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

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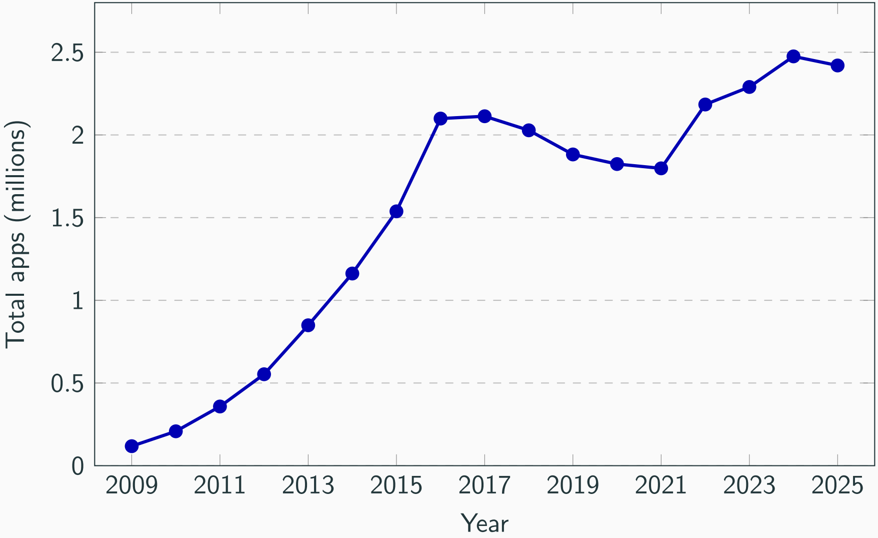
Total Apps in the US Apple App Store



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  - Number of available apps growing dramatically
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  - 91% smartphone penetration in the US, 2+ million apps (95% free)

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- **Digital consumption is exploding:**
  - Users across 80 markets on average now spend close to 4 hours per day in apps
  - 91% smartphone penetration in the US, 2+ million apps (95% free)
- **The measurement challenge:**
  - Free digital goods largely invisible in GDP (Brynjolfsson et al., 2025: AEJ Macro)
  - Welfare gains from variety expansion unexplored

TL;DR: Setup data, headline findings

What we do:

- Measure welfare gains from expanding digital variety using comprehensive app-level time-use data from China (2018–2025)
- Develop framework: Digital apps are free but compete for users' time
- Combine time-use data with survey-based valuations to estimate key parameters
- Quantify welfare impact of rapid expansion in digital variety

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Preview of findings

- Welfare gains: **8%** over 2018–2025 period
- Equivalent to **20% of income growth** in China
- Highlights quantitative importance of free digital goods for consumer welfare

Contribution to Existing Literature

1. **Time-use data and internet services**
   - e.g., Goolsbee & Klenow (2006), Brynjolfsson, Kim & Oh (2024)
   - Focus: Value of aggregate time online
   - Our contribution: Quantify welfare from *expanding digital variety*

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3. **Survey-based valuation of digital goods**
   - e.g., Brynjolfsson et al. (2019, 2026)
   - Focus: Individual services, less scalable
   - Our contribution: Combine surveys with time-use data + structural framework for scalable measurement

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Basically, CES demand aggregator over available digital apps within a Becker-style time-allocation framework.

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- Time shares linked with compensating variation via CES, allows recovery of σ with WTA estimates from surveys
- Welfare gains if new apps compete away attention from old apps ($\lambda \downarrow$, CES price index $\downarrow$, welfare $\uparrow$)

Model Setup

Utility: $U_t = \left[O_t^{\frac{\rho-1}{\rho}} + B_t^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}$ where $\rho > 0$ = elasticity between composites

Two composites:

1. **Other goods:** $O_t = C_t^{\alpha_O} L_{C,t}^{1-\alpha_O}$ (money C_t + time $L_{C,t}$)
2. **Digital apps:** $B_t = \left[\sum_{i \in \Omega_t} (\phi_i l_{i,t})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$
   - Time only (free); ϕ_i: quality; σ: elasticity; Ω_t: app set

Budget: $P_t^C C_t = W_t (1 - \sum_{i \in \Omega_t} l_{i,t} - L_{C,t})$ (expenditure = wage income)

Measuring Welfare Gains from Digital Variety

Comp Variation: Extra income in $t+1$ to reach same utility when app set fixed at t

$$\Delta CS = \left(\frac{P(P^C_{t+1}, W_{t+1} | \Omega_t)}{P_{t+1}} - 1 \right) W_{t+1}$$

Key: Welfare impact = price index changes

Time share of common apps: $\lambda_{t+1} = \frac{\sum_{i \in \Omega^*_{t,t+1}} l_{i,t+1}}{\sum_{i \in \Omega_{t+1}} l_{i,t+1}}$ where $\Omega^*_{t,t+1}$ = common apps

Price index: $\frac{P_{t+1}}{P(P^C_{t+1}, W_{t+1} | \Omega_t)} = \left(\frac{\lambda_{t+1}}{\lambda_t} \right)^{\frac{\omega_B}{\sigma - 1}}$

- ω_B: Sato-Vartia weight of digital composite B_t
- More new apps $\rightarrow$ lower λ $\rightarrow$ lower price $\rightarrow$ higher welfare
- Stronger when σ is low (less substitutable)

Final Formula and Measurement

Welfare gains: $\frac{\Delta CS}{W_{t+1}} = \left(\frac{\lambda_{t+1}}{\lambda_t}\right)^{\frac{\omega_B}{1-\sigma}} - 1$

Measurement:

1. λ_t**:** Time share of persisting apps (directly from time-use data)
2. ω_B**:** Time share on digital apps (from time-use data, Sato–Vartia weights)
3. σ**:** Elasticity of substitution
   - Combine time-use + survey WTA valuations
   - Regression equation: $\frac{\Delta CS_i}{W} = (1 - s_{i,t+1})^{\frac{\omega_{B,i}}{1-\sigma}} - 1$
   - Estimate via nonlinear least squares

Data: App-Level Time Use

Source: Leading data service provider in China

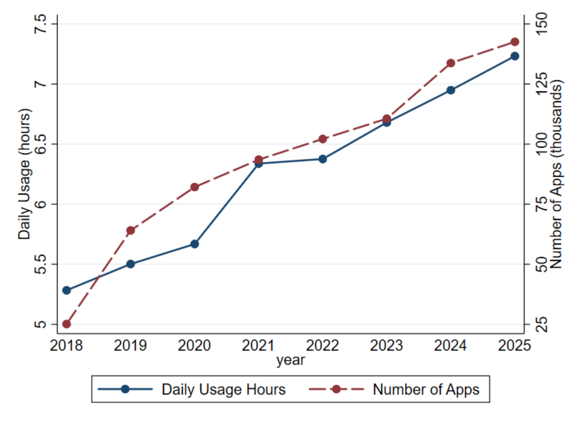
Coverage:

- Universe of apps with $\geq$ 10,000 minutes/month usage
- Monthly data: July 2018 – July 2025
- For each app: Total usage time, monthly active users (MAU)

Summary Statistics:

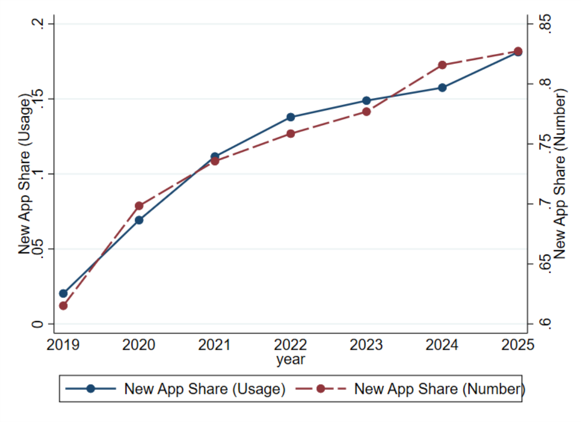
	Monthly Usage Time (million minutes)		Monthly Active Users (thousands)	
Year	No. Apps	Mean (Median)	Mean (Median)	Max
2018	25,119	367.87 (0.68)	951.42 (13.29)	940,345
2025	142,577	104.39 (0.54)	274.56 (28.26)	1,106,358

Rise of Digital Variety



- Daily usage: 5.3 hours (2018) → 7.2 hours (2025)
- Number of apps: 25,119 (2018) → 142,577 (2025)
- **5.7-fold increase** in app variety over 7 years

New Apps Attract Significant Attention



- New apps account for large share by count
- Smaller/niche but growing share of total usage time (eg. WeChat still accounts for 18%)
- Persistent expansion and gradual reallocation of user attention

SBDC Survey Design

Platform: Credamo (China)

Design: Single Binary Discrete Choice (SBDC) experiments

Question format:

> *"Starting tomorrow morning, would you give up Wechat for one month in return for a payment of RMB 5,000?"*

Sample:

- 2,000 respondents (1,892 after quality checks)
- Each respondent: 10 most popular apps by MAU
- Compensation: 7 levels per app (experimentally varied)
- Demographics: Age, gender, income, location
- Quality checks: Explicit attention check, fake app filter

Survey Design Screenshot

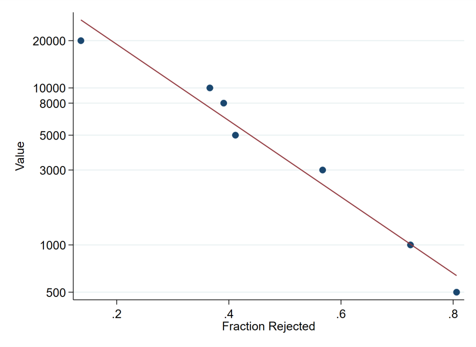
One of the top 10 apps shown in a random order

Choose Accept or Reject

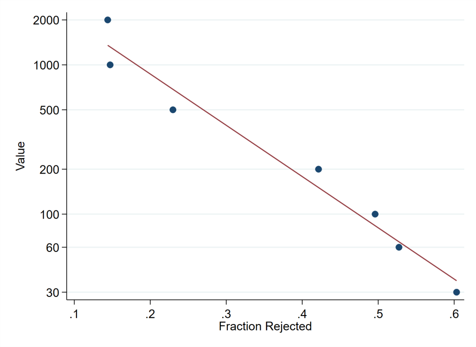
Starting tomorrow morning, would you give up Wechat for one month in return for a payment of RMB 1,000?

Randomly drawn from 7 app-specific values

WTA Demand Curves: Wechat and Taobao



Wechat



Taobao

Inferring median valuations: Plot rejection rate vs. log(compensation); fit demand curve; median WTA = compensation where rejection rate = 0.5. Wechat: Much higher (super-app); Taobao: Lower but substantial. 1,000 RMB ∼ 145 USD.

Survey Results: Median Valuations

App (Rank)	Median WTA (RMB/month)	95% CI
Wechat (1)	3,537.7	[2,739.9, 4,568.0]
Taobao (2)	81.0	[55.6, 118.1]
Alipay (3)	440.5	[379.5, 511.2]
Amap (4)	88.5	[69.7, 112.2]
Douyin (5)	244.9	[195.3, 307.1]
Pinduoduo (6)	45.4	[35.4, 58.2]
Baidu (7)	32.6	[24.9, 42.7]
QQ (8)	41.6	[28.8, 59.9]
Sogou Keyboard (9)	63.9	[49.8, 82.0]
Baidu Maps (10)	50.2	[36.3, 69.4]

Key finding: Wechat has substantially higher valuation than others (super-app in China)

Measuring Compensating Variation from Data

How to measure $\frac{\Delta CS_i}{W}$ from survey data:

$$\frac{\Delta CS_i}{W} = \frac{WTA_i \times 12}{Income^k} \times 35.7\%$$

- WTA_i: Median monthly WTA from survey
- $Income^k$: Annual income (median: 50,000–100,000 RMB)
  - $k = l$: 50K; $k = m$: 75K; $k = u$: 100K RMB
- 35.7%: Working time fraction (40 hrs/week, 112 hrs/week total, 8 h sleep)

Regression equation:

$$\frac{\Delta CS_i}{W} = (1 - s_{i,t+1})^{\frac{\omega_{B,i}}{1-\sigma}} - 1$$

where $s_{i,t+1} = \frac{l_{i,t+1}}{\sum_{i \in \Omega_{t+1}} l_{i,t+1}}$ is time-use share

Estimation: Nonlinear least squares to recover σ

Estimated Elasticity of Substitution

Elasticity estimates under alternative income assumptions:

Income assumption	Median	Upper CI	Lower CI
Lower (50K RMB)	1.483 (0.107)	1.381 (0.082)	1.613 (0.138)
Midpoint (75K RMB)	1.708 (0.162)	1.557 (0.125)	1.904 (0.209)
Upper (100K RMB)	**1.934 (0.217)**	1.732 (0.168)	2.195 (0.280)

Benchmark: $\sigma = 2.0$ (conservative, using upper income threshold)

Key insights:

- Larger valuations relative to income $\rightarrow$ lower σ estimates
- Welfare gains are *decreasing* in σ
- Lower σ = less substitutable = larger variety gains

Welfare Gains from Digital Variety

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

Main result: 8.08% cumulative welfare gain by 2025 (benchmark)

Putting the Results in Context

Welfare gains: 8% over 2018–2025

- Average: $\sim$**1% per year**
- Steady growth over time

Comparison to income growth

- China GDP per capita growth: $\sim$**5% per year**
- Digital variety gains: $\sim$**20% of income growth**

Quantitatively important source of welfare growth

Takeaways

1. **Main finding:** Digital variety expansion raises consumer welfare by **8%** over 2018–2025
2. **Magnitude:** Equivalent to **20% of income growth** in China
3. **Method:** Time-use data + structural framework enables scalable welfare measurement
4. **Implication:** Free digital goods are quantitatively important for welfare

Robustness Checks and Discussion - I

Estimating elasticity using the top apps

- **Benchmark:** estimate σ using SBDC valuations for the **top 10 apps** + observed time-use shares
- **Why top 10 is informative:** attention is concentrated (top 10 apps $\approx$ 46% of total usage time)
- **Simulation check:**
  - Combine survey valuations for top 10 with *simulated* valuations for the remaining apps (using the demand equation)
  - Assume non-top-10 apps have higher elasticity of 3 or 4 and re-estimate σ using the full app universe (remember: lower σ = higher welfare)
  - **Result:** $\sigma = 1.999$ (SE 0.002) or $\sigma = 2.020$ (SE 0.002)

Robustness Checks and Discussion - II

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

Role of behavioral biases and overusage

- **Concern: Weight of free digital goods should be smaller**
  - assume only 70% of time on social networks, short-video, and games contributes to ω_B (Allcott, Gentzkow and Song, 2022)
  - welfare gain (2018–2025) = 6.4% or 0.9% per year
- **Concern: New apps are more addictive**
  - usage $l_{i,t} = MAU_{i,t} \times \frac{l_{i,t}}{MAU_{i,t}}$
  - recompute new-app penetration using user-count shares (equal usage intensity)
  - welfare gains $\approx$ 13% $\Rightarrow$ new apps are unlikely to be "more addictive" in a way that drives results (remember: people spend less time with them)

Robustness Checks and Discussion - III

✓ Accounting for nonusers

- Scaling median down by usage rates or re-estimating WTA assuming nonusers accept any positive compensation yield similar estimates

✓ Alternative working hours

- 35–45 hours/week: similar results

$\rightarrow$ Results robust across specifications

Extensions

- σ not the same across app categories
  - Nested CES is possible but costly.
- Reasonable to assume more time spent = higher value?
  - We observe this empirically with surveys
- Relax Feenstra assumption of constant quality
  - Welfare gains would be larger. Regular surveys can help
- Can apps be complements?
  - In terms of leisure time at least they should be substitutes
- Digital consumption substitutes non-digital?
  - Possible. Can be specified, doesn't change welfare estimation

Limitations and Caveats

Assumptions:

- CES structure (constant elasticity)
- Representative consumer
- Survey valuations reflect true WTA

What we abstract from:

- General equilibrium effects
- Quality changes (focus on variety)
- Negative externalities (addiction, misinformation)

Nonetheless: Provides transparent, tractable method for measuring welfare gains from free digital variety.

Appendix: Survey Design Details

Sample characteristics:

- 1,892 respondents (after quality checks)
- Nearly balanced by gender (50.9% male, 49.1% female)
- Broad age distribution (18–46+)
- Geographic coverage: All major provinces

Quality checks:

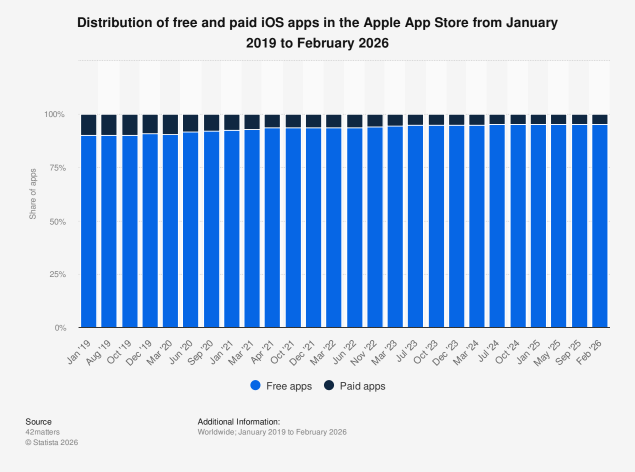
- Explicit attention check
- Fake app filter (excluded 108 respondents)
- Income validation

Appendix: Additional Robustness

Specification	σ	(SE)
Account for nonusers (scaled)	1.939	(0.220)
Account for nonusers (re-estimated)	1.951	(0.227)
35 hours/week	2.063	(0.248)
45 hours/week	1.834	(0.192)
Top 5 apps only	1.917	(0.311)

All estimates close to benchmark ($\sigma = 1.934$)

Appendix: Share of free apps in the United States



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