.00	0.00	0.03	0.07	-0.01	0.09	0.56	-0.03
			Panel E: Varying all parameters at once								
1.5	**0.2**	**0.22**	**0.00**	**0.00**	**0.00**	**0.04**	**0.10**	**-0.01**	**0.10**	**1.04**	**-0.04**
1.88	0.25	0.28	0.00	-0.01	0.00	0.03	0.09	-0.01	0.11	0.82	-0.06
2.25	0.3	0.33	-0.01	-0.01	0.00	0.03	0.07	-0.01	0.11	0.55	-0.06
2.63	0.35	0.38	-0.01	-0.02	0.00	0.01	0.04	-0.01	0.08	0.29	-0.04
3.0	0.40	0.44	-0.01	-0.03	0.01	-0.01	-0.02	0.01	0.00	0.00	0.00

Notes: Table reports the lower- and upper-bound on estimated percentage change in ad load and consumer surplus caused by a de-merger between Facebook and Instagram. The percentage change in ad load is given by $\left(\alpha_i^d - \alpha_i^c\right)/\alpha_i^c$. The joint consumer surplus after the de-merger is given by $\frac{1}{2}\kappa_0\left(\overline{Z}_0^d\right)^2/b_{00} + \frac{1}{2}\kappa_1\left(\overline{Z}_1^d\right)^2/b_{11}$ where $\overline{Z}_i^d$ is estimated total user minutes after the de-merger. The joint consumer surplus before the de-merger is given by $\frac{1}{2}\kappa_0\left(\overline{Z}_0^c\right)^2/b_{00} + \frac{1}{2}\kappa_1\left(\overline{Z}_1^c\right)^2/b_{11}$. Marginal cost c_i correspond to a percentage of current average revenue (e.g. 22%). The specification assumes that the diversion ratios between Facebook and Instagram correspond to our experimental estimates from section 3: $D_{01}^U = 0.13$ and $D_{10}^U = 0.05$.

6.3 De-Merger Analysis under FTC's market definition

We conclude our analysis with a comparison between the results in Section 6.1 and those we obtain if we follow the FTC in assuming that the relevant user market consists only of Facebook, Instagram, and Snapchat (FTC, 2021). In our model, such a market definition can be thought of as imposing the restrictions that i) time-intensive commodities cannot be substitutes if they differ in functionality, and ii) Facebook, Instagram, and Snapchat are the only commodities with similar functionality.

Formally, restrictions i) and ii) can be embedded in our analysis by assuming an infinite elasticity of substitution $1/(1-\theta)$ between the PSN commodities (Facebook, Instagram, and Snapchat). Under this assumption, the diversion ratio between any pair of these platforms k and j is given by k's share of total PSN consumption excluding j:

Corollary 3. *Assuming $\theta = 1$ (i.e. infinite elasticity of substitution between PSN commodities), the diversion ratio between PSN origin commodity $j \in \mathcal{P}$ and PSN destination commodity $k \in \mathcal{P}$ is given by k's share of total PSN consumption excluding j:*

$$D_{kj} = \frac{z_k}{\sum_{i \in \mathcal{P} \setminus j} z_i} \tag{22}$$

where z_i is time spent on commodity i. Summing across all PSN commodities other than j, we obtain that total diversion to other PSN commodities is one:

$$\sum_{k \in \mathcal{P} \setminus j} D_{kj} = 1$$

The Corollary follows easily from Proposition 4 (see Appendix A.4.3 for the proof).

To perform the de-merger analysis under the FTC's assumptions about market definition, we first compute $z_k / \sum_{i \in \mathcal{P} \setminus j} z_i$ in equation (22) from our data on the use of each app. This gives us estimates of user diversion ratios between Facebook and Instagram of $D^U_{01} = 0.95$ and $D^U_{10} = 0.92$. Next, we re-estimate the model in Section 5 using these diversion ratios instead of the experimentally estimated ones. The results are presented in Figure 5.

There are two key findings. The first finding is that employing the market definition of FTC leads to the conclusion that the de-merger would necessarily raise the consumer surplus of the users of Facebook and Instagram. This finding is true no matter the advertiser diversion ratios. The reason is that FTC's market definition gives very high user diversion ratios, and, as a result, creates strong incentives to lower ad load in response to the de-merger.

The second key finding is that employing the market definition of FTC matters substantially if one believes that advertisers view these platforms as substitutes. The reason is that larger advertiser diversion ratios means advertiser demand needs to be more elastic to rationalize the observed equilibrium level of ad load. Higher elasticity of advertiser demand reinforces the contribution of very high user diversion ratios to reduce ad load and increase consumer surplus in response to the de-merger.[32]

[32]For Facebook, the ad load after the merger is always lower under FTCs market definition than in our analysis, no matter the advertiser diversion ratio. For Instagram, this is not the case at very high values of the

Taken together, these two findings highlight the importance of (experimentally) estimating the user diversion ratios as opposed to defining the market without data on actual user substitution.

7 Conclusion

This paper extends Becker's foundational time allocation theory to the digital economy, offering a novel lens on consumer demand and market competition for time-intensive goods. By combining theoretical modeling with large-scale field experiments on Facebook and Instagram usage, we show that time shares and time intensity—not just functional similarity—shape substitution patterns across online and offline leisure markets. Our findings challenge conventional market definitions: seemingly dissimilar activities can be close substitutes simply because they vie for consumers' finite attention.

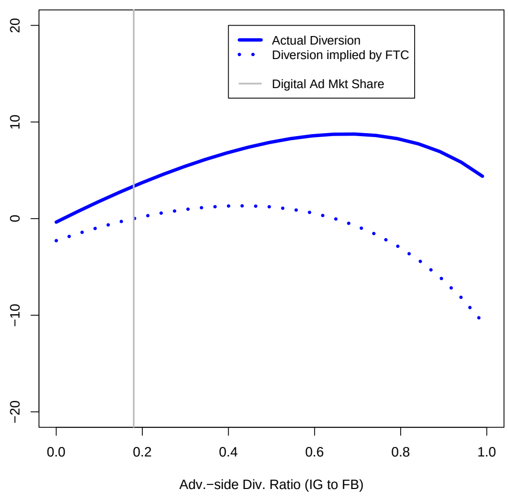
These insights have direct antitrust implications. The Federal Trade Commission's narrow market framing underweights competition from non-PSN platforms and offline activities, potentially mischaracterizing the effects of a proposed de-merger. In contrast, our two-sided platform model suggests that separating Facebook and Instagram may reduce consumer welfare—particularly if advertisers treat them as substitutes.

For academics, this study opens new research avenues in economics and beyond. It advances Becker's framework for analyzing digital economies, encourages empirical research on time-based substitution, and provides methodological tools for studying two-sided platform markets. By bridging theoretical innovation, experimental rigor, and policy relevance, our work sets the stage for future studies in digital consumption, market design, and competition policy. In time-constrained markets, time is the critical currency—one that regulators, economists, and platforms must center in both analysis and policy.

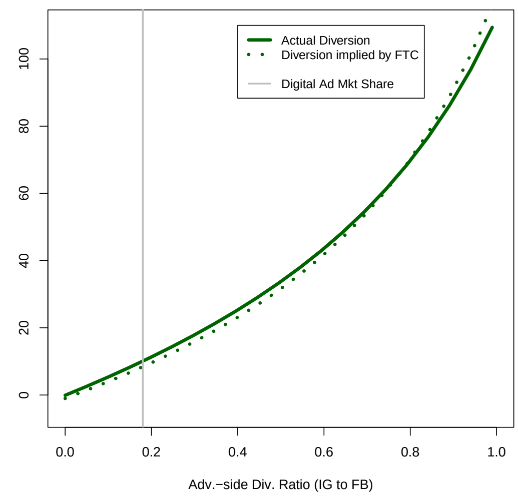
advertiser diversion ratio. This is because an additional user minute generates more ad revenue on Facebook than Instagram prior to the merger. When user diversion ratios become sufficiently large, joint ownership will make it optimal for Instagram to divert users to Facebook by having relatively high ad load.

Figure 5: De-Merger Analysis under the FTC's Assumptions about Market Definition

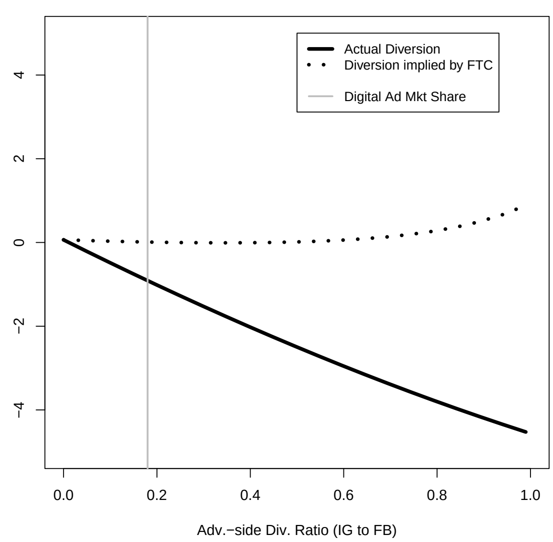
(A) Percentage Change in Ad Load on Facebook



(B) Percentage Change in Ad Load on Instagram



(C) Percentage Change in Joint Consumer Surplus



Notes: Figure (A) shows the estimated percentage change in ad load on Facebook caused by a de-merger between Facebook and Instagram: $\left(\alpha_i^d - \alpha_i^c\right)/\alpha_i^c$. It compares our main specification using the experimental estimates of the user-side diversion ratios to an alternative specifications using diversion ratios consistent with the FTC's market definition ($D_{01}^U = 0.94$ and $D_{10}^U = 0.92$) Figure (B) shows the same estimates for Instagram. Figure (C) shows the estimated percentage change in joint consumer surplus from Facebook and Instagram. The joint consumer surplus after the de-merger is given by $\frac{1}{2}\kappa_0 \left(\overline{Z}_0^d\right)^2/b_{00} + \frac{1}{2}\kappa_1 \left(\overline{Z}_1^d\right)^2/b_{11}$ where $\overline{Z}_i^d$ is estimated total user minutes after the de-merger. The joint consumer surplus before the de-merger is given by $\frac{1}{2}\kappa_0 \left(\overline{Z}_0^c\right)^2/b_{00} + \frac{1}{2}\kappa_1 \left(\overline{Z}_1^c\right)^2/b_{11}$. The specifications assume $\mu_0 = \mu_1 = 1.5$, $\xi_0 = \xi_1 = 0.2$, $c_0 = 0.15$, and $c_1 = 0.15$. Both marginal costs estimates c_i correspond to 22% of current average revenue per unit.

Academic references

Aguiar, M., Bils, M., Charles, K. K., and Hurst, E. (2021). Leisure luxuries and the labor supply of young men. *Journal of Political Economy*, 129(2):337–382.

Aguiar, M. and Hurst, E. (2016). Chapter 4 - the macroeconomics of time allocation. volume 2 of *Handbook of Macroeconomics*, pages 203–253. Elsevier.

Allcott, H., Braghieri, L., Eichmeyer, S., and Gentzkow, M. (2020). The welfare effects of social media. *American Economic Review*, 110(3):629–76.

Allcott, H., Gentzkow, M., Mason, W., Wilkins, A., Barberá, P., Brown, T., Cisneros, J. C., Crespo-Tenorio, A., Dimmery, D., Freelon, D., González-Bailón, S., Guess, A. M., Kim, Y. M., Lazer, D., Malhotra, N., Moehler, D., Nair-Desai, S., Barj, H. N. E., Nyhan, B., de Queiroz, A. C. P., Pan, J., Settle, J., Thorson, E., Tromble, R., Rivera, C. V., Wittenbrink, B., Wojcieszak, M., Zahedian, S., Franco, A., de Jonge, C. K., Stroud, N. J., and Tucker, J. A. (2024). The effects of facebook and instagram on the 2020 election: A deactivation experiment. *Proceedings of the National Academy of Sciences*, 121(21):e2321584121.

Allcott, H., Gentzkow, M., and Song, L. (2022). Digital addiction. *American Economic Review*, 112(7):2424–2463.

Anderson, S. P., Foros, , and Kind, H. J. (2017). Competition for advertisers and for viewers in media markets. *The Economic Journal*, 128(608):34–54.

Anderson, S. P. and Peitz, M. (2020). Media see-saws: Winners and losers in platform markets. *Journal of Economic Theory*, 186:104990.

Aridor, G. (2025). Measuring substitution patterns in the attention economy: An experimental approach. RAND Journal of Economics, Forthcoming.

Athey, S. and Imbens, G. W. (2017). The econometrics of randomized experiments. In *Handbook of economic field experiments*, volume 1, pages 73–140. Elsevier.

Becker, G. S. (1965). A theory of the allocation of time. *The Economic Journal*, 75(299):493–517.

Benzell, S. and Collis, A. (2020). Multi-sided platform strategy, taxation, and regulation: A quantitative model and application to facebook. Technical report.

Brynjolfsson, E., Collis, A., Diewert, W. E., Eggers, F., and Fox, K. J. (2019a). GDP-B: Accounting for the Value of New and Free Goods in the Digital Economy. NBER Working Papers 25695, National Bureau of Economic Research, Inc.

Brynjolfsson, E., Collis, A., and Eggers, F. (2019b). Using massive online choice experiments to measure changes in well-being. *Proceedings of the National Academy of Sciences*, 116(15):7250–7255.

Brynjolfsson, E., Collis, A., Liaqat, A., Kutzman, D., Garro, H., Deisenroth, D., and Wernerfelt, N. (2024). The consumer welfare effects of online ads: Evidence from a 9-year experiment. Working Paper 32846, National Bureau of Economic Research.

Bursztyn, L., Gentzkow, M., Jiménez-Durán, R., Leonard, A., Milojević, F., and Roth, C. (2025). Measuring markets for network goods. Working Paper 33901, National Bureau of Economic Research.

Bursztyn, L., Handel, B., Jiménez-Durán, R., and Roth, C. (2024). When product markets become collective traps: The case of social media. mimeo.

Chiappori, P. and Lewbel, A. (2015). Gary becker's a theory of the allocation of time. *The Economic Journal*, 125(583):410–442.

CMA (2020). Online platforms and digital advertising: Market study final report. Technical report, UK Competition and Markets Authority.

Collis, A. and Eggers, F. (2022). Effects of restricting social media usage on wellbeing and performance: A randomized control trial among students. *PLOS ONE*, 17(8):1–22.

Conlon, C. and Mortimer, J. H. (2021). Empirical properties of diversion ratios. *RAND Journal of Economics*, 52(4):693–726.

Corrigan, J. R., Alhabash, S., Rousu, M., and Cash, S. B. (2018). How much is social media worth? estimating the value of facebook by paying users to stop using it. *PLOS ONE*, 13(12):1–11.

Czibor, E., Jimenez-Gomez, D., and List, J. A. (2019). The dozen things experimental economists should do (more of). *Southern Economic Journal*, 86(2):371–432.

Evans, D. S. (2013). Attention rivalry among online platforms. *Journal of Competition Law Economics*, 9(2):313–357.

Facebook, Inc. (2021). Memorandum in support of defendant's motion to dismiss. Court Filing. Federal Trade Commission v. Facebook, Inc., No. 1:20-cv-03590-JEB (D.D.C. Oct. 4, 2021).

Froeb, L. M. and Werden, G. J. (1992). The reverse cellophane fallacy in market delineation. *Review of Industrial Organization*, 7:241–274.

FTC (2021). Amended complaint for injunctive and other equitable relief. Court Filing. Federal Trade Commission v. Facebook, Inc., No. 1:20-cv-03590-JEB (D.D.C. Aug. 19, 2021).

Ghanem, D., Hirshleifer, S., and Ortiz-Beccera, K. (2023). Testing attrition bias in field experiments. *Journal of Human Resources*.

Giuntella, O., Hyde, K., Saccardo, S., and Sadoff, S. (2021). Lifestyle and mental health disruptions during covid-19. *Proceedings of the National Academy of Sciences*, 118(9):e2016632118.

Guess, A. M., Malhotra, N., Pan, J., Barberá, P., Allcott, H., Brown, T., Crespo-Tenorio, A., Dimmery, D., Freelon, D., Gentzkow, M., González-Bailón, S., Kennedy, E., Kim, Y. M., Lazer, D., Moehler, D., Nyhan, B., Rivera, C. V., Settle, J., Thomas, D. R., Thorson, E., Tromble, R., Wilkins, A., Wojcieszak, M., Xiong, B., de Jonge, C. K., Franco, A., Mason, W., Stroud, N. J., and Tucker, J. A. (2023). How do social media feed algorithms affect attitudes and behavior in an election campaign? *Science*, 381(6656):398–404.

Haaland, I., Roth, C., and Wohlfart, J. (2023). Designing information provision experiments. *Journal of economic literature*, 61(1):3–40.

Harrison, G. W. and List, J. A. (2004). Field experiments. *Journal of Economic Literature*, 42(4):1009–1055.

Hausman, J., Moresi, S., and Rainey, M. (2011). Unilateral effects of mergers with general linear demand. *Economics Letters*, 111(2):119–121.

Heckman, J. J. (2015). Introduction to a theory of the allocation of time by gary becker. *The Economic Journal*, 125(583):403–409.

Jaffe, S. and Weyl, E. G. (2013). The first-order approach to merger analysis. *American Economic Journal: Microeconomics*, 5(4):188–218.

Jullien, B., Pavan, A., and Rysman, M. (2021). Two-sided markets, pricing, and network effects. In *Handbook of Industrial Organization*, volume 4, pages 485–592. Elsevier.

Kaplow, L. (2025). Improving economic analysis in merger guidelines. *Journal of Economic Perspectives*, 39(1):29–52.

Katz, J. and Allcott, H. (2025). Digital media mergers: Theory and application to facebook-instagram. Working Paper 34028, National Bureau of Economic Research.

List, J. A. (2025). *Experimental Economics: Theory and Practice*. University of Chicago Press, 1st edition. Forthcoming.

List, J. A., Shaikh, A. M., and Xu, Y. (2019). Multiple hypothesis testing in experimental economics. *Experimental Economics*, 22(4):773–793.

Morton, F. M. S. and Dinielli, D. C. (2022). Roadmap for an antitrust case against facebook. *Stanford Journal of Law, Business Finance*, 27(2):268–317.

Mosquera, R., Odunowo, M., McNamara, T., Guo, X., and Petrie, R. (2020). The economic effects of Facebook. *Experimental Economics*, 23(2):575–602.

Nelson, P. (2015). Monopoly power, market definition, and the cellophane fallacy. *FTC Memo*.

O'Brien, D. and Wickelgren, A. (2003). A critical analysis of critical loss analysis. *Antitrust Law Journal*, 71(1):161–184.

Renner, C. (2020). An analysis of the 'road-map for an antitrust case against facebook'. SSRN Working Paper.

Rochet, J.-C. and Tirole, J. (2006). Two-sided markets: a progress report. *The RAND Journal of Economics*, 37(3):645–667.

Romano, J. P. and Wolf, M. (2016). Efficient computation of adjusted p-values for resampling-based stepdown multiple testing. *Statistics & Probability Letters*, 113:38–40.

Rubin, M. (2021). When to adjust alpha during multiple testing: A consideration of disjunction, conjunction, and individual testing. *Synthese*, 199(3):10969–11000.

Shapiro, C. (1996). Mergers with differentiated products. *Antitrust*.

Stevenson, J. and Stevenson, J. (2021). Application names, android package name, and id. *Android Software Internals Quick Reference: A Field Manual and Security Reference Guide to Java-based Android Components*, pages 51–60.

Valletti, T. and Zenger, H. (2021). Mergers with differentiated products: Where do we stand? *Review of Industrial Organization*, 58:179–212.

Wu, T. (2019). Blind spot: The attention economy and the law. *Antitrust Law Journal*, 82(3):pp. 771–806.

Meta Internal Documents

Meta, Internal Doc. (0051). PALM-005188590.

Meta, Internal Doc. (0119). PALM-011945678.

Meta, Internal Doc. (0122). PALM-012283618.

Meta, Internal Doc. (0123a). PALM-012326587.

Meta, Internal Doc. (0123b). PALM-012326467.

Meta, Internal Doc. (0143). Is there a network effect that we're not measuring? PALM-014393921.

Meta, Internal Doc. (0170a). PALM-017052280.

Meta, Internal Doc. (0170b). PALM-017052282.

Online Appendix (For Online Publication Only)

"Consumer Demand and Market Competition with Time-Intensive Goods"

July 2025

A Theoretical Derivations of Time Shares, and Diversion Ratios in Model from Section 2

A.1 Proof of Proposition 1

Proof. Let us define the non-time component of the full price for every commodity $i \in \mathcal{Z}$: $\pi_i \equiv \kappa_i \alpha_i + p_i$. We can re-write the first-order conditions of the model (4) and (5) as a function of $\{\pi_i\}_{i\in\mathcal{Z}}$ instead of their individual components:

$$\gamma \left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho} + \sum_{i=P+1}^{N} \omega_i z_i^{\rho}\right)^{\frac{\gamma}{\rho}-1} \omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho-1} \left(\sum_{i=0}^{P} \delta_i z_i^{\theta}\right)^{\frac{1}{\theta}-1} \delta_k z_k^{\theta-1} = \nu + \pi_k, \ \forall k \in \mathcal{P}$$

and

$$\gamma \left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho} + \sum_{i=P+1}^{N} \omega_i z_i^{\rho}\right)^{\frac{\gamma}{\rho}-1} \omega_g z_g^{\rho-1} = \nu + \pi_g, \ \forall g \in \mathcal{Z} \setminus \mathcal{P}$$

The system of equations defined by these first-order conditions fully determine the equilibrium choices of each commodity. Note that, written as a function of $\{\pi_i\}_{i\in\mathcal{Z}}$, the individual components ($\kappa_i\alpha_i$ and p_i) of the non-time portion of the full price disappear from the system. Applying the implicit function theorem, one can derive the own- and cross-price responses of any commodity i to a change in π_j.

Therefore, it is clear that, for any two commodities i and j:

$$\begin{aligned} \frac{\partial z_j}{\partial p_j} &= \frac{\partial z_j}{\partial \pi_j}\frac{\partial \pi_j}{\partial p_j} = \frac{\partial z_j}{\partial \pi_j} \\ \frac{\partial z_j}{\partial \alpha_j} &= \frac{\partial z_j}{\partial \pi_j}\frac{\partial \pi_j}{\partial \alpha_j} = \kappa_j \frac{\partial z_j}{\partial \pi_j}, \end{aligned}$$

and similarly:

$$\begin{aligned} \frac{\partial z_i}{\partial p_j} &= \frac{\partial z_i}{\partial \pi_j}\frac{\partial \pi_j}{\partial p_j} = \frac{\partial z_i}{\partial \pi_j} \\ \frac{\partial z_i}{\partial \alpha_j} &= \frac{\partial z_i}{\partial \pi_j}\frac{\partial \pi_j}{\partial \alpha_j} = \kappa_j \frac{\partial z_i}{\partial \pi_j}, \end{aligned}$$

The result in Proposition 1 follows directly. □

A.2 Deriving the time shares and related elasticities

In this section, we derive three important objects: the time shares (ψ_i^H), the spending shares (ψ_i^S), and the response of total leisure time to a change in a commodity's non-time price ($\frac{d\ln H}{d\ln \pi_j}$). In the first part of the section, we show how we recover each object needed for the shares. Then, in the second section we show how we get the elasticity of total leisure time. These three objects, as well as many of the other objects that we derive in this section, are used to derive the diversion ratios in section A.3.

A.2.1 Derivations of the consumption shares (ψ_i^H)

Step 1: Demand for individual PSN commodity z_k ($\forall k \in \mathcal{P}$) conditional on composite PSN demand $z_{\mathcal{P}}$

Recall the first-order conditions for PSN commodities ($\forall k \in \mathcal{P}$):

$$\gamma \left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho} + \sum_{i=P+1}^{N} \omega_i z_i^{\rho}\right)^{\frac{\gamma}{\rho}-1} \omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho-1} \left(\sum_{i=0}^{P} \delta_i z_i^{\theta}\right)^{\frac{1}{\theta}-1} \delta_k z_k^{\theta-1} = \underbrace{\nu + \kappa_k \alpha_k + p_k}_{\equiv P_k}, \tag{4}$$

Evaluate (4) for two PSN commodities j and k, take their ratio, and re-arrange:

$$z_j = \left(\frac{P_j}{P_k}\frac{\delta_k}{\delta_j}\right)^{\frac{1}{\theta-1}} z_k \tag{A.1}$$

Let us raise both sides of (A.1) to exponent θ, and multiply by δ_j:

$$\delta_j z_j^{\theta} = \delta_j^{\frac{1}{1-\theta}} P_j^{\frac{\theta}{\theta-1}} \left(\frac{\delta_k}{P_k}\right)^{\frac{\theta}{\theta-1}} z_k^{\theta} \tag{A.2}$$

Summing both sides of (A.2) across all $j \in \mathcal{P}$, then raising to exponent $1/\theta$, we obtain:

$$z_{\mathcal{P}} \equiv \left(\sum_{j\in\mathcal{P}} \delta_j z_j^{\theta}\right)^{\frac{1}{\theta}} = \left[\sum_{j\in\mathcal{P}} \delta_j^{\frac{1}{1-\theta}} P_j^{\frac{\theta}{\theta-1}}\right]^{\frac{1}{\theta}} \left(\frac{\delta_k}{P_k}\right)^{\frac{1}{\theta-1}} z_k \tag{A.3}$$

Like in the main text, let us define $\overline{P}_{\mathcal{P}} \equiv \left[\sum_{j\in\mathcal{P}} \delta_j^{\frac{1}{1-\theta}} P_j^{\frac{\theta}{\theta-1}}\right]^{\frac{\theta-1}{\theta}}$ as the price index for the composite PSN commodity $z_{\mathcal{P}}$. We can re-arrange (A.3):

$$z_k = \left(\delta_k \frac{\overline{P}_{\mathcal{P}}}{P_k}\right)^{\frac{1}{1-\theta}} z_{\mathcal{P}}, \ \forall k \in \mathcal{P} \tag{A.4}$$

Step 2: Two useful intermediary results.

First, start from (A.4), multiply both sides by the full price P_k and sum across $k \in \mathcal{P}$. We obtain:

$$\sum_{k\in\mathcal{P}} P_k z_k = \underbrace{\left[\sum_{k\in\mathcal{P}} \delta_k^{\frac{1}{1-\theta}} P_k^{\frac{\theta}{\theta-1}}\right]}_{\equiv \overline{P}_{\mathcal{P}}^{\frac{\theta}{\theta-1}}} \overline{P}_{\mathcal{P}}^{\frac{1}{1-\theta}} z_{\mathcal{P}}$$

Thus, we can define total spending on PSN commodities:

$$S_{\mathcal{P}} \equiv \sum_{k\in\mathcal{P}} P_k z_k = \overline{P}_{\mathcal{P}} \times z_{\mathcal{P}} \tag{A.5}$$

Further, we can define the total spending on all commodities:

$$S \equiv \overline{P}_{\mathcal{P}} z_{\mathcal{P}} + \sum_{g \in \mathcal{Z} \setminus \mathcal{P}} P_g z_g \tag{A.6}$$

Second, let us start from (4), multiply both sides by z_k, then sum across all $k \in \mathcal{P}$, we obtain:

$$\gamma \left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho} + \sum_{i=P+1}^{N} \omega_i z_i^{\rho} \right)^{\frac{\gamma}{\rho}-1} \omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho} = \underbrace{\sum_{k \in \mathcal{P}} P_k z_k}_{\equiv S_{\mathcal{P}}} \tag{A.7}$$

Dividing both sides of (A.7) by $z_{\mathcal{P}}$ and using (A.5), we obtain:

$$\gamma \left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho} + \sum_{i=P+1}^{N} \omega_i z_i^{\rho} \right)^{\frac{\gamma}{\rho}-1} \omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho-1} = \overline{P}_{\mathcal{P}} \tag{A.8}$$

which is an analog to the first-order conditions for non-PSN commodities (5) but for the composite PSN commodity $z_{\mathcal{P}}$.

Step 3: Derive total time spent on PSN commodities ($H_{\mathcal{P}}$)

Let us denote total leisure time by $H = \sum_{i \in \mathcal{Z}} z_i$, and total time spent on PSN commodities by $H_{\mathcal{P}} \equiv \sum_{k \in \mathcal{P}} z_k$. Using (A.4), we have:

$$H_{\mathcal{P}} = \frac{\sum_{k \in \mathcal{P}} \delta_k^{\frac{1}{1-\theta}} P_k^{\frac{1}{\theta-1}}}{\overline{P}_{\mathcal{P}}^{\frac{1}{\theta-1}}} z_{\mathcal{P}} \equiv \Lambda_{\mathcal{P}} z_{\mathcal{P}} \tag{A.9}$$

where we defined $\Lambda_{\mathcal{P}} \equiv \frac{\sum_{k \in \mathcal{P}} \delta_k^{\frac{1}{1-\theta}} P_k^{\frac{1}{\theta-1}}}{\overline{P}_{\mathcal{P}}^{\frac{1}{\theta-1}}}$. Note that, under the assumption that $\tau_k = \tau_{\mathcal{P}}$ $\forall k \in \mathcal{P}$ (see page 9), we have that $\Lambda_{\mathcal{P}}$ is a constant:

$$\Lambda_{\mathcal{P}} = \left[\sum_{k \in \mathcal{P}} \delta_k^{\frac{1}{1-\theta}} \right]^{\frac{\theta-1}{\theta}} = 1 \tag{A.10}$$

The second equality directly follows from the normalization imposed on $\delta_0, ..., \delta_P$ (see page 8). Intuitively, this normalization allows to measure the composite PSN commodity $z_{\mathcal{P}}$ in number of minutes spent (on all PSN commodities) whenever their full price P_k is equalized across all $k \in \mathcal{P}$.

Step 4: Derive demand for non-PSN commodity z_g ($\forall g \in \mathcal{Z} \setminus \mathcal{P}$) conditional on total Leisure time H

Recall the first-order conditions for non-PSN commodities ($\forall g \in \mathcal{Z} \setminus \mathcal{P}$):

$$\gamma \left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho} + \sum_{i=P+1}^{N} \omega_i z_i^{\rho} \right)^{\frac{\gamma}{\rho}-1} \omega_g z_g^{\rho-1} = \underbrace{\nu + \kappa_g \alpha_g + p_g}_{\equiv P_g} \tag{5}$$

Evaluate (5) for two non-PSN commodities j and g, take their ratio, and re-arrange:

$$z_j = \left(\frac{P_j}{P_g}\frac{\omega_g}{\omega_j}\right)^{\frac{1}{\rho-1}} z_g \tag{A.11}$$

Similarly, evaluate (5) for non-PSN commodity g and take the ratio with (A.8):

$$z_{\mathcal{P}} = \left(\frac{\overline{P}_{\mathcal{P}}}{P_g}\frac{\omega_g}{\omega_{\mathcal{P}}}\right)^{\frac{1}{\rho-1}} z_g \tag{A.12}$$

Plugging (A.12) into (A.9), and using the normalization $\Lambda_{\mathcal{P}} = 1$, we have, $\forall g \in \mathcal{Z} \setminus \mathcal{P}$:

$$H_{\mathcal{P}} = \left(\frac{\overline{P}_{\mathcal{P}}}{P_g}\frac{\omega_g}{\omega_{\mathcal{P}}}\right)^{\frac{1}{\rho-1}} z_g \tag{A.13}$$

Using (A.11) and summing across all non-PSN commodities, we have:

$$\sum_{j\in\mathcal{Z}\setminus\mathcal{P}} z_j = \left[\sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{1}{\rho-1}}\right] \omega_g^{\frac{1}{\rho-1}} P_g^{\frac{1}{1-\rho}} z_g \tag{A.14}$$

Summing (A.13) and (A.14), we have:

$$H = H_{\mathcal{P}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} z_j = \left[\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{1}{\rho-1}}\right] \omega_g^{\frac{1}{\rho-1}} P_g^{\frac{1}{1-\rho}} z_g$$

Re-arranging yields the demand for non-PSN commodity z_g conditional on total leisure time:

$$z_g = \frac{\omega_g^{\frac{1}{1-\rho}} P_g^{\frac{1}{\rho-1}}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{1}{\rho-1}}} H, \ \forall g \in \mathcal{Z} \setminus \mathcal{P} \tag{A.15}$$

The expression for the share $\psi_g^H \equiv z_g/H$ follows directly from (A.15).

Step 5: Derive demand for composite PSN $z_{\mathcal{P}}$ conditional on total leisure time.

Re-arranging (A.12) to isolate z_g then plugging into (A.15), we obtain the demand for the composite PSN $z_{\mathcal{P}}$ conditional on total leisure:

$$z_{\mathcal{P}} = \frac{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{1}{\rho-1}}} H \tag{A.16}$$

Step 6: Derive demand for individual PSN commodities z_k ($\forall k \in \mathcal{P}$) conditional on total leisure time H

Lastly, we can derive the demand for individual PSN commodities as a function of total time spent on PSNs ($H_{\mathcal{P}}$). Indeed, starting from (A.1), summing across all $j \in \mathcal{P}$, and re-arranging:

$$z_k = \frac{\delta_k^{\frac{1}{1-\theta}} P_k^{\frac{1}{\theta-1}}}{\sum_{j\in\mathcal{P}} \delta_j^{\frac{1}{1-\theta}} P_j^{\frac{1}{\theta-1}}} H_{\mathcal{P}},\ \forall k \in \mathcal{P} \tag{A.17}$$

Recall that, under the normalization $\Lambda_{\mathcal{P}} = 1$, we have $z_{\mathcal{P}} = H_{\mathcal{P}}$. The expression for the share ψ_k^H, $\forall k \in \mathcal{P}$, follows from plugging $H_{\mathcal{P}} = z_{\mathcal{P}}$ into (A.16), plugging the resulting expression into (A.17), and dividing by H.

A.2.2 Response of total leisure time H to a change in price p_j

Step 1: define and derive expressions for the spending shares ψ_j^S and $\psi_{\mathcal{P}}^S$.

Let us Denote "full spending" on all commodities by $S \equiv \sum_{l\in\mathcal{Z}} P_l z_l$. Let $\psi_j^S \equiv \frac{P_j z_j}{\sum_{i=0}^N P_i z_i}$ be the share of j in full spending, and $\psi_{\mathcal{P}}^S \equiv \frac{\sum_{k\in\mathcal{P}} P_k z_k}{\sum_{i=0}^N P_i z_i}$ be the total share of PSN commodities in full spending. We first derive an expression for the spending shares.

Multiply both sides of (A.11) by P_j and sum across all non-PSN commodities:

$$\sum_{j\in\mathcal{Z}\setminus\mathcal{P}} P_j z_j = \left[\sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{\rho}{\rho-1}}\right] \left(\frac{\omega_g}{P_g}\right)^{\frac{1}{\rho-1}} z_g \tag{A.18}$$

Multiply both sides of (A.12) by $\overline{P}_{\mathcal{P}}$ and sum with (A.18) to obtain:

$$\underbrace{\overline{P}_{\mathcal{P}} z_{\mathcal{P}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} P_j z_j}_{=\sum_{j\in\mathcal{Z}} P_j z_j \equiv S \text{ by (A.6)}} = \left[\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{\rho}{\rho-1}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{\rho}{\rho-1}}\right] \left(\frac{\omega_g}{P_g}\right)^{\frac{1}{\rho-1}} z_g \tag{A.19}$$

We can re-arrange (A.19) into the conditional demand for individual non-PSN commodities:

$$z_g = \frac{\omega_g^{\frac{1}{1-\rho}} P_g^{\frac{1}{\rho-1}}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{\rho}{\rho-1}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{\rho}{\rho-1}}} S,\ \forall g \in \mathcal{Z} \setminus \mathcal{P} \tag{A.20}$$

Similarly, we can write the conditional demand for the composite PSN commodity:

$$z_{\mathcal{P}} = \frac{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{\rho}{\rho-1}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{\rho}{\rho-1}}} S \tag{A.21}$$

Lastly, plugging (A.21) into (A.4), we obtain the conditional demand for individual PSN commodities:

$$z_k = \left(\frac{\delta_k}{P_k} \overline{P}_{\mathcal{P}}\right)^{\frac{1}{1-\theta}} \left[\frac{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{\rho}{\rho-1}} + \sum_{j\in\mathcal{Z}\setminus\mathcal{P}} \omega_j^{\frac{1}{1-\rho}} P_j^{\frac{\rho}{\rho-1}}}\right] S \tag{A.22}$$

The expressions for the shares of full spending ψ_k^S ($\forall k \in \mathcal{P}$), ψ_g^S ($\forall g \in \mathcal{Z} \setminus \mathcal{P}$), and $\psi_{\mathcal{P}}^S$ follow from multiplying the conditional demands in (A.20), (A.21), and (A.22) by the relevant full price and dividing by S.

Step 2: Characterizing total leisure time H.

Multiply both sides of (5) by z_g, multiply both sides of (4) by z_k, then sum across all $g \in \mathcal{Z} \setminus \mathcal{P}$, and all $k \in \mathcal{P}$, we obtain:

$$\overline{P}_{\mathcal{P}} z_{\mathcal{P}} + \sum_{g \in \mathcal{Z} \setminus \mathcal{P}} P_g z_g = \gamma \left(\omega_{\mathcal{P}} z_{\mathcal{P}}^{\rho} + \sum_{g \in \mathcal{Z} \setminus \mathcal{P}} \omega_g z_g^{\rho} \right)^{\frac{\gamma}{\rho}} \tag{A.23}$$

Plugging (A.15) and (A.16) into (A.23), then re-arranging, we have:

$$H = \gamma^{\frac{1}{1-\gamma}} \left[\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}} + \sum_{g \in \mathcal{Z} \setminus \mathcal{P}} \omega_g^{\frac{1}{1-\rho}} P_g^{\frac{1}{\rho-1}} \right] \times \left[\omega_{\mathcal{P}}^{\frac{1}{1-\rho}} \overline{P}_{\mathcal{P}}^{\frac{\rho}{\rho-1}} + \sum_{g \in \mathcal{Z} \setminus \mathcal{P}} \omega_g^{\frac{1}{1-\rho}} P_g^{\frac{\rho}{\rho-1}} \right]^{\frac{(\gamma-1)-(\rho-1)}{\rho(1-\gamma)}} \tag{A.24}$$

Step 3: Derive the response of total leisure time.

Similar to Section A.1, let us define the non-time component of the full price for every commodity $j \in \mathcal{Z}$: $\pi_j \equiv \kappa_j \alpha_j + p_j$. We focus on deriving the response to a change in π_j for PSN commodity $j \in \mathcal{P}$.

Some helpful intermediary results. First, let us note that, since $\nu \equiv \eta w H^{\eta-1}$, we have:

$$\frac{d \ln \nu}{d \ln \pi_j} = (\eta - 1) \frac{d \ln H}{d \ln \pi_j} \tag{A.25}$$

Second, starting from the definition of $\overline{P}_{\mathcal{P}}$ and totally differentiating, we have:

$$\frac{d \ln \overline{P}_{\mathcal{P}}}{d \ln \pi_j} = \frac{\theta - 1}{\theta} \left[\frac{\theta}{\theta - 1} \sum_{k \in \mathcal{P}} \psi_k^{\mathcal{P},S} \frac{\nu}{\nu + \pi_k} \frac{d \ln \nu}{d \ln \pi_j} + \frac{\theta}{\theta - 1} \psi_j^{\mathcal{P},S} \frac{\pi_j}{\nu + \pi_j} \right]$$

Simplifying, and using the assumption that time-intensity is the same across all PSNs ($\frac{\nu}{\nu+\pi_i} \equiv \tau_i = \tau_{\mathcal{P}} \; \forall i \in \mathcal{P}$), we have:

$$\frac{d \ln \overline{P}_{\mathcal{P}}}{d \ln \pi_j} = \left[\tau_{\mathcal{P}} \frac{d \ln \nu}{d \ln \pi_j} + (1 - \tau_{\mathcal{P}}) \, \psi_j^{\mathcal{P},S} \right] \tag{A.26}$$

Another implication from the assumption that time-intensity is the same across all PSNs is that: $\psi_j^{\mathcal{P},S} \equiv \frac{(\nu+\pi_j)z_j}{\sum_{i \in \mathcal{P}} (\nu+\pi_i) z_i} = \frac{z_j}{\sum_{i \in \mathcal{P}} z_i}$.

Elasticity of total leisure time. Let us start from (A.24), take the log, and totally differentiate it with respect to $\ln \pi_j$. This gives us:

$$\frac{d\ln H}{d\ln \pi_j} = \frac{1}{\rho-1}\left[\frac{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}}\overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}\frac{d\ln \overline{P}_{\mathcal{P}}}{d\ln\pi_j}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}}\overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}+\sum_{g\in\mathcal{Z}\setminus\mathcal{P}}\omega_g^{\frac{1}{1-\rho}}P_g^{\frac{1}{\rho-1}}}\right]$$
$$+\frac{1}{\rho-1}\left[\frac{\sum_{g\in\mathcal{Z}\setminus\mathcal{P}}\omega_g^{\frac{1}{1-\rho}}P_g^{\frac{1}{\rho-1}}\frac{d\ln P_g}{d\ln\pi_j}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}}\overline{P}_{\mathcal{P}}^{\frac{1}{\rho-1}}+\sum_{g\in\mathcal{Z}\setminus\mathcal{P}}\omega_g^{\frac{1}{1-\rho}}P_g^{\frac{1}{\rho-1}}}\right]$$
$$+\frac{\gamma-\rho}{(\rho-1)(1-\gamma)}\left[\frac{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}}\overline{P}_{\mathcal{P}}^{\frac{\rho}{\rho-1}}\frac{d\ln \overline{P}_{\mathcal{P}}}{d\ln\pi_j}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}}\overline{P}_{\mathcal{P}}^{\frac{\rho}{\rho-1}}+\sum_{g\in\mathcal{Z}\setminus\mathcal{P}}\omega_g^{\frac{1}{1-\rho}}P_g^{\frac{\rho}{\rho-1}}}\right]$$
$$+\frac{\gamma-\rho}{(\rho-1)(1-\gamma)}\left[\frac{\sum_{g\in\mathcal{Z}\setminus\mathcal{P}}\omega_g^{\frac{1}{1-\rho}}P_g^{\frac{\rho}{\rho-1}}\frac{d\ln P_g}{d\ln\pi_j}}{\omega_{\mathcal{P}}^{\frac{1}{1-\rho}}\overline{P}_{\mathcal{P}}^{\frac{\rho}{\rho-1}}+\sum_{g\in\mathcal{Z}\setminus\mathcal{P}}\omega_g^{\frac{1}{1-\rho}}P_g^{\frac{\rho}{\rho-1}}}\right]$$

Using the definitions of the spending and time shares gives us:

$$\frac{d\ln H}{d\ln\pi_j} = \frac{\psi_{\mathcal{P}}^H}{\rho-1}\frac{d\ln\overline{P}_{\mathcal{P}}}{d\ln\pi_j}+\frac{1}{\rho-1}\sum_{g\in\mathcal{Z}\setminus\mathcal{P}}\psi_g^H\frac{d\ln P_g}{d\ln\pi_j}$$
$$+\frac{(\gamma-\rho)\psi_{\mathcal{P}}^S}{(\rho-1)(1-\gamma)}\frac{d\ln\overline{P}_{\mathcal{P}}}{d\ln\pi_j}+\frac{\gamma-\rho}{(\rho-1)(1-\gamma)}\sum_{g\in\mathcal{Z}\setminus\mathcal{P}}\psi_g^S\frac{d\ln P_g}{d\ln\pi_j}$$

Note that $\frac{d\ln P_g}{d\ln\pi_j} = \tau_g\frac{d\ln\nu}{d\ln\pi_j}\forall g\in\mathcal{Z}\setminus\mathcal{P}$ (and $g\neq j$). After plugging in (A.26), (A.25), and finally re-arranging, we obtain:

$$\frac{d\ln H}{d\pi_j} = -\psi_j^{\mathcal{P},S}(1-\tau_{\mathcal{P}})\times\underbrace{\frac{\frac{\gamma-\rho}{1-\rho}\psi_{\mathcal{P}}^S+\frac{1-\gamma}{1-\rho}\psi_{\mathcal{P}}^H}{1-\gamma+(\eta-1)\sum_{i=0}^N\left(\frac{\gamma-\rho}{1-\rho}\psi_i^S+\frac{1-\gamma}{1-\rho}\psi_i^H\right)\tau_i}}_{\equiv\Sigma_{\mathcal{P}}},\ \forall j\in\mathcal{P} \tag{A.27}$$

where $\psi_j^{\mathcal{P},S}\equiv\frac{(\nu+\pi_j)z_j}{\sum_{i\in\mathcal{P}}(\nu+\pi_i)z_i} = \psi_j^S/\psi_{\mathcal{P}}^S$.

A.3 Full expressions of the diversion ratios

A.3.1 Proof of Proposition 4

Proposition 4. *The diversion ratio between PSN origin commodity $j\in\mathcal{P}$ and PSN destination commodity $k\in\mathcal{P}$ is given by:*

$$D_{kj} = \frac{\psi_k^H}{\psi_j^H}\frac{\left[\frac{1}{1-\theta}-\frac{1}{1-\rho}\left(\left(1-\psi_{\mathcal{P}}^H\right)-\left(\tau_{\mathcal{P}}-\sum_{i=0}^N\psi_i^H\tau_i\right)(\eta-1)\Sigma_{\mathcal{P}}\right)-\Sigma_{\mathcal{P}}\right]\psi_j^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right)+\left[\frac{1}{1-\rho}\left((1-\psi_{\mathcal{P}}^H)-\left(\tau_{\mathcal{P}}-\sum_{i=0}^N\psi_i^H\tau_i\right)(\eta-1)\Sigma_{\mathcal{P}}\right)+\Sigma_{\mathcal{P}}\right]\psi_j^{\mathcal{P},S}}$$

Proof. Let us start from the conditional demand for some PSN commodity $k\in\mathcal{P}$ given by (A.4). Totally (log) differentiate with respect to $\pi_j\equiv\kappa_j\alpha_j+p_j$, and plug in (A.25), (A.26), and (A.27) in order to obtain $\frac{d\ln z_k}{d\pi_j}$ as a function of $\frac{d\ln z_{\mathcal{P}}}{d\pi_j}$:

$$\begin{aligned}\frac{d\ln z_k}{d\pi_j} &= \frac{\eta-1}{\pi_j(1-\theta)}\frac{d\ln H}{d\ln\pi_j}(\tau_{\mathcal{P}}-\tau_k)+\frac{1-\tau_{\mathcal{P}}}{\pi_j(1-\theta)}\psi_j^{\mathcal{P},S}+\frac{d\ln z_{\mathcal{P}}}{d\pi_j}\\ &= \frac{1-\tau_{\mathcal{P}}}{\pi_j(1-\theta)}\psi_j^{\mathcal{P},S}+\frac{d\ln z_{\mathcal{P}}}{d\pi_j}\end{aligned}$$

The second line above follows by assumption that all PSN commodities are equally time intensive (i.e. $\tau_k=\tau_{\mathcal{P}}$).

Next, totally differentiate (with respect to π_j) the (log) conditional demand for composite PSN $z_{\mathcal{P}}$ given by (A.16), and plug in (A.25), and (A.26), in order to obtain $\frac{d\ln z_{\mathcal{P}}}{d\pi_j}$ (where $\frac{d\ln H}{d\ln\pi_j}$ is given by (A.27)):

$$\frac{d\ln z_{\mathcal{P}}}{d\pi_j}=\frac{1}{\pi_j}\frac{d\ln H}{d\ln\pi_j}\left[1+\frac{\eta-1}{\rho-1}\left(\tau_{\mathcal{P}}-\sum_{i=0}^{N}\psi_i^H\tau_i\right)\right]+\psi_j^{\mathcal{P},S}(1-\tau_{\mathcal{P}})\frac{1-\psi_{\mathcal{P}}^H}{\pi_j(\rho-1)}$$

Combining yields the cross-price elasticity of z_k with respect to π_j:

$$\frac{d\ln z_k}{d\ln\pi_j}=\psi_j^{\mathcal{P},S}\frac{1-\tau_{\mathcal{P}}}{\tau_j}\left[\frac{1}{1-\theta}-\frac{1}{1-\rho}\left(\left(1-\psi_{\mathcal{P}}^H\right)-\left(\tau_{\mathcal{P}}-\sum_{i=0}^{N}\psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right)-\Sigma_{\mathcal{P}}\right]$$

Follow the same steps to derive the own-price elasticity of z_j with respect to π_j. We get the following expression for the own-price (semi-) elasticity conditional on $\frac{d\ln z_{\mathcal{P}}}{d\pi_j}$:

$$\frac{d\ln z_j}{d\pi_j}=\frac{1-\tau_{\mathcal{P}}}{\pi_j(1-\theta)}\psi_j^{\mathcal{P},S}-\frac{1-\tau_j}{\pi_j(1-\theta)}+\frac{d\ln z_{\mathcal{P}}}{d\pi_j}$$

Plugging in the expression for $\frac{d\ln z_{\mathcal{P}}}{d\pi_j}$ yields:

$$\begin{aligned}\frac{d\ln z_j}{d\pi_j} &= -\frac{1-\tau_{\mathcal{P}}}{\pi_j}\\ &\times\left\{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right)+\left[\frac{1}{1-\rho}\left(\left(1-\psi_{\mathcal{P}}^H\right)-\left(\tau_{\mathcal{P}}-\sum_{i=0}^{N}\psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right)+\Sigma_{\mathcal{P}}\right]\psi_j^{\mathcal{P},S}\right\}\end{aligned}$$

Then:

$$D_{kj}\equiv-\frac{\partial z_k/\partial\pi_j}{\partial z_j/\partial\pi_j}=-\frac{\partial\ln z_k/\partial\pi_j}{\partial\ln z_j/\partial\pi_j}\times\frac{\psi_k^H}{\psi_j^H}$$

Plugging in the expressions for $\partial\ln z_k/\partial\pi_j$ and $\partial\ln z_j/\partial\pi_j$, we obtain the desired result.

□

A.3.2 Proof of Proposition 5

Proposition 5. *The diversion ratio between PSN origin commodity $j \in \mathcal{P}$ and non-PSN destination commodity $g \in \mathcal{Z} \setminus \mathcal{P}$ is given by:*

$$D_{gj} = \frac{\psi_g^H}{\psi_j^H} \frac{\left[\frac{1}{1-\rho}\left(\psi_{\mathcal{P}}^H + \left(\tau_g - \sum_{i=0}^N \psi_i^H \tau_i\right)(\eta-1)\Sigma_{\mathcal{P}}\right) - \Sigma_{\mathcal{P}}\right]\psi_j^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right) + \left[\frac{1}{1-\rho}\left((1-\psi_{\mathcal{P}}^H) - \left(\tau_{\mathcal{P}} - \sum_{i=0}^N \psi_i^H \tau_i\right)(\eta-1)\Sigma_{\mathcal{P}}\right) + \Sigma_{\mathcal{P}}\right]\psi_j^{\mathcal{P},S}}$$

Proof. Let us start from the conditional demand for some non-PSN commodity $g \in \mathcal{Z} \setminus \mathcal{P}$ given by (A.15). Take the log, totally differentiate with respect to $\pi_j \equiv \kappa_j \alpha_j + p_j$, and plug in (A.25), (A.26), and (A.27) in order to obtain the cross-price elasticity $\frac{d \ln z_g}{d \pi_j}$:

$$\frac{d \ln z_g}{d \pi_j} = \frac{1-\tau_{\mathcal{P}}}{\pi_j}\psi_j^{\mathcal{P},S}\left[\frac{1}{1-\rho}\left(\psi_{\mathcal{P}}^H + \left(\tau_g - \sum_{i=0}^N \psi_i^H \tau_i\right)(\eta-1)\Sigma_{\mathcal{P}}\right) - \Sigma_{\mathcal{P}}\right]$$

To obtain the own-price elasticity of z_j with respect to π_j, start from the conditional demand for $j \in \mathcal{P}$ given by (A.4). Totally (log) differentiate with respect to π_j, and plug in (A.25), (A.26), and (A.27) in order to obtain $\frac{d \ln z_j}{d \pi_j}$ as a function of $\frac{d \ln z_{\mathcal{P}}}{d \pi_j}$. Next, totally differentiate (with respect to π_j) the conditional demand for composite PSN $z_{\mathcal{P}}$ given by (A.16), and plug in (A.25), (A.26), and (A.27) in order to obtain $\frac{d \ln z_{\mathcal{P}}}{d \pi_j}$. Combining yields the own-price elasticity of z_j with respect to π_j (see Appendix A.3.1 for details). Then:

$$D_{gj} \equiv -\frac{\partial z_g / \partial \pi_j}{\partial z_j / \partial \pi_j} = -\frac{\partial \ln z_g / \partial \pi_j}{\partial \ln z_j / \partial \pi_j} \times \frac{\psi_g^H}{\psi_j^H}$$

Plugging in the expressions for $\partial \ln z_g / \partial \pi_j$ and $\partial \ln z_j / \partial \pi_j$, we obtain the desired result. □

A.4 Useful corollaries of the diversion ratios

A.4.1 Proof of Corollary 1

Proof. Assuming $\eta = 1$, the diversion ratio between PSN origin commodity $j \in \mathcal{P}$ and PSN destination commodity $k \in \mathcal{P}$ presented in Proposition 4 is now given by:

$$\begin{aligned}
D_{kj} &= \frac{\psi_k^H}{\psi_j^H} \frac{\left[\frac{1}{1-\theta} - \frac{1}{1-\rho}\left(1 + \frac{\gamma-\rho}{1-\gamma}\psi_{\mathcal{P}}^S\right)\right]\psi_j^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right) + \frac{1}{1-\rho}\left(1 + \frac{\gamma-\rho}{1-\gamma}\psi_{\mathcal{P}}^S\right)\psi_j^{\mathcal{P},S}} \\
&= \frac{\psi_k^H}{\psi_j^H} \frac{\left[\frac{1}{1-\theta} - \frac{1}{1-\rho}\left(1 + \frac{1-\rho-(1-\gamma)}{1-\gamma}\psi_{\mathcal{P}}^S\right)\right]\psi_j^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right) + \frac{1}{1-\rho}\left(1 + \frac{1-\rho-(1-\gamma)}{1-\gamma}\psi_{\mathcal{P}}^S\right)\psi_j^{\mathcal{P},S}} \\
&= \frac{\psi_k^H}{\psi_j^H} \frac{\left[\frac{1}{1-\theta} - \frac{1}{1-\rho}\left(1 - \psi_{\mathcal{P}}^S\right) - \frac{1}{1-\gamma}\psi_{\mathcal{P}}^S\right]\psi_j^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right) + \left[\frac{1}{1-\rho}(1-\psi_{\mathcal{P}}^S) + \frac{1}{1-\gamma}\psi_{\mathcal{P}}^S\right]\psi_j^{\mathcal{P},S}}
\end{aligned}$$

Similarly, the diversion ratio between PSN origin commodity $j \in \mathcal{P}$ and non-PSN destination commodity $g \in \mathcal{Z} \setminus \mathcal{P}$ presented in Proposition 5 is now given by:

$$\begin{aligned}
D_{gj} &= \frac{\psi_g^H}{\psi_j^H} \frac{\frac{1}{1-\rho}\left(\frac{\rho-\gamma}{1-\gamma}\right)\psi_j^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right)+\frac{1}{1-\rho}\left(1+\frac{\gamma-\rho}{1-\gamma}\psi_{\mathcal{P}}^S\right)\psi_j^{\mathcal{P},S}} \\
&= \frac{\psi_g^H}{\psi_j^H} \frac{\frac{1}{1-\rho}\left(\frac{1-\gamma-(1-\rho)}{1-\gamma}\right)\psi_j^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right)+\frac{1}{1-\rho}\left(1+\frac{1-\rho-(1-\gamma)}{1-\gamma}\psi_{\mathcal{P}}^S\right)\psi_j^{\mathcal{P},S}} \\
&= \frac{\psi_g^H}{\psi_j^H} \frac{\left[\frac{1}{1-\rho}-\frac{1}{1-\gamma}\right]\psi^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right)+\left[\frac{1}{1-\rho}\left(1-\psi_{\mathcal{P}}^S\right)+\frac{1}{1-\gamma}\psi_{\mathcal{P}}^S\right]\psi_j^{\mathcal{P},S}}
\end{aligned}$$

Note that, under $\eta = 1$:

$$\begin{aligned}
\Sigma_{\mathcal{P}} &= \frac{1}{1-\rho}\left(\frac{\gamma-\rho}{1-\gamma}\psi_P^S+\psi_P^H\right) \\
&= \frac{1}{1-\rho}\left(\left(\frac{1-\rho}{1-\gamma}-\frac{1-\gamma}{1-\gamma}\right)\psi_{\mathcal{P}}^S+\psi_{\mathcal{P}}^H\right) \\
&= \left(\frac{1}{1-\gamma}-\frac{1}{1-\rho}\right)\psi_{\mathcal{P}}^S+\frac{1}{1-\rho}\psi_{\mathcal{P}}^H
\end{aligned}$$

An inspection of the above expressions for D_{kj} and D_{gj} reveals that they are not a function of the relative time-intensity of j, or k (i.e., $\tau_{\mathcal{P}} - \sum_{i=0}^N \psi_i^H \tau_i$), nor are they a function of the relative time-intensity of g (i.e., $\tau_g - \sum_{i=0}^N \psi_i^H \tau_i$). □

A.4.2 Proof of Corollary 2

Proof. The result on relative diversion ratios follows immediately from the expressions for diversion ratios in Proposition 4 and 5. For the ratio of cross-price elasticities, we use $\frac{d\ln z_k}{d\ln p_j} = \frac{p_j}{z_k}\frac{dz_k}{dp_j}$ and $\frac{d\ln z_g}{d\ln p_j} = \frac{p_j}{z_g}\frac{dz_g}{dp_j}$. Therefore:

$$\frac{d\ln z_k/d\ln p_j}{d\ln z_g/d\ln p_j} = \frac{\psi_g^H}{\psi_k^H} \times \frac{D_{kj}}{D_{gj}}$$

□

A.4.3 Proof of Corollary 3

Proof. Let us start from Proposition 4, take the limit as $\theta \to 1$ and apply l'Hopital's rule: $\lim_{\theta\to 1} D_{kj} =$

$$\begin{aligned}
&\lim_{\theta\to 1}\frac{\psi_k^H}{\psi_j^H}\frac{\left[\frac{1}{1-\theta}-\frac{1}{1-\rho}\left(\left(1-\psi_{\mathcal{P}}^H\right)-\left(\tau_{\mathcal{P}}-\sum_{i=0}^N\psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right)-\Sigma_{\mathcal{P}}\right]\psi_j^{\mathcal{P},S}}{\frac{1}{1-\theta}\left(1-\psi_j^{\mathcal{P},S}\right)+\left[\frac{1}{1-\rho}\left(\left(1-\psi_{\mathcal{P}}^H\right)-\left(\tau_{\mathcal{P}}-\sum_{i=0}^N\psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right)+\Sigma_{\mathcal{P}}\right]\psi_j^{\mathcal{P},S}} \\
&= \frac{\psi_k^H}{\psi_j^H}\frac{\psi_j^{\mathcal{P},S}}{1-\psi_j^{\mathcal{P},S}}
\end{aligned}$$

Using the definitions of ψ_i^H and $\psi_i^{P,S}$, we have:

$$\lim_{\theta\to 1} D_{kj} = \frac{z_k/H}{z_j/H}\frac{\frac{(\nu+\alpha_j+p_j)z_j}{\sum_{i\in\mathcal{P}}(\nu+\alpha_i+p_i)z_i}}{1-\frac{(\nu+\alpha_j+p_j)z_j}{\sum_{i\in\mathcal{P}}(\nu+\alpha_i+p_i)z_i}}$$
$$= \frac{z_k}{z_j}\frac{\frac{(\nu+\alpha_j+p_j)z_j}{\nu}}{\sum_{i\in\mathcal{P}}\frac{(\nu+\alpha_i+p_i)z_i}{\nu}-\frac{(\nu+\alpha_j+p_j)z_j}{\nu}}$$

Using the assumption that relative time-intensity is equal across PSN commodities: $\tau_i^{-1} = \frac{(\nu+\alpha_i+p_i)z_i}{\nu} = \tau_{\mathcal{P}}^{-1}$:

$$\lim_{\theta\to 1} D_{kj} = \frac{z^k}{z^j}\frac{(1/\tau_{\mathcal{P}})z_j}{\sum_{i\in\mathcal{P}}(1/\tau_{\mathcal{P}})z_i-(1/\tau_{\mathcal{P}})z_j}$$
$$= \frac{z_k}{\sum_{i\in\mathcal{P}\setminus j} z_i}$$

□

A.5 The role of time-intensity and functionality in determining relative cross-price elasticities

We formally illustrate the role of time-intensity and functionality with Corollary 4 and 5. Each of these corollaries presents an expression for the ratio of cross-price elasticities in a special case of the model. Each special case corresponds to shutting down differences in either factor (relative time-intensity or functionality) so as to better emphasize the role of the remaining factor.

Corollary 4. *Assume $\theta = \rho$, and consider an increase in the price of PSN commodity $j \in \mathcal{P}$. Then, the ratio of cross-price elasticities for PSN commodity $k \in \mathcal{P}$ and non-PSN commodity $g \in \mathcal{Z} \setminus \mathcal{P}$ is given by:*

$$\frac{d\ln z_k/d\ln p_j}{d\ln z_g/d\ln p_j} = \frac{\frac{1}{1-\rho}\left(\psi_{\mathcal{P}}^H + \left(\tau_k - \sum_{i=0}^N \psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right)-\Sigma_{\mathcal{P}}}{\frac{1}{1-\rho}\left(\psi_{\mathcal{P}}^H + \left(\tau_g - \sum_{i=0}^N \psi_i^H\tau_i\right)(\eta-1)\,\Sigma_{\mathcal{P}}\right)-\Sigma_{\mathcal{P}}}$$

which depends crucially on the relative time-intensity of both goods.

Proof. Start from the expression for the ratio of cross-price elasticities in Corollary 2, plug in $\frac{1}{1-\theta} = \frac{1}{1-\rho}$, and simplify. □

Corollary 5. *Assume $\eta = 1$, and consider an increase in the price of PSN commodity $j \in \mathcal{P}$. Then, the ratio of cross-price elasticities for PSN commodity $k \in \mathcal{P}$ and non-PSN commodity $g \in \mathcal{Z} \setminus \mathcal{P}$ is given by:*

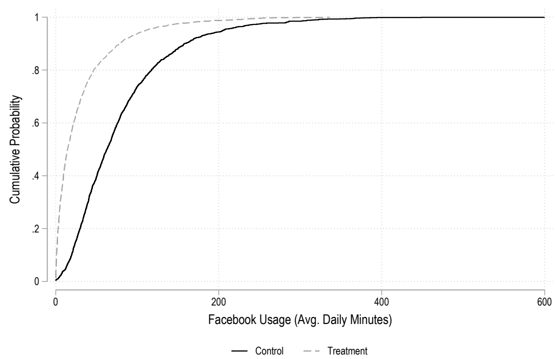
$$\frac{d\ln z_k/d\ln p_j}{d\ln z_g/d\ln p_j} = 1 + \frac{\frac{1}{1-\theta}-\frac{1}{1-\rho}}{\frac{1}{1-\rho}\psi_{\mathcal{P}}^H - \Sigma_{\mathcal{P}}}$$

which depends crucially on the relative substitutability of the two commodities with j (i.e. $\frac{1}{1-\theta}-\frac{1}{1-\rho}$)

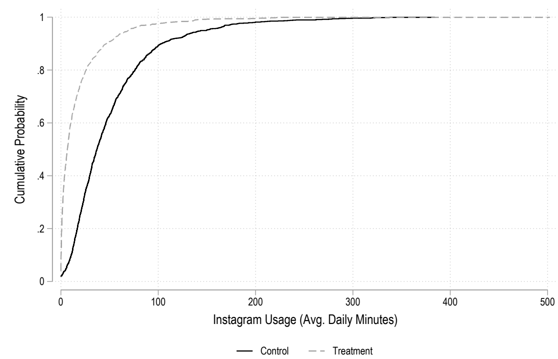
Proof. Start from the expression for the ratio of cross-price elasticities in Corollary 2, plug in $\eta = 1$, and simplify. $\square$

B Additional Experimental Results

Figure B.1: Differences in the Distribution of Focal App Usage



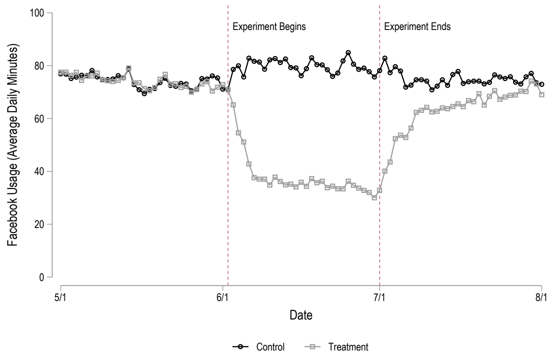
(a) Facebook



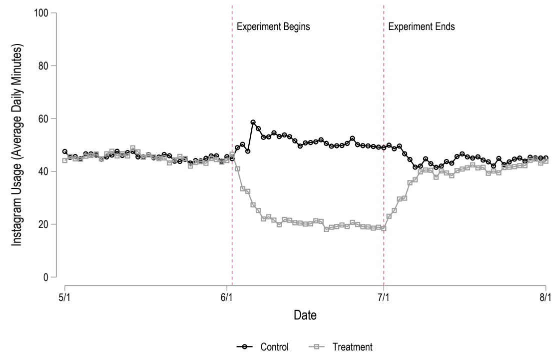
(b) Instagram

Note: Figure presents the CDF of usage of the focal app, averaged over all four weeks of the post period. Panel A displays Facebook usage for 3,418 observations. Panel B displays the Instagram usage for 2,708 observations.

Figure B.2: Daily Usage of Focal App



(a) Facebook



(b) Instagram

Note: Figure presents the average daily usage for the focal app from Meta data. Panel A displays Facebook usage for 325,500 user-day observations for 3,500 unique users. Panel B displays the Instagram usage for 257,424 user-day observations for 2,768 unique users.

Table B.1: Robustness: Ad Holdout Experiment (Facebook) by primary OS

	First-Stage		**Reduced-Form**		**Wald Estimate**	
Outcome variable:	Ad load		User Time			
	(1)		(2)		(3)	
		%	Min.	%	*Own-Resp.*	*Implied Elast.*
Panel (a): Facebook (Android users only)						
Estimates	-1.0	-100	1.7	8.9	-1.7	0.09
Panel (b): Facebook (iOS users only)						
Estimates	-1.0	-100	2.3	9.1	-2.3	0.09

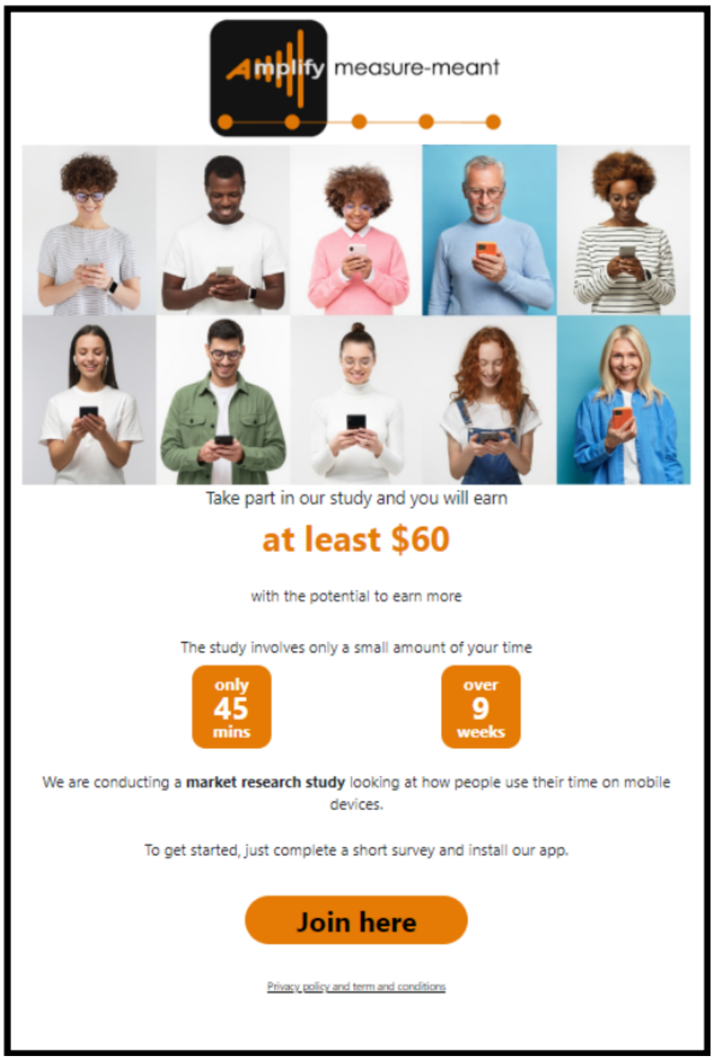
Notes: Based on U.S. data for exposed users as of January 2023. Restricted to users with an identified gender and age group and a primary OS of Android or iOS. Time use excludes FB messenger. Figures include inactive users. Ad load in (1) is defined as ad impressions as a percent of total impressions in June 2022. The reported values for ad load are normalized to reflect relative magnitudes compared to Facebook's ad load in June 2022.

C Pricing Experiment Materials

C.1 Recruitment

Participants were recruited through: (1) Facebook and Instagram ads; (2) ads placed directly with third-party publishers accessed through Toluna, which used its network of third-party publishers and affiliates, who recruited respondents directly to the study; and (3) firms that maintain panels of potential participants for internet-based market research, including Kantar, Prodege, Dynata, Symmetric Sampling, Dynata, QuestMindshare, Sago, ROI, MakeOpinion, ThinkNow, PureSpectrum, ValueMe and Luth. We directed interested participants to the landing page shown in Appendix Figure C.1.

Figure C.1: Recruitment Landing Page



C.2 Screener Survey Description

1. **Introduction:** Subjects received an introduction that explained the experiment, were asked to complete a Captcha to screen out automated programs, and respondents who

were detected to be using a device other than Android were removed from the study. We then obtained informed consent from the subjects. Participants who did not consent were excluded from the study. Finally, subjects had to acknowledge the Terms & Conditions, and the Privacy Policy.

2. **Demographics:** Subjects answered demographic questions on their gender, age, and primary state of residence.

3. **Facebook and/or Instagram use** Subjects were asked about their baseline Facebook and Instagram use before the experiment. Those who reported that they spent at least 15 minutes on Facebook and/or at least 10 minutes on Instagram were asked to move forward. Others were excluded.

4. **Device used to assess Facebook or Instagram** Next, we asked subjects about the device used to access the apps and whether they were the only user of the device used to access the apps.

5. **Attention Check and Participation in Other Studies:** Subjects needed to pass an attention check and declare whether they were the participants in other studies.

C.3 Dashboard

Figure C.2: Dashboard in Facebook Experiment

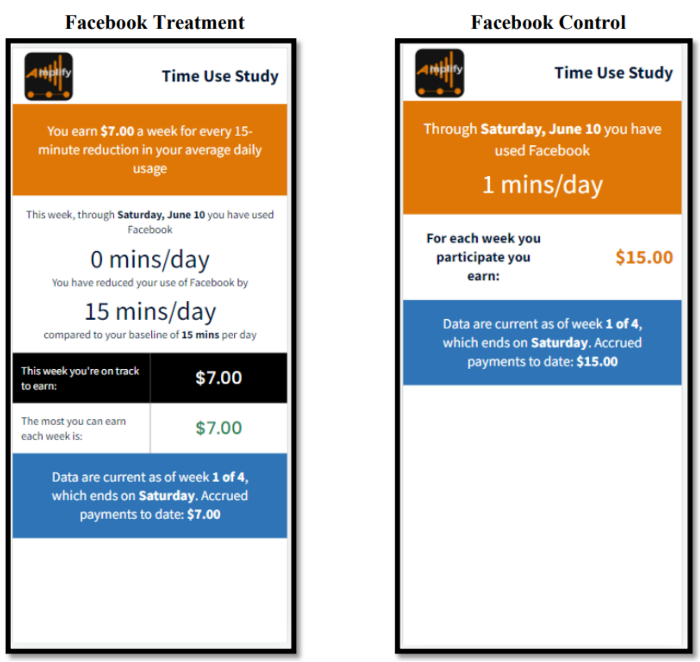
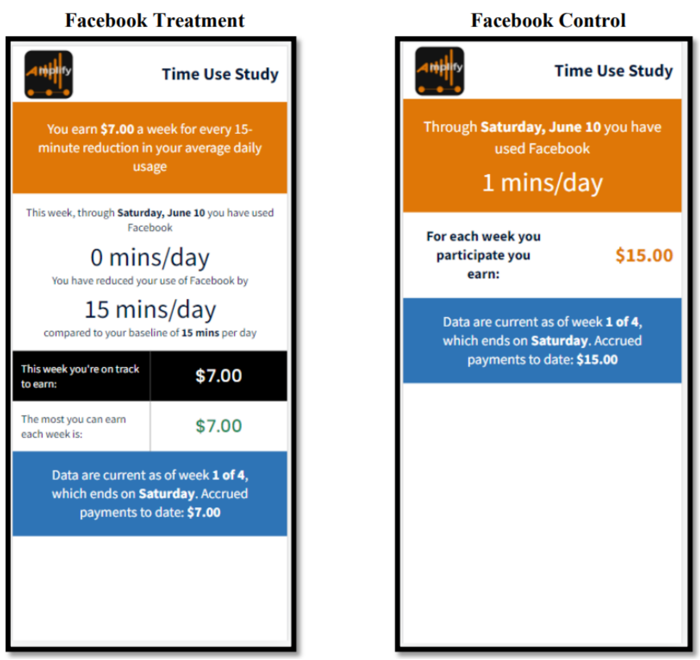
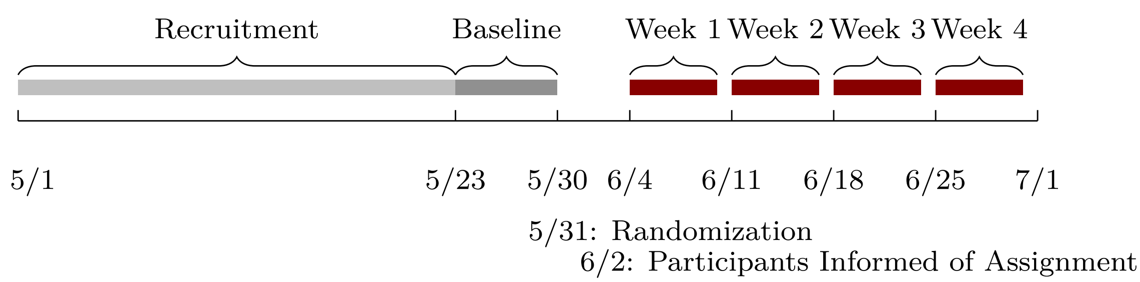


Figure C.3: Dashboard in Instagram Experiment



D Pricing Experiment Design and Analysis Details

Figure D.1: Experiment Timeline



D.1 Aggregation of Apps to Categories

In this section, we describe the method used to aggregate individual apps measured in the RealityMine data into the set of commodity categories used in the analysis. RealityMine assigns individual apps with a unique identifier associated with the application in the Google Play Store (Stevenson and Stevenson, 2021). We excluded apps that likely captured time spent on background activities rather than capturing the user's attention.

We first aggregated apps into the personal social network (PSN) category based on the proposed definitions in CMA (2020) and FTC (2021). The PSN category contains the non-focal Meta app (e.g., Facebook in the Instagram experiment) and Snapchat. The Non-PSN category contains all other phone apps that are not included in the definitions put forth by the FTC and CMA. Off-phone time is a residual category that contains offline time, time spent on other devices, and the excluded time spent on background activities.

Within non-PSN time, apps were aggregated into different categories. We considered Snapchat separately because it was proposed as the major competitor by CMA (2020) and FTC (2021). We further study YouTube, TikTok, and Messenger separately. YouTube and TikTok commanded a substantial share of attention from the average user relative to other apps. Messenger commanded a large share of user attention and required logging in with a Facebook account, which may suggest complementarity with Facebook.

We aggregated the remaining non-PSN apps into one of eight categories. We followed Aridor (2025) and aggregated apps into these categories based on the definition of Google Play Store, which aligns with the default way that RealityMine categorizes apps. In some cases, there was a direct correspondence between the RealityMine categories and the Google Play Store definitions. In other cases, RealityMine categories were more detailed than the aggregated categories we used in the analysis. In these cases, we mapped the RealityMine category to the less detailed category from the Google Play Store. We manually assigned some apps to the Google Play Store definitions when RealityMine failed to classify them. Table D.7 summarizes the mapping between the RealityMine and analysis categories.

Table D.1: Mapping from RealityMine Categories to Analysis Categories

Analysis Category	RealityMine Category	Description	Examples
Browser	Search	Accessing websites	Google Chrome, Safari
Communication	Communication	Texting & Messaging	SMS/MMS, Gmail, WhatsApp
Entertainment	Entertainment Music & Audio Photo & Video Media & Video	Leisure or having fun	Netflix, Spotify
Games	Card, Board, & Casino Puzzle & Trivia RPG & Simulation Action, Adventure, & Arcade Racing	Gaming apps	Coin Master, Candy Crush
Lifestyle	Lifestyle Social Networking Health & Fitness Dating House & Home Beauty Family	Fitness, dating, food	Twitter, Reddit, Pinterest
Productivity	Business & Finance Productivity	Aim to improve efficiency	CashApp, DoorDash, Uber
Shopping	Shopping	Browse and buy goods and services	Amazon, eBay, Instacart
Other	Books & Reference Food & Drink Travel & Local Sports News & Magazines Education Art & Design Weather Auto & Vehicles Reference Events Utilities	All other apps	Unidentifiable categories

Notes: Table presents a summary of the mapping from RealityMine categories to the categories used in the analysis. Table excludes Facebook, Instagram, Snapchat, TikTok, YouTube, and Messenger which are considered separately. All of the apps in this table are considered Non-PSN time under the definitions laid out by FTC (2021) and CMA (2020).

D.2 Allocation to experimental samples

In total, the Facebook experiment included 3,500 participants, and the Instagram experiment included 2,768 participants. We discuss below how we arrived at these sample sizes. We had targeted a sample sample size of 3,500 for each experiment. As noted above, we set minimum thresholds for baseline usage of 15 minutes of Facebook for the Facebook experiment and 10 minutes of Instagram for the Instagram experiment. Depending on their baseline usage, participants could be eligible for the Facebook experiment only, Instagram experiment only, or both the Facebook and Instagram experiments. For the Facebook experiment, we targeted a balance of 83% Facebook-only eligible participants and 17% Facebook/Instagram participants, which matches the Meta population data. For the Instagram experiment, we targeted a balance of 56% Instagram-only eligible participants and 44% Facebook/Instagram participants, also to match the Meta population data.

The recruitment process generated more Facebook-only eligible participants (n=3,457) and more Facebook/Instagram participants (n=2,237) than Instagram-only eligible participants (n=1,127). This occurred for several reasons, including: (i) a smaller share of participants who provided their Instagram IDs were successfully matched to Meta data; (ii) a smaller share of Instagram users met the required average daily use requirement; and (iii) lower click through rates on Instagram ads compared to Facebook ads during recruitment.

We first allocated participants to the Facebook experiment in order to achieve a target sample size of 3,500 with a balance of approximately 83% Facebook-only (n=2,904) and approximately 17% Facebook/Instagram-eligible participants (n=596). Within each subgroup – Facebook-only and Facebook/Instagram eligible – we stratified eligible participants based on gender, age and baseline usage. We then randomly selected participants from each strata with the aim of best matching the proportions of each strata in the Meta population, given the characteristics of our participants. After we had selected the Facebook-only participants for the Facebook experiment randomization, we excluded the remaining Facebook-only eligible participants from the remainder of the experiment. After we selected the Facebook/Instagram eligible participants for the Facebook experiment randomization, we allocated the remaining Facebook/Instagram eligible participants to the Instagram experiment. We also assigned all Instagram-only participants to the Instagram experiment.

This approach maximized the potential sample size for the Instagram experiment but left the sample with a lower share of Instagram-only users as opposed to Instagram/Facebook users relative to the target. Following this approach, a total of 3,500 participants were assigned to the Facebook experiment, and 2,768 participants were assigned to the Instagram experiment. Of the 3,500 Facebook experiment participants, 596 (17.0%) were eligible for both experiments, as targeted. Of the 2,768 Instagram experiment participants, 1,641 (59.3%) were eligible for both experiments. This is higher than the target of 46%. We describe the allocation procedure more specifically below.

To allocate enough Facebook/Instagram eligible participants to the Facebook experiment, the 2,237 participants who were eligible for both experiments were first stratified into eight strata based on: gender (female, male), age (under 40, 40 or older), average time spent on the mobile device during the baseline period (less than 400 minutes, 400 minutes or more).

Then, a total of 596 Facebook/Instagram eligible participants were randomly selected from the eight strata in proportion to the mix of stratified characteristics observed in the joint distribution of Facebook/Instagram eligible users and assigned to the Facebook experiment. The remaining 1,641 Facebook/Instagram eligible participants (= 2,237 − 596) were assigned to the Instagram experiment, which had a total of 2,768 participants. This approach ensures that characteristics of the Facebook/Instagram eligible participants allocated to the Facebook experiment mirrors that observed in the Facebook population as closely as possible.

The remaining 2,904 (= 3,500 − 596) Facebook experiment participants were randomly selected from a total of 3,457 Facebook-only eligible participants in an iterative process. Prior to selecting Facebook-only participants, we determined the target distribution of Facebook participants based on the distribution of Facebook-eligible participants observed in Meta's Study data for 32 combinations of the following characteristics:[33] gender (female, male), age (18–29, 30–39, 40–49, 50 or older), average time spent on the mobile device during the baseline period (less than 200 minutes, 200–399 minutes, 400–599, 600 minutes or more).

After accounting for the distribution of the 596 Facebook/Instagram eligible participants already selected for the Facebook experiment, Facebook-only participants were then randomly selected from each of the 32 bins in proportion to the mix of stratified characteristics observed in Meta Study. If a bin remained unfilled after the initial iteration, then a new iteration of the allocation was performed at a higher level of aggregation based on non-exhausted bins. For example, if a given category (say, men/600+ minutes/ages 30–39) remained unfilled after the initial iteration, then a second iteration of the allocation was performed aggregating to two age groups: less than 40 and 40 and older. This process was followed iteratively until the desired number of Facebook-only participants were selected. This process ensures that the selected participants mirror the distribution of users observed in the Meta Study data for the 32 categories of participants, subject to the constraints of the characteristics of the recruited sample.

In round 1 of the sample selection, each of the 3,457 Facebook-only eligible participants were assigned a randomly generated number. For each of the 32 bins, a participant was selected in ascending order of the randomly assigned number as long as the bin was not yet filled. A total of 2,472 participants were selected from the Facebook-only eligible participants in round 1. A total of 985 participants (= 3,457 − 2,472) were not selected in round 1 and were retained to be potentially selected in subsequent rounds.

In round 2, prior to generating a new random number for the 985 retained participants from round 1, the age bins were collapsed into 2 bins (less than 40, 40 and older), resulting in 16 bins. Each of the retained 985 participants were assigned a new randomly generated number. For each of the 16 bins, a retained participant was selected in ascending order of the randomly assigned number as long as the bin was not yet filled. A total of 17 participants were selected from the Facebook-only eligible participants in round 2. A total of 968 participants (= 985 − 17) were not selected in round 2 and were retained to be potentially selected in

[33] The Meta Study data were used in this allocation because they contain a measure of average daily time spent on their mobile device.

subsequent rounds.

In round 3, prior to generating a new random number for the 968 retained participants from round 2, the time spent bins were collapsed into 2 bins (less than 400 minutes, 400 minutes or more), resulting in 8 bins. Each of the retained 968 participants were assigned a new randomly generated number. For each of the 8 bins, a retained participant was selected in ascending order of the randomly assigned number as long as the bin was not yet filled. A total of 60 participants were selected from the Facebook-only eligible participants in round 3. A total of 908 participants (= 968 - 60) were not selected in round 3 and were retained to be potentially selected in round 4.

In round 4, prior to generating a new random number for the 908 retained participants from round 3, the gender bins were collapsed into 1 bin, resulting in 4 bins. Each of the retained 908 participants were assigned a new randomly generated number. For each of the 4 bins, a retained participant was selected in ascending order of the randomly assigned number as long as the bin was not yet filled. A total of 355 participants were selected, resulting in a total of 3,500 Facebook experiment participants.

D.3 Randomization

For the Facebook experiment, we stratified the randomization on: (i) deciles of Facebook use in the baseline period; (ii) whether or not they had used Instagram in the baseline period; and (iii) whether or not they had used Snapchat in the baseline period. For the Instagram experiment, we stratified the randomization on: (i) quintiles of Instagram use in the baseline period; (ii) terciles of Facebook use in the baseline period; and (iii) whether or not they had used Snapchat in the baseline period.

For each experiment, we conducted 3,000 randomizations using the relevant strata. For each randomization, we conducted balance tests on our stratified variables as well as 60 (63) balancing variables in the Facebook (Instagram) experiment. The balancing variables were: Average baseline usage of Facebook and Instagram in the past 28 days, according to Meta data; Facebook friend counts and Instagram follows, according to Meta data; average Instagram follower count; average Instagram follow count; average number of Facebook friends; terciles of number of Facebook friends (Facebook experiment only); terciles of Instagram follower count (Instagram experiment only); terciles of Instagram follow count (Instagram experiment only); baseline daily usage of apps and app categories, according to RealityMine data: Browser, Communication, Entertainment, Facebook, Games, Instagram, Lifestyle, Messenger, Productivity, Shopping, Snapchat, TikTok, YouTube, All Other Apps, All Apps; share of total time spent on device according to RealityMine data for the apps and categories above (except for "All Apps"); zero/non-zero use according to RealityMine data for the apps and categories above (except for "All Other apps", "All Apps", Facebook in the Facebook experiment, and Instagram in the Instagram experiment); demographics: % female, % age 18–34, % age 35–54. % age 55+, average age; region: south (%), northeast (%), midwest (%), west (%); recruitment source: % sourced from panels; % of days with missing device monitor data in the baseline period.

The balance tests include F-tests of equality of means across the treatment and control groups for each balancing variable; and Kolmogorov-Smirnov test statistics of average daily time spent on the main apps and app categories: Facebook, Instagram, Snapchat, YouTube, TikTok, games category, and total phone time. A total of 43 iterations in the Facebook experiment and 34 iterations in the Instagram experiment resulted in no significant differences (using a 10% significance level) between treatment and control groups for each balancing variable. The final iteration was selected based on having the highest minimum p-value from the F-tests among the main apps and app categories for all eligible iterations.

Table D.2: Balance of Additional Baseline Characteristics

	All (1)	Control (2)	Treatment (3)	p-value test (4)
		Treatment Arm		
a. Facebook Experiment:				
Female (%)	78.714	78.686	78.743	0.967
	(0.692)	(0.979)	(0.978)	
Age (Years)	41.642	41.493	41.791	0.411
	(0.181)	(0.257)	(0.255)	
Facebook Friend Count	587.720	571.057	604.384	0.170
	(12.149)	(16.692)	(17.653)	
Instagram Follower Count	193.125	189.288	196.962	0.532
	(6.135)	(8.417)	(8.929)	
Instagram Followings Count	414.690	409.072	420.308	0.693
	(14.244)	(19.392)	(20.873)	
Recruited from Advertisements (%)	10.314	10.057	10.571	0.617
	(0.514)	(0.719)	(0.735)	
Observations	3,500	1,750	1,750	
b. Instagram Experiment:				
Female (%)	69.581	69.725	69.436	0.869
	(0.875)	(1.235)	(1.239)	
Age (Years)	38.471	38.403	38.539	0.741
	(0.205)	(0.295)	(0.285)	
Facebook Friend Count	535.187	527.049	543.325	0.541
	(13.316)	(18.536)	(19.127)	
Instagram Follower Count	346.172	346.064	346.281	0.991
	(9.237)	(13.709)	(12.389)	
Instagram Followings Count	870.905	840.046	901.764	0.160
	(21.979)	(29.444)	(32.628)	
Recruited from Advertisements (%)	13.945	13.078	14.812	0.188
	(0.659)	(0.907)	(0.955)	
Observations	2,768	1,384	1,384	

Notes: Table presents the average baseline characteristics of subjects in the Experiment. Standard errors are reported in parentheses. The statistics in panel are based on survey responses or information from Meta. Panel (a) displays information from the Facebook experiment and Panel (b) displays information from the Instagram experiment. Column (1) is based on the entire Facebook experiment subject pool. Column (2) is based on subjects who do not receive financial incentives to reduce Facebook Usage. Column (3) is based on subjects who do receive financial incentives to reduce Facebook usage. Column (4) reports the p-value of a test of equal means across the two treatment groups.

D.4 Representativeness and Reweighting

In the Facebook experiment, we weighted the sample observations to match internal Meta data on the share of all Facebook users who would be eligible for the Facebook experiments on two sets of usage categories. The first category is based on Instagram use in the baseline period. It includes three groups: those with zero Instagram use, those with an average (positive) daily Instagram use of 10 minutes or less, and those with an average daily Instagram use of over 10 minutes. The second category is based on Facebook usage in the baseline period. It includes two groups: one with an average daily Facebook use above 60 minutes and the other with an average use of 60 minutes or less. We also use demographic weights to account for the age and gender distributions of the target population. We classify the target population into two gender groups (female and male) and three age categories (18–34, 35–54, and 55+).

In the Instagram experiment, we weighted the sample observations to match internal Meta data on Instagram users who would be eligible for the Instagram experiment across two usage categories. The first category is based on Facebook use in the baseline period. It includes three groups: those with zero Facebook use, those with an average (positive) daily Facebook use of 50 minutes or less, and those with an average daily Facebook use of more than 50 minutes. The second category is based on Instagram use in the baseline period. It includes two groups: one with an average daily Instagram use above 40 minutes and the other with an average daily Instagram use of 40 minutes or less. We also use demographic weights to account for the age and gender distributions of the target population. We classify the target population into two gender groups (female and male) and three age categories (18–34, 35–44, and 45+). For Instagram users, Meta does not maintain complete data for user gender. As a result, the gender distribution for Instagram users relies on the data available, which covers approximately 82% of the target population.

Table D.3: Comparison of Weighted and Unweighted Samples with the Population

	Sample	**Weighted**	**Target Population**
Panel A: Facebook Experiment			
Facebook ADU	75 min/day	80 min/day	83 min/day
Instagram ADU	9 min/day	7 min/day	7 min/day
Demographics			
Ages 18-34	27.5%	20.1%	23.1%
Ages 35-54	58.7%	41.1%	43.1%
Ages 55+	13.8%	38.9%	33.8%
Female	78.7%	50.9%	50.8%
Non-Female	21.3%	49.1%	49.2%
Focal Meta App			
Facebook Use: <= 60 min	52.9%	45.9%	45.8%
Facebook Use: > 60 min	47.1%	54.1%	54.2%
Non-Focal Meta App			
No Instagram Use	42.5%	68.7%	58.5%
IG Use	57.5%	31.3%	41.5%
<= 10 min	71.5%	52.1%	59.4%
> 10 min	28.5%	47.9%	40.6%
Panel B: Instagram Experiment			
Facebook ADU	45 min/day	32 min/day	37 min/day
Instagram ADU	47 min/day	52 min/day	48 min/day
Demographics			
Ages 18-34	37.6%	47.5%	43.5%
Ages 35-54	54.0%	44.1%	43.5%
Ages 55+	8.4%	8.4%	13.0%
Female	69.6%	44.3%	46.7%
Non-Female	30.4%	55.7%	53.3%
Focal Meta App			
Instagram Use: <= 40 min	61.7%	57.9%	57.9%
Instagram Use: > 40 min	38.3%	42.1%	42.1%
Non-Focal Meta App			
No Facebook Use	16.9%	43.0%	36.4%
Facebook Use	83.1%	57.0%	36.6%
<= 50 min	60.3%	57.3%	56.0%
> 50 min	39.7%	42.7%	44.0%

Notes: Table presents the mean values for the unweighted experimental sample, the reweighted experimental sample, and the target population.

Table D.4: Balance of Baseline Usage in the Facebook Experiment (reweighted)

		Treatment Arm		
	All (1)	Control (2)	Treatment (3)	p-value test (4)
Facebook Minutes	72.086	72.508	71.666	0.676
	(1.009)	(1.432)	(1.423)	
Facebook Minutes (Meta)	80.189	79.622	80.752	0.603
	(1.087)	(1.504)	(1.572)	
Instagram Minutes	6.875	7.130	6.622	0.464
	(0.347)	(0.514)	(0.466)	
Instagram Minutes (Meta)	7.109	7.258	6.961	0.684
	(0.365)	(0.517)	(0.515)	
Snapchat Minutes	2.094	2.007	2.180	0.573
	(0.153)	(0.228)	(0.205)	
YouTube Minutes	22.897	22.494	23.298	0.647
	(0.878)	(1.135)	(1.340)	
TikTok Minutes	9.405	9.727	9.085	0.517
	(0.496)	(0.722)	(0.680)	
Browser Minutes	62.397	59.556	65.224	0.004
	(0.975)	(1.357)	(1.396)	
Games Minutes	74.431	75.163	73.703	0.671
	(1.718)	(2.485)	(2.374)	
Communication Minutes	42.585	41.504	43.661	0.116
	(0.686)	(0.910)	(1.027)	
Entertainment Minutes	27.094	25.357	28.823	0.037
	(0.831)	(1.066)	(1.275)	
Lifestyle Minutes	16.363	17.046	15.684	0.137
	(0.457)	(0.679)	(0.613)	
Messenger Minutes	20.154	19.554	20.751	0.296
	(0.573)	(0.766)	(0.851)	
Productivity Minutes	18.276	18.597	17.956	0.449
	(0.423)	(0.616)	(0.580)	
Shopping Minutes	14.796	14.458	15.131	0.407
	(0.406)	(0.555)	(0.592)	
Other App Minutes	18.725	19.069	18.382	0.496
	(0.505)	(0.735)	(0.692)	
Total Phone Minutes	408.178	404.170	412.166	0.200
	(3.116)	(4.501)	(4.310)	
Percent of Missing Days	1.492	1.504	1.480	0.856
	(0.065)	(0.091)	(0.094)	
Observations	3,500	1,750	1,750	

Notes: Table presents reweighted means and then standard errors in parentheses for the Facebook experiment sample. Column (1) uses the full sample. Column (2) uses those who did not receive incentives to reduce Facebook Usage. Column (3) uses those who do receive incentives to reduce Facebook usage. Column (4) reports the p-value of a test of equal means across the two treatment groups. Data collected from RealityMine unless otherwise stated.

Table D.5: Balance of Baseline Usage in the Instagram Experiment (reweighted)

		Treatment Arm		
	All (1)	Control (2)	Treatment (3)	p-value test (4)
Facebook Minutes	29.973	29.808	30.132	0.867
	(0.966)	(1.335)	(1.397)	
Facebook Minutes (Meta)	31.817	32.346	31.304	0.600
	(0.993)	(1.402)	(1.408)	
Instagram Minutes	48.433	49.264	47.630	0.382
	(0.933)	(1.362)	(1.277)	
Instagram Minutes (Meta)	52.255	53.491	51.059	0.235
	(1.024)	(1.639)	(1.237)	
Snapchat Minutes	5.677	5.697	5.658	0.956
	(0.353)	(0.505)	(0.493)	
YouTube Minutes	40.813	36.711	44.780	0.006
	(1.475)	(1.682)	(2.408)	
TikTok Minutes	19.920	21.179	18.701	0.180
	(0.923)	(1.342)	(1.269)	
Browser Minutes	61.860	63.241	60.523	0.184
	(1.023)	(1.411)	(1.481)	
Games Minutes	51.791	50.301	53.232	0.326
	(1.492)	(1.972)	(2.234)	
Communication Minutes	42.792	44.940	40.715	0.006
	(0.775)	(1.057)	(1.130)	
Entertainment Minutes	31.758	32.746	30.804	0.285
	(0.907)	(1.305)	(1.262)	
Lifestyle Minutes	25.980	24.465	27.445	0.052
	(0.765)	(0.978)	(1.174)	
Messenger Minutes	7.952	8.520	7.403	0.156
	(0.393)	(0.554)	(0.556)	
Productivity Minutes	17.010	16.561	17.443	0.310
	(0.435)	(0.516)	(0.696)	
Shopping Minutes	14.172	14.038	14.301	0.777
	(0.465)	(0.649)	(0.666)	
Other App Minutes	25.179	24.925	25.426	0.740
	(0.756)	(1.016)	(1.118)	
Total Phone Minutes	423.310	422.397	424.194	0.795
	(3.448)	(4.808)	(4.944)	
Percent of Missing Days	1.128	1.220	1.040	0.167
	(0.065)	(0.096)	(0.089)	
Observations	2,768	1,384	1,384	

Notes: Table presents reweighted means and then standard errors in parentheses for the Instagram experiment sample. Column (1) uses the full sample. Column (2) uses those who did not receive incentives to reduce Instagram Usage. Column (3) uses those who do receive incentives to reduce Instagram usage. Column (4) reports the p-value of a test of equal means across the two treatment groups. Data collected from RealityMine unless otherwise stated.

Table D.6: Balance of Additional Baseline Characteristics (reweighted)

		Treatment Arm		
	All	Control	Treatment	p-value test
	(1)	(2)	(3)	(4)
a. Facebook Experiment:				
Female (%)	50.866	50.641	51.090	0.790
	(0.845)	(1.195)	(1.195)	
Age (Years)	47.178	46.882	47.472	0.178
	(0.219)	(0.308)	(0.311)	
Facebook Friend Count	513.843	500.078	527.540	0.235
	(11.552)	(15.812)	(16.840)	
Instagram Follower Count	121.150	126.945	115.384	0.312
	(5.711)	(8.494)	(7.639)	
Instagram Followings Count	261.646	278.425	244.950	0.163
	(12.008)	(17.898)	(16.013)	
Recruited from Advertisements (%)	10.513	10.813	10.214	0.564
	(0.519)	(0.743)	(0.724)	
Region: South (%)	44.541	46.218	42.872	0.046
	(0.840)	(1.192)	(1.183)	
Region: Northeast (%)	14.320	13.105	15.530	0.041
	(0.592)	(0.807)	(0.866)	
Region: Midwest (%)	25.676	25.618	25.732	0.938
	(0.739)	(1.044)	(1.045)	
Region: West (%)	15.463	15.059	15.866	0.509
	(0.611)	(0.855)	(0.874)	
Observations	3,500	1,750	1,750	
b. Instagram Experiment:				
Female (%)	44.321	46.047	42.651	0.072
	(0.944)	(1.340)	(1.330)	
Age (Years)	36.795	36.816	36.774	0.926
	(0.224)	(0.327)	(0.308)	
Facebook Friend Count	376.244	374.638	377.798	0.893
	(11.751)	(16.183)	(17.034)	
Instagram Follower Count	306.903	311.707	302.257	0.583
	(8.595)	(12.739)	(11.565)	
Instagram Followings Count	813.091	773.323	851.553	0.075
	(21.990)	(28.515)	(33.386)	
Recruited from Advertisements (%)	14.825	13.903	15.718	0.180
	(0.676)	(0.930)	(0.979)	
Region: South (%)	41.509	41.922	41.110	0.665
	(0.937)	(1.327)	(1.323)	
Region: Northeast (%)	17.073	18.843	15.360	0.015
	(0.715)	(1.052)	(0.970)	
Region: Midwest (%)	17.230	17.636	16.837	0.578
	(0.718)	(1.025)	(1.006)	
Region: West (%)	24.189	21.598	26.694	0.002
	(0.814)	(1.107)	(1.190)	
Observations	2,768	1,384	1,384	

Notes: Table presents the reweighted average baseline characteristics of subjects in the Experiment. Standard errors are reported in parentheses. The statistics in panel are based on survey responses or information from Meta. Panel (a) displays information from the Facebook experiment and Panel (b) displays information from the Instagram experiment. Column (1) is based on the entire Facebook experiment subject pool. Column (2) is based on subjects who do not receive financial incentives to reduce Facebook Usage. Column (3) is based on subjects who do receive financial incentives to reduce Facebook usage. Column (4) reports the p-value of a test of equal means across the two treatment groups.

D.5 Missing Outcome Data

In this section, we describe the attrition of subjects from our experiment. Attrition in this experiment refers to missing outcome data, which is not an absorbing state. That is, subjects may be missing outcome data for some week of the experiment, even though we observe data for a later week. Outcome data is missing because the participant stopped sending device monitor data in that week. This could be because the subject removed the device monitor from their phone or because their phone was off for the entire week.

Table D.7 reports the number of missing observations by experiment, treatment, and week of the experiment. Because having a week of baseline data was a condition for randomization, we are not missing any of the baseline outcome data for any subject. In week 1, 125 (3.5%) of the Facebook experiment subjects and 96 (3.5%) of the Instagram experiment subjects have missing outcome data. The amount of missing outcome data increases to its maximum in week 4, where it is 7.2% in the Facebook experiment and 6.6% in the Instagram experiment. This is substantially lower than the 15.3% attrition typically found in field experiments and the 20.7% found in similar high-income countries (Ghanem et al., 2023). We find evidence that the subjects are more likely to have missing outcome data in the control group of the Instagram experiment during week 1. However, this pattern does not persist significantly in later weeks.

Table D.7: Missing Outcome Data

	Facebook Experiment			Instagram Experiment		
	Treatment	Control	P-value	Treatment	Control	P-value
Baseline	0	0	1.000	0	0	1.000
Week 1	65	60	0.649	39	57	0.062
Week 2	84	89	0.697	58	72	0.209
Week 3	123	105	0.218	77	82	0.683
Week 4	136	119	0.269	85	98	0.320

Notes: Table presents the number of observations with missing outcome data by experiment, week, and treatment. P-values correspond to a test of whether the portion of missing observations differs based on treatment within an experiment. In the Facebook Experiment, 1,750 subjects were randomized to each treatment. In the Instagram experiment, 1,384 subjects were randomized to each treatment.

Next, we investigate whether any baseline characteristics determine whether a subject has missing outcome data in any week of the experiment. Table D.8 presents the results from linear regressions where the outcome variable is an indicator equal to one if the participant is missing any outcome data throughout the duration of the experiment. We regress this outcome on the baseline outcome, baseline usage of other PSN and non-PSN commodities, and baseline demographics. Column (1) displays the coefficient estimates of this regression for the Facebook experiment and Column (2) displays the coefficient estimates of this experiment from the Instagram experiment. This table shows that subjects who use more of the focal app at baseline are less likely to leave the experiment. Subjects who are recruited from ads are also more likely to have missing outcome data than subjects who are recruited from panels.

Table D.8: Determinants of Attrition Test

	(1) Facebook Experiment	(2) Instagram Experiment
Treated	0.553	-0.756
	(0.995)	(1.086)
Baseline Facebook Usage	-0.0354***	
	(0.00862)	
Baseline Instagram Usage		-0.0274**
		(0.0134)
Baseline Other PSN Usage	-0.0235	-0.00981
	(0.0210)	(0.00997)
Baseline Non-PSN Usage	0.00120	-0.00407
	(0.00297)	(0.00344)
Female	-3.941***	-1.695
	(1.366)	(1.229)
Age 35 - 54	-1.807	-0.393
	(1.200)	(1.172)
Age 55+	-3.461**	-1.707
	(1.623)	(1.989)
Subject in the Midwest	0.0166	-0.0397
	(1.603)	(1.921)
Subject in the South	1.630	-0.238
	(1.523)	(1.601)
Subject in West	2.915	-1.168
	(1.860)	(1.746)
Source is Ads	3.482*	3.860**
	(1.831)	(1.766)
Average Friends Count	0.00104	0.00129
	(0.000805)	(0.000931)
Average Followings Count	-0.000284	-0.000801
	(0.000725)	(0.000522)
Average Followers Count	-0.00348**	0.00174
	(0.00143)	(0.00147)
Constant	14.90***	13.13***
	(2.291)	(2.396)
F-Stat	3.991	1.362
R-Squared	0.015	0.008
Observations	3500	2768

Notes: Table displays coefficients from regressions of treatment assignment and baseline covariates on indicators for whether the subject is ever missing an observation. Column (1) displays the results o the Facebook Experiment. Column (2) displays the results of the Instagram experiment. Table includes all 3,500 subjects randomized in the Facebook experiment and all 2,768 subjects randomized in the Instagram experiment. Significant at *10%, **5%, ***1%. Robust standard errors in parentheses.

Finally, in Table D.9, we conduct the two mean tests of internal validity recommended by Ghanem et al. (2023). Columns display regression estimates of the mean of baseline outcomes based on interactions of their treatment status and whether they ever have missing outcome data. Columns (1) through (4) display these regressions for the four main commodity categories in the Facebook experiment while Columns (5) through (8) display these regressions for the four main commodity categories in the Instagram experiment.

For each baseline outcome, we provide mean tests of internal validity for respondents (IV-R). Here, we test whether the average potential outcome without the treatment is identical for the treatment and control responders as well as the treatment and control attritors. Ghanem et al. (2023) shows that when the IV-R assumption holds, the estimates from Section 3.3 represent those for the respondent population. Across all eight columns, we fail to reject null hypothesis for any of the baseline outcomes, supporting the internal validity of respondents.

We additionally provide mean tests of internal validity for participants (IV-P). Here, we test whether the average potential outcome without treatment is identical across all treatment and responder categories. Ghanem et al. (2023) shows that when the IV-P assumption holds, the estimates from Section 3.3 identify the treatment effects for the study population. By in large, we find support for this assumption. However, we reject the equality of the means across these four categories for the baseline Facebook usage in the Facebook experiment.

Table D.9: Selective Attrition Test

	(1) Facebook	(2) Other PSN	(3) Non-PSN	(4) Non-Phone	(5) Instagram	(6) Other PSN	(7) Non-PSN	(8) Non-Phone
Treated × Ever Missing	58.30	10.30	356.2	1015.2	33.32	43.14	322.9	1040.6
	(4.704)	(1.830)	(12.89)	(14.18)	(3.585)	(5.258)	(17.62)	(18.57)
Control × Ever Missing	53.78	9.521	336.8	1039.9	40.71	46.40	322.7	1030.2
	(4.235)	(1.821)	(13.24)	(13.73)	(4.599)	(5.086)	(14.63)	(16.79)
Treated × Never Missing	71.95	11.61	340.7	1015.7	43.20	48.42	334.0	1014.4
	(1.519)	(0.590)	(4.209)	(4.453)	(1.181)	(1.658)	(4.706)	(4.975)
Control × Never Missing	71.66	12.10	341.4	1014.8	43.64	46.93	336.4	1013.0
	(1.461)	(0.654)	(4.295)	(4.513)	(1.279)	(1.600)	(4.682)	(5.064)
Experiment	Facebook	Facebook	Facebook	Facebook	Instagram	Instagram	Instagram	Instagram
IV-R Test	0.768	0.820	0.571	0.452	0.434	0.734	0.936	0.900
IV-P Test	0.000	0.496	0.691	0.378	0.052	0.763	0.739	0.409
R-squared	0.587	0.183	0.803	0.970	0.489	0.403	0.799	0.970
Observations	3500	3500	3500	3500	2768	2768	2768	2768

Notes: This table displays regressions of four baseline outcomes on interactions between the treatment status and whether the subject was ever missing data during the experiment without a constant term. The IV-R Test evaluates whether the average potential outcome without the treatment is identical for the treatment and control responders as well as the treatment and control attritors. The IV-P test evaluates whether the average potential outcome without treatment is identical across all treatment and responder categories.

D.6 Specification Checks

First, we investigate whether the results we find are false positives resulting from not adjusting the significance level of our hypotheses to reflect the fact that we are testing for differences across many commodities (List et al., 2019). We use the Romano and Wolf (2016) procedure to control the family-wise error rate and allow for dependence amongst p-values within a family. We follow Rubin (2021) and group hypotheses into a family when performing disjunction testing among that group of commodities. These criteria leave us with four families: (1) individual commodities in the Facebook experiment, (2) aggregate commodities in the Facebook experiment, (3) individual commodities in the Instagram experiment, and (4) aggregate commodities in the Instagram experiment. Columns (2) in Table D.10 and Table D.11 display reproductions of estimates using the main specification with adjusted p-values. Panels (a) show that the statistical significance of substitution towards individual commodities is largely unchanged for both the Facebook and Instagram experiments. Similarly, Panels (b) show the same pattern for aggregated commodity categories.

In Columns (3), we control for strata fixed effects rather than linear functions of the variables on which we stratified and other baseline characteristics to reflect the randomization strategy (Athey and Imbens, 2017; Czibor et al., 2019). Columns (4) control only for the strata variables linearly rather than discretized variables used in the randomization or including other baseline covariates. The results are qualitatively similar to the main results but with more substitution towards non-PSN commodities and less substitution away from phone use. In the Facebook experiment, we also see substantially more substitution towards browser and communication apps. In comparison, we see even more substitution towards YouTube and slightly more substitution towards Facebook in the Instagram experiment.

As discussed in Section 3.3, our analysis focuses on weeks 2-4 of the post-period to estimate diversion ratios once the subjects' behavior stablized. Columns (5) evaluate how our results would change if we included the first week in our analysis. We find that, across all apps and aggregated categories, the results are not materially affected by excluding the first week of data.

In Columns (6), we study the role of missing data in our results. Because of how the RealityMine app worked, we can observe all commodity usage for a week or no app usage over that week. Overall, missingness in the experiment is low.[34] We are missing RealityMine data for 5.58% of the subject-weeks in the Facebook experiment and 5.13% of the subject-weeks in the Instagram experiment.

Across both experiments, we find that roughly 4% of data is missing in week 1, 5% in week 2, 6% in week 3, and 7% in week 4. Because the attrition rate is so low, we do not expect the missingness to substantially bias our estimates. Nevertheless, we follow Giuntella et al. (2021) and repeat the analysis, replacing missing outcome data with an individual's baseline value. This imputation will lead us to find less evidence of substitution because we are not allowing any substitution for users with missing outcome data. We show the results in Columns (6) of

[34] Ghanem et al. (2023) finds that on average, longitudinal experiments have substantially higher attrition at 15%, with higher rates in high-income countries.

Table D.10 and Table D.11 and confirm that our results are not substantially influenced by missing outcome data.

Table D.10: Robustness: Facebook Experiment

	Diversion Ratio						
	Main (1)	MHT (2)	Strata FE (3)	Sparse (4)	Incl. Week 1 (5)	Imputed (6)	Unweighted (7)
Panel (a): Aggregated Categories							
PSN	-0.057***	-0.057***	-0.059***	-0.057***	-0.056***	-0.057***	-0.075***
	(0.012)	(0.012)	(0.019)	(0.012)	(0.011)	(0.012)	(0.011)
Non-PSN Time	-0.550***	-0.550***	-0.639***	-0.620***	-0.527***	-0.560***	-0.608***
	(0.093)	(0.093)	(0.192)	(0.194)	(0.089)	(0.093)	(0.065)
Offline Time	-0.393***	-0.393***	-0.302	-0.323*	-0.418***	-0.382***	-0.318***
	(0.094)	(0.094)	(0.194)	(0.195)	(0.090)	(0.094)	(0.066)
Panel (b): Individual Apps							
Instagram	-0.050***	-0.050***	-0.049***	-0.050***	-0.049***	-0.051***	-0.072***
	(0.011)	(0.011)	(0.017)	(0.012)	(0.010)	(0.011)	(0.010)
Snapchat	-0.007*	-0.007*	-0.010*	-0.007*	-0.007*	-0.007*	-0.003
	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)
Messenger	-0.010	-0.010	-0.034	-0.025	-0.008	-0.011	0.031***
	(0.020)	(0.020)	(0.041)	(0.043)	(0.020)	(0.020)	(0.012)
TikTok	-0.047**	-0.047**	-0.045	-0.030	-0.051***	-0.047**	-0.066***
	(0.019)	(0.019)	(0.031)	(0.031)	(0.017)	(0.019)	(0.016)
YouTube	-0.084***	-0.084**	-0.091	-0.089	-0.081***	-0.085***	-0.063***
	(0.032)	(0.032)	(0.062)	(0.063)	(0.029)	(0.031)	(0.019)
Browser	-0.095***	-0.095**	-0.168***	-0.168***	-0.094***	-0.098***	-0.090***
	(0.034)	(0.034)	(0.060)	(0.062)	(0.033)	(0.034)	(0.022)
Communication	-0.057**	-0.057**	-0.110***	-0.102**	-0.059***	-0.056**	-0.036**
	(0.024)	(0.024)	(0.042)	(0.043)	(0.022)	(0.024)	(0.015)
Entertainment	-0.034	-0.034	-0.072	-0.072	-0.033	-0.036	-0.052**
	(0.028)	(0.028)	(0.052)	(0.053)	(0.027)	(0.028)	(0.021)
Games	-0.145**	-0.145**	-0.090	-0.104	-0.129**	-0.149**	-0.224***
	(0.061)	(0.061)	(0.124)	(0.126)	(0.057)	(0.061)	(0.039)
Lifestyle	-0.010	-0.010	0.018	0.018	-0.013	-0.011	-0.028**
	(0.025)	(0.025)	(0.038)	(0.037)	(0.024)	(0.025)	(0.013)
Productivity	-0.035**	-0.035**	-0.018	-0.017	-0.030**	-0.036**	-0.017
	(0.016)	(0.016)	(0.026)	(0.027)	(0.015)	(0.016)	(0.011)
Shopping	-0.004	-0.004	-0.012	-0.011	0.001	-0.004	-0.036***
	(0.015)	(0.015)	(0.024)	(0.024)	(0.016)	(0.015)	(0.011)
Other	-0.029	-0.029	-0.017	-0.022	-0.028	-0.028	-0.027**
	(0.018)	(0.018)	(0.032)	(0.033)	(0.018)	(0.019)	(0.013)
Strata Fixed Effects			✓				
Strata Covariates	✓	✓		✓	✓	✓	✓
Additional Covariates	✓	✓			✓	✓	✓
Weights	✓	✓	✓	✓	✓	✓	
Romano Wolf p-values		✓					
Include First Post Week					✓		
Impute Missing Data						✓	
F Statistic	39.22	39.22	32.62	186.65	45.85	40.25	93.66
Subjects	3,361	3,361	3,361	3,361	3,418	3,500	3,361
Observations	9,844	9,844	9,844	9,844	13,219	10,500	9,844

Notes: Significant at *10%, **5%, ***1%. Standard errors in parentheses are clustered at the individual level. This table reports 2SLS estimates of regressions discussed in Section 3.3. Panel (a) reports the estimates from separate regressions for each commodity where the dependent variable is the weekly usage of that category. Panel (b) reports analogous results for aggregated commodity categories. The PSN category contains Instagram and Snapchat. The Non-PSN category contains all other commodities. Column (1) replicates the main specification in Table 3. Column (2) replicates the main specification with stars from p-values that correct for multiple comparisons using the procedure from Romano and Wolf (2016). Column (3) replaces the controls with strata fixed effects. Column (4) controls only for linear versions of the variables used to construct the strata (baseline Facebook usage, Instagram usage, and Snapchat usage). Column (5) adds data from week 1 to the main specification. Column (6) replicates the main specification but imputes zeros for all missing values. Column (7) removes the weights from the main specification.

Table D.11: Robustness: Instagram Experiment

	Diversion Ratio						
	Main (1)	MHT (2)	Strata FE (3)	Sparse (4)	Incl. Week 1 (5)	Imputed (6)	Unweighted (7)
Panel (a): Aggregated Categories							
PSN	-0.156***	-0.156***	-0.170***	-0.150***	-0.153***	-0.156***	-0.235***
	(0.037)	(0.037)	(0.048)	(0.038)	(0.034)	(0.037)	(0.034)
Non-PSN Time	-0.552***	-0.552***	-0.611**	-0.609**	-0.589***	-0.548***	-0.524***
	(0.145)	(0.145)	(0.287)	(0.294)	(0.139)	(0.144)	(0.100)
Offline Time	-0.292*	-0.292**	-0.219	-0.241	-0.258*	-0.296**	-0.241**
	(0.150)	(0.150)	(0.292)	(0.297)	(0.143)	(0.148)	(0.105)
Panel (b): Individual Apps							
Facebook	-0.134***	-0.134***	-0.150***	-0.129***	-0.130***	-0.133***	-0.206***
	(0.032)	(0.032)	(0.040)	(0.032)	(0.030)	(0.032)	(0.032)
Snapchat	-0.022	-0.022	-0.020	-0.021	-0.023	-0.024	-0.029**
	(0.019)	(0.019)	(0.025)	(0.020)	(0.016)	(0.018)	(0.013)
Messenger	0.022**	0.022*	0.040*	0.049**	0.019*	0.021*	0.024*
	(0.011)	(0.011)	(0.022)	(0.024)	(0.011)	(0.011)	(0.013)
TikTok	-0.105***	-0.105***	-0.026	-0.022	-0.085**	-0.102***	-0.104***
	(0.040)	(0.040)	(0.087)	(0.091)	(0.037)	(0.038)	(0.026)
YouTube	-0.189***	-0.189***	-0.419**	-0.437**	-0.193***	-0.190***	-0.147***
	(0.061)	(0.061)	(0.168)	(0.176)	(0.059)	(0.061)	(0.036)
Browser	-0.183***	-0.183***	-0.121	-0.133	-0.195***	-0.183***	-0.129***
	(0.051)	(0.051)	(0.090)	(0.091)	(0.051)	(0.051)	(0.033)
Communication	0.007	0.007	0.105	0.107	-0.018	0.008	0.013
	(0.039)	(0.039)	(0.071)	(0.070)	(0.037)	(0.039)	(0.026)
Entertainment	-0.006	-0.006	0.050	0.060	-0.027	-0.005	-0.041
	(0.049)	(0.049)	(0.072)	(0.072)	(0.047)	(0.049)	(0.041)
Games	-0.029	-0.029	-0.104	-0.088	-0.008	-0.026	-0.104*
	(0.080)	(0.080)	(0.123)	(0.125)	(0.073)	(0.079)	(0.058)
Lifestyle	-0.037	-0.037	-0.061	-0.074	-0.043	-0.046	-0.036
	(0.044)	(0.044)	(0.069)	(0.072)	(0.043)	(0.043)	(0.024)
Productivity	0.036	0.036	0.005	0.007	0.031	0.036	0.036**
	(0.024)	(0.024)	(0.039)	(0.037)	(0.022)	(0.024)	(0.017)
Shopping	-0.013	-0.013	-0.025	-0.024	-0.010	-0.007	-0.016
	(0.017)	(0.017)	(0.030)	(0.031)	(0.017)	(0.017)	(0.016)
Other	-0.056	-0.056	-0.054	-0.054	-0.061	-0.055	-0.020
	(0.042)	(0.042)	(0.072)	(0.076)	(0.039)	(0.042)	(0.027)
Strata Fixed Effects			✓				
Strata Covariates	✓	✓		✓	✓	✓	✓
Additional Covariates	✓	✓			✓	✓	✓
Weights	✓	✓	✓	✓	✓	✓	
Romano Wolf p-values		✓					
Include First Post Week					✓		
Impute Missing Data						✓	
F Statistic	33.97	33.97	23.82	168.89	42.79	37.08	57.11
Subjects	2,677	2,677	2,677	2,677	2,706	2,768	2,677
Observations	7,832	7,832	7,832	7,832	10,504	8,304	7,832

Notes: Significant at *10%, **5%, ***1%. Standard errors in parentheses are clustered at the individual level. This table reports 2SLS estimates of regressions discussed in Section 3.3. Panel (a) reports the estimates from separate regressions for each commodity where the dependent variable is the weekly usage of that category. Panel (b) reports analogous results for aggregated commodity categories. The PSN category contains Facebook and Snapchat. The Non-PSN category contains all other commodities. Column (1) replicates the main specification in Table 3. Column (2) replicates the main specification with stars from p-values that correct for multiple comparisons using the procedure from Romano and Wolf (2016). Column (3) replaces the controls with strata fixed effects. Column (4) controls only for linear versions of the variables used to construct the strata (baseline Facebook usage, Instagram usage, and Snapchat usage). Column (5) adds data from week 1 to the main specification. Column (6) replicates the main specification but imputes zeros for all missing values. Column (7) removes the weights from the main specification.

E Comparing iOS and Android Users in the Pilot

We conducted a pilot study to assess the feasibility of various logistical aspects of the experiment and calibrate the study parameters. This study did not utilize a device monitor or evaluate diversion to other apps. This choice ensured that the parameters chosen for the experiment were not affected by considerations of diversion to other apps and allowed us to study the behavior of iOS users.

In the pilot, there were four randomizations using procedures similar to the main experiment, one for each operating system (Android or iOS) and focal app (Facebook and Instagram) combination. We randomized the iOS users to either a treatment where they were paid $8/hour to reduce focal app usage or the control group used in the main experiment. We randomized Android users into these treatments along with additional treatments that varied whether engagement was shown to the control group subjects, the payment for reducing focal app usage, and the compensation baseline to help calibrate the experiment. For brevity, we discuss the two treatment conditions that we administered to both iOS and Android users.

We conducted the pilot study from January 3, 2023, through February 11, 2023. We recruited participants from Facebook and Instagram ads and a panel provider, Prodege. Potential recruits took a "screener survey" to determine whether they met the eligibility criteria, including that they must have spent 15 minutes or more on Facebook and/or 10 minutes or more on Instagram on average in the prior 28 days.

Table E.1 displays the average baseline usage of the focal app for subjects by treatment over four baseline weeks, measured using data from Meta. In the baseline period, both Android and iOS subjects used about 72 minutes of Facebook and about 42 minutes of Instagram. There are no statistically significant differences across groups.

Table E.2 displays the changes in average engagement of the focal app in the treatment and control group, along with the difference-in-differences separately for both Android and iOS subjects. It also displays the difference in these values between Android and iOS users.

As in the main experiment, charging a pecuniary price for focal app engagement leads to large and statistically significant reductions in engagement for both platforms relative to the control groups. Table E.2 shows that both Android and iOS users had similar and statistically indistinguishable average reductions relative to baseline and relative to the control groups. These results show that engagement on Facebook and Instagram is similar between Android and iOS users. Thus, there is no reason to suspect that the diversion ratios would be different between these two samples.

Table E.1: Baseline Usage in First-Stage Pilots

Operating System	Focal App	(1) Control	(2) Treatment	(3) p-value
Android	Facebook	72.55	71.12	0.80
			(64.24)	(51.67)
			N = 204	N = 204
Android	Instagram	41.99	41.88	0.97
			(36.78)	(37.76)
			N = 174	N = 174
iOS	Facebook	72.03	72.03	1.00
			(54.41)	(51.48)
			N = 198	N = 199
iOS	Instagram	43.40	43.39	1.00
			(31.67)	(33.57)
			N = 122	N = 122

Notes: Table presents the baseline usage of the focal app for Android and iOS users in the first-stage pilot experiments with standard deviations in parentheses. Column (1) presents these values for the control groups that received no incentive to reduce focal app usage. Column (2) presents these values for those who received $8 to reduce focal app usage. Column (3) presents the p-value from the test of equality between means.

Table E.2: Changes in Average Engagement from Baseline

	(1) Control	(2) Treatment	(3) Treatment − Control
Panel A: Facebook Pilot			
Android Subjects	-12.91***	-37.65***	-24.74***
	(2.55)	(3.53)	(4.35)
	N = 204	N = 204	N = 408
iOS Subjects	-15.01***	-37.73***	-22.72***
	(2.83)	(3.45)	(4.46)
	N = 199	N = 199	N = 398
Android - iOS	2.10	0.08	-2.01
	(3.81)	(4.94)	(6.23)
	N = 403	N = 403	N = 806
Panel B: Instagram Pilot			
Android Subjects	-7.36***	-23.26***	-15.90***
	(2.25)	(2.19)	(3.13)
	N = 174	N = 174	N = 348
iOS Subjects	-4.26**	-20.35***	-16.09***
	(2.11)	(2.59)	(3.34)
	N = 122	N = 122	N = 244
Android - iOS	-3.10	-2.91	0.19
	(3.08)	(3.39)	(4.58)
	N = 296	N = 296	N = 592

Notes: Table presents the difference in average post period usage of the focal app from baseline usage of the focal app separately by operating system and focal app. Standard errors are in parentheses. Column (1) presents these values for the control groups that received no incentive to reduce focal app usage. Column (2) presents these values for those who received $8 to reduce focal app usage. Column (3) presents the difference between the treatment and control groups. Engagement changes based on regression estimates of changes in focal app usage between the baseline period and experiment weeks using Meta data. Regressions control for users' demographic characteristics.

F Optimal Ad load under One-Sided Model

In this section, we estimate the optimal ad load in a counterfactual model where the net profit per ad shown on the platform, $P_i - c_i$, is fixed, and thus does not depend on the total number of ads on the platform Q_i^A, or the number of ads on competing platforms Q_j^A, or the ad load α_i.[35] P_i denotes the average revenue per ad and c_i is a constant marginal cost. This model is essentially a one-sided model. Accounting for joint ownership of Facebook and Instagram,

[35] We assume no ad-blindness and normalize $\lambda(\alpha_i) = 1$. We also assume no social multiplier (i.e. $\mu_i = 1$).

the objective function of the merged platforms is

$$\max_{\alpha_0,\alpha_1} (P_0 - c_0)\,\alpha_0 Z_0 + (P_1 - c_1)\,\alpha_1 Z_1$$

The associated first-order conditions are:

$$\varepsilon_i^Z = 1 + \frac{(P_j - c_j)\,\alpha_j Z_j}{(P_i - c_i)\,\alpha_i Z_i}\varepsilon_{ji}^Z \geq 1$$

where $\varepsilon_i^Z \equiv -d_{ii}\kappa_i \frac{\alpha_i}{Z_i(p,\alpha)}$ is the own ad load elasticity of demand, and $\varepsilon_{ji}^Z \equiv d_{ji}\kappa_i \frac{\alpha_i}{Z_j(p,\alpha)}$ is the elasticity of demand for j to ad load on platform i. Plugging in the assumption of linear demand (12) and estimated demand parameters, we solve for the implied optimal level of ad load. The calibration of P_i and c_i is summarized in panel B of Tigure 6 (more details are also provided in Section 5.4). The basic model predicts that current ad loads should be:

$$\text{Facebook: } \alpha_0 = 6.5$$
$$\text{Instagram: } \alpha_1 = 10.3$$

Note that reported ad loads are normalized to reflect relative magnitudes compared to Facebook's ad load in June 2022, and that observed levels are 1.0 on Facebook and 0.74 on Instagram. The above predictions fail to rationalize the current equilibrium. The implied equilibrium ad load is $7 - 14$ times as large as currently observed ad load.

Intuitively, the large implied levels of ad load are driven by the fact that the estimated responses in user engagement to ad load are relatively low. In this basic model, it would therefore be optimal for Facebook and Instagram to substantially increase ad loads so as to raise (and maximize) the number of ad impressions on the platform. This suggests that it is important to allow for either a social multiplier thereby making aggregate user responses more elastic to ad load, or to model the firms as two-sided platforms, or both.

G Additional Robustness on De-Merger Results

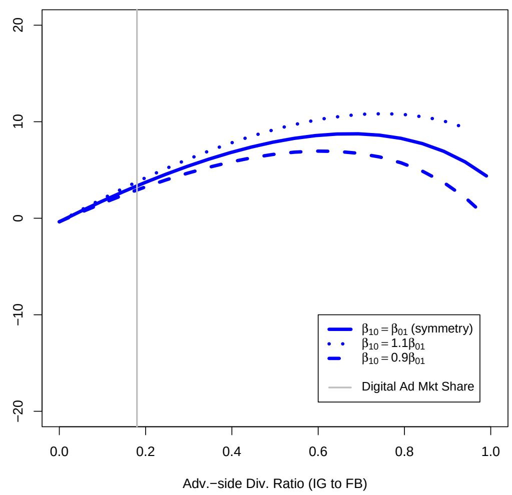
Table G.1: Robustness - Implied Own-Price Elasticity of Residual Advertiser Demand to Facebook and Instagram.

Model Parameters			Lower Bound		Diversion equal to market share		Upper Bound	
			Implied Advertiser Demand					
μ_i	ξ_i	c_i	**FB**	**IG**	**FB**	**IG**	**FB**	**IG**
			Panel A: Baseline Model					
1.5	**0.2**	**0.22**	**1.8**	**1.8**	**2.0**	**2.1**	**12.4**	**25.9**
			Panel B: Sensitivity on μ_i					
1.0	0.2	0.22	1.8	1.7	1.9	2.1	14.5	31.6
1.5	**0.2**	**0.22**	**1.8**	**1.8**	**2.0**	**2.1**	**12.4**	**25.9**
2.0	0.2	0.22	1.9	1.8	2.0	2.1	10.7	21.4
3.0	0.2	0.22	2.0	1.8	2.1	2.1	8.4	14.9
4.0	0.2	0.22	2.1	1.8	2.3	2.1	6.9	10.5
5.0	0.2	0.22	2.4	1.8	2.6	2.1	6.1	7.4
			Panel C: Sensitivity on ξ_i					
1.5	0.1	0.22	1.5	1.5	1.6	1.8	13.3	30.4
1.5	**0.2**	**0.22**	**1.8**	**1.8**	**2.0**	**2.1**	**12.4**	**25.9**
1.5	0.3	0.22	2.3	2.2	2.5	2.6	12.1	22.6
1.5	0.4	0.22	3.1	2.8	3.4	3.3	12.5	20.0
1.5	0.5	0.22	4.9	3.9	5.3	4.6	14.4	18.0
			Panel D: Sensitivity on c_i					
1.5	0.2	0.00	1.3	1.3	1.4	1.5	10.0	21.6
1.5	0.2	0.11	1.5	1.5	1.6	1.8	11.1	23.6
1.5	**0.2**	**0.22**	**1.8**	**1.8**	**2.0**	**2.1**	**12.4**	**25.9**
1.5	0.2	0.33	2.3	2.2	2.5	2.6	14.1	28.8
1.5	0.2	0.44	3.0	2.9	3.3	3.4	16.5	32.2
1.5	0.2	0.55	4.5	4.2	4.9	5.0	20.3	37.0
			Panel E: Varying all parameters at once					
1.5	**0.2**	**0.22**	**1.8**	**1.8**	**2.0**	**2.1**	**12.4**	**25.9**
1.88	0.25	0.28	2.3	2.2	2.6	2.6	11.5	21.2
2.25	0.3	0.33	3.4	2.9	3.7	3.4	11.3	16.8
2.63	0.35	0.38	5.8	4.1	6.3	4.7	13.4	13.0
3.0	0.40	0.44	54.6	8.6	58.9	8.8	81.5	10.1

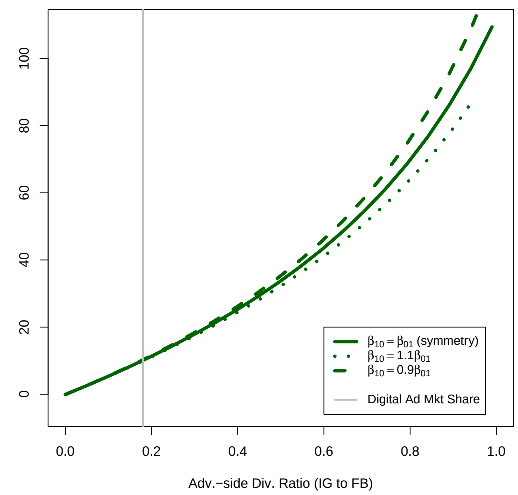
Notes: Table reports the implied own-price elasticity of advertiser demand evaluated at the current equilibrium: $-1/\frac{\partial \ln P_i}{\partial \ln Q_i^A}$. Marginal cost c_i correspond to a percentage of current average revenue (e.g. 22%). The specification assumes that the diversion ratios between Facebook and Instagram correspond to our experimental estimates from section 3: $D_{01}^U = 0.13$ and $D_{10}^U = 0.05$.

Figure G.1: De-Merger when Symmetry is Violated

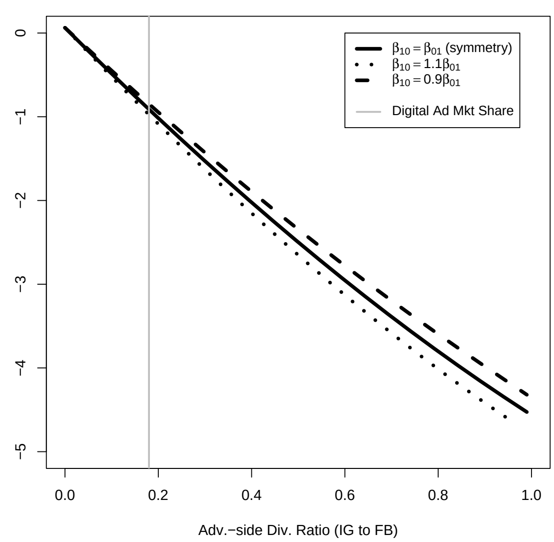
(A) Percentage Change in Ad Load on Facebook



(B) Percentage Change in Ad Load on Instagram



(C) Percentage Change in Joint Consumer Surplus



Notes: Figure (A) shows the implied own-price elasticity of advertiser demand evaluated at the current equilibrium: $-1/\frac{\partial \ln P_i}{\partial \ln Q_i^A}$. Figure (B) shows the estimated percentage change in ad load caused by a de-merger between Facebook and Instagram: $\left(\alpha_i^d - \alpha_i^c\right)/\alpha_i^c$. Figure (C) shows the estimated percentage change in joint consumer surplus from Facebook and Instagram. The joint consumer surplus after the de-merger is given by $\frac{1}{2}\kappa_0\left(\overline{Z}_0^d\right)^2/b_{00} + \frac{1}{2}\kappa_1\left(\overline{Z}_1^d\right)^2/b_{11}$ where $\overline{Z}_i^d$ is estimated total user minutes after the de-merger. The joint consumer surplus before the de-merger is given by $\frac{1}{2}\kappa_0\left(\overline{Z}_0^c\right)^2/b_{00} + \frac{1}{2}\kappa_1\left(\overline{Z}_1^c\right)^2/b_{11}$. The specification assumes $\mu_0 = \mu_1 = 1.5$, $\xi_0 = \xi_1 = 0.2$, $c_0 = 0.15$, and $c_1 = 0.15$. Both marginal costs estimates c_i correspond to 22% of current average revenue per unit. The specification also assumes that the diversion ratios between Facebook and Instagram correspond to our experimental estimates from Section 3: $D_{01}^U = 0.13$ and $D_{10}^U = 0.05$. On the advertiser-side, we make different assumptions about the relative size of the cross-price effects.