Measuring Welfare Gains from Digital Variety: Evidence from App-level Time Use in China

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March 2026

Abstract

This paper measures the welfare gains from the rapid expansion of digital apps using comprehensive app-level time-use data from China. We develop a framework in which apps are offered at zero monetary price but compete for users' time, allowing the welfare effects of new digital varieties to be inferred from reallocations of consumer attention. Applying the framework to data covering major digital apps between 2018 and 2025, we estimate that expanding digital variety raises consumer welfare by about 8 percent—roughly one-fifth of income growth. The results highlight the importance of accounting for free digital goods in welfare measurement.

Keywords: Digital Apps, Welfare Gains, Time Use
JEL Classification: C43, D60, E23, O3, O4

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1. Introduction

As economic activity increasingly shifts toward digital environments, consumers devote a growing share of their time and attention to online services. Recent evidence indicates that users across 80 markets spend, on average, nearly four hours per day on digital applications (hereafter, apps).[1] At the same time, the number of available apps has expanded dramatically, providing users with an ever-wider set of free consumption options.[2] While prior research documents substantial welfare gains from internet services using time-use data, it largely abstracts from changes in the variety of digital services over time. Meanwhile, studies that measure the value of product variety typically focus on paid goods in narrowly defined product categories, leaving the welfare implications of rapidly expanding free digital variety largely unexplored.

This paper measures the welfare gains from expanding digital variety using comprehensive app-level time-use data from China. We combine a CES framework with data covering the universe of major digital apps between 2018 and 2025 to infer the value of new digital varieties from observed reallocations of consumer time. Using time-use measures as an objective metric, our approach complements survey-based methods while remaining scalable and suitable for macro-level welfare analysis.

The core of the analysis is a framework in which digital apps are offered at zero monetary price but compete for users' time. We model digital consumption using a CES aggregator over apps, embedded in a broader time-allocation problem. This structure implies that the welfare contribution of a new digital variety can be identified from the extent to which it draws time away from existing apps. In this setting, changes in observed time-use shares are sufficient statistics for measuring the welfare gains from expanding digital variety, conditional on the elasticity of substitution across apps.

We apply this framework to comprehensive app-level time-use data covering the universe of major digital apps in China between 2018 and 2025. Over this period, the number of available apps increases more than fivefold, while newly introduced apps attract a significant share of consumer attention. To discipline the key parameter governing substitution across apps, we complement the time-use data with large-scale consumer survey experiments that elicit individuals' willingness to accept compensation

[1] See the recent report from Sensor Tower.

[2] Survey evidence suggests that more than 95% of apps are free. See statistics from Statista.

for giving up access to major digital apps. These survey-based valuations allow us to map observed time allocation into welfare units and to estimate the elasticity of substitution across apps.

Bringing these components together, we quantify the welfare gains from the expansion of digital variety over the sample period. We find that the rapid growth in the set of available digital apps generates large consumer welfare gains—amounting to about 8% over the sample period—which is equivalent to roughly 20% of income growth in China. These results highlight the quantitative importance of free digital variety as a source of consumer welfare growth and suggest that conventional growth measures can substantially understate welfare improvements in the digital era.

This paper contributes to several strands of the literature. First, it relates to the growing literature that measures the welfare gains from internet services using time-use data (e.g., Goolsbee and Klenow, 2006; Brynjolfsson et al., 2024). This literature primarily focuses on the value of aggregate time spent online and does not explicitly quantify welfare gains arising from the expansion of digital variety over time. While experimental evidence suggests that usage of certain social media apps may exceed normative levels due to behavioral biases and self-control problems (e.g., Allcott et al., 2020, 2022), our framework instead focuses on welfare gains from expanding digital variety on the extensive margin. These gains arise from the reallocation of consumer attention toward new apps.

Second, our paper is related to the literature quantifying the welfare gains from increased physical product variety in online markets (e.g., Brynjolfsson et al., 2003; Quan and Williams, 2018; Dolfen et al., 2023; Brynjolfsson et al., 2025b). These studies provide compelling evidence that variety expansion in online markets matters for welfare. However, they typically focus on narrowly defined product categories of paid physical goods and do not account for the growth of free digital variety. In contrast, we quantify the welfare gains from the expansion of digital apps and show that these gains are significant. Our theoretical framework employs a CES demand structure to study gains from variety, following the tradition of the trade literature (e.g., Krugman, 1979; Feenstra, 1994; Broda and Weinstein, 2006).

Third, this paper contributes to recent work that uses survey-based methods to quantify the welfare gains from free digital goods (e.g., Brynjolfsson et al., 2019, 2025a). These

studies use willingness-to-accept surveys to estimate the value of access to major digital services. While this approach has proven powerful for measuring the value of individual services, it is less well suited for capturing the welfare effects of ongoing entry and expansion across a large number of digital varieties. Our contribution is to combine survey-based valuations with comprehensive time-use data and a structural framework, allowing us to infer welfare gains from the expansion of digital variety at scale. Time-use data provide a more objective and scalable metric that complements survey evidence and enables economy-wide welfare measurement.

The remainder of the paper is organized as follows. Section 2 develops a framework for measuring consumer welfare gains from free digital variety. Section 3 describes the data and survey design. Section 4 applies the framework to the data and reports the resulting welfare gains from digital variety. Section 5 concludes.

2. Model

We extend the approach of Goolsbee and Klenow (2006) to measure the welfare gains from the expansion of free digital variety. A representative consumer derives utility from a composite of free digital apps B_t and a composite of other goods and services O_t:

$$U_t = U(O_t, B_t) = \left[O_t^{\frac{\rho-1}{\rho}} + B_t^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}, \tag{1}$$

where $\rho > 0$ denotes the elasticity of substitution between the two composites. Consumption O_t is produced using purchased goods and services C_t and the fraction of time spent on it, $L_{C,t}$,

$$O_t = C_t^{\alpha_O} L_{C,t}^{1-\alpha_O}, \tag{2}$$

where $1 - \alpha_O$ measures the time intensity of consuming O_t.

Unlike other goods and services, digital apps are largely free. The digital composite B_t depends only on the time spent on each individual app $i \in \Omega_t$:

$$B_t = \left[\sum_{i \in \Omega_t} (\phi_i l_{i,t})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \tag{3}$$

where $l_{i,t}$ denotes the fraction of time spent on app i in period t, ϕ_i denotes the quality shifter, and σ is the elasticity of substitution across apps.

The representative consumer maximizes utility in (1) subject to the budget constraint

$$P_t^C C_t = W_t(1 - \sum_{i \in \Omega_t} l_{i,t} - L_{C,t}), \tag{4}$$

where W_t is the wage rate and P_t^C is the price of C_t. Equation (4) states that expenditure on goods and services equals wage income. The full income of the representative consumer, W_t, corresponds to wage income plus the value of leisure time.

A key advantage of the CES specification is that it delivers exact price indexes for U_t, O_t, and B_t:

$$P_t = \left[\left(P_t^O\right)^{1-\rho} + \left(P_t^B\right)^{1-\rho} \right]^{\frac{1}{1-\rho}}, \tag{5}$$

where

$$P_t^O = \left(\frac{P_t^C}{\alpha_O}\right)^{\alpha_O} \left(\frac{W_t}{1-\alpha_O}\right)^{1-\alpha_O}, \; P_t^B = \left[\sum_{i \in \Omega_t} \left(\frac{W_t}{\phi_i}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}. \tag{6}$$

We are interested in the welfare gains from expanding the set of digital apps Ω_t over time. We measure welfare gains using the compensating variation ΔCS, defined as the additional income in $t+1$ needed to reach the same utility when the set of apps is held fixed at the period-t level:

$$\Delta CS = E(U_{t+1}, P_{t+1}^C, W_{t+1} | \Omega_t) - W_{t+1} = \left(\frac{P(P_{t+1}^C, W_{t+1} | \Omega_t)}{P_{t+1}} - 1 \right) W_{t+1}. \tag{7}$$

Under the CES specification, the welfare impact of app dynamics can be summarized by changes in the aggregate price index. We first focus on how changes in Ω_{t+1} affect the price index P_{t+1}^B.

For a given app i, utility maximization implies that its time-use share depends on

app quality:

$$s_{i,t+1} = \frac{l_{i,t+1}}{\sum_{i\in\Omega_{t+1}} l_{i,t+1}} = \frac{\left(\frac{W_{t+1}}{\phi_i}\right)^{1-\sigma}}{\sum_{i\in\Omega_{t+1}}\left(\frac{W_{t+1}}{\phi_i}\right)^{1-\sigma}} = \frac{\left(\frac{W_{t+1}}{\phi_i}\right)^{1-\sigma}}{(P^B_{t+1})^{1-\sigma}}. \tag{8}$$

With elastic consumer demand ($\sigma > 1$), apps of higher quality attract more attention.

Let $\Omega^{\star}_{t,t+1}$ denote the set of apps common to Ω_t and Ω_{t+1}. Summing time-use shares across these common varieties yields the following expression for the aggregate share of common apps:

$$\lambda_{t+1} = \frac{\sum_{i\in\Omega^{\star}_{t,t+1}} l_{i,t+1}}{\sum_{i\in\Omega_{t+1}} l_{i,t+1}} = \frac{\sum_{i\in\Omega^{\star}_{t,t+1}}\left(\frac{W_{t+1}}{\phi_i}\right)^{1-\sigma}}{\sum_{i\in\Omega_{t+1}}\left(\frac{W_{t+1}}{\phi_i}\right)^{1-\sigma}} = \frac{(P^{B\star}_{t+1})^{1-\sigma}}{(P^B_{t+1})^{1-\sigma}}, \tag{9}$$

where $P^{B\star}_{t+1}$ is the cost function for the common apps. The time-use share of an individual variety, $s_{i,t+1}$, can then be written as its share among common varieties ($s^{\star}_{i,t+1}$) times the aggregate share of common varieties, λ_{t+1}:

$$s_{i,t+1} = s^{\star}_{i,t+1}\lambda_{t+1}. \tag{10}$$

Using the optimal allocation of time in equations (8), (9) and (10), we derive the impact of changing Ω_{t+1} on the price index P^B_{t+1}:

$$\frac{P^B_{t+1}}{P^B(W_{t+1}|\Omega_t)} = \left(\frac{\lambda_{t+1}}{\lambda_t}\right)^{\frac{1}{\sigma-1}}. \tag{11}$$

Equation (11) shows that an increase in digital variety that reduces the time share of common varieties lowers the cost of B_t.[3] This variety channel becomes stronger when products are less substitutable, i.e., when σ is low.

The corresponding change in the aggregate price index is given by

$$\frac{P_{t+1}}{P(P^C_{t+1}, W_{t+1}|\Omega_t)} = \left(\frac{P^B_{t+1}}{P^B(W_{t+1}|\Omega_t)}\right)^{\omega_B} = \left(\frac{\lambda_{t+1}}{\lambda_t}\right)^{\frac{\omega_B}{\sigma-1}}, \tag{12}$$

[3]Equation (11) has been applied extensively in the trade literature to estimate the gains from import variety (e.g., Feenstra, 1994; Broda and Weinstein, 2006).

where ω_B is the Sato–Vartia weight of B_t.[4] Finally, a convenient normalization expresses welfare gains as a fraction of full-income W_{t+1}:

$$\frac{\Delta CS}{W_{t+1}} = \left(\frac{\lambda_{t+1}}{\lambda_t}\right)^{\frac{\omega_B}{1-\sigma}} - 1. \tag{13}$$

In the following sections, we describe the app-level time-use data and the methods we use to estimate σ by complementing the time-use data with a consumer survey.

3. Data

3.1 Data on App-Level Time Use

We obtain app-level time-use data from July 2018 to July 2025 from a leading data service provider in China. The data cover the universe of digital apps with at least ten thousand minutes of total usage per month in China. For each app, we observe monthly total usage time and the number of monthly active users (MAU).

Panel (a) of Figure 1 illustrates the evolution of average daily time spent on digital apps per user and the expansion of the app universe. Daily usage is constructed by summing time spent across all apps and dividing by the total number of users.[5] On average, users devote a substantial and increasing amount of time to digital apps, with daily usage rising from 5.3 hours in 2018 to 7.2 hours in 2025. This increase underscores the growing importance of digital consumption in users' daily time allocation. Alongside this rapid growth in usage, the number of available digital apps expands sharply. The total number of apps increases more than fivefold, from 25,119 in 2018 to 142,577 in 2025.

Table 1 reports summary statistics of app-level usage and user counts by year. As

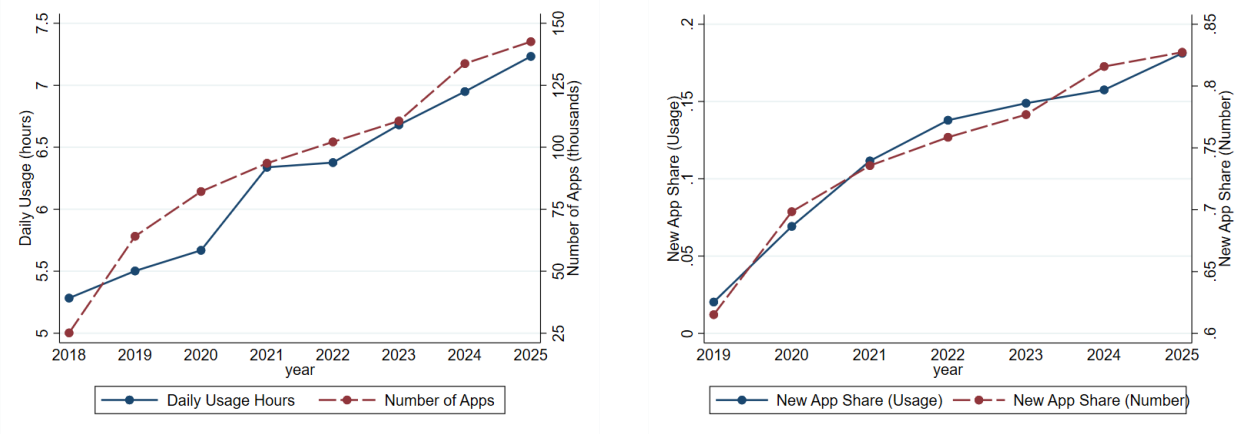
[4] The Sato–Vartia weight is given by

$$\omega_{B,t,t+1} = \frac{\frac{s_{B,t+1}-s_{B,t}}{ln(s_{B,t+1})-ln(s_{B,t})}}{\sum_{k\in\{O,B\}} \frac{s_{k,t+1}-s_{k,t}}{ln(s_{k,t+1})-ln(s_{k,t})}},$$

where $s_{B,t}$ is the fraction of time spent on digital apps.

[5] The total number of users is measured using the MAU of Wechat, which reaches 1.1 billion in 2025, comparable to the number of internet users reported by the government. See http://finance.people.com.cn/n1/2025/0722/c1004-40526679.html.

Figure 1: Rise of Digital Variety



(a) Daily usage and app number

(b) New app share

Notes: This figure shows the rise of digital variety over time. Panel (a) shows per-user daily time spent on digital apps and the total number of apps in the dataset. Daily usage hours are constructed by summing total time spent across all apps and dividing by the total number of users (measured as Wechat MAU). The number of apps counts all apps in the dataset by year. Panel (b) shows the share of apps that are new relative to 2018 (by count) and the share of total usage time accounted by new apps, for each year 2019–2025.

the set of available apps expands rapidly over time, both average usage time and average monthly active users decline, reflecting the entry of many smaller and more niche apps. The table also highlights substantial heterogeneity across apps: usage time and user counts are highly skewed, with large standard deviations and a wide gap between means and medians in every year. At the upper end of the distribution, a small number of dominant apps attract a significant share of user attention. For example, the most widely used app, Wechat, reaches approximately 1.1 billion monthly active users in 2025 and accounts for about 2.8 trillion minutes of total usage time, representing 18% of total time spent on digital apps.

Panel (b) of Figure 1 summarizes app turnover between 2018 and later years, highlighting substantial growth in the set of available apps. New apps account for a large share of apps by count but a smaller share of total usage time, indicating that most entrants attract limited attention while remaining collectively important. Both the count share and the time share of new apps rise steadily over time, consistent with a persistent expansion of digital variety and a gradual reallocation of user time toward newly

Table 1: Summary Statistics by Year

Variable	Year	No. Apps	Mean	Median	SD	Min	Max
Monthly Usage Time	2018	25,119	367.87	0.68	14284.27	0.01	1914523.75
(in million minutes)	2019	64,071	150.52	0.35	8700.09	0.01	1734952.00
	2020	82,126	123.36	0.44	8235.28	0.01	1841910.00
	2021	93,541	125.76	0.45	9177.31	0.01	2059636.38
	2022	102,144	119.01	0.48	9287.98	0.01	2180180.75
	2023	110,583	117.64	0.51	9852.07	0.01	2397024.50
	2024	133,735	102.24	0.53	9841.06	0.01	2634800.50
	2025	142,577	104.39	0.54	10486.82	0.01	2793516.75
Monthly Active Users	2018	25,119	951.42	13.29	14551.96	0.62	940344.75
(in '000)	2019	64,071	444.83	12.24	10033.04	0.65	942422.29
	2020	82,126	356.10	14.50	9312.26	0.69	960946.39
	2021	93,541	355.69	22.13	9470.43	0.73	997817.07
	2022	102,144	330.58	23.57	9280.86	0.78	1024983.64
	2023	110,583	320.54	25.23	9299.08	0.83	1046986.20
	2024	133,735	276.19	26.32	8640.59	0.87	1057927.05
	2025	142,577	274.56	28.26	8856.79	0.93	1106358.18

Notes: This table shows summary statistics of app-level usage time and user counts by year. The sample includes the universe of apps with at least 10,000 total minutes per month; monthly usage time is in million minutes and monthly active users (MAU) are in thousands, with statistics computed across apps within each year.

introduced apps.[6]

3.2 Data from Survey Experiments

We estimate compensating variation for the most widely used apps using a large-scale online survey. Following prior work in the U.S. context (e.g., Brynjolfsson et al., 2019, 2025a), we elicit individuals' willingness to accept (WTA), in RMB, to give up access to a specific app for a fixed period of time. The survey is designed to recover users' valuations for digital services that are free in monetary terms but require time and attention.

We ask single binary discrete-choice (SBDC) questions, such as: "Starting tomorrow morning, would you give up Wechat for one month in return for a payment of RMB 5,000?" We experimentally vary the compensation amount to trace out the full distribution of valuations—equivalently, a demand curve for access to each app. Additional details on the survey design are reported in Appendix A.

In the SBDC survey, each respondent provides valuations for the ten most popular apps. The survey also collects detailed demographic information, including personal income, age, gender, and place of residence. To ensure data quality, we implement both an explicit attention check and an implicit check using a fake app. Respondents who report using the fake app are excluded from the analysis.

Appendix Figures 2 and 3 plot inferred demand curves for the ten most popular apps. For each app, the corresponding subplot displays the fraction of respondents who reject each of the seven compensation levels offered in the SBDC questions. Across all ten apps, the relationship between the logarithm of the compensation amount and the rejection rate is approximately linear, yielding well-behaved downward-sloping demand curves. We use the estimated demand curves to infer the median valuation for each app.

Table 2 reports inferred median valuations together with their corresponding 95% confidence intervals. Consistent with its unique role as a super-app in China, Wechat exhibits a substantially higher median valuation—3,537.7 RMB per month—than any other app in the sample. Following Wechat, Alipay and Douyin (the Chinese version of TikTok) have median valuations of approximately 440.5 RMB and 244.9 RMB per month, respectively. The remaining apps have median valuations below 100 RMB per month,

[6]Apps also exit over time, but the usage share of exiting apps is tiny relative to that of new apps. For instance, apps that exit between 2018 and 2025 account for less than 0.1% of time spent in 2018.

indicating a sharp drop-off in valuations outside the top tier of digital services.

Table 2: Median Monthly WTA

App rank (MAU)	App Name	Median (RMB)	Lower CI	Upper CI
1	Wechat	3537.7	2739.9	4568.0
2	Taobao	81.0	55.6	118.1
3	Alipay	440.5	379.5	511.2
4	Amap	88.5	69.7	112.2
5	Douyin	244.9	195.3	307.1
6	Pinduoduo	45.4	35.4	58.2
7	Baidu	32.6	24.9	42.7
8	QQ	41.6	28.8	59.9
9	Sogou Keyboard	63.9	49.8	82.0
10	Baidu Maps	50.2	36.3	69.4

Notes: This table reports inferred median monthly willingness-to-accept (WTA) to give up access to each app for one month. Values are inferred from the estimated SBDC demand curves, and 95% confidence intervals are reported.

4. Results

4.1 Demand Elasticity Estimation

Using the theoretical results from Section 2, we can derive the compensating variation associated with blocking access to a single digital variety. For a digital app i, the welfare loss from removing access to the app, expressed relative to full income in period $t+1$, is given by

$$\frac{\Delta CS_i}{W_{t+1}} = \left(1 - \frac{l_{i,t+1}}{\sum_{i\in\Omega_{t+1}} l_{i,t+1}}\right)^{\frac{\omega_{B,i}}{1-\sigma}} - 1. \tag{14}$$

This expression links the welfare contribution of an individual app to its time-use share and the elasticity of substitution across apps, σ.

Because each app's time-use share is directly observable in the data, equation (14) allows us to estimate the elasticity σ if we can obtain empirical estimates of the com-

pensating variation $\Delta CS_i/W_{t+1}$. We construct these estimates using the survey-based median valuations reported in Table 2. Specifically, for each app i, we measure compensating variation relative to full income as the ratio of the app's median WTA value to median reported wage income, multiplied by the fraction of total time allocated to work:[7]

$$\frac{\Delta CS_i}{W} = \frac{WTA_i \times 12}{Income^k} \times \left(1 - L_{C,t} - \sum_i l_{i,t}\right) = \frac{WTA_i \times 12}{Income^k} \times 35.7\%.$$

Reported income in the survey is provided in brackets. The median income group corresponds to an annual income between 50,000 and 100,000 RMB. We consider three alternative income measures: $k = l$ uses the lower threshold (50,000 RMB), $k = u$ uses the upper threshold (100,000 RMB), and $k = m$ uses the midpoint between the two thresholds (75,000 RMB).

We estimate σ using nonlinear least squares applied to equation (14).[8] Table 3 reports the resulting elasticity estimates under different combinations of valuation measures from Table 2 and income assumptions. Specifications that imply larger valuations relative to income yield lower estimates of the elasticity of substitution. Because welfare gains from the expansion of digital variety are decreasing in σ, we adopt a conservative benchmark value of $\sigma = 2$, corresponding roughly to the estimate obtained using the median valuation and the upper income threshold ($k = u$). We assess the robustness of our welfare results to alternative values of σ in subsequent analysis.

4.2 Gains from Digital Variety

We now use the app-level time-use data to quantify welfare gains from the expansion of digital variety over time. For each year from 2019 to 2025, we compute (i) the time share allocated to apps that are common with 2018 and (ii) the Sato–Vartia weight on the digital composite. Together with a value for the elasticity of substitution across apps,

[7] We assume 40 hours of work per week and 8 hours of sleep per day, which implies a weekly time endowment of 112 hours. Under this assumption, the fraction of time spent working is approximately 35.7%. Results based on alternative working hours are reported in Appendix Table 8.

[8] Alternatively, a linear regression of $\log\left(1 + \frac{\Delta CS}{W}\right)$ on $\omega_{B,i} \log\left(1 - \frac{l_{i,t+1}}{\sum_{i \in \Omega_{t+1}} l_{i,t+1}}\right)$ yields similar elasticity estimates.

Table 3: Estimated Demand Elasticity Across Apps

Income	Median	Upper CI	Lower CI
$k = l$	1.483	1.381	1.613
	(0.107)	(0.0820)	(0.138)
$k = m$	1.708	1.557	1.904
	(0.162)	(0.125)	(0.209)
$k = u$	1.934	1.732	2.195
	(0.217)	(0.168)	(0.280)

Notes: This table shows estimated elasticities of substitution across apps under alternative valuation and income assumptions. Estimates are obtained by nonlinear least squares using equation (14), relating compensating variation (constructed from survey WTA) to app time-use shares. Standard errors are reported in parentheses.

σ, these objects map directly into welfare gains via equation (13).

Table 4 reports the resulting welfare gains from digital apps relative to 2018. Under our benchmark elasticity $\sigma = 2$, welfare gains rise steadily over time, reaching 8.08% by 2025. The gains are decreasing in σ: when apps are more substitutable, entry yields smaller welfare gains. By 2025, cumulative gains range from 6.69% ($\sigma = 2.2$) to 21.45% ($\sigma = 1.4$).

To put these figures in context, China's annual growth rate of GDP per capita over the same period is approximately 5%. With our benchmark elasticity estimate, welfare gains from digital variety average about 1% per year over the sample period, corresponding to roughly 20% additional growth annually, highlighting the quantitative importance of free digital variety as a source of consumer welfare growth. These results underscore that expanding free digital variety can generate large welfare improvements that are not captured by conventional income-based statistics.

Table 4: Welfare Gains from Digital Variety

	2019	2020	2021	2022	2023	2024	2025
$\sigma = 2.0$	0.69%	2.48%	4.38%	5.54%	6.19%	6.74%	8.08%
$\sigma = 2.2$	0.58%	2.07%	3.64%	4.60%	5.13%	5.59%	6.69%
$\sigma = 1.8$	0.87%	3.11%	5.51%	6.97%	7.80%	8.50%	10.20%
$\sigma = 1.6$	1.16%	4.17%	7.41%	9.40%	10.53%	11.49%	13.83%
$\sigma = 1.4$	1.74%	6.32%	11.32%	14.43%	16.21%	17.71%	21.45%

Notes: This table shows welfare gains from digital variety relative to 2018. Welfare gains are computed using equation (13) based on the time share of apps common with 2018 and the Sato–Vartia weight on the digital composite; rows report gains under alternative values of the elasticity of substitution across apps, σ.

4.3 Robustness and Discussion

We now consider several robustness checks that gauge the sensitivity of our results to alternative elasticity estimation strategies and behavioral adjustments. Additional details and supporting evidence are provided in Appendix B.

Demand elasticity estimation from top 10 apps.—Our benchmark elasticity estimate uses the top 10 apps because they account for nearly half of total usage time and therefore provide the dominant variation in time shares. Restricting estimation to the top five apps delivers a very similar elasticity, despite substantial heterogeneity in usage shares within the top 10. We also consider a conservative scenario in which apps outside the top 10 have much more elastic demand (e.g., $\sigma = 3$ or 4); the implied elasticity of substitution for the full app universe changes little. These results indicate that our benchmark elasticity is not driven by the particular choice of top apps.

Impact of overusage and behavioral biases.—Experimental evidence suggests that some social media usage may exceed normative levels because of self-control problems on the intensive margin (e.g., Allcott et al., 2020, 2022). Although welfare gains in our context arise from the reallocation of consumer attention on the extensive margin, behavioral biases can still affect the estimates through two channels. First, following the estimate in Allcott et al. (2022), we down-weight time spent on social networks, short-video apps, and games when constructing the welfare-relevant digital composite ω_B. Welfare gains remain sizable, declining from about 8% to roughly 6.4% between 2018

and 2025. Second, to address the possibility that new apps are more addictive, we recompute the new-app share using user counts rather than time shares; this implicitly assumes equal usage intensity across apps. This alternative yields welfare gains of about 13%, consistent with evidence that new apps have lower time spent per user and are therefore unlikely to be disproportionately "addictive" in a way that inflates our results.

Additional robustness checks.—We also report additional checks for the elasticity estimates, including alternative treatments of nonusers and different assumptions about working hours. Accounting for nonusers has little effect on the estimated elasticity. Varying assumed working hours between 35 and 45 hours per week shifts the elasticity only modestly. Across these checks, the resulting welfare gains remain close to the benchmark.

5. Conclusion

This paper quantifies the welfare gains from the rapid expansion of free digital variety using a unified framework that combines time-use data with survey-based valuations. We develop a model in which digital apps are offered at zero monetary price but compete for users' time, allowing welfare gains from new varieties to be identified from observed time allocation. Applying this framework to comprehensive app-level data from China between 2018 and 2025, we find that the expansion of digital variety raises consumer welfare by approximately 8% over the sample period—equivalent to roughly 20% of income growth—highlighting the quantitative importance of free digital variety as a source of consumer welfare growth in the digital era.

These findings underscore the importance of accounting for free digital goods in welfare analysis. Because many digital services are priced at zero, their contributions are largely invisible in conventional measures such as GDP. Our results suggest that growth in digital variety is a quantitatively meaningful source of improvements in consumer well-being that complements measured income growth. The analysis nonetheless has limitations: our welfare calculations rely on assumptions about substitution patterns across apps and abstract from general-equilibrium effects. Despite these limitations, the approach developed in this paper provides a transparent and tractable method for measuring welfare gains from free digital variety and illustrates how time-use data can

be combined with economic theory to improve welfare measurement in an economy in which digital goods play an increasingly important role.

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Online Appendix

A. SBDC Survey Design and Additional Results

Following Brynjolfsson et al. (2019), we use SBDC surveys to elicit consumer valuations of free digital apps. Combined with app-level time-use shares, these estimates allow us to identify the elasticity of substitution between apps, which governs welfare gains from expanding digital variety.

We surveyed 2,000 respondents using the Credamo platform in China. Each respondent was presented with a series of SBDC questions of the form: "Starting tomorrow morning, would you be willing to give up access to *App* i for one month in return for a payment of E RMB?" Respondents chose to accept or reject the offer. For each of the ten most widely used digital apps, SBDC responses were collected only if the respondent reported using the app in the previous month. We also collected demographic information, including age, gender, personal income, and place of residence.

The SBDC format allows us to trace a demand curve for access to each app by experimentally varying the compensation amount E across respondents. For each app, E was randomly assigned from a discrete set of seven app-specific values spanning a wide range, chosen to generate meaningful variation in rejection rates and to estimate the distribution of valuations.

To ensure data quality, we implemented multiple checks. First, the survey included an explicit attention check question. Second, we included a fake app in the app list; respondents who reported using this nonexistent app were excluded. We further dropped respondents with unknown income levels in the past year. Together, these filters removed 108 respondents, leaving 1,892 respondents in the analysis sample.

A.1 Respondent Characteristics

Credamo allows quota targets on two demographics. In our implementation, quotas were applied to gender and age. The resulting sample is nearly balanced by gender (963 male and 929 female respondents; 50.9% vs. 49.1%). The age distribution is broad: 18–25 (11.3%), 26–30 (9.8%), 31–35 (11.4%), 36–40 (11.6%), 41–45 (8.6%), and 46+ (47.4%).

Overall, the gender and age composition closely matches the corresponding demographic statistics published by the National Bureau of Statistics of China, suggesting that the survey sample is broadly representative along these key dimensions.

Even for demographics that were not explicitly targeted by quotas—in particular province of residence and income—survey responses display substantial variation. As shown in Table 5, respondents are drawn from a wide range of provinces, with sizable representation from both coastal and inland regions. No single province dominates the sample, and the largest provinces each account for only a modest share of respondents, indicating broad geographic coverage.

Table 6 reports the income distribution. The median income falls in the 50,000–100,000 RMB annual income group, which is broadly comparable to national statistics.[9] About 11.5% of respondents report annual income above 200,000 RMB, which is consistent with the figures reported by Piketty et al. (2019).[10]

One concern regarding the income distribution in Table 6 is the relatively low coverage of low-income consumers: only 23.89% of respondents report annual income below 50,000 RMB. The underrepresentation of low-income individuals has two offsetting effects on $\Delta CS_i/W$: it tends to overstate median valuations in the numerator while also overstating median income in the denominator.

To further gauge the impact, Table 7 reports results from regressing the rejection decision (0/1) on offered compensation levels scaled by income. Using individual-level SBDC data, we find that rejection decisions are negatively correlated with compensation scaled by income and that low-income respondents exhibit higher rejection rates at a given compensation-to-income ratio. This suggests that our online sample, which underrepresents low-income individuals, would tend to understate $\Delta CS_i/W$, implying conservative welfare gains.

[9] Recent national statistics report that median income in 2025 is about 36,000 RMB; this figure includes the population below age 18. Piketty et al. (2019) estimate that the median income for residents aged 20 and above was about 35,000 RMB in 2015. Extrapolating this number using income growth reported by the statistical agency suggests that median income in 2025 should be about 60,000 RMB.

[10] Piketty et al. (2019) estimate that the top 10% income for residents aged 20 and above was 116,489 RMB in 2015. Again, extrapolating this number using income growth reported by the statistical agency suggests that top 10% income in 2025 should be about 200,000 RMB.

Table 5: Geographic Distribution of Survey Respondents

Province / State	Freq.	Percent	Cum.
Shanghai	49	2.59	2.59
Yunnan	46	2.43	5.02
Inner Mongolia	11	0.58	5.60
Beijing	91	4.81	10.41
Jilin	33	1.74	12.16
Sichuan	86	4.55	16.70
Tianjin	25	1.32	18.02
Ningxia	7	0.37	18.39
Anhui	42	2.22	20.61
Shandong	172	9.09	29.70
Shanxi	72	3.81	33.51
Guangdong	233	12.32	45.82
Guangxi	67	3.54	49.37
Xinjiang	14	0.74	50.11
Jiangsu	117	6.18	56.29
Jiangxi	68	3.59	59.88
Hebei	132	6.98	66.86
Henan	113	5.97	72.83
Zhejiang	78	4.12	76.96
Hainan	6	0.32	77.27
Hubei	59	3.12	80.39
Hunan	69	3.65	84.04
Gansu	12	0.63	84.67
Fujian	54	2.85	87.53
Guizhou	19	1.00	88.53
Liaoning	77	4.07	92.60
Chongqing	37	1.96	94.56
Shaanxi	48	2.54	97.09
Qinghai	8	0.42	97.52
Heilongjiang	47	2.48	100.00
Total	1,892	100.00	

Notes: This table shows the geographic distribution of survey respondents across provinces. Percent is the share of the full analysis sample ($N = 1{,}892$).

Table 6: Income Distribution of Survey Respondents

Income group	Freq.	Percent	Cum.
1 (below 10,000 RMB)	55	2.91	2.91
2 (10,000–20,000 RMB)	117	6.18	9.09
3 (20,000–50,000 RMB)	280	14.80	23.89
4 (50,000–100,000 RMB)	606	32.03	55.92
5 (100,000–200,000 RMB)	616	32.56	88.48
6 (above 200,000 RMB)	218	11.52	100.00
Total	1,892	100.00	

Notes: This table shows the income distribution of survey respondents. Income groups are self-reported annual personal income brackets in RMB; percent is the share of the full analysis sample ($N = 1{,}892$).

Table 7: Role of Sample Selection

	(1)	(2)
$log((E \times 12)/Income)$	-0.075	-0.123
	(0.002)	(0.004)
$HighInc$		-0.051
		(0.014)
$log((E \times 12)/Income) \times HighInc$		0.037
		(0.004)
App FE	Yes	Yes
Obs.	20,571	20,571

Notes: This table reports regression results where the dependent variable is the individual's rejection decision (0/1) and the key regressor is the offered compensation scaled by reported income. Column (2) additionally includes a high-income indicator and its interaction with scaled compensation. Respondents with reported income greater than 50,000 RMB are classified as high-income. Standard errors are reported in parentheses.

A.2 Demand Curves for the Top 10 Apps

This section describes the SBDC demand curves used to infer app-level valuations. For each app, we plot the fraction of respondents who reject an offer to give up access to the app for one month at seven app-specific compensation levels. We also overlay a fitted line relating the rejection rate to the logarithm of the compensation amount.

Figure 2 reports demand curves for the top five apps by MAU (Wechat, Taobao, Alipay, Amap, and Douyin). The curves reveal substantial heterogeneity in valuations, with Wechat exhibiting consistently higher rejection rates across compensation levels.

Figure 3 reports demand curves for apps ranked 6–10 (Pinduoduo, Baidu, QQ, Sogou Keyboard, and Baidu Maps). Relative to the top-five group, these apps generally exhibit lower rejection rates at comparable compensation levels, consistent with lower median WTA values.

Across all ten apps, rejection rates generally decline as compensation increases. We use these downward-sloping demand curves to recover the median monthly WTA values reported in Table 2.

B. Additional Robustness Checks

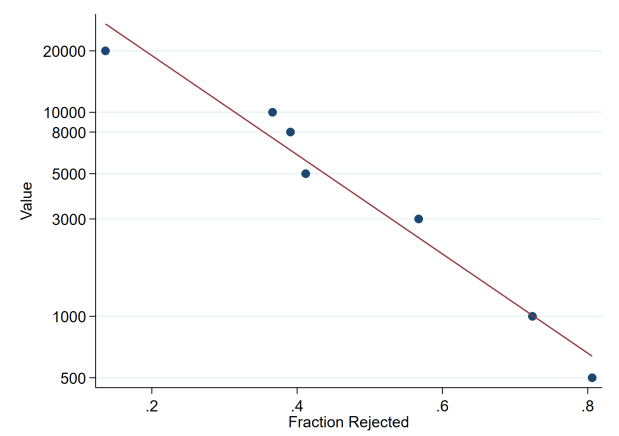
This section reports additional robustness checks. Table 8 reports the estimated elasticity of substitution across apps under alternative assumptions.

Accounting for nonusers.—In the SBDC surveys, we estimate median valuations by restricting the sample to respondents who report having used the relevant app in the previous month. To account for nonusers, we re-estimate median valuations using two approaches: (i) scaling down median valuations by the fraction of respondents who report using the app; and (ii) re-estimating median valuations under the assumption that individuals who do not use an app would accept any positive compensation.

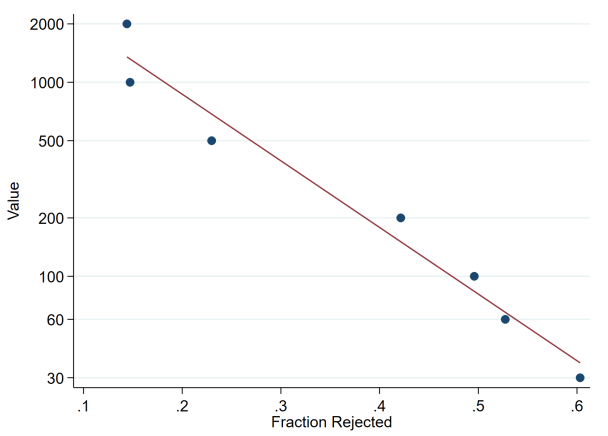
Columns (1) and (2) of Table 8 report the elasticity estimates under these adjustments (using the updated median valuations with $k = u$). Relative to the benchmark, accounting for nonusers has little effect on the estimated elasticity.

Alternative working hours.—In the benchmark estimate, we assume 40 working hours per week. Columns (3) and (4) of Table 8 report elasticity estimates assuming 35 and

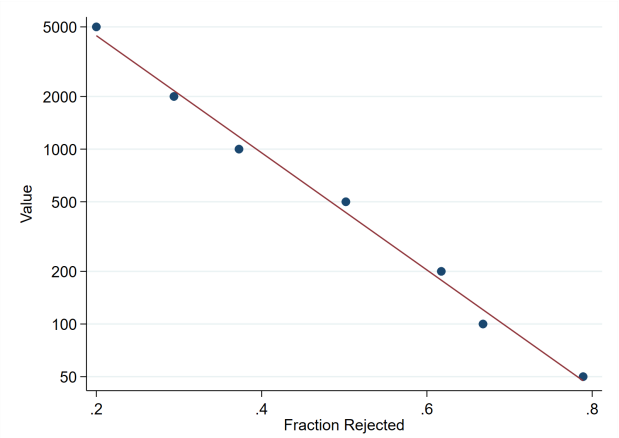
Figure 2: WTA Demand Curves for Top 5 Apps



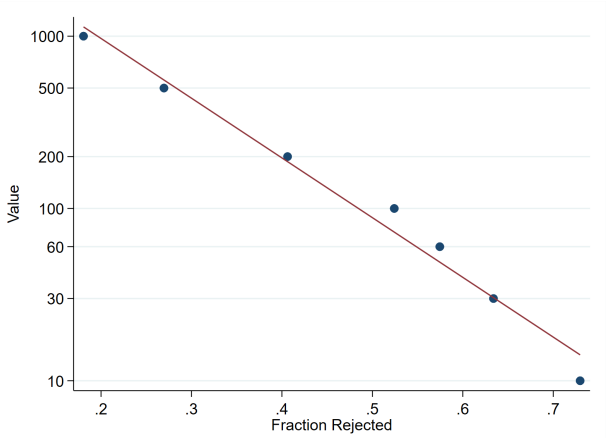
(a) Wechat



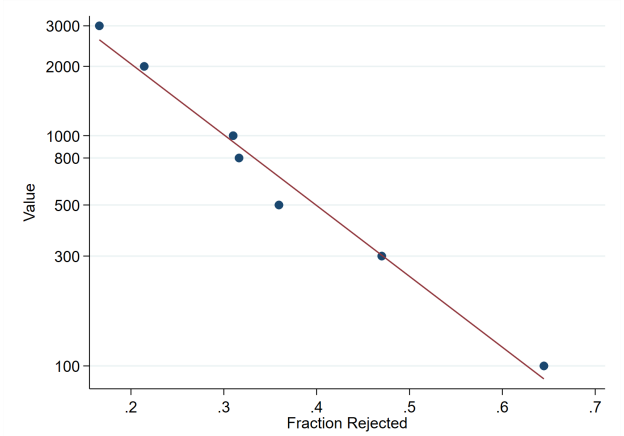
(b) Taobao



(c) Alipay



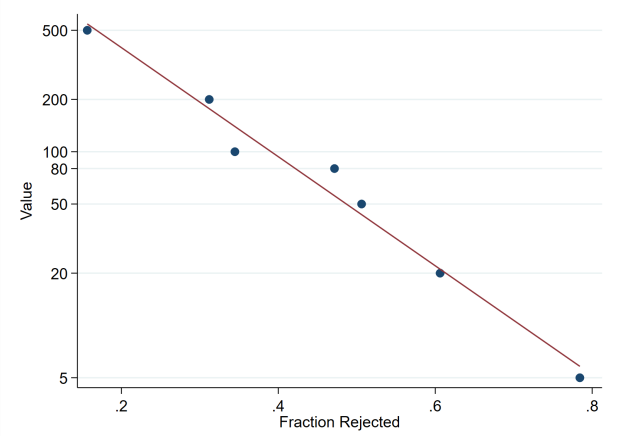
(d) Amap



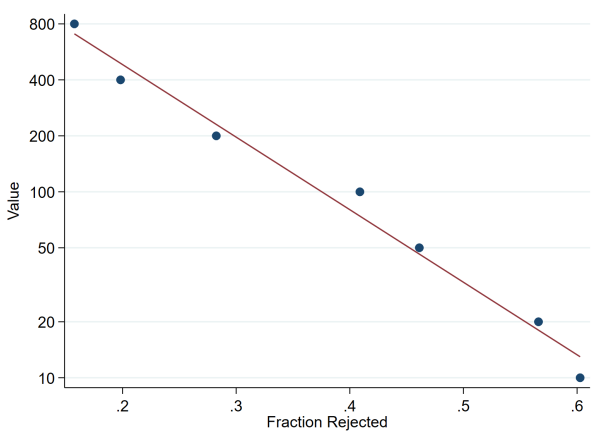
(e) Douyin

Notes: This figure shows SBDC demand curves for giving up access to the top five apps for one month. Each panel plots the fraction of respondents who reject the offer at seven experimentally assigned compensation levels and the corresponding fitted demand curve.

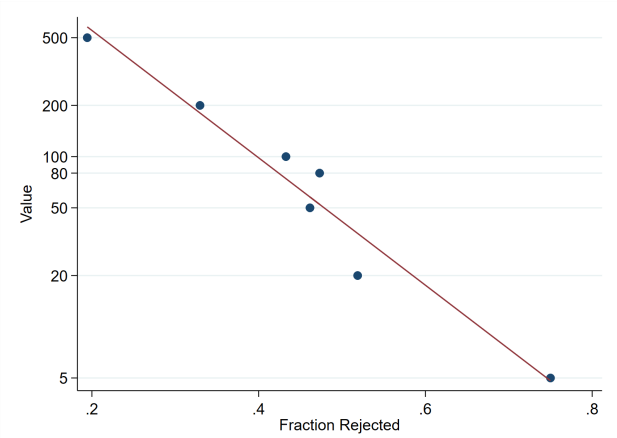
Figure 3: WTA Demand Curves for Apps Ranked 6–10



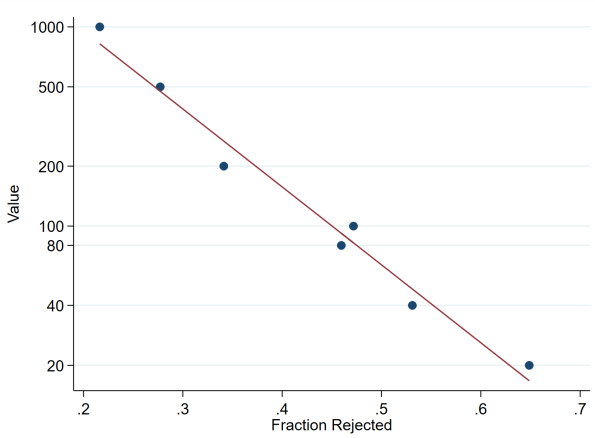
(a) Pinduoduo



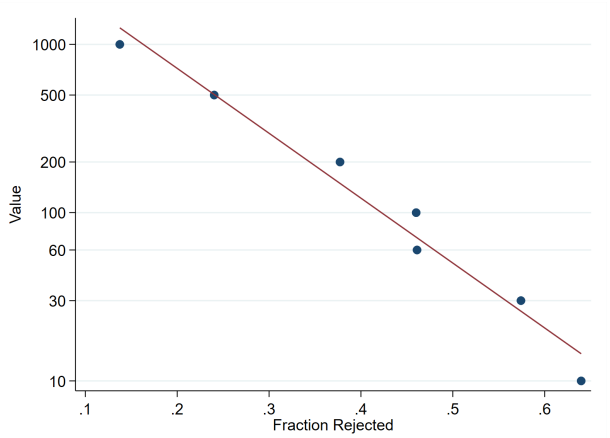
(b) Baidu



(c) QQ



(d) Sogou Keyboard



(e) Baidu Maps

Notes: This figure shows SBDC demand curves for giving up access to apps ranked 6–10 for one month. Each panel plots the fraction of respondents who reject the offer at seven experimentally assigned compensation levels and the corresponding fitted demand curve.

Table 8: Estimated Demand Elasticity Across Apps: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
σ	1.939	1.951	2.063	1.834	1.917	1.999	2.020
	(0.220)	(0.227)	(0.248)	(0.192)	(0.311)	(0.002)	(0.002)

Notes: This table shows robustness checks for the estimated elasticity of substitution across apps with income assumption $k = u$ but under alternative valuations. Column (1) scales median WTA valuations by the fraction of respondents who report using the app; column (2) updates the median valuation after accounting for nonusers; columns (3) and (4) use alternative assumptions of 35 and 45 working hours per week, respectively; and column (5) restricts the estimation to the top five apps. Columns (6) and (7) examine how a more elastic demand among non-top-10 apps affects the estimated elasticity. In particular, column (6) assumes an elasticity of 3 for apps outside the top 10, while column (7) assumes an elasticity of 4. Standard errors are reported in parentheses.

45 working hours per week, respectively. Assuming fewer working hours increases the elasticity estimate slightly. The impact of these alternative estimates on welfare gains are already reflected in Table 4.

Top 10 apps for elasticity estimation.—Our benchmark estimates use the top 10 apps to estimate the elasticity. Usage shares, however, vary substantially even within the top 10 apps. For example, Wechat's usage share is about 50 times that of Baidu Maps. Column (5) of Table 8 reports the elasticity estimate when restricting attention to the top five apps; the estimate remains similar to the benchmark.

Another concern with estimating elasticity using only the top 10 apps is that this restriction could bias the estimates, given that the sample includes more than 140,000 apps in 2025. However, this concern is mitigated by the highly concentrated distribution of attention across apps. The top 10 apps account for about 46% of total usage time, making them the primary source of variation for estimating the elasticity σ. To illustrate this point, we assume that apps outside the top 10 have a much more elastic demand and then re-estimate elasticity using the full sample. Specifically, we combine valuations for the top 10 apps from the SBDC survey with hypothetical valuations for the remaining apps, simulated using equation (14). Columns (6) and (7) of Table 8 report results assuming elasticities of 3 and 4, respectively, for apps outside the top 10. These

results suggest that even if apps outside the top 10 have a much more elastic demand curve, their impact on the estimated elasticity is small.

Role of behavioral biases.—Recent experimental evidence suggests that usage of some social media apps may exceed normative levels because of behavioral biases and self-control problems (e.g., Allcott et al., 2020, 2022). Although our framework focuses on welfare gains from expanding digital variety on the extensive margin, we can still assess how potential overuse affects the estimated welfare gains in equation (13).

We consider two exercises. First, the welfare-relevant weight of free digital consumption, ω_B, may be lower than that implied by the observed time allocation. We implement this adjustment by assuming that only 70% of consumers' time spent on social networks, short-video apps, and games contributes to ω_B.[11] Using the benchmark elasticity of $\sigma = 2$, the welfare gains from new apps remain sizable. Between 2018 and 2025, the expansion of digital variety raises welfare by about 6.4%, or about 0.9% per year on average.

Second, welfare gains from new apps depend crucially on their usage share. If new apps are more addictive than incumbent apps, the benchmark measure based on time shares could overstate welfare gains. To address this concern, we recompute the new-app share using user counts, which implicitly assumes the same usage intensity across apps. Using this user-count–based share yields welfare gains of about 13%. This result is consistent with the fact that new apps tend to have lower usage intensity (time spent per user). New apps are thus unlikely to be more addictive than incumbent apps in a way that drives our results.

[11] Allcott et al. (2022) estimate that about 30% of social media usage reflects self-control problems.